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Seog-Chan Oh
Alfred J. Hildreth

# Analytics for Smart Energy Management

## Tools and Applications for Sustainable Manufacturing

Springer

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# Preface

## Subject

The growing awareness of energy demand and concerns about climate change from within the manufacturing industry as well as the public and legislators has created the concept of sustainable manufacturing. The purpose of sustainable manufacturing is to process resources into products while keeping the equilibrium with ecological, social, and financial systems. Smart energy management is a key component required to realize sustainable manufacturing where analytics are considered as an effective means to achieve the smart energy management. Although analytics have been popularly used by energy utility companies in the energy-sourcing sector, the energy-consuming sector including the manufacturing industry has little benefit to date from analytics due to the lack of suitable tools and applications.

This book is written to introduce analytical tools and applications with illustrative examples with an attempt to address issues and problems raised during the process of realizing smart energy management for sustainable manufacturing focused on automotive manufacturing industry. This book would be distinguishable because it targets the energy management of automotive manufacturing facilities, which involves most types of manufacturing technology and various levels of energy consumption. Through illustrative applications of analytics to automotive manufacturing, this book will demonstrate how analytical tools can help improve energy management processes including forecasting, consumption, performance analysis, and emerging new technology identification as well as investment decision for establishing smart energy consumption practices. Analytical tools introduced in the book include stochastic frontier analysis, data envelopment analysis, machine learning for pattern detection and recognition, activity-based forecasting, stochastic optimization as well as energy process simulation.

This book also details practical energy management systems in the last two chapters to round out the theory portions in earlier chapters, making it a valuable resource for professionals involved in real energy management processes.

## Audience and Style

The intended audience of this book includes:

- Graduate school students including engineering programs, technology management programs, and MBA programs
- Third/fourth-year undergraduate students pursuing environment engineering, mechanical engineering, civil engineering, industrial engineering, and management information system (MIS) degrees
- Practitioners in the areas of energy and environment management with an interest in using data or model-driven analytics

This book uses mathematical formulations of various analytical solutions aligned with smart energy management processes including forecasting, simulation, performance analysis, decision making, and operation. However, this book emphasizes the practical application of theories and interpretations of the mathematical formulations by introducing various illustrative examples. Moreover, this book provides exercises at the end of each chapter and manuals for Excel Solver, Python and EnergyPlus$^{TM}$ in Chaps. 2, 5, and 7, allowing readers to implement the presented procedures and applications in their projects and studies.

Instructors may use this unique book style to bring in rich learning benefits for students. If a student is a working professional involved in real energy management processes, he/she may replicate procedures presented in this book to implement new projects in his/her facility or practice. If a student is a full-time student without practical experience, meanwhile, he/she can earn rich industry knowledge, therefore, become better prepared for future industry carrier.

## Acknowledgements

The book reflects intuitions, experiences and material that the authors have acquired from real-world projects. We would like to thank numerous people who had been involved in those projects.

Our special thanks to Mr. Anthony Doyle, Senior Editor, Engineering at Springer London, for his kind invitation in publishing this book and also to all of those involved in the publication process.

We also would like to thank to our family members for their support and encouragement through the preparation of this book: Ki-Won Oh, Alex Oh, and Frances Hildreth.

March 2016

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# Contents

# Chapter 1
# Introduction

**Abstract** The goal of this chapter is to introduce subjects and methods covered in this book and give an overview of the remaining chapters. It first gives the background of sustainable manufacturing and reviews energy consumption in US automotive industry. Then, it discusses the energy and environment management in the automotive industry. It also discusses the idea of using data and model-based analytics for smart energy and environment management. To provide a flavour of approaches used in this book, a cost comparison of pneumatic and electric actuator systems is illustrated as an example decision problem in energy management. Compressed air is frequently used in manufacturing plants to power pneumatic actuators, which are used for many applications including clamping, loading and spray-painting. On average, compressed air accounts for more than 10 % of total energy costs in a manufacturing plant. Unfortunately, it is highly inefficient because as much as 50 % of compressed air can be lost through leaks or excess pressurization in the distribution system. Given these flaws of compressed air, it becomes an important decision problem to compare the cost of pneumatic and electric actuators (as an alternative to pneumatic actuators) and find the right solution. Lastly, this chapter provides summaries of the contents of the remaining chapters in this book.

## 1.1 Background of Sustainable Manufacturing

The growing awareness of global energy demand issues has become one of major contributors to create the concept of sustainability. According to International Energy Agency, the average energy use per person has increased 10 %, while the world population has increased 27 % from 1990 to 2008. Energy-related $CO_2$ emissions are expected to rise from an estimated 31.2 Gt in 2011 to 37.0 Gt in 2035. The concept of sustainability was first used to describe an economic vision in equilibrium with basic ecological support systems in the 1970s. The concept has since been applied to a wide range of areas, including government and industry, thus, motivating the change in energy consumption trends.

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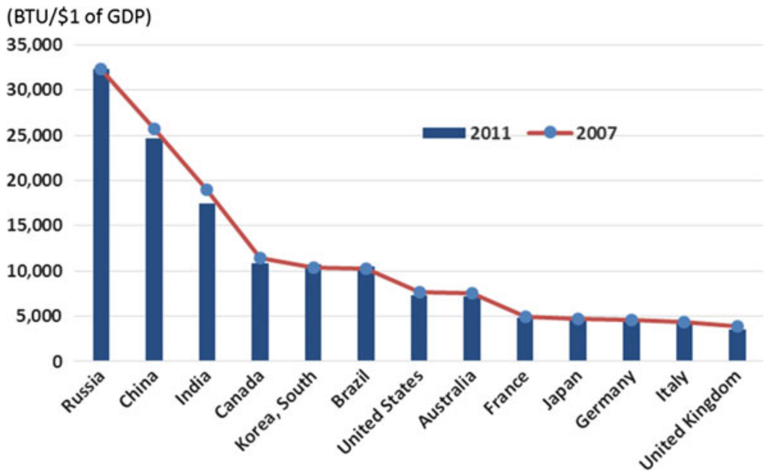


**Fig. 1.1** Total primary energy consumption per dollar of GDP (Btu per year 2005 U.S. dollars) for 13 countries with the largest gross domestic product (*GDP*) (*Data source* U.S. Energy Information Administration)

Moving toward sustainability, many countries are proactively taking strategic actions to establish energy and environment legislation and to limit carbon emissions in order not to compromise energy needs of future generations. Their efforts have cut the energy and carbon intensity as shown in Figs. 1.1 and 1.2 where figures show the total primary energy consumption per dollar of GDP (Btu per Year 2005 U.S. dollars) and the carbon intensity for 13 countries with the largest gross domestic product (GDP), respectively.

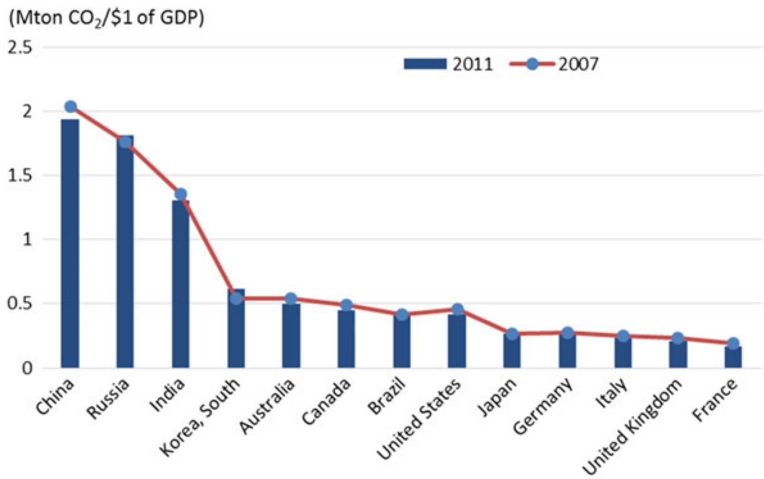


**Fig. 1.2** Carbon intensity per dollar of GDP (metric tons of carbon dioxide per thousand year 2005 U.S. dollars) for 13 countries with the largest gross domestic product (*GDP*) (*Data source* U.S. Energy Information Administration)

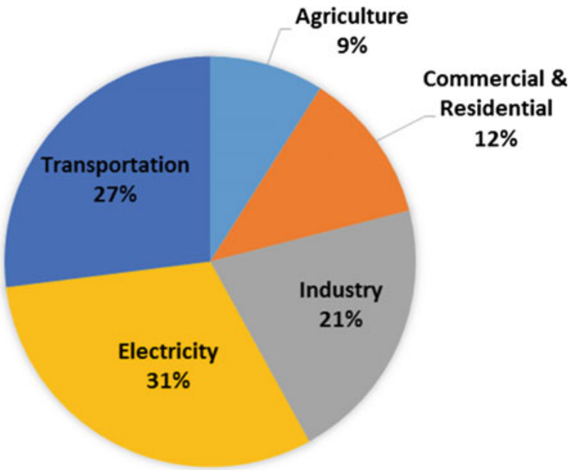


**Fig. 1.3** Greenhouse gas emissions by sector (Environmental Protection Agency 2013)

Regarding energy consumption and greenhouse gas emission by sector, the industrial sector consumes about 52 % of the energy worldwide, implying that the industry is one of the main drivers of increasing electricity demand worldwide. Two major sources contributing to greenhouse gas emissions are the industrial sector and electricity generation. Figure 1.3 presents US greenhouse gas emission by section in 2013. It indicates and recognizes the importance of implementing measures toward sustainable manufacturing in the industrial sector.

There are three primary reasons that are driving the manufacturing industry to move toward sustainable manufacturing. The first compelling driver is a financial reason to reduce energy costs. It is true that a bulk of the energy consumed for enabling manufacturing operations is used to add value from raw materials or intermediates products to final products, and therefore, the energy savings influence a company's bottom line positively. The second driver is the compliance with stringent energy and environmental regulations enacted by countries around world in response to increasing climate change. The third driver is the enhanced marketability of products and services because the producing companies are recognized as environmentally friendly.

Although the benefits from addressing aforementioned three drivers are clear: energy conservation, a reduced environmental impact and an enhanced competitive position, the concept of sustainability presents huge challenges to manufacturing companies in the automotive industry. The reason for this challenge is because the automotive manufacturing industry contributes large amounts of energy consumption and $CO_2$ emissions directly from their facilities or indirectly due to their long and complex supply chain and also puts in place almost all kinds of manufacturing technology, requiring energy consumption at various levels. However, at the same time, this challenge might be a chance for a company to gain competitive advantages over other companies.

## 1.2 Energy Consumption Review in the US Automotive Industry

Regarding the energy use associated with the U.S. automotive enterprise, over 200 trillion BTU (British thermal units) per year has been roughly estimated, as shown in Fig. 1.4. Note that auto-manufacturing industries include motor vehicle manufacturing, motor vehicle body and trailer manufacturing, and motor vehicle parts manufacturing classified in NAICS (North American Industry Classification System).

However, if a complex supply chain is included in calculating the contribution, the total energy consumption related to the car manufacturing industry will be considerably greater, as the complex supply chain includes the following: producing raw materials, such as steel, aluminum, plastics, and glass; forming and fabricating parts, components, and subsystems; assembling hundreds of these elements to manufacture the vehicles; and distributing and selling the vehicles.

Table 1.1 summarizes and compares the intensity of utility use (e.g., electricity/vehicle, fuel/vehicle and water/vehicle) and carbon emission to produce one vehicle among major car companies. Note that Scopes 1 and 2 refer to the direct emissions by the firm at its installations and to the indirect emissions by the firm through electricity use, respectively. Scope 3 often refers to supply chain emissions. Some car making companies report their Scope 3 emissions to the Carbon Disclosure Project (CDP), which is an independent organization supported by major

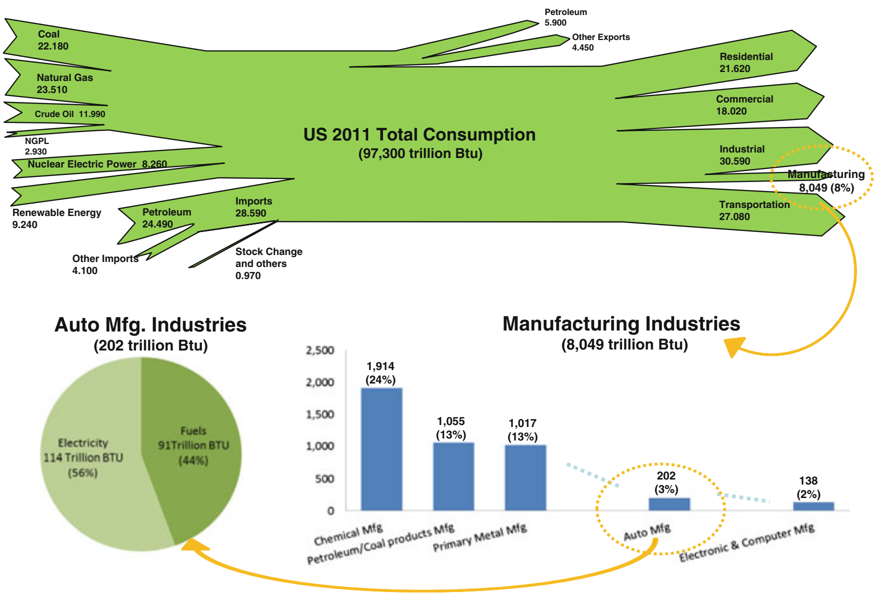


**Fig. 1.4** Energy flows into the US auto manufacturing industry 2011 (*Data sources* 2011 Annual energy review and 2011 Annual survey of manufacturers available in US Census Bureau)

**Table 1.1** Resources used to manufacture a vehicle (2012)

| Intensity (use/vehicle) | GM | Volkswagen | Ford | BMW | Toyota (North America) | Equivalence |
|---|---|---|---|---|---|---|
| Energy (electricity + fuel) MWh/vehicle | 2.30 | 2.21 | 2.45 | 2.44 | 2.13 | Energy for the production of 4 vehicles equals approximately the average annual electricity consumption for a U.S. residential utility customer |
| Carbon (scope 1 and 2) ton/vehicle | 0.88 | 0.89 | 0.9 | 0.68 | 0.78 | Carbon emitted from the production of 1 vehicle equals approximately the carbon offset of 80 trees grown for 10 years |
| Water $m^3$/vehicle | 4.62 | 4.55 | 4.3 | 2.1 | 3.41 | Water for the production of 1 vehicle is similar to that required to fill a small pool |

institutional investors. Note that the energy data in this section are based on on-site energy consumption except that the flow diagram in Fig. 1.4 is based on the source Btu and the carbon emission amount in Scopes 1 and 2 emission types in Table 1.1 includes the indirect emission for purchased utilities in the energy generation sites.

Figure 1.5 depicts the magnitude of total energy consumption in the car manufacturing industry compared to Boeing and major US government agencies; as shown, energy consumption in the car manufacturing industry is considerably greater, with the exception of the U.S. Department of Defense, with an energy consumption of approximately 900 trillion BTU.

Although the total energy consumption is large, the energy intensity of the car manufacturing industry is not so large. When energy intensity is calculated as the share of total energy expenditures (electricity and fuel) as a fraction of total operating expenditures (the sum of materials' costs, labor compensation and new capital expenditures), the U.S. motor vehicle manufacturing industry (NAICS code: 3361) is merely 0.4 %, compared to other energy intensive industry. For example, the energy intensity of the U.S. lime manufacturing (32741) and the U.S. industrial gas manufacturing industries (32512) is 37.15 and 34.60 %, respectively.

Although the expense may be a small portion of operating expense, the cost and environmental impact is significant for many companies. As an example, at General Motors (GM), although the expenditure for energy is less than 1 % of total expenses, the cost is in excess of $1 Billion USD annually.

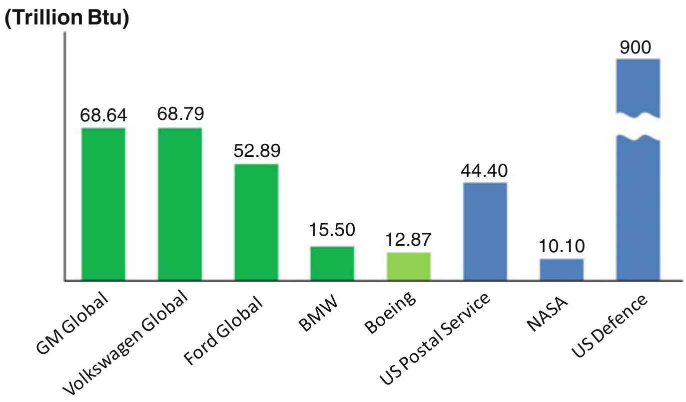


**Fig. 1.5** Energy consumption in auto manufacturing industries in 2011 (*Data sources* 2011 Annual energy review and 2011 Annual survey of manufacturers available in US Census Bureau)

When sustainability is the main issue in an automotive manufacturing company, the company need to make a strategic choice considering following factors among many:

- Energy sources (currently available) for manufacturing facilities that minimize greenhouse gas emissions and carbon footprint
- Efficient technologies that reduce demand for energy at manufacturing facilities
- Impact of government legislation—proactively addresses future legislation and emissions caps
- Changes in regulatory environment that impacts emission standards
- Cost of energy supply sources, corresponding investment cost and expected payback
- Future grid price volatility and risk exposure/tolerance
- Robust energy management process to meet the fiscal and environmental responsibility of businesses to remain sustainable and satisfy investors' and customers' demands
- Systematic approach to gain company support and funding for new energy efficiency projects and to track each project to demonstrate accountability

The purpose of sustainable manufacturing is to process resources into products while keeping the equilibrium with ecological, social, and financial systems. Smart energy management is a key component required to realize sustainable manufacturing and analytics are considered as an effective means to achieve the smart energy management. Although analytics have been popularly used by energy utility companies in the energy-sourcing sector, the energy-consuming sector including the manufacturing industry has little benefit to date from analytics due to the lack of suitable tools and applications. This book will introduce analytical tools and applications with illustrative examples with an attempt to help realize smart energy management for sustainable manufacturing focused on automotive manufacturing industry. Accordingly, the next section will overview energy and environment management in automotive manufacturing industry.

## 1.3 Energy and Environment Management in Automotive Manufacturing

A typical automobile manufacturing process generally consists of three main processes: body shop, paint shop, and general assembly. The body shop transforms raw materials into the structure of the vehicle. Then, the paint shop applies a protective and visual coating to the product. Finally, the general assembly assembles all sub-components, such as the engine and seats, into the vehicle.

Two main types of energy utility used in a typical vehicle assembly plant are electricity and fuel (including natural gas). In general, fuel is used for direct heating or to generate steam that is considered as a secondary utility similar to compressed air in vehicle assembly plants. Steam is then used mainly in painting but is also utilized for space heating, car wash and other non-manufacturing activities. Electricity is the main energy source in vehicle assembly plants, and its main uses are painting, HVAC (heating, ventilation, and air conditioning), lighting, compressed air systems, and welding and materials handling/tools.

Figure 1.6 associates automotive manufacturing operations with the distribution of their energy use. Four identified largest energy-consuming operations are painting (27–50 %), HVAC and lighting (11–20 and 15–16 %, respectively), and

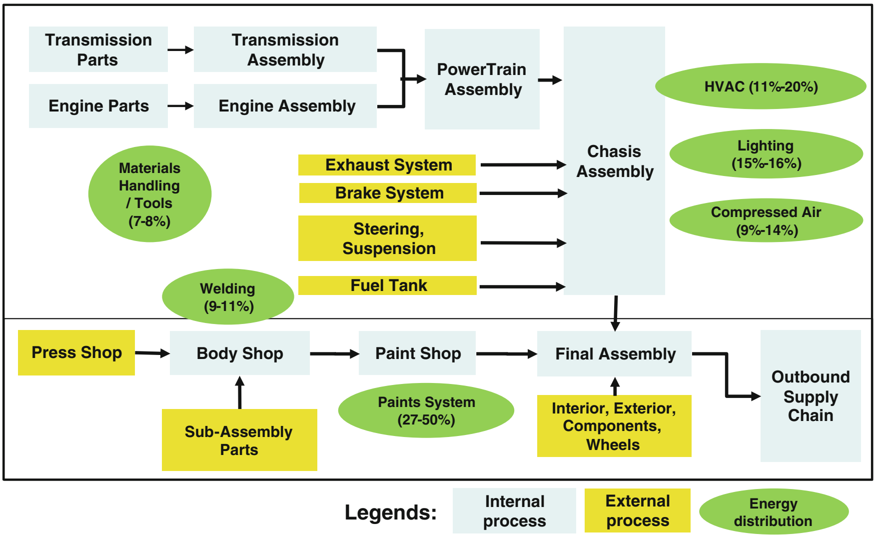


**Fig. 1.6** A typical vehicle assembly process and its energy distribution—modified from (US DOE 2008)

compressed air (9–14 %). Each of major energy-using activities in the current automotive production process and several energy saving opportunities (US DOE 2008) are as follows:

- Painting: The process of painting cars is the largest source of energy consumption in the car making process. Along with the drying or baking of the cars after a new coat of paint is applied, energy is consumed to remove volatile organic compounds (VOCs) from the air so they are not allowed to be released into the atmosphere. In addition to adjusting the air temperature, energy is used to increase the temperatures of the car bodies as well as the mechanisms carrying the car bodies. Ventilation is also a significant consumer of energy in the painting process. Potential energy saving opportunities can be found in new technologies, such as wet-on-wet painting system, infrared (IR) paint curing, ultraviolet (UV) paint curing, carbon filters and other VOC removal processes.
- Lighting: The lighting may waste energy by simply by having lights on when they are not needed. In response to this, suggestions have been made to have lighting controlled remotely or by artificial intelligence to shut off lights when production or maintenance is not occurring. Potential energy saving projects include daylight utilization, light emitting diodes (LEDs) or radium strips utilization.
- Heating ventilation and air conditioning (HVAC): The amount of energy used for the HVAC system of a plant will vary by location and season due to the required temperature difference between the inside of a plant and its external environment. Potential energy-saving opportunities include solar heating, setback temperatures on weekends, recovering cooling water from other sources to use in cooling chillers, and energy efficient chillers.
- Compressed air: Compressed air is a vital secondary utility in a car making facility, but due to its poor efficiency, it is considered quite expensive. The overall efficiency from start to end use of compressed air is relatively low compared with other utilities; thus, monitoring for leaks and reducing waste become important in the compressed air processes. Potential energy-saving projects include the design of distribution system to minimize pressure drops, proper regulator sizing, leak reduction in pipes and in equipment, and energy efficient automatic compressor load balancing and management.
- Body welding and stamping: Automation levels of body shop or stamping activities are relatively high, so it is not easy to improve energy efficiency without introducing game-changing green technologies. Compressed air is a major energy consuming utility in the body shop and in stamping activities. Potential energy saving technologies include high-efficiency welding/inverter technology utilization and rapid freeform sheet metal forming.
- Material handling/tools: There are a significant number of belts used in various motors in vehicle assembly plants as well as mobile assets, such as forklifts and aerial lifts to move parts. Potential energy saving opportunities include mobile asset scheduling to increase equipment utilization and the utilization of high efficiency cog belts.

Galitsky and Worrell (2008) collected energy efficiency improvement opportunities available to car manufacturers. They identified many energy efficiency improvement opportunities for each automotive manufacturing operation.

## 1.4 Smart Energy and Environment Management Using Data and Model-Based Analytics

Analytics means the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions (Davenport and Harris 2007). Simply, analytics is a set of technology and processes that use data to understand and analyze business performance. As Fig. 1.7 suggests, people should think about the use of analytics in three stages: description, prediction, and prescription. Each of these stages addresses a range of questions about an organization's business practices and present the higher value.

Today, most large organizations do not worry much about the description stage because probably they have already been through. This stage is all about collecting data in databases which have to be designed for the purpose. For example, across all of U.S. facilities, GM now monitors about 2.5 million points of energy data per minute. They monitors energy use to ensure non-production shutdown levels and that heating, ventilating and air conditioning ("HVAC") equipment meets targets. To adequately manage this amount of data, GM developed a dashboard system called "Energy OnStar" that was, in particular, developed for HVAC systems. With Energy Onstar, GM plants can easily compare hourly performance of HVAC equipment and their energy use to various targets—heat/cool energy, fan energy, outside air index and rate, runtimes, temperature setpoints, supply air index and hourly energy intensity.

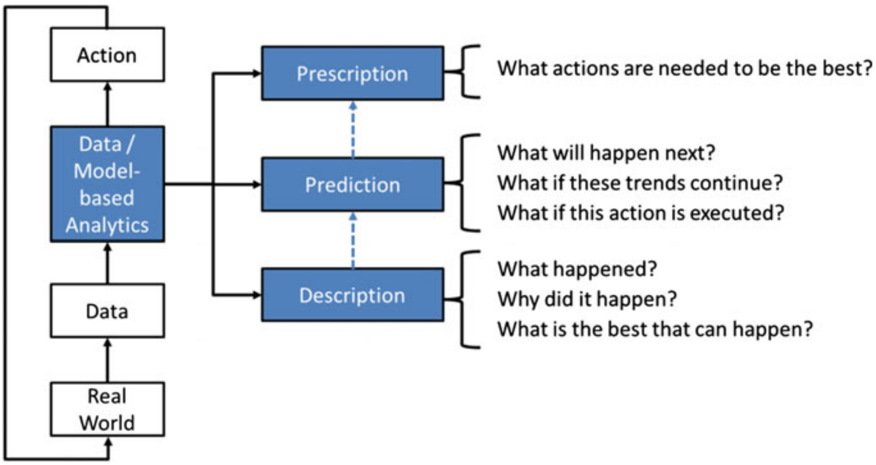


**Fig. 1.7** The role of data/model-based analytics

The prediction is considered a stage to embrace with much more urgent need. Thanks to today's good information management capabilities to integrate, extract, transform, and access business transaction data, it is well allowed to look at their historical data but also to predict behavior or outcomes in the future. For example, GM developed a patent-protected activity based energy accounting (ABEA) method (Oh and Hildreth 2013) to improve the accuracy of forecasting for plants with extraordinary circumstances which are becoming more prevalent. ABEA is based on the fact that the operation of a production facility requires distinct levels of energy depending on different activities such as full-capacity production, reduced-capacity production, and non-production. The method first obtains highly accurate hourly energy use rates for different energy use activities and the rates are used to estimate the amount of energy that will be consumed during a subsequent time period. One advantage of the method is easily tailored to the flexible production schedule so that it can minimize the problems caused by over- or under-estimation of energy use with standard multi-variable regression analysis models. There are five distinct states which the manufacturing system can be in at any given time and each state has a different energy load characteristic. More details regarding this method will be described in Chap. 4.

The third most advanced stage of data analytics is to investigate the opportunities of the future—the prescription stage—that must command strong attentions from decision makers. In this stage, the role of human translators is especially important because they can reframe the complex results from data analytics as actionable insights that generalist managers can execute. In this stage, some of complex mathematical methods are required including frontier benchmarking analysis using SFA (stochastic frontier analysis) or DEA (data envelopment analysis) to identify what is the best that can happen and stochastic optimization models to identify what actions are needed to be the best. Chapters 2 and 3 in the book will discuss over these topics.

Meanwhile, Fig. 1.8 depicts a mapping between each stage of analytics and its typical methods and tools. Due to the broad range of applications and data in energy and environment fields, various analytical tools and methods are introduced and used in this book. A short summary of the analytical methods covered in this book for energy and environment fields is as follows. Readers will find the details of each method in the related chapter.

- Stochastic Frontier Analysis (SFA): SFA was introduced by Aigner, Lovell and Schmidt (1977) as a benchmarking method targeting on economic modeling. SFA aims to form a frontier line that can be considered an optimal combination of outputs producible from a set of inputs (or an optimal combination of outputs with the lowest inefficiency). Main advantage of using SFA is to distinguish between inefficiency and noise with sufficient accuracy. Chapter 2 uses SFA to measure the effectiveness of energy saving initiatives for the automotive industry, particularly vehicle assembly plants.

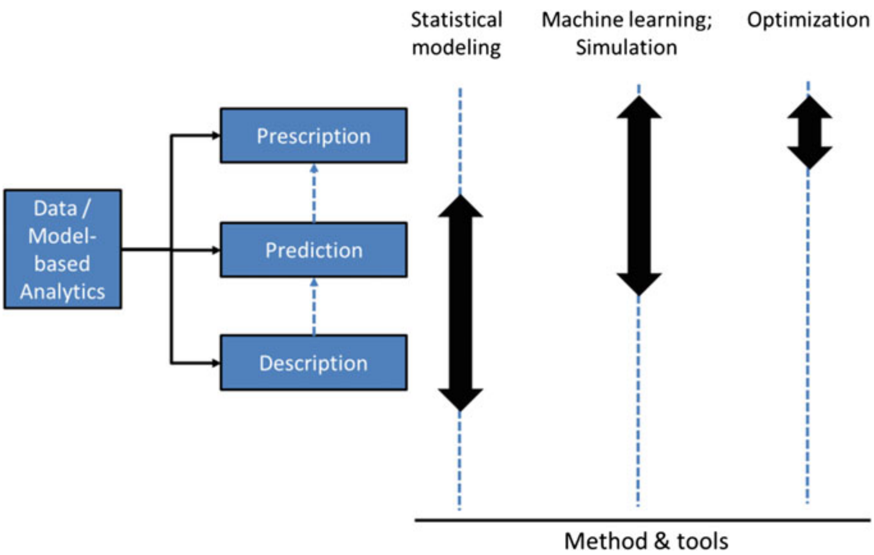


**Fig. 1.8** Typical method and tools for each stage of analytics

- Ordinary Least Square (OLS): OLS means a linear regression model that aims to find a line such that the sum of squares of the errors of a line passing through the data is minimized. OLS reveals overall sample-based information, representing average practices. Meanwhile, Corrected OLS (COLS) aims to find a frontier line by shifting an OLS line up (production model) or down (cost model) until a single observation with a measured efficiency index of one remains. This method is still often used due to its simplicity in real fields where the capability of more advanced benchmarking technologies are not well-developed.
- Maximum Likelihood Estimation (MLE): MLE is a method to estimate parameters when a parametric modeling is adopted as a principle for the model building. The likelihood function indicates how likely the observed sample can be accounted as a function of possible parameter values. Therefore, maximizing the likelihood function estimates the parameters that are most likely to produce the observed data. Chapter 2 uses this method to estimate parameters of SFA models.
- Data Envelopment Analysis (DEA): DEA was introduced by Charnes, Cooper and Rhodes (1978) as a non-parametric benchmarking model. While SFA is subject to modeler's judgement during the initial process of model assumption and setting as SFA takes a parametric modeling approach, DEA is relatively objective because it is based on linear programming optimization models. DEA also useful when multiple inputs and outputs should be incorporated. However it is susceptible when outliers in the data set exist because DEA erroneously extends the estimated frontier line outward to envelop outliers. Chapter 2 uses both DEA and SFA to measure the effectiveness of energy saving initiatives for the automotive industry and checks the consistency of two models.

- Stochastic Programming (recourse type): stochastic programming is a special mathematical optimization technology to model optimization problems when uncertainty is involved. Specifically, recourse type stochastic programming considers two or multi-stage linear programs where the decision maker takes some action in the first stage, after which a random event occurs affecting the outcome of the first-stage decision. During the second stage, a recourse decision can then be made to compensate for any negative effects that might have been experienced as a result of the first-stage decision. Therefore, the optimal policy from recourse type stochastic programming consists of a single first-stage decision and a collection of recourse decisions in the second-stage in response to each random outcome. This technology can be applied to identify the optimal investment plan for sustainable manufacturing projects to reduce energy and $CO_2$ emission costs for manufacturing processes involving uncertain decision parameters, such as future $CO_2$ credit market price. Chapter 3 illustrates this technology with an example application of automotive manufacturing plant.
- Stochastic Programming (chance constraint type): The chance constraint type stochastic programming is a special type of stochastic programming which formulation aims to ensure that the probability of meeting a certain constraint is above a certain level. In other words, it restricts the feasible region with the probabilistic confidence level. This approach has applications traditionally in water reservoir management or financial risk management but nowadays, expands the range covering unmanned autonomous vehicle navigation as well as optimal renewable energy generation. Chapter 4 illustrates this technology with an example application of demand response program between an energy supplier and an industrial consumer.
- Activity-based energy costing: Activity-based costing (ABC) was developed as an accounting method used to trace costs to a product or process of an organization. ABC is characterized by assigning costs to the activities performed by the organization, rather than assigning costs directly to the products. Due to this characteristic, the cost of the products can be calculated by determining how much each product uses each activity (Weil and Maher 2005). This accounting technology can be applicable to build an energy accounting model. By applying ABC to the energy modelling in manufacturing sectors, it is possible to overcome limited metering devices to determine the energy distribution within the process and to predict energy loads in the future which is useful for effectively evaluating energy demand and response offers. Chapter 4 shows how ABC helps build an energy model for a manufacturing plant based on which a chance constraint stochastic model is formulated to make an optimal decision regarding demand response program.
- Principle Component Analysis (PCA): PCA is a statistical technique for finding patterns in data represented in high dimensions. Its purpose is to provide a way of identifying patterns in data and expressing the data in such a way as to highlight their similarities and differences (Smith 2002). In the case that the dimension of the data is too high to use the graphical representation, this technology is useful to compress the data by reducing the number of

dimensions, without much loss of information. Chapter 5 shows how to use PCA for a pattern-based energy consumption analysis.

- Multinomial Logistic Regression: it is a classification method that generalizes logistic regression to multiclass problems where more than two possible discrete outcomes are concerned (Greene 2012). The goal of multinomial logistic regression is to construct a statistical parametric model that accounts for the relationship between the explanatory variables and the outcome (a category), so that the outcome of a new data point can be correctly predicted when the explanatory variables are available but the out-come is not available. In order to train the relationship between the explanatory variables and the outcome, the possible categorical range of outcomes should be known. Chapter 5 illustrates a pattern-based energy consumption analysis by pipelining PCA and multinomial logistic regression.
- K-Means Clustering: it is an clustering algorithm for partitioning a dataset into k subsets, or clusters, that minimize the sum-of-squares distances from each cluster's mean. This algorithm is an unsupervised algorithm and fits in the absence of manually logged training data in contrast to the multinomial logistic regression model that is a supervised model working with the manually clustered training data. Chapter 5 explains the steps to take to implement this algorithm
- Ontology: Ontology means a specification of a conceptualization in philosophy. In the knowledge sharing and reuse of artificial intelligent community, an ontology is a description (like a formal specification of a program) of the concepts and relationships that machine agents commit to use. Precisely speaking, an ontological commitment is an agreement to use a vocabulary (i.e., ask queries and make assertions) in a way that is consistent among machine agents to share and reuse knowledge. Chapter 6 presents an ontology that enables manufacturing companies to improve agility and efficiency in their energy or environment related decision making process.
- Energy analysis and thermal load simulation: it is a model based simulation technology on heating, cooling, lighting, ventilating, and other energy flows as well as water in buildings. For this purpose, BLAST (Building Loads Analysis and System Thermodynamics) and DOE-2 were developed and released in the late 1970s and early 1980s, respectively as energy load simulation tools. These simulation tools were made out of concerns driven by the energy crisis of the early 1970s and recognition that building energy consumption is a major component of the US energy usage statistics. Later on, the two tools had been combined and EnergyPlus™ was born. EnergyPlus™ allows high fidelity modelling of building energy requirements and waste. In Chap. 7, two HVAC control approaches such as air conditioning economizer and dynamic mist control are evaluated with EnergyPlus™.

To provide a taste of the value of using data analytics, the following section will introduce a simple data decision problem in energy management and illustrate how to use analytical cost models to address the decision problem.

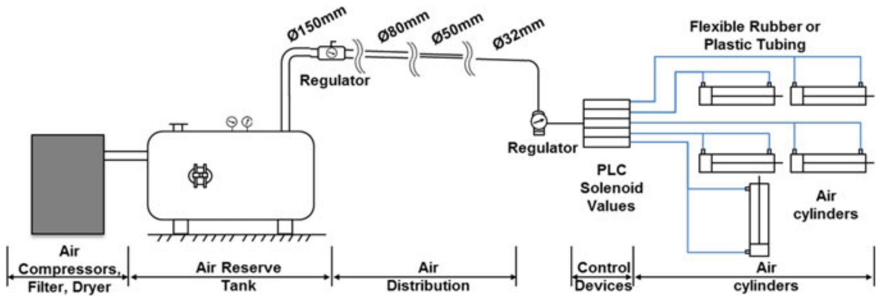


**Fig. 1.9** Conventional compressed air distribution system

### 1.4.1 *Example Decision Problem in Energy Management: A Cost Comparison of Pneumatic and Electric Actuator Systems*

This section illustrates an example decision problem in energy management that is the cost comparison of pneumatic and electric actuator systems. Compressed air is frequently used in manufacturing plants to power pneumatic actuators, which are used for many applications including clamping, loading and spray-painting. Unfortunately, compressed air is now considered a very expensive technology. On average, it accounts for more than 10 % of total energy costs in a manufacturing plant. It is also highly inefficient because as much as 50 % of compressed air can be lost through leaks or excess pressurization in the distribution system (US DOE 2003). Figure 1.9 shows a conventional compressed air distribution system from compressors to end point uses. Given these flaws of compressed air, it becomes an important decision problem to compare the cost of pneumatic and electric actuators and find the right solution.

Electric motor actuators can be used for the same applications as pneumatic actuators. In general, the start-up costs of electric motor actuators are approximately two and a half times higher than those of pneumatic actuators. These high start-up costs are due to the high unit cost, which can be as high as $2000. The unit cost of electric motor actuators stays constant as actuators are added to the system. The unit cost of pneumatic actuators decreases as actuators are added to the system. This trend exists because the initial costs of a pneumatic system are associated with the compressor costs, not the actuator unit cost.

The total cost structure is developed based on the previous study (Kral 2011) to show how the total costs are calculated with consideration of the following factors.

- Setup costs
- Maintenance costs
- Compressor capacity utilization

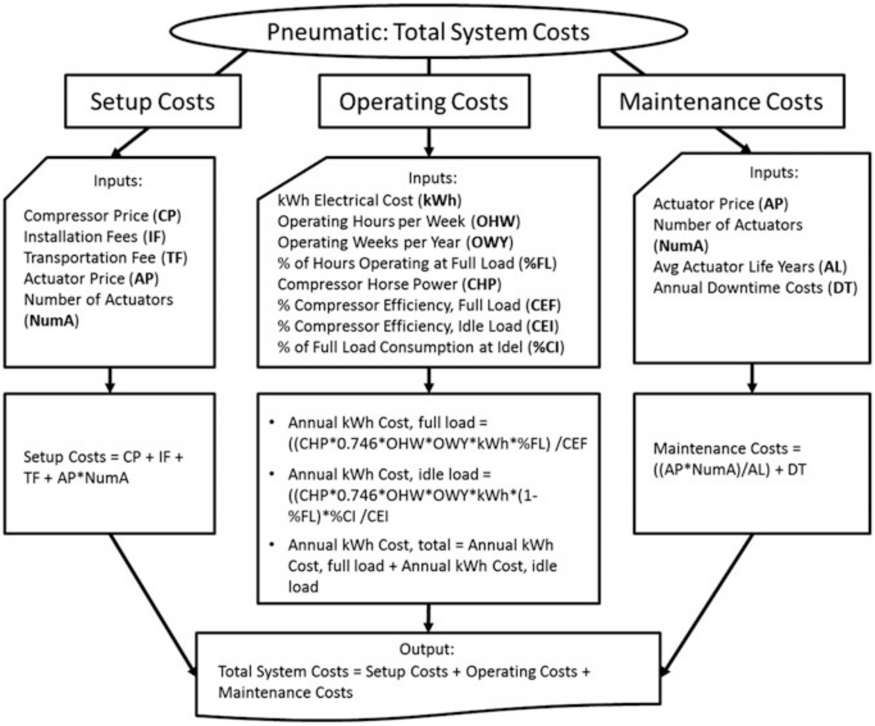


**Fig. 1.10** Total cost structure of pneumatic system

The total cost structure for pneumatic system is draw as shown in Fig. 1.10. The structure shows the inputs, formulas, and output used to calculate the costs of pneumatic systems. Figure 1.11 explains how to measure required air flow rate (CFM) in a pneumatic cylinder. Note that the required CFM for retreating the piston is greater than when advancing the piston because of the volume occupied by the piston itself. The counterpart electric system total cost structure is shown in Fig. 1.12. Similar to the pneumatic system, Fig. 1.12 shows the inputs, formulas, and output which are used in this case to calculate the costs of an electric system. Some of input data are collected from the previous research (Yuan et al. 2006).

The unit and total cost of pneumatic and electric actuators as a function of the number of actuators in the system. Therefore, this example sets up 3 scenarios subject to the unit price of electric actuator:

- Scenario-1: the unit price of electric actuator is assumed $1,760
- Scenario-2: the unit price of electric actuator is assumed $1,000
- Scenario-3: the unit price of electric actuator is assumed $500

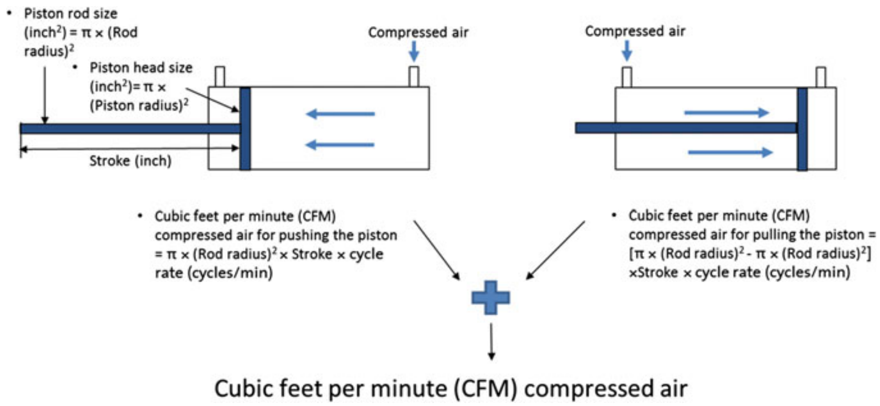


**Fig. 1.11** Measuring required air flow rate (CFM) in a pneumatic cylinder

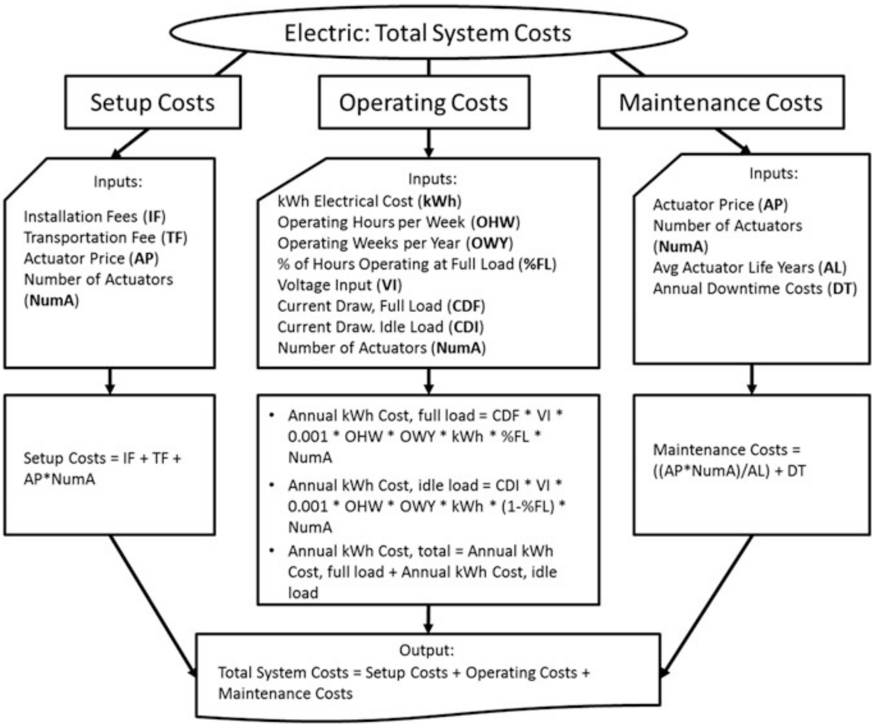


**Fig. 1.12** Total cost structure of electric actuator system

**Table 1.2** List of input cost factors with corresponding example data and assumptions for pneumatic system

| Input cost factor | Example data and assumptions |
|---|---|
| Compressor price | $12,252 (average market price of 40 Hp rotary screw type air compressor) |
| Installation fees | Installation fees = $1,300 (average market price of small size pneumatic system installation) |
| Transportation fees | Transportation fees = $285 (assumed) |
| Actuator price | Actuator price = $150 (average market price for commonly used 50 mm bore cylinder) |
| Number of actuators | Variable (system costs and actuator unit cost calculated for systems with 1–100 actuators, but can be extended beyond 100) |
| kWh electricity cost | $0.0648 (assumed) |
| Operating hours per week | 168 h (assuming that compressors are always operating at either full load or idle load) |
| Operating weeks per year | 52 weeks (assuming that compressors are always operating at either full load or idle load) |
| % of hours operating at full load | 40.37 % (based on 2 × 8 h shifts per day × 221 days per year/24 h per day × 365 days per year) |
| Compressor horse power | 40 hp (assuming that the compressor can cover one machining centre or small-size sub assembly line required around 40–50 actuators) |
| % compressor efficiency, full load | 92.4 % (average practice) |
| % compressor efficiency, idle load | 85 % (average practice) |
| % of full load consumption at idle | 25 % (average practice) |
| Piston radius | 1 in. (25 mm, most commonly sold actuator's size in the manufacturing industry) |
| Rod radius | 0.25 in. (assumed) |
| Stroke | 60 in. (assumed) |
| Cycle rate | 60 cycles/min (assumed) |
| Pressure | 72.5 psi (based on 5 bar pressure, most commonly adapted in the manufacturing industry) |
| % air attributed to leaks | 25 % (assumed) |
| % air attributed to excess pressurization | 15 % (assumed) |
| Compressor capacity | 984.38 scfm (average capacity of 40 Hp rotary screw type air compressor) |
| Average actuator life | 3 years (assumed based on 3 million cycle life in ideal conditions) |
| Average downtime costs | $0 (assumed unknown) |

The sources of the inputs as well as their values can be seen in Tables 1.2 and 1.3. Table 1.4 shows a summary of the breakeven cost points for the three scenarios.

Figures 1.13, 1.14, 1.15, 1.16, 1.17 and 1.18 show the cost analysis results from unit versus total cost perspective by each of those 3 scenarios aforementioned.

**Table 1.3** List of input cost factors with corresponding example data and assumptions for electric system

| Input cost factor | Example data and assumptions |
|---|---|
| Installation fees | $1,000 (assumed less than pneumatic system) |
| Transportation fees | $285 (assumed equivalent to pneumatic system) |
| Actuator price | $1,760 (based on SMC price for actuator (LCA50-100-17) with similar capabilities to pneumatic actuator used above) |
| Number of actuators | Variable (system costs and actuator unit cost calculated for systems with 1–100 actuators, but can be extended beyond 100) |
| kWh electricity cost | $0.0648 |
| Operating hours per week | 168 h (assumed equivalent to pneumatic system) |
| Operating weeks per year | 52 weeks (assumed equivalent to pneumatic system) |
| % of hours operating at full load | % of hours operating at full load = 40.37 % (based on 2 × 8 h shifts per day × 221 days per year/24 h per day × 365 days per year) |
| Voltage input | 24 V (based on SMC actuator voltage, LCA50-100-17) |
| Power supply: current draw and current output | 1 A (assume analyzing an AC actuator) |
| Actuator: current draw, full load | 1.667 A (based on SMC data, LEY 25) |
| Actuator: current draw, idle load | 0.625 A (based on SMC data, LEY 25) |
| Average actuator life | 3 years (assumed based on 3 million cycle life in ideal conditions) |
| Average downtime costs | $0 (assumed unknown) |

**Table 1.4** Breakeven cost points of pneumatic and electric actuators

| Scenario | Number of actuators | Unit cost of electric actuators with the unit cost of pneumatic actuators fixed |
|---|---|---|
| Scenario-1 | 9 | $1,760 |
| Scenario-2 | 16 | $1,000 |
| Scenario-3 | 91 | $500 |

In detail, Figs. 1.13 and 1.14 report that pneumatic actuators have a higher unit cost than electric actuators if there are less than 9 actuators in the system for scenario-1 where the unit of price of electric actuator is assumed $1,760.

Figures 1.15 and 1.16 report that pneumatic actuators have a higher unit cost than electric actuators if there are less than 16 actuators in the system for scenario-2 where the unit of price of electric actuator is assumed $1,000.

Figures 1.17 and 1.18 report that pneumatic actuators have a higher unit cost than electric actuators if there are less than 91 actuators in the system for scenario-3 where the unit of price of electric actuator is assumed $500.

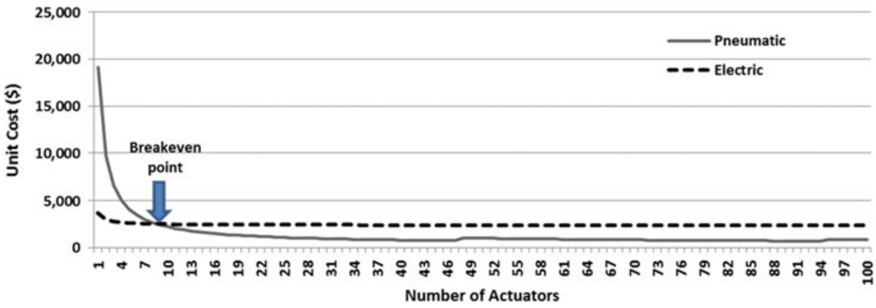


**Fig. 1.13** Unit cost of pneumatic and electric actuators for scenario-1

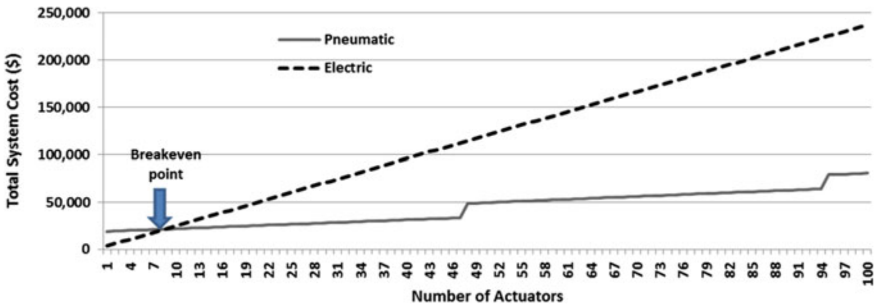


**Fig. 1.14** Total cost of pneumatic and electric actuators for scenario-1

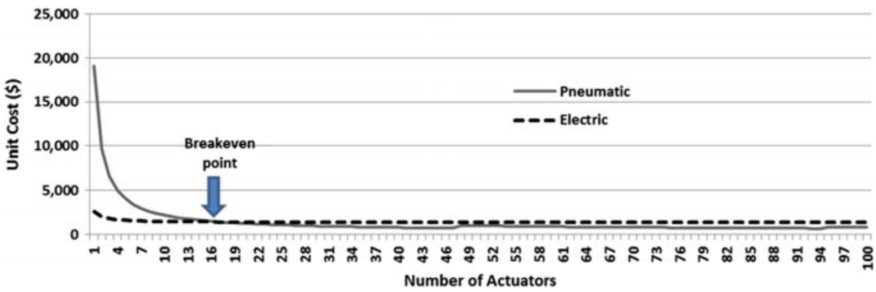


**Fig. 1.15** Unit cost of pneumatic and electric actuators for scenario-2

Table 1.4 reveals that the breakeven cost point differs depending on the scenario. The suggestion of this example decision making study is that when a large number of actuators are required, a pneumatic system is cost effective, or otherwise an electric system is favourable.

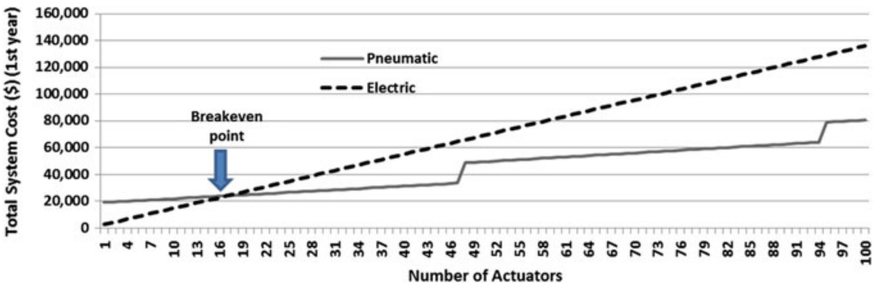


**Fig. 1.16** Total cost of pneumatic and electric actuators for scenario-2

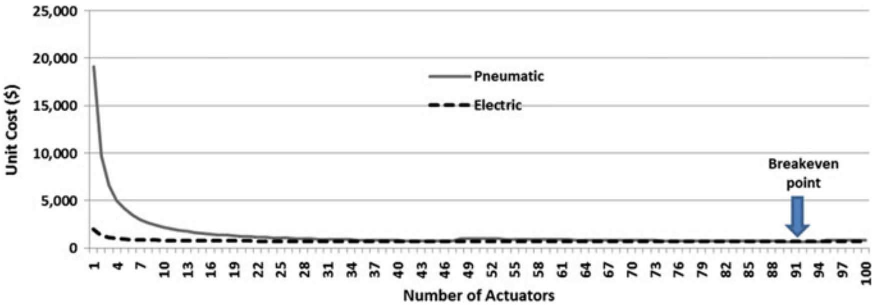


**Fig. 1.17** Unit cost of pneumatic and electric actuators for scenario-3

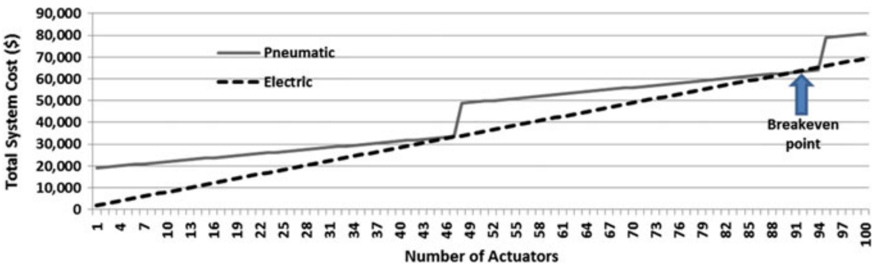


**Fig. 1.18** Total cost of pneumatic and electric actuators for scenario-3

## 1.5 Outline of Chapters

Summaries of the contents of the remaining 8 chapters are provided below.

**Chapter 2. Energy Performance Analysis: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DES) for Energy Performance Analysis**: This chapter explains stochastic and deterministic frontier benchmarking models such as the stochastic frontier analysis (SFA) model and the data envelopment analysis (DEA) model to measure the effectiveness of energy saving initiatives in terms of the technical improvement of energy efficiency for the automotive industry, particularly vehicle assembly plants. Illustrative examples of the application of the proposed models are presented and demonstrate the overall benchmarking process to determine best practice frontier lines and to measure technical improvement based on the magnitude of frontier line shifts over time. Log likelihood ratio and Spearman rank order correlation coefficient tests are conducted to determine the significance of the SFA model and its consistency with the DEA model. ENERGY STAR® EPI (Energy Performance Index) are also calculated. This chapter also provides a short instruction to Excel Solver by illustrating three examples: (1) SFA parameters estimation (2) DEA LP problem and (3) traveling compressed air expert problem, with an attempt to help readers learn and use GRG method, Simplex LP method and evolutionary method, respectively.

**Chapter 3. Energy Decision-Making 1: Strategic Planning of Sustainable Manufacturing Projects based on Stochastic Programming**: This chapter describes a new stochastic programming approach to identify the optimal investment plan for sustainable manufacturing projects to reduce energy and $CO_2$ emission costs for manufacturing processes subject to various time, budget, technology and environmental constraints. The principle underlying approach is to solve a multi-period stochastic programming involving uncertain decision parameters, such as future $CO_2$ credit market price, through the use of sample averaging approximation (SAA). An illustrative example application of the proposed model is presented. In Appendix, this chapter also provides an overview of the available standards and methods that can be used for preparing Scope 3 green house gas inventories and carbon footprints for organizations and their specific products or services.

**Chapter 4. Energy Decision-Making 2: Demand Response Option Contract Decision based on Stochastic Programming**: This chapter introduces a novel decision model based on activity-based costing (ABC) and stochastic programming, developed to accurately evaluate the impact of load curtailments and determine as to whether or not to accept an energy load curtailment offer. The introduced model specifically targets state-transition flexible and Quality-of-Service (QoS) flexible energy use activities to reduce the peak energy demand rate. An illustrative example with the proposed decision model under a call-option based energy demand response scenario is presented.

**Chapter 5. Pattern-Based Energy Consumption Analysis by Chaining Principle Component Analysis and Multinomial Logistic Regression**: To introduce how the inferring technology can be used in the energy management, this chapter presents a pattern-based energy consumption analysis by chaining Principle Component Analysis (PCA) and logistic regression. The PCA provides an unsupervised dimension reduction to mitigate the issue of multicollinearity (high dependence) among the explanatory variables, while the logistic regression does the prediction based on the reduced dataset expressed in orthogonal axes that are uncorrelated principle components represented by Eigenvectors found in the PCA. By chaining the PCA and logistic regression, it is possible to train manually time-logged energy data and to infer the events associated with the data related to manufacturing operations. This chapter also provides a short instruction to Python and IPython Notebook. It illustrates a supervised learning process by using Python to carry out pipelining PCA and logistic regression and applying a grid search to training and inference energy consumption patterns.

**Chapter 6. Ontology-Enabled Knowledge Management in Environmental Regulations and Incentive Policies**: This chapter presents the Environmental Regulation and Incentive Policies Acquisition and Dissemination (ERIPAD) ontology. This ontology can enable systematic knowledge acquisition and personalized knowledge dissemination via reasoning query languages like SPARQL. The ERIPAD ontology is currently customized for the European Union Emission Trading Scheme and the Waxman-Markey bill because of their comprehensiveness and inclusiveness. It is expected that the ERIPAD ontology will enable manufacturing companies to improve agility and efficiency in their energy or environment related decision making process.

**Chapter 7. Energy Simulation Using EnergyPlus™ Under Different Plant Building Energy Management Scenarios**: In this chapter, plant energy simulation models are developed by customizing EnergyPlus™ and two new HVAC control approaches such as air conditioning economizer and dynamic mist control are evaluated with the developed energy models. The simulation results reveal that (1) the use of air conditioning economizer can save 8.4 % yearly cooling energy compared to the business-as-usual case without compromising the working quality for a selected example location; (2) the application of dynamic mist control system can save significant cooling and heating energy for machining plants in three selected example locations keeping worker health protection foremost. This chapter also provides a short instruction to EnergyPlus™. EnergyPlus™ was originally developed as a public domain software package to estimate energy consumptions of a building complex. Therefore, its applications are limited to commercial buildings, not industrial facilities. In order to use it for manufacturing facilities, its expansion is required. With an example of a room with welding equipment, the instruction provides step by step guidance toward understanding the details of the building construction and operation.

**Chapter 8. Energy Management Process on the Plant Floor**: This chapter describes the needs for a robust energy management in business and suggests a method to include the energy management into business with General Motors (GM) as an example of how to implement the method. Energy use is a large, but mandatory, expense incurred by manufacturers or facility operators and contributes to Greenhouse Gas (GHG) emissions. Depending on the type of business, energy cost can range from less than 1 % of operating expense to more than 30 %. Additionally, energy use in facilities and operations accounts for 66 % of the total greenhouse gas emissions, with transportation being the remaining 34 % of GHG emissions. Although the expense may be a small portion of operating expense, the cost and environmental impact is significant for many companies. As an example, at GM, although the expenditure for energy is less than 1 % of total expenses, the cost is in excess of $1 Billion USD annually. Hence, a robust energy management process is needed to meet the fiscal and environmental responsibility of businesses to remain sustainable and satisfy investors' and customers' demands. Management of energy and carbon to reduce environmental impact is important enough to be included in the company's business plan, similar to safety, people, quality, and cost. Following a model similar to EPA Energy Star's seven step approach, based on **P**lan, **Do**, **C**heck, **A**ct methodology (PDCA), energy management can be integrated into a company's standard business plan.

**Chapter 9. Energy Efficiency Accounting to Demonstrate Performance**: This chapter describes a systematic approach covering how to gain company support and funding for new energy efficiency projects and how to track each project to demonstrate accountability. An important method to reduce greenhouse gas and energy is through energy efficiency projects. To gain top-level support and funding, a systematic approach is best using data and benchmarking other companies. Explaining why support and funding is required is the first step toward selling the need. To compete with other internal funding needs—product programs, asset sustainment, and maintenance…, a strategic approach is required utilizing company's standard business practices for energy savings projects. A long-term plan including energy use forecasting, business as usual, the gap to meet the company's goals, and the spending and savings for multiple years demonstrates a strategic plan to meet the objective. Based on the available funds, prioritize projects based on return on investment, $CO_2e$ reduction, and probability of success. Tracking each project throughout the planning and implementation process demonstrates accountability. Additionally, having a list of shovel ready projects and the status of each can provide an opportunity to gain more funding if it becomes available. Reducing next year's operating budget by the savings is a good method to sustain the funding year over year. Standardized measure and verification methods provide confirmation to customers and management that energy efficiency efforts really reduce the bottom-line cost and provide an attractive return on investment.

## 1.6 Exercises

1. Energy is an ability to do work and neither created nor destroyed but only transformed from one form into another. Meanwhile, work is defined as the force times distance. Try to define the following physical terminologies and identify the differences:

   - Mass
   - Force
   - Work
   - Energy
   - Power

   For the energy or environment project you worked or are working, try to identify applications of aforementioned physical terminologies.

2. There are many ways to accomplish 10 hp worth of mechanical work throughout an entire year. Compare the four cases to accomplish the job from the business perspective such as (1) employing people (2) employing horses (3) employing air (4) employing an electric motor. Use the following parameters:

   - 0.2 hp/man
   - 3 shifts for 24 h work are required; people work 1 shift (=8 h)
   - $100,000/man-year
   - 1 hp/horse
   - A horse works 1 shift
   - $1,000/horse; $600 hay/horse-year
   - 10 hp/air actuator
   - $200/air actuator
   - $30,000 for 5:1 compressor-to-end user; $8000 for piping; the compressor needs 7000 kWh/hp; $0.1/kWh
   - $2500/electric motor; $9500 cable and maintenance/year; the electric motor needs 7000 kWh/hp; $0.1/kWh

3. One way of achieving sustainability from the point of energy sourcing is to in-crease the use of renewable energies. Assume that your company considers the use of renewable energy as part of energy or environment projects. For the optimal decision on the capacity of renewable energy, try to formulate an objective function and constraints in such a way to maximize the total profits by referring to Fig. 1.19. Consider energy demand/supply and regulations or

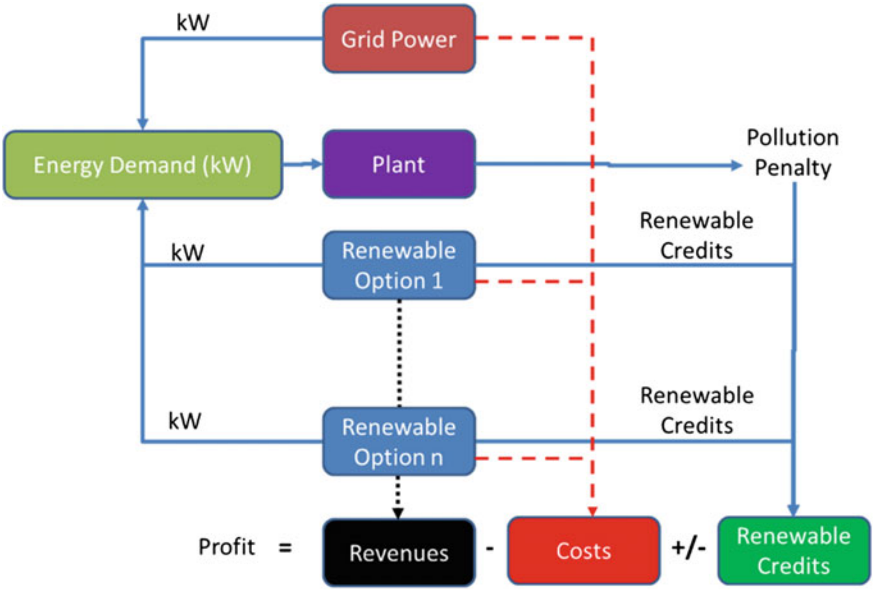


**Fig. 1.19** Cost function breakdown of renewable energy optimization

**Table 1.5** Alternative energy sources in the automotive industry

| Source | Configuration | Example |
|---|---|---|
| Solar PV | • Electric current is generated when solar irradiance from the Sun hits solar panels<br>• Current Silicon based cells have limitations—cost, limited efficiency, fragility<br>• 3rd generation includes non-semiconductor based cells, quantum dot, solar thermal, and nano-structures<br>• Shift in materials that enable more rapid manufacturing—the 'printing' or 'rolling' of thin film solar cells | • GM Zaragoza, Spain where 12 MW power is available; 2 M sq ft and 85,000 solar panels; followed by GM installation of multi-MW facilities in California |
| Wind | • Industrial rotors range in size from 10 m (45 MWh) to 71 m (5600 MWh)<br>• Typical wind turbines have a horizontal axis configuration | • Ford Dagenham facility where 2 turbines (3 blades, 85 m high) in 2004 were installed with a combined capacity of 3.6 MW (generating over 6.7 MM kWh of electricity/year). Reduced $CO_2$ emissions by 6000 tons. It was built by a 3rd party, Ecotricity who covers the capital costs, installation, and maintenance; Ford buys the electricity produced |
| Geothermal | • Best for direct heating rather than electricity generation<br>• Requires no fuel, is highly scalable, and does not produce pollution<br>• Capacity factor is estimated to be 96 % (global average was 73 % in 2005)<br>• Existing wells are 2mi deep but optimal levels should be 6mi deep | • Chevron is the largest producer of geothermal energy in the world. It started more than 30 years ago in Darajat, Indonesia. Three more have been built since in Indonesia and the Philippines. Combined, generate 1273 MW of energy |
| Hydro | 4 types of hydropower plants:<br>• Pumped storage schemes are only commercially important means of large-scale grid energy storage<br>• Run-of-the river—no reservoir capacity<br>• Tidal power plant—uses daily rise and fall of water due to tides<br>• Use water's kinetic energy and undammed sources such as waterwheels (less common) | • New small hydro-power installations for GM facilities in Mexico that became operational in 2007 |
| Landfill Gas | • It is produced when microorganisms break down organic material in the landfill, and is comprised of approximately 50–60 % methane and 40–50 % carbon dioxide | • GM facilities in (1) Toledo, Ohio; (2) Orion, Michigan; (3) Fort Wayne, Indiana, and (4) Shreveport, Louisiana use landfill gas to power plant boilers |

(continued)

**Table 1.5** (continued)

| Source | Configuration | Example |
|---|---|---|
| | • Viable gas streams run for ~20 years<br>• EPA requires landfill operators to collect the methane produced on site, so where it is not being used for energy production it is, and will be, flared to prevent the release of greenhouse gas | • Annual savings greater than $500,000 at each plant |
| Biomass | • Bio-refinery is a facility that integrates biomass conversion processes and equipment to produce fuels, power, and chemicals<br>• The cost of biomass fuel is generally less than half the cost of fuel oil on a Btu basis | • Kimberly-Clark paper pulp mill in Everett, WA, USA<br>• Kimberly-Clark offsets the carbon dioxide emissions in producing more than 220 million kilowatt-hours of biomass-derived power, or approximately 7 % of the company's annual electrical use |

mandates when specifying the constraints. For better understanding real-world renewable energy usage, see Table 1.5 that summarizes success stories in renewable energy usage reported by many manufacturing companies.

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# Chapter 2
# Energy Performance Analysis: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DES) for Energy Performance Analysis

**Abstract** Energy performance analysis in the car manufacturing industry is intriguing. The car manufacturing industry, one of the largest energy consuming industries, has been making a considerable effort to improve its energy intensity by implementing energy efficiency programs, in many cases supported by government research or financial programs. While many car manufacturers claim that they have made substantial progress in energy efficiency improvement over the past years through their energy efficiency programs, the objective measurement of energy efficiency improvement has not been studied due to the lack of suitable quantitative methods. This chapter proposes stochastic and deterministic frontier benchmarking models such as the stochastic frontier analysis (SFA) model and the data envelopment analysis (DEA) model to measure the effectiveness of energy saving initiatives in terms of the technical improvement of energy efficiency for the automotive industry, particularly vehicle assembly plants. Illustrative examples of the application of the proposed models are presented and demonstrate the overall benchmarking process to determine best practice frontier lines and to measure technical improvement based on the magnitude of frontier line shifts over time. Log likelihood ratio and Spearman rank-order correlation coefficient tests are conducted to determine the significance of the SFA model and its consistency with the DEA model. ENERGY STAR® EPI (Energy Performance Index) are also calculated. This chapter also provides a short instruction to Excel Solver by illustrating three examples: (1) SFA parameters estimation (2) DEA LP problem and (3) traveling compressed air expert problem, with an attempt to help readers learn and use GRG method, Simplex LP method and evolutionary method, respectively.

## 2.1 Background of Energy Performance Analysis

The growing awareness of global energy demand issues has become one of major contributors to create the concept of sustainability. The concept of sustainability was first used to describe an economic vision in equilibrium with basic ecological support systems in the 1970s. The concept has since been applied to a wide range of

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Springer Series in Advanced Manufacturing, DOI 10.1007/978-3-319-32729-7_2

areas, including the car manufacturing industry, thus, motivating the change in energy consumption trends.

The typical vehicle manufacturing plants of car companies consume energy at different rates, depending on many external or internal factors, such as plant utilization, heating degree days (HDD) and cooling degree days (CDD), which are positively correlated to such factors as heating and cooling energy requirements, product type and size. Although car companies recognize that energy consumption is a large but mandatory expense, most of them have recently invested in energy saving initiatives for their plants every year to reduce energy consumption inspired by the concept of sustainability and its implication for firm values such as enhanced brand value or cost savings in energy. A notable fact is that those energy saving initiatives have been, in many cases, supported by government research or financial programs (e.g., R&D and funding programs offered by US Department of Energy Office of Energy Efficiency and Renewable Energy) because those initiatives are also aligned with the government's energy saving polices. The benefits from energy demand reduction could be significant, ranging from energy conservation and reduced environmental impact to an enhanced competitive position.

Nonetheless, as the benefits from reducing energy demand are significant, many car companies have invested considerably in strategic energy saving initiatives with the support of government R&D or financial subsidies. Now, as a logical following step, car companies and the government endeavor to investigate whether the implemented energy saving initiatives have been effective and further, institutionalized as a managed process or as a part of organizational capability because they seek to determine whether their investment or subsidies were justified and whether they have been recovered. An industry or a company, if the energy saving initiative are implemented and fully institutionalized, starts to have the potential to deliver sustained energy savings, thereby demonstrating best practices in decreasing energy intensity (kWh/vehicle in the context of car manufacturing industry). When the industry or company obtains the potential to deliver sustained energy savings and the potential is expressed as best practices, a structural technical improvement in the industry (or company) is considered to have been made. Therefore, it is possible to use the term technical improvement as a performance indicator to identify the effectiveness of energy saving initiatives, in other words, the extent to which strategic energy saving initiatives become institutionalized or part of organizational standard processes. The challenge is the lack of suitable quantitative methods to measure a structural technical improvement objectively. This chapter applies a benchmarking approach to measure technical improvement. A benchmark is a process for identifying best practices in an industry (or a large company controlling many individual producers insides) and estimating each industry's or company's efficiency by measuring the difference between actual performance and best practices. In the context of the car manufacturing industry, the difference between the actual energy use at a plant and its best practice, i.e., the lowest achievable energy use, is considered. The problem is that what is the best achievable is influenced by different operating conditions of plants (e.g., heating or cooling energy requirements, product size, or plant utilization), thus, the measuring of best practices must

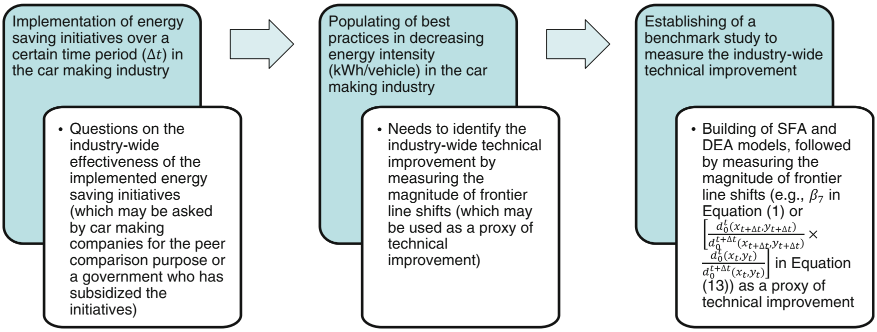



**Fig. 2.1** The idea process for measuring the effectiveness of energy saving initiatives

account for these different operation conditions. A suitable benchmark model should normalize these conditions and identify a frontier line that connects the best practices in the industry. This work utilized a benchmarking approach, with the shifts of a frontier line between the time period from t and t + Δt used as a proxy to measure a structural technical improvement. Figure 2.1 depicts the idea process for measuring the effectiveness of energy saving initiatives with a benchmarking process.

This chapter aims to determine and to measure the effectiveness of energy reduction initiatives in terms of a technical improvement that corresponds to a certain structural change in industry-wide energy efficiency between two distinct time periods, namely, by proposing benchmarking models: SFA (stochastic frontier analysis) models based on Hicksian neutral technological change concept and DEA (data envelopment analysis) models incorporating the Malmquist Productivity Change Index (Sect. 2.2 discusses Hicksian concept and Malmquist index in detail). Through the SFA and DEA benchmarking processes, it is possible to identify best practice frontier lines and to analyze the technical improvement based on the magnitude of the frontier line shifts over time.

### *2.1.1 Background of the Auto Manufacturing Process and the Energy Consumption*

A typical automobile manufacturing process generally consists of three main processes: body shop, paint shop, and general assembly. The body shop transforms raw materials into the structure of the vehicle. Then, the paint shop applies a protective and visual coating to the product. Finally, the general assembly assembles all sub-components, such as the engine and seats, into the vehicle.

Two main types of energy utility used in a typical vehicle assembly plant are electricity and fuel (including natural gas). In general, fuel is used for direct heating or to generate steam that is considered as a secondary utility similar to compressed air in vehicle assembly plants. Steam is then used mainly in painting but is also utilized for space heating, car wash and other non-manufacturing activities. Electricity is the main energy source in vehicle assembly plants, and its main uses are painting, HVAC (heating, ventilation, and air conditioning), lighting, compressed air systems, and welding and materials handling/tools.

It is possible to more holistically understand the factors affecting energy consumption by checking the consistency of the analytical results from two different models, SFA and DEA (Lin and Tseng 2005). Previous findings from performance benchmarking literature indicate that DEA and SFA have comparative advantages against each other, thereby offering the possibility of complementary use. In general, DEA is preferable in applications in which the frontier model cannot be expressed in algebraic form or does not have a known inefficiency distribution. The SFA method is preferable when certain classical assumptions are satisfied regarding the composite error terms, including the contributions from the inefficiency distribution and measurement errors. Often, SFA and DEA estimates are highly correlated in terms of rank order, regardless of inefficiency and random error variation, meaning that the feasibility and robustness of the model estimation can be demonstrated by showing a high correlation between two models. Hence, in this chapter, the Spearman rank correlation is used to check the consistency of two different models. This chapter also calculates ENERGY STAR® plant energy performance indicator values based on the SFA models.

The chapter is organized as follows: Introduction section surveys some efforts and studies related to energy use in the automotive industry and overviews benchmarking models including parametric and non-parametric approaches. Sections 2.2 and 2.3 describe SFA and DEA and the concept of technical improvement in additional detail with graphics and proposes benchmarking models to assess the significance of technical improvements in energy use alongside background data about energy consumption in vehicle manufacturing processes. Section 2.4 provides illustrative studies by using hypothetical but representative panel data sets (note: panel data refer to a group of cross-sectional data sets separated into periods of time, thus, appearing as a combination of cross-sectional and time series data sets). For confidentiality reasons, hypothetical data sets are used for the studies. In addition to implementing models, the final proposed models are analyzed and validated. Section 2.5 concludes this chapter. Appendix A shows the derivation of the log likelihood function and first-order partial derivatives for cost frontier model and the resulting parameters obtained from SFA and DEA models. Appendix B provides a short instruction to Excel Solver by illustrating three examples: (1) SFA parameters estimation (2) DEA LP problem and (3) traveling compressed air expert problem, with an attempt to help readers learn and use GRG method, Simplex LP method and evolutionary method, respectively. Note that this chapter expands on previous researches (Oh and Al 2014) by adding detailed procedures of deriving the log likelihood function and first-order partial derivatives for cost frontier model and a short instruction to Excel Solver.

## 2.1.2 Literature Review

Several studies related to demand, supply and management for energy use in the car manufacturing industry have been conducted.

Galitsky and Worrell (2008) collected energy efficiency improvement opportunities available to car manufacturers. They identified many energy efficiency improvement opportunities for each automotive manufacturing operation. Boyd (2005) developed plant-level energy performance indicators (EPIs) in support of the Environmental Protection Agency's ENERGY STAR program in which 35 automotive manufacturing plants of five auto companies had participated. The participating plants were plants having only body welding, assembly and painting operations. Sullivan et al. (2010) discussed calculating the environmental burdens of the part manufacturing and vehicle assembly stage of the vehicle life cycle. Their approach is bottom-up, with a particular focus on energy consumption and $CO_2$ emissions. They applied their models to both conventional and advanced vehicles, the latter of which include aluminum-intensive, hybrid electric, plug-in hybrid electric and all-electric vehicles. Oh and Hildreth (2014) proposed a novel decision model based on activity based costing (ABC) and stochastic programming that was developed to accurately evaluate the impact of load curtailments and to determine whether to accept an energy load curtailment offer in the smart grid.

Many previous studies on SFA and DEA, as well as the comparison of their differences are available. In research on SFA, Aigner et al. (1977) and Meeusen and Broeck (1977) proposed the stochastic frontier production function independently. The original model specification considered a production function specified for cross-sectional data in which an error term is divided into two components, one to account for random effects and another to account for technical inefficiency. Subsequently, the original model specification has been used in a large number of empirical applications over the past decades and has also been altered or extended in several ways. One extension is the two-stage estimation procedure to measure the technical change over two time periods in which firm-level efficiencies are predicted using the estimated stochastic frontiers, after which the predicted firm-level efficiencies are regressed upon firm-specific variables (such as managerial skill level change and first decision maker's characteristics) to distinguish reasons for technical changes over time. However, the two-stage estimation procedure has been criticized because it is inconsistent with its assumptions regarding the independence of the inefficiency effects over two time periods. This work follows the model specifications proposed by Battese and Coelli (1995) that addressed the issues inherent to the two-stage procedure.

Regarding research on DEA, Charnes et al. (1978) proposed the constant returns of scale (CRS) restricted DEA model by combining the Farrell efficiency rating concept and a non-parametric mathematical programming better known as CCR (Charnes-Cooper-Rhodes) model, named after its inventors. The CCR model was updated by Banker et al. (1984), who relaxed the constant returns of scale restriction to be variable returns to scale (VRS), thereby able to evaluate both the technical efficiency and the scale efficiency of decision making units (DMUs). The DEA model with the VRS concept is also called a BCC (Banker-Charnes-Cooper) model, likewise named after its inventors. To implement the VRS concept, the BCC model added an additional constraint to the CCR model, that is, the convexity restriction. When a panel data set is available and one would like to measure the technical improvement using DEA models, the Malmquist total factor productivity (TFP) index can be used to reveal a positive or negative technical change across consecutive years. The Malmquist TFP index (Färe et al. 2011) requires four distance function values, and each distance function has an equivalent DEA model. This chapter discusses those four distance functions in detail in Sect. 2.3.

Despite the fact that both SFA and DEA methods are benchmarking methods based on efficiency frontier analysis, they differ markedly. SFA is a parametric model that requires a modeler's assumption in building models. SFA is well suited to separate firms' inefficiency from statistical noise. By contrast, DEA is a non-parametric model not subject to a modeler's assumption and useful when multiple inputs and outputs should be incorporated, but susceptible when outliers in the data set exist. Lin and Tseng (2005) compared SFA and DEA extensively and summarized the differences.

Although the literature on the various methods to establish a benchmark including SFA and DEA is vast, those methods can be categorized into four approaches for benchmarking, as specified in Table 2.1. Regarding examples in the table, OLS (Ordinary Least Squares) means a linear regression model that aims to find a line such that the sum of squares of the errors of a line passing through the data is minimized. OLS reveals overall sample-based information, representing average practices. Corrected OLS aims to find a frontier line by shifting an OLS line up (production model) or down (cost model) until a single observation with a measured

**Table 2.1** Four benchmarking approaches—modified from (Productivity Commission 2013)

| Approach | Brief description | Examples |
|---|---|---|
| Statistical methods | Parametric modeling that requires parameter estimation, with data allowing for imprecision; the frontier line could be a production or a cost function | Ordinary least squared error (OLS), corrected OLS, SFA, structural time series |
| Non-parametric methods | Non-parametric modeling without any assumptions regarding population distributions (inefficiency distribution, measurement error distribution) | Total factor productivity indexes, DEA |
| Hybrid methods | A method combining non-parametric and parametric methods using a reinforced learning algorithm | Stochastic DEA (Daraio 2012) |
| Engineering model methods | Creating an artificial reference model as "bottom-up" based on expert knowledge and information to use as a benchmark | Swedish NPAM (network performance assessment model), bottom-up energy model |

efficiency index of one remains. Structural time series models are upgraded time series models incorporating distinct parameters that may shift over time because of structural shifts, such as slowly declining or increasing productivity growth. A stochastic DEA model follows a linear programming model, such as DEA, but is extended to account for the influence of statistical noise.

### 2.1.3 Energy Performance Assessment

The following sections outline two primary methods to measure technical or efficiency change: SFA and DEA. SFA and DEA models are commonly represented by a form of frontier line that can be considered an optimal combination of outputs producible from a set of inputs (or an optimal combination of outputs with the lowest inefficiency). Observed shifts of the frontier line from one point in time to another suggest technical improvement, thereby implying, moreover, an institutionalized structural technological change in a given industry or company.

The rationale for developing two models concurrently is the fact that SFA and DEA have competitive advantages against each other and could be used complementarily. In detail, when the DEA frontier estimate is biased high because of outlier data beyond the true frontier, the DEA method erroneously extends the estimated frontier outward. If the SFA method can distinguish between inefficiency and noise with sufficient accuracy, then this method can be used to detect the DEA outlier problem. Similarly, DEA can be used to detect the type-II error in SFA when the SFA frontier line reduces to a standard linear regression line. Figure 2.2 illustrates various relationships between energy intensity and non-energy factors (where the best practice indicates the lowest energy use achievable at the given operation conditions), with Fig. 2.2a, b depicting a concave-up increasing energy intensity and a concave-up decreasing energy intensity, respectively. The

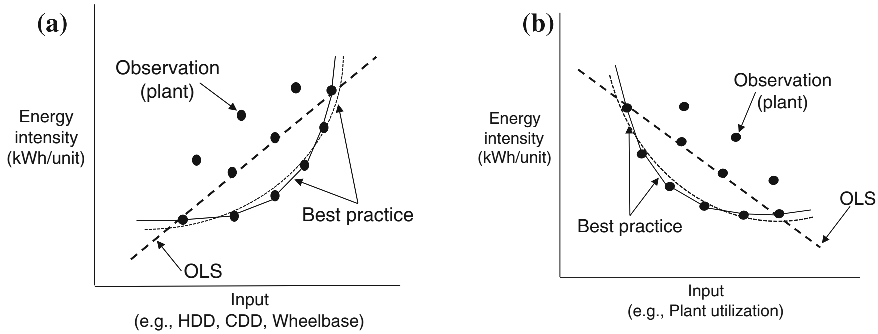



**Fig. 2.2** Various relationships between energy intensity and non-energy factors (based on a cross-sectional data set). **a** Concave-up increasing energy intensity; **b** Concave-up decreasing energy intensity

concave-up increasing patterns may be observed when the energy intensity increases as the input variables (e.g., HDD, CDD, or wheelbase) increase, while the concave-up decreasing patterns may be observed when the input variables (e.g., plant utilization) have a negative relationship with the energy intensity.

It is pertinent to observe that the plant energy efficiency at one point in time is subject to the impact of a structural technical improvement as follows:

- The frontier line may shift independently of a set of observations where plants appear less efficient in the (t + Δt)-th year than in the t-th year. This occurrence happens when a technical improvement is made in the industry (or company) during the time period between the t-th and the (t + Δt)-th years, but the energy performances of target assessing plants remains unchanged and thus, the latter's energy efficiency appears less efficient because the difference between the actual efficiency score and the best practice score increases. In the Malmquist literature, this occurrence is called technical change. Figure 2.3a depicts this case.
- A set of observations may move independently closer to a frontier line while the frontier line remains unchanged during the period between the t-th and (t + Δt)-th years. This occurrence happens when a technical improvement has not been made during the time period, but the target assessing plants have improved their energy performance during the same time period and, thus, their energy efficiency appears more efficient in the (t + Δt)-th year than in the t-th year because the difference between the actual energy use and the best practice decreases. In the Malmquist literature, this occurrence is called efficiency change. Figure 2.3b depicts this case.

Aside from the two cases above, both a frontier line shift and a positive movement of a set of observations can happen simultaneously, in which case it may not be easy to differentiate the energy performance improvement of individual plants because the efficiency improvement of individual plants can be offset by the technical improvement of the industry. While SFA is likely to have trouble in

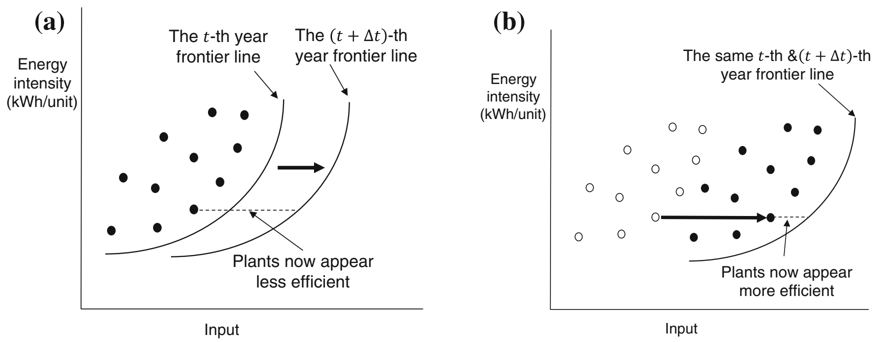



**Fig. 2.3** Two main sources affecting changes in the plant energy efficiency over time. **a** Shifts in frontier line independent of a set of observations; **b** Movement of a set of observations closer to the frontier line

distinguishing technical improvements from efficiency improvements, DEA can do so by implementing the Malmquist total factor productivity (TFP) index, which will be discussed in detail in Sect. 2.3.

This study uses Spearman's rank-order correlation coefficient test to determine the consistency in ranks between SFA and DEA models in the illustrative study. The rationale for using this test is that though efficiency levels (or scores) differ between models, these methods may nonetheless generate similar rankings. If the two models' rankings are completely different, then any action taken based on the assessment may be temporary and depend on which frontier model is employed.

## 2.2 SFA for Energy Performance Analysis

The SFA models in this study follow the model specification proposed by Battese and Coelli (1995) and expands the cross-sectional data model specified by Boyd (2005) to a panel data model by incorporating two cross-sectional data sets. The YEAR variable involved in the resultant SFA models accounts for a Hicksian neutral technological change model. Note that Hicksian models assume special parameters that may shift the frontier line due to structural change, such as the year of the observation. Although this concept does not sufficiently account for the balance between parameters, this work uses the Hicksian neutral technical change concept because the balance between parameters is likely to remain unchanged for the time period until a technical improvement occurs. This stability occurs because the parameters used in this chapter (e.g., HDD, CDD, wheelbase, utilization) are exogenous variables, thus effecting different operation conditions in different plants. This study developed two stochastic frontier models for electricity and fuel because they are the main energy utilities consumed in vehicle manufacturing plants (note: the background on the inclusion of each term in each model is discussed in Boyd (2005). For example, why are quadratic terms for HDD and CDD included in the electricity model and the quadratic term of plant utilization included in fuel model? Why is the wheelbase of a vehicle used as a control variable rather than some other variable(s) that may also reflect the vehicle size?). The proposed SFA model for electricity is:

$$\begin{aligned} E_i/Y_i = A &+ \beta_1 WBASE_i + \beta_2 HDD_i + \beta_3 HDD_i^2 \\ &+ \beta_4 CDD_i + \beta_5 CDD_i^2 + \beta_6 Util_i + \beta_7 Year_i + u_i - \mathrm{v}_i \end{aligned} \tag{2.1}$$

where:

| | |
|---|---|
| $E_i$ | Total site electricity use at plant $i$ in kWh; |
| $Y_i$ | Number of vehicles produced; |
| $WBASE_i$ | Wheelbase (the distance between its front and rear wheels) of the largest vehicle produced in the plant in inch; |
| $HDD_i$ | Thousand heating degree days for the plant location and year; |

| | |
|---|---|
| $HDD_i^2$ | $HDD_i$ squared; |
| $CDD_i$ | Thousand cooling degree days for the plant location and year; |
| $CDD_i^2$ | $CDD_i$ squared; |
| $Util_i$ | Plant utilization rate, defined as output/capacity, where the denominator, capacity is a normalized capacity defined as equal to capacity line rate (or job per hour) × 235 working days × 16 working hours per day; |
| $Year_i$ | $t$ and $t + \Delta t$ where $\Delta t$ is the time period at which a significant technical improvement in energy efficiency is observed; and |
| β | Vector of parameters to be estimated |

Note that HDD is a metric for quantifying the amount of heating that buildings in a particular location require for a certain period (e.g., a specific month or year) such that $\text{HDD} = \sum_{no.days} \max(0.65\,°\text{F}(\text{or } 60\,°\text{F}) - \text{average day temperature})$. Similar to HDD, CDD is a metric for quantifying the amount of cooling that buildings in a particular location require for a certain period (e.g., a specific month or year) such that $\text{CDD} = \sum_{no.days} \max(0, \text{average day temperature} - 65\,°\text{F}(\text{or } 60\,°\text{F}))$. Note that this study scales HDD and CDD by 1000. The variable $v$ represents a measurement error to be distributed as a symmetric normal distribution, and $N(0, \sigma_v^2)$ and the variable $u$ account for a technical inefficiency to be distributed as a half normal distribution, $N^+(0, \sigma_u^2)$. Meanwhile, the proposed SFA model for fuel is:

$$\begin{aligned} F_i/Y_i = A + \beta_1 WBASE_i + \beta_2 HDD_i + \beta_3 HDD_i^2 \\ + \beta_4 Util_i + \beta_5 Util_i^2 + \beta_6 Year_i + u_i - \text{v}_i \end{aligned} \tag{2.2}$$

where, all the notations are specified identically to Eq. (2.1) except that $F_i$ is the total site fuel use at plant $i$ in $10^6$ BTU. Note that this fuel model may not account for the real operation if the given plant uses steam-powered absorption chillers for air conditioning. Such chillers contribute more to the "fuel" load than the "electricity" load. If it is the case, CDD should be included in this model.

Equations (2.1) and (2.2) require several parameters to be solved, such as β, $\sigma_v^2$ and $\sigma_u^2$. This work uses the maximum likelihood method for parameter estimation and utilizes the parameterization of Battese and Corra (1977), who replaced $\sigma_v^2$ and $\sigma_u^2$ with $\varepsilon = u - \text{v}, \sigma = \sigma_u^2 + \sigma_v^2, \lambda = \sqrt{\frac{\sigma_u^2}{\sigma_v^2}}$ and $\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)}$. This parameterization is useful for calculating the maximum likelihood estimates because the parameter γ is now confined to exist between 0 and 1, a range that can be more easily searched to provide a good estimate in an iterative maximization process. The first step of the maximum likelihood method is defining the log-likelihood function of the model and the log of the density function for ε:

$$log\,\varphi_\varepsilon(\varepsilon) = -\frac{1}{2} log\left(\frac{\pi}{2}\right) - \frac{1}{2} log\,\sigma^2 + log\Phi\left(\frac{\varepsilon\lambda}{\sqrt{\sigma^2}}\right) - \frac{1}{2}\frac{\varepsilon^2}{\sigma^2}$$

with $N$ independent observations, the log of the joint density function $\varepsilon_1, \ldots, \varepsilon_N$ is:

$$log\varphi(\varepsilon_1, \ldots, \varepsilon_N) = \sum_{i=1}^{N} log\, \varphi_\varepsilon(\varepsilon_i)$$
$$= -\frac{1}{2}N\, log\left(\frac{\pi}{2}\right) - \frac{1}{2}N\, log\, \sigma^2 + \sum_{i=1}^{N} log\Phi\left(\frac{\lambda\varepsilon_i}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2}\sum\nolimits_{i=1}^{N} \varepsilon_i^2$$

To emphasize that the error term $\varepsilon$ depends on the parameter (vector) $\beta$, the log likelihood function can be expressed alternatively as:

$$\begin{aligned} l(\beta, \sigma^2, \lambda) = & -\frac{1}{2}N \log\left(\frac{\pi}{2}\right) \\ & -\frac{1}{2}N \log \sigma^2 + \sum_{i=1}^{N} \log \Phi\left(\frac{\lambda(y_i - f(x_i; \beta))}{\sqrt{\sigma^2}}\right) \\ & -\frac{1}{2\sigma^2}\sum_{i=1}^{N} (y_i - f(x_i; \beta))^2. \end{aligned} \tag{2.3}$$

The function $l(\beta, \sigma^2, \lambda)$ is the log-likelihood function, which depends on parameters to be estimated (in this case $\beta$, $\sigma^2$ and $\lambda$) and on the data $(x_1, y_1), \ldots, (x_N, y_N)$. The derivation of the log likelihood function is available in Appendix A following Bogetoft and Otto (2011). With $\sigma^2$ replaced with $\frac{1}{N}\sum_{i=1}^{N} (y_i - f(x_i; \beta))^2$, first-order partial derivatives for the function can be obtained.

First, the partial derivative of $l(\beta, \lambda)$ with respect to $\beta$ is:

$$\begin{aligned} \frac{\partial}{\partial\beta_j} l(\beta, \lambda) = & -\frac{\lambda}{\sigma}\sum_{i=1}^{N} \frac{\phi\left(\frac{\lambda\varepsilon_i}{\sigma}\right)}{\Phi\left(\frac{\lambda\varepsilon_i}{\sigma}\right)} X_{ji} \\ & + \frac{\sum_{i=1}^{N} \varepsilon_i X_{ji}}{\sigma^2}\left(1 + \frac{\lambda}{N\sigma}\sum_{i=1}^{N} \frac{\phi\left(\frac{\lambda\varepsilon_i}{\sigma}\right)}{\Phi\left(\frac{\lambda\varepsilon_i}{\sigma}\right)} \varepsilon_i\right). \end{aligned} \tag{2.4}$$

Second, the partial derivative of $l(\beta, \lambda)$ with respect to $\lambda$ is:

$$\frac{\partial}{\partial\lambda} l(\beta, \lambda) = \sum_{i=1}^{N} \frac{\phi\left(\frac{\lambda\epsilon_i}{\sigma}\right)}{\Phi\left(\frac{\lambda\epsilon_i}{\sigma}\right)} \frac{\epsilon_{\mathrm{i}}}{\sigma}. \tag{2.5}$$

Coelli et al. (2005) suggested a one-sided likelihood-ratio test to determine whether the variation in inefficiency $(u_i)$ is significant. The purpose of the test is to compare the parameter estimates in an ordinary least square regression model (OLS) with respect to the null-hypothesis, $H_0{:}\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} = 0$, and the parameter estimates in SFA under the alternative hypothesis, $H_1{:}\gamma > 0$. The test value is calculated using Eq. (2.6).

$$LR = -2\left\{ln\left[\frac{L(OLS)}{L(SFA)}\right]\right\} = -2\{ln[L(OLS)] - ln[L(SFA)]\} \tag{2.6}$$

where, $L(OLS)$ and $L(OLS)$ are the values of the likelihood function under OLS and SFA, respectively. In the illustrative study, this study will calculate and compare the *LR* statistic with $\chi^2_{1-2\alpha}(1)$, then determine to accept or reject the null hypothesis. In other words, if the *LR* statistic exceeds $\alpha\%$ critical value, we reject the null hypothesis of no inefficiency effects. If the null hypothesis $H_0{:}\gamma = 0$ is accepted, it would indicate that $\sigma_u^2$ is zero and hence that the inefficiency term $u_i$ should be removed from the model, thus, specifying parameters that can be consistently estimated using OLS.

This study developed an Excel spreadsheet tool to obtain the maximum likelihood estimation of subset parameters in the aforementioned SFA models rapidly and intuitively. The tool can accommodate panel data, a half-normal inefficiency distribution and a normal measurement error distribution. Section 2.4 will show what the tool looks like. Regarding an energy performance indicator developed by a credential governmental organization, the U.S. Environmental Protection Agency (EPA) introduced energy performance indicators (EPIs) through its ENERGY STAR program to encourage a variety of U.S. industries to use energy more efficiently. One of the EPIs was developed for a plant-level energy performance indicator to benchmark manufacturing energy use in the automobile industry based on the SFA model (Boyd 2005). Because a typical SFA model has a composite error term including symmetric (normal) measurement errors denoted by $\mathrm{v}_i$ and one-sided (half-normal) inefficiencies denoted by $u_i$, the frontier model takes the form of the following equation, as in Eqs. (2.1) and (2.2):

$$E_i/Y_i = f(X;\beta) + \varepsilon_i \tag{2.7}$$

where, $\varepsilon_i = u_i - \mathrm{v}_i, v_i \sim N(0, \sigma_v^2)$ and $u_i \sim N^+(0, \sigma_u^2)$. In addition, $E_i$ is the energy use of company $i$; $Y_i$ is the measured production or service measured of company $i$; $X_i$ is the economic decision variables (i.e., labor-hours worked, materials processed, plant capacity, or utilization rates) or external factors (i.e., heating and cooling energy loads); and β is the vector of parameters to be estimated statistically.

Given company data, Eq. (2.7) can be expressed as Eq. (2.8), thereby providing a way to compute the difference between the actual energy use and the predicted frontier energy use:

$$E_i/Y_i - f(X;\beta) + \mathrm{v}_i = u_i \tag{2.8}$$

Then, the EPI of company $i$ is calculated from the probability distribution of $u_i$ as follows:

$$\begin{aligned} EPI &= probability(energy\ inefficiency \geq E_i/Y_i - f(X;\beta) + \mathrm{v}_i) \\ &= 1 - F(E_i/Y_i - f(X;\beta) + \mathrm{v}_i) \end{aligned} \tag{2.9}$$

$F()$ is the cumulative probability density function of the appropriate one-sided density function for $u_i$ (e.g., gamma, exponential, truncated normal, and other functions). The value $1 - F()$ in Eq. (2.9) defines the EPI score and may be interpreted as a percentile ranking of the company's energy efficiency. However, in practice, the only measureable value is $u_i - \mathrm{v}_i = E_i/Y_i - f(X;B)$. By implication, the EPI score $1 - F(u_i - \mathrm{v}_i)$ is affected by the random component of $\mathrm{v}_i$, that is, the score will reflect the random influences that are not accounted for by the function $F()$. Because this ranking is based on the distribution of inefficiency for the entire industry, but normalized to the specific regression factors of the given company, this statistical model enables the user to answer the hypothetical but practical question, "How does my company compare to everyone else's in my industry, if all other companies were similar to mine?". This study will calculate the EPI scores of each plant based on the proposed SFA models in Sect. 2.4. Yee and Oh (2012) used the EPI score as described in this section for selecting the optimal supply partner for composing semantic web services, when performance metrics for sustainable supply chain are important for automatic business composition, particularly at the service matchmaking phase.

## 2.3 DEA for Energy Performance Analysis

When a panel data set is available and one is interested in measuring the technical improvement in energy efficiency, the Malmquist total factor productivity (TFP) index can be used to reveal a positive or negative technical change across two distinct years such as $t$ and $t + \Delta t$. One advantage of using the Malmquist TFP index is that it can be decomposed into a structural technical change (improvement or deterioration) and a technical efficiency change, where the structural technical change may account for the technical improvement (e.g., frontier line shifts between two distinct years), while the efficiency change indicates how well companies are improving to the frontier line. For example, when a frontier line shifts independently of the DMU set, DMUs appear less efficient, reflecting a positive technical change. By contrast, when a set of DMUs moves independently closer to the frontier line, DMUs appear more efficient, resulting in a positive technical efficiency change. If the frontier line shifts to a higher efficiency and simultaneously, a set of DMUs shifts to a higher efficiency, a positive TFP has occurred. Depending on the orientation used to measure the efficiency, (i.e., either output oriented or input oriented) the TFP indices differ. Recently, a new approach adopting a directional distance function was introduced to provide a flexibility in measurement by allowing negative input and output quantities. For more details on the underlying theory and application of directional distance function, see Nin et al. (2003).

For the consistency between SFA and DEA models, a new vector variable $Z_i = \left(\mathrm{HDD}_i, \mathrm{CDD}_i, \mathrm{Wheelbase}_i, \frac{1}{\mathrm{Utilization}_i}\right)$ is introduced to represent the systematic external factors given for $i$-th company or plant. Note that $Z_i$ takes the inverse of utilization because this study is based on the assumption of strong disposability where all the variables must have a non-decreasing relationship with the energy intensity. Then, our interest in defining the minimum energy intensity requirement to produce one unit of vehicle under the given external condition to $i$-th plant is expressed in the following function:

$$(E_i/Y_i)^* = inf\{can\ process\ Z_i\ to\ produce\ one\ unit\ of\ vehicle\} \tag{2.10}$$

Equation (2.10) motivates the minimal energy density requirement in terms of micro-economic concept. It is possible to connect this motivation expressed in Eq. (2.10) with the interpretation of input distance function that we need to calculate TFP indices. For more specific details of the theoretical development on this connection, see Boyd (2008). An input oriented distance function corresponding to Eq. (2.10) is as follows:

$$D_I(Z_i, E_i/Y_i) = sup\left\{\emptyset : \left(\frac{E_i/Y_i}{\emptyset}\right) can\ process\ Z_i\ to\ produce\ one\ unit\ of\ vehicle\right\} \tag{2.11}$$

Since a distance function is defined, it is possible to calculate the TFP index. In our context, the TFP index requires four distance function values, specifically, $D_I^t(Z_t, E_t/Y_t)$, $D_I^{t+\Delta t}(Z_t, E_t/Y_t)$, $D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})$, and $D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})$, where the notation $D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})$ represents the distance from the period $t+\Delta t$ observation to the period $t$ technology. Vector forms, $Z_t$ and $E_t/Y_t$ represent $(Z_{1t}, Z_{2t}, \ldots, Z_{Nt})$ and $(E_{1t}/Y_{1t}, E_{2t}/Y_{2t}, \ldots, E_{Nt}/Y_{Nt})$, respectively. The subscript "$I$" has been introduced to remind that this is an input-orientated measures. Note that each distance function has an equivalent DEA model. For example, $D_I^t(Z_t, E_t/Y_t)$ is identical to the following DEA model:

$$\begin{aligned} & D_I^t(Z_t, E_t/Y_t) = \min_{\phi,\lambda}\phi \\ s.t.\quad & -Z_{it} + Z_t\lambda \geq 0, \\ & -\phi(E_{it}/Y_{it}) + (E_t/Y_t)\lambda \leq 0 \\ & \lambda \geq 0 \end{aligned} \tag{2.12}$$

The remaining three DEA models are simple variants of this form. Table 2.2 summarizes all the forms.

LP (Linear Program) (2.12) is used to calculate the efficiency of the $t$-th time period relative to $t$-th time period technology, while LP (2.13) is used to calculate the efficiency of $(t+\Delta t)$-th time period relative to $(t+\Delta t)$-th time period technology. Similarly, LP (2.14) is used to calculate the efficiency of the $(t+\Delta t)$-th time period relative to $t$-th time period technology, while LP (2.15) is used to calculate the efficiency of the $t$-th time period relative to $(t+\Delta t)$-th time period technology. Once $D_I^t(Z_t, E_t/Y_t)$, $D_I^{t+\Delta t}(Z_t, E_t/Y_t)$, $D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})$, and

**Table 2.2** DEA models required to calculate Malmquist TFP indices

| Input oriented envelopment forms | |
|---|---|
| $D_I^{t+\Delta t}(E_{t+\Delta t}/Y_{t+\Delta t}, Z_{t+\Delta t}) = \min_{\phi,\lambda}\phi,$ <br> $s.t.\quad -Z_{it+\Delta t} + Z_{t+\Delta t}\lambda \geq 0,$ <br> $-\phi(E_{it+\Delta t}/Y_{it+\Delta t}) + E_{t+\Delta t}/Y_{t+\Delta t}\lambda \leq 0,$ <br> $\lambda \geq 0.$ | (2.13) |
| $D_I^{t}(E_{t+\Delta t}/Y_{t+\Delta t}, Z_{t+\Delta t}) = \min_{\phi,\lambda}\phi$ <br> $s.t.\quad -Z_{it+\Delta t} + Z_{t}\lambda \geq 0,$ <br> $-\phi(E_{it+\Delta t}/Y_{it+\Delta t}) + E_{t}/Y_{t}\lambda \leq 0,$ <br> $\lambda \geq 0.$ | (2.14) |
| $D_I^{t+\Delta t}(Z_t, E_t/Y_t) = \min_{\phi,\lambda}\phi,$ <br> $s.t.\quad -Z_{it} + Z_{t+\Delta t}\lambda \geq 0,$ <br> $-\phi(E_{it}/Y_{it}) + E_{t+\Delta t}/Y_{t+\Delta t}\lambda \leq 0,$ <br> $\lambda \geq 0.$ | (2.15) |

$D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})$ are obtained, the Malmquist TFP index can be calculated and then rearranged such that it is equivalent to the product of a technical efficiency change index and an index of technical change.

$$\begin{aligned} & m_I(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t}, Z_t, E_t/Y_t) \\ & = \left[\frac{D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^t(Z_t, E_t/Y_t)} \times \frac{D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^{t+\Delta t}(Z_t, E_t/Y_t)}\right]^{1/2} \\ & = \frac{D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^t(Z_t, E_t/Y_t)} \left[\frac{D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})} \times \frac{D_I^t(Z_t, E_t/Y_t)}{D_I^{t+\Delta t}(Z_t, E_t/Y_t)}\right]^{1/2} \end{aligned} \tag{2.16}$$

The first and second term of Eq. (2.16) correspond to an efficiency change and a structural technical change, respectively, as follows:

$$\textit{Efficiency change} = \frac{D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^t(Z_t, E_t/Y_t)} \tag{2.17}$$

Meanwhile,

$$\textit{Technical change} = \left[\frac{D_I^t(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})}{D_I^{t+\Delta t}(Z_{t+\Delta t}, E_{t+\Delta t}/Y_{t+\Delta t})} \times \frac{D_I^t(Z_t, E_t/Y_t)}{D_I^{t+\Delta t}(Z_t, E_t/Y_t)}\right]^{1/2} \tag{2.18}$$

Note that the $\phi$ and $\lambda$ are likely to assume different values in the four DEA models in Table 2.2. Furthermore, these four models must be calculated for each plant in the sample. Thus, if there are 10 plants and two time periods, then 40 linear programing problems must be solved. To streamline this multiple calculation procedure, this study developed an Excel spreadsheet tool as does for the SFA models. The developed tool uses VBA in Excel and automates iterations for solving multiple linear programing models. Section 2.4 will show what the tool looks like.

## 2.4 Illustrative Study

This chapter uses artificial data sets for illustrative studies because of intellectual property issues. The data sets were generated to resemble real-world data as close as possible. Although SFA and DEA are generally conducted with real industry data to suggest new insights or interesting finds, the authors believe that the use of artificial data sets will not be detrimental to the overall purpose of this chapter that is to demonstrate the benchmarking process from building frontier models to identifying any structural technical improvement. The generated artificial data sets are listed in Table 2.3 in which two different years' data (years $t$ and $t + \Delta t$) for 10 vehicle

**Table 2.3** Plant data used in the illustrative studies

| Plant | $t$-th year | | | | | |
|---|---|---|---|---|---|---|
| | Wheel base (inch) | HDD (1000) | CDD (1000) | Util | Electricity intensity (kWh/unit) | Fuel intensity ($10^6$ BTU/unit) |
| 1 | 133.50 | 6.69 | 1.22 | 1.19 | 914.64 | 2.18 |
| 2 | 105.75 | 6.20 | 1.48 | 1.27 | 1242.57 | 2.97 |
| 3 | 155.32 | 5.17 | 2.91 | 1.07 | 2098.37 | 5.01 |
| 4 | 112.01 | 5.40 | 1.71 | 1.60 | 1212.36 | 2.90 |
| 5 | 130.63 | 3.22 | 3.03 | 1.78 | 1589.27 | 3.80 |
| 6 | 133.50 | 6.47 | 1.41 | 1.94 | 1336.01 | 3.19 |
| 7 | 105.87 | 6.12 | 1.43 | 1.58 | 1553.32 | 3.71 |
| 8 | 155.51 | 5.33 | 3.09 | 0.77 | 1714.51 | 4.10 |
| 9 | 112.24 | 5.85 | 2.35 | 0.80 | 1548.68 | 3.70 |
| 10 | 130.63 | 3.03 | 3.43 | 1.13 | 1718.41 | 4.10 |
| Plant | $(t + \Delta t)$-th year | | | | | |
| | Wheel base (inch) | HDD (1000) | CDD (1000) | Util | Electricity intensity (kWh/unit) | Fuel intensity ($10^6$ BTU/unit) |
| 1 | 133.50 | 5.83 | 1.96 | 0.73 | 1272.92 | 3.04 |
| 2 | 105.75 | 5.87 | 1.84 | 2.09 | 784.46 | 1.87 |
| 3 | 155.32 | 3.86 | 2.82 | 1.13 | 1950 | 4.66 |
| 4 | 112.01 | 4.53 | 2.52 | 2.00 | 921.72 | 2.20 |
| 5 | 130.63 | 2.51 | 3.99 | 0.50 | 1384.39 | 3.31 |
| 6 | 133.50 | 5.87 | 1.46 | 1.77 | 1008.52 | 2.41 |
| 7 | 105.87 | 6.17 | 1.11 | 0.51 | 789.69 | 1.89 |
| 8 | 155.51 | 4.32 | 3.23 | 0.77 | 1898.7 | 4.54 |
| 9 | 112.24 | 4.72 | 2.03 | 2.22 | 1100.04 | 2.63 |
| 10 | 130.63 | 2.72 | 3.75 | 2.29 | 995.48 | 2.38 |

assembly plants are considered. Regarding the scope of assembly plant, the authors are only considering body shop, paint shop and GA. In fact, these areas vary widely in terms of work volume, labor hours or energy usage depending on their level of in-house *versus* outsourced tasks. The data are generated with an in-house case assumed. In addition, the authors assumed that the major energy-consuming operations are similar among plants. For example, plants are assumed to use electricity-powered chiller, solvent-borne paint system, gas-fired direct heating system, and air conditioning in place.

This chapter uses a commercially available spreadsheet package, Excel, to build the SFA and DEA models. Excel provides an add-on tool called Solver with different solving method options such as Simplex or GRG (Generalized Reduced Gradient). Using the GRG solver method facilitates the maximum likelihood estimation of subset parameters of the proposed SFA models. The example in Fig. 2.4 illustrates a case in which the tool accommodates plant-level input panel data on electricity and builds a model corresponding to Eq. (2.1), thus, estimating parameters for the half-normal inefficiency distribution and the normal measurement error distribution.

The estimated parameters for the electricity and fuel SFA models are shown in Table 2.4 where $\beta_6$ and $\beta_7$ are the coefficient representing YEAR in the fuel SFA model and in the electricity SFA model, respectively. The one-sided likelihood-ratio test values (*LR*) for both models reveal that the models are adequate at the 99.5 % significance level and that the models have very little error attributable to random noise, with most departures attributable to inefficiency. Therefore, the null-hypothesis, $H_0{:}\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} = 0$, is rejected, and the alternative

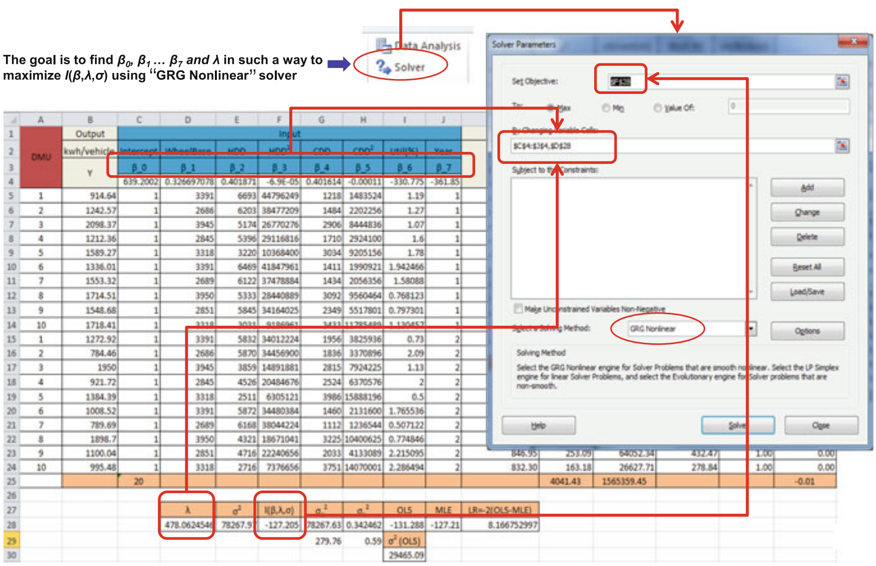



**Fig. 2.4** SFA model estimation using MS-Excel Solver with "GRG Nonlinear" selected

**Table 2.4** Parameter estimates for the SFA models

| Variables | Estimates for the electricity SFA model (standard error; *t*-ratio) | Estimates for the fuel SFA model (standard error; *t*-ratio) |
|---|---|---|
| $\beta_0$ | 650.49 | 0.67 |
| $\beta_1$ | 8.22 (6.05; 1.36) | 0.02 (0.00; 10.15)*** |
| $\beta_2$ | 394.87 (1159.16, 0.34) | 1.53 (1.38; 1.11) |
| $\beta_3$ | −68.34 (123.01; −0.56) | −0.21 (0.15; −1.40) |
| $\beta_4$ | 410.22 (1297.51; 0.32) | −0.21 (2.83; −0.07) |
| $\beta_5$ | −107.80 (268.42; −0.4) | −0.16 (1.03; −0.16) |
| $\beta_6$ | −331.85 (173.66; −1.91)** | −0.86 (0.53; −1.60)* |
| $\beta_7$ | −361.87 (191.46; −1.89)** | NA |
| $\sigma_u$ | 279.79 | 0.68 |
| $\sigma_v$ | 0.55 | 0.00 |
| $\lambda = \sqrt{\frac{\sigma_u}{\sigma_v}}$ | 505.96 | 614.92 |
| $L(OLS)$ | −131.28 | −10.29 |
| $L(SFA)$ | −127.21 | −6.81 |
| $LR$ | $8.17 > \chi^2_{1-2\times 0.005}(1) = 6.635$ | $6.97 > \chi^2_{1-2\times 0.005}(1) = 6.635$ |

Notations for significance level in a two-tailed test: ***(99 %); **(90 %); *(85 %)

hypothesis $H_1\!:\!\gamma > 0$ with technical inefficiency effect is accepted for both the electricity and fuel SFA models. This statistical results show that a structural technical improvement in electricity ($\beta_7$ of the electricity SFA model) and fuel ($\beta_6$ of the fuel SFA model) occurred during the period. Furthermore, $\beta_7$ and $\beta_6$ are statistically significant at the 90 % level $(-1.91 < t_{0.95}(12) = -1.782)$ and the 85 % level $(t_{0.95}(13) = -1.771 < -1.6 < t_{0.9}(13) = -1.350)$ in a two-tailed test, respectively. These results indicate that, all other factors being equal, an average reduction of 330.77 (kWh) and 253.55 (kWh) in the electricity and fuel per vehicle has occurred, leading to efficiency gains of \$41.73/vehicle (note: the calculation assumes \$0.1/kWh for electricity and \$0.03413/kWh (=0.03413 therm/kWh × \$1/therm) for natural gas). This magnitude of efficiency gains may seem small in the unit cost of production but may offer considerable energy cost savings and significantly reduce the environmental impact when the total production is considered. For example, let us assume that a car manufacturing company produces nine million cars per year and must solely purchase $CO_2$ credits from a market to emit $CO_2$. Given these condition, if the company achieved the aforementioned magnitude of efficiency gains, then the total cost savings from energy reduction and a reduced environment impact would be \$428 M (note: \$428 M ≈ 9,000,000 × [\$41.73 + (330.77 + 253.55 kWh)/1000 × \$10]; the $CO_2$ credit price in the market is assumed to be \$10 per $CO_2$ ton). ENERGY STAR® plant energy performance indicator (EPI) values are also calculated, and the results are summarized in Table 2.5.

Note that DMUs 6 and 7 show the lower efficiency in Table 2.5 in *t*-th Year. These low efficiencies are caused by the large difference between their average practices and best practices. These results, however, also indicate that DMUs 6 and 7 have higher potentials to further improvement in energy savings.

**Table 2.5** SFA results in terms of EPI

| DMU | $t$-th year | | (t + Δt)-th year | |
|---|---|---|---|---|
| | Electricity (%) | NG (%) | Electricity (%) | NG (%) |
| 1 | 100 | 100 | 66 | 42 |
| 2 | 26 | 31 | 24 | 28 |
| 3 | 16 | 16 | 26 | 14 |
| 4 | 98 | 100 | 100 | 100 |
| 5 | 99 | 86 | 81 | 100 |
| 6 | 6 | 6 | 40 | 40 |
| 7 | 1 | 2 | 99 | 92 |
| 8 | 99 | 100 | 26 | 24 |
| 9 | 35 | 30 | 37 | 31 |
| 10 | 93 | 96 | 56 | 83 |
| Mean | 57 | 57 | 56 | 55 |

Using the Simplex solver, this study developed a spreadsheet tool for DEA, too. The developed tool uses VBA in Excel and automates iterations for solving multiple linear programing models. Briefly, with respect to automation logic, the tool uses “For” loop to automate iterations of solving multiple linear programing models in which the Solver with the “Simplex” optimization option calculates the efficiency for each DMU and the results are recorded in a table using the copy/paste function (note: the three major functions used in the loop statement of the VBA programing are as follows: (1) “SolverOk”—defines the objective function and the decision variables; (2) “SolverAdd”—defines model constraints; and (3) “SolverSolv”—runs Solver). Figure 2.5 illustrates an example in which the tool accommodates

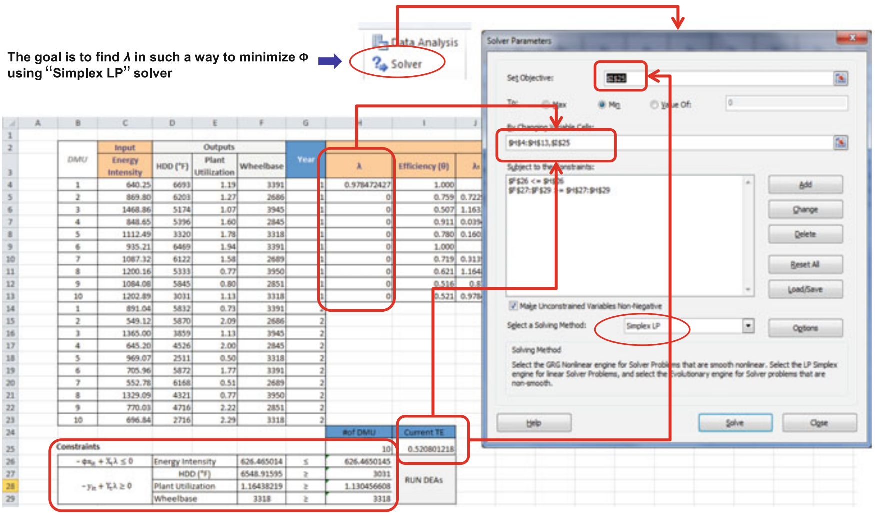



**Fig. 2.5** DEA model implementation using MS-Excel Solver with “Simplex LP”

**Table 2.6** Malmquist index summary (electricity)

| DMU | Efficiency change (%) | Technical change (%) | Total factor productivity change (%) |
|---|---|---|---|
| 1 | 78 | 106 | 82 |
| 2 | 123 | 155 | 190 |
| 3 | 77 | 138 | 106 |
| 4 | 92 | 166 | 152 |
| 5 | 76 | 175 | 133 |
| 6 | 98 | 131 | 128 |
| 7 | 135 | 124 | 166 |
| 8 | 62 | 147 | 91 |
| 9 | 85 | 172 | 147 |
| 10 | 100 | 187 | 187 |
| Mean | 92 | 149 | 139 |

plant-level input panel data on fuel corresponding to LP (2.7). Tables 2.6 and 2.7 present the Malmquist indices obtained by solving the DEA models for electricity and fuel, respectively. Three indices are presented for each firm, such as efficiency change (relative to a CRS technology), technical change, and total factor productivity change. It should be noted that the technical change of each model from $t$ to $t + \Delta t$ increases (greater than 100 %), indicating that there has been a structural technical improvement in energy performance over the years. The DEA efficiency at each year is also calculated and summarized in Tables 2.8 and 2.9.

In order to measure the consistency between the SFA and the DEA approaches on the efficiency ranking results for firms, a Spearman's rank correlation coefficient test was conducted. Spearman's rank correlation coefficient values are 0.9 and 0.25 for $t$ and $t + \Delta t$, respectively, in electricity, and 0.3 and 0.38 for $t$ and $t + \Delta t$,

**Table 2.7** Malmquist index summary (natural gas)

| DMU | Efficiency change (%) | Technical change (%) | Total factor productivity change (%) |
|---|---|---|---|
| 1 | 78 | 92 | 72 |
| 2 | 132 | 146 | 192 |
| 3 | 117 | 92 | 108 |
| 4 | 99 | 148 | 146 |
| 5 | 90 | 109 | 98 |
| 6 | 98 | 129 | 127 |
| 7 | 139 | 122 | 169 |
| 8 | 98 | 92 | 90 |
| 9 | 147 | 132 | 194 |
| 10 | 187 | 122 | 229 |
| Mean | 113 | 121 | 143 |

**Table 2.8** DEA results (electricity)

| DMU | $d_0^t(x_t, y_t)$ (%) | $d_0^{t+\Delta t}(x_t, y_t)$ (%) | $d_0^t(x_{t+\Delta t}, y_{t+\Delta t})$ (%) | $d_0^{t+\Delta t}(x_{t+\Delta t}, y_{t+\Delta t})$ (%) |
|---|---|---|---|---|
| 1 | 100 | 108 | 94 | 78 |
| 2 | 82 | 65 | 192 | 100 |
| 3 | 77 | 55 | 81 | 59 |
| 4 | 100 | 69 | 173 | 92 |
| 5 | 100 | 62 | 144 | 76 |
| 6 | 100 | 74 | 125 | 98 |
| 7 | 74 | 52 | 107 | 100 |
| 8 | 99 | 68 | 91 | 61 |
| 9 | 89 | 58 | 146 | 76 |
| 10 | 100 | 58 | 202 | 100 |
| Mean | 92 | 67 | 135 | 84 |

**Table 2.9** DEA results (natural gas)

| DMU | $d_0^t(x_t, y_t)$ (%) | $d_0^{t+\Delta t}(x_t, y_t)$ (%) | $d_0^t(x_{t+\Delta t}, y_{t+\Delta t})$ (%) | $d_0^{t+\Delta t}(x_{t+\Delta t}, y_{t+\Delta t})$ (%) |
|---|---|---|---|---|
| 1 | 100 | 109 | 72 | 78 |
| 2 | 76 | 65 | 183 | 100 |
| 3 | 51 | 55 | 55 | 59 |
| 4 | 91 | 69 | 149 | 90 |
| 5 | 78 | 61 | 65 | 70 |
| 6 | 100 | 75 | 123 | 98 |
| 7 | 72 | 52 | 107 | 100 |
| 8 | 62 | 67 | 56 | 61 |
| 9 | 52 | 54 | 138 | 76 |
| 10 | 52 | 56 | 158 | 97 |
| Mean | 73 | 66 | 111 | 83 |

respectively, in natural gas. All of the rank correlation coefficient values are positive, indicating that the ranks of the SFA and DEA results have moderate (in $t$) and small (in $t + \Delta t$) positive linear relationships.

It makes sense to compare the estimated parameters to those of existing estimated models in terms of value and sign as part of cross-validation if there have been similar estimation works. The 2000 and 2005 models elicited by Boyd (2014) have the identical model configuration with this study. Therefore, a comparison on the estimated parameters was conducted between those models and the results are summarized in Tables 2.10 and 2.11. One challenge against the comparison was that the datasets of two models are significantly different. The 2000 and 2005 models were based on real data composed by collecting some sample plant data from major car making companies in U.S. while this study generated an artificial

Table 2.10 Comparison of electricity SFA model parameters

| Parameter | This study (based on simulated data) | 2000 model | 2005 model | Direction of the relationship |
|---|---|---|---|---|
| Constant | 650.49 | 369.39 | −91.84 | N/A |
| Wbase | 8.22 | 2.77 | 2.03 | ↗ |
| HDD | 394.87 | −48.41 | 163.06 | ↗ |
| $HDD^2$ | −68.34 | 4.79 | −15.17 | |
| Util | −331.85 | −138.61 | −112.54 | ↘ |
| CDD | 410.22 | −59.32 | −223.89 | ↗ |
| $CDD^2$ | −107.80 | 41.91 | 86.61 | |

Table 2.11 Comparison of fuel SFA model parameters

| Parameter | This study (based on simulated data) | 2000 model | 2005 model | Direction of the relationship |
|---|---|---|---|---|
| Constant | 0.67 | 3.827 | −0.526 | N/A |
| Wbase | 0.02 | 0.00322 | 0.019 | ↗ |
| HDD | 1.53 | −0.545 | 0.439 | ↗ |
| $HDD^2$ | −0.21 | 0.11 | | |
| Util | −0.21 | −6.788 | −0.072 | ↘ |
| $Util^2$ | −0.16 | 2.399 | | |

dataset by simulating a population that resembles GM plants located in a specific region. Due to the large difference between datasets, the differences in magnitude between parameter values exist. However, the orders of magnitude between parameter values are in the same range and the directions of relationships between systematic external factors and energy intensity (i.e., signs of estimated parameters) turned out consistent. The authors again want to clarify that the datasets used in this chapter are simulated and should not be taken to be applicable to the industry, but are only illustrative of the proposed models.

It seems that it would be more useful to compare best practices with inefficient practices to identify energy reduction opportunities after computing numerical efficiencies and locating the best and inefficient performance plants. Finding energy reduction opportunities must be preceded by understanding high energy cost drivers for inefficient plants. For this purpose, Oh and Hildreth (2013), Jurek et al. (2012), and Oh et al. (2011) proposed activity-based decision steps including a step of comparing hourly average energy use of each activity between best practice plants and less efficient plants followed by figuring out which activity are problematic cost drivers for less efficient plants.

## 2.5 Summary

This chapter proposes a benchmarking process using stochastic and deterministic frontier analysis models, specifically, SFA and DEA, to identify industry-wide or company-wide structural technical improvement in energy efficiency with a focus on the car manufacturing industry. The quantitative identification of technical improvement in energy efficiency is important to help car manufacturing companies evaluate the effectiveness of the various energy efficiency programs that they may have implemented, in many cases supported by government R&D or financial programs. This study proposed SFA models that incorporate the Hicksian neutral technological change concept and DEA models implemented to calculate Malmquist Productivity Change indices. Illustrative examples of the proposed models are presented to demonstrate the overall benchmarking process to find frontier lines and to measure the shifts of the frontier line that were used to proxy the structural technical improvement in energy efficiency. A log likelihood ratio test and a Spearman rank-order correlation coefficient test were conducted to test the significance of the SFA model and its consistency with the DEA model, respectively. ENERGY STAR® plant energy performance indicator values were also calculated. The results of the analysis based on the SFA models calculated total efficiency gains of $41.73/vehicle during the tested period. The tools developed for illustrative examples are available upon request at authors.

Regarding future work, one priority is to enhance the proposed SFA and DEA models to enable them to account for structural technological change by including the time-varying behavior of the inefficiency effects, thereby identifying more extensive factors affecting the technical change. Additionally, the implementation of a directional distance function in calculating the Malmquist TFP indices is of interest.

## 2.6 Exercises

1. Figures 2.4 and 2.5 illustrate how to implement SFA and DEA models in MS-Excel Solvers including “GRG Non-linear” and “Simplex LP” solvers. Refer to Appendix B (“Getting Started with Excel Solver for SFA and DEA Analyses”) and replicate the illustrated work.
2. Equation (2.3) is a derivation for the case that a SFA model demonstrates half-normal inefficiency and produces a normal measurement error. The product of the densities of a half-normal inefficiency distribution $(u \sim N^{+}(0, \sigma_u^2))$ and a normal measurement error distribution $((v \sim N(0, \sigma_v^2)))$ is:

$$\varphi_v(\varepsilon-u)\varphi_u(u) = \frac{1}{\sqrt{2\pi\sigma_v^2}}\mathrm{e}^{-\frac{1}{2}\frac{(\varepsilon-u)^2}{\sigma_v^2}}\frac{2}{\sqrt{2\pi\sigma_u^2}}\mathrm{e}^{-\frac{1}{2}\frac{u^2}{\sigma_u^2}}$$
$$= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}}\mathrm{e}^{-\frac{1}{2}\frac{\left(\sigma_u^2+\sigma_v^2\right)u^2-2\sigma_u^2\varepsilon u+\sigma_u^2\varepsilon^2}{\sigma_u^2\sigma_v^2}}.$$

Starting from the equation above, drive Eqs. (2.3)–(2.5). Refer to Appendix A ("Derivation of the log likelihood function and first-order partial derivatives for cost frontier model") for the solution.

3. In reality, many firms are involved in production activities that often generate undesirable outputs such as harmful side products (e.g., pollution, waste, noise, and etc.) to the environment. Those undesirable outputs can be disposable and the disposability assumptions for undesirable products cause difficulties in the measurements of the overall performance of firms. Meanwhile, DEA has been considered as a successful means to address the disposability issues. Read the paper (Toshiyuki and Mika 2012) and gain the insight on the various DEA models to assess the energy and environment performance in the light of disposability assumptions.
4. Section 2.2 introduces EPI (Energy Performance Indicator) which is developed as part of EPA's ENERGY STAR program to measure the energy performance of companies who usually manufacture consumer products. Technically, EPI is calculated as a percentile ranking of the energy efficiency of the given company by adopting a parametric modeling-based benchmarking technique so-called Stochastic Frontier Analysis (SFA). Suppose that the one-sided inefficiency distribution for $u_i$ follows a half-normal distribution such that $u_i \sim N^+(0, \sigma_u^2)$, where we additionally assume that $\sigma_u = 0.5$ MWH/Unit and the best practice company in the industry has 2 MWH/Unit as its energy performance. With these assumptions, answer the following questions by referring to the procedures set forth in Sect. 2.2:

- If your company's energy performance is 5 MWH/Unit, what is your company's EPI in the industry?
- If your company wants to achieve 75 % EPI in the industry, what energy performance (MWH/Unit) should your company meet?

## Appendix A: Derivation of the Log Likelihood Function and First-Order Partial Derivatives for Cost Frontier Model

This derivation is for the case in which a SFA model demonstrates half-normal inefficiency and produces a normal measurement error. The derivation of the log likelihood function is modified from Bogetoft and Otto (2011). The product of the densities of a half-normal inefficiency distribution $(u \sim N^{+}(0, \sigma_u^2))$ and a normal measurement error distribution $(v \sim N(0, \sigma_v^2))$ is:

$$\begin{aligned}
\varphi_v(\varepsilon - u)\varphi_u(u) &= \frac{1}{\sqrt{2\pi\sigma_v^2}} \mathrm{e}^{-\frac{1}{2}\frac{(\varepsilon-u)^2}{\sigma_v^2}} \frac{2}{\sqrt{2\pi\sigma_u^2}} \mathrm{e}^{-\frac{1}{2}\frac{u^2}{\sigma_u^2}} \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \mathrm{e}^{-\frac{1}{2}\frac{u^2}{\sigma_u^2}-\frac{1}{2}\frac{(\varepsilon-u)^2}{\sigma_v^2}} \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \mathrm{e}^{-\frac{1}{2}\frac{(\sigma_u^2+\sigma_v^2)u^2-2\sigma_u^2\varepsilon u+\sigma_u^2\varepsilon^2}{\sigma_u^2\sigma_v^2}}.
\end{aligned}$$

The integration of the aforementioned joint density is given by the following:

$$\begin{aligned}
\varphi_\varepsilon(\varepsilon) &= \int_0^\infty \varphi_v(\varepsilon - u)\varphi_u(u)du \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \int_0^\infty \mathrm{e}^{-\frac{1}{2}\frac{(\sigma_u^2+\sigma_v^2)u^2-2\sigma_u^2\varepsilon u+\sigma_u^2\varepsilon^2}{\sigma_u^2\sigma_v^2}} du \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \int_0^\infty \mathrm{e}^{-\frac{1}{2}\left(\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)u^2-\frac{2}{\sigma_v^2}\varepsilon u+\frac{1}{\sigma_v^2}\varepsilon^2\right)} du \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \int_0^\infty \mathrm{e}^{-\frac{1}{2}\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\left(u^2-\frac{2\varepsilon u}{\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2}+\frac{\varepsilon^2}{\left(\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2\right)^2}-\frac{\varepsilon^2}{\left(\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2\right)^2}\right)} \mathrm{e}^{-\frac{\varepsilon^2}{2\sigma_v^2}} du \\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}} \int_0^\infty \mathrm{e}^{-\left(\frac{1}{\sqrt{2}}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\left(u-\frac{\varepsilon}{\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2}\right)\right)^2} \mathrm{e}^{\left(\frac{\varepsilon^2}{2\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)(\sigma_v^2)^2}-\frac{\varepsilon^2}{2\sigma_v^2}\right)} du.
\end{aligned}$$

Let $t = \frac{1}{\sqrt{2}}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\left(u - \frac{\varepsilon}{\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2}\right)$, $u = \frac{\sqrt{2}}{\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}}t + \frac{\varepsilon}{\left(\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}\right)\sigma_v^2}$ and $du = \frac{\sqrt{2}}{\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}}dt$. Then, if $u \to \infty$, then $t \to \infty$. If $u = 0$, then $t = \frac{-\varepsilon}{\sqrt{2}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\sigma_v^2}$.

$$
\begin{aligned}
\varphi_\varepsilon(\varepsilon) &= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}}\left(\int_{\frac{-\varepsilon}{\sqrt{2}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\sigma_v^2}}^{\infty} e^{-t^2}\frac{\sqrt{2}}{\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}}dt\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{(\sigma_u^2+\sigma_v^2)}}\\
&= \frac{1}{\pi\sqrt{\sigma_u^2\sigma_v^2}}\frac{\sqrt{2}}{\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}}\frac{\sqrt{\pi}}{2}\left(\frac{2}{\sqrt{\pi}}\int_{\frac{-\varepsilon}{\sqrt{2}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\sigma_v^2}}^{\infty}\mathrm{e}^{-t^2}dt\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{(\sigma_u^2+\sigma_v^2)}}\\
&= \frac{1}{\sqrt{2\pi}\sqrt{\sigma_u^2+\sigma_v^2}}\left(1+erf\left(\frac{\varepsilon}{\sqrt{2}\sqrt{\frac{1}{\sigma_u^2}+\frac{1}{\sigma_v^2}}\sigma_v^2}\right)\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{(\sigma_u^2+\sigma_v^2)}}\\
&= \frac{1}{\sqrt{2\pi}\sqrt{\sigma_u^2+\sigma_v^2}}\left(1+erf\left(\frac{\varepsilon}{\sqrt{2}\sqrt{\sigma_v^2+\sigma_u^2}}\sqrt{\frac{\sigma_u^2}{\sigma_v^2}}\right)\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{(\sigma_u^2+\sigma_v^2)}}\\
&\quad(\text{Set } \sigma^2=\sigma_v^2+\sigma_u^2 \quad \text{and} \quad \lambda=\sqrt{\frac{\sigma_u^2}{\sigma_v^2}})\\
&= \frac{1}{\sqrt{2\pi\sigma^2}}\left(1+erf\left(\frac{\varepsilon}{\sqrt{2}\sqrt{\sigma^2}}\lambda\right)\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}} \quad \left(erf(x)=\frac{2}{\sqrt{\pi}}\int_0^x \mathrm{e}^{-x^2}dx\right)\\
&= \frac{1}{\sqrt{2\pi\sigma^2}}2\Phi\left(+\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}} \quad (\Phi \textit{ is the normal cumulative density function})\\
&= \frac{\sqrt{2}}{\sqrt{\pi\sigma^2}}\Phi\left(+\frac{\lambda\varepsilon}{\sqrt{\sigma^2}}\right)\mathrm{e}^{-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}}.
\end{aligned}
$$

where $\sigma^2=\sigma_v^2+\sigma_u^2$, and $=\sqrt{\frac{\sigma_u^2}{\sigma_v^2}}$ . The error function $erf(x)=\frac{2}{\sqrt{\pi}}\int_0^x \mathrm{e}^{-t^2}dt$ has the following property: $erf(-x)=-erf(x)$. Its relationship to the normal distribution is given by $\Phi(x)-\frac{1}{2}=\frac{1}{\sqrt{2\pi}}\int_0^x \mathrm{e}^{-\frac{1}{2}t^2}dt=\frac{1}{2}erf\left(\frac{x}{\sqrt{2}}\right)$ such that $\Phi(x)=\frac{1}{2}\left(1+erf\left(\frac{x}{\sqrt{2}}\right)\right)$. Then, the log of this density is:

$$\log\varphi_\varepsilon(\varepsilon)=-\frac{1}{2}\log\left(\frac{\pi}{2}\right)-\frac{1}{2}\log\sigma^2+\log\Phi\left(\frac{\varepsilon\lambda}{\sqrt{\sigma^2}}\right)-\frac{1}{2}\frac{\varepsilon^2}{\sigma^2}.$$

With $K$ independent observations and $K$ firms, the joint density is $\varphi(\varepsilon_1,\ldots,\varepsilon_K)=\prod_{k=1}^{K}\varphi_\varepsilon(\varepsilon_K)$ and the log of the joint density is:

$$\begin{aligned}
\log \varphi(\varepsilon_1, \ldots, \varepsilon_K) &= \sum_{k=1}^{K} \log \varphi_\varepsilon(\varepsilon_k) \\
&= -\frac{1}{2} K \log\left(\frac{\pi}{2}\right) \\
&\quad -\frac{1}{2} K \log \sigma^2 + \sum_{k=1}^{K} \log \Phi\left(\frac{\lambda \varepsilon_k}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2} \sum_{k=1}^{K} \varepsilon_k^2.
\end{aligned}$$

We can rewrite this equation to emphasize that the error term $\epsilon$ depends on the parameter (vector) $\beta$, such that the log likelihood function is given by:

$$\begin{aligned}
l(\beta, \sigma^2, \lambda) &= \log \varphi_\varepsilon(\varepsilon_1(\beta), \ldots, \varepsilon_K(\beta); \sigma^2, \lambda) \\
&= \log \varphi_\varepsilon(y_1 - f(x_1; \beta), \ldots, y_K - f(x_K; \beta); \sigma^2, \lambda) \\
&= -\frac{1}{2} K \log\left(\frac{\pi}{2}\right) \\
&\quad -\frac{1}{2} K \log \sigma^2 + \sum_{k=1}^{K} \log \Phi\left(\frac{\lambda(y_k - f(x_k; \beta))}{\sqrt{\sigma^2}}\right) \\
&\quad -\frac{1}{2\sigma^2} \sum_{k=1}^{K} (y_k - f(x_k; \beta))^2.
\end{aligned}$$

The function $l(\beta, \sigma^2, \lambda)$ is the log-likelihood function, which depends on the parameters to be estimated (in this case $\beta$, $\sigma^2$, and $\lambda$) and on the data $(x_1, y_1), \ldots, (x_K, y_K)$. Then, the gradient of $l(\beta, \lambda)$ with respect to $\beta, \lambda$ is as follows, with $\sigma^2$ defined as $\frac{1}{K} \sum_{k=1}^{K} (y_k - f(x_k; \beta))^2$.

$$\begin{aligned}
l(\beta, \lambda) &= -\frac{k}{2} \log\left(\frac{\pi}{2}\right) - \frac{k}{2} \log(\sigma^2) + \sum_{k=1}^{K} \log \Phi\left(\frac{\varepsilon_k \lambda}{\sigma}\right) - \frac{k}{2} \\
&= \frac{k}{2} \log\left(\frac{\pi}{2}\right) - k \log \sigma + \sum_{k=1}^{K} \log \Phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right) - \frac{k}{2}.
\end{aligned}$$

Let $\sigma' = \frac{\partial}{\partial \beta_j}(\sigma)$. Then, $\sigma' = \frac{\partial}{\partial \beta_j}\left(\sqrt{\frac{1}{k}\sum_{K=1}^{K} \varepsilon_k^2}\right) = \frac{-2\sum_{k=1}^{K} \varepsilon_k X_{jk}}{2\sqrt{k}\sqrt{\sum_{k=1}^{K} \varepsilon_k^2}} = -\frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sqrt{k}\sqrt{\sum_{k=1}^{K} \varepsilon_k^2}}$.

Similarly, $\varepsilon_k' = -X_{jk}$.

$$-k\left(\frac{\sigma'}{\sigma}\right) = -k\left(\frac{\frac{1}{2\sqrt{k}\sqrt{\sum_{k=1}^{K} \varepsilon_k^2}} \sum_{k=1}^{K} 2\varepsilon_k(-X_{jk})}{\sqrt{\frac{1}{k}\sum_{k=1}^{K} \varepsilon_k^2}}\right) = k\frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sum_{k=1}^{K} \varepsilon_k^2},$$

So,

$$\left(\frac{\lambda \varepsilon_k}{\sigma}\right)' = \frac{\lambda \varepsilon_k' \sigma - \lambda \varepsilon_k \sigma'}{\sigma^2} = \frac{-\lambda \sigma X_{jk} + \lambda \varepsilon_k \frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sqrt{k}\sqrt{\sum_{k=1}^{K} \varepsilon_k^2}}}{\sigma^2}.$$

Now, first, the partial derivative of $l(\beta, \lambda)$ with respect to $\beta$ is:

$$\begin{aligned}
\frac{\partial}{\partial \beta_j} l(\beta, \lambda) &= -k\left(\frac{\sigma'}{\sigma}\right) + \sum_{k=1}^{K} \frac{\phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)}{\Phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)} \left(\frac{\lambda \varepsilon_k}{\sigma}\right) \\
&= k \frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sum_{k=1}^{K} \varepsilon_k^2} + \sum_{k=1}^{K} \frac{\phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)}{\Phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)} \frac{\lambda \left(-\sigma X_{jk} + \varepsilon_K \frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sqrt{k}\sqrt{\sum_{k=1}^{K} \varepsilon_k^2}}\right)}{\sigma^2} \\
&= -\frac{\lambda}{\sigma} \sum_{k=1}^{K} \frac{\phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)}{\Phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)} X_{jk} + \frac{\sum_{k=1}^{K} \varepsilon_k X_{jk}}{\sigma^2} \left(1 + \frac{\lambda}{k\sigma} \sum_{k=1}^{K} \frac{\phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)}{\Phi\left(\frac{\lambda \varepsilon_k}{\sigma}\right)} \varepsilon_k\right).
\end{aligned}$$

Second, the partial derivative of $l(\beta, \lambda)$ with respect to $\lambda$ is:

$$\frac{\partial}{\partial \lambda} l(\beta, \lambda) = \sum_{k=1}^{K} \frac{\phi\left(\frac{\lambda \epsilon_k}{\sigma}\right)}{\Phi\left(\frac{\lambda \epsilon_k}{\sigma}\right)} \frac{\epsilon_k}{\sigma}.$$

## Appendix B: Getting Started with Excel Solver for SFA and DEA Analyses

### *Introducing, Getting and Installing Excel Solver*

In this chapter and Chap. 4, this book uses Excel Solver to solve optimization problems such as maximum likelihood estimation for SFA, DEA LP problem, and chance-constrained stochastic programming problem. Although the major PC-based spreadsheets provides built-in optimizers, Excel Solver is considered the most widely used optimization software today in the world because of its simple user interface without a need of knowing that the calculations inside the Excel Solver performs are heavily complex in reality. Excel Solver provides three available solving methods such as Simple LP (Linear Programming) method, GRG (Generalized Reduced Gradient) Nonlinear method, and Evolutionary method. An overview of each solving method is discussed in Fig. 2.6.

This Appendix illustrates three examples: (1) SFA parameters estimation (2) DEA LP problem and (3) traveling compressed air expert problem, with an attempt to use GRG method, Simplex LP method and evolutionary method, respectively.

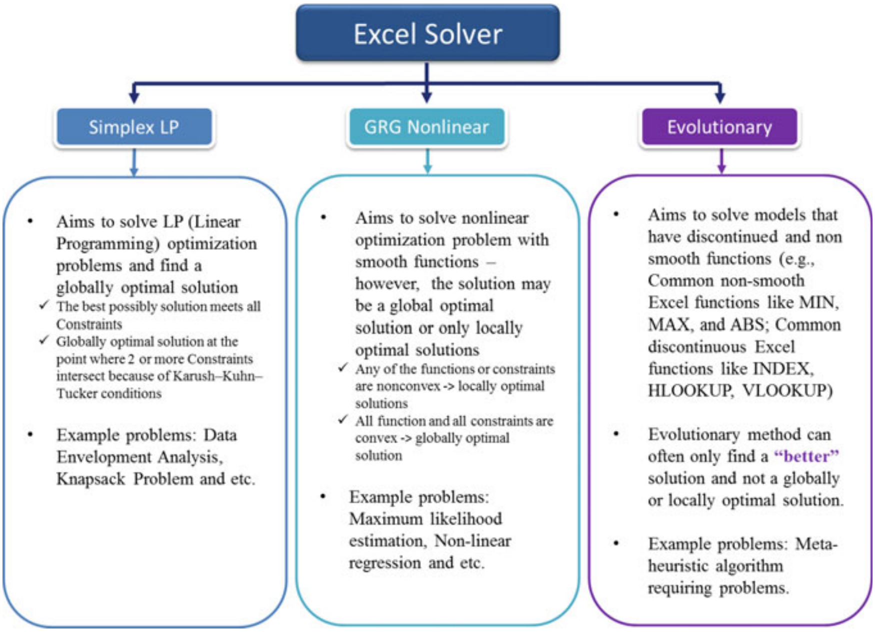



**Fig. 2.6** Three methods provided by Excel Solver

However, this Appendix is not an introduction to all of Excel Solver, but to the selected parts of Excel Solver used in the book. For further instructions, see *An Introduction to Spreadsheet Optimization Using Excel Solver*, which is available on http://www.meiss.com/download/Spreadsheet-Optimization-Solver.pdf. Another useful introduction is *Step-By-Step Optimization with Excel Solver*, which is available on http://excelmasterseries.com/D-_Loads/New_Manuals/Step-By-Step_Optimization_S.pdf and provides a detailed introduction for beginners to successfully implement Excel Solver, in particular, by separating a problem solving path into 6 steps such as (1) Step 1—Determine the objective (2) Step 2—Determine the decision variables (3) Step 3—Build the Excel equations that combine the objective with all decision variables (4) Step 4—List all constraints (5) Step 5—Test the Excel Spreadsheet (6) Step 6—Insert all data into the Solver dialog box.

Excel Solver is available in the *Analysis* group on the *Data* tab in Excel as Fig. 2.7. If the *Data* tab does not have the choice *Solver* available, then the following installation procedure should be taken. Note that this guide is based on Microsoft Excel 2013 version.

1. Open *Office Button|Excel Options* to see if the *Add-Ins* option appears
2. If the *Add-Ins* option appears, select *Excel Add-Ins* from the drop down dialog box
3. Click *Go* then *Solver* is enabled.
4. If the *Add-Ins* option does not appear, run the *Setup* program again to install it

Once Excel Solver is installed, it can be used.


**Fig. 2.7** Excel Solver in data tab|analysis group

## *SFA Parameters Estimation Using GRG Method*

This example is made to provide an opportunity to learn how to use the generalized reduced gradient (GRG) method of Excel Solver. This method aims to solve nonlinear optimization problem with smooth functions—however, the solution may be a global optimal solution or only locally optimal solutions. In case that any of the functions or constraints are nonconvex, it may obtain locally optimal solutions. If all function and all constraints are convex, it is likely to obtain globally optimal solution. Problems including maximum likelihood estimation or non-linear regression can be solvable with GRG method. This example will use the SFA analysis example discussed in this chapter.

### Define Problem, Objective and Decision Variables

This example problem aims to determine and to measure the effectiveness of energy reduction initiatives in terms of a technical improvement that corresponds to a certain structural change in industry-wide energy efficiency between two distinct time periods by proposing a benchmarking model: SFA (stochastic frontier analysis) model based on Hicksian neutral technological change concept.

The proposed SFA model for electricity is:

$$\begin{aligned} E_i/Y_i = {} & A + \beta_1 WBASE_i + \beta_2 HDD_i + \beta_3 HDD_i^2 \\ & + \beta_4 CDD_i + \beta_5 CDD_i^2 + \beta_6 Util_i + \beta_7 Year_i + u_i - \mathrm{v}_i \end{aligned}$$

where:

- $E_i$: Total site electricity use at plant $i$ in kWh;
- $Y_i$: Number of vehicles produced;
- $WBASE_i$: Wheelbase (the distance between its front and rear wheels) of the largest vehicle produced in the plant in inch;
- $HDD_i$: Thousand heating degree days for the plant location and year;

- $HDD_i^2$: $HDD_i$ squared;
- $CDD_i$: Thousand cooling degree days for the plant location and year;
- $CDD_i^2$: $CDD_i$ squared;
- $Util_i$: Plant utilization rate, defined as output/capacity, where the denominator, capacity is a normalized capacity defined as equal to capacity line rate (or job per hour) × 235 working days × 16 working hours per day;
- $Year_i$: $t$ and $t + \Delta t$ where $\Delta t$ is the time period at which a significant technical improvement in energy efficiency is observed; and
- β: Vector of parameters to be estimated.

The SFA model above requires several parameters to be estimated, such as β, $\sigma_v^2$ and $\sigma_u^2$. This work uses the maximum likelihood method for parameter estimation. The log likelihood function can be expressed as:

$$l\left(\beta, \sigma^2, \lambda\right) = -\frac{1}{2} N \log\left(\frac{\pi}{2}\right) - \frac{1}{2} N \log \sigma^2 + \sum_{i=1}^{N} \log \Phi\left(\frac{\lambda(y_i - f(x_i;\beta))}{\sqrt{\sigma^2}}\right) - \frac{1}{2\sigma^2} \sum_{i=1}^{N} (y_i - f(x_i;\beta))^2.$$

The objective of this example is to estimate parameters (decision variables) β, $\sigma^2$ and λ on the data $(x_1, y_1), \ldots, (x_N, y_N)$ in such a way that maximizes $l(\beta, \sigma^2, \lambda)$ that is the log-likelihood function. The data set are shown below.

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | DMU | Output | Input | | | | | | | |
| 2 | | kwh/vehicle | Intercept | WheelBase (in) | 1000 HDD | $(1000\ HDD)^2$ | 1000 CDD | $(1000\ CDD)^2$ | Util(%) | Year |
| 3 | | Y | β_0 | β_1 | β_2 | β_3 | β_4 | β_5 | β_6 | β_7 |
| 4 | | | -174.39 | 9.35 | 491.55 | -66.06 | 447.36 | -95.38 | -205.77 | -358.18 |
| 5 | 1 | 914.64 | 1 | 133.50 | 6.69 | 44.80 | 1.22 | 1.48 | 1.19 | 1 |
| 6 | 2 | 1242.57 | 1 | 105.75 | 6.20 | 38.48 | 1.48 | 2.20 | 1.27 | 1 |
| 7 | 3 | 2098.37 | 1 | 155.32 | 5.17 | 26.77 | 2.91 | 8.44 | 1.07 | 1 |
| 8 | 4 | 1212.36 | 1 | 112.01 | 5.40 | 29.12 | 1.71 | 2.92 | 1.60 | 1 |
| 9 | 5 | 1589.27 | 1 | 130.63 | 3.22 | 10.37 | 3.03 | 9.21 | 1.78 | 1 |
| 10 | 6 | 1336.01 | 1 | 133.50 | 6.47 | 41.85 | 1.41 | 1.99 | 1.94 | 1 |
| 11 | 7 | 1553.32 | 1 | 105.87 | 6.12 | 37.48 | 1.43 | 2.06 | 1.58 | 1 |
| 12 | 8 | 1714.51 | 1 | 155.51 | 5.33 | 28.44 | 3.09 | 9.56 | 0.77 | 1 |
| 13 | 9 | 1548.68 | 1 | 112.24 | 5.85 | 34.16 | 2.35 | 5.52 | 0.80 | 1 |
| 14 | 10 | 1718.41 | 1 | 130.63 | 3.03 | 9.19 | 3.43 | 11.79 | 1.13 | 1 |
| 15 | 1 | 1272.92 | 1 | 133.50 | 5.83 | 34.01 | 1.96 | 3.83 | 0.73 | 2 |
| 16 | 2 | 784.46 | 1 | 105.75 | 5.87 | 34.46 | 1.84 | 3.37 | 2.09 | 2 |
| 17 | 3 | 1950 | 1 | 155.32 | 3.86 | 14.89 | 2.82 | 7.92 | 1.13 | 2 |
| 18 | 4 | 921.72 | 1 | 112.01 | 4.53 | 20.48 | 2.52 | 6.37 | 2.00 | 2 |
| 19 | 5 | 1384.39 | 1 | 130.63 | 2.51 | 6.31 | 3.99 | 15.89 | 0.50 | 2 |
| 20 | 6 | 1008.52 | 1 | 133.50 | 5.87 | 34.48 | 1.46 | 2.13 | 1.77 | 2 |
| 21 | 7 | 789.69 | 1 | 105.87 | 6.17 | 38.04 | 1.11 | 1.24 | 0.51 | 2 |
| 22 | 8 | 1898.7 | 1 | 155.51 | 4.32 | 18.67 | 3.23 | 10.40 | 0.77 | 2 |
| 23 | 9 | 1100.04 | 1 | 112.24 | 4.72 | 22.24 | 2.03 | 4.13 | 2.22 | 2 |
| 24 | 10 | 995.48 | 1 | 130.63 | 2.72 | 7.38 | 3.75 | 14.07 | 2.29 | 2 |
| 25 | | SUM | 20 | | | | | | | |

**Build Excel Equations Associating the Objective and Decision Variables**

Decision variable cells are in cells C4 to J4 representing β and D28 representing λ. The formula of each cell is as follows.

```
>>> K5=SUMPRODUCT($C$4:$J$4,C5:J5)#1st DMU's best practice level in 1st year.
>>> K6=SUMPRODUCT($C$4:$J$4,C6:J6)#2nd DMU's best practice level in 1st year.
>>> K7=SUMPRODUCT($C$4:$J$4,C7:J7)#3rd DMU's best practice level in 1st year.
>>> K8=SUMPRODUCT($C$4:$J$4,C8:J8)#4th DMU's best practice level in 1st year.
>>> K9=SUMPRODUCT($C$4:$J$4,C9:J9)#5th DMU's best practice level in 1st year.
>>> K10=SUMPRODUCT($C$4:$J$4,C10:J10)#6th DMU's best practice level in 1st year.
>>> K11=SUMPRODUCT($C$4:$J$4,C11:J11)#7th DMU's best practice level in 1st year.
>>> K12=SUMPRODUCT($C$4:$J$4,C12:J12)#8th DMU's best practice level in 1st year.
>>> K13=SUMPRODUCT($C$4:$J$4,C13:J13)#9th DMU's best practice level in 1st year.
>>> K14=SUMPRODUCT($C$4:$J$4,C14:J14)#10th DMU's best practice level in 1st year.
>>> K15=SUMPRODUCT($C$4:$J$4,C15:J15)#1st DMU's best practice level in 2nd year.
>>> K16=SUMPRODUCT($C$4:$J$4,C16:J16)#2nd DMU's best practice level in 2nd year.
>>> K17=SUMPRODUCT($C$4:$J$4,C17:J17)#3rd DMU's best practice level in 2nd year.
>>> K18=SUMPRODUCT($C$4:$J$4,C18:J18)#4th DMU's best practice level in 2nd year.
>>> K19=SUMPRODUCT($C$4:$J$4,C19:J19)#5th DMU's best practice level in 2nd year.
>>> K20=SUMPRODUCT($C$4:$J$4,C20:J20)#6th DMU's best practice level in 2nd year.
>>> K21=SUMPRODUCT($C$4:$J$4,C21:J21)#7th DMU's best practice level in 2nd year.
>>> K22=SUMPRODUCT($C$4:$J$4,C22:J22)#8th DMU's best practice level in 2nd year.
>>> K23=SUMPRODUCT($C$4:$J$4,C23:J23)#9th DMU's best practice level in 2nd year.
>>> K24=SUMPRODUCT($C$4:$J$4,C24:J24)#10th DMU's best practice level in 2nd year.
```

Similar to formulas in Column `K`, columns `L`, `M`, `L`, `O`, and `P` contains pertinent formulas as follows:

- `L:` $\varepsilon = y_i - f(x_i; \beta)$
- `M:` $\varepsilon^2$
- `N:` $\log \Phi\left(\frac{\lambda(y_i - f(x_i;\beta))}{\sqrt{\sigma^2}}\right)$ `where` $\sigma^2$ `replaced with` $\frac{1}{N}\sum_{i=1}^{N}(y_i - f(x_i;\beta))^2$
- `O:` $u = y_i - f(x_i; \beta)$
- `P:` $EPI = probability(energy\ inefficiency \geq E_i/Y_i - f(X;\beta) + v_i)$ .
  $= 1 - F(E_i/Y_i - f(X;\beta) + v_i)$

| | A | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|
| 1 | DMU | Estimates | | | | | |
| 2–4 | | $f(x_K, \beta)$ | $\varepsilon$ | $\varepsilon^2$ | LN(Φ(ελ/σ)) | u | EPI(Energy Performance Indicator) |
| 5 | 1 | 1204.13 | -289.49 | 83803.87 | -3.08 | -289.49 | 198% |
| 6 | 2 | 1155.33 | 87.24 | 7611.65 | -0.36 | 87.24 | 47% |
| 7 | 3 | 1968.00 | 130.37 | 16996.95 | -0.25 | 130.37 | 28% |
| 8 | 4 | 1399.87 | -187.51 | 35159.01 | -1.99 | -187.51 | 188% |
| 9 | 5 | 1699.03 | -109.76 | 12046.50 | -1.34 | -109.76 | 163% |
| 10 | 6 | 1171.90 | 164.11 | 26930.65 | -0.19 | 164.11 | 18% |
| 11 | 7 | 1110.14 | 443.18 | 196404.92 | 0.00 | 443.18 | 0% |
| 12 | 8 | 1976.54 | -262.03 | 68661.84 | -2.76 | -262.03 | 197% |
| 13 | 9 | 1492.99 | 55.69 | 3101.21 | -0.47 | 55.69 | 65% |
| 14 | 10 | 1750.21 | -31.80 | 1011.26 | -0.85 | -31.80 | 121% |
| 15 | 1 | 1336.53 | -63.61 | 4046.11 | -1.03 | -63.61 | 140% |
| 16 | 2 | 776.32 | 8.14 | 66.22 | -0.66 | 8.14 | 95% |
| 17 | 3 | 1744.75 | 205.25 | 42128.51 | -0.12 | 205.25 | 9% |
| 18 | 4 | 1137.41 | -215.69 | 46524.00 | -2.26 | -215.69 | 192% |
| 19 | 5 | 1312.60 | 71.79 | 5153.74 | -0.41 | 71.79 | 55% |
| 20 | 6 | 1051.90 | -43.38 | 1881.66 | -0.92 | -43.38 | 128% |
| 21 | 7 | 892.31 | -102.62 | 10531.77 | -1.29 | -102.62 | 160% |
| 22 | 8 | 1744.32 | 154.38 | 23834.33 | -0.20 | 154.38 | 20% |
| 23 | 9 | 1066.51 | 33.53 | 1124.18 | -0.55 | 33.53 | 78% |
| 24 | 10 | 1043.27 | -47.79 | 2283.50 | -0.94 | -47.79 | 131% |
| 25 | | SUM | 0.00 | 589301.87 | -19.68 | | |

Other cells used to estimate decision variables are as follows:

```
>>> D28=1 # λ, the initial value is set to 1.
>>> E24=M25/(C25) # σ²
>>> F24=-(1/2)*C25*LN(PI()/2)-(1/2)*C25*LN(E28)
>>>   +N25-(1/2)*(M25/E28)      # l(β,σ²,λ)
>>> G24=(D28^2/(1+D28^2))*E28 # σ_u²
>>> H24=E28-G28     # σ_v²
>>> I24=-T16/(2*I30)-(S11/2)*LN(2*PI())-
>>>    (S11/2)*LN(I30)    # OLS
>>> J24=F28 # MLE
>>> K24=-2*(I28-J28)     # LR
>>> I30=T16/S11    #σ²
```

| | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|
| 26 | | | | | | | | | | |
| 27 | | λ | $\sigma^2$ | l(β,λ,σ) | $\sigma_u^2$ | $\sigma_v^2$ | OLS | MLE | LR=-2(OLS-MLE) | |
| 28 | | 1 | 29465.09 | -137.1053419 | 14732.55 | 14732.5468 | -131.288 | -137.11 | -11.63391097 | |
| 29 | | | | | 121.38 | 121.38 | $\sigma^2$ (OLS) | | | |
| 30 | | | | | | | 29465.09 | | | |
| 31 | | | | | | | | | | |

**Find Initial Decision Variables Using OLS (Ordinary Least Square)**

| | Q | R | S | T | U | V | W | X | Y | Z |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | | SUMMARY OUTPUT | | | | | | | | |
| 5 | | | | | | | | | | |
| 6 | | *Regression Statistics* | | | | | | | | |
| 7 | | Multiple R | 0.895573461 | | | | | | | |
| 8 | | R Square | 0.802051825 | | | | | | | |
| 9 | | Adjusted R Square | 0.686582056 | | | | | | | |
| 10 | | Standard Error | 221.6043531 | | | | | | | |
| 11 | | Observations | 20 | | | | | | | |
| 12 | | | | | | | | | | |
| 13 | | ANOVA | | | | | | | | |
| 14 | | | *df* | *SS* | *MS* | *F* | *gnificance F* | | | |
| 15 | | Regression | 7 | [illegible] | 341107.1 | 6.94599 | 0.001887 | | | |
| 16 | | Residual | 12 | 589301.9 | 49108.49 | | | | | |
| 17 | | Total | 19 | 2977051 | | | | | | |
| 18 | | | | | | | | | | |
| 19 | | | *Coefficients* | *andard Err* | *t Stat* | *P-value* | *Lower 95%* | *Upper 95%* | *ower 95.0%* | *pper 95.0%* |
| 20 | | Intercept | -174.3869921 | 1184.868 | -0.14[illegible] | 0.885435 | -2755.99 | 2407.219 | -2755.99 | 2407.219 |
| 21 | | X Variable 1 | 9.345086254 | 3.710522 | [illegible].518537 | 0.026982 | 1.260554 | 17.42962 | 1.260554 | 17.42962 |
| 22 | | X Variable 2 | 491.5494671 | 711.[illegible] | 0.69119 | 0.502599 | -1057.94 | 2041.043 | -1057.94 | 2041.043 |
| 23 | | X Variable 3 | -66.06286442 | [illegible].47096 | -0.87534 | 0.39857 | -230.5 | 98.37424 | -230.5 | 98.37424 |
| 24 | | X Variable 4 | 447.3627186 | 796.0417 | 0.561984 | 0.584471 | -1287.06 | 2181.789 | -1287.06 | 2181.789 |
| 25 | | X Variable 5 | -95.38169061 | 164.6779 | -0.5792 | 0.573166 | -454.184 | 263.4207 | -454.184 | 263.4207 |
| 26 | | X Variable 6 | -205.7693536 | 106.545 | -1.93129 | 0.077408 | -437.911 | 26.37216 | -437.911 | 26.37216 |
| 27 | | X Variable 7 | -358.1837952 | 117.4608 | -3.04939 | 0.010096 | -614.109 | -102.259 | -614.109 | -102.259 |

Total observation

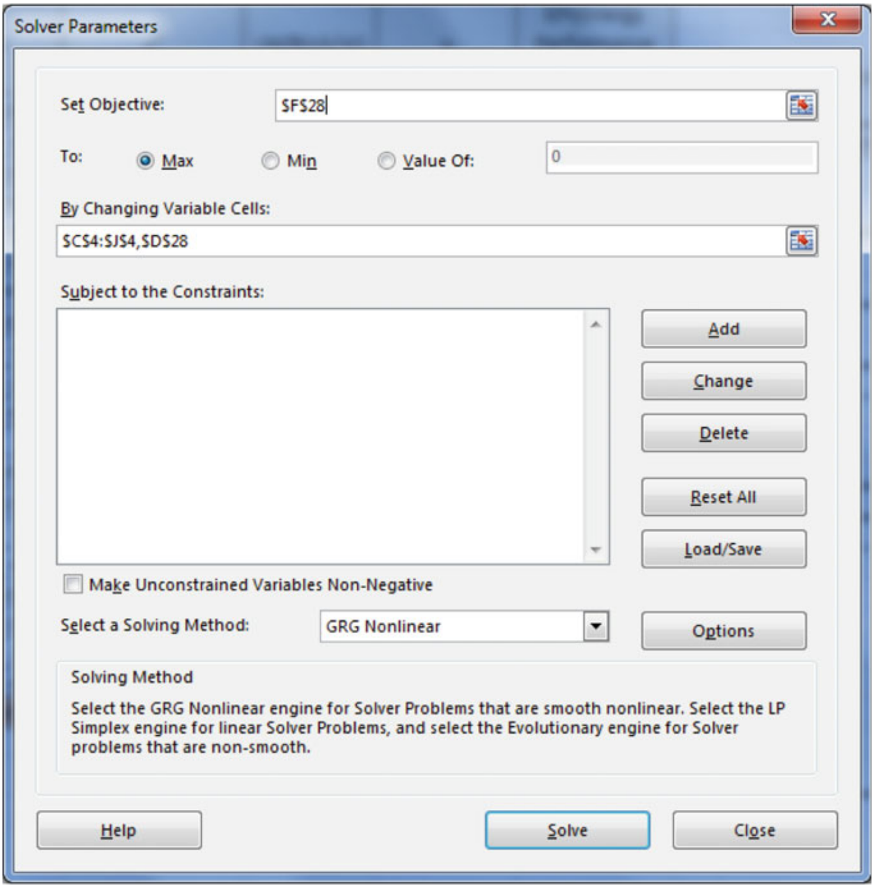
SSE

Initial values of coefficients

Decision variable cells require initial values. Cells C4 to J4 representing β take values found by ordinary linear regression as their initial values while and D28 representing λ is set to 1 as its initial value. Therefore, the formula of each cell is as follows.

```
>>> C4=S20 #initial value for intercept.
>>> D4=S21 #initial value for WheelBase(in).
>>> E4=S22 #initial value for 1000 HDD.
>>> F4=S23 #initial value for (1000 HDD)².
>>> G4=S24 #initial value for 1000 CDD.
>>> H4=S25 #initial value for (1000 CDD)².
>>> I4=S25 #initial value for Util(%).
>>> J4=S26 #initial value for Year.
>>> D28=1 #λ, the initial value is set to 1.
```

## Insert All Data into Excel Solver Box




The objective is set to `F28` representing $l(\beta, \sigma^2, \lambda)$ with a maximization option chosen and variable cells are set to `C4` to `J4` representing β and `D28` representing λ. This problem does not need any constraint. Note that s solving method is set to `GRG Nonlinear`.

## Understand the Results from Excel Solver

Once the Solve button in the previous Excel Solver Box is hit, the solution appears as shown below. Cells from `C4` to `J4` shows the final parameters for β.

| | A | B | C | D | E | F | G | H | I | J |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | DMU | Output | Input | | | | | | | |
| 2 | | kwh/vehicle | Intercept | WheelBase (in) | 1000 HDD | (1000 HDD)$^2$ | 1000 CDD | (1000 CDD)$^2$ | Util(%) | Year |
| 3 | | Y | β_0 | β_1 | β_2 | β_3 | β_4 | β_5 | β_6 | β_7 |
| 4 | | | 636.92 | 8.39 | 397.44 | -68.83 | 405.06 | -107.60 | -331.47 | -359.36 |

Note that the one-sided likelihood-ratio test value (*LR*) in cell `K28` for this model reveals that the model is adequate at the 99.5 % significance level $(8.17 > \chi^2_{1-2\times0.005}(1) = 6.635)$ and that the model has very little error attributable to random noise, with most departures attributable to inefficiency. Therefore, the null-hypothesis, $H_0{:}\gamma = \frac{\sigma_u^2}{(\sigma_v^2 + \sigma_u^2)} = 0$, is rejected, and the alternative hypothesis $H_1{:}\gamma > 0$ with technical inefficiency effect is accepted for this model.

| | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|
| 26 | | | | | | | | | | |
| 27 | | λ | σ$^2$ | l(β,λ,σ) | σ$_u$$^2$ | σ$_v$$^2$ | OLS | MLE | LR=-2(OLS-MLE) | |
| 28 | | 871.5364051 | 78017.57 | -127.1677954 | 78017.47 | 0.102711906 | -131.288 | -127.17 | 8.241182104 | |
| 29 | | | | | 279.32 | 0.32 | σ$^2$ (OLS) | | | |
| 30 | | | | | | | 29465.09 | | | |
| 31 | | | | | | | | | | |

The GRG method generates Answer Report. The Answer Report tells an important information that is how long Solver took to solve the problem. In this case, the total run time was just 0.03 s.

| | A | B | C | D | E | F | G | H | I | J | K |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | **Microsoft Excel 15.0 Answer Report** | | | | | | | | | | |
| 2 | **Worksheet: [GRG (SFA).xlsx]SFA** | | | | | | | | | | |
| 3 | **Report Created: 11/9/2015 8:39:12 AM** | | | | | | | | | | |
| 4 | **Result: Solver found a solution. All Constraints and optimality conditions are satisfied.** | | | | | | | | | | |
| 5 | **Solver Engine** | | | | | | | | | | |
| 6 | | Engine: GRG Nonlinear | | | | | | | | | |
| 7 | | Solution Time: 0.031 Seconds. | | | | | | | | | |
| 8 | | Iterations: 4 Subproblems: 0 | | | | | | | | | |
| 9 | **Solver Options** | | | | | | | | | | |
| 10 | | Max Time Unlimited, Iterations Unlimited, Precision 0.000001, Use Automatic Scaling | | | | | | | | | |
| 11 | | Convergence 0.0001, Population Size 100, Random Seed 0, Derivatives Forward, Require Bounds | | | | | | | | | |
| 12 | | Max Subproblems Unlimited, Max Integer Sols Unlimited, Integer Tolerance 1% | | | | | | | | | |

The Answer Report also provides the information about object, variable cells and constraints as below:

Objective Cell (Max)

| Cell | Name | Original Value | Final Value |
|---|---|---|---|
| $F$2 | l(β,λ,σ) | -127.1678196 | -127.1677954 |

Variable Cells

| Cell | Name | Original Value | Final Value | Integer |
|---|---|---|---|---|
| $C$4 | β_0 | 636.92 | 636.92 | Contin |
| $D$4 | β_1 | 8.39 | 8.39 | Contin |
| $E$4 | β_2 | 397.44 | 397.44 | Contin |
| $F$4 | β_3 | -68.83 | -68.83 | Contin |
| $G$4 | β_4 | 405.06 | 405.06 | Contin |
| $H$4 | β_5 | -107.60 | -107.60 | Contin |
| $I$4 | β_6 | -331.47 | -331.47 | Contin |
| $J$4 | β_7 | -359.36 | -359.36 | Contin |
| $D$2 | λ | 871.5362262 | 871.5364051 | Contin |

Constraints

NONE

## *DEA LP Problem Solving Using Simplex LP*

This example is made to provide an opportunity to learn how to use the Simplex method of Excel Solver. This method aims to solve LP (Linear Programming) optimization problems and find a globally optimal solution. The best possibly solution meets all constraints globally to be an optimal solution at the point where 2 or more Constraints intersect because of Karush–Kuhn–Tucker conditions. Data Envelopment Analysis and Knapsack Problem can be solvable with Simplex method. This example will use the DEA example discussed in this chapter.

### Define Problem, Objective and Decision Variables

This example problem aims to calculate the efficiency of the $t$-th time period relative to $t$-th time period technology, that is, $D_I^t(Z_t, E_t/Y_t)$, which is identical to the following DEA model

$$\begin{aligned} & D_I^t(Z_t, E_t/Y_t) = \min_{\phi,\lambda}\phi \\ s.t.\quad & -Z_{it} + Z_t\lambda \geq 0, \\ & -\phi(E_{it}/Y_{it}) + (E_t/Y_t)\lambda \leq 0 \\ & \lambda \geq 0 \end{aligned}$$

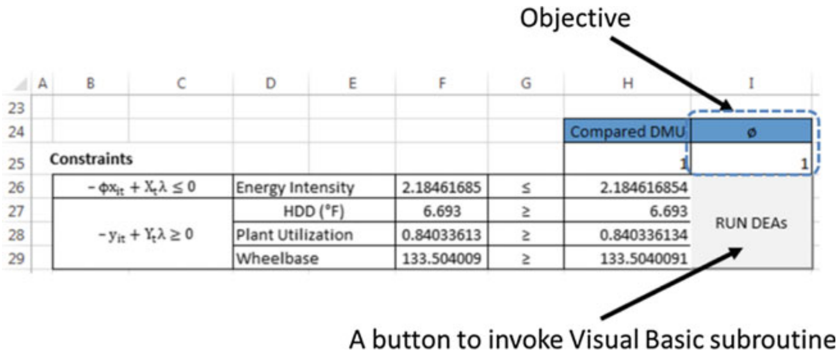
Note that this LP is input-oriented and CRS (Constant Return Scale) is assumed. The dataset for this example is shown below. 10 DMUs (decision making units), each with input (energy intensity) and outputs (HDD, plant utilization, wheelbase) are provided.

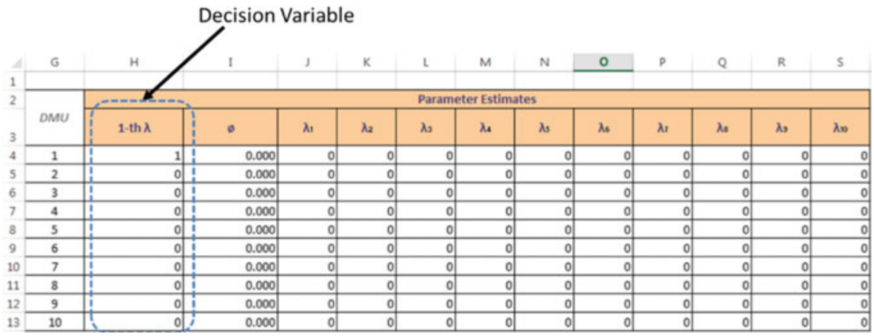
| DMU | Input | Outputs | | |
|---|---|---|---|---|
| | Energy Intensity | HDD (°F) | Plant Utilization | Wheelbase |
| 1 | 2.184616854 | 6.693 | 0.84 | 133.504009 |
| 2 | 2.967877378 | 6.203 | 0.79 | 105.748089 |
| 3 | 5.011954943 | 5.174 | 0.93 | 155.315045 |
| 4 | 2.895720819 | 5.396 | 0.63 | 112.007935 |
| 5 | 3.79597003 | 3.22 | 0.56 | 130.629992 |
| 6 | 3.191058737 | 6.469 | 0.51 | 133.504009 |
| 7 | 3.710103486 | 6.122 | 0.63 | 105.866199 |
| 8 | 4.095105662 | 5.333 | 1.30 | 155.511895 |
| 9 | 3.69902085 | 5.845 | 1.25 | 112.244155 |
| 10 | 4.104420809 | 3.031 | 0.88 | 130.629992 |

**Build Excel Equations Associating the Objective and Decision Variables**

The objective of this example is to determine λ and ϕ in such a way to minimize ϕ (technical efficiency). The objective cell is `H25` represenging ϕ. The decision variable cells are from `H4` to `H13` representing λ. Note that this constraint cells use the Excel `INDEX` function which is used to locate the data which corresponds to the pertinent DMU that appears in the column `H25`. The `INDEX` function has a formula, that is = `INDEX (range, row number, column number)`.

>>> # $-\phi\left({}^{E_{it}}/_{Y_{it}}\right)+\left({}^{E_t}/_{Y_t}\right)\lambda \le 0$: Energy Intensity (input)
```
>>> F26=SUMPRODUCT($C$4:$C$13,$H$4:$H$13)
>>> H26=$I$25*INDEX(C4:C13,H25,1)
>>>
```
>>> # $-Z_{it}+Z_t\lambda \ge 0$ : HDD (°F) (output)
```
>>> F27=SUMPRODUCT($D$4:$D$13,$H$4:$H$13)
>>> H27=INDEX(D4:D13,H25,1)
>>>
```
>>> # $-Z_{it}+Z_t\lambda \ge 0$ : Plant Utilization (output)
```
>>> F28=SUMPRODUCT($E$4:$E$13,$H$4:$H$13)
>>> H28=INDEX(E4:E13,H25,1)
>>>
```
>>> # $-Z_{it}+Z_t\lambda \ge 0$ : Wheelbase (output)
```
>>> F29=SUMPRODUCT($F$4:$F$13,$H$4:$H$13)
>>> H29=INDEX(F4:F13,H25,1)
```



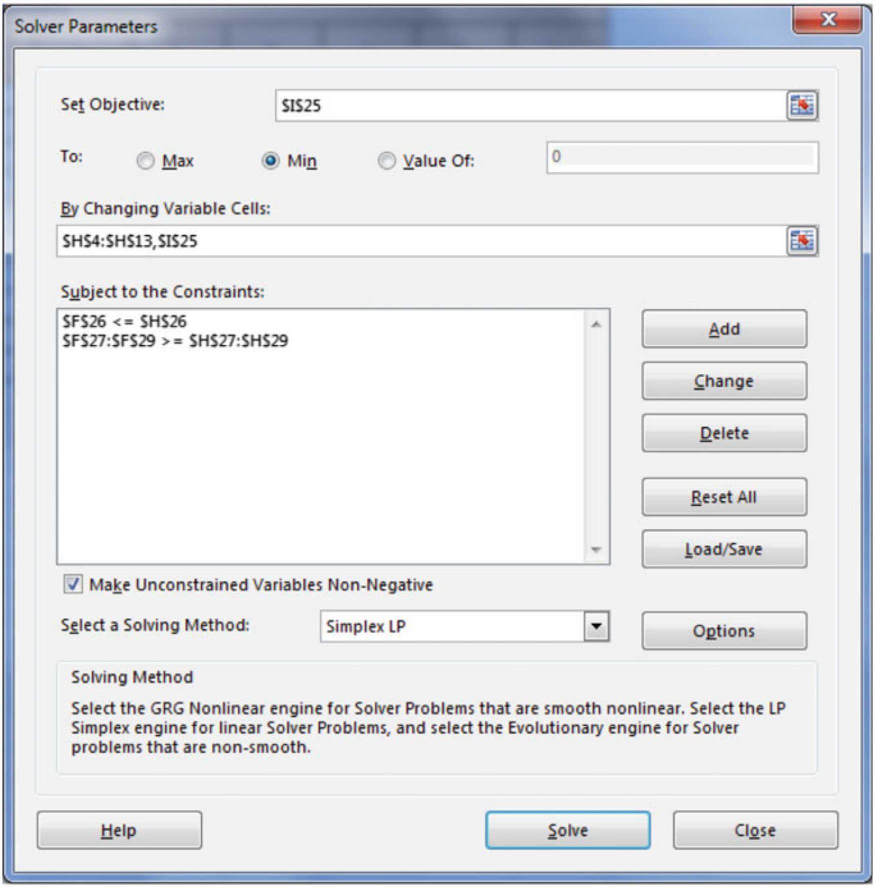

## Insert All Data into Excel Solver Box

This example uses VBA in Excel and automates iterations for solving multiple linear programing models with the Simplex method. Briefly, with respect to automation logic, the tool uses "For" loop to automate iterations of solving multiple linear programing models in which Excel Solver with the "Simplex" optimization option calculates the efficiency for each DMU and the results are recorded in a table using the copy/paste function (note: the three major functions used in the loop statement of the VBA programing are as follows: (1) "SolverOk"—defines the objective function and the decision variables; (2) "SolverAdd"—defines model constraints; and (3) "SolverSolv"—runs Solver). The detailed codes are shown below:

```
>>> Sub CommandButton_Click()
>>> Call DEA
>>> End Sub
>>>
>>> Sub DEA()
>>> Dim nDMUs As Long
>>>
>>> nDMUs = Application.InputBox(Prompt:="How many
>>> plants (DMU's) do you want to evaluate?", Type:=1)
>>>
>>> ‘Declare DMU as Integer, DMU iterations 1 through
>>> nDMUs
>>> Dim DMU As Long
>>> For DMU = 1 To nDMUs
>>>
>>> 'Sets the Value of E12 to the DMU Under Evaluation
>>> Range("H25") = DMU
>>>
>>> 'Calls SolverRun Sub
>>> Call SolverRun
>>>
>>> 'Place efficiency value into column J
>>> Range("I" & DMU + 3) = Range("I25")
>>>
>>> 'Select the cells containing the optimal Lambdas
>>> Range("H4:H13").Select
>>>
>>> 'Copy selected lambas and place them in row "DMU +
>>> 2"
>>> Selection.Copy
>>> Range("J" & DMU + 3).Select
>>> Selection.PasteSpecial Paste:=xlPasteValues,
>>> Transpose:=True
>>>
>>> Next DMU
>>> End Sub
>>>
>>> Sub SolverRun()
>>> 'This sub sets up the objective, changing varia-
bles, >>> and constraints of solver
>>>
```

```
>>> 'Reset Solver
>>> SolverReset
>>> 'Defines optimization cell and changing variables
>>>     SolverOk     SetCell:="$I$25",     MaxMinVal:=2,
ValueOf:=0,  >>>  ByChange:=  "$H$4:$H$13,  $I$25",  En-
gine:=2,
>>> EngineDesc:="Simplex LP"
>>> 'Defines the constraints of the model, relation 1
is >>> <=, relation 2 is =, relation 3 is >=
>>> SolverAdd CellRef:="$F$26", Relation:=1, Formu
>>> laText:="$H$26"
>>> SolverAdd CellRef:="$F$27:$F$29", Relation:=3, Fo
>>> rmulaText:="$H$27:$H$29"
>>>
>>> 'Runs Solver model, UserFinish prevents Solver
>>> results dialog box from appearing
>>> SolverSolve UserFinish:=True
>>> End Sub
```

Whenever `SolverRun()` is called, the solver toolbox is filled and run invisibly.



### Understand the Results from Excel Solver

Once the `RUN DEAs` button in the spreadsheet is hit, the solution appears as shown below. Cells from `I4` to `I13` shows each DMU's technical efficiency representing $\phi$. Meanwhile, cells from `J4` to `S4` shows $\lambda$ when 1st DMU is considered as a target comparing DMU. Similarly, cells from `J` to `S` associating with each row from 5 to 13 rows shows $\lambda$ for each DMU.

| | G | H | I | J | K | L | M | N | O | P | Q | R | S |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | | | | |
| 2 | DMU | Parameter Estimates | | | | | | | | | | | |
| 3 | | 10-th $\lambda$ | $\phi$ | $\lambda_1$ | $\lambda_2$ | $\lambda_3$ | $\lambda_4$ | $\lambda_5$ | $\lambda_6$ | $\lambda_7$ | $\lambda_8$ | $\lambda_9$ | $\lambda_{10}$ |
| 4 | 1 | 1.052671984 | 1.000 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 2 | 0 | 0.690 | 0.937008 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 | 3 | 0 | 0.507 | 1.163374 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 | 4 | 0 | 0.633 | 0.838986 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 | 5 | 0 | 0.563 | 0.978472 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 | 6 | 0 | 0.685 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 7 | 0 | 0.539 | 0.914687 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 11 | 8 | 0 | 0.826 | 1.54923 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 12 | 9 | 0 | 0.881 | 1.492535 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 13 | 10 | 0 | 0.560 | 1.052672 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

## *Traveling Compressed Air Expert Problem Using Evolutionary Method*

This example is made to provide an opportunity to learn how to use the evolutionary method of Excel Solver. The evolutionary method is used the objective contains any cells holding non-smooth or discontinuous formulas. Excel functions such as `INDEX`, `LOOKUP` are common discontinuous functions while `MIN`, `MAX` and `ABS` are common non-smooth Excel functions. This example is modified from the traveling salesman problem located in *Step-By-Step Optimization with Excel Solver* in the context.

### Define Problem, Objective and Decision Variables

Assume that a compressed air expert must visit 5 GM engine plants located in US and Canada in order to audit plant's compressed air use practice. He must pick the shortest path that will reach every plants and bring him back to his starting point. In this example, the evolutionary method is used because the objective contains `INDEX` and `LOOKUP` Excel functions, which are discontinuous functions. In addition, this example illustrates how to use `Alldifferent` constrain when solving the problem.

**Distance Chart (mile)**

| | Flint | Spring Hill | St. Catherines | Romulus | Tonawanda |
|---|---|---|---|---|---|
| Flint | 0 | 610 | 244 | 75 | 268 |
| Spring Hill | 610 | 0 | 755 | 557 | 753 |
| St. Catherines | 244 | 755 | 0 | 257 | 27 |
| Romulus | 75 | 557 | 257 | 0 | 281 |
| Tonawanda | 268 | 753 | 27 | 281 | 0 |

The problem in this example is formally defined as follows: a compressed air expert must make stops in 5 cities where GM engine plants are located: Flint (MI, USA), Spring Hill (TN, USA), St. Catherines (ON, Canada), Romulus (MI, USA), Tonawanda (NY, USA) in such as way that the total length of the trip is minimized. See the distance chart above to refer to the distance between cities in mile.

In this case, the objective is to minimize the total distance travelled when traveling between all 5 cities. The evolutionary method is used to minimize the objective. The decision variables are the order of cities to visit. To specify the order, each city is designated by the row that they appear in the distance chart. For example, Flint appears in the 1st row of the distance chart and therefore, Flint is designated with a "1". Similar to Flint, other cities will be designated by its pertinent row number. At the end, Excel solver will determine the order of cities to visit to minimize the total miles travelled.

### Build Excel Equations Associating the Objective and Decision Variables

The decision variables are in cells `B11` to `B15`. The order of the decision variables shown below `(1, 2, 3, 4, 5)` indicates that the expert will visit the cities in this order: Flint (row 1 in the distance chart) → Spring Hill (row 2 in the distance chart) → St. Catherines (row 3 in the distance chart) → Romulus (row 4 in the distance chart) → Tonawanda (row 5 in the distance chart) → Flint.

The objective is in cell `D17` where `D17 = SUM(D11:D15)`.

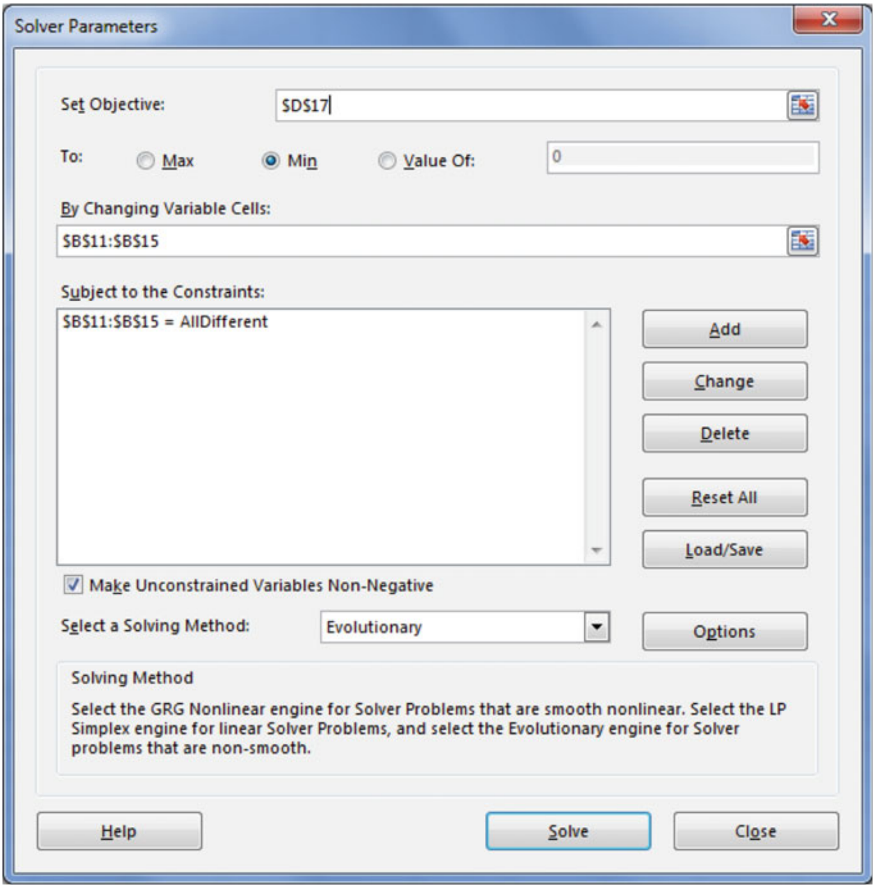
**Decision variables & Objective**

| visiting order (decision variables) | city | distance (mile) |
|---|---|---|
| 1 | Flint | 268 |
| 2 | Spring Hill | 610 |
| 3 | St. Catherines | 755 |
| 4 | Romulus | 257 |
| 5 | Tonawanda | 281 |
| | | total (objective) |
| | | 2171 |

The formula of each cell is as follows. Note that the Excel `INDEX` function is used to locate the city which corresponds to the Distance Chart row number that appears in the column `B`. The `INDEX` function has a formula, that is `= INDEX (range, row number, column number)`.

```
>>> C11=INDEX($B$3:$B$7,B11,1) #1st visit city name
>>> C12=INDEX($B$3:$B$7,B12,1) #2nd visit city name
>>> C13=INDEX($B$3:$B$7,B13,1) #3rd visit city name
>>> C14=INDEX($B$3:$B$7,B14,1) #4th visit city name
>>> C15=INDEX($B$3:$B$7,B15,1) #5th visit city name
>>>
>>> # Distance between 5th visit city and 1st visit
city
>>> D11=INDEX($C$3:$G$7,B11,B15)
>>>
>>> # Distance between 2nd visit city and 1st visit
city
>>> D12=INDEX($C$3:$G$7,B11,B12)
>>>
>>> # Distance between 3rd visit city and 2nd visit
city
>>> D13=INDEX($C$3:$G$7,B12,B13)
>>>
>>> # Distance between 4th visit city and 3rd visit
city
>>> D14=INDEX($C$3:$G$7,B13,B14)
>>>
>>> # Distance between 5th visit city and 4th visit
city
>>> D15=INDEX($C$3:$G$7,B14,B15)
>>>
>>> # Objective cell
>>> D17=SUM(D11:D15)
```

## Insert All Data into Excel Solver Box




This problem uses `Alldifferent` constraint because the problem requires that the expert must visit each city only once without repeating. `Alldifferent` constraint ensures that each city will be visited only once and that all cities will be visited by grouping `B11:B15` cells simultaneously in which the five cells hold the integers 1–5 and no 2 cells in this group will be assigned the same number. Excel Solver Box shown above is set to have `D17` as objective cell and `B11:B15` as decision variables cells. Note that the evolutionary method is set to its solving method.

### Understand the Results from Excel Solver

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 9 | | Decision variables & Objective | | | |
| 10 | | visiting order (decision variables) | city | distance (mile) | |
| 11 | | 2 | Spring Hill | 753 | |
| 12 | | 4 | Romulus | 557 | |
| 13 | | 1 | Flint | 75 | |
| 14 | | 3 | St. Catherines | 244 | |
| 15 | | 5 | Tonawanda | 27 | |
| 16 | | | | total (objective) | |
| 17 | | | | 1656 | |
| 18 | | | | | |

Once the Solve button in the previous Excel Solver Box is hit, the solution appears as shown above. The solution could be interpreted as follows: The compressed air experts starts in Spring Hill. He then visits Flint, St. Catherine, Tonawanda, and finally back to Spring Hill in that order. The total miles travelled on this route are 1,656 miles. This is the shortest route that will cover all 5 cities starting and ending in Spring Hill. This solution improves the original solution by 23.7 % (=(2,171 − 1,656)/2,171).

| | A | B | C | D | E |
|---|---|---|---|---|---|
| 1 | Microsoft Excel 15.0 Answer Report | | | | |
| 2 | Worksheet: [Evolutionary.xlsx]Sheet1 | | | | |
| 3 | Report Created: 11/6/2015 1:24:54 PM | | | | |
| 4 | Result: Solver cannot improve the current solution. All Constraints are satisfied. | | | | |
| 5 | Solver Engine | | | | |
| 6 | | Engine: Evolutionary | | | |
| 7 | | Solution Time: 57.019 Seconds. | | | |
| 8 | | Iterations: 0 Subproblems: 165249 | | | |
| 9 | Solver Options | | | | |
| 10 | | Max Time Unlimited, Iterations Unlimited, Precision 0.000001, Use Automatic Scaling | | | |
| 11 | | Convergence 0.0001, Population Size 100, Random Seed 0, Mutation Rate 0.075, Time w/o Improve 30 sec, Require Bounds | | | |
| 12 | | Max Subproblems Unlimited, Max Integer Sols Unlimited, Integer Tolerance 1%, Assume NonNegative | | | |
| 13 | | | | | |
| 14 | Objective Cell (Min) | | | | |
| 15 | | Cell | Name | Original Value | Final Value |
| 16 | | $D$17 | total (objective) | 2171 | 1656 |

The evolutionary method generates two reports: Answer Report and Population Report. The Answer Report tells an important information that is how long Solver took to solve the problem. Especially it is important because the evolutionary method can controlled by the Option settings where the options such as the maximum allowable run time, iterations, or subproblems are available for control. In this case, the total run time was 57 s.

| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| 19 | Variable Cells | | | | | | | | |
| 20 | | Cell | Name | Original Value | Final Value | Integer | | | |
| 21 | | $B$11 | visiting order (decision variables) | 1 | 2 | AllDiff | | | |
| 22 | | $B$12 | visiting order (decision variables) | 2 | 4 | AllDiff | | | |
| 23 | | $B$13 | visiting order (decision variables) | 3 | 1 | AllDiff | | | |
| 24 | | $B$14 | visiting order (decision variables) | 4 | 3 | AllDiff | | | |
| 25 | | $B$15 | visiting order (decision variables) | 5 | 5 | AllDiff | | | |
| 26 | | | | | | | | | |
| 27 | | | | | | | | | |
| 28 | Constraints | | | | | | | | |
| 29 | | | NONE | | | | | | |
| 30 | | $B$11:$B$15=AllDiff | | | | | | | |

The Answer Report also provides the information about variable cells and constraints. Note the difference of decision variables between their original and final values. Also, note that the unique `Alldifferent` constraint is bound meaning that no slack is still available.

| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| 1 | **Microsoft Excel 15.0 Population Report** | | | | | | | | |
| 2 | **Worksheet: [Evolutionary.xlsx]Sheet1** | | | | | | | | |
| 3 | **Report Created: 11/6/2015 1:24:54 PM** | | | | | | | | |
| 4 | | | | | | | | | |
| 5 | | | | | | | | | |
| 6 | Variable Cells | | | | | | | | |
| 7 | | | | Best | Mean | Standard | Maximum | Minimum | |
| 8 | | Cell | Name | Value | Value | Deviation | Value | Value | |
| 9 | | $B$11 | visiting order (decision variables) | 2 | 3.234693878 | 1.353125594 | 5 | 1 | |
| 10 | | $B$12 | visiting order (decision variables) | 4 | 2.489795918 | 1.451944292 | 5 | 1 | |
| 11 | | $B$13 | visiting order (decision variables) | 1 | 3.489795918 | 1.159851554 | 5 | 1 | |
| 12 | | $B$14 | visiting order (decision variables) | 3 | 2.693877551 | 1.501944878 | 5 | 1 | |
| 13 | | $B$15 | visiting order (decision variables) | 5 | 3.091836735 | 1.377931624 | 5 | 1 | |
| 14 | | | | | | | | | |
| 15 | Constraints | | | | | | | | |
| 16 | | NONE | | | | | | | |

The Population Report gives useful information about the entire population of candidate solutions maintained by the Evolutionary Solving method at the end of the solution process. With the Population Report, a modeler gets some insight into the performance of the Evolutionary method and can decide whether additional runs of the Evolutionary method are likely to yield even better solutions. For each variable and constraint, the Population Report shows the best value found by the Evolutionary method, and the mean (average) value, standard deviation, maximum value, and minimum value of that variable or constraint across the entire population of candidate solutions at the end of the solution process as shown above. These values gives an idea of the diversity of solutions represented by the population. From the sense, the way of interpreting the Population Report is important. For example, if the Best Values are similar from run to run (i.e., the Standard Deviations are small), this may be reason for the high confidence that the final solution is close to the global optimum. However, if the Best Values vary from run to run (i.e., the Standard Deviations are large) might indicate a lack of diversity in the population, suggesting that the modeler should increase the Mutation Rate and run Excel Solver again.

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# Chapter 3
# Energy Decision-Making 1: Strategic Planning of Sustainable Manufacturing Projects Based on Stochastic Programming

**Abstract** The need of energy decision making happens in realizing sustainable manufacturing. Many companies in the manufacturing industry have realized the importance of sustainability and have made a strategic move toward sustainable manufacturing to face the uncertainty of future energy availability and stringent environment regulations enacted around the world. However, it is a challenge to build a strategic plan for implementing sustainable manufacturing projects in such a way as to optimize energy efficiency opportunities while remaining in compliance with environmental regulations especially when future uncertainties, such as a fluctuation in energy prices or $CO_2$ credit costs, are involved. This chapter proposes a new stochastic programming approach to identify the optimal investment plan for sustainable manufacturing projects to reduce energy and $CO_2$ emission costs for manufacturing processes subject to various time, budget, technology and environmental constraints. The principle underlying the proposed approach is to solve a multi-period stochastic programming involving uncertain decision parameters, such as future $CO_2$ credit market price, through the use of sample averaging approximation (SAA). An illustrative example application of the proposed model to an automotive company is presented. In Appendix, this chapter also provides an overview of the available standards and methods that can be used for preparing Scope 3 green house gas inventories and carbon footprints for organizations and their specific products or services.

## 3.1 Background of Planning Sustainable Manufacturing Projects in the Manufacturing Industry

In recent years, many manufacturing companies have begun to take a strategic move toward sustainable manufacturing using alternative energy sources or by implementing new manufacturing technologies that are more energy efficient and environmentally friendly. There are three primary reasons that are driving the manufacturing industry to move toward sustainable manufacturing. The first compelling driver is a financial reason to reduce energy costs. It is true that a bulk of the

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energy consumed for enabling manufacturing operations is used to add value from raw materials or intermediates products to final products, and therefore, the energy savings impact a company's bottom line positively. The second driver is the compliance with stringent energy and environmental regulations enacted by countries around world in response to increasing climate change. The third driver is the enhanced marketability of products and services because the producing companies are recognized as environmentally friendly.

Although the benefits from addressing aforementioned three drivers are clear: energy conservation, a reduced environmental impact and an enhanced competitive position, compliance with energy and environmental regulations presents huge challenges to manufacturing companies in the automotive industry. The reason for this challenge is because the automotive industry contributes large amounts of $CO_2$ emissions directly from their facilities or indirectly due to their long and complex supply chain; thus, the industry should be seriously affected by regulations (Ford Motor Company 2005; General Motors Corporation 2008). However, at the same time, this challenge might be a chance for a manufacturing company to gain competitive advantages over other companies.

Until now, many countries in the world have self-pledged $CO_2$ emission reduction targets, as shown in Table 3.1. To achieve these ambitious $CO_2$ emission reduction targets, many energy and environmental regulations, policies or schemes have been enacted. In market-based approach to limit $CO_2$ emissions, which is referred to a cap-and-trade system, the central authority determines a cap (sum of emission allowance) in terms of a value of credits or tons of emissions to each company. Specifically, credits can be traded in the market, and companies are permitted to buy or sell carbon credits in case they emit more or less than the emission limits. Therefore, this scheme is recognized as a cost effective manner to reduce emissions, and allows organizations to determine how and where they reduce emissions. One resulting impact of the cap-and-trade system provides an economic incentive for companies to invest in greener technologies because these new technologies are expected to be more energy efficient, which reduces utility costs and carbon credit expenditure. In this case, manufacturing companies are

**Table 3.1** 2030 Country emission targets

| Country | Emission target |
|---|---|
| United States | 26–28 % below 2005 levels (plan to achieve this by 2025) |
| EU | 40 % below 1990 levels |
| Swiss | 50 % below 1990 levels |
| Canada | 30 % below 2005 levels |
| Russia | 25–30 % below 1990 levels |
| Japan | 25 % below 2013 levels |
| South Korea | 37 % below 2030 business-as-usual levels |

looking for an answer to the question of which is more profitable: (1) investing in greener technologies to reduce emissions or (2) trading credits. Choosing only one option is too risky because the price of carbon is subject to the uncertainty of future demand. Instead, it is appropriate to balance the two options to mitigate the impact of regulations and to gain benefits of energy conservation and of having a competitive advantage over others.

Recognizing the need for balance between greener technologies and carbon trading to minimize the impact of energy and environmental regulations, companies must look for an optimal strategic plan for implementing sustainable manufacturing projects and trading credits in such a way to optimize energy efficiency opportunities while complying with environmental regulations. However, it is a challenge to build such an optimal strategy when future uncertainty, such as the fluctuation of energy prices or $CO_2$ credit cost, is involved.

### *3.1.1 Literature Review*

There have been several previous studies to use optimization methods to produce energy strategies each having different decision variables and parameters depending on what the objective and constraints were and where the target application is running. A mixed-integer linear programming model was suggested to plan and schedule offshore oil facilities (Iyer et al. 1998). A stochastic dynamic programming model was developed to identify relations between time, investment decisions, construction periods and uncertainty (Mo et al. 1991). A mixed integer non-linear programming model was developed to satisfy the electricity demand and $CO_2$ emission constraint at the least cost (Hashim et al. 2005). Most recently, Sirikitputtisak et al. (2009) proposed a multi-period, mixed-integer, non-linear programming model and solved it using a general algebraic modeling system (GAMS) that could produce an energy strategy where demand was satisfied at the least cost while considering $CO_2$ emissions. However, all of the aforementioned previous studies focused on energy sourcing, storing and consumption in the energy utility industry sector by taking into account conditions specific to their sector. Compared to the energy utility industry sector, the manufacturing industry sector is relatively lacking decision making knowledge to assist in their energy and environmental decisions.

There are many global cap-and-trade programs that are in process or are being considered. For example, the European Union Emission Trading System (EU-ETS) was the first established carbon market scheme. The aim of the EU-ETS scheme is to reduce emissions in a cost effective manner allowing organizations to trade emission allowances and, thereby, determine how and where they reduce emissions. The emission target is 6 % reduction in $CO_2$ emission from the year of 2008 to 2012, 20 % by 2020 and 60 to 80 % reduction in 2050 compared with the emission level of the base year 1990. Organizations participating in the emission scheme are assigned a $CO_2$ emission allowance or $CO_2$ emission cap, which is an enforceable limit. The allocation plan for the $CO_2$ emission allowance or cap is divided into three stages: Phase 1: 2005–2007, Phase 2: 2008–2012 and Phase 3: 2012–2020. The cap is allotted using the following steps. First, countries define the cap amount on a national basis. Second, this amount is broken into sectors participating in the emission scheme. Third, the total amount for a sector is split off to each individual company belonging to the sector. There will be free allocation with some limited auctioning on country-by-country basis by phase 2. From phase 3, approximately 60 % of allowances will be auctioned, and the remainder will be allocated free-of-charge to the worst affected sectors. Then, free allocation will be phased out by 2020. Individual national regulators are responsible for enforcing the regulation (Duerr 2007; Ellerman and Joskow 2008). In the United States, meanwhile, the Waxman-Markey Bill (the official name of the Waxman-Markey Bill is the American Clean Energy and Security Act of 2009 or H.R. 2454 of the 111th Congress) was proposed to implement a federal cap-and-trade scheme where the emission target of $CO_2$ emissions is 3 % by 2012, 17 % by 2020, 42 % by 2030, and 83 % by 2050 relative to the 2005 base level (Capoor and Ambrosi 2010). This law was passed by the U.S. House of Representatives in June 2009 but did not pass the U.S. Senate. Recently, the Korean cap-and-trade system started in January 2015 and 525 companies are participating to the cap-and-trade scheme with the country's goal to reduce its greenhouse gas emissions by 37 % in 2030 compared with business-as-usual levels.

Berendt et al. (2007) forecasted $CO_2$ credit prices in three different price cases: high price case, reference price case, and low price case. In the reference price case, the $CO_2$ credit price was forecasted to reach \$5 per metric ton of $CO_2$ by 2015 and grow to \$23 per metric ton of $CO_2$ by 2030. Meanwhile, Jognston et al. (2011) studied $CO_2$ credit price forecasting comprehensively and made a projection based on a larger sample of forecasts from institutions, such as the U.S. Energy Information Administration and Massachusetts Institute of Technology. This work will use this projection to generate scenarios for future $CO_2$ credit price changes.

Mani et al. (2008) discussed the benefits of implementing sustainable manufacturing including efficient energy use, compliance with environmental regulations, and enhanced marketability of their products and services. In the context of energy data management and analytics in the automotive industry, Oh and Hildreth (2013, 2014) proposed activity-based decision steps including a step of comparing average hourly energy use for each activity between the best practice plants and less efficient plants followed by determining which activities are problematic cost drivers for less efficient plants. Oh and Shin (2015) studied the impact of mismeasurement in performance benchmarking using a Monte Carlo comparison of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) with different multi-period budgeting strategies that can be applied to enhance budget allocation performance for sustainable manufacturing.

## 3.2 A Problem Formulation in Stochastic Programming

In the case of implementing a carbon cap and trade system, manufacturing companies expect their manufacturing costs to rise if their $CO_2$ emission level exceeds the emission allowance allocated by the cap and trade system. Therefore, the potential approval of a carbon cap and trade system calls for immediate action from the manufacturers to invest in greener technologies in their manufacturing processes to reduce their $CO_2$ emission level and, consequently, reduce the need to purchase carbon credits. However, investments in greener technology will not be economical if the investment cost is not offset by a reduction in utility cost and $CO_2$ credit expenditure. Therefore, manufactures are looking for an optimal strategy for investing in greener technology that minimize the investment cost, utility cost, and $CO_2$ credit expenditure. The absence of a good investment strategy may increase per unit production cost, which will negatively affect the company's profitability. To address this challenge, a two-stage stochastic optimization model is proposed in this section.

The proposed model aims to incorporate the uncertainty in $CO_2$ credit cost into the model and to find a detailed plan to implement new technologies in such a way as to minimize the investment cost, utility cost, and $CO_2$ credit expenditure and to meet $CO_2$ emission levels as specified by a potential carbon cap and trade system. The indices, Boolean operators, sets, parameters and variables used in the model are summarized in Tables 3.2, 3.3, and 3.4.

Note that in the light of two-stage decision concept, technology investments $(z_{jkt})$ are made in the first stage of decisions and carbon trading/using/storing decisions are made in the second stage $(CreditTraded_{st}, CreditUsed_{st}, CreditIn_{st})$.

### 3.2.1 Objective Function

The objective of the two-stage stochastic model is to minimize the total costs including the utility cost, the green technology investment cost and the carbon credit and option costs to obtain the optimal investment strategy as follows:

**Table 3.2** Indices, sets, and Boolean operators used in the model

| Notation | Description |
|---|---|
| $i \in I$ | $I$ is a set of utility $i$ (e.g., $I$ = {electricity, natural gas, gasoline}) |
| $j \in J$ | $J$ is a set of facility $j$ (e.g., $J$ = {body shop, paint shop, general assembly}) |
| $k \in K$ | $K$ is a set of technology $k$ (e.g., $K$ = {hydroforming, 3-layered wet paint system, LET lamps, …}) |
| $s \in S$ | $S$ is a set of scenarios of $CO_2$ credit price fluctuation |
| $t \in T$ | $T$ is a set of planning period under consideration ($T = \{0, 1, 2, \ldots, T_f\}$) |
| $BF$ | $BF$: $M \rightarrow B$ where $M$ is a mathematical statement and $B = \{0, 1\}$ such that if $M$ is logically or mathematically true then $BF$(M) = 1; otherwise $BF(M) = 0$ |

**Table 3.3** Parameters used in the model

| Notation | Description |
|---|---|
| $CoC$ | Cost of capital (%) |
| $Production_t$ | Production level (%) during period $t$ w.r.t the production level at period $t = 0$ |
| $EtoCO_{2_i}$ | $CO_2$ emissions from using utility $i$ (metric tons) |
| $ILimit_t$ | Investment limit in period $t$ ($) |
| $PtoE_i$ | Demand of utility $i$ w.r.t. production levels (%) based on the level at $t = 0$ |
| $CreditPrice_{st}$ | Carbon credit price under scenario $S$ in period $t$ ($) |
| $Q_k$ | Investment cost of technology $k$ ($) |
| $CO_2Limit_t$ | Amount of allowable $CO_2$ emissions in period $t$ (metric tons) |
| $r_k$ | Saving rate ($CO_2$/energy) due to implementing technology $k$ (%) |
| $Lead_k$ | Lead periods until technology $k$ is fully implemented (usually greater than 1) |
| $EDemandBaU_{ij}$ | Business-as-usual demand of utility $i$ by facility $j$ |
| $p_s$ | Probability of the occurrence of scenario $s$ |
| $EPrice_{it}$ | Unit cost of using utility $i$ in period $t$ ($) |
| $CO_2Only_k$ | $CO_2Only_k = 1$ if technology $k$ is applicable to reduce $CO_2$ emissions only; $CO_2Only_k = 0$ if technology $k$ is applicable to reduce both energy and $CO_2$ emissions |
| $Applicable_{i,j,k}$ | $Applicable_{i,j,k} = 1$ if technology $k$ is applicable to utility $i$ and facility $j$; $Applicable_{i,j,k} = 0$ otherwise |

**Table 3.4** Variables used in the model

| Notation | Description |
|---|---|
| $z_{jkt}$ | $z_{jkt} = 1$ if technology $k$ is implemented at facility $j$ in period $t$; $z_{jkt} = 0$, otherwise |
| $CO_2Emissions_t$ | Amount of $CO_2$ emissions in period $t$ (metric tons) |
| $CreditTraded_{st}$ | Amount of carbon credits traded under scenario $S$ in period $t$ (metric tons) |
| $CreditUsed_{st}$ | Amount of carbon credits used under scenario $S$ in period $t$ (metric tons) |
| $CreditIn_{st}$ | Amount of carbon credits in inventory under scenario $S$ in period $t$ (M \metric tons) |
| $ESavings_{ijt}$ | Energy savings of utility $i$ at facility $j$ in period $t$ from technology implementations (%) based on $t = 0$ level |
| $CO_2Savings_{ijt}$ | $CO_2$ savings of utility $i$ at facility $j$ in period $t$ from technology implementations (%) based on $t = 0$ level |
| $EDemand_{ijt}$ | Energy demand of utility $i$ at facility $j$ in period $t$ after offsetting any realisable energy savings |

$$Min(Investement\ cost + Utility\ cost + CO_2\ credit\ expenditures) \tag{3.1}$$

The investment costs are computed by multiplying the fixed investment cost ($Q_k$) of a particular technology ($k \in K$) with the decision as to whether the technology is implemented ($z_{jkt} = 1$, if technology is implemented; $z_{jkt} = 0$, otherwise) as follows:

$$Investement\ cost = \sum_{j \in J} \sum_{k \in K} \sum_{t \in T} \frac{Q_k \times z_{jkt}}{(1 + CoC)^t} \tag{3.2}$$

The utility costs are computed by multiplying the unit cost ($EPrice_{it}$) of a particular utility ($i \in I$) with the demand of this utility ($EDemand_{ijt}$) as follows:

$$Utility\ cost = \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} \frac{EPrice_{it} \times EDemand_{ijt}}{(1 + CoC)^t} \tag{3.3}$$

The $CO_2$ credit expenditures are calculated by multiplying the $CO_2$ credit unit cost ($CreditPrice_{st}$) with the amount of carbon credit traded ($CreditTraded_{st}$) considering the probability of a specific scenario occurring ($p_s$) as follows:

$$CO_2\ credit\ expenditures = \sum_{i \in I} \sum_{j \in J} \frac{p_s \times CreditPrice_{st} \times CreditTraded_{st}}{(1 + CoC)^t} \tag{3.4}$$

The savings for each energy utility at each facility and $CO_2$ emission level during each period are computed using Eqs. (3.5) and (3.6). We assume that the impacts of technology $k$ are independent. A minimum function is used to avoid the case when the total energy savings is greater than 100 %.

$$\begin{aligned} ESavings_{ijt} = Min\Bigg( & 1, \sum_{k \in K} \sum_{cur=1}^{t} Bf\left(Applicable_{i,j,k} = 1\right) \\ & \times Bf(t - cur \geq Leadt_k) \times (1 - CO_2Only_k) \times z_{jkcur} \times r_k\Bigg) \quad \forall i, \forall j, \forall t \end{aligned} \tag{3.5}$$

$$\begin{aligned} CO_2Savings_{ijt} = Min\Bigg( & 1, \sum_{k \in K} \sum_{cur=1}^{t} Bf(Applicable_{i,j,k} = 1) \\ & \times Bf(t - cur \geq Leadt_k) \times z_{jkcur} \times r_k\Bigg) \quad \forall i, \forall j, \forall t \end{aligned} \tag{3.6}$$

The energy demand of each utility at each facility for each scenario is computed using Eq. (3.7) in which the required energy demand ($EDemand_{ijt}$) is calculated by multiplying the production level ($Production_t$) with the adjusted utility demand due to the change in the production level ($PtoE_i \times EDemandBaU_{ij}$). The required energy is then discounted by the energy savings due to implementation of greener technologies ($1 - ESavings_{ijt}$). A similar approach is used to compute $CO_2$ emission levels for each period by changing the energy savings parameter to $CO_2$ savings in Eq. (3.8) in which $CO_2$ emissions associated with using a particular utility are also considered.

$$EDemand_{ijt} = Production_t \times PtoE_i \times EDemandBaU_{ij} \times (1 - ESavings_{ijt}) \quad \forall i, \forall j, \forall t \tag{3.7}$$

$$CO_2Emissions_t = Production_t \times \sum_{i \in I} \sum_{j \in J} (PtoE_i \times EDemandBaU_{ij} \times (1 - CO_2Savings_{ijt}) \times EtoCO_{2_i}) \quad \forall t \tag{3.8}$$

### 3.2.2 Constraints

The number of traded carbon credits $(CreditTraded_{st})$ during the period is computed by finding the difference between the $CO_2$ emission level ($CO_2Emissions_t$) and the amount of freely allocated carbon credits ($CO_2Limit_t$) and between the number of used carbon credits and the carbon credits in inventory ($CreditIn_{st}$). Excess credits could be stored as inventory and used in the following years. No commission fee for trading is assumed. $CreditTraded_{st} \geq 0$ indicates that carbon credits are purchased, and $CreditTraded_{st} \leq 0$ indicates that carbon credits are sold. The $CO_2$ credit inventory for the first period is assumed to be 0 as in Eq. (3.11). The maximum $CO_2$ credit purchase is assumed to be bounded by $CO_2Limit_t$ to regulate any speculation, as in Eq. (3.12).

$$CO_2Emissions_t - CreditUsed_{st} \leq CO_2Limit_t \quad \forall t \tag{3.9}$$

$$CreditIn_{s(t+1)} \leq CreditIn_{st} + CreditTraded_{st} - CreditUsed_{st} \quad \forall t \tag{3.10}$$

$$CreditIn_{s(t=1)} = 0 \quad \forall s \tag{3.11}$$

$$CreditTraded_{st} \leq CO_2Limit_t \quad \forall s, \forall t \tag{3.12}$$

The amount of investment cannot exceed a preset yearly limit ($ILimit_t$), as in Eq. (3.13), and each technology is assumed to be implemented at a facility only once during the entire time horizon, as in Eq. (3.14).

$$\sum_{j \in J} \sum_{k \in K} Q_k \times z_{jkt} \leq ILimit_t \quad \forall t \tag{3.13}$$

$$\sum_{t \in T} z_{jkt} \leq 1 \quad \forall j, \forall k \tag{3.14}$$

## 3.3 Sample Averaging Approximation as a Solving Method

Formally, the objective function and the constraints described in Sect. 3.2 can be written as:

$$\begin{array}{ll} \text{Min} & g(x) \\ \text{s.t} & C_1(x) \leq 0 \\ & C_2(x) = 0 \end{array} \tag{3.15}$$

However, the problem solving has to consider uncertainty in the model due to the price of $CO_2$ credit costs. Therefore, it is natural to regard the objective function $g(x)$ as the expected value taking all possible scenarios into account with a suitable probability distribution. That is, the objective function is, therefore,

$$\text{Min } E[g(x; s)] \tag{3.16}$$

where s represents a scenario of $CO_2$ credit price fluctuations that are represented by a random variable and E[·] is the corresponding expected value operator.

Because this objective function does not have a closed form, or the closed form is very complicated, this type of two-stage stochastic program is difficult to solve or even approximately. For example, if a binomial tree model is used to generate scenarios for 15 periods, there will be $2^{15}$ different possibilities. Considering a long computation time, this study uses sample average approximation (SAA) to solve the proposed two-stage stochastic optimization problem approximately. The basic idea of this method is that a random sample is generated, and consequently, the expected value function is approximated by the corresponding sample average function. More precisely, we solve

$$\text{Min} \quad \widehat{g}_N(x) \tag{3.17}$$

Here $\widehat{g}_N(x) = \frac{1}{N}\sum_{l=1}^{N} g(x; s_l)$. Obviously $\mathrm{E}[\widehat{g}_N(x)] = E[g(x; s)]$ and the solution obtained from the SAA algorithm converges to the original stochastic solution as $N \to \infty$ by the Law of Large Numbers. Indeed, it is known (Kleywegt et al. 2002) that the solution converges exponentially as $N \to \infty$ under certain conditions. More precisely, they showed that

$$\mathrm{P}\left(\widehat{X}_N^\delta \not\subset X^\varepsilon\right) \leq |X \backslash X^\varepsilon| e^{-N\gamma} \tag{3.18}$$

where $X$ is the feasible set of $x$, $\widehat{X}_N^\delta$ and $X^\varepsilon$ are δ, ε-optimal solutions of Eqs. (3.17) and (3.16), respectively such that

$$\widehat{g}_N(\overline{x}) \leq \text{Min } \widehat{g}_N(x) + \delta, \quad \text{if } \overline{x} \in \widehat{X}_N^{\delta} \tag{3.19}$$

$$E[g(\overline{x}; s)] \leq \text{Min } E[g(x; s)] + \varepsilon, \quad \text{if } \overline{x} \in X^{\varepsilon} \tag{3.20}$$

and $\gamma$ is a positive function under certain assumption. It can be also shown that a sufficient condition for the probability of $\mathrm{P}\left(\widehat{X}_N^{\delta} \subset X^{\varepsilon}\right)$ to be at least $1 - \alpha$ is

$$\mathrm{N} \geq \frac{3\sigma^2}{(\varepsilon - \delta)^2} \ln \frac{|X|}{\alpha} \tag{3.21}$$

for a constant $\sigma$, which is difficult to estimate.

$E[g(x;s)]$ must be estimated by the sample average $\widehat{g}_N(x)$. This estimation usually has a lower computational cost than solving SAA. For this reason, a larger sample size $N'$ is used to obtain more accurate estimate $\widehat{g}_{N'}(\widehat{x}_N)$ for an optimal solution $\widehat{x}_N$ to the SAA problem. Selection of the sample sizes $N$ and $N'$ is one of the issues in SAA and it involves a trade-off between accuracy and computational cost. In the simulation, this work takes various values of $N$ with $N' = 4096$ and demonstrate the convergence numerically. See Fig. 3.4.

The SAA algorithm is defined in the following steps:

Step 1: Choose the sample sizes ($N$ and $N'$) and a decision rule for the replications ($M$).

Step 2: Input $N$ generated scenarios into the stochastic model, solve the stochastic model for $M$ iterations and determine the objective value and the objective solution. The random samples generated by the Monte Carlo sampling techniques are assumed to be distributed independently of one another.

Step 3: Generate $N'$ new random, independent scenarios. Keep the carbon trading strategy constant and apply each of the $M$ solutions to the $N'$ scenarios to calculate the carbon credit cost and total cost.

Step 4: Determine the solution with the best optimal value.

Step 5: Obtain the bounds for the optimal solution value $v^*$.

- Upper bound: Apply the best solution obtained in step (4) to the $N'$ scenarios and calculate the total cost for each of the $N'$ scenarios. Find the average and standard deviation of the cost and calculate the confidence interval for the upper bound.
- Lower bound: Find the average and the standard deviation of the total cost for the $M$ replications and calculate the confidence interval for the lower bound.

Step 6: If the gap between the bounds is too large, increase the sample sizes $N$ and/or $N'$, and return to Step 2. Otherwise, choose the best solution among all candidate solutions from $M$ replications. Stop.

It is important to know how much the solution is improved by the stochastic model. To calculate the improvement due to the stochastic model, the value of the stochastic solution (*VSS*) needs to be calculated, which is defined by the following equation:

$$VSS = EEV - HN \tag{3.22}$$

The expected value solution (*EEV*) is a solution from a deterministic model in which the average $CO_2$ credit cost of all scenarios was used as the $CO_2$ credit cost. Then, the performance of the deterministic optimal investment strategy is evaluated in a stochastic environment. In other words, for each scenario, the total sum of the investment cost, the utility cost, and the $CO_2$ credit expenditures is calculated if the deterministic optimal investment strategy is implemented. The average total cost of all scenarios is then termed the *EEV* solution. Meanwhile, the here and now (*HN*) solution, which is the stochastic optimal investment strategy, is obtained using the proposed stochastic model and the SAA method. The total cost incurred from using this strategy is termed the here and now (*HN*) solution. The difference between the *HN* and the *EEV* was defined as the value of the stochastic solution (*EEV*), as in Eq. (3.22). *VSS* indicates how much the strategy is improved by considering the uncertainty of the $CO_2$ credit cost. This study will discuss the *EEV* by comparing the *HN* and the *EEV* solutions in terms of the carbon credit expenditure in the next section.

## 3.4 Illustrative Study

### *3.4.1 Carbon Cost Scenario Generation*

Many studies have been conducted regarding the projection of upper and lower bounds of credit price forecast (Berendt et al. 2007; Jognston et al. 2011). Given the upper and lower bounds of credit price forecast, it is possible to create scenarios so that fluctuation in the carbon credit price could be taken into account. Many ways to generate scenarios are available using different stochastic models, such as the uniform distribution model, the gamma distribution model or the binomial tree model. This study uses a binomial tree model because of the shortcomings of other approaches. For example, the use of the uniform model may generate extremely large price fluctuations (i.e., random variables between the lower and upper bounds year by year) resulting in unrealistic results, whereas the use of the gamma distribution may generate credit prices that are always close to the upper bound and not realistic either. The mechanism of running a binomial tree model to generate the scenarios is as follows:

Step 1: Choose a reliable source of the upper and lower bounds of the credit price forecast. This study chose the forecast for 2020–2030 years made by Synapse Energy Economics, Inc. (Jognston et al. 2011). The data from 2020 to 2030 in Table 3.5 correspond to the chosen data set.

**Table 3.5** Lower and upper bounds of the carbon credit price projection based on (Jognston et al. 2011)

| Year | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|
| Lower bound | 6.1 | 7.6 | 9.1 | 10.6 | 12.1 | 15.0 | 16.5 | 18.0 |
| Upper bound | 16.4 | 20.8 | 25.1 | 29.4 | 33.8 | 36.7 | 41.0 | 45.3 |
| Year | 2023 | 2024 | 2025 | 2026 | 2027 | 2028 | 2029 | 2030 |
| Lower bound | 19.5 | 21.0 | 22.5 | 24.0 | 25.5 | 27.0 | 28.5 | 30.0 |
| Upper bound | 49.7 | 54.0 | 58.3 | 62.7 | 67.0 | 71.3 | 75.7 | 80.0 |

Step 2: Find the macro and micro trend factors from the given upper and lower bounds. The macro factor represents the price change caused by the macro environment of the market throughout the years whereas the micro factor represents the price change caused by some accidental events in a particular year. Since the carbon credit price is expected to increase in the long term, the macro trend factor is positive.

Step 3: Extend the upper and lower bounds backward or forward to increase the time span for the strategic planning. This study extended the upper and lower backward to cover the years from 2015 to 2019 considering the macro trend factor.

Step 4: Apply a binomial tree model to generate scenarios. In this study, a random price in 2015 is first generated from a normal distribution, and to forecast 2016 price, the 2015 price is added by the macro uptrend factor and micro increasing or decreasing factor with the probability of both increasing and decreasing being 50 %. If the price goes beyond the upper bound or below the lower bound, a new set of factors is generated until the new price is within the range of bounds. Using the same process, the credit prices for the entire time span are generated.

To follow these steps and to calculate the parameters required to generate the carbon credit price scenarios, the following notations are defined:

- $P_u(t)$: A forecast of the carbon credit price at year $t$ for the upper bound projection
- $P_l(t)$: A forecast of the carbon credit price at year $t$ for the lower bound projection
- $\Delta_u(t)$: The difference of carbon credit prices between years $t$ and $t-1$ for the upper bound projection
- $\Delta_l(t)$: The difference of carbon credit prices between years $t$ and $t-1$ for the lower bound projection.

Given that the projection data for carbon credit price from 2020 to 2030 are available as in Table 3.5, it is possible to calculate the following parameters to characterize trends required to generate scenarios for the carbon credit price:

- Upper bound trend = $\frac{1}{10}\sum_{t=2021}^{t=2030} \Delta_u(t) = 4.33$
- Lower bound trend = $\frac{1}{10}\sum_{t=2021}^{t=2030} \Delta_l(t) = 1.50$
- Major trend = $\frac{1}{10}\sum_{t=2021}^{t=2030}\left[\frac{1}{2}(\Delta_u(t) - \Delta_l(t)) - \frac{1}{2}(\Delta_u(t-1) - \Delta_l(t))\right] = 2.92$
- Increasing minor trend = $\frac{1}{10}\sum_{t=2021}^{t=2030}\left[\left(P_u(t) - \frac{1}{2}(\Delta_u(t) - \Delta_l(t))\right) - (P_u(t-1) - \frac{1}{2}(\Delta_u(t-1) - \Delta_l(t-1)))\right] = 1.42$
- Decreasing minor trend = $\frac{1}{10}\sum_{t=2021}^{t=2030}\left[\left(P_l(t) - \frac{1}{2}(\Delta_u(t) - \Delta_l(t))\right) - (P_l(t-1) - \frac{1}{2}(\Delta_u(t-1) - \Delta_l(t-1)))\right] = -1.42$

Note that this study extended the upper and lower bound projections backward to cover the years from 2015 to 2019 by considering the upper and lower bound trends.

### 3.4.2 Parameter Settings for a Hypothetical Plant

To help formulate a stochastic problem, this study sets parameters for a hypothetical plant as follows:

- The annual production volume: 123,000 vehicles
- Energy intensity (MWh/vehicle): 2.3 (Note: this number is an average of major car making companies in 2013 (Oh and Hildreth 2014), e.g., GM: 2.3, VW: 2.21, Ford: 2.45, BMW: 2.44, Toyota North America: 2.13)
- Total energy consumption per year (MWh/year): 283,638 (=123,000 × 2.3)
- Energy distribution:
  - (Electricity: Natural Gas) = (45 %: 55 %)
  - Electricity

    (Body shop: Paint shop: General Assembly) = (45 %: 45 %: 10 %)
  - Natural Gas

    (Body shop: Paint shop: General Assembly) = (4 %: 92 %: 4 %)
- Total $CO_2$ emissions (Ton): 112,646 (Note: this is calculated based on energy to $CO_2$ conversions: $EtoCO_{2_{electrity}} = 0.0006$ Ton/kWh; $EtoCO_{2_{natural\ gas}} = 0.0531$ Ton/MBtu)
- $CO_2$ per vehicle: 0.92 Ton/Vehicle
- Utility price of the first year: (Electricity: Natural Gas) = ($0.06: $6.75)
- Annual investment limit for sustainability projects ≤$900,000 (Note: this limit corresponds to approximately 8 % of the total first year utility costs).

### 3.4.3 Assumptions and Cases for Study

To help formulate a stochastic problem, this worker made some assumptions to the extent that they will not be detrimental to deliver the major points of this study as follows:

- Use of an artificial set of green technologies, as shown in Table 3.6—the list of technologies was generated to closely resemble real-world data.
- Excessive credit could be stored as inventory for use in the following years.
- No commission fee for credit trading.
- In the scenario generation, the data from 2015 to 2030 in Table 3.5 corresponds to the planning time span from $t = 0$ to $t = 15$.
- For the utility price forecast $(EPrice_{it})$, the energy price outlook data collected from the U.S. Energy Information Administration were used (U.S. Energy Information Administration 2010).
- For energy to $CO_2$ conversions, the conversion rate calculated based on data from the Energy Information Administration ($Eto\mathrm{CO}2_{electrity} = 0.0006$ Tons/kWh; $Eto\mathrm{CO}2_{natural\ gas} = 0.0531$ Tons/MBtu) was used.
- For the energy demand forecast ($EDemandBaU_{ij}$), a hypothetical vehicle assembly plant with an annual production volume of 123,000 is postulated. The average energy intensity (kWh/vehicle; energy required to build a vehicle) is set to be 2.3 by averaging energy intensities of major car producing companies in 2013 (Oh and Hildreth 2014) (e.g., GM: 2.3, VW: 2.21, Ford: 2.45, BMW: 2.44, Toyota North America: 2.13). The energy distribution of vehicle manufacturing

**Table 3.6** Hypothetical energy saving opportunities

| Greener technologies to invest in | Investment cost ($) | Energy or $CO_2$ savings (%) | $CO_2$ savings only? (yes/no) | Lead time to install (years) |
|---|---|---|---|---|
| EI_PJ_1 | 450,000 | 5 | No | 1 |
| EI_PJ_2 | 95,000 | 5 | No | 2 |
| NGI_BJ_1 | 100,000 | 15 | No | 2 |
| EI_BJ_1 | 77,500 | 10 | No | 2 |
| EI_BJ_2 | 500,000 | 25 | No | 4 |
| EI_BJ_3 | 75,000 | 5 | No | 1 |
| NGI_PJ_$CO_2$Only_1 | 800,000 | 25 | Yes | 2 |
| EI_GJ_$CO_2$Only_1 | 100,000 | 16 | Yes | 3 |
| EI_BJ_3 | 43,500 | 25 | No | 2 |
| EI_BGJ_$CO_2$Only_1 | 100,000 | 7 | Yes | 2 |
| EI_GJ_1 | 132,000 | 4 | No | 1 |
| ENI_PJ_1 | 79,000 | 8 | No | 2 |
| EI_PJ_3 | 500,000 | 5 | No | 3 |

processes is taken in account to forecast the annual energy demand for each facility (US Department of Energy 2008).
- $N = N' = 1000$ if not explicitly stated otherwise.

This study implemented two cases considering different capital costs (5, 10, and 15 %) based on the 15 year span from $t = 0$ to $t = 15$ imposing different constraints as follow:

- Case-1: Base case scenario where no $CO_2$ emission limits are applied.
- Case-2: A series of $CO_2$ emission reduction scenarios are imposed such that the emission of $CO_2$ must be 3 % less than (for first 5 years), 17 % less than (6th–10th years), and 35 % less than (11th to the end) emissions at $t = 0$ l similar to the step-wise reduction scheme proposed by EU-ETC or the Waxman-Markey Bill.

### *3.4.4 Results*

To provide a better understanding of the study results, this section reports annual total costs and carbon credit expenditure for two different cases with different capital costs. Additionally, this section will compare the HN and the EEV solution by year with respect to carbon credit expenditure to understand what better information can be obtained through the use of the stochastic model compared with traditional deterministic models. This study used GLPK solver (2008) externally to implement SAA problem solving process. An example of a greener technology investment plan resulting from this case study is shown in Table 3.7.

Figures 3.1 and 3.2 show the annual total costs and carbon credit expenditure costs or two different cases with different capital costs. It should be noted that the negative expenditure for carbon credit means the company sells the reserved credits in the market and makes money. Several interesting results were obtained. First, an intensive investment in technologies is made in the first three years, which directly contributes to a decrease in utility and credit costs, respectively. This result means that the investment in technology effects the reduction in $CO_2$ emissions. A major component of total cost is the utility cost, and although the study indicated that there was no significant decrease in the utility cost from the technology installation, the investments did take effect because the increasing trend of the utility cost

**Table 3.7** Investment strategy example (based on scenario 2 with a 15 % capital cost)

| t-th year | Greener technologies to invest in |
|---|---|
| 1 | EI_PJ_2, EI_BJ_1, EI_BJ_2, EI_BJ_3, EI_BJ_3, ENI_PJ_1 |
| 2 | EI_PJ_1, NGI_BJ_1, EI_GJ_$CO_2$Only_1, EI_GJ_1, EI_BGJ_$CO_2$Only_1 |
| 3 | EI_BGJ_$CO_2$Only_1, EI_PJ_3 |
| 4 | NGI_PJ_$CO_2$Only_1 |

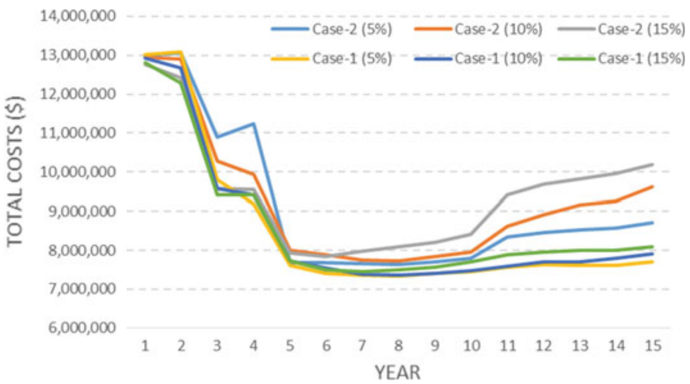


**Fig. 3.1** Annual total costs for cases having different capital costs

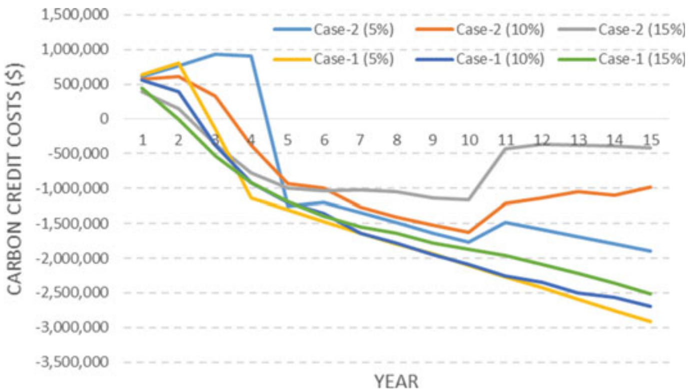


**Fig. 3.2** Annual carbon credit expenditure for the various cases with different capital costs

flattened. Note that if a technology reduces energy and $CO_2$ emissions over a short lead-time period with low costs, the chance that this technology will be selected earlier is greater than other technologies. Second, the cost of Case-2 exceeds the cost of Case-1. Recall that Case-2 implements a step-wise reduction scheme proposed by the EU-ETC or the Waxman-Markey Bill. Accordingly, Case-2 has the greatest cost flow with 15 % capital cost whereas Case-1, with 5 % capital cost, demonstrates the lowest cost flow throughout the project period. An interesting observation commonly found in Case-2 studies is that when the 35 % reduction is enforced as the third stage starts in the 11th year, there is an spike in expenditure on carbon credits. This observation is made because it is impossible to meet the 35 % reduction requirement by solely relying on technology investment, and instead, the company must purchase extra carbon credits from the market to fill the discrepancy


**Fig. 3.3** Comparison of the *HN* and *EEV* solutions by year on carbon credit expenditure

between actual emissions and the enforced limit. Third, the capital costs also affect the results significantly. The results indicate that the cases with less capital cost are more active in purchasing carbon credits for future usage when the price is low in the early stages of the project. For example, when 5 % capital cost is applied in Case-2, although the expenditure on carbon credits spikes in the 11th year, the expenditure decreases again in time because the enough credits had been purchased previously for future usage. When 15 % capital cost is applied in Case-1, the expenditure on carbon credits increase in the 11th year and remains constant for the rest of project period because there is not enough inventory.

This study also compares the annual carbon credit expenditure between the *HN* and *EEV* solutions to understand how much the solution is improved using the stochastic model compared with the traditional deterministic models. When using Case-2 with 15 % capital cost, the carbon credit expenditure for the *HN* solution is \$2,849,325 whereas the carbon credit expenditure for the *EEV* solution is \$2,786,093, which is the net present value of total costs, as shown in Fig. 3.3. From this result, we can see that the *HN* solution has a 2 % improvement. Although the value of $z_{jkt}$ is the same for both the *HN* and *EEV* solutions, which results in $VSS = 0$ in this small size case study, this results may still inspire managers that responsible for sustainability activities to make more informed decisions regarding the most appropriate budgeting strategy (i.e., the upper limit of investment in a sustainable project) for their particular circumstances.

It is a good idea to verify whether SAA converges to the optimal solution using a convergence graph. In general, the use of a convergence graph aims to show changes in the upper and lower bounds of the optimal solution based on different scenario sizes. Figure 3.4 shows the convergence based on $2^4$, $2^6$, $2^8$, $2^{10}$ and $2^{12}$ scenarios. Note that the length of 95 % mean value confidence range, which is used to define the lower bound (colored in blue), becomes smaller as $N$ increases. The decreased variance of the lower bound is an indicator to the convergence of the SAA solutions to the optimal solution. This convergence test also reveals that when

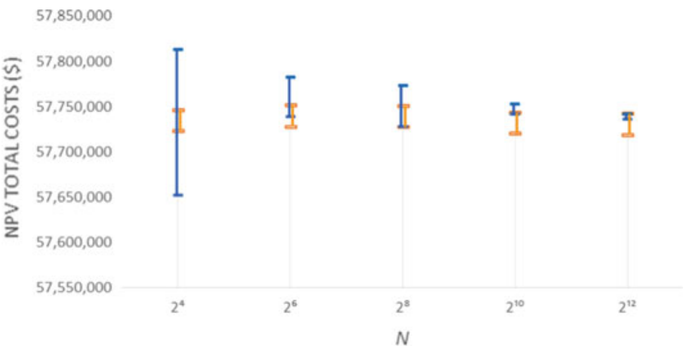


**Fig. 3.4** Convergence graph showing the convergence of SAA solutions (*blue line* the lower bound; *yellow line* the upper bound). $N'$ is fixed to $2^{12}$

$N$ becomes $2^{12}$, the difference between the upper and the lower is less than 0.1 % of the average optimal value, which indicates that the SAA solution for $N$ equal to $2^{12}$ (=4096) is very close to the true optimal solution.

## 3.5 Summary

This chapter proposed a new stochastic programming approach to identify the optimal investment plan for sustainable manufacturing projects to reduce energy costs and $CO_2$ emission costs at manufacturing processes under various time, budget, technology and environmental constraints by solving a multi-period stochastic program that considers uncertain decision parameters, such as future $CO_2$ credit market price. SAA is used to solve the proposed stochastic problem, and an illustrative example of the application of the proposed model and the solving approach is presented. The illustrative case study indicates that even if a company is not able to meet the $CO_2$ emission reduction enforced by authorities through installing greener technologies, it can still meet the energy and environment regulation in a cost effective manner by leveraging a carbon trading system.

With regard to future work, it is of interest to extend this work to incorporate other market-based mechanisms, such as joint implementation (JI) and clean development mechanisms (CDMs), into the model as an alternative to $CO_2$ credit trading. Additionally, it is also of interest to conduct the same study over an automotive life cycle because an automotive life cycle analysis reveals that the supply chain for automotive parts is ten times more energy intensive than OEM operations. This demonstrates that the automotive part supply chain can contribute a major reduction in the automotive industry's carbon footprint; thus, there is an opportunity to extend the proposed model to cover the automotive part supply chain as a possible future work.

## 3.6 Exercises

1. For the energy or environment project you worked or are working, try to explain the potential application of a stochastic programming approach and make a business case of the application as detailed as possible.
2. Try to download GNU Linear Programming Kit (http://www.gnu.org/software/glpk/glpk.html) and replicate the illustrated example in this chapter following the procedures as stated.
3. Assume that your facility emits the following greenhouse gases into the air and you are interested in measuring the carbon footprint of your facility. Calculate the total greenhouse gas emissions of your facility in tons of carbon dioxide equivalent (Hint: refer to Table 3.8).
   - 100 ton of Methane
   - 50 ton of CFC-12
   - 10 ton of HFC-134a
4. This chapter proposed a stochastic programming approach to identify the optimal investment plan for sustainable manufacturing projects to reduce energy and $CO_2$ emission costs for manufacturing processes subject to various time, budget, technology and environmental constraints. The principle underlying the proposed approach is to maximize the value of information accessible at the 1st stage of decision process. In order to test your sense of measuring the value of information, try to understand the following scenario and address the subsequent questions (revised from Birge and Louveaux 2011):
   - Scenario: Suppose that your company carries out retail sale of an environmentally-hazardous chemical. Your company purchases the chemical at a price of $6 (million) per tank and sells it to customers. Any unsold chemical should be disposed at a price of $10 (million) per tank and if any stock out event happens, a penalty is charged at a price of $10 (million) per

**Table 3.8** Global warming potentials for the six Koyoto protocol GHGs

| Greenhouse gas | Average lifetime in the atmosphere (years) | Global warming potential of one molecule of the gas over 100 years (relative to $CO_2$ = 1) |
|---|---|---|
| Carbon dioxide | 50–200 | 1 |
| Methane | 12 | 21 |
| Nitrous oxide | 120 | 310 |
| CFC-12 | 100 | 10,600 |
| CFC-11 | 45 | 4600 |
| HFC-134a | 14.6 | 1300 |
| Sulfur hexafluoride | 3200 | 23,900 |

tank according to the service level agreement. Unfortunately, the demand from the customers is not certain. Let x and $\xi$ be a single decision variable representing the amount of purchase and random variable representing the uncertain demand, respectively. Then, your concern is to solve the following problem

$$\begin{array}{ll} \min_x & z(x,\xi) = 6x + 10|x-\xi| \\ \text{s. t.} & x \geq 0 \end{array} \tag{3.23}$$

Due to lack of information, you cannot be aware of the exact distribution of $\xi$ but know the expectation of $\xi$ that is, $E[\xi] = 1/2$. In this situation, you can solve the problem (min $6x + 10|x - 1/2|$, s. t. $x \geq 0$) and obtain the optimal value as 3 at $x = 1/2$. We call this optimal value to be *expected value* (EV), that is, EV = \$3 (million).

- Question-1: Suppose that you built an information system that analyses the sales history and provides a distribution of $\xi$ with 100 % assurance. Let us call the information system to be "Stochastic information DSS (Decision Support System)". So, you get to know that $\xi$ takes two values $\xi_1$ and $\xi_2$, with probability $p_1$ and $1 - p_1$, respectively. Let $\xi_1 = 1/3$ and $\xi_2 = 2/3$, $p_1 = 1/2$ serve as reference. Then, your concern is to solve the following problem instead of Eq. (3.23).

$$\begin{array}{ll} \min_x & E_\xi z(x,\xi) = 6x + 10E_\xi|x-\xi| \\ \text{s.t.} & x \geq 0 \end{array} \tag{3.24}$$

If you solve Eq. (3.24), then you can obtain the optimal value to be 11/3 at $x = 1/3$. We call this optimal value to be *here and now value* (HN), that is, HN = \$11/3 (million). Since you now know the distribution of $\xi$, you can validate EV by calculating $E_\xi(z(1/2, \xi))$. We call $E_\xi(z(1/2, \xi))$ as *expectation of expected value* (EEV). Furthermore, we can define *value of stochastic solution* (VSS) as the difference between EEV and HN, that is VSS = EEV – HN. Calculate EEV and VSS and see if your solutions for EEV and VSS are \$14/3 (million) and \$1 (million)

- Question-2: Suppose that you built another advanced information system that predicts perfect future demand. Let us call the information system to be "Perfect information DSS". In this situation, you can solve the problem, $E_\xi[\min z(x, \xi)]$. We call this optimal solution to be *wait and see* (WS). Furthermore, we can define expected value of perfect information (EVPI) as the difference between HN and WS, that is EVPI = HN − WS. Calculate WS and EVPI and see if your solutions for WS and EVPI are \$3 (million) and \$2/3 (million)
- Question-3: You calculated VSS and EVPI from Questions 1 and 2. The positive value of VSS and EVPI leads to justify the implementation of information systems. However, if you spent \$0.5 (million) and \$1 (million)

to build Stochastic information DSS and Perfect information DSS, respectively, do you think these investment make sense from the investment evaluation perspective?

## Appendix: Methods and Standards for Preparing Scope-3 Carbon Footprints

Greenhouse gases (referred to as GHGs here forth) are gases that trap heat in the earth's atmosphere. In more technical terms, GHGs are gases that absorb and emit radiation within the thermal infrared range, a process representing the fundamental cause of the greenhouse effect. Six greenhouse gases have been identified by the Koyoto protocol (2011) as the main reduction targets for 37 industrialized countries and the European community involved in the agreement:

- Carbon dioxide ($CO_2$)
- Methane ($CH_4$)
- Nitrous oxide ($N_2O$)
- Hydrofluorocarbons (HFCs)
- Perfluorocarbons (PFCs)
- Sulphur hexafluoride ($SF_6$)

In the United States, GHG emissions caused by human activities increased by 14 % from 1990 to 2008 (EPA 2011). Worldwide GHG emissions from human activities increased by 26 % from 1990 to 2005. Many governments are taking steps to reduce GHG emissions through national policies, emissions trading programs, carbon or energy taxes, and regulations and legislations on energy efficiency and emissions. Firms worldwide are responding to the threat of these legislations, the incentives offered by some programs, and the concerns raised by their own consumers. These firms are continuously undertaking new initiatives to reduce their GHG emissions.

A first, and crucial, step to such initiatives is to prepare a GHG inventory. A GHG inventory is an accounting of the amount of greenhouse gases emitted to or removed from the atmosphere over a specific period (e.g., one year). It also provides information on the activities that cause emissions and removals, as well as background on the methods used to make the calculations. Policy makers use greenhouse gas inventories to track emission trends, develop strategies and policies and assess progress. Preparing a GHG inventory is a non-trivial task. Gathering the required information in a comprehensive and systematic manner is very challenging. This information includes energy usage, waste stream data, air emissions, facilities, water usage, vehicle and transportation, and production, among others. Subsequently, necessary parameters need to be calculated and reports need to be created. The process can be slow and error prone, leading to potential inaccuracies.

## *Carbon Footprint*

One of the primary outputs of a GHG inventory is the "carbon footprint". The carbon footprint measures the total greenhouse gas emissions in tonnes of carbon dioxide equivalent ($tCO_2e$). Measuring the emissions of all six Koyoto protocol greenhouse gases in $CO_2$ equivalent has two main motivations. First, it allows the different greenhouse gases to be compared on a like-for-like basis relative to one unit of $CO_2$. Second, there is a growing consensus that $CO_2$ emissions are the leading cause of global warming, an important component of climate change. Carbon dioxide equivalent ($CO_2e$) is calculated by multiplying the emissions of each of the six greenhouse gases by its 100 year global warming potential shown in Table 3.8 (IPCC 1995).

## *Types of Carbon Footprint*

Carbon footprint can be categorized either according to the entity under consideration or the boundary of measurement. With the entity under consideration, carbon footprint is categorized into either organizational or product footprint.

- Organizational carbon footprint: it measures the GHG emissions from the activities across the organization, including for example energy used in buildings, industrial processes, power generation, company vehicles, and employee commuting, among others. Quantifying the carbon footprint for organization helps identify key emission sources as well as opportunities to reduce your emissions. It is also a crucial step for developing carbon reduction plans, since the organization needs to first measure its current carbon footprint, implement reduction activities, then measure the carbon footprint again to track progress.
- Product carbon footprint: it measures the GHG emissions over the whole life of a product (goods or services) throughout its cradle-to-grave lifecycle, from the extraction of raw materials and manufacturing through its distribution, use, and disposal. Measuring a product's carbon footprint offers a number of benefits such as attracting customers, emissions savings, cost savings, and engaging with the supply chain.

Defining the boundaries of a carbon footprint is categorized into Scope-1, Scope-2 and Scope-3.

- Scope-1: Direct GHG emissions that occur from sources owned or controlled by the company, for example, emissions from combustion in owned or controlled boilers, furnaces, vehicles, etc.; emissions from chemical production in owned or controlled process equipment.
- Scope-2: Electricity indirect GHG emissions account for GHG emissions from the generation of purchased electricity consumed by the company. Purchased electricity is defined as electricity that is purchased or otherwise brought into the

organizational boundary of the company. Scope-2 emissions physically occur at the facility where electricity is generated.

- Scope-3: Other indirect GHG emissions are a consequence of the activities of the company, but occur from sources not owned or controlled by the company. Some examples of scope-3 activities are extraction and production of purchased materials; transportation of purchased fuels; and use of sold products and services.

Note that from the description, Scope-3 stands out to be the most challenging GHG inventory to measure. The reason for this is twofold; first determining the boundaries of measurement is challenging and needs to be done carefully in order to avoid double counting. Second, Scope-3 emissions typically come from sources over which the organization would not have financial or operational control. Collecting complete and reliable data from these emissions sources is a difficult task. Although preparing a Scope-3 GHG inventory is a tedious task, it cannot be ignored. Scope-3 emissions are often the largest source of emissions for companies and therefore often represent the largest opportunity for greenhouse gas reductions. Studies show that, on average, more than 75 % of an industry sector's carbon footprint is attributed to Scope 3 sources (Huang et al. 2009).

It is evident that in many countries, the legal boundary for financial accounting is the company. This means that companies generally only have a statutory obligation to track liabilities associated with Scope-1 (and potentially, Scope-2) gases because Scope-3 emissions are controlled or owned by other organizations. Many standards have been developed to aid in measuring Scope-1 and Scope-2 emissions, but no official and internationally recognized standards are yet available for Scope 3 emissions as shown in Table 3.9.

## *Scope-3 Carbon Footprint Reporting Methods and Standards for Organizations*

The two most internationally recognized standards for organization carbon footprint accounting are the ISO 14064 standard (ISO 2006) and the GHG Protocol Corporate Value Chain Standard (WRI and WBCSB 2010).

### ISO 14064 Standard

ISO 14064 details internationally agreed requirements on what needs to be done in GHG accounting and verification efforts, while the GHG Protocol outlines, not only what needs to be done, but also how to undertake GHG accounting and reporting. In fact, the publisher of ISO 14064, that is, ISO (International Organization for Standardization) and the publishers of the GHG Protocol standard, that are World Resources Institute (WRI) and the World Business Council for Sustainable

**Table 3.9** Some national and regional GHG reporting programs

| Jurisdiction | Program | GHGs covered | Scope-1 | Scope-2 | Scope-3 |
|---|---|---|---|---|---|
| Europe | EU Emissions Trading | $CO_2$ | Yes | – | – |
| US | GHG Reporting Rule | All 6 Kyoto gases plus additional fluorinated gases | Yes | – | – |
| US | Regional Greenhouse Gas Initiative | $CO_2$ | Yes | – | – |
| US | Western Climate Initiative | All 6 Kyoto gases | Yes | – | – |
| US | California Climate Action Register | All 6 Kyoto gases | Yes | Yes | Optional |
| US | EIA (Energy Information Agency) 1605b Program | All 6 Kyoto gases plus CFCs | Yes | – | – |
| US | EPA Climate Leaders | All 6 Kyoto gases | Yes | – | – |
| Canada | GHG Emissions Reporting Program | $CO_2$, $CH_4$ and $N_2O$ | Yes | – | – |
| Australia | National Greenhouse and Energy Register | All 6 Kyoto gases plus additional fluorinated gases | Yes | Yes | Optional |
| Japan | GHG Accounting and Reporting System | All 6 Kyoto gases | Yes | Yes | – |
| Japan | Voluntary Emissions Trading System | $CO_2$ | Yes | – | – |
| UK | CRC Energy Efficiency Scheme | $CO_2$ | Yes | Yes | – |
| International | Carbon Disclosure Project (CDP) | All 6 Kyoto gases | Yes | Yes | Optional |

Development (WBCSD) have signed a Memorandum of Understanding (MoU) in 2007 under which they have agreed to jointly promote the ISO 14064 standards and the GHG Protocol standards. Hence, the ISO 14064 standard is completely compatible with the GHG Protocol Corporate Value Chain Standard.

### GHG Protocol Corporate Value Chain Standard

The Greenhouse Gas Protocol (GHG Protocol) is the most widely used international accounting tool for government and business leaders to understand, quantify, and manage greenhouse gas emissions. The GHG Protocol is a decade-long partnership between the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). It provides the accounting framework for nearly every GHG standard and program in the world—from the International Standards Organization to The Climate Registry—as well as hundreds of GHG

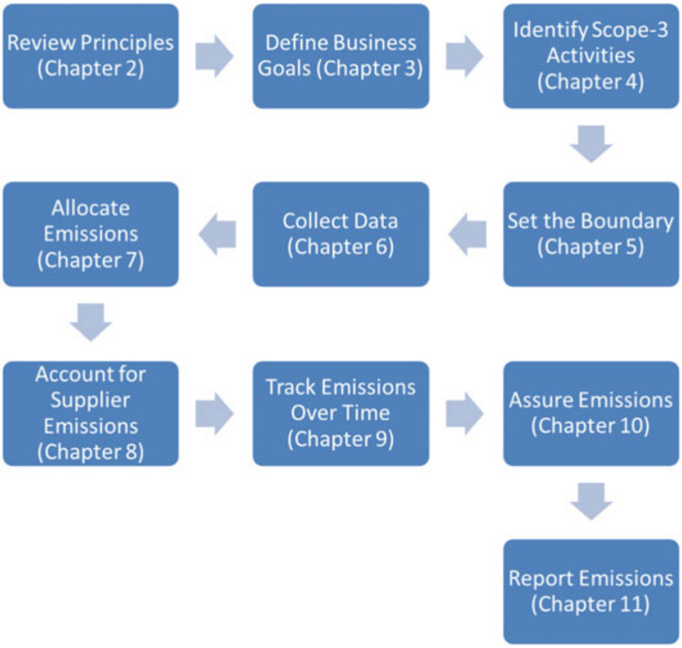


**Fig. 3.5** Steps required to complete the Scope 3 inventory covered by the GHG Protocol

inventories prepared by individual companies. Note that the standard development process for the GHG Protocol Scope 3 Standard has occurred in parallel with the process to develop the GHG Protocol Product Standard mentioned in the next section.

Figure 3.5 shows the steps that an organization needs to complete a Scope-3 GHG inventory, each step covered by a chapter of the Corporate Value Chain (Scope 3) standard. The interested reader should refer to the full standard for guidance regarding the details.

Figure 3.6 displays an example from a typical organization from the manufacturing sector. Scope-1, scope-2 and scope-3 are mutually exclusive. In other words, there is no double counting of emissions between the scopes for the reporting company. Therefore, a company's scope-3 inventory does not include any emissions already accounted for as scope-1 or 2. Scope-3 emissions are released from sources owned and controlled by other entities in the value chain, such as materials suppliers, third party logistics providers, waste management suppliers, travel suppliers, lessees and lessors, franchisees, retailers, employees, and customers.

The first step in accounting for corporate emissions (whether they are Scope-1, 2, or 3) is to define the company's organizational boundary. It is the most important steps because the selection of the boundaries affects which activities in the company's value chain are categorized as direct emissions and indirect emissions and

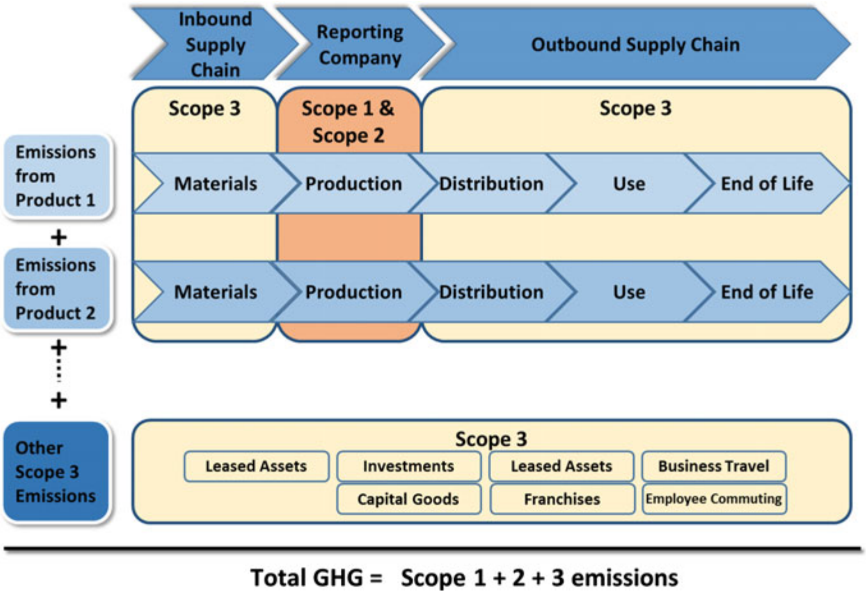


**Fig. 3.6** Total GHG emissions from a manufacturing sector organization

**Table 3.10** Alternate consolidation approaches for defining organizational boundaries defined in the GHG Protocol

| Consolidation approach | Description |
|---|---|
| Equity share | Under the equity share approach, a company accounts for GHG emissions from operations according to its share of equity in the operation. The equity share reflects economic interest, which is the extent of rights a company has to the risks and rewards flowing from an operation |
| Financial control | Under the financial control approach, a company accounts for 100 % of the GHG emissions over which it has financial control. It does not account for GHG emissions from operations in which it owns an interest but does not have financial control |
| Operational control | Under the operational control approach, a company accounts for 100 % of the GHG emissions over which it has operational control. It does not account for GHG emissions from operations in which it owns |

which emissions are categorized as scope-1, scope-2, and scope-3. The standard defines three consolidation approaches for companies to use in defining their organizational boundaries, summarized in Table 3.10.

## *Scope-3 Carbon Footprint Reporting Methods and Standards for Products*

A product carbon footprint measures the GHG emissions over the whole life of a product. Since it includes emission sources from outside the boundaries or an organization, product carbon footprint is most closely related to measuring Scope 3 emissions for an organization, but focused on one product or service. In other words, Scope 3 GHG emissions for an organization are equal to the sum of carbon footprints of all its products and/or services. As in the case with organizational carbon footprints, there are many methods and standards for performing product carbon footprints such as the PAS 2050 standard and Greenhouse Gas Protocol Product Life Cycle Standard. In addition, as a recent method that has gained good recognition within the community, there is the Economic Input-Output Life Cycle Assessment (EIO-LCA) method.

- PAS 2050: A PAS (Publicly Available Specification) is a consultative document in which the development process and written format is based on the British Standard model. Any organization, association or group who wish to document standardized best practice on a specific subject, can commission a PAS, subject to the BSI acceptance process. A PAS occupies the intellectual space between in-house and national standards; it allows you to set the standard for an entire industry.
- GHG Protocol Product Standard: This is a standard development process which is occurring in parallel with the process to develop the GHG Protocol Scope 3 Standard. While each standard can be implemented without using the other, both standards are mutually supportive. Before implementing the Product Standard, companies may find it useful to account for Scope 3 emissions in order to identify the individual product categories that contribute most to total value chain emissions. Companies can conduct life cycle inventories for targeted products using the Product Standard, which can inform more detailed GHG reduction strategies. Conversely, companies conducting Scope 3 inventories may use product level GHG data based on the GHG Protocol Product Standard to calculate upstream and downstream Scope 3 emissions of associated products.
- Economic Input-Output Lifecycle Assessment (EIO-LCA): Most internationally recognized standards for preparing a product carbon footprint belong to the class of **process-based LCA**. In a process-based LCA, one itemizes the inputs (materials and energy resources) and the outputs (emissions and wastes to the environment) for a given step in producing a product. Even for a simple product, the process involves very tedious work, requires intensive data collection, can be extremely time consuming, and is highly prone to data collection errors. In response to this, the Green Design Institute of Carnegie Mellon University proposed EIO-LCA in an effort to simplify LCA. EIO-LCA is a mathematically defined procedure. Let $\boldsymbol{A}$ denote the direct requirement matrix. The elements

of $\boldsymbol{A}$, $a_{ij}$, indicate the amount of output from industry $i$ required to produce one dollar of output from industry $j$. The matrix $\boldsymbol{A}$ is also known as the Technical Coefficients matrix. Next, let $\boldsymbol{x}$ denote the vector of total outputs of the industrial sectors. The elements of $\boldsymbol{x}$ represent the output of sector $i$ used to fulfill the demand of other sectors. For example, the output of the steel industry can be used to fulfil the demand to the auto industry and other industries. Furthermore, let $\boldsymbol{f}$ denote the vector of final demand where elements of denote the final demand of the product of sector $i$. The total output of any sector is equal to the quantity needed to meet its own final demand, plus the demand of other sectors that use its product as an input. Consider the electrical power industry for instance. This sector needs to have total output of generated electricity to meet the demand of other industries, but also to meet its own demand of electricity (power generators also need electricity). This can be mathematically expressed as follows:

$$\begin{aligned}\text{Total Output of a Sector} &= \text{Demand of other Sectors} \\ &\quad + \text{Sector's Final Demand} \\ &\rightarrow \boldsymbol{x} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{f} \\ &\rightarrow \boldsymbol{x} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}\boldsymbol{f}\end{aligned}$$

Where $\boldsymbol{I}$ denotes the identity matrix. The term $[\boldsymbol{I} - \boldsymbol{A}]^{-1}$ is known as the Leontief Inverse matrix. If successfully computed, it is possible to determine the change on total output of any sector $i$ resulting from the increased or decreased demand of other sectors. For example: if the demand of the auto industry increases by 200,000 vehicles, and the demand of aluminium industry increases by 200 tons of aluminium, how much will these changes affect the total output of the electrical industry in megawatts? This relationship can be readily expressed as follows:

$$\Delta\boldsymbol{x} = [\boldsymbol{I} - \boldsymbol{A}]^{-1}\Delta\boldsymbol{f}$$

The above mathematical development characterizes the Economical Input-Output model developed by Leontief (1970). The EIO-LCA method extends this model to determine the total external outputs (e.g. GHG emissions) associated with each dollar of output (i.e. product of a sector). This is done by adding external information to the EIO model; in particular by augmenting it with additional environmental data as follows. Let $\boldsymbol{R}$ denote the matrix of environmental burden coefficients. The elements of $\boldsymbol{R}$, $r_{kj}$, represent the amount of environmental burden $k$ for each dollar output of sector $j$. For example, an element of $\boldsymbol{R}$ can represent the tons of $CO_2$ resulting from one dollar of output of the steel industry. Finally, let $\boldsymbol{B}$ denote the vector of total environmental burdens, with each element representing the environmental burden (e.g. GHG emissions) associated with the products of each sector. The vector $\boldsymbol{B}$ can be computed using the following relationship:

$$\Delta \boldsymbol{B} = \boldsymbol{R}[\boldsymbol{I} - \boldsymbol{A}]^{-1} \Delta \boldsymbol{f}$$

For the detailed mathematical development and examples of applying the EIO-LCA method, see the homepage of the Green Design Institute Green (Carnegie Mellon University 2011).

Today, reporting Scope-1 and Scope-2 GHG emissions is well documented and many companies have a system in place for collecting Scope-1 and Scope-2 emission data, but not for Scope-3. Corporate reporting of Scope 3 emissions is still optional. However, mandating the reporting and setting reduction targets is almost inevitable. The US government has already put mandatory regulations on Scope-3 carbon footprint and set a reduction target for federal businesses through executive order 13514 (EO 13514 2009). Therefore, companies especially in manufacturing industry needs to be able to respond to any regulations in a timely manner.

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# Chapter 4
# Energy Decision-Making 2: Demand Response Option Contract Decision Based on Stochastic Programming

**Abstract** The need of energy decision making happens in smart grids. Smart grids enable a two-way energy demand response capability through which a utility company offers its industrial customers various call options for energy load curtailment. If a customer has the capability to accurately determine whether to accept an offer or not, then in the case of accepting an offer, the customer can earn both an option premium to participate, and a strike price for load curtailments if requested. However, today most manufacturing companies lack the capability to make the correct contract decisions for given offers. This chapter introduces a novel decision model based on activity-based costing (ABC) and stochastic programming, developed to accurately evaluate the impact of load curtailments and determine as to whether or not to accept an energy load curtailment offer. The introduced model specifically targets state-transition flexible and Quality-of-Service (QoS) flexible energy use activities to reduce the peak energy demand rate. An illustrative example with the proposed decision model under a call-option based energy demand response scenario is presented. As shown from the example results, the proposed decision model can be used with emerging smart grid opportunities to provide a competitive advantage to the manufacturing industry.

## 4.1 Background of Energy Demand Response

Increasing energy demand and concerns about climate change have driven energy market participants to agree on establishing the so-called smart grid (EPRI 2009). The main objective of the smart grid is to achieve and facilitate interoperable collaboration between energy producer and consumer, and generate benefits from collaboration. The benefits include more efficient distribution of energy resources, and engagement of energy use patterns in support of business objectives. The most important aspect of the smart grid initiative is the energy demand and response contract program that is a voluntary load curtailment contract between a utility company and industrial customers.

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In general, electricity demand response encourages consumers to shift or reduce their power consumption during peak hours to achieve more economic and environmentally responsible usage patterns. Federal Energy Regulatory Commission (FERC 2010) defined it as “the changes in electricity usage by end-use customers from their normal consumption patterns in response to the changes in the price of electricity over time or the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized”. Once the program is implemented properly, it can benefit both electricity suppliers and consumers. In the United Stated, peak hour power plants that have been built to satisfy the electricity demand increase are, in reality, only utilized a few hundred hours a year (Michael et al. 2007). From the supplier’s perspective, demand response can help reduce electricity power consumption and redistribute power flow to off peak hours; thus assisting electric power plants to avoid the need to build new power plants to satisfy the extra high demand during the peak periods. Similarly, it brings benefits to customers by reduce their electricity billing cost and so increases their competitive advantage.

The approaches for energy load curtailment fall into two categories: load-shedding (dropping load completely) and load-shifting (moving load from peak to off-peak periods). Note that this chapter mainly focuses on the load-shedding energy demand and response contract program.

A contract program allows industrial customers to obtain incentives in return for reducing their energy demand rate (kW) during specified times. In general, the program is modeled as an option contract with a specified curtailment amount in the rate of delivery (kW) associated with an option premium price and a strike price. In an energy option contract, a utility company and an industrial customer become a buyer and a seller, respectively. If a company has an extensive ability to understand their internal energy use processes well enough to shed or shift their energy demand according to the signed contract, then they can gain a competitive advantage from participating in the program.

### 4.1.1 Motivating Example

For a better understanding of the smart grid energy demand response program, a simple scenario is described below between an industrial customer and utility service provider (USP) where the utility service provider is the retailer who is selling electrical energy to the end customers (e.g., DTE Energy, Consumers Energy in Michigan, USA). The scenario is slightly modified from a load curtailment example in (Cazalet 2012):

1. USP’s call option offer: USP offers to an industrial customer a call option offer according to a predefined energy demand response program. The option has an option premium price of \$20/kW per month and a strike price of \$1/kW per hour for actual energy load curtailments. The option allows exercise during the life of

the option that is in the months of June through September. The option is constrained to be exercised during peak hours (12 noon–8 p.m.) of weekdays and up to 20 h per month.

2. Customer's acceptance of the offer: The industrial customer agrees to provide 200 kW of load curtailment at any time during the contracted period. The total option premium given to the industrial customer is $16,000 (=4 months × $20/kW × 200 kW).
3. USP's exercise of the option: On a certain day during the contracted period, USP falls into a situation where the overall energy demand increases rapidly and so it needs to exercise the option. USP then commands the industrial customer to curtail 200 kW from 2 to 6 p.m.
4. Customer's load curtailment: According to the contract, the industrial customer reduces 200 kW from its contracted baseline usage rate. The determination if the customer abides by the command is verified through reading of metering devices. If the load curtailment is not achieved, the customer is subject to penalty. If the reduction is made per contract, the customer is paid $800 (=200 kW × 4 h × $1/kW per hour) that corresponds to the strike price.

From the aforementioned motivating scenario, again it is immediately evident that if the industrial customer accepts the offer (*i.e.*, agreement with energy load curtailments) after having assessed the offer accurately, they will be paid both an option premium ($16,000) to participate and a strike price ($1/kW per hour) for any requested energy load curtailments. However, in the case that the customer did not assess the offer accurately, the acceptance of the offer should adversely affect the customer's core business processes and so the customer may not realize the contract and accordingly, pay relevant penalties along with losing credibility for load-shedding.

In the end, the ability to make a right contract decision on energy demand response offers is the key enabler for industry customers who are interested in participating and benefiting from the smart grid. However, in reality, most industrial customers are limited in their capability to assess the energy demand response opportunities and risks in an optimal and rapid way. Especially, the limitation is evident in manufacturing industries because a manufacturing system is typically complex, large, and stratified so that it is very hard to understand the energy distribution across the system.

In order to determine if a specific energy demand and response offer is viable for a manufacturing company, the company should first build its energy accounting model which provides a high-resolution of energy distribution across the system and insight to the causes of energy usage. In a general term, energy accounting refers to a tool or system used to measure, analyse and report the energy consumption of different energy use activities on a regular basis. One way to build such an energy accounting model is to implement an energy monitoring system. However, this approach runs into accuracy problems if the target system is complex, large, and stratified as in manufacturing systems. For example, an automobile manufacturing process generally consists of three main processes: Body Shop, Paint Shop, and General Assembly. The body shop transforms the raw materials into the structure of the vehicle. Then the paint shop applies a protective and visual coating to the product. Finally general assembly assembles all sub-components into the vehicle such as the engine and seats (Kolta 1992; Streitberger and Dössel 2008). Typically, energy monitoring in such complex automotive manufacturing processes is performed only at a main process level because the metering devices cost thousand dollars and the information gained at the sub-system level is not as useful as at the process levels—Body, Paint, General Assembly. Due to this lack of information, the modeling of energy usage based on an energy monitoring system in manufacturing facilities is usually done as a "black box" approach, leaving little visibility or understanding as to the causes of the energy usage by the system, or how to prioritize improvement efforts to curb their energy usage. The alternate method to build an energy accounting model is to use Activity-Based Costing (ABC) which offers a proven structure for evaluating the cost of processes and products in both the financial and industrial sectors. By applying ABC to the energy modeling in manufacturing sectors, it is possible to overcome limited metering devices to determine the energy distribution within the process and to predict energy loads in the future which is useful for effectively evaluating energy demand and response offers. The core idea of ABC is that cost objects (e.g., product or service) consume activities, which in turn consume resources (e.g., labor, materials, equipment) and the amount of consumption in these resources results in cost. The activities are discrete actions which must be performed to create the cost objects. A cost distribution created in ABC is used to trace resources to activities then to cost objects. Note that a traditional ABC method cannot be used for this purpose but this study will use an advanced ABC method that is modified to include both economic and environmental factors (Emblemsvag and Bras 2001; Romaniw et al. 2009). Next section will discuss both traditional and advanced ABC methods in detail. This chapter proposes a novel decision model based on activity-based costing (ABC) and stochastic programming, developed to evaluate the impact of load curtailments accurately and determine as to whether or not to accept a load curtailment offer. The proposed model targets state-transition flexible and QoS flexible activities to reduce the peak energy demand rate during the option exercising time period.

The chapter is organized as follows: Introduction section surveys some efforts and studies related to energy, smart grid, ABC, chance-constrained stochastic programming and also discusses the benefits and challenges arising from participation in the energy demand response programs. In particular, activity-based accounting method is introduced. Section 4.2 introduces the chance constraint stochastic model as background material. Section 4.3 proposes a new decision process based on ABC and chance-constrained stochastic programing. Section 4.4 provides an illustrative example for an application of the proposed model. Section 4.5 concludes this chapter. The notations used through this chapter are summarized in Table 4.1.

Note that this work expands on previous researches (Jurek et al. 2012; Oh et al. 2011; Oh and Hidreth 2013b) and applies ABC-based energy accounting model and chance constraint stochastic programing model to build a new decision process

**Table 4.1** Summary of notations

| Notation | Description |
|---|---|
| $I$ | Set of activity $i$ (e.g., $I$ = {operating robots, moving conveyors, air conditioning, building lighting, …}) where $I_{MC}$, $I_{STF}$, and $I_{QoSF}$ represent sets for mission-critical activities, state-transition flexible activities, and QoS flexible activities, respectively (see Sect. 4.1.2 for details) |
| $J$ | Set of state $j$ where $J$ = {production, shutdown, startup, setback, maintenance} |
| $U$ | Set of utility $u$ (e.g., $U$ = {electricity, natural gas, oil, compressed air, …}) |
| $r_{i,j} \in \mathbb{R}$ | Rate of energy demand (also called power, kW) of activity $i$ at state $j$ |
| $Z_{i,j}(t) \in \{0, 1\}$ | Activity state time function; $\Sigma_j Z_{i,j}(t) = 1$ at any given $i$ and time $t$ (see Sect. 4.1.2 for details) |
| $\tau \in \mathbb{R}$ | Time period of energy demand response option exercising defined in an energy demand response option contract (e.g., 2 h starting from noon, which is represented by $t \in [t_s, t_s + \tau]$ where $t_s = 12:00$ p.m. and $\tau = 2$) |
| $C \in \mathbb{R}$ | Energy delivery rate (kW) during $t \in [t_s, t_s + \tau]$ defined in an energy demand response option contract |
| $P \in \mathbb{R}$ | Peak rate of energy demand (kW) during $t \in [t_s, t_s + \tau]$ where $P_{MC}$, $P_{STF}$, and $P_{QoSF}$ represent the peak rate of energy demands (kW) for activities in $I_{MC}$, $I_{STF}$, $I_{QosF}$, respectively for a given time period |
| $L \in \mathbb{R}$ | Energy load (kWh) during $t \in [t_s, t_s + \tau]$ where $L_{MC}$, $L_{STF}$, and $L_{QoSF}$ represent energy demands (kWh) for activities in $I_{MC}$, $I_{STF}$, $I_{QosF}$, respectively for a given time period |
| $x_u \in \mathbb{R}$ | Energy supply rate (kW) of utility $u$ for activity $u \in U$ |
| $y_i \in \mathbb{R}$ | Energy demand rate (kW) of activity $i$ for activity $i \in I_{QoSF}$ |
| $\alpha_{i,u} \in \mathbb{R}$ | Probability to fail meet a quality of service (QoS) required to activity $i \in I_{QoSF}$ that consumes utility $u$. Accordingly, $(1 - \alpha_{i,u})$ represents the probability to meet the required level of QoS |

through which industrial energy customers (focusing on manufacturing companies) evaluate the impact of energy demand response offer on their core business operations and determine whether or not to accept the offer.

## *4.1.2 Activity-Based Costing*

ABC was developed as an accounting method used to trace costs to a product or process of an organization. ABC is characterized by assigning costs to the activities performed by the organization, rather than assigning costs directly to the products. Due to this characteristic, the cost of the products can be calculated by determining how much each product uses each activity (Weil and Maher 2005).

ABC is considered to be more accurate than classical volume-based costing methods that assign all indirect costs based on a certain rate such as direct labor rates or area rate, and etc. Indeed, although ABC requires in-depth knowledge of the system under consideration, if it is properly used, it can show the high-resolution cost distribution across the system so that operation planning personnel can secure visibility into the causes of costs in the process and further allows for predictions of costs for future scenarios (Cokins 2001). The concept of ABC can be also applied to energy management and provide an energy usage distribution for the process to identify and evaluate energy consumption and cost saving opportunities (Cox 2009).

Figure 4.1 depicts the core idea of ABC that cost objects consume activities, which in turn consumes resources and the amount of consumption of these resources results in cost. A cost object is typically a product or service, while the activities are discrete actions which must be performed to create the cost objects. Resources are objects used by the activities which end up becoming costs such as labor, materials, equipment, and etc. Note that the diagram involves multiple dimensional cost units including energy (kWh), environmental factors (kg $CO_2$e) or other eco-indicators. The original purpose of using ABC was to distribute overhead costs more accurately and typically associated with monetary values. However, this method can easily be expanded to involve multiple dimensional cost units because it measures the amount of resources consumed by the products or services. For better understanding of this multi-dimensional cost unit feature, let us assume that one is interested in calculating the specific total costs consisting of energy costs and environmental impact. In the US, on the average, the electricity cost is \$100 per MWh and the environmental impact is about 1000 kg $CO_2$ per MWh. If 5 MWh of electricity is required to produce a product, the total energy and environment costs of this product would be \$500 and five metric tons $CO_2$. If the company needs to purchase $CO_2$ credits from a market in order to emit five metric tons $CO_2$ and if the

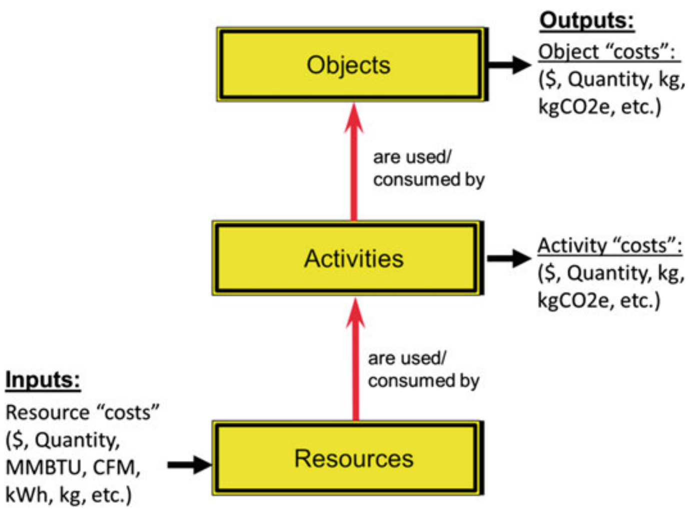



**Fig. 4.1** Multi-dimensional ABC to trace resource and activity consumptions using each driver

$CO_2$ credit price in the market is \$10 per $CO_2$ ton, then the monetary environment costs will be \$50. Then, the total monetary costs will become \$550.

From the manufacturing system perspective, ABC is a practical tool to help identify activities. For example, a well-automated manufacturing system performs common activities such as moving the product on conveyer belts, operating robots and controlling air movement for curing, and etc. Note that these activities require equipment operations and the equipment requires energy as resources. Activities by ABC can be broken down into three categories: mission-critical, state-transition flexible, and QoS flexible activities. Mission critical business processed refers to any process of a system whose failure will result in the failure of business operations. So, mission critical business processes must be carried out in a given time period, otherwise there will be an occurrence of production loss. Those activities including moving the product on conveyer belts, operating robots and controlling air movement for curing are mission critical in the context of manufacturing system.

On the contrary, many activities taking place in a manufacturing system are flexible in terms of state transition or quality of service (QoS) requirements due to non-mission critical business needs. For example, there is a state-flexible activity such as the shift of building lighting system during daylight hours to the setback state that will save considerable amount of electricity usage. Meanwhile, the air conditioning activity is a QoS-flexible activity where the comfort cooling level can be lowered temporarily by raising the indoor temperature. Both building lighting and air conditioning activities are not kinds of aforementioned mission critical activities so that they do not cause a critical problem even though their states are changed or their QoS level is compromised in certain range for short periods of time. Figure 4.2 depicts the principle of ABC and the breakdown of activities into the three sets: mission critical activities, state-transition flexible activities and QoS flexible actives.

**Definition 1** (**Mission critical activity**) An activity is mission-critical if the activity's failure results in the failure of business operations where $I_{MC}$ denotes a set of mission-critical activities.

**Definition 2** (**State-transition flexible activity**) An activity is state-transition flexible if the activity's state can transition to any or some of the defined states as a result of energy load-shedding processes where $I_{STF}$ denotes a set of state-transition flexible activities.

**Definition 3** (**QoS flexible activity**) An activity is QoS flexible if the quality of service (QoS) level imposed on the activity can be adjusted in terms of the probability to meet the QoS where $I_{QoSF}$ denotes a set of QoS flexible activities.

**Proposition 1** (**Flexibility of activities**) Any activity $i$ is flexible if $i \in (I_{STF} \cup I_{QoSF})$.

In addition, any energy use activity in a manufacturing system has the following five distinct states: production, shutdown, startup, setback, maintenance where the

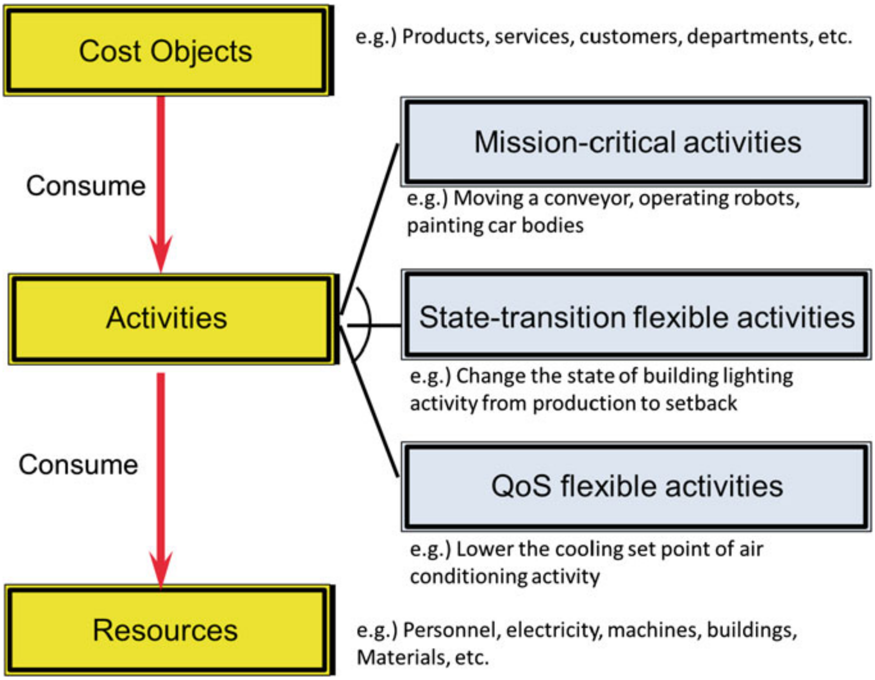


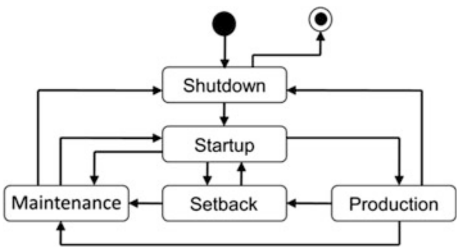

**Fig. 4.2** ABC costing model and three different sets of activities

activity can transition from one state to other state according to a production schedule in such a way that the activity is always put in only one state at any given time. The important observation is that all of these states use resources at different loads and there is an opportunity to change the states of activities to reduce energy consumption. Figure 4.3 shows these states in a Universal Modeling Language (UML) state diagram along with the transition options from each state.

The details of five distinct states are as follows:

- Production state: It is a state in which products are being produced on the manufacturing system. This state requires a high level of energy due to most equipment in the facility running at high levels when in this state;

**Fig. 4.3** Activity states in a manufacturing system



- Setback state: It is a state for lunch or between shifts which occur during a normal working days when the system can be put in a ready state to save energy. In this state, the equipment of the system is turned down to a lower level or off until production resumes again;
- Shutdown state: If there is an extended period in which the system does not need to run such as weekends or holidays, the system can be put in the shutdown state, in which the system is turned off and uses minimal energy;
- Startup state: To transfer from the shutdown state to the production state, the system requires a high level of energy and is put into a startup state. This state is a high consumer of energy because the system is operated to quickly increase system conditions to operating conditions. This is similar to the time when a vehicle accelerates, in which it requires more gas than when cruising or parked;
- Maintenance state: During the maintenance state, necessary repairs are performed with minimal energy requirement.

In general, a manufacturing system has its associated Bill of Equipment (BOE) which includes all pieces of information about equipment placed in the system including energy demand rate (kW) of equipment. Since most activities require equipment operations, the amount of energy consumed by each state of activities can be easily determined by averaging meter readings and estimated for future changes by investigating BOE. Let $r_{ij}$ denote the energy demand rate (kW) for each state $j$ of activity $i$. Since each activity changes its state in time depending on the production plan, it is useful to have a built-in function to keep track of the state of activity $i$ at time $t$. We denote $Z_{ij}(t)$ to be activity-state time function which is defined as below:

$$Z_{ij}(t) = \begin{cases} 1, & \text{if activity } i \text{ is put in state } j \text{ at time } t \\ 0, & \text{otherwise} \end{cases} \tag{4.1}$$

Note that $\Sigma_j Z_{i,j}(t) = 1$ at any given $i$ and time $t$ because the activity is always put in only one state at any given time. Given the information of $r_{ij}$ and $Z_{ij}(t)$, one can calculate their peak rate of energy demand ($P$) and energy load ($L$) as follows:

$$P = \max_t \left( \sum_i \sum_j r_{ij} \times Z_{ij}(t) \right) \quad \text{for } t \in [t_s, t_s + \tau] \tag{4.2}$$

$$L = \int_{t_s}^{t_s+\tau} \sum_i \sum_j r_{ij} \times Z_{ij}(t) dt \tag{4.3}$$

where, $\tau$ is the duration of exercising the option starting from $t_s$ (refer to Table 4.1 to find the notation description). Equations (4.2) and (4.3) are used to determine how much energy a company would save from the change of activity states later on. Since the operation specifications of activity $i \in I_{STF}$ are given in ranges allowing flexibility in the change of state, those flexible activities are targeted to investigate if the company is able to remain within operating specifications while still meeting the electricity reduction requirements. For example, a shift of some or the entire system to the setback state will save considerable amount of electricity usage. Cutting the amount of air or liquid moved for a short period of time will save some amount of electricity usage, as well. It is also meaningful to note that the ABC model also allows for a long-term future improvement by prioritizing target activities for improvement, as well as a short-term evaluation of energy demand and response offers.

### *4.1.3 Activity-Based Plant Energy Forecasting Method*

From a plant manager perspective, energy use is a large, but mandatory, expense incurred by operating facilities. Plant managers are always interested in receiving any forms of discount on energy prices. One way to get a discount on energy prices is to reserve or pre-purchase energy at a discounted rate. However, this requires that the manufacturer or facility operator accurately estimate how much energy will be used over a time period. A manufacturer or facility operator does not want to overestimate the amount of energy needed because the unused energy is generally non-refundable. Similarly, a manufacturer or facility operator does not want to underestimate the amount of energy needed because that requires purchasing the energy at a non-discounted rate thereby defeating the benefits of the pre-purchased discount, wasting efforts of estimating the amount of energy needed over a time period, and causing financial burdens due to urgent budget reconciliation. To best determine how much energy is needed, historically, the standard multi-variable regression analysis has been used.

However, the regression model works only fine for plants with fairly steady-state production and minimal process variations. In that case, the efforts of correlating energy and water use to production and climate conditions come to effect for forecasting future energy use to establish budget and intensity targets. However, if a facility has major changes in either production—1 shift to 3 shift, significant variance year over year, or major production process changes—adding paint booths, processing a new part, or new equipment technology, then the traditional regression method is not accurate for budgeting and forecasting purposes.

To address the issues of traditional regression method and improve the accuracy of energy forecasting, activity-based energy accounting (ABEA) method is developed. ABEA is based on the fact that the operation of a production facility requires distinct levels of energy depending on different activities such as full-capacity production, reduced-capacity production, and non-production. The method first uses highly accurate hourly energy use data from sub-meters for different energy use activities along with the associated production activity to determine the rates of energy use that will be consumed during an activity-based time period. This method is easily tailored to the flexible production schedule so that it can minimize the problems caused by over- or underestimation of energy use with traditional regression models. There are five distinct states which the manufacturing system can be in at any given time and each state has a different energy load characteristic as shown in a Universal Modelling Language (UML) state diagram in Fig. 4.3 along with the transition options from each state. The varying loads for each state must be considered when creating a predictive model to ensure accurate results.

To account for variations in climate, the ABEA method must be applied on a monthly basis and for extreme variances to average heating degree day and cooling degree day excursions, normalization is used to correct to ten-year average climate conditions. GM has patented this method ("Method to obtain high accuracy in forecasting plant energy use", US Patent 8,606,421) (Oh and Hildreth 2013a). Chapter 8 discusses in detail as to how the ABEA method is incorporated into GM's global manufacturing system. The mathematical form of the ABEA method is as follows:

$$T_e = \left[\left(\frac{N_v}{JPH}\right) \times e_p\right] + \left[((365 - N_{wd}) \times 24 - \left(\frac{N_v}{JPH}\right)) \times e_{np}\right] + \left[N_{wd} \times 24 \times e_{npw}\right] \tag{4.4}$$

In Eq. (4.4), $N_v$ is a number of estimated items produced in a target year period, $JPH$ is a number of items produced per hour, $N_{wd}$ is a total number of weekend days and holidays in the target year, $e_p$ is an energy use (Kilowatt hours) in one production hour during the production period, $e_{np}$ is an energy use (Kilowatt hours) in one non-production hour during the non-production period, and $e_{npw}$ is energy use (Kilowatt hours) in one non-production hour during a weekend or holiday non-production period.

### 4.1.4 Literature Review

There have been many efforts implemented individually or jointly as countermeasures to steadily rising energy costs at present and to the prediction that the rising trend continues going into the future. As an example of individual effort, GM has built or retrofitted their facilities in such a way to use methane vented from local landfills to replace natural gas, thus reducing cost and the effect on the environment (Vlasic 2011). As an example of joint effort, energy market participants are beginning to agree upon establishing the smart grid to increase the efficiency of energy distribution (EPRI 2009). There have been several studies related to smart grid. Yoo et al. (2012) presented look-ahead energy management system for a grid-connected residential photovoltaic system with battery under critical peak pricing for electricity, enabling effective and proactive participation of consumers in the smart grid's demand response. In their proposed system, the photovoltaic system is the primary energy source with the battery for storing (or retrieving) excessive (or stored) energy to pursue the lowest possible electricity bill. Soares et al. (2012) presented a simulator for electric vehicles in the context of smart grids and distribution networks with an aim to support network operators' planning and operations. However, few studies have been done to date on the impact of smart grid energy demand response program from the industrial energy consumer perspective, on which this study intends to make a contribution.

It is true that the success of smart grid relies on efficient and seamless collaboration between utility companies and industrial consumers. To achieve the efficient and seamless collaboration, it is necessary to establish information standards for exchanging energy demand response signals. A group of experts have created the OASIS Energy Market Information Exchange Technical Committee (EMIX) and proposed a series of standards (Cazalet 2012).

Although the participation in the energy demand response program can provide industrial customers with a chance for significant cost savings, it is still at an incipient stage to induce industrial customers to participate in the collaboration. In order to facilitate the participation, it is required to help industrial customers in assessing energy demand response options and addressing some key organizational and operational challenges before determining the participation. Ghatikar et al. (2010) identified three challenges: (1) perception of risk to business and operations, (2) performance measurement strategies, and (3) lack of Information. There are works on the application electricity demand response to industrial sectors to reduce production energy cost (Leah at el. 2014; Yong and Li 2013, 2014; Mayela et al. 2013; Sun et al. 2014a, b). However, the reduction of production energy cost results in additional costs, such as, labor costs and setup time, which were not considered.

Industrial customers should themselves answer the question as to whether a specific energy demand and response offer is viable for their operations before determining to participate in the program. To answer this question correctly, they should first build their own energy accounting model which provides insight to the causes of energy usage. One way to build such an energy accounting model is to use Activity-Based Costing (ABC). Different from the traditional volume-based accounting approach, the ABC approach is useful, especially when the rapid assessment of energy load curtailment options is required. There were several studies to modify ABC with an intention to expand to include environmental factors. Jurek et al. (2012) proposed an ABC-based energy consumption prediction model used to clarify the production energy load and non-production energy load rapidly, thereby being able to figure out the amount of possible load curtailment quickly. Another case involved utilization of ABC in the manufacturing industry to perform Life Cycle Assessments (LCA) on the manufacturing processes (Popesko 2010). Also, successful studies to show how the flexibility of ABC contributes to process improvement were reported (Moolman et al. 2010).

There have been many applications of optimization programming approaches to energy and environmental problems in the scientific literature. However, most of them had just focused on deterministic programming approaches. For example, Sirikitputtisak and Mirzaesmaeeli (2009) reported that they developed a large scale multi-period mixed integer linear programming optimization model for energy planning with consideration of multi-period constraints such as construction lead time, fluctuation of fuel price, $CO_2$ emission reduction targets, and so on.

To date, relatively few studies reported on the application of stochastic programming approaches to energy and environmental problems with consideration of uncertainty in energy demand and supply. When uncertainty is incorporated in an optimization process, two types of stochastic optimization models can be applicable: recourse type and chance constraint type (Charnes and Cooper 1963; Sen and Higle 1999). When a circumstance allows an implicit acceptance of stochastic constrains, the chance constraint stochastic type is preferred. Luedtke et al. (2007) studied the conversion of chance constraint type of stochastic programming model to a deterministic type of programming model. Oh et al. (2011) studied the assessment of demand response options using stochastic programming where they proposed an optimal stochastic programming model in such a way that the economic values under the demand response scheme is maximized while the mission critical manufacturing processes are not sacrificed for that maximization.

## 4.2 Chance-Constrained Stochastic Programming for Strategic Decision Making

When uncertainty is incorporated in an optimization process, two types of stochastic optimization models can be applicable: recourse type and chance constraint type (Charnes and Cooper 1963; Sen and Higle 1999). When a business condition allows an acceptance of flexibility in maintaining the level of quality of service (QoS) (e.g., comfort cooling level of air conditioning activity), the business condition can be represented as stochastic constraints where the constrains are not needed at all times but just enough to hold at least $\alpha$ of time, where $\alpha$ is referred to as the confidence level provided as an appropriate safety margin by the decision maker. If stochastic constraints are present, the chance constraint stochastic programming model type is preferred.

Luedtke et al. (2007) studied the conversion of chance constraint type of stochastic programming model to a deterministic type of programming model. As a baseline model, let us assume that there are $m$—numbers of energy utilities indexed by $u$ (e.g., electricity, natural gas, compressed air) and $n$—numbers of energy use activities indexed by $i$ (e.g., manufacturing operation, air conditioning). When $x$ denotes the vector of energy supply rate (kW) of utility $u \in U$, the goal of the problem is to obtain the optimal energy demand subject to energy balancing constraints. Then, the general structure of the demand and supply Equation (total supply $\geq$ total demand) is formulated as follows:

$$\min c^T x;\ \text{s.t.};\ Ax \geq \delta\,(\text{demand}) \tag{4.5}$$

where $c \in R^m$(energy utility unit cost), $A \in n \times m$ (energy demand and supply conservation equations), $\delta \in R^n$ (energy demand for each activity in the delivery rate). Let us consider the case where the demand, $\delta$ is a random variable that has K-bin discretized probability distribution. Then, the above optimal energy balancing Eq. (4.5) can be rewritten as a chance-constraint stochastic optimization problem where $1 - \alpha$ is a confidence rate with which the required demands are filled $(0 \leq \alpha \leq 1)$:

$$\min c^T x;\ \text{s.t.};\ \Pr[Ax \geq \delta] \geq 1 - \alpha,\ x \in R^m_+ \tag{4.6}$$

where $\delta \in \{\delta^1 w.r.p.p^1,\ \delta^2 w.r.p.p^2, \ldots,\ \delta^K w.r.p.p^K\},\quad \delta^k \geq 0,\ 0 \leq p^k \leq 1,\quad \forall$ $k = 1, 2, \ldots, K$.

Equation (4.6) is a probabilistically constrained linear programming problem with random parameters right-hand side and so can be reformulated as a mixed integer programming problem. To do so, a binary variable $z_i^k \in \{0, 1\}$ for each $k \in \{1, 2, \ldots, K\}$ is introduced such that $z_i^k = 0$ guarantees $Ax \geq \delta$ . Observe that $Ax \geq \delta$ must be true at least one $k \in \{1, 2, \ldots, K\}$ because $\alpha < 1$. Also, since $\delta^k > 0$ for all $k$, this implies $Ax \geq 0$ in every feasible solution of (4.5). Then, letting $y = Ax$, the mixed integer programming formulation can be obtained as in Eq. (4.7). Readers who want more information about the reformulation procedure can refer to Sect. 2 in Luedtke et al. (2007).

$$\begin{aligned} &\min c^T x; \text{s.t.} y = Ax;\ y_i \geq \delta_i^k - \delta_i^k z_i^k \quad k = 1, \ldots, K;\quad i = 1, \ldots, n \\ &\sum_{k=1}^{K} p_i^k z_i^k \leq \alpha_i \quad i = 1, \ldots, n \end{aligned} \tag{4.7}$$

where $z_i^k \in \{0, 1\} k = 1, 2, \ldots, K$. $\sum_{k=1}^{K} p_i^k z_i^k \leq \alpha_i$ is equivalent to $\sum_{k=1}^{K} p_i^k (1 - z_i^k) \geq (1 - \alpha_i)$. Equation (4.7) is an energy resource allocation problem where decision variables can be disaggregated into energy supply side (utility denoted by $u \in U$) and energy demand side (activity denoted by $i \in I$). To meet the energy demand by energy use activities, Eq. (4.7) enforces the flow conservation of energy utility $u$ across each energy use activity $i$. This concept of energy resource allocation and flow conservation can be captured as a transportation network as in Fig. 4.4. Note that Eq. (4.7) does not have any probabilistic constraints. So, the problem can be solved using standard solvers like Microsoft Excel Solver, CPLEX, or GLPK. For better understanding of Eq. (4.7), an illustrative example will be provided in Sect. 4.4.

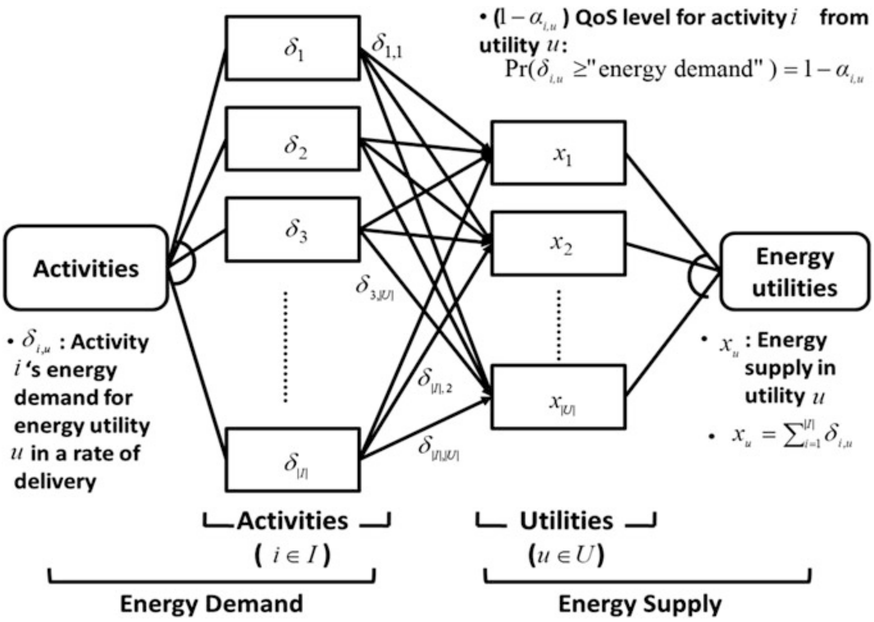



**Fig. 4.4** General energy demand and supply model with uncertainty in demand

## 4.3 Decision Model for Determining Energy Demand Response Option Contract

This model expands on previous research (Jurek et al. 2012; Oh et al. 2011) to specialize in accurately evaluating the impact of an energy demand and response offer and determine as to whether or not to sign the contract and undertake the load curtailment. This model is based on activity-based costing (ABC) and stochastic programming with a target on state-transition flexible and QoS flexible energy use activities to reduce the peak energy demand rate. This model is especially valuable when their energy demands are not deterministic values but stochastic variables following certain distributions. Even though the model would be applied to any industrial company, it is likely to be especially effective for a manufacturing company that has a complex, large and stratified system. Therefore, this section will describe the decision model in the context of its specific application to a manufacturing system.

When an energy curtailment offer from a utility company arrives, in general, two baseline contracts are requested: (1) $C$: rate of energy delivery (kW); and (2) $\tau$: duration of exercising the option starting from $t_s$ (refer to Table 4.1 to find the notation description). With the arrived offer, the decision model proceeds as follows:

- Step 1: With a new load curtailment offer arrived, use the ABC model and identify $I_{MC}, I_{STF}, I_{QoSF}$ and calculate the current peak energy demand rate, $P$. This step requires an ABC-based energy accounting model for manufacturing operations. The basic idea in modeling is that each activity has five distinct states (i.e., production, shutdown, startup, setback, maintenance) and makes transitions from one state to other state according to a production schedule such that an activity is always put in only one state in any given time. The key point is that each state has a different energy load characteristic. And furthermore, the activities listed in the ABC-based energy accounting model are broken down into mission-critical $(I_{MC})$ and non-mission critical activities $(I_{STF}, I_{QoSF})$. Again, the operation specifications of non-mission critical activities are given in ranges allowing flexibility of the state transition or QoS adjustment, resulting in a lower energy demand.
- Step 2: Investigate the amount of possible reduction in the energy demand (kW) for each activity $i \in I_{STF}$ by transition to a low-energy required state (*i.e.*, transition $j$ to $j^*$, such that $r_{ij^*} < r_{ij}$).
- Step 3: Investigate the amount of possible reduction in the energy demand (kW) for each activity $i \in I_{QoSF}$ by solving a chance-constraint stochastic problem through varying the QoS level (*i.e.*, reduce $(1 - \alpha_i)$ such that $y_i$ decreases).
- Step 4: Recalculate the peak energy demand level and denote the new peak energy demand level by $P^*$ and determine whether to accept or reject the offer based on $P^*$ and $C$.

Figure 4.5 depicts the proposed decision process and next section will illustrate this process with a hypothetical simple manufacturing system considered as a target application.

## 4.4 Illustrative Example

The purpose of this section is to illustrate the decision process set forth in the previous section by applying it to a hypothetical example case where a simple manufacturing system is assumed to receive an energy demand response option and need to determine as to whether or not to accept the offer by figuring out their capability to reduce energy consumption as required by the offer. Throughout this illustration, the scenario for a manufacturing system and an energy curtailment option offer is assumed as follows:

$I$ {Manual assembly, Operating robots, Moving conveyors, Operating repairing centers, Air conditioning, Building lighting, Operating chillers, Liquid moving, Air abatement};

$J$ {production, shutdown, startup, setback, maintenance};

$U$ {electricity};

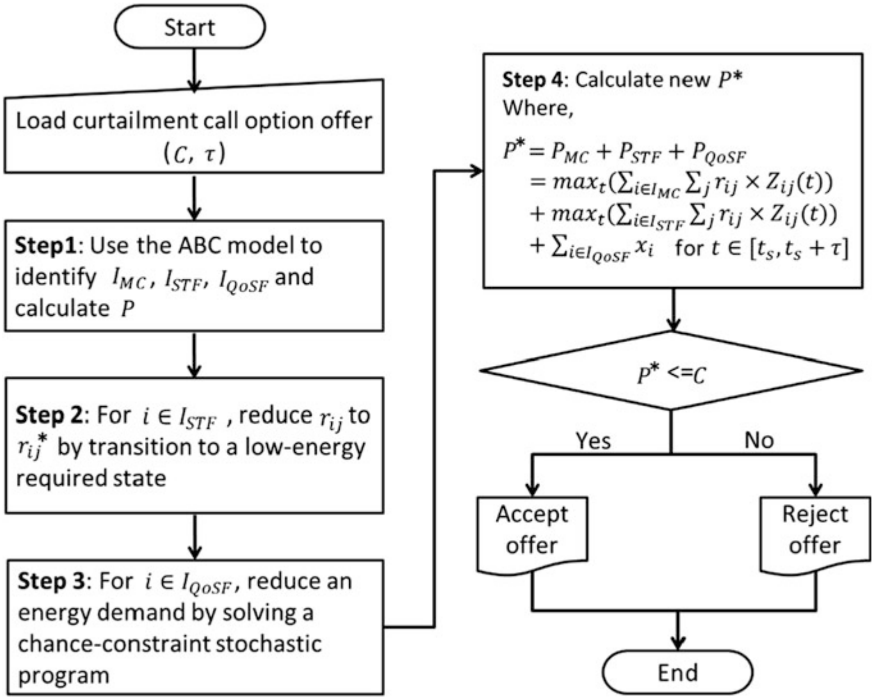



**Fig. 4.5** Overview of energy demand response call option assessment decision process

$\tau$ 2 h with the start time at 12:00 p.m., implying that the time period of energy demand response option exercising is $t \in [t_s, t_s + \tau]$, where $t_s$ = 12:00 p.m.;
$C$ 280 kW that is an energy delivery rate (kW) defined in the option contract

The example activities presented herein $I$ are straightforward and easy to understand except the last three activities—"Operating chillers", "Liquid moving" and "Air abatement". First, the understanding of activities such as "Liquid moving" and "Air abatement" requires a specific knowledge on painting process although they are common processes in many manufacturing systems. A general painting process follows five steps: (1) pretreatment of product (2) application of ELPO (3) sealing application (4) paint booth (5) post-paint repairs (including cavity wax). The pretreatment stage cleanses contaminants from the product which may have been collected in the previous processes (e.g., welding process). This is performed over a series of water and cleaning solution rinses. These are usually performed in a combination of rinse and spray application methods to get optimal results. Also in this stage is where a phosphate coating is applied to the product to provide a layer of protective coating and assist in the application of the paint layers. After the pretreatment, the product is cleaned and prepped to move onto next stage. The Electro Coat Primer Operation (ELPO) applies a layer of charged primer solution to the product to increase the effectiveness of the paint application in the later stages. The product will remain in the charged solution for a specified period of time to build the appropriate layer thickness across the surface. The solution must be circulated to avoid settling of the particles. The solution is then baked onto the product and the product is processed to the next stage. After the ELPO application, the product moves to the sealing line where the seams of the product are sealed to protect against weather effects. Recently, a majority of these tasks are performed by robots, but there are some aspects which require human operators to perform. The sealants are then baked onto the product as it moves to the paint booth for the coating application. In the paint booth, primer, basecoat, and topcoat are applied depending on the product. To make the best result, the application of these layers is performed by robots to provide a consistent layer of paint to the product. This stage is very sensitive to temperature and humidity, so the environment is tightly controlled within the paint booth. Also, a large amount of air is circulating through the paint booth during operations to help capture overspray from the painting robots. Finally, the post paint stage is performed where the product is inspected for any defects and the cavity wax is applied, if required. If any defects are detected, the product is either fixed in a repair zone or reinserted into the line to go through the process again. These defects can be very costly to companies as they double the amount of activities which some of their products consume resulting in higher costs and time per vehicle. Each of these five processes requires common activities such as "Liquid moving" and "Air abatement". However, due to the flexibility of paint process, the state of each activity can be transitioned for short time period unless the product quality or human safety requirement is compromised. Similarly, "Operating chillers" is a good enabler to control the environment conditions such as temperature and humidity, and maintain a constant machining tool temperature. Since this activity is more related to maintain the comfort cooling level, it can be considered to be a QoS-Flexible activity.

### 4.4.1 Identification of Input Parameters

The first step of the proposed decision process is to identify $I_{MC}$, $I_{STF}$, $I_{QoSF}$ and calculate the current peak energy demand rate (kW) as follows:

$I_{MC}$ {Manual assembly, Operating robots, Moving conveyors, Operating repairing centers};

$I_{STF}$ {Building lighting, Liquid moving, Air abatement};

$I_{QoSF}$ {Air conditioning, Operating chillers}; The ordinary peak rate of energy demand (kW), $P(=P_{MC} + P_{STF} + P_{QoSF})$ during $t \in [t_s, t_s + \tau]$ is assumed to be higher than $C$ implying that the company needs to determine as to whether they can reduce their peak energy demand by $(P - C)$

## 4.4.2 Reduction in the Rate of Energy Demand (kW) for State-Transition Flexible Activities

The second step is to investigate the amount of reduction in the rate of energy demand (kW) for each activity $i \in I_{STF}$ by transition to a low-energy required state (*i.e.*, transition $j$ to $j^*$, such that $r_{ij^*} < r_{ij}$). Since there is only one state-transition flexible activity, that is the building lighting activity; the activity can simply reduce its energy demand rate from current 10–4 kW by transition from the production state to the setback state as in Table 4.2.

## 4.4.3 Reduction in the Rate of Energy Demand (kW) for QoS Flexible Activities

The third step is to investigate the amount of reduction in the rate of energy demand (kW) for each activity $i \in I_{QoSF}$ by solving a chance-constraint stochastic problem through varying the QoS level (*i.e.*, reduce $(1 - \alpha_i)$ such that $y_i$ decreases). Note that since $|U| = 1$, we will omit writing index $u$ for simplicity. Furthermore, there is only one QoS flexible activity, that is, the air conditioning activity. Let us assume that we are aware of the demand's K-bin discretized probability distribution as shown in Table 4.3. Note that the values of energy demand in the table are not real data but derived from an energy distribution over activities proportional to actual energy usage distribution.

### 4.4.3.1 Objective Function, Variables, and Parameters

Since this study assumes the utility unit cost ($c$) equal to 1 for simplicity, the objective function of the stochastic model becomes Eq. (4.8) where variables and parameters of the stochastic model are summarized Tables 4.4 and 4.5. Note that the values of energy demand in Table 4.5 are not real data but derived from an energy distribution over activities proportional to actual energy usage distribution:

$$\min cx \tag{4.8}$$

**Table 4.2** Illustrative activities with different energy demand per state

| Activity ($i \in I_{STF}$) | State ($j \in J$) | | | | |
|---|---|---|---|---|---|
| | Startup (kW) | Production (kW) | Setback (kW) | Shutdown (kW) | Maintenance (kW) |
| Building lighting | 10 | 10 | 4 | 1 | 4 |
| Liquid moving | 55 | 20 | 10 | 0 | 0 |
| Air abatement | 30 | 10 | 2 | 0 | 0 |

**Table 4.3** 5-bin discretized energy demand distribution for air conditioning and chillers activities

| Demand | $\boldsymbol{k} = 1$ | $\boldsymbol{k} = 2$ | $\boldsymbol{k} = 3$ | $\boldsymbol{k} = 4$ | $\boldsymbol{k} = 5$ |
|---|---|---|---|---|---|
| $\delta_5^k$ | 2 kW s.t.<br>$\Pr(\delta_5 \leq \delta_5^1) = 0.65$ | 3 kW s.t.<br>$\Pr(\delta_5^1 \leq \delta_5 \leq \delta_5^2) = 0.1$ | 4 kW s.t.<br>$\Pr(\delta_5^2 \leq \delta_5 \leq \delta_5^3) = 0.1$ | 5 kW s.t.<br>$\Pr(\delta_5^3 \leq \delta_5 \leq \delta_5^4) = 0.1$ | 6 kW s.t.<br>$\Pr(\delta_5^4 \leq \delta_5 \leq \delta_5^5) = 0.05$ |
| $\delta_7^k$ | 20 kW s.t.<br>$\Pr(\delta_5 \leq \delta_5^1) = 0.7$ | 40 kW s.t.<br>$\Pr(\delta_5^1 \leq \delta_5 \leq \delta_5^2) = 0.15$ | 60 kW s.t.<br>$\Pr(\delta_5^2 \leq \delta_5 \leq \delta_5^3) = 0.1$ | 80 kW s.t.<br>$\Pr(\delta_5^3 \leq \delta_5 \leq \delta_5^4) = 0.04$ | 100 kW s.t.<br>$\Pr(\delta_5^4 \leq \delta_5 \leq \delta_5^5) = 0.01$ |

**Table 4.4** Definition of variables in the model

| Variables | Definition |
|---|---|
| $x \in R$ | Total demand in electricity load |
| $y_5 \in R$ | Variables corresponding to the stochastic electricity demand for air conditioning |
| $z_5^k \in \{0, 1\}$ | 1 if $k$-th demand (air conditioning) is satisfied in the K-bin discretized demand distribution, otherwise 0 |
| $y_7 \in R$ | Variables corresponding to the stochastic electricity demand for air conditioning |
| $z_7^k \in \{0, 1\}$ | 1 if $k$-th demand (operating chillers) is satisfied in the K-bin discretized demand distribution, otherwise 0 |

**Table 4.5** Definition of parameters in the model

| Variables | Definition |
|---|---|
| $\delta_1 \in R$ | Electricity demand for manual assembly (6 kW) |
| $\delta_2 \in R$ | Electricity demand for operating robots (8 kW) |
| $\delta_3 \in R$ | Electricity demand for moving conveyors (163 kW) |
| $\delta_4 \in R$ | Electricity demand for operating repairing centers (17 kW) |
| $\delta_5 \in R$ | Stochastic electricity demand for air conditioning as specified in Table 4.3 |
| $\delta_6 \in R$ | Electricity demand for building lighting at Setback state (4 kW) |
| $\delta_7 \in R$ | Stochastic electricity demand for operating chillers as specified in Table 4.3 |
| $\delta_8 \in R$ | Electricity demand for liquid moving at Setback state (10 kW) |
| $\delta_9 \in R$ | Electricity demand for air abatement at Setback state (2 kW) |
| $\alpha_5$ | Probability to fail in meeting a quality of service (QoS) required for the air conditioning activity |
| $\alpha_7$ | Probability to fail in meeting a quality of service (QoS) required for the operating chillers activity |

#### 4.4.3.2 Constraints

Equation (4.9) corresponds to the constraint of energy demand and supply conservation as described in Eq. (4.5). Equations (4.10)–(4.14) jointly represent the constraints on the energy demand required by air conditioning activity in such a way to guarantee that $y_5 \geq \delta_5^k$ must be true for at least one $k = 1, 2, \ldots, K$. Equation (4.15) is the knapsack inequality that enforces the QoS of air conditioning activity to meet $(1 - \alpha_5)\%$. Similarly, Eqs. (4.16)–(4.20) jointly represent the constraints on the energy demand required for operating chillers in such a way to guarantee that $y_7 \geq \delta_7^k$ must be true for at least one $k$ = 1, 2, … $K$. Equation (4.21) is the knapsack inequality that enforces the QoS of operating chillers to meet $(1 - \alpha_7)\%$. Eventually, both Eqs. (4.15) and (4.21) imply the acceptance of the inability to meet the requirements for air conditioning and operating chillers at all times. Indeed, the manufacturing system under consideration continues to work properly even if the constraints to meet the energy demand for air conditioning and operating chillers are violated for a short time period. In such a circumstance, it makes sense that one would rather insist on decisions guaranteeing feasibility “as much as possible”:

$$6 + 8 + 163 + 17 + y_5 + 4 + y_7 + 10 + 2 = x \tag{4.9}$$

$$y_5 \geq 2 - 2z_5^1 \tag{4.10}$$

$$y_5 \geq 3 - 3z_5^2 \tag{4.11}$$

$$y_5 \geq 4 - 4z_5^3 \tag{4.12}$$

$$y_5 \geq 5 - 5z_5^4 \tag{4.13}$$

$$y_5 \geq 6 - 6z_5^5 \tag{4.14}$$

$$0.65z_5^1 + 0.1z_5^2 + 0.1z_5^3 + 0.1z_5^4 + 0.05z_5^5 \leq \alpha_5(=0.35) \tag{4.15}$$

$$y_7 \geq 20 - 20z_7^1 \tag{4.16}$$

$$y_7 \geq 40 - 40z_7^2 \tag{4.17}$$

$$y_7 \geq 60 - 60z_7^3 \tag{4.18}$$

$$y_7 \geq 80 - 80z_7^4 \tag{4.19}$$

$$y_7 \geq 100 - 100z_7^5 \tag{4.20}$$

$$0.7z_7^1 + 0.15z_7^2 + 0.1z_7^3 + 0.04z_7^4 + 0.01z_7^5 \leq \alpha_7(=0.1) \tag{4.21}$$

where $x \geq 0;\ y_5,\ y_7 \geq 0;\ z_5^k,\ z_7^k \in \{0, 1\} \quad k = 1, 2, \ldots, K.$

#### 4.4.3.3 Problem Solving Using Simplex LP

Once a probabilistically constrained linear programming problem with random parameters right-hand side is reformulated as a mixed integer programming problem through the procedure aforementioned, it is possible to use Microsoft Excel Simplex solver to solve the problem. The Simplex solver aims to solve LP (Linear Programming) optimization problems and find a globally optimal solution. The best possibly solution meets all constraints globally to be an optimal solution at the point where 2 or more Constraints intersect because of Karush–Kuhn–Tucker conditions. Figure 4.6 illustrates how the Simplex solver accomodates objective function,

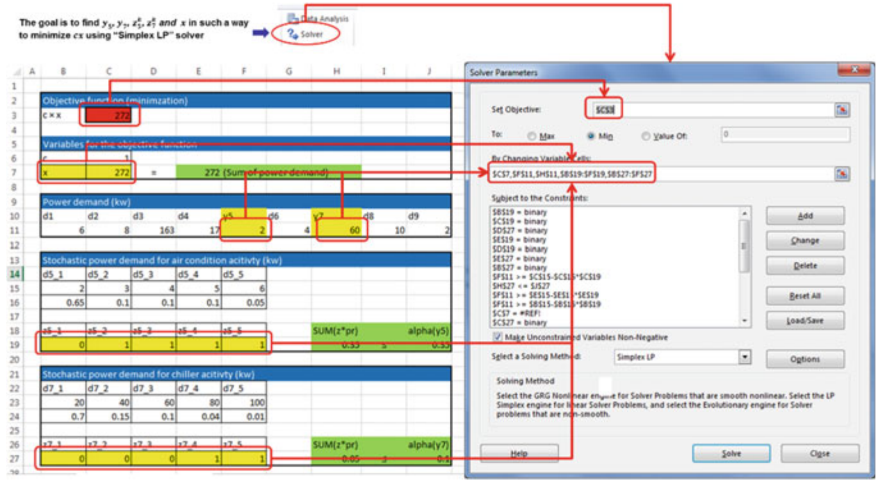



**Fig. 4.6** Using MS-excel solver with “simplex LP” to solve the example problem

decision variables and constraints as stated in Eqs. (4.8)–(4.21). For details about using the Simplex solver, refer to the appendix of Chap. 2 (“Getting Started with Excel Solver for SFA and DEA Analyses”).

#### 4.4.3.4 Results

Microsoft Excel Solver is used to solve the above deterministic linear problem consisting of Eqs. (4.8)–(4.21). Under 65 % QoS for air conditioning activity ($\alpha_5$ = 0.35) and 90 % QoS for operating chillers ($\alpha_7$ = 0.1), the optimal values of decision variables are: $\left[z_5^1, z_5^2, z_5^3, z_5^4, z_5^5\right] = [0, 1, 1, 1, 1]$; $\left[z_7^1, z_7^2, z_7^3, z_7^4, z_7^5\right] = [0, 0, 0, 1, 1]$; $[y_5, y_7] = [2, 60]$; $x = 272$. The corresponding optimal value of the objective function that is, Eq. (4.8) becomes 272 because we assume that $c$ = 1. The illustrative example still has a relatively small size, however, this approach still holds effective even when it is expanded to include real life multiple stochastic variables and constraints where the computation complexity is so high that the manual solving is no longer trace.

#### 4.4.3.5 Calculation of a New Peak Energy Demand and Decision Making

The final step is to recalculate the peak energy demand level ($P^*$) and determine whether to accept or reject the offer. In this study, each activity $i \in I_{MC}$ is set to receive energy at the demand rate (kW) corresponding to the production state. Meanwhile, each activity $i \in I_{STF}$ = {Building lighting, Liquid moving, Air abatement} is set to demand energy corresponding to its setback state. Furthermore, for activities in $I_{QoSF}$ = {Air conditioning, Operating chillers}, the air conditioning activity and the chiller operation activity lower its QoS level down to 65 and 90 %, respectively. As a result, the overall peak energy demand rate $P^*$ becomes as follows:

$$\begin{aligned} P^* &= P_{MC} + P_{STF} + P_{QoSF} \\ &= \max_t\left(\Sigma_{i\in I_{MC}}\Sigma_j r_{ij} \times Z_{ij}(t)\right) + \max_t\left(\Sigma_{i\in I_{STF}}\Sigma_j r_{ij} \times Z_{ij}(t)\right) + \Sigma_{i\in I_{QoSF}} y_i \\ &= 272\ \text{kW}. \end{aligned}$$

Since $P^* \leq C = (280\ \text{kW})$, the offer is finally accepted.

## 4.5 Summary

This chapter proposes a new decision process to assess the impact pertaining to energy demand response program participation and determination as to whether or not to participate in the program. The participation in the program will offer an opportunity to reduce the cost of electricity or to gain incentives, but in the meantime requires facing a challenge to secure a high-resolution understanding of energy usage and its causes. The decision process presented here uses ABC-based energy accounting model and chance constraint stochastic programing model as assessment methodologies and focuses on state-transition flexible activities and QoS-flexible activities to reduce the peak energy demand rate. Also, this work illustrates the proposed decision process in the context of its specific application to a simple hypothetical manufacturing system where mission-critical activities and other non-mission critical activities are mixed. The illustrative study result showed that the proposed decision model can be used with emerging smart grid opportunities to provide a competitive advantage to the manufacturing industry.

Although there are many ways to extend this work, one direction is to further investigate the possibility of the integration of the proposed decision process with transactional energy market information system (e.g., OpenADR or Open Auto-DR) so that energy demand response transactions can be implemented automatically. While all work presented here has been based on the "load-shedding" approach to demand response targeting at state-transition or QoS flexible activities, there may be additional opportunities in "load-shifting" for mission-critical activities through utilizing variable real-time energy demand profiles.

## 4.6 Exercise

1. This chapter discusses over a chance-constraint stochastic problem to meet the varying QoS levels for different energy consumption activities. The linear problem for the stochastic model consists of Eqs. (4.8)–(4.21) and can be solved in MS-Excel using "Simplex LP" solver. Refer to Appendix-B of Chap. 2 ("Getting Started with Excel Solver for SFA and DEA Analyses") and solve the illustrative problem and check if the results is the same as in the illustrated work.
2. You have learned about Activity-based costing (ABC) approach in this chapter. Different from ABC, considered as a more effective decision support-oriented accounting approach, Resource Consumption Accounting (RCA) has been came up recently. RCA has been recognized for having the capability of helping organization improve their understanding of environmental (and social) costs through their costing systems and models. Find articles about RCA on the internet and identify benefits of RCA over ABC, in particular, in the light of sustainable manufacturing.
3. One application to use a chance-constraint stochastic model is the case of power plant expansion for electricity generation where the decision maker wants to find optimal levels of investment in various types of power plants to meet future electricity demand. In many power plant expansion problems, a common concern is how to keep the reliability of the system to meet demand. The reliability is often described as expressing a minimum probability for meeting demand using the non backstop but affordable technologies. See Sect. 1.3 of "Introduction to Stochastic Programming" (Birge and Louveaux 1997) to see the case and understand the stochastic model. Discuss over the difference between Birge and Louveaux's model and the model illustrated in this chapter.

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# Chapter 5
# Pattern-Based Energy Consumption Analysis by Chaining Principle Component Analysis and Logistic Regression

**Abstract** It is often required to carry out sensor-based condition monitoring for machines or operations (e.g., machining centre, foundry) during production to ensure the effectiveness. Due to the requirements of a non-invasive installation or no interruption during production, however, it may be difficult to fully instrument the machine or production equipment with monitoring sensors. As an alternative to the direct monitoring, it is possible to use energy power or temperature data, and other easy-to-install sensors measured with relatively high time resolution ($\sim 2$ s) to provide enough information to effectively infer events and other properties. From this reason, the ability of inferring becomes important. To introduce how the inferencing technology can be used in the energy management, this chapter presents a pattern-based energy consumption analysis by chaining Principle Component Analysis (PCA) and logistic regression. The PCA provides an unsupervised dimension reduction to mitigate the issue of multicollinearity (high dependence) among the explanatory variables, while the logistic regression does the prediction based on the reduced dataset expressed in orthogonal axes that are uncorrelated principle components represented by Eigenvectors found in the PCA. By chaining the PCA and logistic regression, it is possible to train manually time-logged energy data and to infer the events associated with the manufacturing operations. It is expected that the proposed analysis method will enable manufacturing companies to correlate energy and operations and further use the power data to predict when operation events of interest (e.g. start up, idle, peak operation, etc.) occur, resulting in determining how current energy usage levels in manufacturing operations compares to the optimal usage patterns. This chapter also provides a short instruction to Python and IPython Notebook. It illustrates a supervised learning process by using Python to carry out pipelining PCA and logistic regression and applying a grid search to training and inference energy consumption patterns.

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## 5.1 Background of Energy Consumption Analysis

Many manufacturing companies currently tracks their energy consumption in their plants to monitor the firm's energy efficiency and its corresponding expenditures. For example, a firm who runs an electric arc furnace may be interested in effectively tracking energy consumption by correlating power data from electrodes connected to an electric arc furnace. For tracking energy consumption, the sensor-based condition monitoring is often required. Due to the requirements of a non-invasive installation or no interruption during production, however, it may be difficult to fully instrument the machine or production equipment with monitoring sensors. As an alternative to the direct monitoring, it is possible to use energy power or temperature data, and other easy-to-install sensors measured with relatively high time resolution ($\sim 2$ s) to provide enough information to effectively infer events and other properties.

Metal working operations may be a good example of why energy consumption tracking is important. In fact, significant energy consumption happens during machine idling as shown in Fig. 5.1. It is an observation of a fact that the amount of energy needed for the active deformation and removal of material is often very small relative to the energy required for manufacturing equipment support functions (Dahmus and Gutowski 2004).

When a job processed on one of the machines is considered, the energy power profile for the machining operations can be drawn as in Fig. 5.2 where x-axis and y-axis represent the processing time and power consumption, respectively. In the profile, the term "Basic" corresponds to activities such as work piece loading/unloading, positioning, and clamping. At this stage, the lighting, the NC controller, the chiller system, the oil pump, and the lubrication system are all turned on as describe in Fig. 5.1. The term "Supporting or idle" represents the processes of tool approaching and retracting from the work piece, tool movements between features, adjusting machine settings, and changing the tools. At this stage, the main spindle is turned on along with the tool changer and cutting fluid pump. Meanwhile,

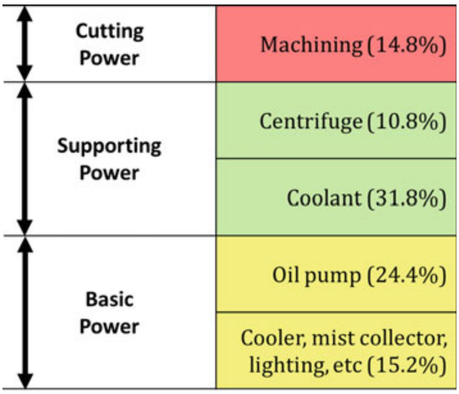



**Fig. 5.1** Energy use breakdown for machining (modified from Gutowski et al. 2005)

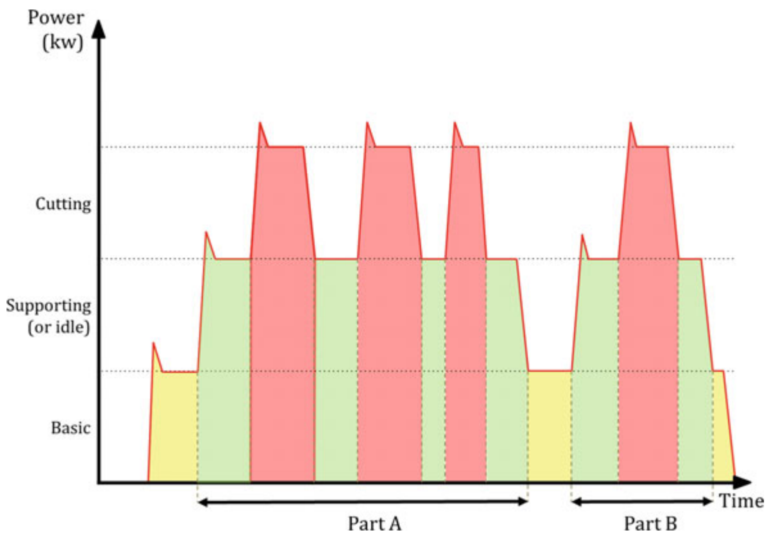



**Fig. 5.2** Energy power profile for a hypothetical machining operation (modified from Fang et al. 2011)

the term "Cutting" corresponds to the actual material removal process. The energy consumption corresponding to actual material removal is assumed constant for different cutting speeds. This assumption is valid if the specific cutting energy is independent of feed rate and cutting speed (Fang et al. 2011).

Regarding energy consumption tracking, unfortunately, today's firms are limited to a conventional approach that is to either manually log energy consumption or to install additional instrumentation to electronically detect energy consumption. However, manual logging is time-consuming and inaccurate, and electronic detection is complex and costly.

The purpose of this chapter is to introduce methodologies to correlate energy usage with manufacturing operations using a learning method based on Principal Component Analysis (PCA) and multinomial logistic regression so that it helps automate the energy tracking process. The methodology will enable to determine how current energy usage levels in manufacturing operations compare to the optimal usage patterns. For details about the energy use of manufacturing processes, for example, vehicle assembly process, see the previous studies (Oh et al. 2011; Oh and Hildreth 2013, 2014).

Many reported pattern analysis applications were based on a research paper written by Turk and Pentland (1991). They used the PCA to develop a facial recognition algorithm by separating the human face into individual parts (i.e. chin, nose, ears). This simplification makes it easier to determine the main components of an individual's face. This study similarly uses the PCA to separate the provided energy data into more discernible parts.

The PCA is a useful statistical technique for finding patterns in data represented in high dimensions. The prime aim of using the PCA analysis is to identify and predict patterns through reducing the dimensions of the target dataset in the original feature space with minimal loss of information onto a smaller subspace that represents the original data effectively and efficiently. The advantage of reducing the dimensions is the reduction of computational costs and the error of parameter estimation because the subspace can describe the data more concisely. The pattern classification is the most possible application of the PCA. However, the PCA itself could not achieve the pattern classification because the main interest of the PCA is to find the directions (called components) that maximize the variance in the dataset.

Since the PCA is designed to project the entire dataset onto a different subspace with the assumption that the entire dataset is one class, it is not possible to distinguish between patterns that belong to different classes. Meanwhile, directions or components can be seen as axes with maximum variances where the data is most spread. Therefore, in typical pattern classification or recognition problems, the PCA is often followed by another post processes like Multiple Discriminant Analysis (MDA) such as K-Means clustering algorithm, support vector machine, or multinomial logistic regression. More details about the technologies are discussed in the following section.

This book chapter is organized as follows. Section 5.2 summarizes the latest pattern recognition technologies such as PCA, multinomial logistic regression and K-Means clustering algorithm. Section 5.3 introduces a classification model for energy consumption pattern training and inference. Section 5.4 illustrates the process of training and inference energy consumption patterns using Python based on machining operations and Sect. 5.5 concludes this book chapter. Appendix provides a short instruction to Python and IPython Notebook. This Appendix illustrates a supervised learning process by using Python to carry out pipelining PCA and logistic regression and applying a grid search to training and inference energy consumption patterns.

## 5.2 Technologies for Pattern Training and Inference

### *5.2.1 Principle Component Analysis (PCA)*

The PCA is a useful statistical technique for finding patterns in data represented in high dimensions. The potential applications include face recognition, image compression, and other pattern recognition.

The prime purpose of this technique is to provide a way of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences (Smith 2002). In the case that the dimension of the data is too high to use the graphical representation, this technology is useful to analyse the data. The other main advantage of PCA is that once patterns in the data are found, it can help compress the data by reducing the number of dimensions, without much loss of information.

The main process of the PCA is to find the directions (called components) that maximize the variance in the dataset. The directions or components can be seen as axes with maximum variances where the data is most spread. It is always questionable to what extent the original dimension should be reduced. This question is identical to find $k$ where $d$-dimensional original dataset is projected onto a $k$-dimensional subspace (where $k < d$). One step involved in the PCA analysis is to compute Eigenvectors that represents the components from the covariance matrix of the original dataset. Each of those Eigenvectors must be associated with an Eigenvalue based on which the magnitude of the Eigenvector can be measured. From this fact, it makes sense to choose only those Eigenvectors with the much larger Eigenvalues, since they contain more information about the distribution of the original dataset. In other words, Eigenvalues that are close to 0 are less informative and can be ignored in constructing a new feature subspace.

The general steps of performing the PCA analysis is listed below where bold-face and lower-case letters and bold-face upper-case letter represent column vectors (e.g., $\boldsymbol{v}$) and matrices (e.g., $V$), respectively.

- Step-1: Normalize the original dataset by computing $\boldsymbol{x} - \bar{\boldsymbol{x}}$ where $\boldsymbol{x}$ is a $d \times 1$-dimensional vector representing one sample data and $\bar{\boldsymbol{x}}$ is the $d \times 1$-dimensional mean vector of the whole dataset.
- Step-2: Compute $\boldsymbol{\Sigma}$, the covariance matrix of the normalized whole dataset.
- Step-3: Compute Eigenvectors $(\boldsymbol{v}_1, \boldsymbol{v}_2, \ldots, \boldsymbol{v}_d)$ and corresponding Eigenvalues $(\lambda_1, \lambda_2, \ldots, \lambda_d)$ for the covariance matrix in such a way as $\boldsymbol{\Sigma v} = \lambda \boldsymbol{v}$
- Step-4: Sort the Eigenvectors by decreasing Eigenvalues and choose the top $k$ Eigenvectors, resulting in forming a $d \times k$ dimensional matrix $\boldsymbol{V}$ consisting of the chosen Eigenvectors.
- Step-5: Project the original dataset into the new subspace by computing $\boldsymbol{y} = \boldsymbol{V}^t \boldsymbol{x}$ where $\boldsymbol{y}$ is the transformed $k \times 1$-dimensional sample in the new subspace.

There are many articles available regarding the implementation of aforementioned steps in programming codes. Raschka (2014) shared Python codes to implement the aforementioned steps.

Meanwhile, since the PCA is designed to project the entire dataset onto a different subspace with the assumption that the entire dataset is one class, it is not possible to distinguish between patterns that belong to different classes. Therefore, in typical pattern classification or recognition problems, the PCA is often followed by another post process like Multiple Discriminant Analysis (MDA) such as K-Means clustering algorithm, support vector machine, or multinomial logistic regression.

### 5.2.2 Multinomial Logistic Regression

Multinomial logistic regression is a classification method that generalizes logistic regression to multiclass problems where more than two possible discrete outcomes are concerned (Greene 2012). The goal of multinomial logistic regression is to construct a statistical parametric model that accounts for the relationship between the explanatory variables and the outcome (a category), so that the outcome of a new data point can be correctly predicted when the explanatory variables are available but the outcome is not available. In order to train the relationship between the explanatory variables and the outcome, the possible categorical range of outcomes should be known.

By continuing the terms used in the previous section, when there are $n$ observed data points and each data point is denoted by $\boldsymbol{x}$ where $\boldsymbol{x}$ is a $d \times 1$-dimensional vector, each data point $\boldsymbol{x_i}$ ($i$ ranging from 1 to $n$) consists of a set of $d$ explanatory variables and $\boldsymbol{x_i}$ has an associated categorical outcome $y_i$ which can take on one of $k$ possible values. These possible values represent logically separate categories (e.g. different energy patterns, different manufacturing operations, etc.). In this setting, the multinomial logistic regression model can be built to predict $\Pr(y_i = c)$ where $c$ consists in $\{1, 2, \ldots, K\}$. From Train (2003), it is known that,

$$\Pr(Y_i = c) = \frac{\exp(\boldsymbol{\beta}_c^t \boldsymbol{x_i})}{\sum_{k=1}^{K} \exp(\boldsymbol{\beta}_c^t \boldsymbol{x_i})} \tag{5.1}$$

In the prediction stage, the outcome is finally predicted from the categorically distributed values, $\Pr(Y_i = k), k \in \{1, \ldots, K\}$ as follows:

$$Y_i = arg \max_{k \in \{1, \ldots, K\}} \Pr(Y_i = k) \tag{5.2}$$

One concern in using the logistic regression model, however, is raised when there is multicollinearity (high dependence) among the explanatory variables. In the presence of multicollinearity, the prediction power of the multinomial logistic model becomes reduced, leading to inaccurate prediction results. One way to address the multicollinearity problem is to reduce the dimension of the data points using the PCA approach (Aguilera et al. 2006; Camminatiello and Lucadamo 2010). The idea of dimension reduction is carried out by obtaining $z_i = \boldsymbol{V^t x_i}$ and then obtain the multinomial logistic model based on the reduced data set $z_i$ represented by orthogonal axes that are principle components expressed by Eigenvectors as seen below.

$$\Pr(Y_i = c) = \frac{\exp(\boldsymbol{\beta}_c^t \boldsymbol{z_i})}{\sum_{k=1}^{K} \exp(\boldsymbol{\beta}_c^t \boldsymbol{z_i})} = \frac{\exp(\boldsymbol{\beta}_c^t \boldsymbol{V}^t \boldsymbol{x_i})}{\sum_{k=1}^{K} \exp(\boldsymbol{\beta}_c^t \boldsymbol{V}^t \boldsymbol{x_i})} \tag{5.3}$$

### 5.2.3 K-Means Clustering Algorithm

For a multiple discriminant analysis, K-Means clustering is an algorithm for partitioning a dataset into k subsets, or clusters, that minimize the sum-of-squares distances from each cluster's mean. This algorithm is an unsupervised algorithm and fits in the absence of manually logged training data in contrast to the multinomial logistic regression model that is a supervised model working with the manually clustered training data. The algorithm consists of the following re-estimation procedure:

- Step-1: The data points are randomly assigned to the $k$ clusters.
- Step-2: The mean is computed for each cluster.
- Step-3: Each data point is assigned to the cluster that minimizes the sum-of-squares distance to the cluster's mean.
- Step-4: Repeat the final two steps until the data points are permanently assigned to an individual cluster.

Note that this study uses the multinomial logistic regression model with an assumption that a set of training data is prepared. Further details about K-Means clustering algorithm is available in many online articles, for example, in the article of Weisstein (2014).

## 5.3 A Classification Model for Energy Consumption Pattern Training and Inference

This section describes a classification model for a pattern-based energy consumption analysis by chaining Principle Component Analysis (PCA) and logistic regression. As introduced in the previous sections, the PCA provides an unsupervised dimension reduction to mitigate the issue of multicollinearity (high dependence) among the explanatory variables, while the logistic regression does the prediction based on the reduced dataset expressed in orthogonal axes that are principle components represented by Eigenvectors found in the PCA. Therefore, the chain of PCA and logistic regression may improve the accuracy of classification. The goal of this classification model is to train manually time-logged energy data and to infer the future events associated with the data related to manufacturing operations. The steps are divided into two stages: training (design time) and inference (real operation time) as shown in Fig. 5.3.

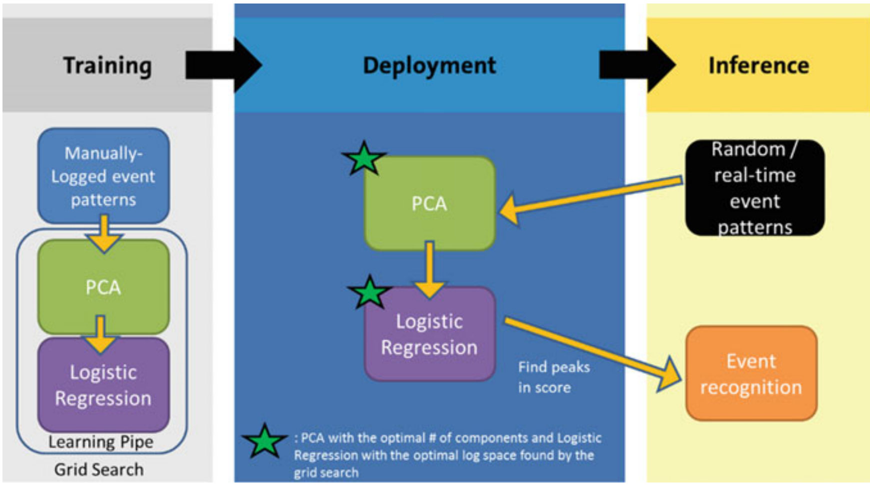



**Fig. 5.3** Proposed learning model for energy consumption pattern training and inference

### *5.3.1 Training Steps: Design Time*

The first training steps correspond to the design time and consist of the following three steps:

- Step-1: Manually cluster the training dataset into six events of interest to monitor as described in Table 5.1 and as shown in Figs. 5.4 and 5.5: $U_{O\to B}, U_{B\to I}, U_{I\to C}, D_{C\to I}, D_{I\to B}$ and $D_{B\to O}$. The provided time series data must be parsed into a $d \times 1$-dimensional vector representing one sample data where the rows are representative of the energy power data within the time window.

**Table 5.1** Events of interest to monitor

| Event notation | Description |
|---|---|
| $U_{O\to B}$ | Occurrence of energy power increase from zero power to the basic energy power level |
| $U_{B\to I}$ | Occurrence of energy power increase from the basic energy power level to the supporting or idle energy power level |
| $U_{I\to C}$ | Occurrence of energy power increase from the supporting or idle energy power level to the cutting power level |
| $D_{C\to I}$ | Occurrence of energy power decrease from the cutting power level to the supporting or idle energy power level |
| $D_{I\to B}$ | Occurrence of energy power decrease from the supporting or idle energy power level to the basic energy power level |
| $D_{B\to O}$ | Occurrence of energy power decrease from the basic energy power level to zero power |

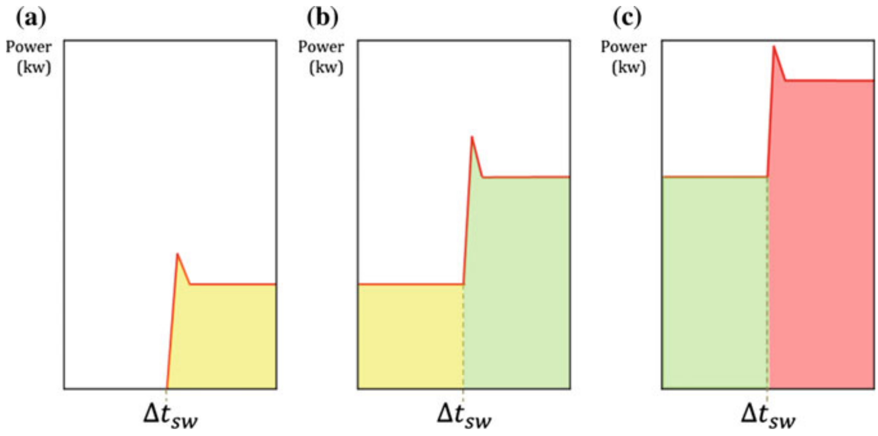



**Fig. 5.4** Power increase patterns of interest to train or predict, **a** $U_{O\rightarrow B}$, **b** $U_{B\rightarrow I}$, **C** $U_{I\rightarrow C}$

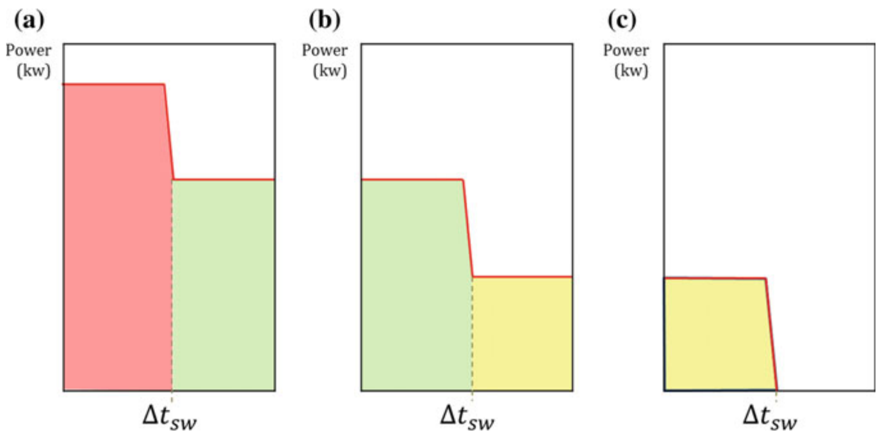



**Fig. 5.5** Power decrease patterns of interest to train or predict, **a** $D_{C\rightarrow I}$, **b** $D_{I\rightarrow B}$, **c** $D_{B\rightarrow O}$

- Step-2: Pipeline a PCA and a multinomial logistic regression model so that the design parameter selection for the PCA and multinomial logistic regression model can be synchronized.
- Step-3: Run a Grid Search to find optimal design parameters for PCA and multinomial logistic regression:
  - PCA: Find the transformation matrix $\boldsymbol{V}$ consisting of the first top Eigenvectors. Mathematically, the number of components extracted in PCA is equal to the number of observed variables to be analysed. To reduce the number of observed variables, the user must decide upon a variance threshold that corresponds to the cumulative variance required of the retained

variables. Many studies sets the variance threshold to 95 % based on a paper written by Cangelosi and Goriely (2007). Typically, the latter principal components tend to be insignificant, accounting for less than 1 % of the total variance. Each principal component is independent and highlights an underlying trend in the original data. For example, the first component may exhibit a steady operation; the second component may exhibit the operation start-up, and so forth.

– Multinomial logistic regression: Find a normalization weight factor in the log space to prevent overflow and underflow. Briefly speaking about the overflow or underflow problems, when computing the probabilities in logistic regression, it needs to compute $\exp(\boldsymbol{\beta}^t\boldsymbol{x})$. When $\boldsymbol{x}$ is big (or small), an overflow (or underflow) error occurs because $\exp(\boldsymbol{\beta}^t\boldsymbol{x})$ is too huge (or tiny).

### 5.3.2 Inference Steps: Real Operation Time

The second inference steps occur during the real operation time and consist of the following three steps:

- Step-1: Parse the real-time data in a fixed interval time window.
- Step-2: Apply $\boldsymbol{V}$ matrix extracted from the PCA to reduce the dimension.
- Step-3: Evaluate the multinomial logistic regression model as in Eqs. (5.2) and (5.3) to predict the event associated with the input data.

### 5.3.3 Scikit-Learn Machine Learning Library in Python

The study aims to illustrate the process of training and inference energy consumption patterns with Python, in particular, using Scikit-Learn machine learning library. Scikit-learn is a powerful tool for machine learning providing several modules for working with classification, regression and clustering problems. It uses python, numpy and scipy and it is open-source. There are four classes used in this study that are playing the role of a big stakeholder for training and inference energy consumption patterns. Following are the brief summary of those classes. The detailed introduction of using the classes is found in Appendix. For further instruction about other Scikit-Learn machine learning library, see *Scikit-Learn Machine Learning in Python*, which is available on: http://scikit-learn.org/stable/.

- `sklearn.decomposition.PCA`: This class implements linear dimensionality reduction using unsupervised Singular Value Decomposition of the data and keeps only the most significant singular vectors to project the data to a lower dimensional space. Among many, two essential functions are: (1) Fit(X)

(2) Transform(X). Fit(X) fits the model with X. Transform(X) applies the dimensionality reduction on X.

- `sklearn.linear_model.LogisticRegression`: This class implements a supervised machine learning algorithm called Logistic Regression Classifier for multi-class classification. Inputs are real valued vectors of fixed dimensionality and outputs are the probability that input vector belongs to the specified class. Two essential functions among many are: (1) Fit(X, y) (2) Predict (X). Fit(X, y) fits the model according to the given training data X and the given target data y. Predict (X) predicts class labels for samples in X.
- `sklearn.pipeline.Pipeline`: This class is built with the purpose of assembling several steps that can be cross-validated together while setting different parameters. For this, it enables setting parameters of the various steps using their names and the parameter name separated by a '__'. One essential functions among many is: Fit(X[, y]) that fits all the transforms one after the other and transform the data, then fit the transformed data using the final estimator.
- `sklearn.grid_search.GridSearchCV`: This class implements exhaustive search over specified parameter values for an estimator. It provides a "fit" method and a "predict" method like any classifier except that the parameters of the classifier used to predict is optimized by cross-validation. Hence, this class works with `sklearn.pipeline.Pipeline`. It has two important member functions: (1) Fit(X[, y]) (2) Predict(*args, **kwargs). Fit(X[, y]) runs fit with all sets of parameters. Predict(*args, **kwargs) calls predict on the estimator with the best found parameters.

## 5.4 Illustrative Example

This section will go through the steps set forth in Sect. 5.3 with hypothetically generated data set. Assume that events listed in Table 5.1 are of interest to monitor. These events correspond to the changes among machining operations explained in Figs. 5.1 and 5.2.

Figures 5.3 and 5.4 depict energy power change patterns, each corresponding to the event of interest to monitor. However, these energy power profile is quite ideal with a smooth pattern. The real pattern must have rough shape with noise.

Figures 5.5, 5.6, 5.7, 5.8, 5.9, 5.10 and 5.11 are energy patterns in bitmap format and vector format corresponding to events of interest to monitor. Totally, 18 bitmap energy patterns are generated artificially, each with $8^2$ pixels from which 18 numbers of 64 dimensional vectors. These vectors are used as input data for the proposed pattern based energy consumption analysis.

This pattern analysis approach suggests to use both Principle Component Analysis (PCA) and logistic regression by chaining them. As introduced in the previous sections, the PCA provides an unsupervised dimension reduction to

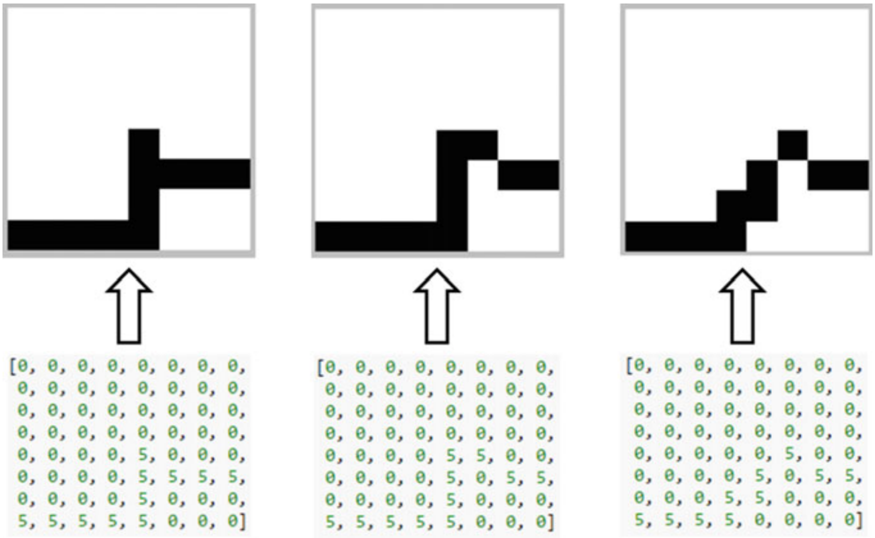



**Fig. 5.6** Training dataset (digitized image with its dot matrix) for $U_{O \to B}$

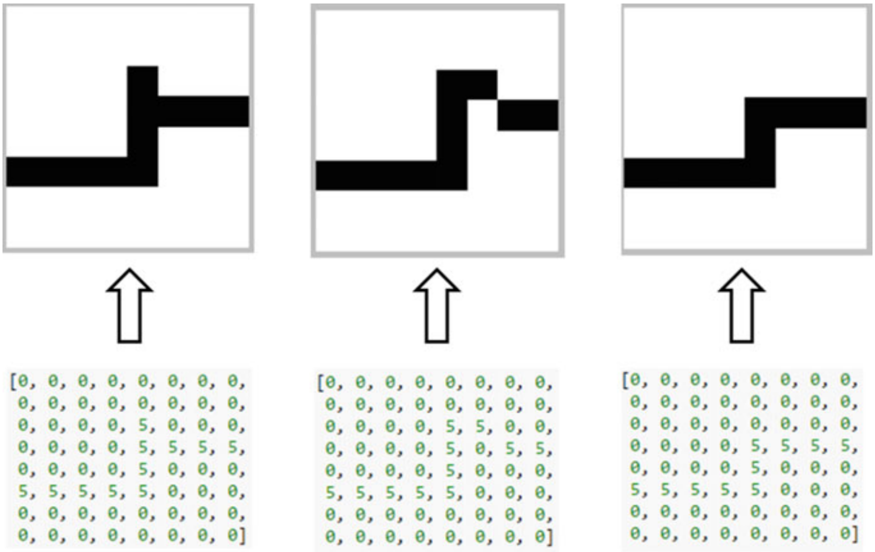



**Fig. 5.7** Training dataset (digitized image with its dot matrix) for $U_{B \to I}$

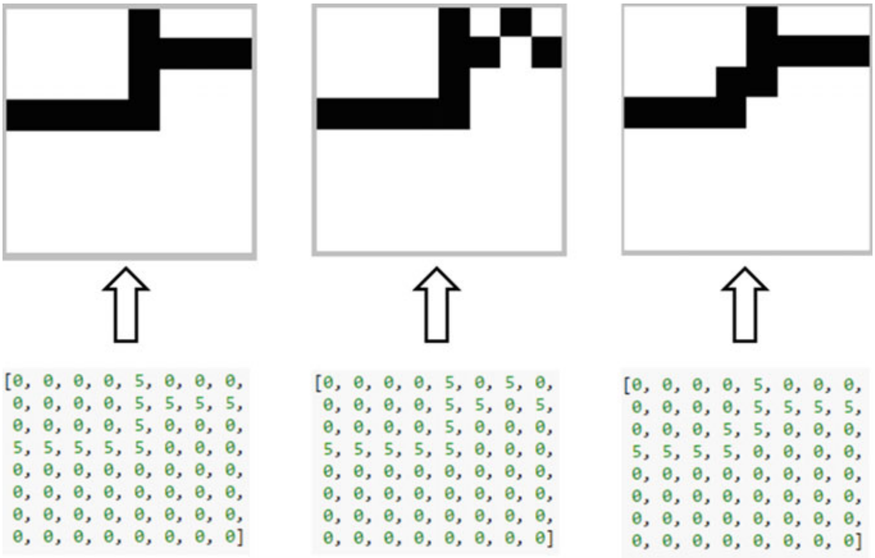



**Fig. 5.8** Training dataset (digitized image with its dot matrix) for $U_{I \to C}$

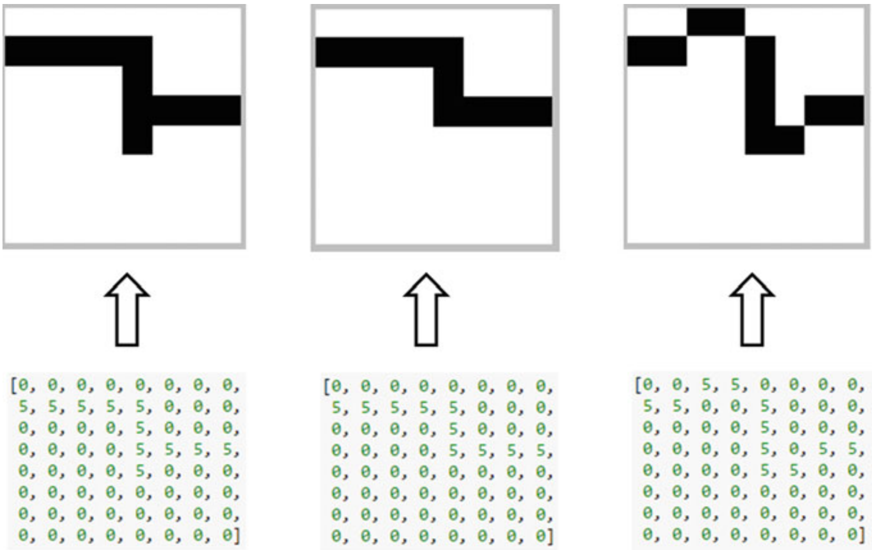



**Fig. 5.9** Training dataset (digitized image with its dot matrix) for $D_{C \to I}$

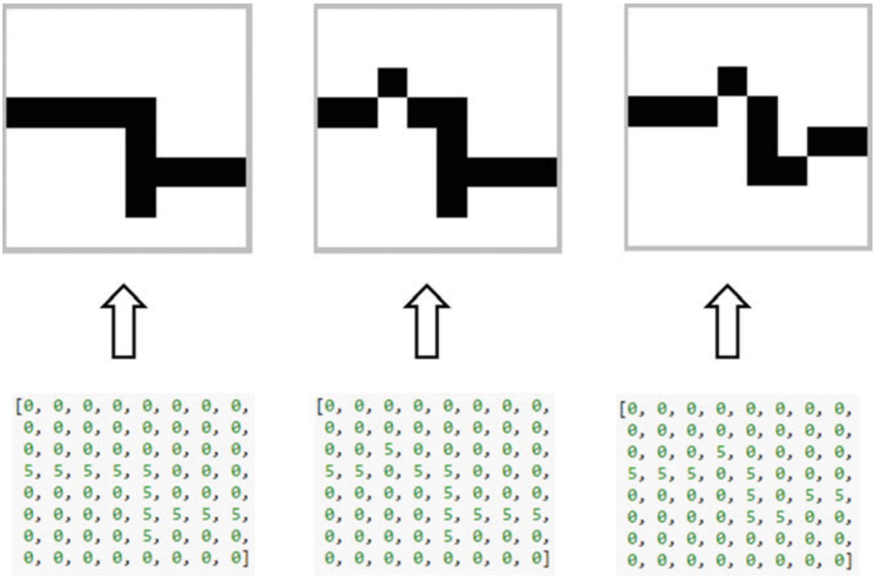



**Fig. 5.10** Training dataset (digitized image with its dot matrix) for $D_{I \to B}$

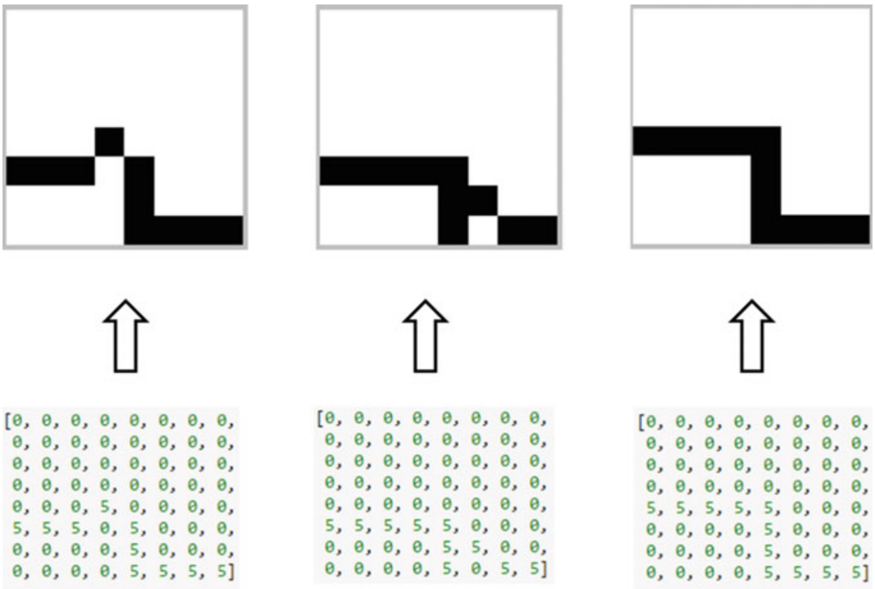



**Fig. 5.11** Training dataset (digitized image with its dot matrix) for $D_{B \to O}$

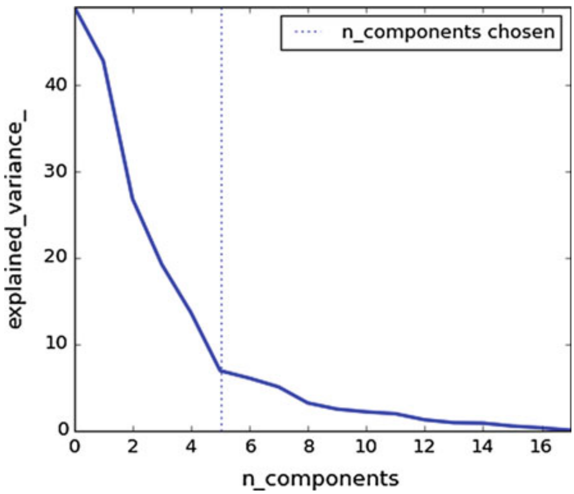



**Fig. 5.12** Fitting results of a grid search through piping PCA and logistic regression model

mitigate the issue of multicollinearity (high dependence) among the explanatory variables, while the logistic regression does the prediction based on the reduced dataset expressed in orthogonal axes that are principle components represented by Eigenvectors found in the PCA. Therefore, the chain of PCA and logistic regression may improve the accuracy of classification.

The detailed process of using Python to carry out these steps such as pipelining PCA and logistic regression and applying a grid search is illustrated in Appendix: Getting Started with IPython Notebook for Energy Pattern Analysis.

Figure 5.12 shows the data decomposition results after performing a grid search through pipelining PCA and logistic regression. The result tells that although there are possibly available 64 Eigenvectors because each input vector is 64-dimensional, the grid search found that using the first 7 Eigenvectors are optimal to compress the data efficiently and effectively. This result indicates that a final data set has 7 dimensions, which has saved the space by approximately 90 % (=(64–7)/64). Note that, however, when the original data is reproduced, the images have lost some of the information. This compression technique is said to be lossy because the decompressed image is not exactly the same as the original, generally worse.

Based on model parameters for PCA and logistic regression model found through the grid search through pipelining PCA and logistic regression, it is possible to infer (predict) events from their energy power profiles. Figure 5.13 shows the results of inference on energy patterns. The inference accuracy for those patterns used for training is 100 %.


**Fig. 5.13** Inference (prediction) results

## 5.5 Summary

This book chapter presented a pattern-based energy consumption analysis by chaining Principle Component Analysis (PCA) and logistic regression with an aim to introduce how the inferring technology can be used in the energy management. By chaining the PCA and logistic regression, it was possible to train manually time-logged energy data and to infer the future events associated with the data related to manufacturing operations. The expected benefits from the proposed analysis method include the increased prediction capability in tracking manufacturing operation events of interest to manufacturing companies (e.g. start up, idle, peak operation, etc.). The increased prediction capability can results in determining how current energy usage levels in manufacturing operations compare to the optimal usage patterns.

This study considered only time and energy usage for variables to monitor but the future study may consider gathering data on outside temperature, facility temperature, humidity, and other environmental factors so that an experimenter could apply the PCA and multinomial regression model to find the more significant variables. Through finding more significant variables, it is possible to automatically identify uncommon patterns that do not conform with any combination of the calculated principal components. Those uncommon patterns should be flagged and the users spend some efforts on understanding the causes of those flagged events. The automatic identification and flagging system on uncommon patterns or events will give a more time-effective alternative to find those low frequency but potentially problematic events.

## 5.6 Exercises

1. For the following square matrix $A$:

$$A = \begin{pmatrix} 2 & 0 & 1 \\ 0 & 2 & 0 \\ 1 & 0 & 2 \end{pmatrix}$$

   - Find Eigenvectors $\boldsymbol{v}$ and Eigenvalues $\lambda$ only when the transformation satisfies the equation: $\boldsymbol{\Sigma v} = \lambda \boldsymbol{v}$ (Hint: find $\lambda$ solutions of the determinant first such that $|\boldsymbol{\Sigma} - \lambda \boldsymbol{I}| = 0$.

2. Discuss about what the eigenvectors of the covariance matrix means in the PCA.
3. Read the appendix: "Getting Started with IPython Notebook for Energy Pattern Analysis" and download IPython Notebook as guided in the appendix and replicate the illustrative example in the main text.
4. For the energy or environment project you worked or are working, try to explain the potential application of the chaining of the PCA and logistic regression to the energy pattern analysis and make a business case of the application as detailed as possible.

## Appendix: Getting Started with IPython Notebook for Energy Pattern Analysis

### *Introducing, Getting and Installing IPython Notebook*

In this chapter, this book uses Python to illustrate the process of training and inference energy consumption patterns for machining operations. Specifically, in this chapter, Scikit-Learn machine learning library is used. Scikit-Learn is a powerful tool for machine learning providing several modules for working with classification, regression and clustering problems. Technically speaking, a learning problem considers a set of $\boldsymbol{n}$ samples of data and then tries to predict properties of unknown data. If each sample is more than a single number and, for instance, a multi-dimensional entry (aka multivariate data), is it said to have several attributes or features. It is, in general, impossible separate learning problems in a few large categories:

- Supervised learning, in which the data comes with additional attributes that are targets for prediction. Supervised learning problem includes classification and regression. Classification is concerned with samples belonging to two or more classes and the goal is to learn from already labeled data as to how to predict the class of unlabeled data. Regression is useful in the situation if the desired output consists of one or more continuous variables. An example of a regression problem would be the prediction of the length of a salmon as a function of its age and weight.
- Unsupervised learning, in which the training data consists of a set of input vectors $\boldsymbol{x}$ without any corresponding or desired target values. The goal of unsupervised learning is to discover groups of similar examples within the data, where it is called clustering, or to determine the distribution of data within the input space, known as density estimation, or to project the data from a high-dimensional space down to two or three dimensions for the purpose of visualization.

This Appendix illustrates a supervised learning process by using Python to carry out pipelining PCA and logistic regression and applying a grid search to training and inference energy consumption patterns as described in this chapter. However, this chapter is not an introduction to all of Python. For further instruction about other Scikit-Learn machine learning library, see *Scikit-Learn Machine Learning in Python*, which is available on: http://scikit-learn.org/stable/. There are many articles available regarding the implementation of Python in programming codes. Raschka (2014) shared Python codes to implement PCA step by step. A Computer Science course offered by Stanford University, *CS231n:Convolutional Neural Networks for Visual Recognition* provides a tutorial for Python with a focus on programing with the help of a few popular libraries such as numpy, scipy, matplolib, which is available on http://cs231n.github.io/python-numpy-tutorial/.

IPython notebook extends the console-based approach of original Python to interactive computing, providing a web-based application. Therefore, IPython notebook lets users write and execute Python code in their web browser. IPython notebook makes it very easy to tinker with code and execute it in bits and pieces being able to use IPython notebook widely in scientific computing.

There are many way to install IPython notebook but the most convenient way is to download WinPython, which is available on https://winpython.github.io/. Once WinPython is downloaded and installed, IPython notebook can be used by activating `IPython Notebook.exe` as in Fig. 5.14.

Once IPython is running, users should point their web browser at http://localhost:8888 to start using IPython notebooks. If everything worked correctly, a user should see a screen as in Fig. 5.15, showing all available IPython notebooks in the current directory. Note that there is `Tutorial.ipynb` available already.

If a user clicks through to the built-in notebook file, `Tutorial.ipynb`, the user will see a screen as in Fig. 5.16.

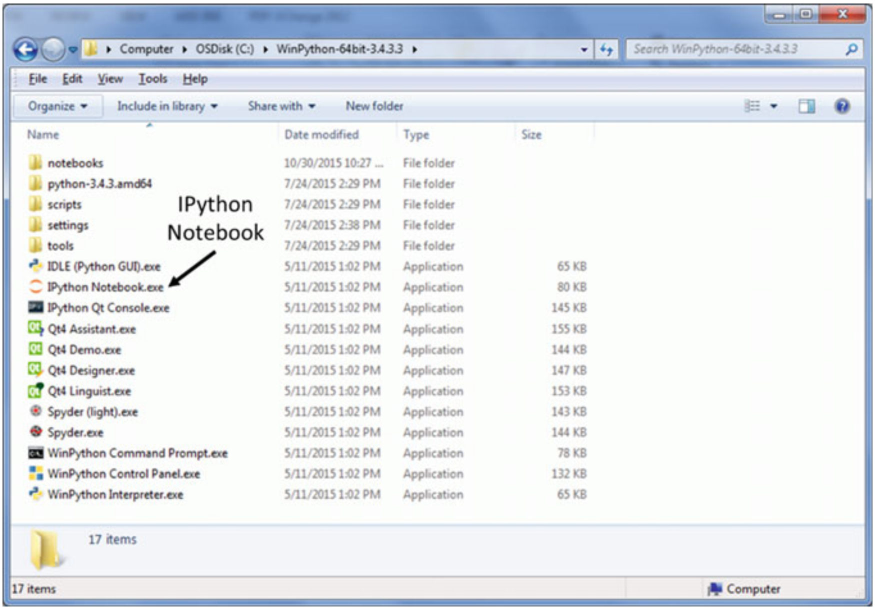



**Fig. 5.14** IPython Notebook in MS Window

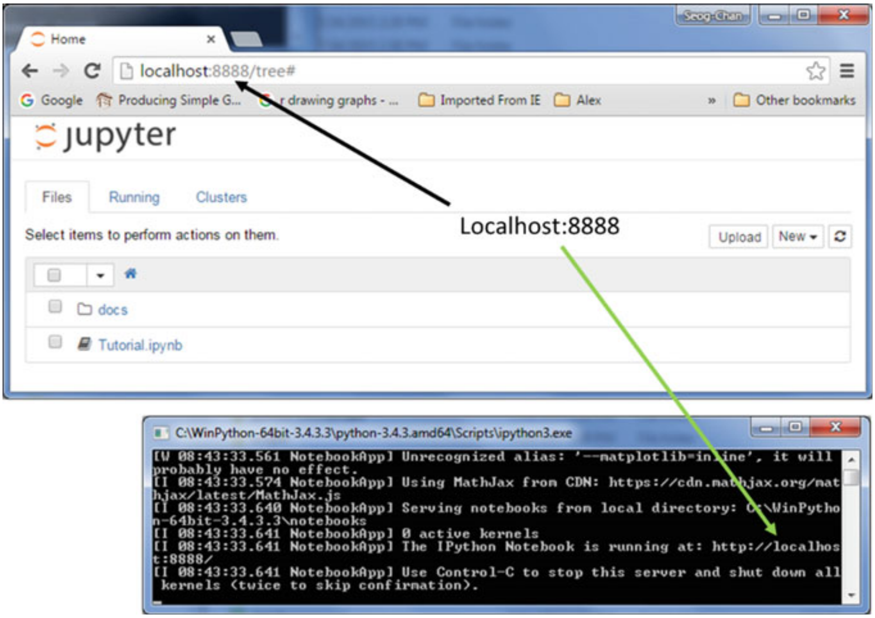



**Fig. 5.15** IPython Notebook in operation in a web browser and its server console

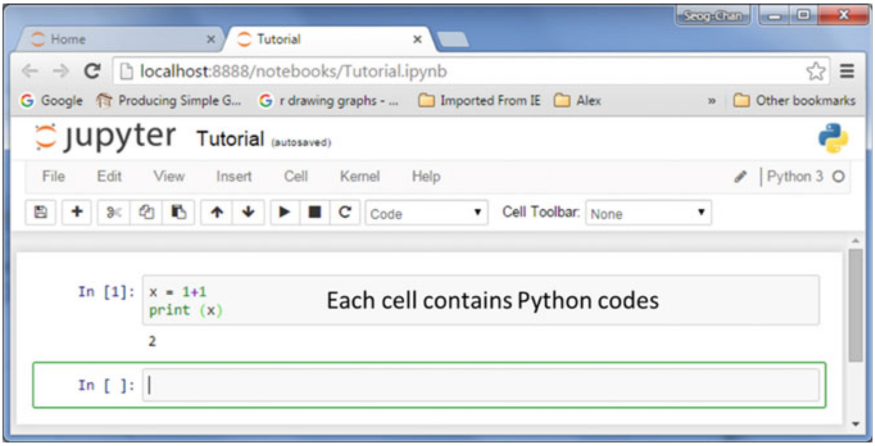



**Fig. 5.16** IPython Notebook cells

IPython notebook is made up of a number of cells with each cell containing Python codes. A user can execute a cell by clicking on *Cell|Run* or pressing *Shift-Enter* directly. Then, the codes in the cell will run, and the output of the cell is displayed beneath the cell as in Fig. 5.16.

## *An Introductory Python Session*

The final goal of this Python tutorial is to let users familiar with Python machine learning library, that is, Scikit-Learn. For the purpose, users need to learn how to manipulate various data types of Python and some science libraries as prerequisites, for example, `numpy.array` and `matplotlib.pyplot`. Like most languages, Python has a number of basic types including integers, floats, booleans, and strings. These data types behave in ways that are familiar from other programming languages. Following examples help learn how to manipulate various data types of Python. Examples below modified and enhanced the examples, which are available on http://cs231n.github.io/python-numpy-tutorial/, to be in accordance with this book theme.

```
>>> x = 1
>>> print (type(x))
<class 'int'>

>>> y = 1.5
>>> print (type(y))
<class 'float'>
```

Note that Python does not provide unary increment (x++) or decrement (x−−) operators.

```
>>> T = True
>>> F = False
```

Python implements all of the usual operators for Boolean logic (e.g., AND, OR, NOT, XOR) using English words like ‘and’, ‘or’, ‘not’ and ‘!=’.

```
>>> print ( T and F)    #Logical AND
False

>>> print ( T or F)     #Logical OR
True

>>> print (not T)       #Logical NOT
False

>>> print (T != F)      #Logical XOR
TRUE
```

Python has great support for strings, providing a bunch of useful methods, for example, upper or lower characterizing, replacing or sprintf style string formatting. Note that it does not matter to use single quotes or double quotes for string literals.

```
>>> HW = "Hello World!"
>>> print (HW.upper())
HELLO WORLD!

>>> print (HW.lower())
hello world!

>>> print (HW.replace('o', 'e'))
>>> # Replace all instances of 'o' with 'e'

Helle Werld!

>>> HW2015 = '%s %d' % (HW, 2015)
>>> # sprintf style string formatting
>>> print (HW2015)
Hello World! 2015
```

The powerful function provided by Python is built-in container types including lists, dictionaries, sets, and tuples. A list is equivalent to an array but is resizable and contains elements of different types. Accessing sublists of a list, called slicing is easy. Also, implementing conditions inside a list, called list comprehension is available.

```
>>> Numbers = [0, 1, 2, 3, 4, 5]
>>> print (numbers)
[0, 1, 2, 3, 4, 5]

>>> print (numbers [2:4])
[2, 3, 4]

>>> print (numbers [2:])
[2, 3, 4, 5]

>>> print (numbers [:4])
[0, 1, 2, 3, 4]

>>> print (numbers [:-1])

>>> squares = [x **2 for x in numbers]
>>> print (squares)
[0, 1, 4, 9, 16, 25]

>>> even squares = [x **2 for x in numbers if x%2==0]
>>> print (squares)
[0, 4, 16]

>>> numbers[2:4] = [10,11,12]
>>> print (numbers)
[0, 1, 10, 11, 12, 12, 4, 5]

>>> numbers[-1] = 'Energy'
>>> print (numbers)
[0, 1, 10, 11, 12, 12, 4, 'Energy']

>>> numbers.append ('Analytics')
>>> print (numbers)
[0, 1, 10, 11, 12, 12, 4, 'Energy', 'Analytics']

>>> x = numbers.pop()
>>> print (x, ': ', numbers)
Energy :  [0, 1, 10, 11, 12, 12, 4]
```

A dictionary is an another type of container types provided by Python. It stores (key, value) pairs, similar to a look up table in other languages. By using the keys, it is efficient to iterate entries to look up values associated with the keys in a dictionary.

```
>>>    energy_intensity    =    {'GM':2.3,    'VW':2.21,
'Ford':2.45, 'BMW':2.44, 'Toyota':2.13}
>>> print (energy_intensity)
{'BMW': 2.44, 'Toyota': 2.13, 'Ford': 2.45, 'GM': 2.3,
'VW': 2.21}

>>>for company in energy_intensity:
>>>    intensity = energy_intensity[company]
>>>    print ('%s has its energy intensity of %.2f MWh
>>>    per vehicle ' % (company, intensity))
BMW has its energy intensity of 2.44 MWh per vehicle
Toyota has its energy intensity of 2.13 MWh per vehicle
Ford has its energy intensity of 2.45 MWh per vehicle
GM has its energy intensity of 2.30 MWh per vehicle
VW has its energy intensity of 2.21 MWh per vehicle
```

A set is an another type of container types provided by Python. It is used to contain an unordered collection of distinct elements. Iterating over a set has the same syntax as iterating over a list but since sets are unordered, it is not sure in which order the elements will be visited.

```
>>> utilities = {'electricity', 'natural gas',
>>>              'compressed air'}
>>> print(len(utilities))
3

>>> utilities.add('landfill gas')
>>> print (len(utilities))
4

>>> utilities.remove('compressed air')
>>> print (len(utilities))
3

>>> for i, utility in enumerate(utilities):
>>>     print ('#%d: %s' % (i + 1, utility))
#1: natural gas
#2: landfill gas
#3: electricity
```

A tuple is an another type of container types provided by Python. It is an immutable ordered list of values and is mainly used as keys in dictionaries and as elements of sets.

```
>>> Company_energy_CO2 = {('GM', 'MWh'):2.3,
>>> ('VW', 'MWh'):2.21, ('Ford', 'MWh'):2.45,
>>> ('GM', 'CO2'):0.88,('VW', 'CO2'):0.89,
>>> ('Ford', 'CO2'):0.9}
>>> print (Company_energy_CO2)
{('Ford', 'MWh'): 2.45, ('VW', 'CO2'): 0.89, ('GM',
'CO2'): 0.88, ('GM', 'MWh'): 2.3, ('VW', 'MWh'): 2.21,
('Ford', 'CO2'): 0.9}

>>> print (Company_energy_CO2[('GM', 'MWh')])
2.3

>>> print (Company_energy_CO2[('GM', 'CO2')])
0.88

>>> print (Company_energy_CO2[('VW', 'MWh')])
2.21

>>> print (Company_energy_CO2[('VW', 'CO2')])
0.89

>>> print (Company_energy_CO2[('Ford', 'MWh')])
2.45

>>> print (Company_energy_CO2[('Ford', 'CO2')])
0.9
```

Since Python is an object-oriented language, it can create a class. Inside a class, a Python functions are defined using the `def` keyword.

```
>>> class Environment_Report:
>>>
>>>   Company_energy_CO2 = {('GM', 'MWh'):2.3,
>>>   ('VW', 'MWh'):2.21, ('Ford', 'MWh'):2.45,
>>>   ('GM', 'CO2'):0.88,('VW', 'CO2'):0.89,
>>>   ('Ford', 'CO2'):0.9}
>>>
>>>   def __init__(self, name):
>>>     self.name = name
>>>
>>>   def report(self, choise):
>>>     if choise == 'MWh':
>>>        print ('%s has used %.2f Mwh per vehicle!'
>>>                % (self.name, Company_energy_CO2
>>>               [(self.name, choise)]))
>>>     if choise == 'CO2':
>>>        print ('%s has emitted %.2f CO2 tons per
>>>                vehicle!' % (self.name,
>>>            Company_energy_CO2[(self.name, choise)]))
```

```
>>> GM = Environment_Report('GM')
>>> GM.report('MWh')
>>> GM.report('CO2')
GM has used 2.30 Mwh per vehicle!
GM has emitted 0.88 CO2 tons per vehicle!

>>> VW = Environment_Report('VW')
>>> VW.report('MWh')
>>> VW.report('CO2')
VW has used 2.21 Mwh per vehicle!
VW has emitted 0.89 CO2 tons per vehicle!

>>> Ford = Environment_Report('Ford')
>>> Ford.report('MWh')
>>> Ford.report('CO2')
Ford has used 2.45 Mwh per vehicle!
Ford has emitted 0.90 CO2 tons per vehicle!
```

Python has a core library for scientific computing, Numpy. It provides a high-performance multidimensional array object, and tools for working with these arrays. A numpy array is a grid of values with all the same type, and is indexed by a tuple of nonnegative integers. The number of dimensions is called, rank while the shape of an array is a tuple of integers giving the size of the array along each dimension. Numpy also provides many functions to create arrays.

```
>>> import numpy as np
>>>
>>> zeros = np.zeros((2,2)) # Create an array of all
>>>                         # zeros
>>> print (zeros)

[[ 0.  0.]
 [ 0.  0.]]

>>> ones = np.ones((2,2))   # Create an array of all
>>>                         # ones
>>> print (ones)
[[ 1.  1.]
 [ 1.  1.]]
```

```
>>> full_7 = np.full((2,2), 7) # Create a constant
>>>                            # array of 7
>>> print (full_7)
[[ 7.  7.]
 [ 7.  7.]]

>>> identity = np.eye(2)        # Create a 2x2 identity
>>>                             # matrix
>>> print (identity)
[[ 1.  0.]
 [ 0.  1.]]

>>> random = np.random.random((2,2)) # Create an array
>>>                         #filled with random values
>>> print (random)
[[ 0.67999305  0.7430317 ]
 [ 0.39055208  0.37449631]]
```

Transposing a matrix is simple in Numpy, using the `T` attribute of an array object.

```
>>> x = np.array([[1,2], [3,4]])
>>> print (x)
[[1 2]
 [3 4]]

>>> print (x.T) # Transpose a matrix
[[1 3]
 [2 4]]
```

Compute the sum of each column or row is simple Numpy, using the `Sum` function.

```
>>> print (np.sum(x))  # Compute sum of all elements
10

>>> print (np.sum(x, axis=0))  # Compute sum of each
>>>                            # column
[4 6]

>>> print (np.sum(x, axis=1))  # Compute sum of each
>>>                            # row
[3 7]
```

Basic array mathematical functions on arrays are available both as operator overloads and as functions in Numpy.

```
>>> x = np.array([[1,2],[3,4]])
>>> y = np.array([[5,6],[7,8]])
>>> print (x)
>>> print (y)
[[1 2]
 [3 4]]
[[5 6]
 [7 8]]

>>> print (x + y) # equal to np.add(x, y)
[[ 6  8]
 [10 12]]

>>> print (x - y) # equal to np.subtract(x, y)
[[-4 -4]
 [-4 -4]]

>>> print (x*y) # equal to np.multiply(x, y)
[[ 5 12]
 [21 32]]

>>> print (x/y) # equal to np.divide(x, y)
[[ 0.2         0.33333333]
 [ 0.42857143  0.5       ]]

>>> print (np.sqrt(x))
[[ 1.          1.41421356]
 [ 1.73205081  2.        ]]
```

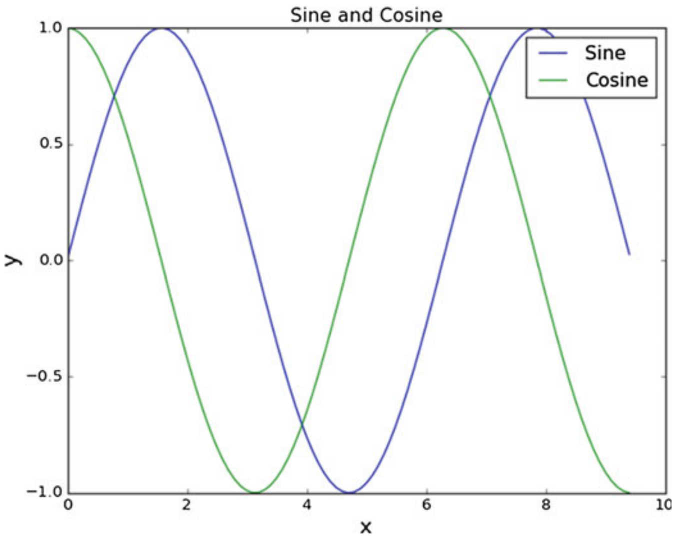
Broadcasting is a powerful mechanism in Numpy, allowing arrays of different shapes to perform arithmetic operations between them. Note that the results of using the broadcasting is the same as that of adding the vector `y` to each row of the matrix `x` with an explicit loop in the example below.

```
>>> x = np.array([[1,2,3], [4,5,6], [7,8,9],
>>> [10, 11, 12]])
>>> y = np.array([1, 1, 1])
>>> z = x + y  # Add y to each row of x using
>>>            # broadcasting
>>> print (z)
[[ 2  3  4]
 [ 5  6  7]
 [ 8  9 10]
 [11 12 13]]
>>> z = np.empty_like(x) # Create an empty matrix
>>>                      #with the same shape as x
>>> for i in range(4):
>>>     z[i, :] = x[i, :] + y
>>> print (z)
[[ 2  3  4]
 [ 5  6  7]
 [ 8  9 10]
 [11 12 13]]
```

Matplotlib is a plotting library in Python. The most important function in matplotlib is plot, which allows you to plot 2D data.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>>
>>> # 1. Compute the x and y points on sine & cosine
>>> curves
>>> x = np.arange(0, 3 * np.pi, 0.1)
>>> sin = np.sin(x)
>>> cos = np.cos(x)
>>>
```

```
>>> # 2. Plot the points using matplotlib
>>> fig = plt.figure()
>>> fig.patch.set_facecolor('none')
>>> plt.plot(x, sin)
>>> plt.plot(x, cos)
>>> plt.xlabel('x ')
>>> plt.ylabel('y ')
>>> plt.title('Sine and Cosine')
>>> plt.legend(['Sine', 'Cosine'])
>>> plt.show()
```




SciPy is a library that builds on Numpy provides a large number of functions that are useful for different types of scientific and engineering applications. SciPy also provides some basic functions to work with images. For further instructions on image processing using SciPy, see http://www.scipy-lectures.org/advanced/image_processing/.

## *A Python Scrip for Energy Pattern Analysis*

This section illustrates a supervised learning process of using Python to carry out pipelining PCA and logistic regression and applying a grid search to training and inference energy consumption patterns as described in this chapter. First, the training data sets are prepared, showing energy patterns in bitmap format and vector format corresponding to events of interest to monitor. Totally, 18 bitmap energy patterns are prepared, each with $8^2$ pixels from which 18 numbers of 64 dimensional vectors. These vectors are used as input data for the proposed pattern based energy consumption analysis.

```
>>> # 1st training data for U_(O→B) energy pattern
>>> print(patterns_img[0])
>>> plt.imshow(patterns_img[0], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0]]
```

```
>>> # 2nd training data for U_(O→B) energy pattern
>>> print(patterns_img[6])
>>> plt.imshow(patterns_img[6], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 0, 0],
 [0, 0, 0, 0, 5, 0, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0]]
```

```
>>> # 3rd training data for U_(O→B) energy pattern
>>> print(patterns_img[12])
>>> plt.imshow(patterns_img[12], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 5, 0, 0],
 [0, 0, 0, 0, 5, 0, 5, 5],
 [0, 0, 0, 5, 5, 0, 0, 0],
 [5, 5, 5, 5, 0, 0, 0, 0]]
```

```
>>> # 1st training data for U_(B→I)energy pattern
>>> print(patterns_img[1])
>>> plt.imshow(patterns_img[1], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

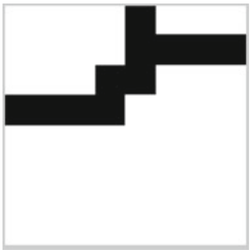
```
>>> # 2nd training data for U_(B→I) energy pattern
>>> print(patterns_img[7])
>>> plt.imshow(patterns_img[7], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 0, 0],
 [0, 0, 0, 0, 5, 0, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 3rd training data for U_(B→I)energy pattern
>>> print(patterns_img[13])
>>> plt.imshow(patterns_img[13], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 1st training data for U_(I→C)energy pattern
>>> print(patterns_img[2])
>>> plt.imshow(patterns_img[2], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 2nd training data for U_(I→C) energy pattern
>>> print(patterns_img[8])
>>> plt.imshow(patterns_img[8], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 5, 0, 5, 0],
 [0, 0, 0, 0, 5, 5, 0, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 3rd training data for U_(I→C) energy pattern
>>> print(patterns_img[14])
>>> plt.imshow(patterns_img[14], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 5, 5, 0, 0, 0],
 [5, 5, 5, 5, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```



```
>>> # 1st training data for D_(C→I) energy pattern
>>> print(patterns_img[3])
>>> plt.imshow(patterns_img[3], cmap=plt.cm.gray_r,
int>>> erpolation='nearest')
>>> plt.show()
[[0, 0, 0, 0, 0, 0, 0, 0],
[5, 5, 5, 5, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 5, 5, 5],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 2nd training data for D_(C→I) energy pattern
>>> print(patterns_img[9])
>>> plt.imshow(patterns_img[9], cmap=plt.cm.gray_r,
int>>> erpolation='nearest')
>>> plt.show()
[[0, 0, 0, 0, 0, 0, 0, 0],
[5, 5, 5, 5, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 5, 5, 5],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0]]
```

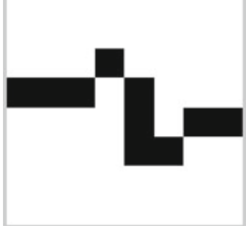
```
>>> # 3rd training data for D_(C→I) energy pattern
>>> print(patterns_img[15])
>>> plt.imshow(patterns_img[15], cmap=plt.cm.gray_r,
int>>> erpolation='nearest')
>>> plt.show()
[[0, 0, 5, 5, 0, 0, 0, 0],
[5, 5, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 5, 5],
[0, 0, 0, 0, 5, 5, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 1st training data for D_(I→B) energy pattern
>>> print(patterns_img[4])
>>> plt.imshow(patterns_img[4], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [5, 5, 5, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 2nd training data for D_(I→B) energy pattern
>>> print(patterns_img[10])
>>> plt.imshow(patterns_img[10], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 5, 0, 0, 0, 0, 0],
 [5, 5, 0, 5, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 5, 5, 5],
 [0, 0, 0, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```

```
>>> # 3rd training data for D_(I→B) energy pattern
>>> print(patterns_img[16])
>>> plt.imshow(patterns_img[16], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()

 [[0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 5, 0, 0, 0, 0],
 [5, 5, 5, 0, 5, 0, 0, 0],
 [0, 0, 0, 0, 5, 0, 5, 5],
 [0, 0, 0, 0, 5, 5, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0],
 [0, 0, 0, 0, 0, 0, 0, 0]]
```



```
>>> # 1st training data for D_(B→O) energy pattern
>>> print(patterns_img[5])
>>> plt.imshow(patterns_img[5], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
[[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 5, 0, 0, 0, 0],
[5, 5, 5, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 5, 5, 5]]
```

```
>>> # 2nd training data for D_(B→O) energy pattern
>>> print(patterns_img[11])
>>> plt.imshow(patterns_img[11], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
[[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[5, 5, 5, 5, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 5, 0, 0],
[0, 0, 0, 0, 5, 0, 5, 5]]
```

```
>>> # 3rd training data for D_(B→O) energy pattern
>>> print(patterns_img[17])
>>> plt.imshow(patterns_img[17], cmap=plt.cm.gray_r,
>>> interpolation='nearest')
>>> plt.show()
[[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[0, 0, 0, 0, 0, 0, 0, 0],
[5, 5, 5, 5, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 0, 0, 0],
[0, 0, 0, 0, 5, 5, 5, 5]]
```

Once patterns for training is prepared, PCA can be performed. Note that the training dataset into six energy consumption events of interest to monitor should be clustered as described in Table 5.1 and as shown in Figs. 5.4 and 5.5. Further, the provided data must be parsed into one dimensional vector representing the energy power within the time window. Due to this reason, this section converts `patterns_img` which type is `list` into patterns which type is `numpy.array`. `patterns` has a shape of (18, 64), meaning that it has 18 numbers of vectors, each with 64 elements.

```
>>> print (patterns)
[[0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 ...,
 [0 0 5 ..., 0 0 0]
 [0 0 0 ..., 0 0 0]
 [0 0 0 ..., 5 5 5]]

>>> print ( type(patterns), patterns.shape)
<class 'numpy.ndarray'> (18, 64)
```

For training, each of vector in patterns should be associated with their pertinent target.

```
>>> print (target)
['Uo-b' 'Ub-i' 'Ui-c' 'Dc-i' 'Di-b' 'Db-o' 'Uo-b' 'Ub-i'
 'Ui-c' 'Dc-i' 'Di-b' 'Db-o' 'Uo-b' 'Ub-i' 'Ui-c' 'Dc-i'
  'Di-b' 'Db-o']

>>> print (type(target), target.shape)
<class 'numpy.ndarray'> (18,)
```

This pattern analysis approach suggests to use both Principle Component Analysis (PCA) and logistic regression by chaining them. As introduced in the previous sections, the PCA provides an unsupervised dimension reduction to mitigate the issue of multicollinearity (high dependence) among the explanatory variables, while the logistic regression does the prediction based on the reduced dataset expressed in orthogonal axes that are principle components represented by Eigenvectors found in the PCA. Therefore, the chain of PCA and logistic regression may improve the accuracy of classification.

The detailed theoretical background of using PCA and logistic regression, see Sect. 5.3. The results of applying a grid search tells that although there are possibly available 64 Eigenvectors because each input vector is 64-dimensional, the grid search found that using the first 7 Eigenvectors are optimal to compress the data efficiently and effectively. This result indicates that a final data set has 7 dimensions, which has saved the space by approximately 90 % (=(64–7)/64). Tables 5.2, 5.3, 5.4 and 5.5 explains the classes in this example.

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>>
>>> from sklearn import linear_model, decomposition,
>>> datasets
>>> from sklearn.pipeline import Pipeline
>>> from sklearn.grid_search import GridSearchCV
>>>
>>> # 1. Create PCA and LR objects
>>> logistic = linear_model.LogisticRegression()
>>> pca = decomposition.PCA()
>>>
>>> # 2. Pipeline PCA and LR objects
>>> pipe = Pipeline(steps=[('pca', pca),
>>>     ('logistic', logistic)])
>>>
>>> # 3. Run PCA
>>> pca.fit(patterns)
```

**Table 5.2** Methods and options of `sklearn.decomposition.PCA` used in this example

| Method | Description |
|---|---|
| `fit(X[, y])` | Fit the model with X |
| `get_covariance()` | Compute data covariance with the generative model |
| Main option | Description |
| `components_: array, [n_components, n_features]` | Components with maximum variance |
| `explained_variance_ratio_: array, [n_components]` | Percentage of variance explained by each of the selected components. n_components is not set then all components are stored and the sum of explained variances is equal to 1.0 |

**Table 5.3** Methods and options of `sklearn.linear_model.LogisticRegression` used in this example

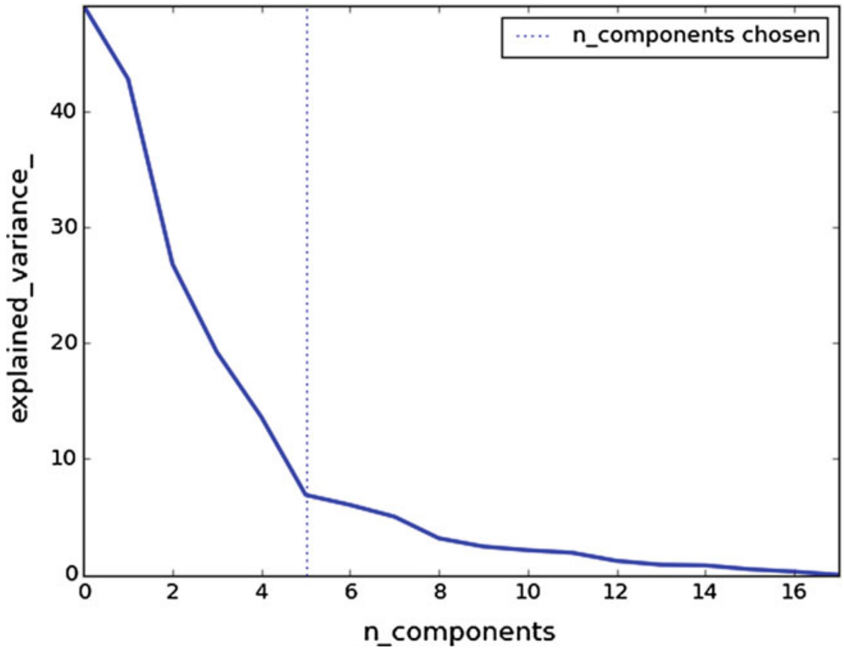
| Method | Description |
|---|---|
| `fit(X, y)` | Fit the model according to the given training data |
| `predict(X)` | Predict class labels for samples in `X` |
| Main option | Description |
| `C: float, optional (default = 1.0)` | Inverse of regularization strength; must be a positive float. Like in support vector machines, smaller values specify stronger regularization |
| `penalty: str, ‘l1’ or ‘l2’` | Used to specify the norm used in the penalization. The newton-cg and lbfgs solvers support only l2 penalties |

**Table 5.4** Methods and options of `sklearn.pipeline.Pipeline` used in this example

| Method | Description |
|---|---|
| `fit(X[, y])` | Fit all the transforms one after the other and transform the data, then fit the transformed data using the final estimator |
| `predict(*args, **kwargs)` | Applies transforms to the data, and the predict method of the final estimator |

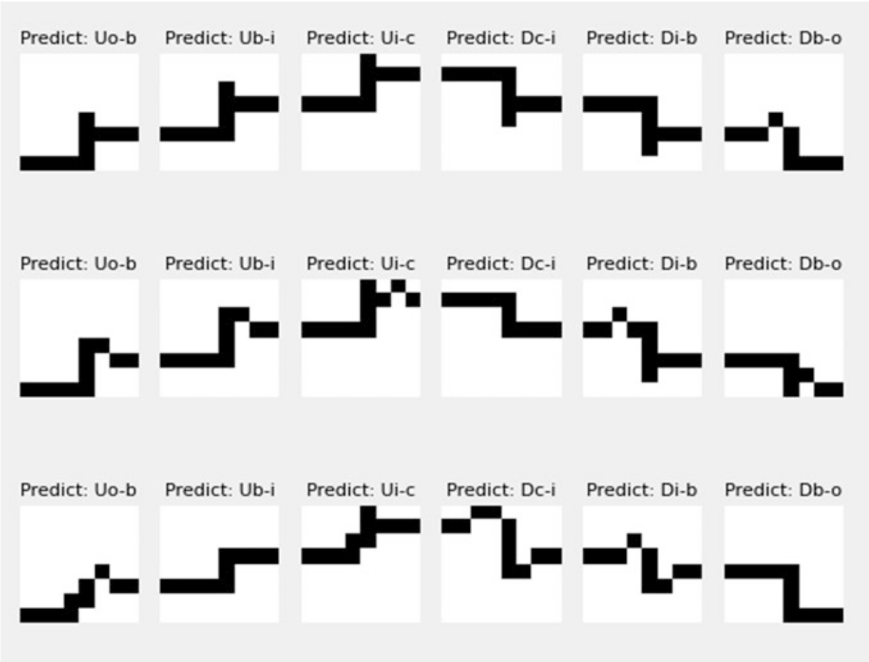
**Table 5.5** Methods and options of `sklearn.grid_search.GridSearchCV` used in this example

| Method | Description |
|---|---|
| `fit(X[, y])` | Run fit with all sets of parameters |
| `predict(*args, **kwargs)` | Call predict on the estimator with the best found parameters |
| `predict_proba(*args, **kwargs)` | Call predict_proba on the estimator with the best found parameters |




Based on model parameters for PCA and logistic regression model found through the grid search through pipelining PCA and logistic regression, it is possible to infer (predict) events from their energy power profiles. Figure 5.13 shows the results of inference on energy patterns. The inference accuracy for those patterns used for training is 100 %.

```
>>> # 4. Run a grid search on the pipeline
>>> n_components = [3, 5, 7]
>>> Cs = np.logspace(-4, 4, 3)
>>>
>>> estimator = GridSearchCV(pipe,
>>>       dict(pca__n_components=n_components,
>>>       logistic__C=Cs))
>>> estimator.fit(patterns, target)
>>>
>>> # 5. Plot the results
>>> fig_ = plt.figure()
>>> fig_.patch.set_facecolor('none')
>>> plt.figure(1, figsize=(4, 3))
>>> plt.clf()
>>> plt.axes([.2, .2, .7, .7])
>>> plt.plot(pca.explained_variance_, linewidth=2)
>>> plt.axis('tight')
>>> plt.xlabel('n_components')
>>> plt.ylabel('explained_variance_')
>>> fig = plt.gcf()
>>> fig.canvas.set_window_title('Plot the PCA s
>>> pectrum')
>>>
>>> plt.axvline(estimator.best_estimator_.
>>> named_steps['pca'].n_components,
>>>  linestyle=':', label='n_components chosen')
>>> plt.legend(prop=dict(size=12))
>>> plt.show()
>>> estimator.predict(patterns)
```




This example used four classes in Scikit-Learn machine learning library that are playing the role of a big stakeholder for training and inference energy consumption patterns. Tables 5.2, 5.3, 5.4 and 5.5 give the brief summary of those classes.

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# Chapter 6
# Ontology-Enabled Knowledge Management in Environmental Regulations and Incentive Policies

**Abstract** It is critical for global manufacturing enterprises to know and understand regional and local environmental regulations and incentive programs/polices. However, there has been little research aimed at acquiring and disseminating the knowledge of environmental regulations and incentive policies within the business decision making context, especially for the manufacturing industry sector. To address this problem, this chapter presents the Environmental Regulation and Incentive Policies Acquisition and Dissemination (ERIPAD) ontology. This ontology can enable systematic knowledge acquisition and personalized knowledge dissemination via reasoning query languages like SPARQL with its query engine, Apache Jena Fuseki. The ERIPAD ontology is currently customized for the European Union Emission Trading Scheme and the Waxman-Markey bill because of their comprehensiveness and inclusiveness. It is expected that the ERIPAD ontology will enable manufacturing companies to improve agility and efficiency in their energy or environment related decision making process.

## 6.1 Background of Energy and Environment Knowledge Management

Driven by ever increasing energy demand and concerns about climate change, countries around world have been enacting more stringent energy and environmental regulations. At the same time, they, through multiple government agencies at different levels (from central to state/city), provide various incentive programs and policies to encourage industries and consumers to use alternative energy sources and to implement new technologies that are more energy efficient and environmental friendly.

The impact of environmental regulation or legislation presents huge challenges to manufacturing enterprises. For example, if the Lieberman-Warner Climate Security Act (S. 2191) had been passed, the production costs of aluminium and steel would have been projected to increase by 2 and 4 % by 2012 and 4 and 10 % by 2023, respectively due to increased energy cost (Bassi et al. 2009). The impact

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of increases in upstream material costs due to the law would have cascaded down to mid- or downstream manufacturing industries along the supply chain.

Though these environmental and energy challenges would be difficult to face, it might be a good chance for innovative manufacturing companies to gain a competitive advantage through resolving the challenges. In other words, if a company can fully understand current and future environmental requirements and local and regional incentives, it can make right total life-cycle cost decisions on either upgrading new equipment/processes or installing on-site alternative energy generation systems. Some potential business questions in the light of these environmental and energy challenges are as follows:

- Q1: "How much is the allowance on green house gas (GHG) emissions in regional countries?"
- Q2: "How can we decide the best alternative for energy saving?"
- Q3: "Which incentives could be available in regional countries if we decide to use renewable energy?"

There are many input factors to consider for making the right decisions, including $CO_2$ cap-and-trade regulation enactment (Galitsky and Worrell 2008), carbon tax implementation, elimination of subsidies on coal and natural gas, or a sudden energy cost shock, just to name a few.

Figure 6.1 shows an environmental decision framework targeting the manufacturing industry sector. The framework has three major input decision factors ($CO_2$ emission allowance, the impact of energy cost, and $CO_2$ credit price) and

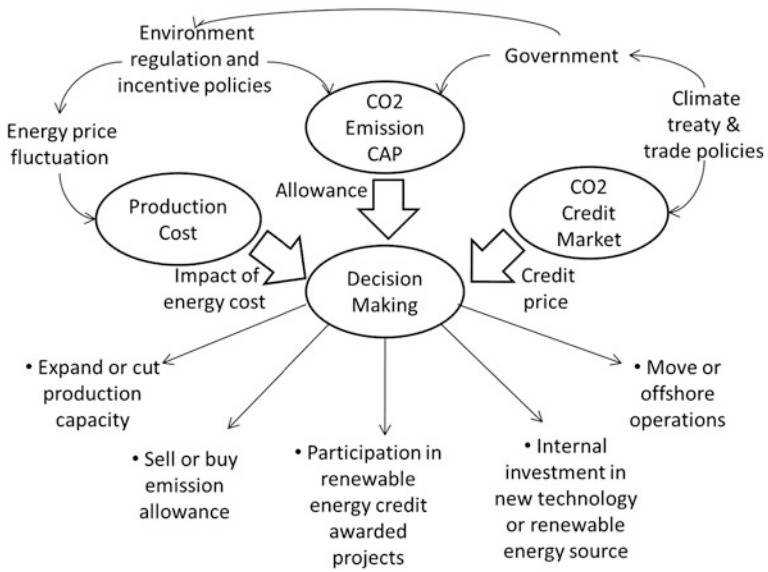


**Fig. 6.1** Environmental decision framework in manufacturing industry [revised from Bassi et al. (2009)]

diverse decision options as strategic outputs (e.g., sell or buy $CO_2$ emission allowance). However, it is immediately evident in the decision framework that the domain knowledge in environmental regulations and incentive policies should be encompassed for making right decisions. However, the knowledge artifacts from environmental regulations and incentive policies are not immediately obvious to the decision makers due to the following special characteristics:

- The legislative knowledge is usually implicit (tacit). Different from explicit knowledge, implicit knowledge is usually obtained through experience or intuition and therefore, difficult to capture or learn without expertise in the domain.
- Many of the environmental regulation and incentive policies are initiated by the regulatory agencies of the government and evolve through the various committees and amendments, primarily in response to the concerns of stakeholders. Besides this regular lifecycle, new executive orders are issued periodically or abruptly. Therefore, without the help of an appropriate knowledge lifecycle management system, tracking these different legislative artifacts and updating to the latest version would require huge human efforts with trials and errors.
- The terms and conditions of the legislative artifacts are not specialized or personalized to the pertinent industry domain. Therefore, decision makers in the manufacturing industry sector should spend considerable times and efforts on crunching the artifacts to make some sense out of them.

With the objective to address aforementioned issues related to knowledge management, ontology-enabled knowledge management systems have been built, toward facilitating the acquisition, indexing and disseminating knowledge artifacts, thereby being able to deliver the knowledge to the right decision makers at the right time in the right customized format, resulting in achieving competitive advantage and organizational efficiencies (George and Jain 2008; Chandrasekaran et al. 1999). In short, the main benefits from the use of ontology-enabled knowledge management in the domain of environmental regulations and incentive policies include:

- (Knowledge externalization) Ontology is applied to transfer implicit knowledge into explicit knowledge, thereby making it accessible to individuals who do not have preliminary experience or intuition in a targeted knowledge domain.
- (Knowledge lifecycle management) The use of ontology is ideal for managing the lifecycle of knowledge, because the ontology provides a central structure that systematically decomposes the domain knowledge into several cognitive aspects like definitions, relationships, constraints and rules and then logically reorganizes those aspects into a machine-understandable knowledge sources.
- (Knowledge personalization) The ontology-enabled knowledge management system can provide decision makers with personalized knowledge; thereby facilitate timeliness and efficiencies in the process of decision making.

This chapter proposes an ontology—Environmental Regulations and Incentive Policies Acquisition and Dissemination (ERIPAD) to enable systematic knowledge acquisition and personalized knowledge dissemination so that companies find the best answer faster from the knowledge management system when facing business questions related to environmental issue. Two influential environmental regulations, the existing EU-ETS (European Union Emission Trading Scheme) and the proposed W-M (Waxman-Markey) bill are selected to design and populate the ERIPAD ontology. For the personalized reasoning query (W3C 2010), SPARQL is used as a query language running on Apache Jena-Fuseki engine which was an extension of JOSEKI web server (HP 2009).

The use of ontology is gaining acceptance in the development of knowledge management systems. It is however still at an incipient stage to apply an ontology-enabled knowledge management system to environmental decision processes in industry sectors. George and Jain proposed the ELRAMP system (George and Jain 2008), a knowledge management system in the environmental legislative and regulatory domain to manage the informational lifecycle of the legislative process from acquisition to dissemination. However, ELRAMP is specialized to government or legislative personnel or groups, especially to the Army rather than industry users who want resulting information to be delivered in a customized manner to the requesting industry sector.

In recent developments in the area of knowledge management systems, many implementations or potentially promising cases have been reported through adopting ontology as an important bearing (Chandrasekaran et al. 1999; Fensel 2002; Antoniou and Van 2004). Though ontology can be used as a systematic conceptualization of one domain knowledge, many recent experiments have shown that global, multiple and hybrid ontologies can be integrated successfully, thereby providing composite information across systems (Uschold and Gruninger 1996; Wache et al. 2001). The integration of multiple ontologies has been an important topic in the web service composition community where diverse efficient and effective composition algorithms have been developed within the category of semantic or syntactic approach (Oh et al. 2008, 2009).

Regarding the real application of knowledge management systems to industry, there have been many high-returns-on-investment success stories. British Telecomm launched a role specific portal knowledge management system in their call center, leading to a marked increase of customer satisfaction (Davenport 2003). Hewlett Packard implemented a knowledge management system, so called, @HP with which HP has saved significant cost related to human resources (Nigama 2004).

This book chapter is organized as follows. Section 6.2 summarizes EU-ETS and the W-M bill. Section 6.3 surveys the latest technologies developed in the knowledge management community. Section 6.4 introduces the ERIPAD ontology in terms of TBox and ABox notations. Section 6.5 illustrates the process of knowledge acquisition and dissemination with the ERIPAD ontology along with a proposed $CO_2$ emission management decision process. In this example, Apache Jena Fuseki is used to process semantics queries written in SPARQL. Section 6.6 concludes this book chapter. Note that this chapter is an updated version of Oh et al. (2010).

## 6.2 EU-ETS and Waxman-Markey Bill (W-M Bill)

Although many governments or regional treaties have taken actions to enforce environmental or energy regulations (whether they are voluntary or mandatory) for last decade, it is obvious that EU-ETS (European Union Emission Trading Scheme) and Waxman-Markey(W-M) bill are considered to be very significant environmental regulations because of their comprehensiveness, inclusiveness and participation. Since the proposed ERIPAD ontology is designed and implemented based on the knowledge artifacts offered by the two regulation bills, in this section, some key concepts and structures of the two bills are discussed.

### *6.2.1 European Emission Trading Scheme (EU-ETS)*

EU-ETS is known to be the first established carbon market scheme. The aim of the EU-ETS scheme is to reduce emissions in a cost effective manner, allowing organizations to trade emission allowances and thereby determine how and where they can reduce emissions. The emission targets are 6 % reduction in $CO_2$ emission from the year of 2008 to 2012, 20 % by 2020 and 60 to 80 % reduction in 2050 compared to the emission level of the base year 1990. Organizations participating in the emission scheme are assigned $CO_2$ emission allowance or $CO_2$ emission cap which is an enforceable limit.

The allocation plan for $CO_2$ emission allowance or cap is divided into three stages such as Phase 1: 2005–2007, Phase 2: 2008–2012 and Phase 3: 2012–2020. The cap is allotted by the following steps. First, countries set the cap amount on a national basis. Second, this amount is broken into sectors participating in the emission scheme. Third, the total amount in a sector is split off to each individual company belonging to the sector.

There will be a free allocation with some limited auctioning on country-by-country basis by phase 2. From phase 3, approximately 60 % of allowances will be auctioned and the remainder will be allocated free-of-charge to the worst-affected sectors. Then, free allocation will be phased out by 2020. Individual national regulators are responsible for enforcing the regulation (Duerr 2007; Ellerman and Joskow 2008).

### *6.2.2 Waxman-Markey Bill (W-M Bill)*

In United States, the W-M Bill was proposed to implement a federal cap-and-trade scheme where the emission target in $CO_2$ emission is 3 % by 2012, 17 % by 2020, 42 % by 2030, and 83 % by 2050 relative to the 2005 base level. The proposed scheme would commence in 2012. At the beginning, approximately 80 % of the

**Table 6.1** Comparison of EU-ETS and W-M bill

| Element | EU-ETS | W-M Bill |
|---|---|---|
| Emissions target | • 6 % below 1990 levels from 2008 to 2012<br>• 20 % below 1990 levels by 2020<br>• 60–80 % below 1990 levels by 2050 | • 3 % below 2005 levels by 2012<br>• 17 % below 2005 levels by 2020<br>• 42 % below 2005 levels by 2030<br>• 83 % below 2005 levels by 2050 |
| Coverage | • 52 % of EU emissions from Phase 3<br>• Covering about 12,000 sites<br>• Covering direct downstream sources (e.g., electricity, iron and steel, cement, paper, aviation) from Phase 3<br>• Excluding transport | • 86 % of US emissions<br>• Coverage of both upstream and downstream sources (e.g., including electricity, iron and steel, cement, paper, refining, transport fuel, natural gas)<br>• Excluding aviation |
| Allocation | • Free allocation with some limited auctioning on country-by-country basis by Phase 2<br>• From Phase 3 estimate about 60 % of allowances will be auctioned and the remainder allocated gratis to worst-affected sectors<br>• Free allocation will be phased out by 2020 | • Free allocation of about 20 % of allowances to selected liable parties (i.e., trade exposed industries) declining over time and phased-out by 2035<br>• Free allocation of about 40 % of allowances to selected sectors (i.e., electricity, natural gas and oil suppliers)<br>• Free allocation of about 20 % of allowances to selected sectors to encourage development of clean technologies<br>• Remaining allowances auctioned, increasing from 18 % in initial years to about 70 % by 2030 |
| Regulation of trading | • Regulation is the responsibility of individual national regulators | • Federal Energy Regulatory Commission is responsible for regulation of cash market in allowances and offsets |

total emission allowance will be allocated free of charge to accomplish three goals; (1) To protect consumers from energy price increases, (2) To assist industry in the transition to a clean energy economy, (3) To spur energy efficiency and the development of clean energy technology. The remainder, about 20 % of emission allowance, would be auctioned. This percentage is increased gradually over time to about 70 % by 2030. The bill sets a minimum auction price of US $10 in 2012, rising at 5 % plus inflation in subsequent years. Federal Energy Regulatory Commission is accountable for introducing/amending regulations on $CO_2$ emission allowances and offsets market (Capoor and Ambrosi 2009).

The official name of W-M bill is currently the American Clean Energy and Security Act of 2009, H.R. 2454 and was passed by the US House of Representatives in June 2009, however, did not get an approval from the US Senate because the law may place US manufacturers at a significant competitive disadvantage. The US Congressional Budget Office (CBO) estimated that the bill would increase government revenues by US$ 873 billion over 2010–2019 and also increase energy costs for an average American household by US$175 a year. Nonetheless, many people believe that this bill becomes a template for future greenhouse gas related legislation. Table 6.1 summarizes EU-ETS and W-M bill and compare them from several key perspectives.

## 6.3 Technologies for Semantic Data Management

### 6.3.1 *Description Logic (DL)*

For the robust description purpose, Description Logics (DL) language was built. DL has powerful expressiveness to accommodate special relations between objects such as subsumption or equality relation, and set definitions between classes and objects, and so forth. There are two major languages branched out from DL: DAML-DL and OWL-DL. DAML-DL and OWL-DL are compatible because OWL-DL is built based on DAML-DL. Table 6.2 presents the primitives of OWL-DL along with corresponding DL terms. DL requires a reasoning service like Java-based Expert System (JESS). Similar to DAML-DL, there are reasoning engines for OWL-DL, such as RACER and Pellet. The use of DL is required to define an ontology. Ontology is comprised of two types of knowledge store: TBox and ABox. TBox (terminological box; a repository of classes) depicts the terminology, i.e. concepts, of an application domain while ABox (assertion box; a repository of instances of classes) depicts assertions about individuals and their roles (Baader et al. 2003). Assertions is a statement that a predicate (i.e., Boolean-valued function,

**Table 6.2** OWL primitives in DL terms

| DL syntax | OWL syntax | Serv. descript. lang. |
|---|---|---|
| C, D | owl:Class | Concept |
| $\top$ | owl:Thing | Thing |
| $\bot$ | owl:Nothing | Nothing |
| $(C \subseteq D)$ | owl:subClassOf | Subsumption |
| $(C \equiv D)$ | owl:sameClassAs | Equivalence |
| R, S | owl:Property | Properties |
| $(C \cap D)$ | owl:intersectionOf | Conjunction |
| $(C \cup D)$ | owl:disjunctionOf | Disjunction |
| $(\neg C)$ | owl:complementOf | Negation |
| $(\forall R.C)$ | owl:toClass | Universal role rest |
| $(\exists R.C)$ | owl:hasClass | Existential role rest |
| $R^{-}$ | owl:inverseOf | Inverse roles |
| $(R \subseteq S)$ | owl:subPropertyOf | Subsumption of roles |
| $(R \equiv S)$ | owl:samePropertyAs | Equivalence of roles |
| $\{o\}$ | XML Type + rdf:value | Nominals |
| $\exists T.\{o\}$ | owl:hasValue | Value restrictions |

a true–false expression) is expected to always be true. The following toy example illustrates the concept of TBox and ABox briefly. More details about TBox and ABox will be discussed in Sect. 6.4.1.

- **TBox: human $\subseteq$ mortal**
- **ABox: human(Aristotle)**

$\rightarrow$ Reasoning: "Aristotle is mortal"

### 6.3.2 Semantic Data Model: RDF

Resource Description Framework (RDF) is first defined by W3C (2004). RDF is originally made with an aim to describe resources that are identifiable by Uniform Resource Identifiers (URIs). RDF is based on the triplet model: subject-property-object, where these triplets together form a graph that serves for the representation of data, information and knowledge in a machine-understandable way. Primarily, RDF aims to provide a data model that supports fast integration of data sources by bridging semantic differences. Therefore, RDF has been used for describing heterogeneous business partners' proprietary document schemas (or knowledge domain) and is translated through the logic programming technique (Oh and Yee 2008). RDF provides many useful features. For example, RDF has three types of containers that can represent collections of resources or literals such as (1) rdf:Bags for unordered lists; (2) rdf:Sequences for ordered lists; (3) rdf:Alternatives to represent lists from which the property can use only one value.

### 6.3.3 Semantic Data Query: SPARQL

SPARQL was proposed to query or update RDF data. The prime objective of SPARQL is to provide a formal language to ask semnatic-driven questions. As SQL is used to query the tables of a relational database, the triples of RDF data are queried using SPARQL. Similar to SQL, SPARQL uses a SELECT statement to determine which subset of the selected data is returned. Inside the SELECT statement, SPARQL uses a WHERE clause to define graph patterns to find a match for the query. A graph pattern in a SPARQL WHERE clause consists of the subject, predicate and object triple to find a match for in the data.

Beside the basic SELECT-WHERE form of SPARQL, it is possible to update RDF files with SPARQL. In most circumstances, however, organizations publishing data in a query-able format may not want anyone to be able to write or make changes to their (valuable) data. For realizing or regulating RDF data query or update, a SPARQL engine is required and this study uses Apache Jena Fuseki that is discussed in Sect. 6.5.

## 6.4 ERIPAD Ontology

ERIPAD ontology is customized to suit the knowledge artifacts in the aforementioned EU-ETS and W-M bill. This ontology is comprised of two types of knowledge store: TBox and ABox as introduced in Sect. 6.3.

### *6.4.1 TBox and ABox*

In terms of description logic (Baader et al. 2003), atomic concepts and roles contained in TBox can be represented. For instance, the concept “EU-ETS” and “Waxman-Markey” can be described as below:

$$\textbf{Environmental Regulation} \sqsubseteq \textbf{EU-ETS} \sqcup \textbf{Waxman-Markey}$$
$$\textbf{EU-ETS} \cap \textbf{Waxman-Markey} \equiv \perp$$

$$\textbf{EU-ETS} \equiv \textbf{Environmental Regulation} \cap \exists\textbf{hasCountry.Country}$$

$$\textbf{Waxman-Markey} \equiv \textbf{Environmental Regulation} \cap \exists\textbf{hasCountry.Country}$$

Likewise, “Germany” and “Country$CO_2$ReductionPlan” concepts can be defined as follows:

$$\textbf{Germany} \sqsubseteq \textbf{Country} \cap \exists\textbf{hasCO}_2\textbf{ReductionPlan.CountryCO}_2\textbf{ReductionPlan} \cap \exists\textbf{hasSector.Sector} \cap \forall\textbf{hasCountry}^{-}\textbf{.EU-ETS}$$

$$\textbf{CountryCO}_2\textbf{ReductionPlan} \equiv \forall\textbf{hasType.Bag} \cap \exists\textbf{hasMember.Phase} \cap \exists\textbf{hasMember.CO}_2\textbf{CapAmount}$$

In Figs. 6.2 and 6.3, TBoxs in ERIPAD are depicted in a white-shaded oval while ABoxs are depicted with a gray-shaded oval. For instance, “Phase1 (2005–2008)” and “453.10” are individual names thus can be described as follows:

$$\textbf{Phase}(\textbf{Phase1}\ (\textbf{2005}-\textbf{2008}))$$
$$\textbf{CO}_2\textbf{CapAmount}(\textbf{453.10})$$

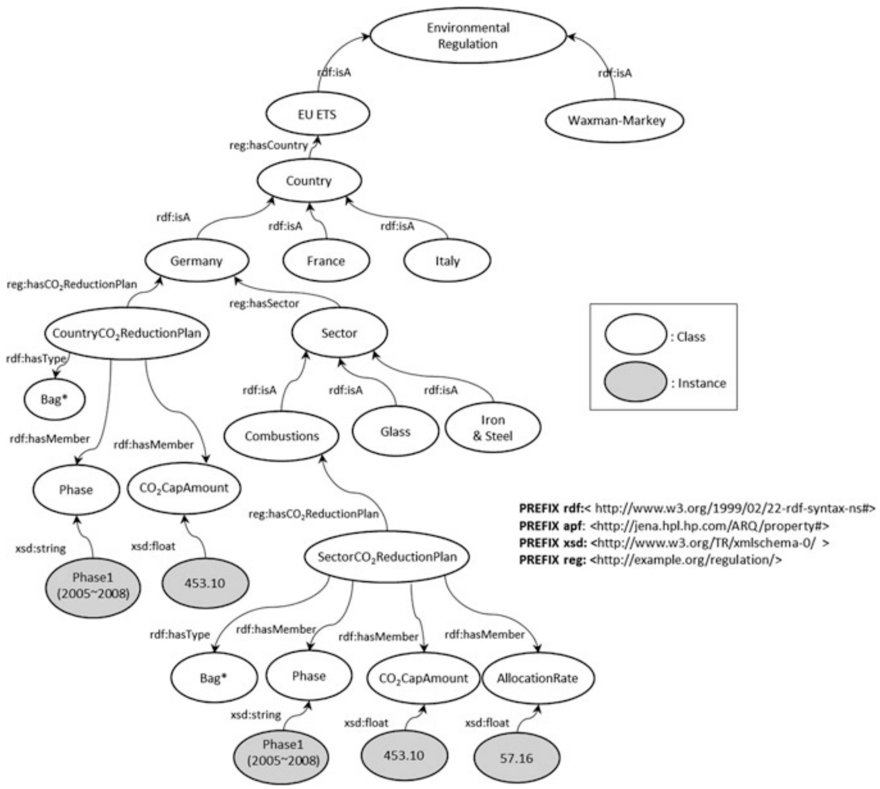


**Fig. 6.2** EU-ETS part of ERIPAD ontology

Due to the lack of space, Figs. 6.2 and 6.3 only shows partial TBox and ABox. Note that in the figure, Bag* refers to a type of container in rdfs, i.e. rdfs:member. This notation is used to represent a group of things that does not necessarily need to be in an ascending or descending order. In ERIPAD Ontology, rdfs:member is used to group each specific $CO_2$ reduction plan.

### *6.4.2 Knowledge Acquisition and Dissemination in ERIPAD*

This section illustrates how the lifecycle of knowledge on environment regulations and incentive policies can be managed from acquisition to dissemination, by leveraging on both aforementioned ERIPAD ontology and semantic reasoning query language, SPARQL.

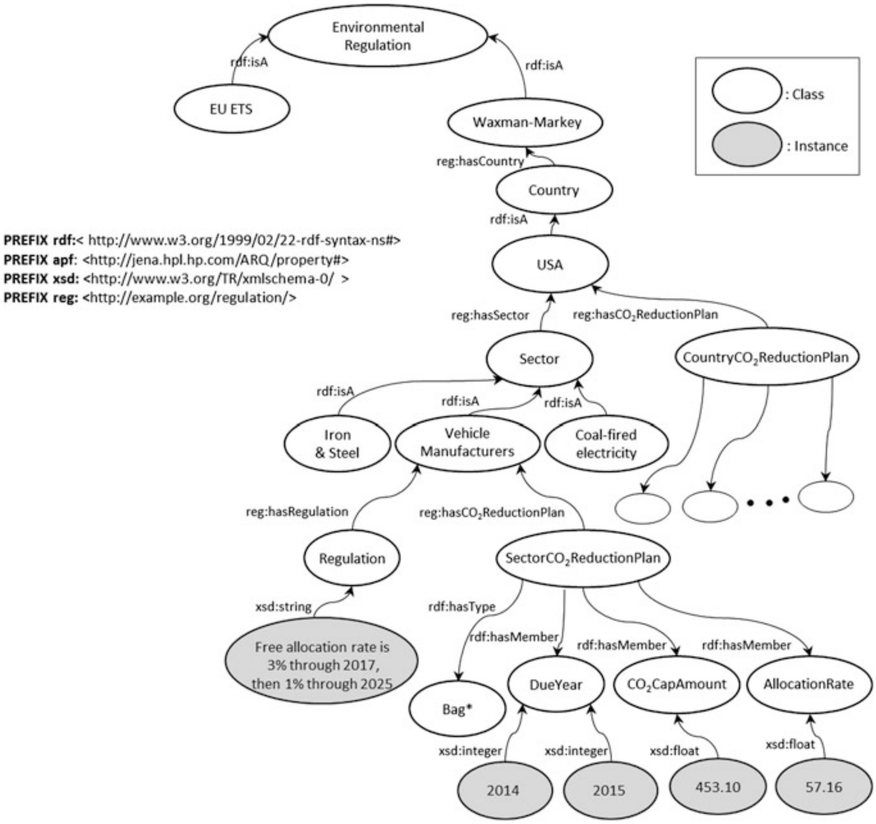


**Fig. 6.3** Waxman-Markey part of ERIPAD ontology

The acquisition process begins with gathering raw data and knowledge from numerous sources of environmental regulations in order to build the ontology database using concepts defined in ERIPAD ontology. Note that raw data and knowledge sources are written in text verbatim for use to human readers as shown in Fig. 6.4, where a sample of environmental regulation is described.

Since machines cannot read or understand the text verbatim directly, it is required to annotate keywords in the text verbatim with pertinent concepts defined in ERIPAD ontology, thereby being able to convert the human-readable verbatim into machine-readable data. In this study, RDF is used for a general data model for

**As-Is (Human-readable only)**

- The EU member countries have devised a scheme for greenhouse gas emission allowance trading, effective from the start of 2005. It is named European Emission Trading Scheme (EU-ETS).
- This commitment means that on average for the period 2008-2012, EU member states emit 8% less $CO_2$ than in 1990.
- Germany has ratified the EU directive on greenhouse gas emission allowance trading and make it into actual law.
- Germany has pledged to reduce its total $CO_2$ emissions by 453.1 tons compared with the 1990 level.
- Target is reducing emissions 6% below 1990 levels over 2008-2012, 20% below 1990 levels by 2020, if a new agreement, Post-2012 is achieved.

**Fig. 6.4** Sample regulation verbatim

machines; representing any data to be structured with 3 elements so as to form a triple—subject, predicate, and object. Figure 6.5 shows how each keyword from Fig. 6.4 was drawn to form properties and objects of RDF triple by the annotation process. The resultant RDF triple set is shown in Table 6.3.

The core of dissemination process is done by using SPARQL. SPARQL is a standard RDF query language and many SPARQL-compliant servers are available in public, providing capabilities of sending queries and receiving results through HTTP. The example of SPARQL reasoning query is shown in Fig. 6.6 where "SELECT" part indicates variables that are expected to be bound (e.g., how much $CO_2$ cap amount is set for the given country under the given regulation type and phase). The remaining parts of the query denote constraints and filtering options. Subject ?x has properties of country and $CO_2$ reduction plan. Moreover, $CO_2$ reduction plan has a set (i.e. rdfs:member) of information, phase and $CO_2$ cap amount. Also among candidate answers, it is possible to filter out information that has sector property and country that is not applied to Germany. Note that the expected answer to this query is shown in Fig. 6.8. More detail regarding how to make queries in SPARQL is described in the next section.

**To-Be (Machine -readable only)**

- The EU member countries have devised a scheme for greenhouse gas emission allowance trading, effective from the start of 2005. It is named **European Emission Trading Scheme (EU-ETS)**.

  [Annotation]

  **European Emission Trading Scheme (EU-ETS) → "Regulation type"**

- This commitment means that on average for **the period 2008-2012**, EU member states emit 8% less $CO_2$ than in 1990.

  [Annotation]

  **the period 2008-2012 → "Phase"**

- **Germany** has ratified the EU directive on greenhouse gas emission allowance trading and make it into actual law.

  [Annotation]

  **Germany → "Country"**

- Germany has pledged to reduce its total $CO_2$ emissions by **453.1 tons** compared with the 1990 level.

  [Annotation]

  **453.1 tons → "$CO_2$CapAmount"**

- **Target is reducing emissions 6% below 1990 levels over 2008-2012, 20% below 1990 levels by 2020, if a new agreement, Post-2012 is achieved**.

  [Annotation]

  The whole sentence is annotated by → **"Regulation"**

**Fig. 6.5** Annotated sample regulation

**Table 6.3** Resultant RDF triples

| Subject | Predicate | Object |
|---|---|---|
| Regulation A | Name | "EU-ETS"^^xsd:string |
| Regulation A | Country | "Germany"^^xsd:string |
| Standard A | $CO_2$CapAmount | "453.1"^^xsd:float |
| Standard A | Regulation | "6 % below 1990 levels over 2008–2012, 20 % below 1990 levels by 2020, if a new agreement, Post-2012 is achieved"^^xsd:string |
| Window A | DueYear | "2005–2008"^^xsd:string |

```
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX reg: <http://example.org/regulation/>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
SELECT ?RegulationType ?country ?sector ?Phase ?CO2CapAmount
{
?x reg:RegulationType ?RegulationType.
?x reg:country ?country.
?x reg:CO2ReductionPlan ?bag.
?bag rdfs:member ?member.
?member reg:Phase ?Phase.
?member reg:CO2CapAmount ?CO2CapAmount.
?x reg:sector ?sector
Filter (?country ="Germany" && regex(?sector, "Comb"))
}
```

**Fig. 6.6** SPARQL reasoning query example

## 6.5 Illustrative Example of Knowledge Management with ERIPAD

### *6.5.1 Semantic Queries with Apache Jena Fuseki*

Fuseki is part of the Apache Jena project and can be run in three ways such as a standalone server or a Web Application inside a container such as Apache Tomcat or Jetty or a service run by the operation system, for example, started when the machine boots. When it is distributed as a separate package, Fuseki is an HTTP server with all the Jena modules embedded inside. Current version of Fuseki allows SPARQL 1.1 queries and updates to a targeted end point using simple HTTP requests and get responses in various formats (JSON, XML, CSV, or a table format). Fuseki provides different configuration options including RDF file storage in memory or in a TDB file. Figure 6.7 shows how to input a SPARQL query in Fuseki.

### *6.5.2 $CO_2$ Emission Management Decision Process with ERIPAD*

ERIPAD is more useful for a $CO_2$ emitting company in the case that the company distributes their manufacturing facilities globally because ERIPAD is capable of helping identify each installation's $CO_2$ cap information by nation, sector, and activity. At the end, the $CO_2$ emitting company may lead to a final decision to invest in alternative solutions for reducing $CO_2$ emission (Galitsky and Worrell 2008)—for example, the use of renewable energy sources such as wind, carbon

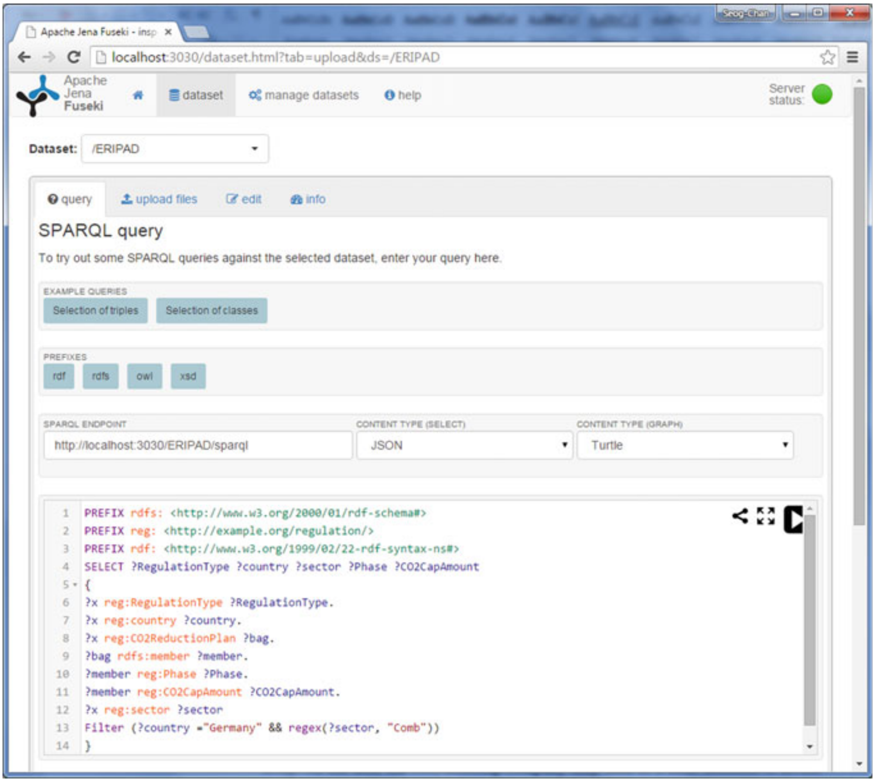


**Fig. 6.7** SPARQL query input in Fuseki

sequestration technology, new pipelines building for compressed air leakage reduction, and other energy saving technologies.

Once users identify their $CO_2$ cap information, the remainder is quite straightforward. The users proceed to find a best decision for their $CO_2$ emission by considering cap-and-trade scheme of carbon market (Dowdey 2010). Any $CO_2$ emitting company should solve the difference between allocated $CO_2$ cap and their verified $CO_2$ emission through either selling the surplus of the $CO_2$ emission allowance at the $CO_2$ credit market ("Allowance" $\geq$0); or buying the lack of the $CO_2$ allowance at the market ("Allowance" <0); or taking a decision to invest in renewable energy sources or energy saving projects ("Return" $\geq$0) as in Fig. 6.9. Many good environment tools may work with ERIPAD in the decision process proposed in Fig. 6.9. Among them, for example, RETScreen (Leng 2010) is a well-established tool as it can help evaluating the economic feasibility of renewable energy sources, calculating the $CO_2$ reduction amount and expected investment cost of renewable energy sources.

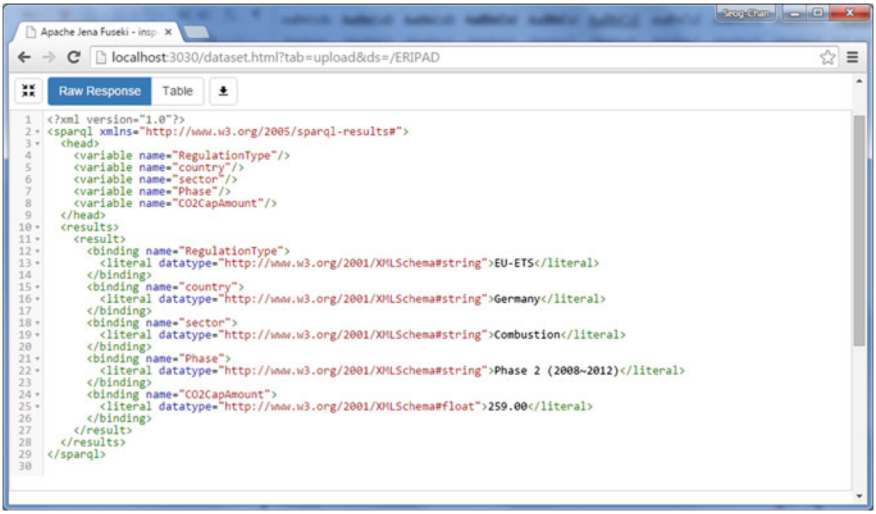


**Fig. 6.8** SPARQL query result in XML in Fuseki

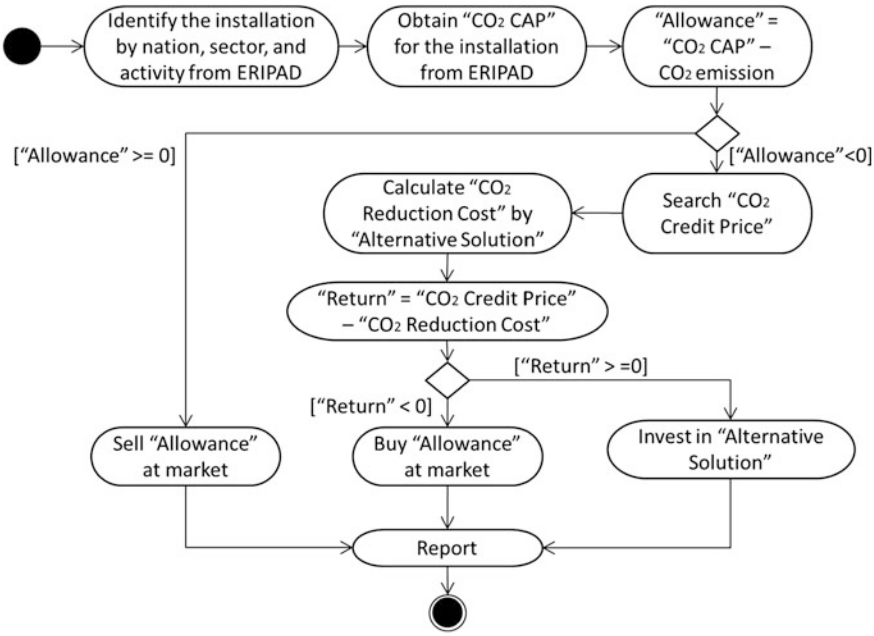


**Fig. 6.9** $CO_2$ emission management decision process with ERIPAD

## 6.6 Summary

This chapter introduced a system called ERIPAD, a knowledge management ontology that is defined specific to the two marked environmental regulatory schemes: EU-ETS and the W-M bill. Based on the ontology, ERIPAD allows a personalized semantic query capability by means of SPARQL and web-based interfaces. At the end, ERIPAD improves agility and efficiency in the process of decision making for industry users who have to consider energy and environmental regulations and incentive policies pertaining to their sectors.

Although there are many ways to extend this work, it is considerable to combine it with a mathematical model for multi-period optimization of new technology investment in energy and environment. In addition, it would be useful to develop an intelligent Web crawler in order to automate the time- and labor-consuming tasks of knowledge acquisition. The developed crawler may contribute to populate ERIPAD database by gathering environmental regulations and incentive policies of different counties.

## 6.7 Exercises

1. Section 6.3 describes Description Logic (DL). Investigate the following DL examples and answer the questions:
   - Example 1: Consider the following statements and answer if $\mathbf{C} \subseteq \mathbf{D}$ is consistent

$$\mathbf{C} \equiv \mathbf{Person} \cap \mathbf{Parent} \cap \mathbf{hasChild}.(\mathbf{Janitor} \cap \mathbf{Doctor} \cap \mathbf{Politician})$$
$$\mathbf{D} \equiv \forall \mathbf{hasChild}.\mathbf{Janitor} \cap \mathbf{Person} \cap \forall \mathbf{hasChild}.\mathbf{Politician}$$

   - Example 2: Consider the following statements and answer if $\mathbf{CrazyCow} \equiv \mathbf{Cow} \cap \exists \mathbf{eats}.\neg \mathbf{Horse}$ is consistent

$$\mathbf{Cow} \equiv \mathbf{Animal} \cap \mathbf{Vegetarian}$$
$$\mathbf{Horse} \subseteq \mathbf{Animal}$$
$$\mathbf{Vegetarian} \equiv \exists \mathbf{eats}.\neg \mathbf{Animal}$$

2. As Sect. 6.3 mentioned, one of useful features provided by RDF is data containerization. Following is an example of rdf:Bag to list the member of EU-ETS. Besides rdf:Bag, RDF also provides rdf:Sequence and rdf:Alternative for handling special types of data collection. Find the use cases of rdf:Sequence and rdf: Alternative in your energy and environment management process. Figure 6.10 illustrates an example of using rdf:Bag.

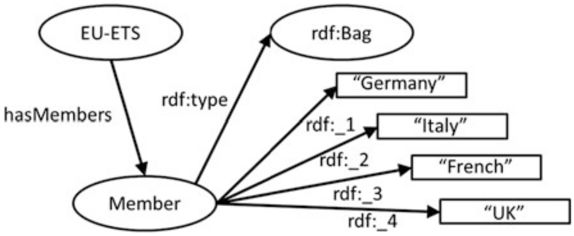


**Fig. 6.10** Example use case of rdf:Bag

3. GREETTM (Greenhouse gases, Regulated Emissions, and Energy use in Transportation) model suite (Argonne National Laboratory) has been modified and expanded with inputs from industrial experts. GREETTM has been used to carry out life-cycle analyses (LCAs) of energy use and greenhouse gas (GHG) emissions for light-duty vehicles. The GREET1 model calculates the energy use and emissions associated with the life of fuel while the GREET2 model calculates the energy use and emissions associated with the life of vehicle. Try to identify regulations associated with each stage of life cycle and build an ontology by following the steps specified in this book chapter. Figure 6.11 shows a combined view of fuel cycle and vehicle cycle activities from the cradle-to-grave analysis perspective.
4. For the energy or environment project you worked or are working, try to explain the potential impact of using ontology technologies and make a business case as detailed as possible.

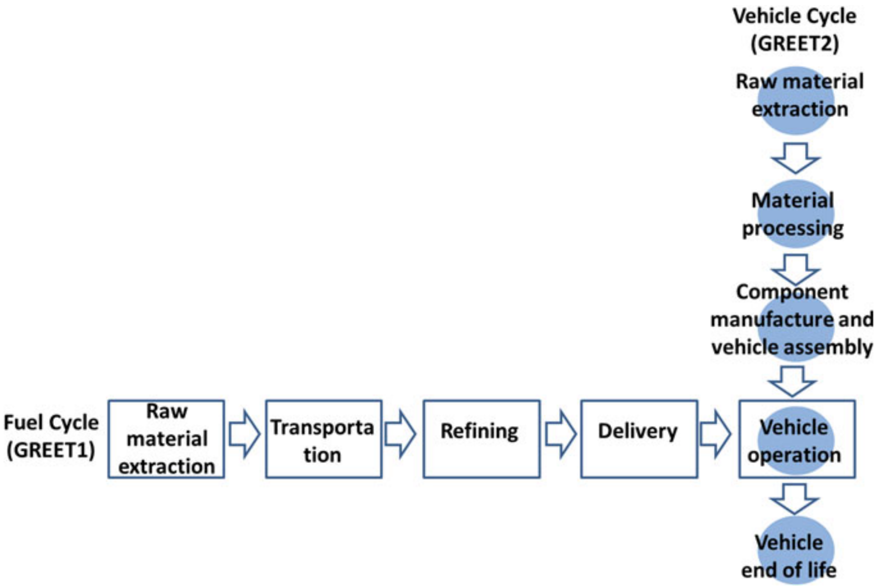


**Fig. 6.11** Combined fuel cycle and vehicle cycle activities included in cradle-to-grave (C2G) analysis

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# Chapter 7
# Energy Simulation Using EnergyPlus™ for Building and Process Energy Balance

**Abstract** Recently, the importance of balancing building and process energy in manufacturing is growing because both comfortable working environment and energy efficiency have emerged as important element for advancing the manufacturing system. One way of achieving the balance is to optimize the operation of HVAC system (Heating, Ventilating and Air Conditioning System) in such a way that temperatures and states of heating and cooling are optimized. In this chapter, plant energy simulation models are developed by customizing EnergyPlus™ (below written as EnergyPlus) and two new HVAC control approaches such as air conditioning economizer and dynamic mist control are evaluated with the developed energy models. The simulation results reveal that (1) the use of air conditioning economizer can save 8.4 % yearly cooling energy compared to the business-as-usual case without compromising the working quality for a selected example location; (2) the application of dynamic mist control system can save significant cooling and heating energy for machining plants in three selected example locations, at the same time, keeping worker health protection foremost. This chapter also provides a short instruction to EnergyPlus. EnergyPlus was originally developed as a public domain software package to estimate energy consumptions of a building complex. Therefore, its applications are limited to commercial buildings, not industrial facilities. In order to use it for manufacturing facilities, its expansion is required. With an example of a room with welding equipment, the instruction provides step by step guidance toward understanding the details of manufacturing process simulation.

## 7.1 Background of Energy Simulation and EnergyPlus

A need to develop an energy simulation model as part of decision support tool with high fidelity grows for right energy and environment investments. The energy decision support tool can help make rapid and accurate decisions related to energy saving investment. Energy simulation models are also built to ensure comfortable working environment for workers.

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Springer Series in Advanced Manufacturing, DOI 10.1007/978-3-319-32729-7_7


**Fig. 7.1** Plant building and manufacturing process energy balance

Recently, the importance of balancing building and process energy in manufacturing is growing because both comfortable working environment and energy efficiencyhave emerged as important element for advancing the manufacturing system. One way of achieving the balance is to optimize the operation of HVACsystem (Heating, Ventilating and Air Conditioning System) in such a way that temperatures and states of heating and cooling are optimized. Figure 7.1 illustrates the plant building and manufacturing process energy balance.

EnergyPlus is an official energy analysis and thermal load simulation program developed by the U.S. Department of Energy (Released April 2001). It is a software which models heating, cooling, lighting, ventilating, and other energy flows as well as water in buildings. It has its roots in both the BLAST and DOE-2 programs. BLAST (Building Loads Analysis and System Thermodynamics) and DOE-2 were both developed and released in the late 1970s and early 1980s as energy load simulation tools. Their intended users include design engineers, architects who wishes to optimize the size of HVAC equipment. They were used for evaluating retrofitting projects. They were born out of concerns driven by the energy crisis of the early 1970s and recognition that building energy consumption is a major component of the US energy usage statistics. However, the two programs attempted to solve the same problems from two slightly different perspective.

Similar to its parent programs, EnergyPlus is an energy analysis and thermal load simulation program allowing high fidelity modelling of building energy requirements and waste. Based on a user's description of a building, it can calculate the heating and cooling loads necessary to maintain thermal control setpoints, conditions throughout a secondary HVAC system and coil loads and the energy consumption of primary plant equipment as well as many other simulation details that are necessary to ensure that the simulation performs as the actual building would.

The primary advantage of the package is that it has a plenty of built-in database (e.g., construction material, world-wide weather data and etc.). Along with the built-in database, its flexible architecture allows the modification of internal modules or the addition of new modules with easy. Various outputs are generated EnergyPlus for deep energy use analysis—energy consumption of equipment energy loss or gain due to the ventilation type and other useful results (e.g. humidity

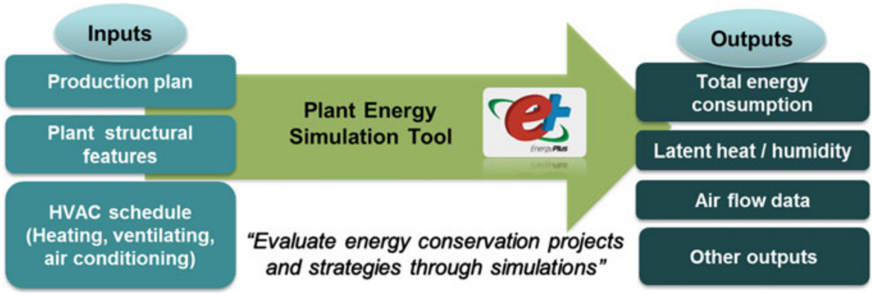



**Fig. 7.2** Plant energy simulation via customizing EnergyPlus

rate, carbon equivalent pollution from $CO_2$, Enthalpy). However, there is a hard limitation of EnergyPlus—it is designed primarily for commercial buildings. For industrial plants, the user customization must be required, for example, the implementation of manufacturing processes for vehicle assembly plants—for details about the features of manufacturing processes for vehicle assembly plants, see the previous studies (Oh et al. 2011; Oh and Hildreth 2013, 2014).

The chapter aims to show the way of customizing EnergyPlus to develop an energy decision support tool with which it is possible to simulate energy consumption and latent heat gain or loss of plants under various scenarios, e.g., weather, job schedule, manufacturing process, and etc. As described in Fig. 7.2, a plant energy simulation tool can be made from customizing EnergyPlus in such a way to generate outputs given inputs.

Although this chapter is focused on EnergyPlus, it should be noted that there are many energy analysis models with potentials to be used in the manufacturing industry. Those models are summarized in Table 7.1.

This chapter is organized as follows. Section 7.2 illustrates the process of building an energy simulation model and analysis for the assessment of the use of air conditioning economizer. The economizer is a ventilation-based air flow control to keep thermal comfort (20–26 °C) without running heater or air conditioner. Section 7.3 illustrates the process of building an energy simulation model with assessment for the use of a mist collection system with different ventilation strategies. A mist collection system is a kind of air cleaning technology that is designed to exhaust or recirculate process air contaminated by metal removal fluids. In the section, a noble idea of dynamic mist control system is introduced. Section 7.5 concludes this book chapter. The appendix provides a short instruction to EnergyPlus with an example of a room with welding equipment. The instruction provides step by step guidance toward understanding the details of manufacturing process simulation.

**Table 7.1** Existing industry energy models

| Models | Purpose | Advantages | Limits |
|---|---|---|---|
| HOMER | • Model to compare both off/on grid systems | • Optimization and sensitivity modules help evaluate technical uncertainty<br>• Wide range of renewable power sources<br>• Includes demand model; input demand load over specified time series | • Unable to vary specific source issues/parameters (e.g., Solar shading/intensity)<br>• No PV array comparison<br>• Only basic financial parameters in the system cost<br>• Limit on forecast variability (e.g., commodity prices) |
| RETScreen | • Simplifies preliminary project evaluation<br>• Enable standardized comparisons | • Only basic inputs required<br>• Comprehensive parameters (technical, cost, environmental)<br>• Integrated databases<br>• Weather (monthly solar irradiance)<br>• Product data | • Unable to alter built-in data<br>• No demand profile mapping<br>• Not able to optimize around specific parameters |
| Solar advisor module | • Compare performance characteristics for various solar systems | • Significant control over technical data and parameters<br>• In-depth financial metrics (financing, tax credits, production credits) | • Fixed cost data<br>• Out-of-date |
| PVWatts | • Basic solar PV calculator<br>• Given meteorological data, models PV performance | • Estimates renewable energy production<br>• Annual cost savings | • Unable to shift PV system specifications<br>• Does not map to demand profile<br>• No optimization around set parameters |

## 7.2 Illustrative Example 1: Assessment of the Use of Air Conditioning Economizer

This section illustrates the process of building an energy simulation model for air conditioning economizer. The simulation results tells that the use of air conditioning economizer can save 8.4 % yearly cooling energy compared to the business-as-usual case without compromising the working.

### 7.2.1 *What Is an Air Conditioning Economizer?*

"Economizer Control" is, in general, defined a ventilation-based air flow control to keep thermal comfort (20–26 °C) without running heater or air conditioner. As part of the HVACcontrol system, an economizer is designed to save energy, typically reducing overall cooling energy consumption by pulling cooler outside air into buildings, reducing the load on the mechanical cooling system.

Regarding the operation mechanism of economizer, when the economizer logic controller decides the outside-air temperature is low enough to take some or all of the cooling load, the outside-air damper opens and the air conditioning compressors are turned off. During the period, exhaust fans always run when the economizer operates, because for the economizer to work effectively, the same amount of air should be exhausted from the building as is taken in. On the other hands, when the outdoor air temperature rises too high to provide useful cooling, the outside-air damper moves to its minimum position, maintaining minimum ventilation. Then the exhaust fans are closed and the compressors take over the cooling process. When properly specified and installed, economizers provide significant cooling energy savings, but require smart control to ensure optimal performance. Figure 7.3 explains how the intake air flow changes by temperature when air conditioning economizer operates.

### 7.2.2 *Modelling and Simulation with EnergyPlus*

EnergyPlus provides a text-based editor so called IDF editor to allow users to specify the simulation configuration. Using IDF editor, the following configuration

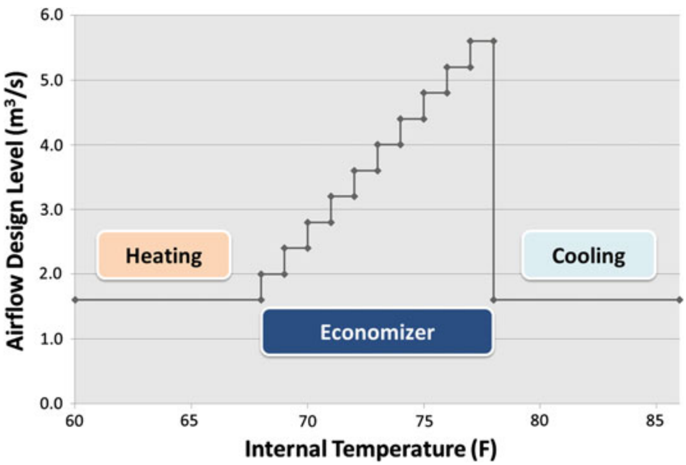



**Fig. 7.3** Intake air flow change by temperature in air conditioning economizer

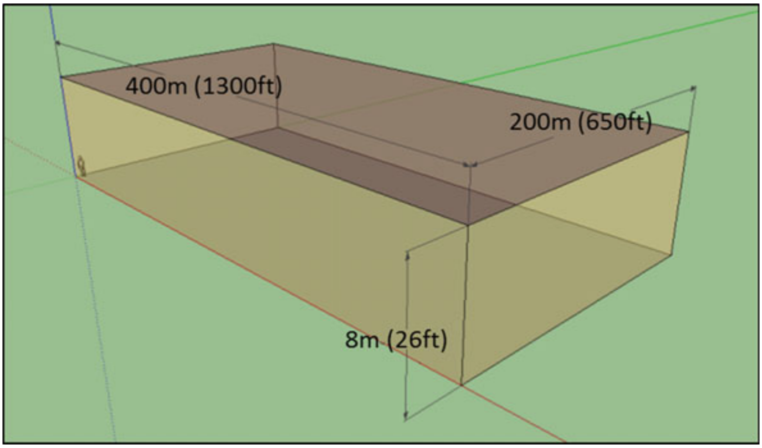



**Fig. 7.4** Machining plant in a rectangular single storey building in the example

information are fed into EnergyPlus. For details about step-by-step procedures to use EnergyPlus, see Appendix: "Getting Started with EnergyPlus for Manufacturing Process Simulation".

1. Plant building
   - Rectangular single storey building
   - Single zone with no interior partitions
   - No window
   - Approximately 80,000 $m^2$ (200 m × 400 m; 1300 ft × 650 ft) (See Fig. 7.4)
2. Weather location
   - Flint, MI, USA
3. Exterior material layers
   - (Layer 1) Metal surface
   - (Layer 2) 50 mm insulation board
   - (Layer 3) Air space resistance
   - (Layer 4) Metal surface
4. Internal load (see Table 7.2 for details)
   - People, light, machining centre

**Table 7.2** Internal loads in the example

| Load item | Object name in EnergyPlus | Design level |
|---|---|---|
| People | Workers | 10 persons |
| Lights | Zone1 lights | 3.6 kW |
| Machining | Machining tool | 85.0 kW |

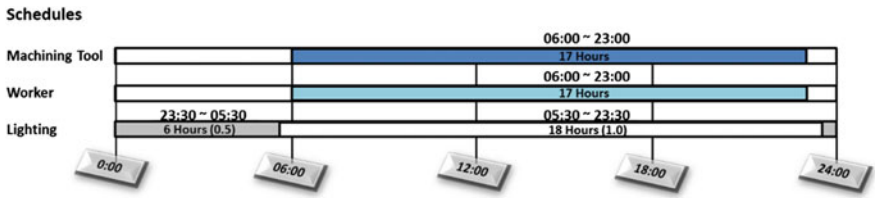



**Fig. 7.5** Load schedule in the example

5. Load schedule (see Fig. 7.5 for details)
   - Based on 2 shift schedule: from 6:00 a.m. to 2:30 p.m. and from 2:30 p.m. to 11:00 p.m.
   - Machining tool and worker schedule follows shift schedules
   - Lights are always on (but half of them are off during the non-operation time)
6. Infiltration and Ventilation (see Table 7.3 for details)
   - Infiltration—12.5 % of minimum intake volume
   - Intake—Heating(1), Economizer(10), Cooling(1)
   - Exhaust—Heating(1), Economizer(10), Cooling(1).

### *7.2.3 Analysis Results*

Figures 7.6 and 7.7 show the energy consumption profile for the business-as-usual case and for the economizer-enabled case, respectively. Simulation results reveals that the use of economizer control can save 8.4 % per year in cooling energy (i.e., $52 \times 10^9$ J) compared to the normal ventilation case (i.e., $57 \times 10^9$ J) in the weather case of Flint, MI, USA. This result implies that plants located in Flint, MI, USA should consider the installation of a ventilation system to implement economizer control as an energy cost saving strategies.

**Table 7.3** Infiltration and ventilation profile for operating the air conditioning economizer

| Item | Heating | Cooling | | | |
|---|---|---|---|---|---|
| Intake design flow rate ($m^3/s$) | 1.6 | 1.6 | | | |
| Exhaust design flow rate ($m^3/s$) | 1.8 | 1.8 | | | |
| Minimum indoor temperature (F) | 50 | 78 | | | |
| Maximum indoor temperature (F) | 68 | 95 | | | |
| Item | Economizer 1 | Economizer 2 | Economizer 3 | Economizer 4 | Economizer 5 |
| Intake design flow rate ($m^3/s$) | 2.0 | 2.4 | 2.8 | 3.2 | 3.6 |
| Exhaust design flow rate ($m^3/s$) | 2.2 | 2.6 | 3.0 | 3.4 | 3.8 |
| Minimum indoor temperature (F) | 68 | 69 | 70 | 71 | 72 |
| Maximum indoor temperature (F) | 69 | 70 | 71 | 72 | 73 |
| Item | Economizer 6 | Economizer 7 | Economizer 8 | Economizer 9 | Economizer 10 |
| Intake design flow rate ($m^3/s$) | 4.0 | 4.4 | 4.8 | 5.2 | 5.6 |
| Exhaust design flow rate ($m^3/s$) | 4.2 | 4.6 | 5.0 | 5.4 | 5.8 |
| Minimum indoor temperature (F) | 73 | 74 | 75 | 76 | 77 |
| Maximum indoor temperature (F) | 74 | 75 | 76 | 77 | 78 |

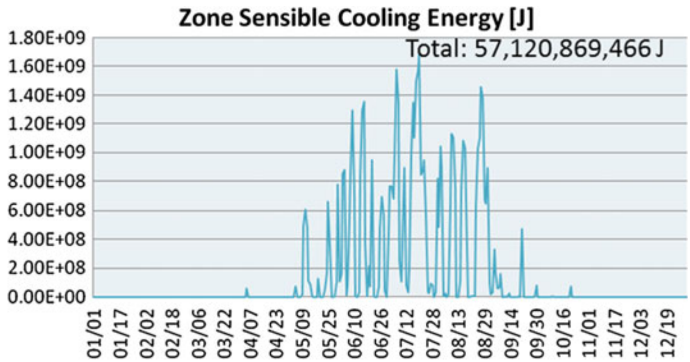



**Fig. 7.6** Business-as-usual cooling energy usage distribution

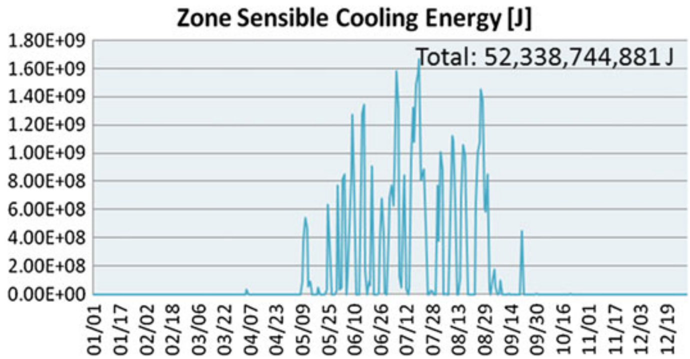



**Fig. 7.7** Economizer-enabled cooling energy usage distribution

## 7.3 Illustrative Example 2: Assessment of the Use of a Mist Collection System with Different Ventilation Strategies

This section illustrates the process of building an energy simulation model for mist collection system with different ventilation strategies. The simulation results tells that the application of dynamic mist control system can save significant cooling and heating energy for machining plants in three selected example locations keeping worker health protection foremost.

### *7.3.1 What Is a Mist Collection System?*

In the machining process like grinding or cutting, the use of metal removal fluids is critical. The metal removal fluids serves functions including lubrication, cooling,

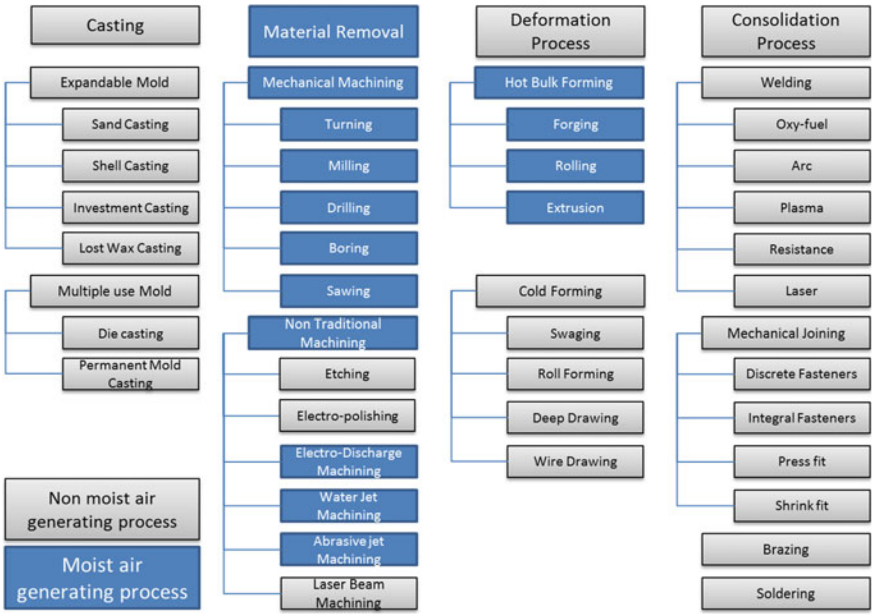



**Fig. 7.8** Moist air generation in manufacturing processes

chip removal and delivery. In addition, metal removal fluids may provide corrosion protection for the newly machined surface of the part being produced. All of these functions have an impact on the process, from tool life and power consumption, to part quality and operability (Khan et al. 2005).

However, the use of metal removal fluids increases adverse health effects when workers are exposed to moist (mist) made out of these fluids during machining process. These adverse health effects include skin diseases, acute respiratory illness, and potentially cancers. Figure 7.8 shows moist air generating manufacturing processes.

A mist collection system is a kind of air cleaning technology that is designed to exhaust or recirculate process air contaminated by metal removal fluids. The mist collection system has become one of machine ventilation requirements. The problem is that most of manufacturing facilities do not optimize energy and environmental requirements of plant buildings to support specific manufacturing processes resulting in excessive costs for mist collection. Those facilities should optimize HVAC and process ventilation to reduce energy, waste, and new system capital while maintaining worker health protections. In summary, there are three manifest constraints for mist collection system as follows:

- Sufficient containment and ventilation of processes to protect workers.
- Minimum outside air during heating and cooling.

- Exhaust of process air when enthalpy inside air > enthalpy outside air (primarily latent) so that the energy is saved.

In order to meet the aforementioned constraints, three options to the control logic are available once the mist is purified through the mist collection system as follows:

- Exhausting the mist directly to outdoor—appropriate when inside temperature or humidity is high as shown in Fig. 7.9.
- Re-circulating the mist inside—appropriate when inside temperature or humidity is low as shown in Fig. 7.10.

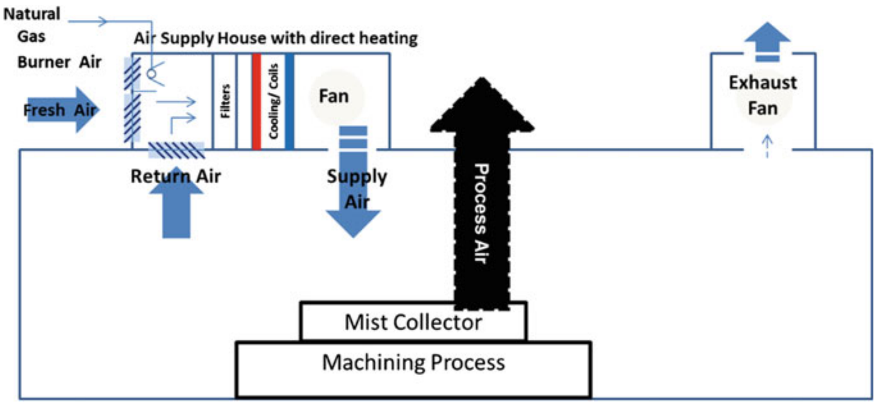



**Fig. 7.9** Schematic of air exhausting option in mist control

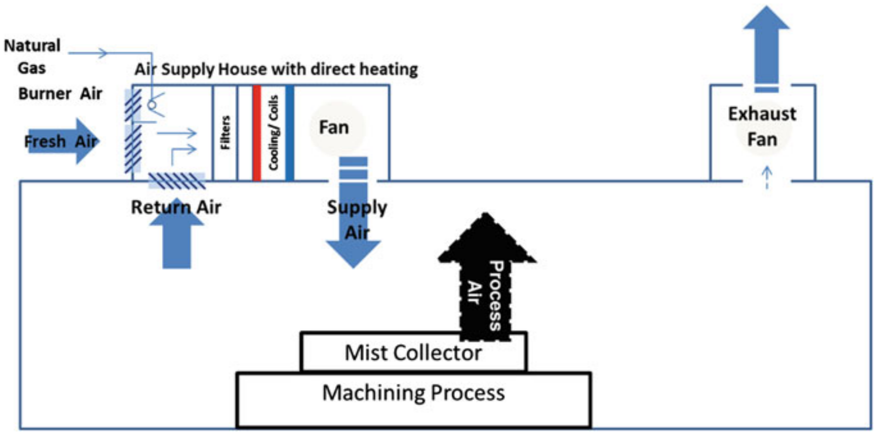



**Fig. 7.10** Schematic of air re-circulating option in mist control

- Dynamic control oscillating the exhausting and re-circulating—appropriate when the system has an intelligent control to decide when and whether exhausting or re-circulating mist with consideration of temperature and humidity of inside and outside of the plant.

### 7.3.2 Dynamic Ventilation Strategy for a Mist Collection System

A dynamic mist control is an intelligent method to control when and whether to exhaust or re-circulate collected mist from machining processes, given short-term, location specific weather forecast data available as described in Fig. 7.11. Figure 7.12 illustrates the dynamic mist control system decision process and Fig. 7.13 explains the decision logic behind the choice of exhausting or re-circulating option.

### 7.3.3 Modelling and Simulation with EnergyPlus

Similar to the illustrative example in the previous section, IDF editor is used to provide the following configuration information for EnergyPlus. Note that this model requires custom controls on the ventilation system. EMS (Energy Management System) is an advanced feature of EnergyPlus to provide a way to develop custom control and modeling routines for EnergyPlus models. The appendix of this book chapter: "Getting Started with EnergyPlus for Manufacturing Process Simulation" provides an instruction on how to use EMS to implement a

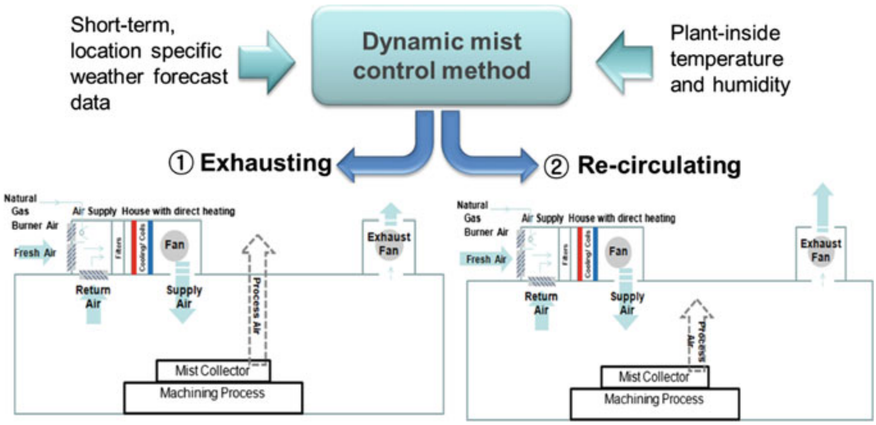
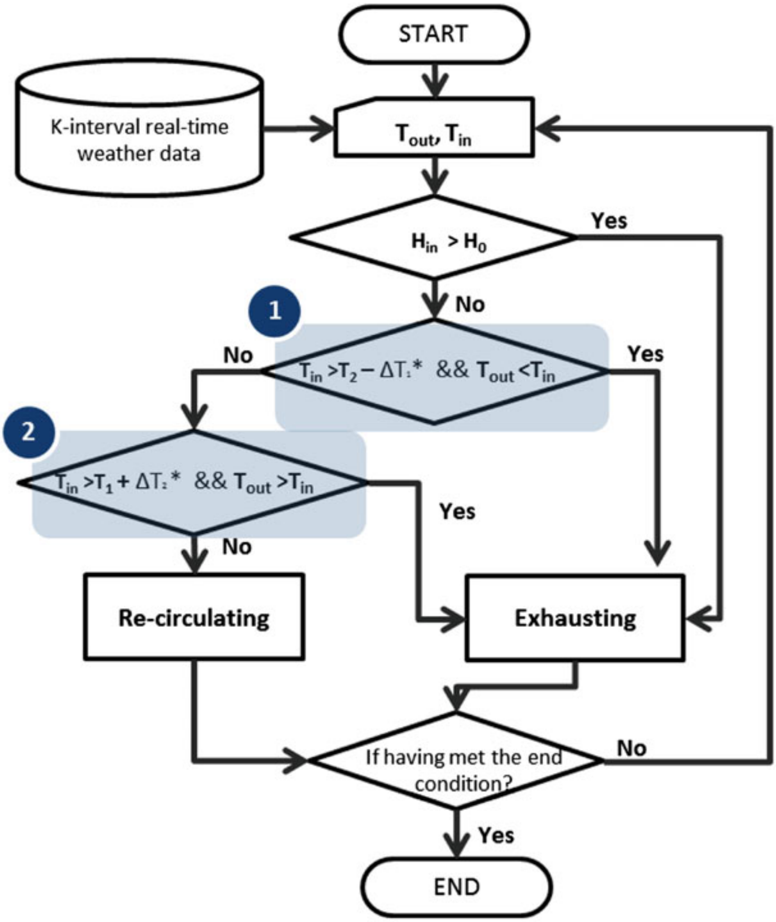



Fig. 7.11 Overview of dynamic mist control system




| Term | Description | Term | Description |
|---|---|---|---|
| $T_{out}$ | Dry bulb temperature of outside | K | Real-time weather data update interval |
| $T_{in}$ | Dry bulb temperature of inside | $T_1$ | Lower bound of inside set point temperature |
| $H_{in}$ | Inside humidity | $T_2$ | Upper bound of inside set point temperature |
| $H_0$ | Humidity set point (e.g., 70%) | $\Delta T^*$ | Optimal Temperature differentiation |

**Fig. 7.12** Dynamic mist control system decision process

simple control logic example. However, it is not a full introduction to EMS. For further instructions about EMS, see *Application Guide for EMS* which is available http://bigladdersoftware.com/epx/docs/8-2/ems-application-guide/index.html. Also see a previous study (Ellis et al. 2008) that presented the new EMS features,

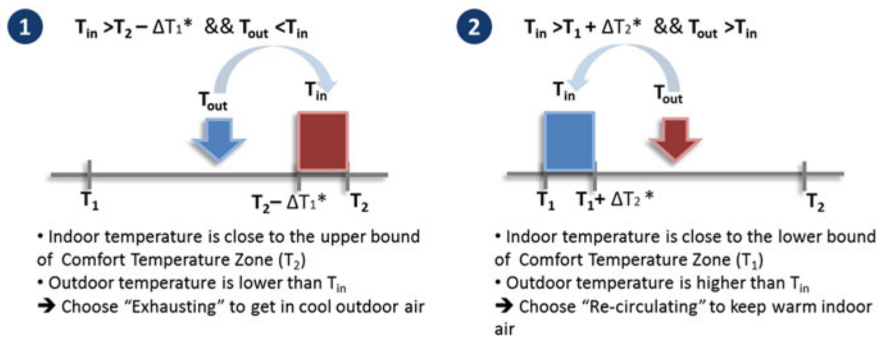
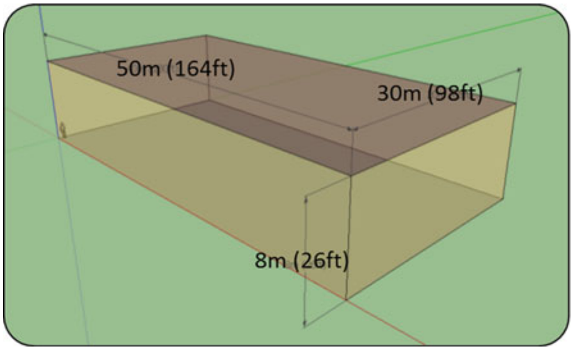



**Fig. 7.13** Decision logic behind the choice of exhausting or re-circulating option

**Fig. 7.14** Machining plant in a rectangular single storey building in the example




described the implementation of the module, and explored some of the possible applications for the new EMS capabilities in EnergyPlus.

1. Plant building
   - Rectangular single storey building
   - Single zone with no interior partitions No window
   - No window
   - Approximately 1200 m$^2$ (50 m × 30 m; 1300 ft × 650 ft) (see Fig. 7.14)
2. Three different weather scenarios
   - Flint, MI, USA
   - Spring Hill, MI, USA
   - Incheon, South Korea

3. Exterior material layers
   - (Layer 1) Metal surface
   - (Layer 2) 50 mm insulation board
   - (Layer 3) Air space resistance
   - (Layer 4) Metal surface
4. Internal load (see Table 7.4 for details)
   - People, light, machining centre, mist collector
5. Load schedule follows the conditions described in Fig. 7.5
6. Infiltration and Ventilation follows the three scenarios
   - Exhausting only
   - Re-circulating only
   - Dynamic mist control.

**Table 7.4** Internal loads in the example

| Load item | Object name in EnergyPlus | Design level |
|---|---|---|
| People | Workers | 2 persons |
| Lights | Zone1 lights | 3.6 kW |
| Machining | Machining tool | 0.3 MW |
| Mist collector | Mist collector | 1.4 MW |

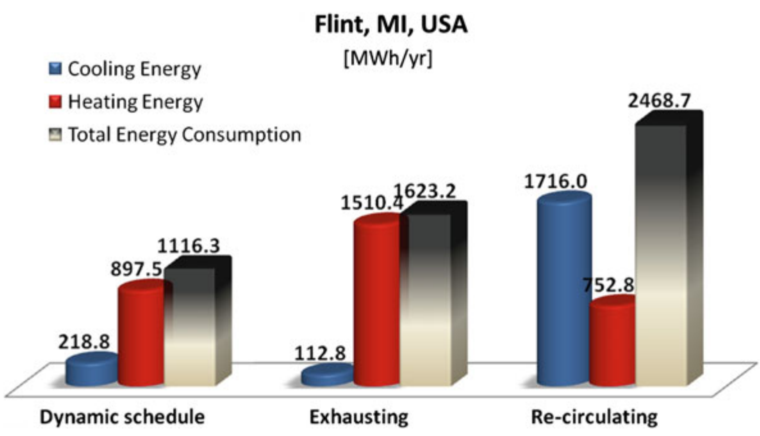



**Fig. 7.15** Simulation results with the weather condition of Flint, MI, USA

### 7.3.4 Analysis Results

This simulation study tested three different weather scenarios for the three mist control options—(1) exhausting only (2) re-circulating only and (3) dynamic control. Note that the mist considered in these cases is all assumed to be purified completely through the mist collection system. The results are as follows:

- In the case of Flint, MI, USA: the dynamic option is 31 % more efficient than the exhausting only option and 55 % more efficient than the re-circulating only option. The exhausting only is 34 % more efficient than the re-circulating only option as shown in Fig. 7.15.
- In the case of Springhill, MI, USA: the dynamic control option is 13 % more efficient than the exhausting only option and 62 % more efficient than the re-circulating option. The exhausting only option is 46 % more efficient than the re-circulating only option as shown in Fig. 7.16.
- In the case of Incheon, South Korea: the dynamic control option is 27 % more efficient than the exhausting only option and 61 % more efficient than the re-circulating only option. The exhausting only option is 46 % more efficient than the re-circulating only option as shown in Fig. 7.17.

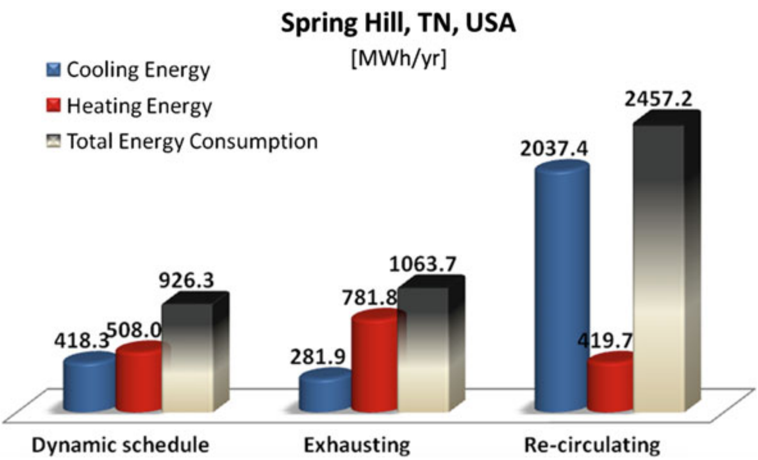



**Fig. 7.16** Simulation results with the weather condition of Spring Hill, TN, USA

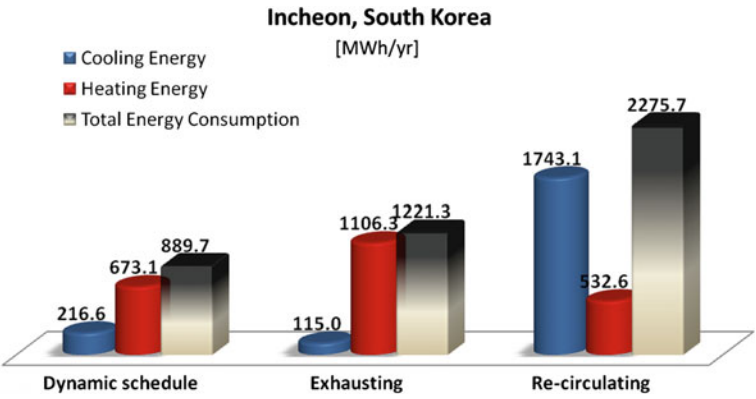



**Fig. 7.17** Simulation results with the weather condition of Incheon, South Korea

## 7.4 Summary

This book chapter plant described a way of building energy simulation models by customizing EnergyPlus and evaluated two new HVAC methods such as air conditioning economizer and dynamic mist control with the developed energy models. The results revealed that the use of air flow economizer can save 8.4 % cooling energy per year compared to the business-as-usual case. Also, the simulation results on the use of dynamic mist collection control proved that the dynamic control is more efficient than the other options. Specifically, in the case of Flint, the dynamic control is 31 % more efficient than the exhausting option and 55 % more efficient than the re-circulating option. In the case of Spring Hill, the dynamic control is 13 % more efficient than the exhausting option and 62 % more efficient than the re-circulating option. In the case of Incheon, the dynamic control is 27 % more efficient than the exhausting option and 61 % more efficient than the re-circulating option.

For further works, it can be considered to populate manufacturing processes and machines in the simulation model to have more realistic simulation results. Also, it is expected to incorporate other factors into the energy simulation model such as (1) human comfort and health requirements (2) corrosion impact on metal products or facilities.

## 7.5 Exercises

1. Read the appendix: "Getting Started with EnergyPlus for Manufacturing Process Simulation" and download EnergyPlus from DOE website (https://energyplus.net/) and replicate the illustrative examples 1 and 2 in the main text.


**Fig. 7.18** Energy equation for boiling water

2. Identify the difference between enthalpy and entropy.

   - Enthalpy $H = E + PV$ where $H$ is heat; $E$ is energy; $P$ is pressure; V is volume. In particular, the $PV$ term represents the mechanical work done on or by the system.
   - Entropy $\Delta S = \frac{\Delta H}{T}$ is a measure of the disorder or randomness of a system where $T$ is time.

3. Once have fully understood the difference between enthalpy and entropy, try to measure the enthalpy and entropy of the balance formula below that shows what happens if methane encounters oxygen:

$$CH_4 + 2O_2 = CO_2 + 2H_2O$$

4. Calculate energy required to vaporize 1 liter water when the current water temperature is 98 F (≈37 °C). Use the following parameters and divide the calculation into boiling energy part and latent heat part. Refer to Fig. 7.18 that describes the energy equation for boiling water.

   - Heat capacity: 1 cal/g * °C
   - Density: 1 g/cc, 1 L = 1000 cc
   - Latent heat: 540 cal/g

5. In the appendix: "Getting Started with EnergyPlus for Manufacturing Process Simulation", one EMS variable called "EMS_N_Ventilation_Intake" is created and used to count the number of occurrences of that the ventilation takes in outdoor air to control inside high humidity. The example in the appendix assumes Chicago weather. Under the Chicago weather condition, such occurrences happen in general during Spring, Summer, Fall and early Winter. Change the weather file to Tampa, FL and see the difference.

## Appendix: Getting Started with EnergyPlus for Manufacturing Process Simulation

In this chapter, this book uses EnergyPlus to develop and evaluates energy simulation models such as air conditioning economizer and dynamic mist control. Although EnergyPlus is a very powerful tool in modelling and evaluating energy consumptions of a building complex, its applications are limited to commercial buildings, not industrial facilities. In order to use EnergyPlus for manufacturing process simulation, the tool needs to be expanded by adding a new module often, calculating some energy consumption separately independent of EnergyPlus.

This chapter illustrates how to expand EnergyPlus for manufacturing process simulation with a single room of welding shop as an example. Note that this chapter is not an introduction to all of EnergyPlus, but to the selected parts of EnergyPlus used in the book. For further instructions, see *Getting Started with EnergyPlus*, which is available https://energyplus.net/sites/default/files/pdfs_v8.3.0/GettingStarted.pdf.

This chapter provides instructions that follows the procedures stated as below:

- Step 1: Calculate the energy consumption of the manufacturing processes (e.g., welding shop) separately.
- Step 2: Classify the manufacturing process as one equipment in the building and calculate the effects of the processes on the environment (i.e., dissipation of heat and moisture generation according to the manufacturing schedules).
- Step 3: Use EnergyPlus to estimate the energy consumption of building pertaining to the building information (e.g., envelopes, windows, and etc.), regional climate conditions and effects of set points and schedules.
- Step 4: Combine the two parts of energy consumption calculation to obtain the total energy consumption of the manufacturing shop.

Assuming that parts are welded in a single room which configuration is defined in Fig. 7.19. It is of interest to estimate the energy consumption of the welding process and the building.

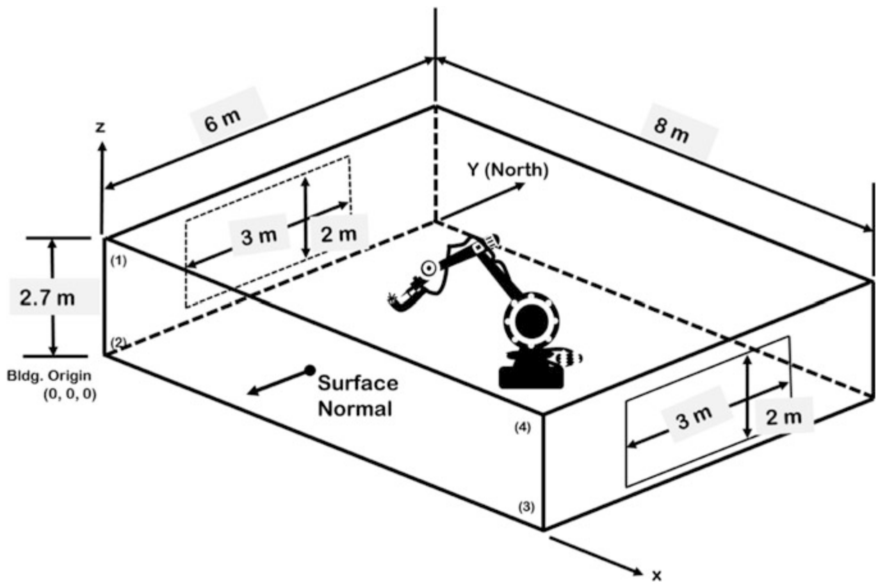



**Fig. 7.19** An example: a single room of welding shop

**Table 7.5** Welding process configuration

| Parameters | Value |
|---|---|
| Number of welders | 1 |
| Average power per welder with no-load (W) | 300 |
| Average energy consumption per spot (J) | 1000 |
| Number of spots per job | 180 |
| Production rate (jobs/h) | 20 |
| Fraction latent | 0 |
| Fraction radiant | 0.1 |
| Fraction lost | 0.8 |

Note that it is possible to calculate energy consumption of welding indepent to EnergyPlus because it is not affected by environmental parameters for example, temperature, moisture, and etc. The total power required to do welding parts ($P_{weld}$) is as follows:

$$P_{weld} = N_{weld} \times P_{idle} + E_{ps} \times N_{spot} \times (\text{Production rate})/3600$$

In the equation above (Roelant et al. 2004), $N_{weld}$ is the number of welders in the shop; $P_{idle}$ is the power per welder when it is idle, $E_{ps}$ is the average energy consumption per spot (J/spot); $N_{spot}$ is the total number of spots; and the production rate is in job/h. $P_{weld}$ multiplied by the total uptime is the energy consumption of the welding process. This example uses welding parameters as listed in Table 7.5.

From the parametric energy model for welding process based on the values stated in Table 7.5, the total power for welding process is calculated to 1.3 kW (=1 × 300 W + 1000 J/Spot × 180 Spots/Job × 20 Jobs/h/3600 s). Note that 1.3 kW will be used to integrate the welding manufacturing process into the building configuration by adding an object instanced from ElectricEquipment class as follows (note that the design level of the object is set to 1.3 kW).

```
ElectricEquipment,
  Welder,    !- Name
  Zone ONE, !- Zone Name
  Welding Schedule,     !- Schedule Name
  EquipmentLevel, !- Design Level Calculation Method
  1300,            !- Design Level {W}
  ,          !- Watts per Zone Floor Area {W/m2}
  ,          !- Watts per Person {W/person}
  0,         !- Fraction Latent
  0.1,             !- Fraction Radiant
  0.8,             !- Fraction Lost
  Welder;    !- End-Use Subcategory
```

The addition of an electrical equipment ultimately appears as heat that contributes to zone loads. EnergyPlus divides the heat into four different fractions. Three of them must be provided by a user as input fields such as Fraction Latent, Fraction Radiant and Fraction Lost. The forth fraction, the heat from electric equipment transported to the zone air by convection is calculated by the program according to the following parametric model:

$$\text{Fraction Convected} = 1.0 - (\text{Fraction Latent} + \text{Fraction Radiant} + \text{Fraction Lost})$$

Note that an error message pops up if (Fraction Latent + Fraction Radiant + Fraction Lost) is greater than 1.0.

More details, Fraction Latent is used to characterize the amount of latent heat given off by electric equipment in a zone. The number specified in the input field is multiplied by the total energy consumption by the electric equipment to calculate the amount of latent energy produced by the electric equipment. This energy ultimately affects the moisture balance inside the zone.

Meanwhile, Fraction Radiant is used to characterize the amount of long-wave radiant heat being given off by the electric equipment in the zone. The number specified in the input field is multiplied by the total energy consumption by the electric equipment to estimate the amount of long wavelength radiation gain from the electric equipment into the zone.

The third heat type, Fraction Lost is used to characterize the amount of "lost" heat being given off by the electric equipment in the zone. The number specified in the input field is multiplied by the total energy consumption by the electric equipment to calculate the amount of heat that is lost and therefore does not affect the zone energy balances. This might correspond to the electrical energy converted to mechanical work or heat that is vented to the atmosphere.

The fourth heat type, Fraction Convected is used to characterize the heat contributing to zone loads directly by welders. Similarly, it is calculated by multiplying the total energy consumption by the electric equipment and the Fraction Convected [or 1.0 − (Fraction Latent + Fraction Radiant + Fraction Lost)].

Apparently, these types of heat energy are important elements that affect the energy flow in the room, and further the overall energy consumption in addition to the energy consumed by welders themselves. Other inputs for EnergyPlus are listed in Tables 7.6, 7.7, 7.8, 7.9, 7.10 and 7.11.

**Table 7.6** Welding shop operation schedule

| Time until | State (on/off) |
|---|---|
| 8:00 | 0 |
| 12:00 | 1 |
| 14:00 | 0 |
| 18:00 | 1 |
| 24:00 | 0 |

**Table 7.7** Lighting configuration

| Light level (W) | 1000 |
|---|---|
| Fraction radiant | 0.72 |
| Fraction visible | 0.18 |
| Fraction replaceable | 1 |

**Table 7.8** Lighting schedule

| Time until | State (on/off) |
|---|---|
| 8:00 | 0 |
| 12:00 | 1 |
| 14:00 | 0 |
| 18:00 | 1 |
| 24:00 | 0 |

**Table 7.9** Worker parameters

| Number of worker | 2 |
|---|---|
| Fraction radiant | 0.3 |
| Activity level per person | 207 |

**Table 7.10** Worker activity schedule

| Time until | State (on/off) |
|---|---|
| 8:00 | 0 |
| 12:00 | 1 |
| 14:00 | 0 |
| 18:00 | 1 |
| 24:00 | 0 |

**Table 7.11** Schedule of required indoor temperature

| Time until | Heating (°C) | Cooling (°C) |
|---|---|---|
| 8:00 | −30 | 40 |
| 12:00 | 21 | 24 |
| 14:00 | 20 | 26 |
| 18:00 | 21 | 24 |
| 24:00 | −30 | 40 |

## *Installing and Running EnergyPlus*

EnergyPlus is available on https://energyplus.net/. Once EnergyPlus is downloaded and installed, various auxiliary programs are available including documentation and example files in the directory as in Fig. 7.20. Two most important auxiliary programs are:

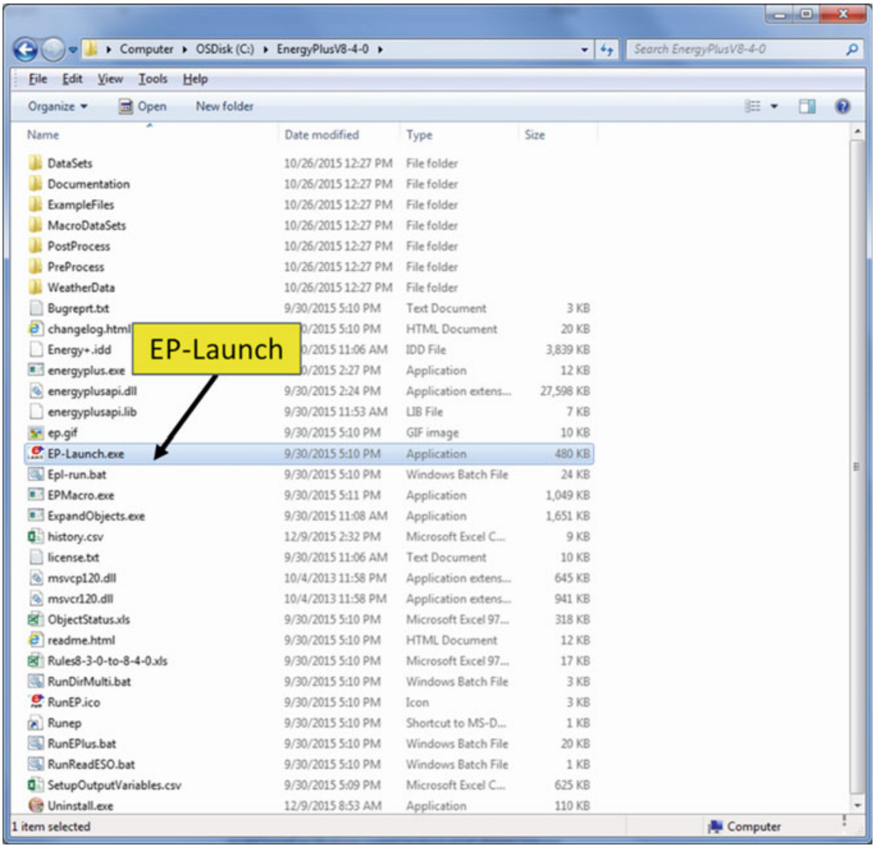



**Fig. 7.20** EP-Launch in MS Window

- EP-Launch: launches EnergyPlus
- IDF Editor: edits input files for EnergyPlus.

Through EP-Launch, mainly users can (1) access EnergyPlus documentation and (2) invoke IDF Editor and (3) select weather files and (4) view output files and (5) run EnergyPlus. With IDF Editor, users can create and edit input files for EnergyPlus. In detail, users can select object types from class list and add/delete/edit objects. The appearance of EP-Launch and IDF Editor is shown in Fig. 7.21.

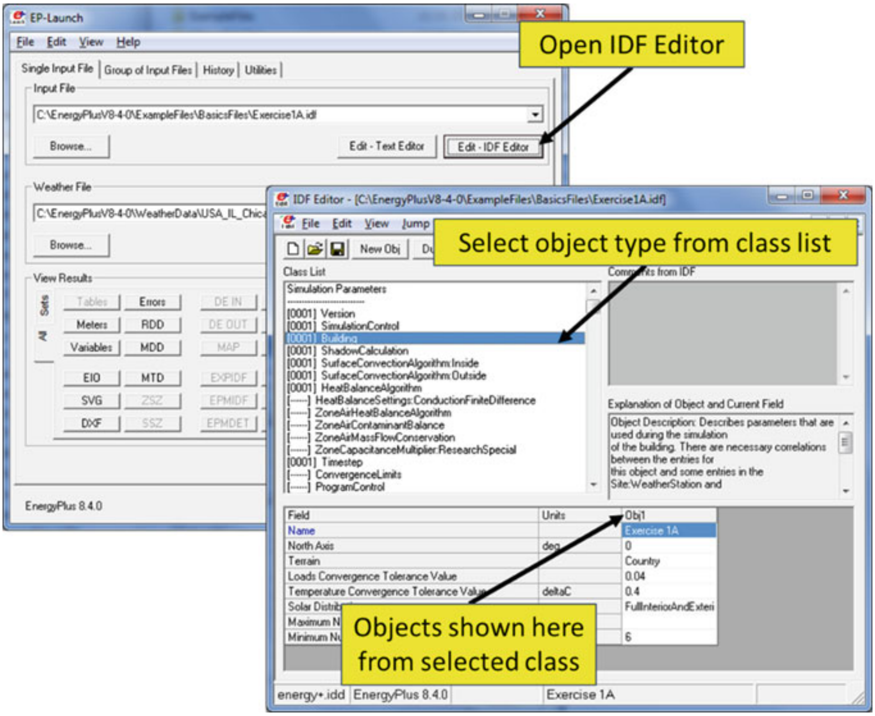



**Fig. 7.21** EP-Launch and IDF editor in operation

## *Modelling Manufacturing Process Simulation Using EnergyPlus*

EnergyPlus is a validated powerful tool. If people want to add manufacturing modules to EnergyPlus, they can avoid reinventing the wheels but only focus on modeling manufacturing process and the integration. Indeed, EnergyPlus can be easily expanded to include energy consumption of manufacturing processes by modifying input files. The first step is to build a model using IDF Editor.

### Define a Building Envelope

This example borrows the building envelope of the training course in *Getting Started with EnergyPlus*, Exercise 1 (https://energyplus.net/sites/default/files/pdfs_v8.3.0/GettingStarted.pdf) where a rectangular single storey building with windows in east and west walls is defined. The zone is single with no interior partitions. The overall building structure is shown in Fig. 7.19 but the details of the building construction and operation can be found in the tables and description of the

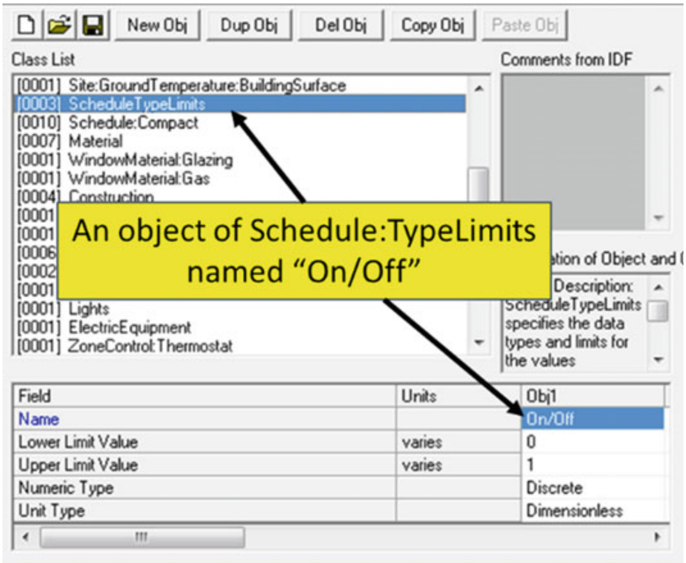
EnergyPlus tutorial. For tutorial purposes, the building is located in Chicago Illinois, one of the weather files supplied with EnergyPlus.

In order to build the example building envelop, the reader should follow the procedure as stated in Exercise 1A and 1B.

## Define Internal Loads

Once the step of modeling the building envelop following the EnergyPlus tutorial is completed, the next step is to learn how to add schedules, internal loads, and report variables.

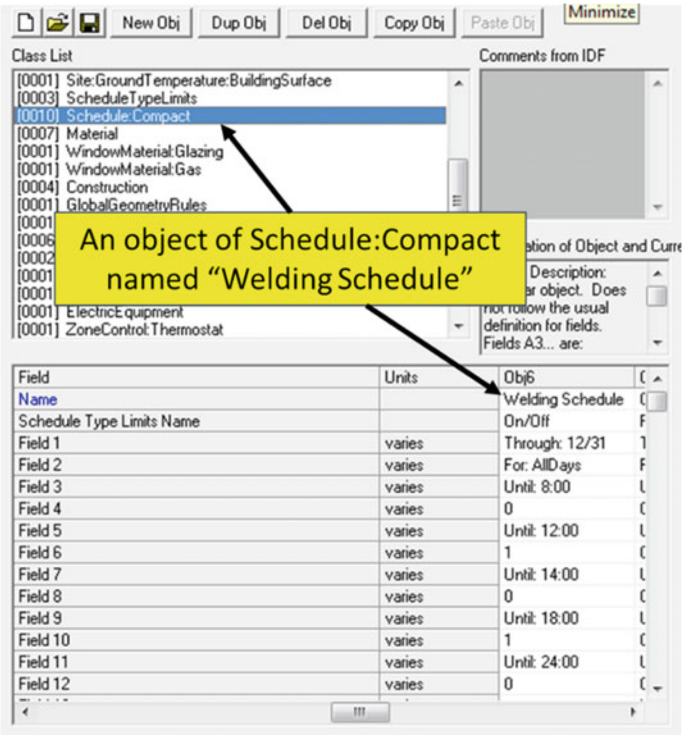
- Save the resultant IDF file in the previous step as WeldingShop.idf in one of working directory of the reader computer.
- Add a ScheduleTypeLimits object named "On/Off".




This object is used to specify the scheduler for welder, workers and light loads. The added object, "On/Off" is read in the IDF file as follows.

```
ScheduleTypeLimits,
    On/Off,                 !- Name
    0,                      !- Lower Limit Value
    1,                      !- Upper Limit Value
    Discrete,               !- Numeric Type
    Dimensionless;          !- Unit Type
```

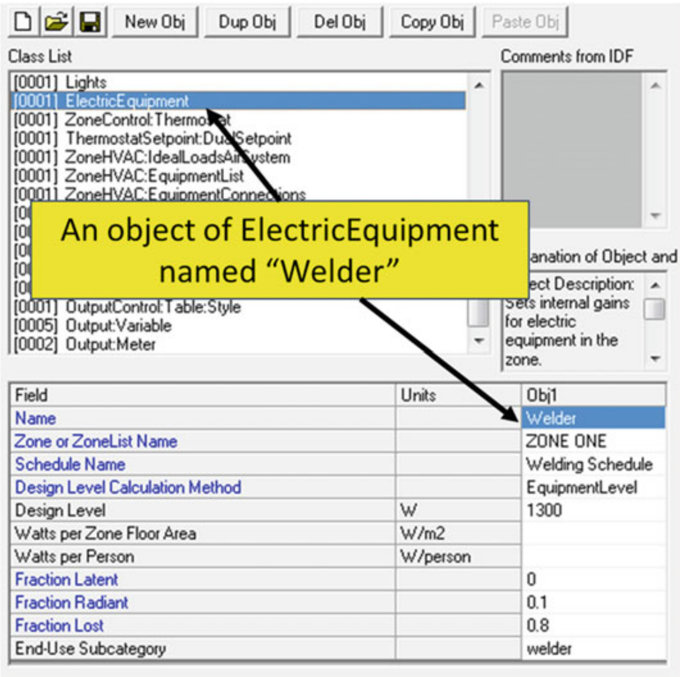
- Add a Schedule:Compact object named "Welding Schedule" to schedule the welding shop.




The added object, "Welding Schedule" is read in the IDF file as follows.

```
Schedule:Compact,
    Welding Schedule,           !- Name
    On/Off,                        !- Schedule Type Limits
Name
    Through: 12/31,             !- Field 1
    For: AllDays,               !- Field 2
    Until: 8:00, 0,             !- Field 4
    Until: 12:00, 1,            !- Field 6
    Until: 14:00, 0,            !- Field 8
    Until: 18:00, 1,            !- Field 10
    Until: 24:00, 0;            !- Field 12
```

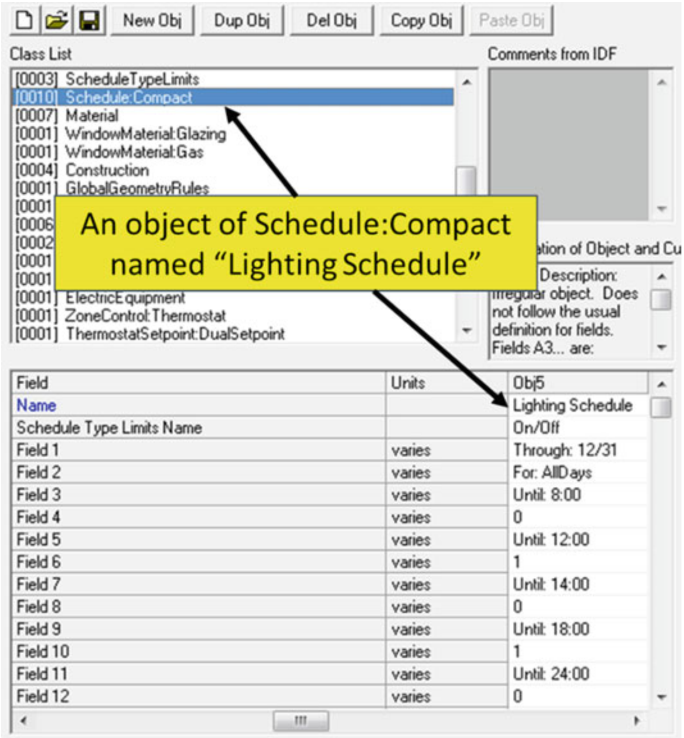
- Add an ElectricEquipment object named “Welder” to represent the welding shop aforementioned.




The added object, “Welder” is read in the IDF file as follows. Note that the design level of the object is set to 1.3 kW which was calculated from the welding energy parametric model previously.

```
ElectricEquipment,
    Welder,                      !- Name
    ZONE ONE,                    !- Zone or ZoneList Name
    Welding Schedule,            !- Schedule Name
    EquipmentLevel,          !-  Design  Level  Calculation
Method
    1300,                        !- Design Level {W}
    ,                        !-  Watts per Zone Floor Area
{W/m2}
    ,                                  !- Watts per Person
{W/person}
    0,                           !- Fraction Latent
    0.1,                         !- Fraction Radiant
    0.8,                         !- Fraction Lost
    welder;                      !- End-Use Subcategory
```

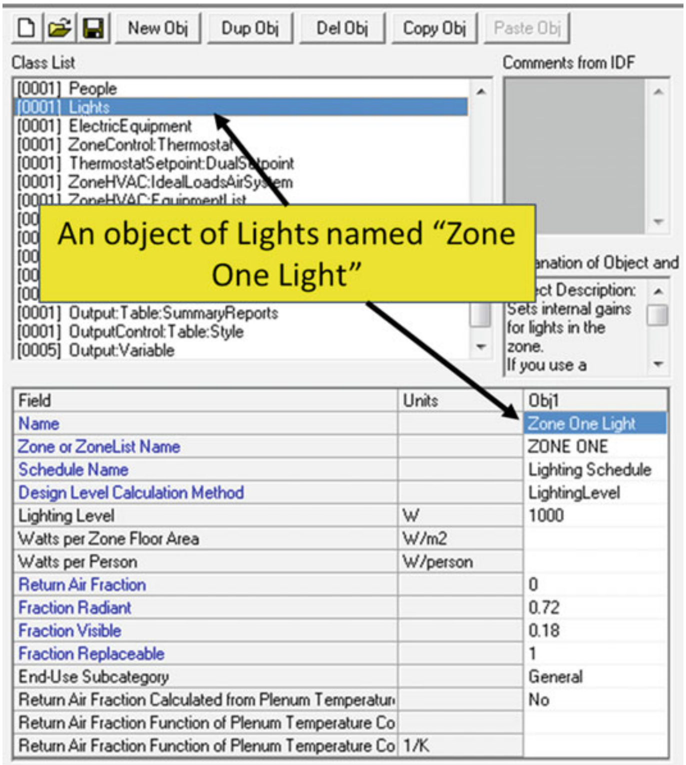
- Add a Schedule:Compact object named "LightingSchedule" according to Table 7.8 to schedule the lighting of the welding shop.



The added object, "Lighting Schedule" is read in the IDF file as follows.

```
Schedule:Compact,
    Lighting Schedule,         !- Name
    On/Off,                  !- Schedule Type Limits Name
    Through: 12/31,            !- Field 1
    For: AllDays,              !- Field 2
    Until: 8:00, 0,            !- Field 4
    Until: 12:00, 1,           !- Field 6
    Until: 14:00, 0,           !- Field 8
    Until: 18:00, 1,           !- Field 10
    Until: 24:00, 0;           !- Field 12
```

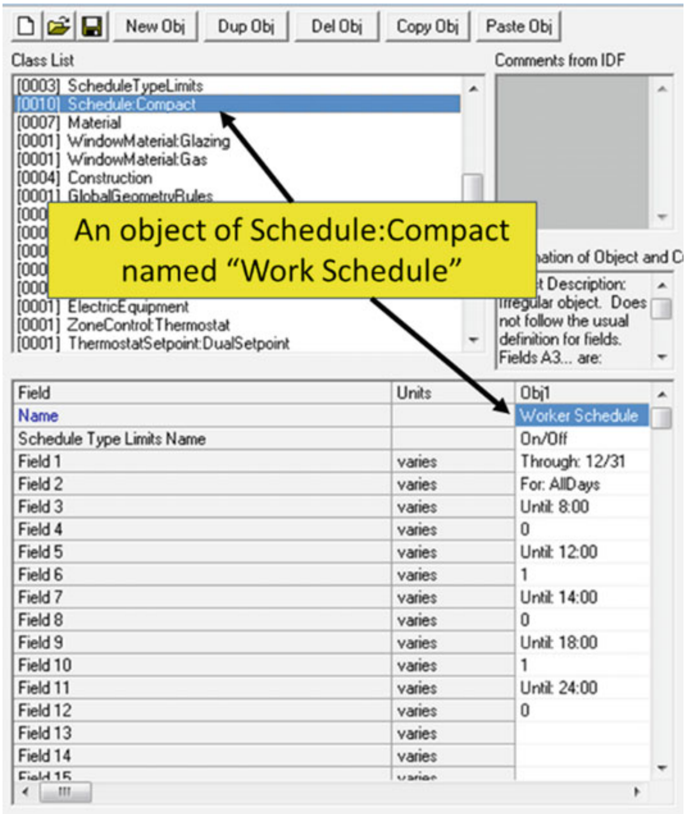
- Add a Light object named "Zone One Light" according to Table 7.7 to schedule the lighting of the welding shop.




The added object, "Zone One Light" is read in the IDF file as follows.

```
Lights,
    Zone One Light,          !- Name
    ZONE ONE,                !- Zone or ZoneList Name
    Lighting Schedule,       !- Schedule Name
    LightingLevel,        !-  Design  Level  Calculation
Method
    1000,                    !- Lighting Level {W}
    ,                      !- Watts per Zone Floor Area
{W/m2}
    ,                                 !- Watts per Person
{W/person}
    0,                       !- Return Air Fraction
    0.72,                    !- Fraction Radiant
    0.18,                    !- Fraction Visible
    1,                       !- Fraction Replaceable
    General,                 !- End-Use Subcategory
    No;  !-  Return  Air  Fraction  Calculated  from  Plenum
Temperature
```

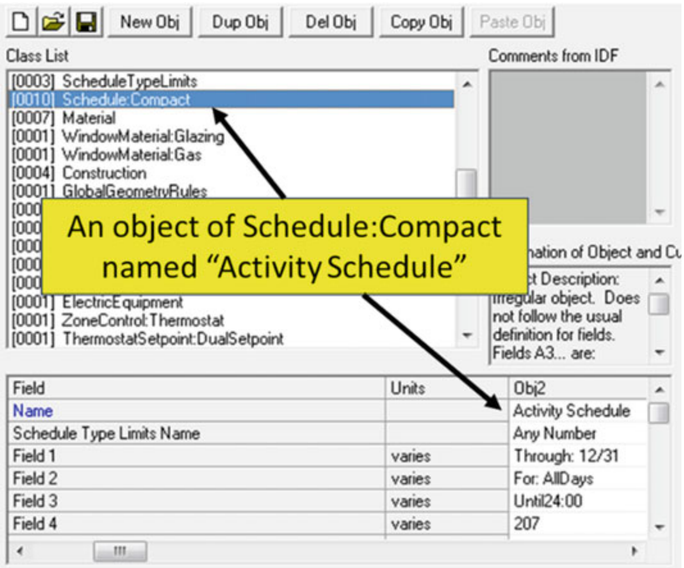
- Add a Schedule:Compact object named “Worker Schedule” according to Table 7.10 to schedule the workers’ activity of the welding shop.



The added object, "Worker Schedule" is read in the IDF file as follows.

```
Schedule:Compact,
    Worker Schedule,            !- Name
    On/Off,                  !- Schedule Type Limits Name
    Through: 12/31,             !- Field 1
    For: AllDays,               !- Field 2
    Until: 8:00, 0,             !- Field 4
    Until: 12:00, 1,            !- Field 6
    Until: 14:00, 0,            !- Field 8
    Until: 18:00, 1,            !- Field 10
    Until: 24:00, 0;            !- Field 12
```

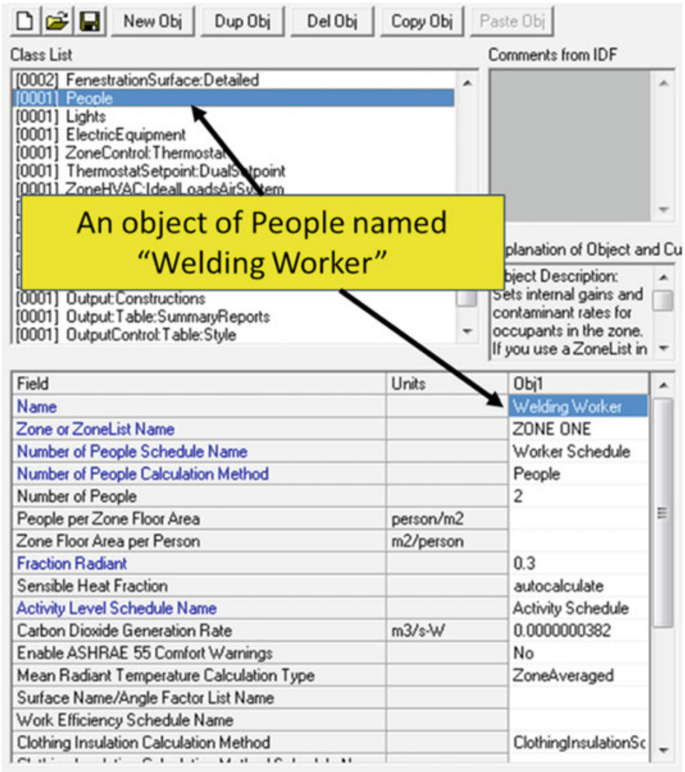
- Add a Schedule:Compact object named "Activity Schedule" according to Table 7.9 to schedule the workers' activity of the welding shop together with "Worker Schedule".



The added object, “Activity Schedule” is read in the IDF file as follows.

```
Schedule:Compact,
    Activity Schedule,          !- Name
    Any Number,              !- Schedule Type Limits Name
    Through: 12/31,             !- Field 1
    For: AllDays,               !- Field 2
    Until24:00,                 !- Field 3
     207;                       !- Field 4
```

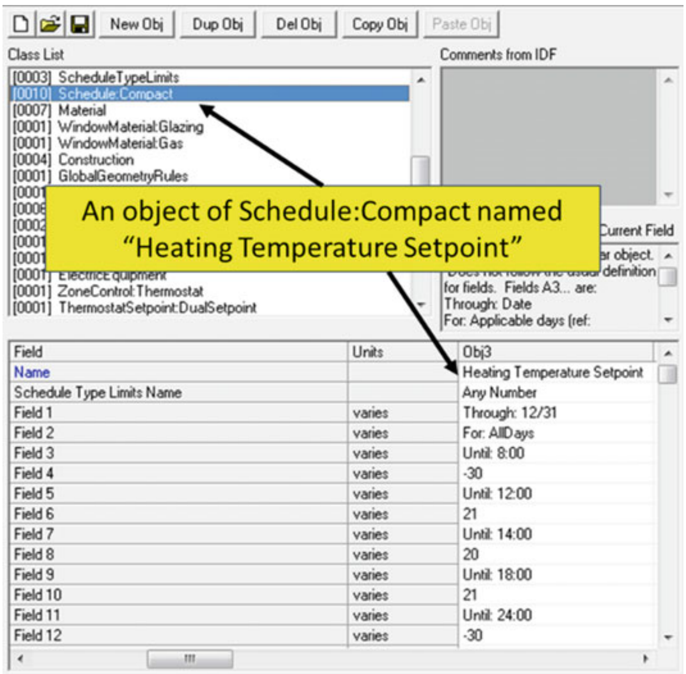
- Add a People object named “Welding Worker” according to Table 7.9 to schedule the workers’ activity of the welding shop.



The added object, “Welding Worker” is read in the IDF file as follows.

```
People,
    Welding Worker,           !- Name
    ZONE ONE,                 !- Zone or ZoneList Name
    Worker Schedule,   !- Number of People Schedule Name
    People,      !- Number of People Calculation Method
    2,           !- Number of People
    ,              !- People per Zone Floor Area {per-
son/m2}
    ,                  !-  Zone  Floor  Area  per  Person
{m2/person}
    0.3,                      !- Fraction Radiant
    autocalculate,            !- Sensible Heat Fraction
    Activity  Schedule,     !-  Activity  Level  Schedule
Name
    0.0000000382,!- Carbon Dioxide Generation  {m3/s-W}
    No,          !- Enable ASHRAE 55 Comfort Warnings
    ZoneAveraged,   !- Mean Radiant Temperature Type
    ,             !- Surface Name/Angle Factor List Name
    ,             !- Work Efficiency Schedule Name
    ClothingInsulationSchedule;  !- Clothing Insulation
```

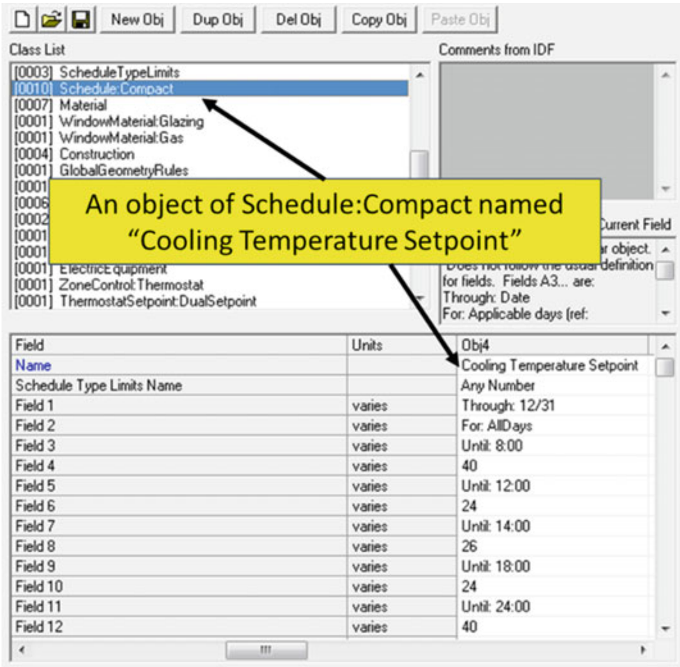
- Add a Schedule:Compact object named “Heating Temperature Setpoint” according to Table 7.11 to program the thermostat of the welding shop.



The added object, "Heating Temperature Setpoint" is read in the IDF file as follows.

```
Schedule:Compact,
    Heating Temperature Setpoint,  !- Name
    Any Number,                !- Schedule Type Limits Name
    Through: 12/31,               !- Field 1
    For: AllDays,                 !- Field 2
    Until: 8:00, -30,             !- Field 4
    Until: 12:00,  21,            !- Field 6
    Until: 14:00,  20,            !- Field 8
    Until: 18:00,  21,            !- Field 10
    Until: 24:00, -30;            !- Field 12
```

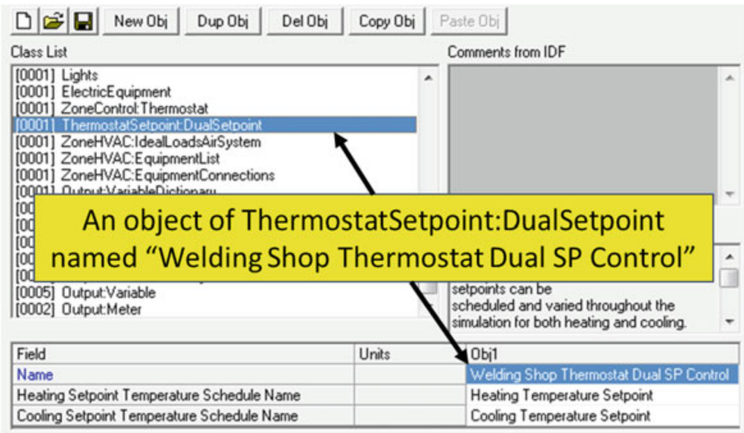
- Add a Schedule:Compact object named "Cooling Temperature Setpoint" according to Table 7.11 to program the thermostat of the welding shop.



The added object, “Cooling Temperature Setpoint” is read in the IDF file as follows.

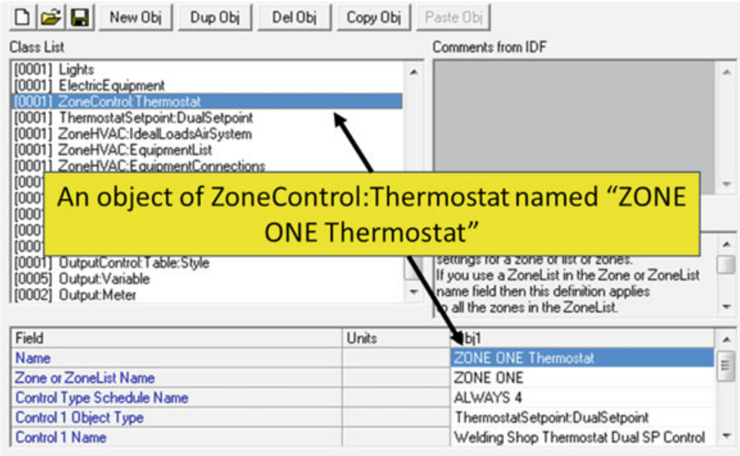
```
Schedule:Compact,
    Cooling Temperature Setpoint,  !- Name
    Any Number,          !- Schedule Type Limits Name
    Through: 12/31,          !- Field 1
    For: AllDays,            !- Field 2
    Until: 8:00,  40,        !- Field 4
    Until: 12:00,  24,       !- Field 6
    Until: 14:00,  26,       !- Field 8
    Until: 18:00,  24,       !- Field 10
    Until: 24:00,  40;       !- Field 12
```

- Edit the ThermostatSetpoint:DualSetpoint object as follows:




```
ThermostatSetpoint:DualSetpoint,
    Welding Shop Thermostat Dual SP Control,  !- Name
    Heating Temperature Setpoint,  !- Heating Schedule
    Cooling Temperature Setpoint;  !- Cooling Schedule
```

- Edit the ZoneControl:Thermostat object as follows:




```
ZoneControl:Thermostat,
    ZONE ONE Thermostat,        !- Name
    ZONE ONE,                   !- Zone or ZoneList Name
    ALWAYS 4,                   !- Control Schedule Name
    ThermostatSetpoint:DualSetpoint,  !- Control
    TypWelding Shop Thermostat Dual SP Control;
```

**Add a Control Logic Using EMS (Energy Management System) Object**

EnergyPlus provides a way to develop custom control and modeling routines for EnergyPlus models. EMS (Energy Management System) is an advanced feature of EnergyPlus and is not for beginners. Nonetheless, it would be still doable for a beginner to come up with a control by following steps set forth in Fig. 7.22. This section will explain each step in Fig. 7.22.

Note that it is not a full introduction to EMS, but to illustrate a simple control logic using EMS. For further instructions, see *Application Guide for EMS* which is available http://bigladdersoftware.com/epx/docs/8-2/ems-application-guide/index.html. The control logic to be implemented in this example is as follows:

```
If (Zone Air Relative Humidity > Setpoint)
    Outdoor Air Intake = Infiltration rate
                       + Ventilation Intake
Then
    Outdoor Air Intake = Infiltration rate
```

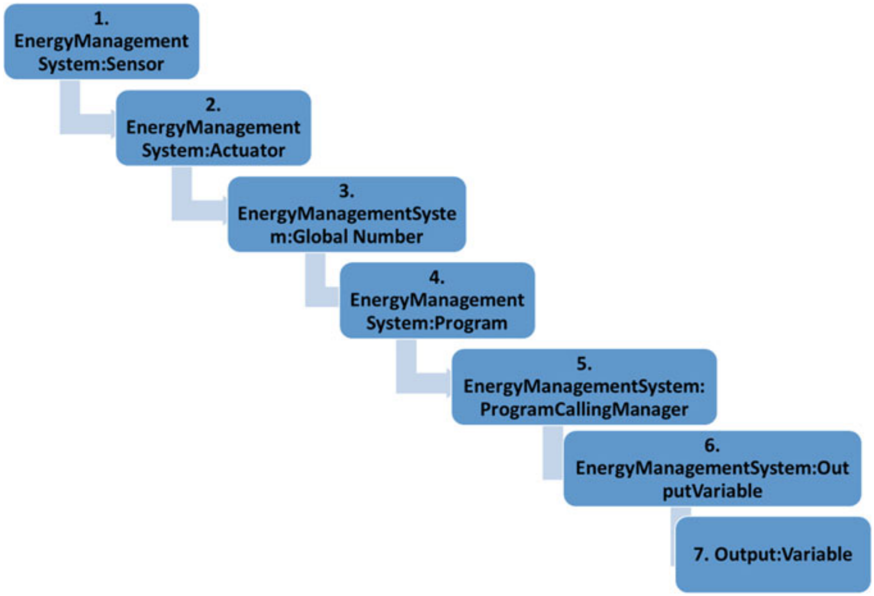
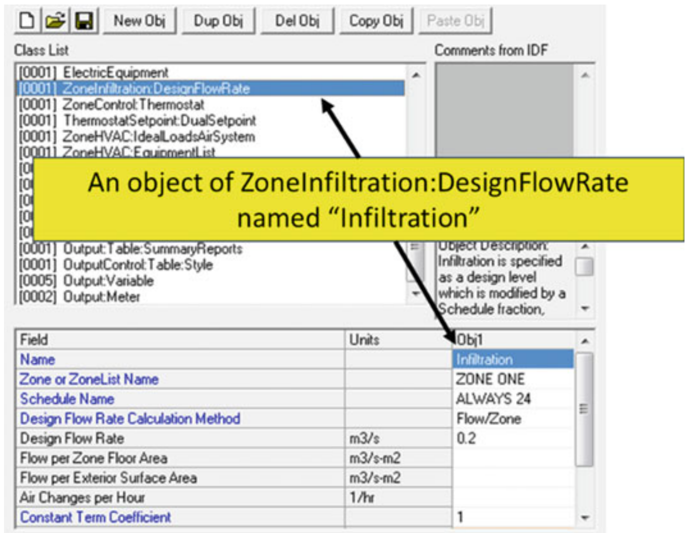



**Fig. 7.22** Steps to implement EMS

In this example, the air infiltration rate (i.e., the unintentional or accidental introduction of outside air into a building, typically through cracks in the building envelope and through use of doors for passage) is set to 0.2 $m^3$/s. If the ventilation works and it intentionally takes outdoor air in, the air flow rate is set to 7.5 $m^3$/s in this example.

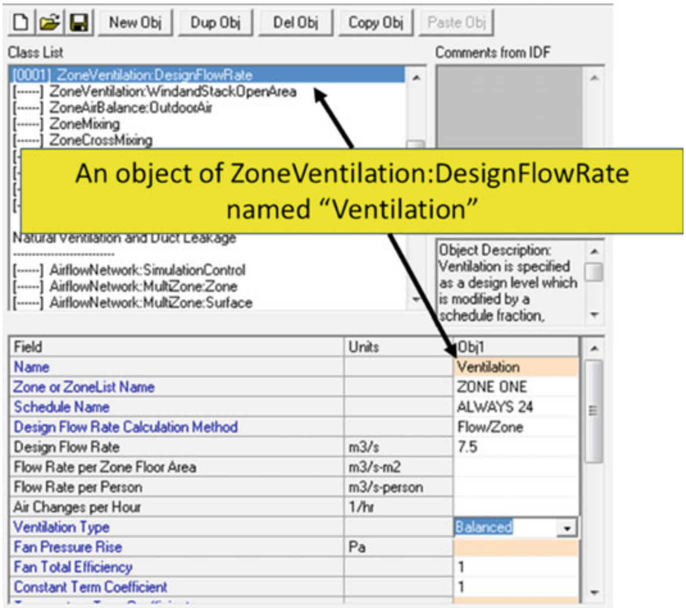
- Add a ZoneInfiltration:DesignFlowRate object named "Infiltration" with the design flow rate set to 0.2 $m^3$/s.



The added object, "Infiltration" is read in the IDF file as follows.

```
ZoneInfiltration:DesignFlowRate,
    Infiltration,               !- Name
    ZONE ONE,                   !- Zone or ZoneList Name
    ALWAYS 24,                  !- Schedule Name
    Flow/Zone,        !-  Design  Flow  Rate  Calculation
Method
    0.2,                    !- Design Flow Rate {m3/s}
    ,           !- Flow per Zone Floor Area {m3/s-m2}
    ,          !- Flow per Exterior Surface Area {m3/s-
m2}
    ,         !- Air Changes per Hour {1/hr}
    1,                           !- Constant Term Coeffi-
cient
    ,                         !- Temperature Term Coeffi-
cient
    ,                            !- Velocity Term Coeffi-
cient
    ;                      !- Velocity Squared Term Coeffi-
cient
```

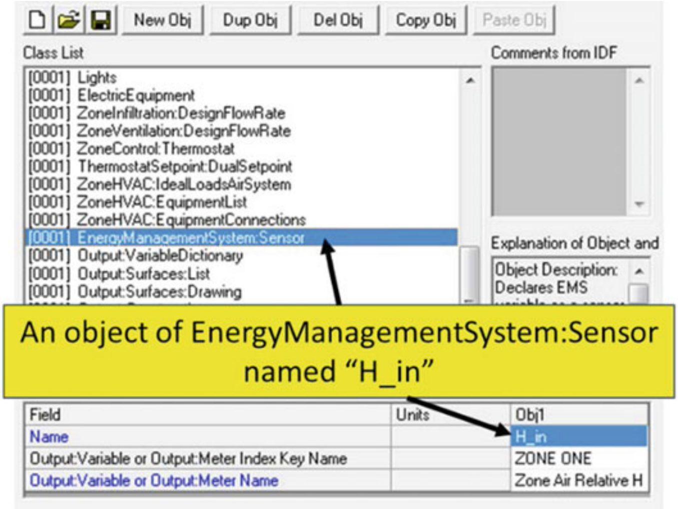
- Add a ZoneVentilation:DesignFlowRate object named "Ventilation" with the design flow rate set to 7.5 $m^3$/s. Make sure that the ventilation type is set to "balanced" so that fans for air intake and exhausting are both working.



The added object, "Ventilation" is read in the IDF file as follows.

```
ZoneVentilation:DesignFlowRate,
    Ventilation,             !- Name
    ZONE ONE,                !- Zone or ZoneList Name
    ALWAYS 24,               !- Schedule Name
    Flow/Zone,       !-  Design  Flow  Rate  Calculation
Method
    7.5,                     !- Design Flow Rate {m3/s}
    ,      - Flow Rate per Zone Floor Area {m3/s-m2}
    ,                  !-  Flow  Rate  per  Person  {m3/s-
person}
    ,             !- Air Changes per Hour {1/hr}
    Balanced,                !- Ventilation Type
    ,                        !- Fan Pressure Rise {Pa}
    1,                       !- Fan Total Efficiency
    1,                         !- Constant Term Coeffi-
cient
    ,                  !- Temperature Term Coefficient
    ,                          !- Velocity Term Coeffi-
cient
    ,                 !- Velocity Squared Term Coeffi-
cient
    -100,       !- Minimum Indoor Temperature {C}
    ,       !- Minimum Indoor Temperature Schedule Name
    100,      !- Maximum Indoor Temperature {C}
    ,       !- Maximum Indoor Temperature Schedule Name
    -100,                     !- Delta Temperature {del-
taC}
    ,              !- Delta Temperature Schedule Name
    -100,      !- Minimum Outdoor Temperature {C}
    ,     !- Minimum Outdoor Temperature Schedule Name
    100,       !- Maximum Outdoor Temperature {C}
    ,      !- Maximum Outdoor Temperature Schedule Name
    40;         !- Maximum Wind Speed {m/s}
```

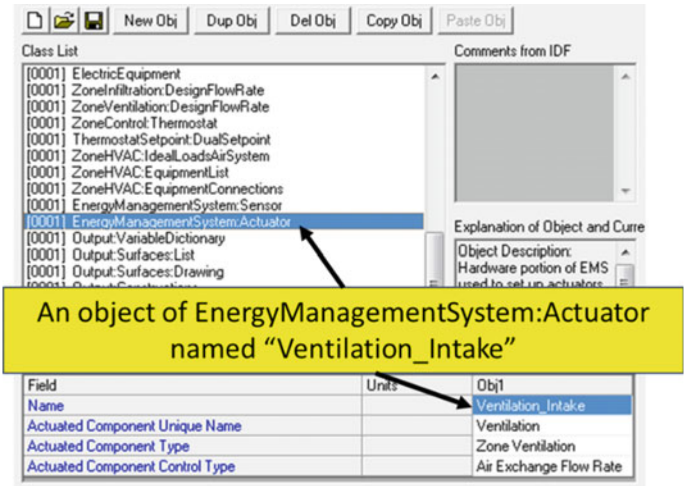
- Add a EnergyManagementSystem:Sensor object named "H_in" to read the value of metering data, Zone Air Relative Humidity in the EMS program.




The added object, "H_in" is read in the IDF file as follows.

```
EnergyManagementSystem:Sensor,
    H_in,                          !- Name
    Zone One,   !- Index Key Name
    Zone Air Relative Humidity ;   !- Output:Meter Name
```

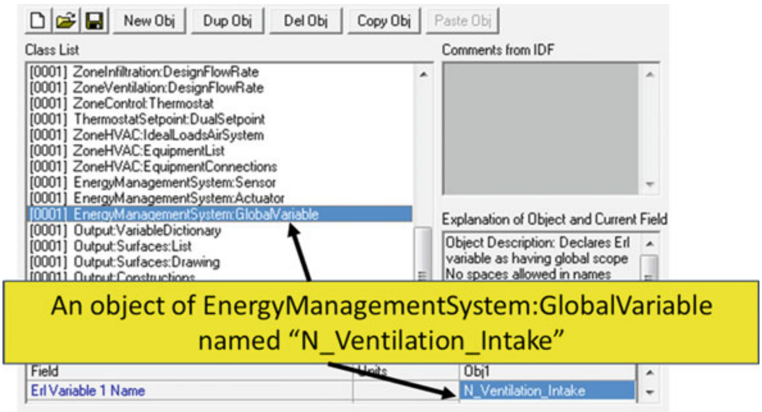
- Add a EnergyManagementSystem:Actuator object named "Ventilation_Intake" to read the value of metering data, Zone Air Relative Humidity in the EMS program.



The added object, "Ventilation_Intake" is read in the IDF file as follows.

```
EnergyManagementSystem:Actuator,
    Ventilation_Intake,        !- Name
    Ventilation,            !- Actuated Component Unique
Name
    Zone Ventilation,          !- Actuated Component Type
    Air Exchange Flow Rate;!- Actuated Component
                            !- Control Type
```

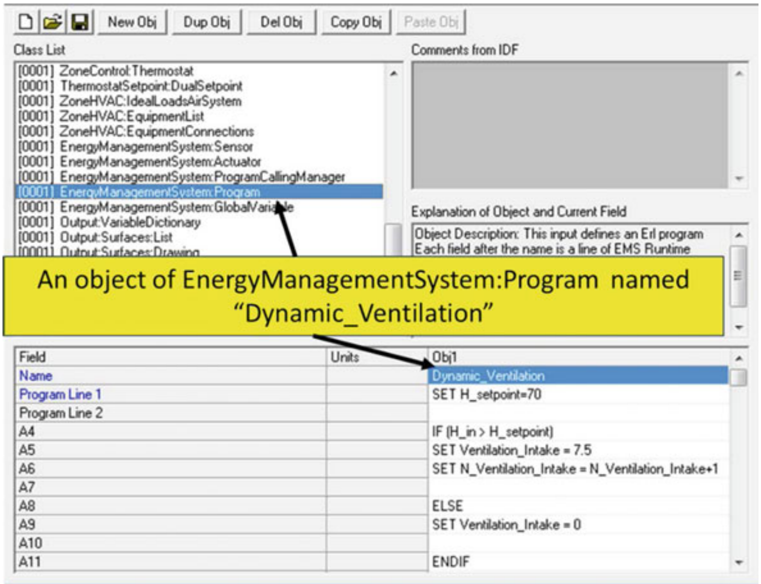
- Add a EnergyManagementSystem:GlobalVariable object named "N_Ventilation_Intake" to count the number of ventilation operation to take air in. This is a global variable and used in the EMS program.




The added object, "N_Ventilation_Intake" is read in the IDF file as follows.

```
EnergyManagementSystem:GlobalVariable,
    N_Ventilation_Intake;     !- Erl Variable 1 Name
```

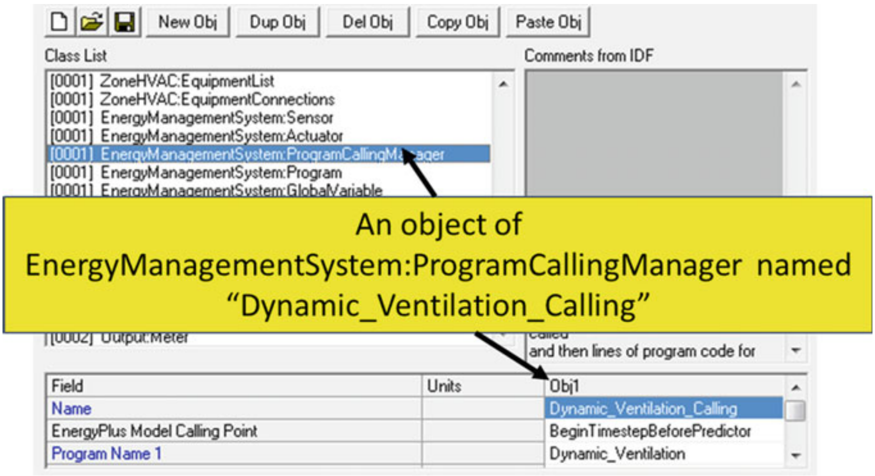
- Add a EnergyManagementSystem:Program object named “Dynamic_Ventilation” to implement the control logic set forth previously.




The added object, “Dynamic_Ventilation” is read in the IDF file as follows. Pay attention to how those sensor (H_in), actuator(Ventilation_Intake) and global variable (N_Ventilation_Intake) objects that are created in the previous steps are used in the program.

```
EnergyManagementSystem:Program,
    Dynamic_Ventilation,      !- Name
    SET H_setpoint=70,        !- Program Line 1
    ,                         !- Program Line 2
    IF (H_in > H_setpoint),   !- A4
    SET Ventilation_Intake = 7.5,   !- A5
    SET N_Ventilation_Intake = 1,     !- A6
    ,                         !- A7
    ELSE,                     !- A8
    SET Ventilation_Intake = 0,  !- A9
    ,                         !- A10
    ENDIF;                    !- A11
```

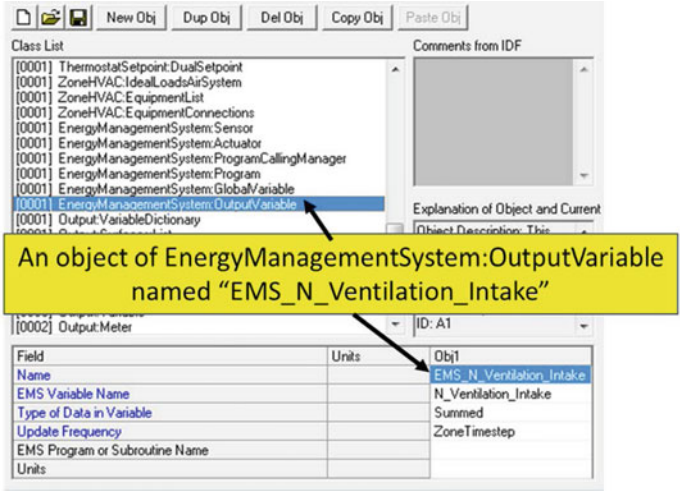
- Add a EnergyManagementSystem:ProgramCallingManager object named "Dynamic_Ventilation_Calling" to schedule when to call "Dynamic_Ventilation" EMS program.




The added object, "Dynamic_Ventilation_Calling" is read in the IDF file as follows.

```
EnergyManagementSystem:ProgramCallingManager,
    Dynamic_Ventilation_Calling,   !- Name
    BeginTimestepBeforePredictor,   !- Calling Point
    Dynamic_Ventilation;      !- Program Name 1
```

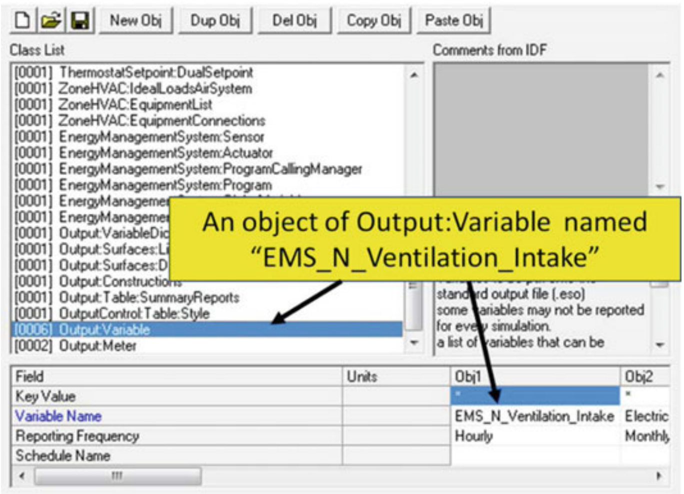
- Add a EnergyManagementSystem:OutputVariable object named "EMS_N_Ventilation_Intake" to report the total occurrence of ventilation operation to take air in after "Dynamic_Ventilation" EMS program runs.




The added object, “EMS_N_Ventilation_Intake” is read in the IDF file as follows.

```
EnergyManagementSystem:OutputVariable,
    EMS_N_Ventilation_Intake,!- Name
    N_Ventilation_Intake ,    !- EMS Variable Name
    Summed,                    !- Type of Data in Vari-
able
    ZoneTimestep;             !- Update Frequency
```

- Add a new Output:Variable object to report “EMS_N_Ventilation_Intake”.



The added object is to be read as follows.

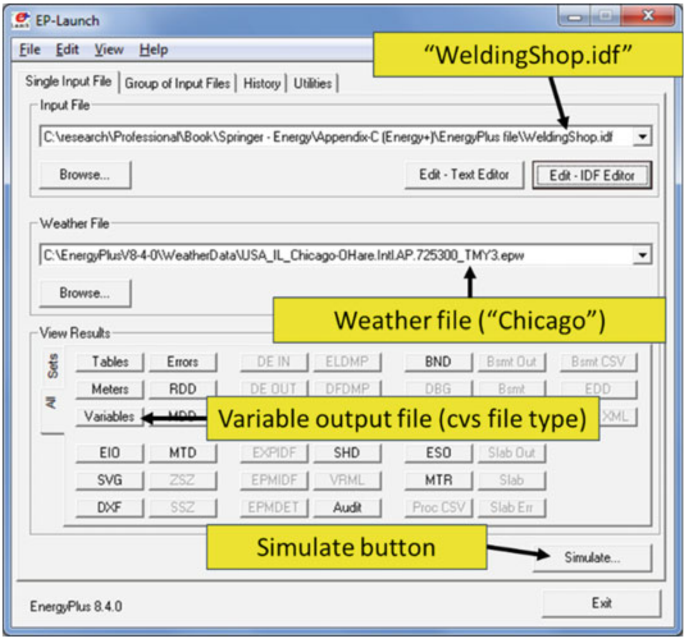
```
Output:Variable,*,EMS_N_Ventilation_Intake,Monthly;
```

## Run Simulation and Read Reports

- Add a new Output:Variable object to report the welding shop electric energy consumption. The added object is to be read as follows. Add more Output: Variable objects as desired.

```
Output:Variable,*,Electric Equipment Electric Energy,
Monthly;
```

- Save and close the IDF file. Run the simulation and review outputs. Check the err file. Find the variables output in the csv file.




The resultant energy consumption profile can be graphed as in Fig. 7.23. Note that this example assumes that the building is located in Chicago Illinois. Figure 7.23 shows that the welding shop needs more heating energy during the winter, meanwhile, more cooling energy during the summer. The energy for welding process itself is relatively steady.

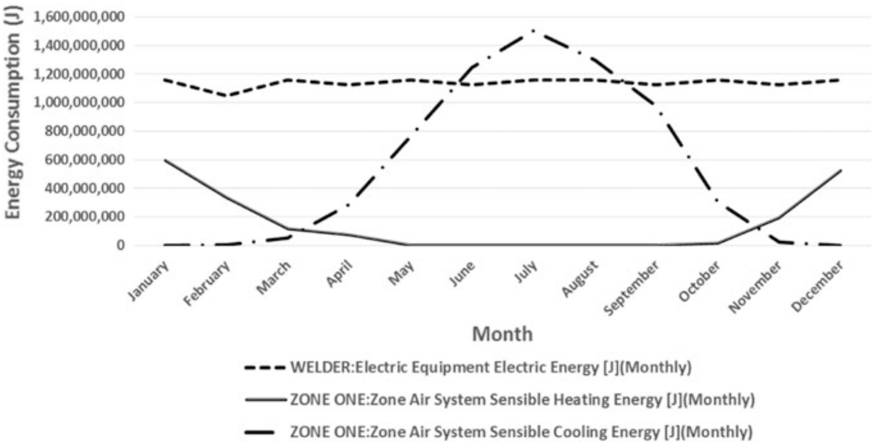



**Fig. 7.23** Energy profile of the example: a single room of welding shop

Remind that it is one example for a room with welding shop. The procedure laid out in this example, however, can be duplicated to other applications. In principle, an entire assembly plant can be modelled using the proposed approach.

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Oh S-C, D'Arcy JB, Arinez JF, Biller SR, Hidreth AJ (2011) Assessment of energy demand response options in smart grid utilizing the stochastic programming approach. In: Proceedings of the IEEE power and energy society general meeting, Detroit, MI, USA, 24–28 July

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# Chapter 8
# Energy Management Process for Businesses

**Abstract** Energy use is a large, but mandatory, expense incurred by manufacturers or facility operators and contributes to Greenhouse Gas (GHG) emissions. Depending on the type of business, energy cost can range from less than 1 % of operating expense to more than 30 %. Additionally, energy use in facilities and operations accounts for 66 % of the total greenhouse gas emissions, with transportation being the remaining 34 % of GHG emissions. Although the expense may be a small portion of operating expense, the cost and environmental impact is significant for many companies. As an example, at General Motors (GM), although the expenditure for energy is less than 1 % of total expenses, the cost is in excess of $1 Billion USD annually. Regardless of any view on climate change, with buildings and facilities being the majority of carbon emissions and the recent reduction emphasis at the United Nations framework convention on climate change, "COP-21" creating international attention from investors and customers, managing GHG emissions has become an important part of business. Hence, a robust Energy Management process is needed to meet the fiscal and environmental responsibility of businesses to remain sustainable and satisfy investors' and customers' demands. Management of energy and carbon to reduce environmental impact is important enough to be included in the company's business plan, similar to safety, people, quality, and cost. Following a model similar to EPA Energy Star's seven step approach, based on Plan, Do, Check, Act methodology (PDCA), energy management can be integrated into a company's standard business plan. This requires top level commitment, resources, business planning, goals, and recognition to manage energy and GHG reductions. The methods used to integrate energy management into the business plan include dedicated resources at all levels in the organization. With people as one of most important resources, having qualified energy leaders at the corporate, global, regional and site levels is key to success. To implement initiatives a dedicated budget for systems and projects is required, similar to other areas of the business. Forecasting energy, establishing targets, implementing projects and processes, regular monitoring, and corrective action when required ensures timely adherence to meeting energy and carbon goals. Recognition can be internal with various processes—Plant energy performance recognition, employee suggestions, employee compensation tied to business results, and others, as well as

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Springer Series in Advanced Manufacturing, DOI 10.1007/978-3-319-32729-7_8

external. The U.S. Environmental Protection Agency (EPA) Energy Star® certifies plants and facilities similar to laptops and refrigerators. Additionally, Energy Star's® Challenge for Industry provides recognition for plants reducing energy intensity by 10 % within five years. The Energy Star®, also sponsored by the Department of Energy (DOE) Partner of the year award in Energy Management, is EPA's highest award for exemplary performance.

## 8.1 Importance of Energy Management to Business

Accounting for energy use in various parts of the business is an important first step to prioritize energy management. As an example, about 83 % of General Motors Company (GM) GHG and energy are resultant from manufacturing operations compared to 17 % for non-manufacturing. Therefore, the majority of environmental efforts are focused on manufacturing for the automaker. A manufacturing plant has processes that are typically complex and consume large fixed and variable amounts of energy resources. Energy costs are steadily rising and are predicted to continue this trend going into the future due to clean energy requirements of many counties according to the International Energy Agency (IEA). Energy and carbon management requires facility monitoring and control of energy sources and carbon emissions to reduce the overall energy and carbon intensity of a business. This requires adherence to goals and objectives throughout the vast number all of facilities globally. From top leadership commitment to dedicated resources centrally, and at each facility, everyone must work toward the same business plan to meet their public and internal goals. When energy management is integrated into the standard manufacturing process, the same "plan, do, check, act" rigor that drives the manufacturing process incorporates energy management as well. EPA's Energy Star® energy management model outlined in 7 steps describes this type of energy management system. Figure 8.1 depicts the 7 steps.

As with any business process, data management is an important tool to be able to understand the quantity of energy consumed and carbon emitted and the effect of the process variables on the usage. As an example, GM gathers and analyses energy, carbon, and water data along with climate, production, and process and equipment variables to be able to set goals, and monitor progress. To evaluate progress to goals, a company must understand the effects of climate, production, and process variables on energy consumption and track energy efficiency and conservation projects at each facility. Benchmarking of energy, carbon, and water intensity allows identification of facilities that may have best practices for investigation, need assistance to improve results, and provides a method to assess performance targets for plants.

The methods and objectives to meet energy, carbon, and water goals become part of a standard business plan deployment on a global, regional, and local plant basis. Top leadership commitment to meet the public goals allows for allocation of the required resources of people, processes, and money to implement a robust

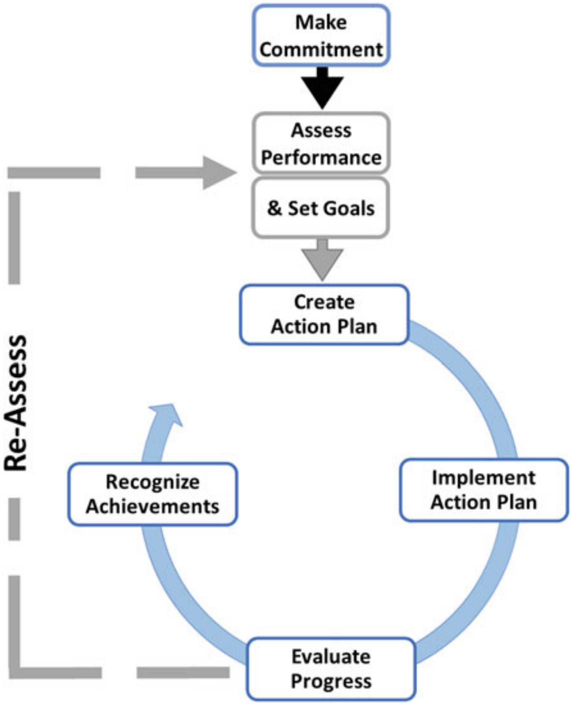


**Fig. 8.1** Energy Star®—energy management model (Energy Star®)

action plan on a long term basis. Some key elements of the action plan include: energy efficiency projects with dedicated budgets, sharing best practices globally and locally, requirements for countermeasures if monthly targets of energy intensity are not attained, dashboards to identify energy metrics and heating ventilation and air conditioning (HVAC) operating indices, and monitoring and reporting of energy shutdown effectiveness or the energy level of the plant during nonproduction.

An important sustainable step in the energy management process is to recognize achievements in energy, carbon, and water performance internally for both individuals and teams or plants using standardized criteria. One example is to regularly monitor energy shutdown effectiveness during extended holiday periods and recognize plants that meet the company goal. Another example is to recognize the plants that have achieved the most year-over-year reduction in energy intensity. Other examples from GM are their commitment and accountability partnership process that regularly evaluates individual performance for those with responsibilities for managing energy, water, and carbon intensity. GM's suggestion plan, in some regions, provides for monetary compensation for individuals and teams that contribute to implemented cost savings ideas. External recognition is also important since it validates commitment and progress compared to other industrial companies.

Finally, continuous improvement needs to be a key part of a global manufacturing system and is an integral part of a robust energy management system. Assessment of results and failures must be completed on a regular basis so that improvements to the energy management system will provide for year over year reductions in energy intensity.

A robust energy management system is not only important to a company internally but many external stakeholders are interested also as evidenced by the growth of the Carbon disclosure project (CDP). Over 800 investors are signatory to CDP and represent USD$95 trillion in assets. These investors are assessing the climate risk in their portfolios based on the disclosure and performance of the 5500 companies responding. These companies are asked to publicly disclose their carbon management practices emission reduction targets performance to those targets and specific carbon reduction activities. Energy management is a key success factor to reduce a company's carbon footprint. Quantitative carbon reporting uses standardized protocols such as the Greenhouse Gas (GHG) protocol to allocate emissions into direct (Scope 1), indirect (Scope 2), and upstream/downstream (Scope 3). Typically Scope 1&2 emissions are the majority of carbon emissions and are resultant from energy use and facilities and operations. Other carbon emissions can include fugitive emissions from refrigeration systems, mobile equipment use, and other production processes. Scope 3 are indirect emissions from the upstream and downstream company activities, including use of products by customers.

Other important stakeholders that are interested in carbon and energy management practices and data are the company's customers. Calculating the total carbon footprint of the company products and services that are emitted can be multiple times more carbon intensive than their own operations. Therefore, customers request carbon and energy information from their supply chain, including carbon and energy reduction targets, management practices, and performance to goals.

Carbon accounting is becoming more important to government regulators based on the concerns of climate change. A growing number of countries requiring reporting and in some cases setting targets for carbon reduction for companies that have a major impact on the countries carbon footprint. As an example in the United States, the EPA requires reporting carbon emissions over 25,000 tons per year of direct emissions. Also regulators are placing emphasis on energy efficiency for carbon reduction as evidenced in the US EPA Boiler maximum achievable control technology (MACT) regulation requiring energy efficiency analysis for major boiler installations.

## 8.2 Integrating Energy Management into the Global Business Plan

### *8.2.1 Make a Commitment*

Top leader support is the first step in developing a robust energy management business system and should be based on strong environmental principles which go beyond simply complying with regulations. As a company's actions are guided by their values an example of strong environmental principles are those contained in the global Sullivan principles which GM endorsed in 1999. These principals are included in the GM Code of Conduct and apply to all GM personnel worldwide.

1. We are committed to actions to restore and preserve the environment.
2. We are committed to reducing waste and pollutants, conserving resources, and recycling materials at every stage of the product life cycle.
3. We will continue to actively participate in educating the public regarding environmental conservation.
4. We will continue to pursue vigorously the development and implementation of technology for minimizing pollutant emissions.
5. We will continue to work with all governmental entities for the development of technically sound and financially responsible environmental laws and regulations.
6. We will continually assess the impact of our plants and products on the environment and the communities in which we live and operate with a goal of continuous improvement.

### *8.2.2 Business Planning*

To incorporate these values into actions, companies use business plans to manage the day-to-day operations within their facilities. It is important to integrate energy management into a company's business plan to make it a sustainable activity for fiscal and environmental accountability. For example, General Motors Global Manufacturing System (GMS) is based on a plan, do, check, act system with 5 key elements—people, standardization, quality, short lead time, and continuous improvement.

This process is closely aligned with EPA Energy Star®'s guidelines for energy management. In GMS, environmental is one of 6 manufacturing goals, along with Safety, People, Quality, Responsiveness, and Cost and includes energy management.

At GM, energy is included in the continuous improvement (CI) element as part of the business plan deployment. This ensures top leadership focus on Energy management similar to other key business goals.

The leadership team establishes objectives and methods to meet annual energy, water, and carbon targets and plants develop action plans with monthly tracking to meet the targets (MWh/Unit, M3/Unit, Tons/Unit). According to GMS, if a target is not achieved, plants and regions must have a countermeasure plan in place to ensure corrective action. Business plans are specific to each level in the organization and extend to the manufacturing teams on the floor, building the components and products.

### 8.2.3 People

Strong company support in a business process requires dedicated people to implement the process. For example, GM employs a central team of energy experts who champion GM's energy business model. Led by a group manager and supported from a senior leadership team, the energy management program focuses on energy and carbon optimization through intensity reduction. Although absolute energy and carbon reduction is desirable, energy intensity or "energy per unit production" is used to measure progress toward goals and allows for normalization of energy using the main driver—production units. As the majority of the work to achieve the goals is accomplished at the plant level, each manufacturing and major non-manufacturing site has a local site utility manager that is focused on site energy, carbon, and water issues, including efficiency and conservation initiatives to meet their target. Larger sites also have a dedicated energy conservation engineer who is focused on specific projects, operations, and keeping employees engaged in the conversation of energy, GHG emissions and water. The business justification to have dedicated energy managers is based on their accountability to provide financial returns, manage the business, and meet the company goals.

## 8.3 Establishing Targets and Public Goals

Establishing appropriate energy targets is an essential part of an energy management system. Gathering and managing data is the first step in establishing baselines and energy and carbon targets. In consideration of climate change, science-based target methodologies have been established to link company targets and to minimize climate affect.

### 8.3.1 Data Management

According to the GHG protocol, the first step in data management is to establish the boundaries for data management. Since many companies are comprised of owned assets and partial equity investments establishing boundaries and documenting in a greenhouse gas management plan provides for transparency in data management. An example of a high-level overview of the greenhouse gas management plan for GM is as follows:

1. Boundaries
   (a) all GM owned assets
   (b) joint venture assets with GM influence on energy management
   (c) leased assets were GM controls energy use
   (d) Scope 3 includes "cradle to grave" emissions of all products
2. Energy data
   (a) fuels used in the operation of facilities and processes
   (b) electricity use and other over the fence energy sources
   (c) energy efficiency project reduction
3. Independent variables
   (a) Production units
   (b) Climate
      (i) Heating degree days, (HDD)
      (ii) Cooling degree days, (CDD)
      (iii) Outside temperature
      (iv) Relative humidity, (RH)
   (c) Buildings
      (i) People
      (ii) Computers
      (iii) type of facility
         - type of industrial operations (e.g., vehicle assembly plant, engine assembly plant, transmission assembly plant, casting plant, stamping plant, component assembly plant)
         - office, warehouse, laboratory…
   (d) Cost
      (i) Rates by utility and tariff information
      (ii) total cost in local currency
      (iii) exchange rate.

The best time intervals for data-gathering are the lowest time period available, for example interval data every 15 min is typically available from utility companies for a facility. Since the independent variables change very rapidly with time a smaller time increment allows for improved analyses. To verify the accuracy of the interval data, monthly invoices, which require verification for payment, are an excellent source of direct data.

The complexity of the company's operations and the number of geographical locations dictates the type of system needed to gather and analyse the data. Small companies with a few locations typically use spreadsheets for data management and reporting. Companies such as GM with hundreds of facilities globally usually use a third-party service for data management. GM has a contract with a third party to measure and report global energy, water, climate, and production usage data for all manufacturing and major non-manufacturing facilities. It currently tracks and reports energy, carbon, and water use intensity on a monthly basis, using interval data in most cases, at about 309 manufacturing and non-manufacturing facilities worldwide. The basis of data validation is from a utility invoice at a site and is allocated further to business units at a site using sub-meter data—Assembly, Casting, Engine, Stamping and Transmission. GM also focus on non-manufacturing operations energy use with normalization by building area for metrics. Carbon dioxide is calculated by the system using standardized GHG protocol emission factors to show energy's effect on carbon emissions.

### *8.3.2 Data Verification and Assurance*

In case of GM, GHG emissions were verified by an independent third party to ISO-14064 and global energy, water, and GHG data was audited for limited assurance to the AA-1000AS standard. These data are used for monitoring, managing and reporting:

- Establish internal benchmarks and calculation of external benchmarks (EPI)
- Budgeting and forecast for energy and water
- Plant level energy and water metrics goals/targets and performance (MWh/Unit)
- $CO_2e$ intensity performance (Tons/Unit or Tons/square meter)
- Renewable energy use
- Internal and external reporting of energy, water and $CO_2e$ to investors, customers, regulators, and other stakeholders.

Across all of GM's U.S. facilities, about 2.5 million points of energy data per minute is monitored. Energy is monitored as a good engineering practice and to monitor non-production shutdown levels and that heating, ventilating and air conditioning ("HVAC") equipment meets targets, as well as other energy management purposes. To adequately manage this amount of data, GM have a dashboard system called "Energy OnStar" that was developed for HVAC systems. Assisted by a third party, plants can easily compare hourly performance of HVAC equipment and their energy use to various targets—heat/cool energy, fan energy, outside air index and rate, runtimes, temperature setpoints, supply air index and hourly energy intensity.

### *8.3.3 Establishing a Baseline*

There are many methods available to establish a baseline of a company's energy use and carbon emissions. A minimum of one year's worth of data is required to establish a valid energy baseline, although 3–4 years is desirable. The year to select for a baseline is dependent on the company's preference to establish performance

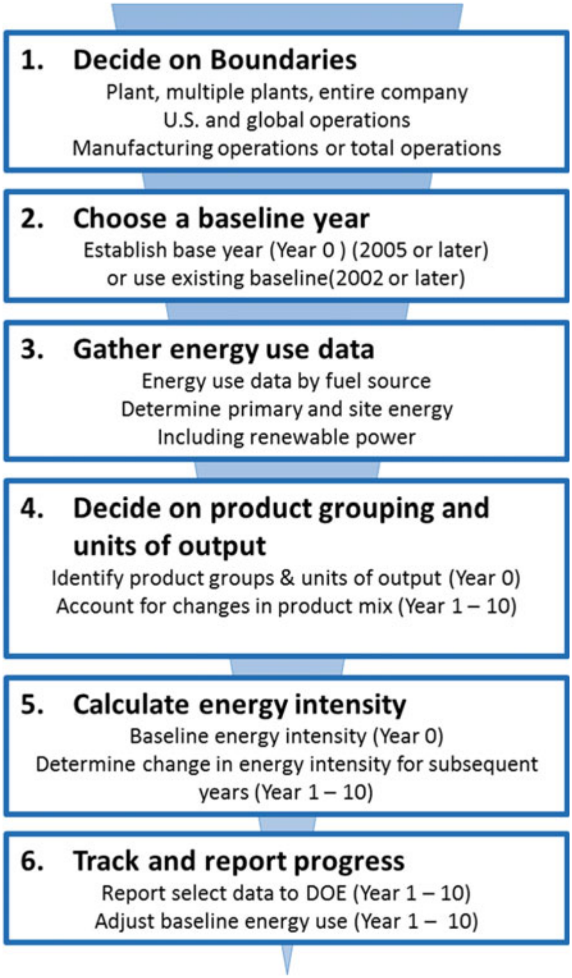


**Fig. 8.2** DOE steps to develop baseline (Department of Energy)

targets for energy and carbon. Although most methods use regression analysis, it is best to select a year of "normal" operations if possible, that coincides with other company baseline goals. One standard method developed by the Department of Energy (DOE) is the international performance measurement and verification protocol (IPMVP). Although any year can be established as a baseline year although it's best to use steady-state operations and prior to major energy efficiency initiatives being implemented. Figure 8.2 depicts the 6 steps to implement IPMVP.

DOE's guide to developing an energy use and energy intensity baseline and reporting describes the process used and purpose to set up a baseline. Additionally DOE provides a regression analysis spreadsheet model to track energy baseline and year-over-year performance called the energy performance indicator tool. Large companies with many facilities usually use a third-party service to provide similar data tracking. Tracking energy use by product grouping is dependent on the level of metering or sub-metering that is available at a production facility. If a facility makes only one product then the production unit selection is simple: however, many facilities make multiple products in a single facility and sub-metering is not easily accomplished. In this case other production metrics can be used to normalize the energy data, such as product weight, cost of goods sold, or other production output, for example strokes of a stamping press.

During the data gathering process it is important to keep consistent units of measure for energy and synchronize the timestamp for all data. As an example, when using monthly invoice data, the timeframe for the energy use must be consistent with other independent variables—climate and production. Therefore, if a company chooses monthly reporting and the invoice is for less than a month's worth of energy use, the company must allocate the energy based on monthly use.

### 8.3.4 Science-Based Targets

"Science-based targets" is a joint initiative by CDP, the United Nations Global Compact, the World Resources Institute (WRI), and World Wildlife Federation (WWF) with the purpose to identify and promote innovative approaches to setting ambitious and meaningful company GHG reduction targets. "The world's carbon budget is the total volume of GHGs that can be emitted while providing a degree of confidence that temperature rise will be limited to a manageable 2 °C. Science-based targets recognize that budget, limiting a company's GHG emissions to an allocation using various existing approaches". The benefit, which is to protect climate and communities, is also good for business:

- drive innovation
- save money and increase competitiveness
- build credibility and reputation
- influence and prepare for shifting public policy.

The Science-based target setting manual describes the methodologies that industrial companies can use to establish targets. The boundary of carbon footprint is categorized into Scope 1, Scope 2 and Scope 3. Figure 8.3 depicts how Scope 1, 2 and 3 are different from their sources and stage (refer to "Appendix: Methods and Standards for Preparing Scope-3 Carbon Footprints" of Chap. 3 for details about the carbon footprint).

Science-based targets are usually based on scope 1 and 2 GHG emissions that are under the direct control of the company. All seven models in the manual require base year, target year, and country inputs with three being specific to the applicable industrial sector. The output is a greenhouse gas target for the target year in either intensity (tons per unit) or absolute tons of carbon dioxide equivalent, $CO_2e$. Links are available to online models in the manual.

The GHG Protocol describes other methods for setting targets with this 10 step process as shown in Fig. 8.4.

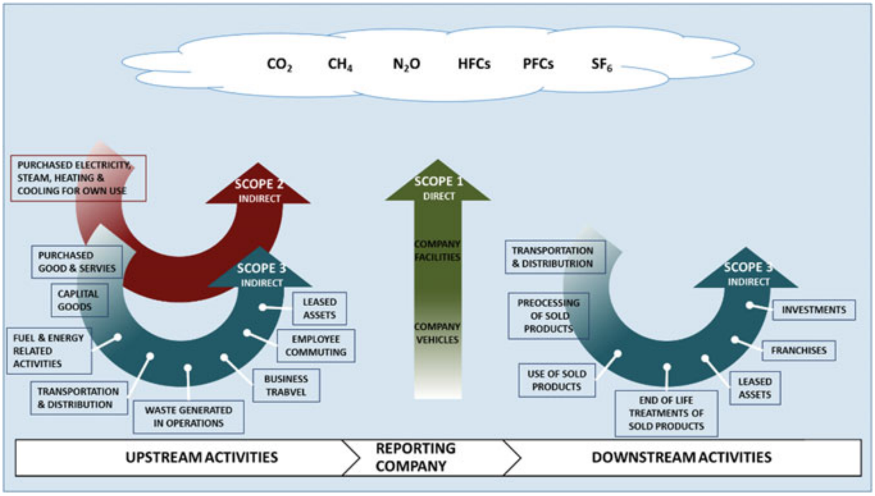


**Fig. 8.3** GHG Protocol emissions scope (Greenhouse Gas Protocol)

**GHC Protocol: 10 steps for setting GHG emission reduction targets**

1. Obtain senior management commitment
2. Decide on the target type
3. Decide on the target boundary
4. Choose the target base year
5. Define the target completion date
6. Define the length of the target commitment period
7. Decide on the use of offsets or credits
8. Establish a target double counting policy
9. Decide on the target level
10. Track and report progress

(Source: GHC Protocol, www.ghgprotocol.org)

**Fig. 8.4** 10 Steps to setting targets (Greenhouse Gas Protocol)

Benchmarking companies compared to industry standards can provide an understanding of the gap to leaders in the industry and assist in establishing reasonable, yet aggressive, energy and carbon reduction targets. As an example, GM reduced carbon intensity by 43 % in 10 years from 2000 baseline. Duplicating this level of performance would be extremely difficult, based on the law of diminishing return, as the resultant intensity approaches zero. Therefore, a reasonable but aggressive 20 % reduction was selected for the next 10 years to 2020.

The processes described provides the tools that companies need to set GHG emission reduction targets, that can either be internal or be publicly disclosed. Public disclosure demonstrates a high level of commitment to external stakeholders.

## 8.4 Benchmarking, Budgets, and Forecasts

### *8.4.1 Benchmarking*

External energy benchmarking is a valuable tool for building and energy managers and can answer these key questions:

- How do I know whether my plants are energy-efficient?
- How much can my plants improve?
- Which plants should I target for efficiency improvements?
- Which plants should I examine for best practices?

Energy Star® has developed energy performance indicators (EPI) for 11 manufacturing plant types:

- Automobile Assembly EPI
- Cement Manufacturing EPI
- Container Glass Manufacturing EPI
- Cookie and Cracker EPI
- Flat Glass Manufacturing EPI
- Frozen Fried Potato Processing EPI
- Integrated Paper and Paperboard Manufacturing EPI
- Juice Processing EPI
- Pharmaceutical Manufacturing EPI
- Pulp Mill EPI
- Wet Corn Milling EPI.

These external benchmarks provide industry with a score of 1–100 indicating where a facility energy use is on a percentile basis compared to other facilities with 100 being the lowest or best. As the model is based on data that correlates to energy use, from many US manufacturing plants, this benchmarking system corrects for the many variables that affect energy use in manufacturing.

As an example for the automotive industry, GM uses annual external energy benchmarking for its vehicle assembly plants, based on the EPA ENERGY STAR® Energy Performance Indicator (EPI). This rating system determines the most efficient plants and is used to set targets for future years. Similarly, for other manufacturing facilities, GM use internal benchmarking tools that were developed using similar algorithms as the EPI to determine the most efficient facilities.

EPA Energy Star® also has a benchmarking system available for buildings in various categories—offices, educational, warehouses… as described at "http://www.energystar.gov/buildings/facility-owners-and-managers/existing-buildings/use-portfolio-manager". As a free service in US, Building Portfolio Manager provides valuable building benchmarking information by category that has been established based on thousands of buildings' energy performance as shown in Fig. 8.5. Additionally, many Energy Performance Indicators (EPI) are available for various industries that provide similar valuable benchmarking data.

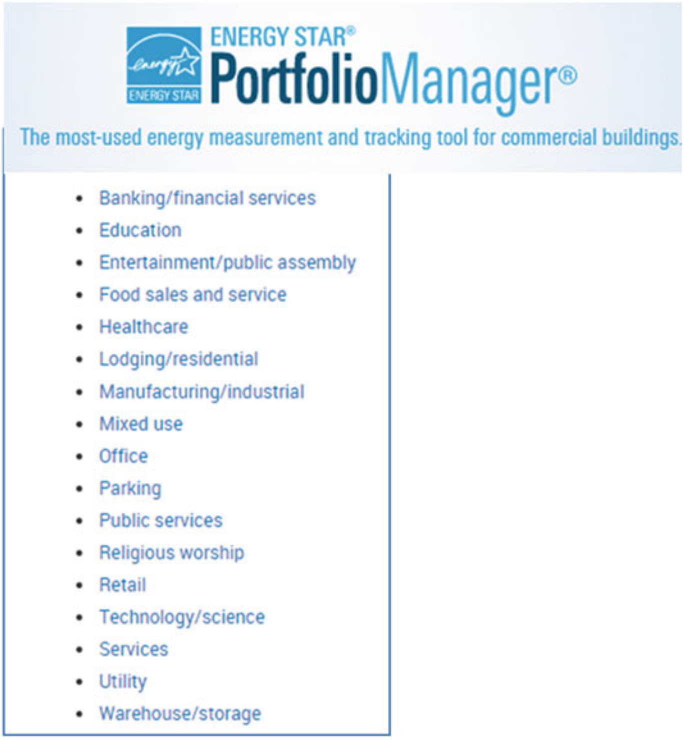


**Fig. 8.5** Building portfolio manager (Energy Star®)

Similar to Energy Star® EPI, GM uses the 75th percentile as a benchmark for both internal and external benchmarking for global facilities and operations. This establishes a strategy to prioritize efforts for continuous improvement for investment, energy conservation efforts (tuning), and other improvements.

Energy Star® Portfolio Manager provides a score of 1–100 showing building's performance relative to others on a percentile basis with 75th percentile set as the benchmark and criteria for certification in USA.

### *8.4.2 Budgets and Forecasts*

For fiscal accounting and operating to a business plan accurate budgets and forecasts for energy expenditures are required. Energy budgets and forecasts can be developed using multivariate regression analysis similar to target setting using IP MVP or other methodology. Budgets typically cover a fiscal year and forecasting can be performed monthly or quarterly.

As an example, to establish monthly energy and water cost budgets and intensity targets, GM uses two main methods for the majority of their facilities—standard multi-variable regression analysis similar to International Performance Measurement and Verification Protocol (IPMVP) and a GM patented energy activity-based accounting method. The IPMVP method is used for plants with fairly steady-state production and minimal process variations and correlates energy and water use to production and climate conditions and works well to forecast future year's monthly use to establish budget and intensity targets. However, if a facility has major changes in either production—1 shift to 3 shift, significant variance year over year, or major production process changes—adding paint booths, processing a new part, or new equipment technology, then the IPMVP method is not accurate for budgeting and forecasting purposes. Using monthly data, these inputs and outputs provide budgeting and forecasting information:

Inputs

- historical monthly energy, production units, climate data (HDD, CDD)
- future production unit forecast and ten-year average climate data
- future performance goals (year-over-year reduction)
- future manual adjustments due to special circumstances
- historical and future energy rates and cost.

Outputs

- future energy use and cost for budget and initial annual forecast
- future year-over-year performance
- normalized energy targets (megawatt hour/unit).

This process is completed for each energy source, e.g., electricity, natural gas, landfill gas, purchase steam, etc. Monthly forecasting is done similarly, each month, based on current and future information respectively. This budgeting process can be done using standard Excel Solver spreadsheet add-in as well as provided by many third-party software-as-a service systems.

GM developed a patented Activity-Based Energy Accounting (ABEA) method to improve the accuracy of forecasting for plants with extraordinary circumstances. ABEA is based on the fact that the operation of a production facility requires distinct levels of energy depending on different activities such as full-capacity production, reduced-capacity production, and non-production. The method first uses highly accurate hourly energy use data from sub-meters for different energy use activities along with the associated production activity to determine the rates of energy use that will be consumed during an activity-based time period as shown in Fig. 8.6. This method is easily tailored to the flexible production schedule so that it can minimize the problems caused by over- or underestimation of energy use with IPMVP. There are five distinct states which the manufacturing system can be in at any given time and each state has a different energy load characteristic. These states are shown in a Universal Modelling Language (UML) state diagram in Fig. 8.7 along with the transition options from each state. The varying loads for each state must be considered when creating a predictive model to ensure accurate results.

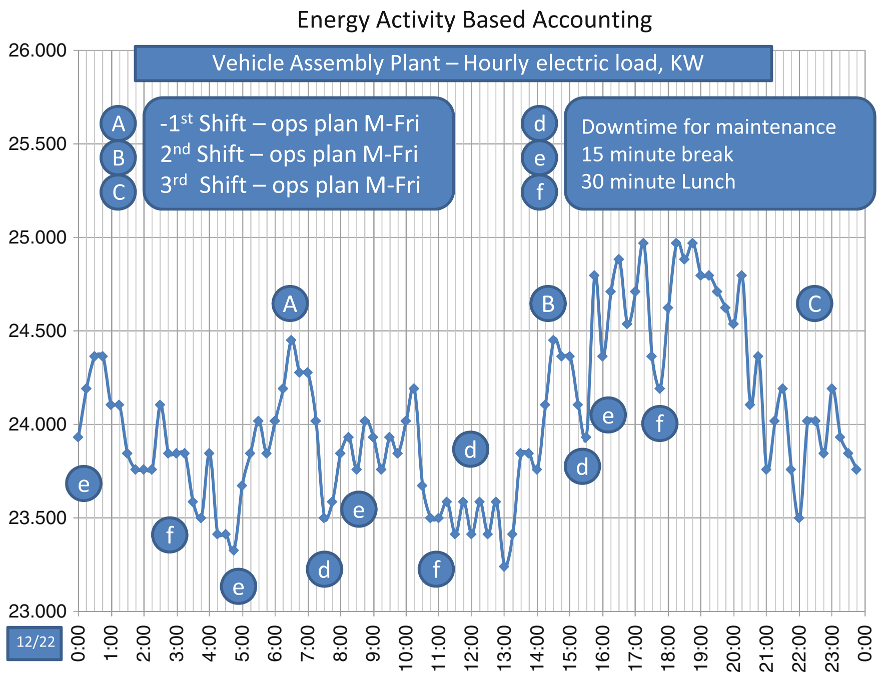


**Fig. 8.6** Building portfolio manager Energy profile for manufacturing operation states (Hildreth and Oh 2012)

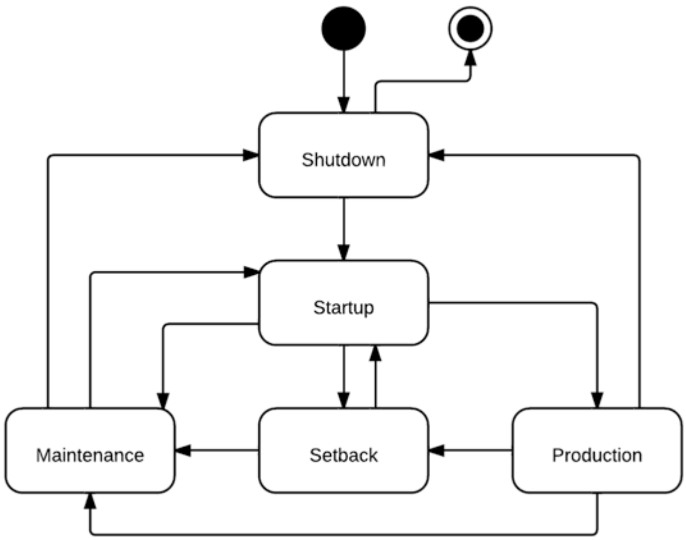


**Fig. 8.7** UML state diagram of plant manufacturing operation states (Hildreth and Oh 2012)

The production state of the system is that in which products are being produced at a production workstation or assembly line. This state is a high consumer of resources due to most equipment in the facility running at high levels. During a normal work day, there will be times such as lunch or between shifts when the system can be put in a setback state to save energy. In this state, the equipment of the system is turned down to a lower level or off until production resumes again.

If there is an extended period in which the system does not need to run—such as weekends or holidays, the system can be put in a shutdown state, in which only a few limited systems are running. This is due to process requirements of minimum air flow, critical operations, and emergency lighting. In this state, the system uses minimal energy. To transfer from shutdown to a higher level state which uses more energy, the system is put into a start-up state. This state is a high consumer of energy because the system is operated at high levels to quickly increase system conditions to operating conditions. This is similar to the time when a vehicle accelerates, in which it requires more gas than when cruising or parked. The final state is the maintenance state, in which the system has minimal system requirements for the necessary repairs to be performed. All these states use energy at different loads so it is important to consider these states and the production schedule for plant energy use prediction purposes. To forecast a future period, modifications to the load may be required based on changes in future months or the hours of production versus non-production will be required. The budget or forecast is determined by the sum of products of the load and hours for each state as shown in Fig. 8.8.

To account for variations in climate, the ABEA method must be applied on a monthly basis and for extreme variances to average heating degree day and cooling degree day excursions, normalization is used to correct to ten-year average climate

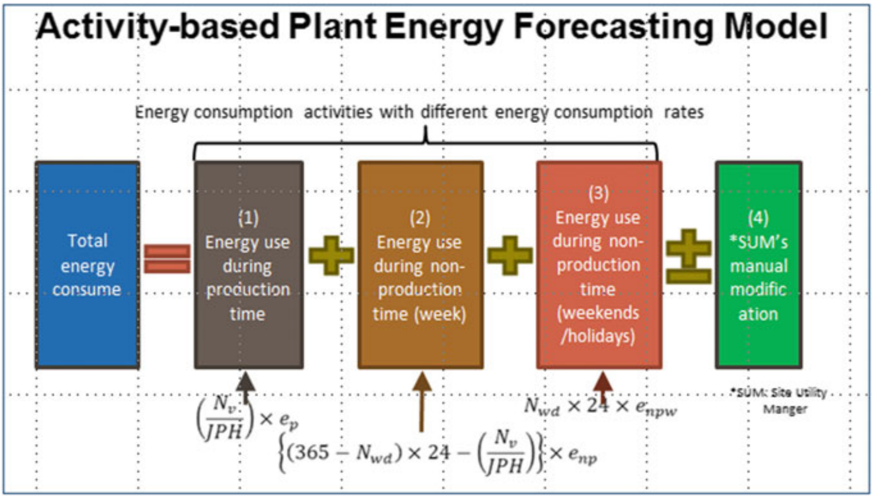


**Fig. 8.8** Calculation of energy from various activity based states (Hildreth and Oh 2012)

conditions. GM has incorporated the ABEA method into Energy OnStar since interval energy data use information is available along with production counts.

Energy budgeting and forecasting is a valuable tool in the business plan process that provides a plan of energy use that meets the company's goals and targets and is used to check each facility's performance to their goals. Although monthly and annual performance reviews are standard and valuable, using hourly models to determine targets provides for hourly and daily verification of performance to company goals, providing near real-time potential corrective action information to better meet the goals. Readers are recommended to read previous studies (Oh et al. 2011; Oh and Hildreth 2013a, b; Oh and Hildreth 2014) to learn details about data and model-driven energy models for automotive assembly plant.

## 8.5 Action Plan

With energy targets established, the next step is to have a robust action plan to meet the targets. Similar to other aspects of the business, energy efficiency and conservation planning must be integrated into the standard business plan process at various levels within the organization—the team, department, plant, regional and global functions. Energy methods must be established at each level of the organization to meet the objectives and tracked along with other manufacturing aspects—safety, people, quality, responsiveness, cost to ensure that required performance is attained. Visual management for "Plan, Do, Act, Check" activities, including BPD boards, scorecards, and dashboards, provides for a constant reminder of the business plan deployment (BPD) status.

### *8.5.1 Sufficiency Plans*

It is essential that each plant and major non-manufacturing facility develop an "energy sufficiency plan" that identifies initiatives and projects that will be implemented to meet the objectives. An example from GM is shown in Fig. 8.9.

| Month (Production) | Dec | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug |
|---|---|---|---|---|---|---|---|---|---|
| Month (Accounting) | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep |
| Item No. 1 (Forecasted) | upgrade compressor controls | | | | | | | | |
| Electric Reduction (MWH) | | | | | | | 125 | 125 | 125 |
| Nat Gas reduction (MWH) | | | | | | | | | |
| Savings ($) * | $0 | $0 | $0 | $0 | $0 | $0 | $8,500 | $8,500 | $8,500 |
| ACTUAL | | | | | | | | | |
| Electric Reduction (MWH) | | | | | | | | | |
| Nat Gas reduction (MWH) | | | | | | | | | |
| Savings ($) * | $0 | $0 | $0 | $0 | $0 | $0 | $0 | $0 | $0 |

**Fig. 8.9** Energy sufficiency plant example from GM

These are tracked and shared between plants for collaboration on methods provide for continuous improvement.

### 8.5.2 Energy Projects and Conservation

Energy efficiency and conservation is the primary method for carbon reduction, followed by fuel switching and the use of renewable energy. Energy reduction projects and initiatives provide attractive return on investment and is used to right size the energy supply requirements for a facility. Fuel switching can also be a cost-effective method to reduce a company's carbon footprint. An example of fuel switching is the conversion of a boiler that combusts coal to make steam to a burner that operates on natural gas. The carbon dioxide emission factor of natural gas is approximately one half that of coal for a significant reduction in carbon emissions. Use of renewable energy, such as solar and wind, is an excellent method to reduce the effect of energy use and carbon emissions; however, the return on investment (ROI) is typically not as good as energy efficiency. For short term ROI calculations, typically *simple payback* is an acceptable indicator:

$$\text{simple payback} = \text{Total cost/savings per year(years)} \tag{8.1}$$

Energy, water, and carbon reduction projects are a significant contributor to the Sufficiency planning process, along with conservation activities. Similar to other aspects of the business, budget monies must be allocated to provide for these efficiency projects. An example of a process used at GM uses a central office team that collects proposed projects from facilities and prioritizes them based on return on investment and probability of successful implementation to develop a project implementation plan. The amount of money to be allocated should be sufficient to implement cost-effective projects to meet the company goals. A detailed process will be described in Chap. 9.

The types of energy projects fall into two categories—retro-fit efficiency and design in energy efficiency. Retro-fit projects are focused on existing equipment and processes for continuous improvement. Design in efficiency is implemented by working closely with manufacturing and product engineers to design new or major modifications of processes—paint shops, welding equipment, casting plants using the latest high energy efficient equipment and systems. Some example energy projects from GM, that will be described in detail in Chap. 9 are:

**Energy Efficiency in Process**

- 3 wet paint process eliminates an oven
- Downsize paint booth for small vehicle
- Use 90 % recirculation in paint booths
- Optimize booth set-points for energy

- Dehumidify cupola hot blast air
- Redesign furnace heating elements.

**Energy Efficiency in Buildings**

- Lighting from HID/T12/T8 to LED
- HVAC controls upgrades
- Variable frequency drives on motors
- Steam elimination using direct fired gas heaters
- Heat recovery
- Free cooling during winter months using cooling tower water instead of mechanical chillers
- Install construction walls to isolate a building during construction
- Compressor controls to optimize system operations.

**Energy Conservation**

- Reduced light levels based on most recent illuminating engineers Society of North America (IESNA) standards
- Right sized HVAC for current occupancy and process
- Lighting controls to shut off lights when not in use and "weld and paint in the dark" as robots don't need light to operate
- Demolish unused building—consolidation
- Repair steam and air leaks.

### *8.5.3 Check Progress*

The BPD process requires regular evaluation of control points for each objective and method for all manufacturing operations, including performance to sufficiency plans, as well as comparison of actual performance of energy, water, and carbon intensity actual results to targets. As an example, GM uses a global utility web-based system to compare monthly energy, water, and $CO_2e$ intensity performance-to-targets which are communicated to plants on monthly scorecards to determine status of meeting business plan goals. Any performance with less than a "Green" status not meeting the target requires a countermeasure to be developed for corrective action, which is also tracked with additional emphasis to ensure achievement to goals.

Status of implementation of projects and energy sufficiency plans should be tracked at all levels of the organization, including central office to identify areas needing additional resources for implementation. Other standard checks of weekly performance to non-production energy shutdown targets can be communicated, using a centralized system, to plants at the department level to show progress and determine if corrective actions are required. Third-party services are available where a dedicated team evaluates opportunities identified in operating HVAC systems using a dashboard system. GM co-developed the "Energy OnStar" system, that constantly monitors HVAC systems for energy efficiency to continuously commission systems that includes dedicated resources to develop corrective action plans for weekly review with central office and plants. In 2015, this process has identified and implemented more than $3 M of energy savings with a six-month simple payback.

As with any business process an effective energy action plan is a key success factor for businesses to meet their energy management goals.

## 8.6 Energy Management Tools

Similar to any job using the right energy management tools makes the task simple and effective. The following list summarizes an effective, top 10, toolkit items for energy management and business, some of which have been described herein:

1. Data management
2. Benchmarking, Goal setting, and scorecards
3. Energy expense budgeting and forecasting system
4. Dedicated team and budget
5. Energy treasure hunts (see Chap. 9 for details)
6. Interval meter data
7. Energy dashboard monitoring system
    (a) continuously commission HVAC systems
    (b) monitor weekly shutdown performance
    (c) report daily performance to targets
8. Business plan deployment
9. Energy project implementation process
10. Internal and external recognition.

### *8.6.1 Internal Recognition*

Everyone likes to be recognized and this is important development in the continuous improvement, energy management process. Recognition for energy management performance should be included in all company internal recognition programs. Examples at GM include:

- Employee performance to goals as measured and rewarded using GM's Commitment and Accountability Program ("CAP").
- Team recognition is available as either monetary in U.S. and Canada, or non-monetary in other countries. The awards are presented to employees from their supervisors for demonstration of various values—commitment, teamwork, trust, growth, recognition, fairness, and health and well-being.
- Non-monetary awards can be initiated peer-to-peer for recognition of achievements.
- In the U.S., GM's Quality Network program includes a formal employee suggestion system. Employees suggest an improvement to an existing process and can receive a portion of the implemented savings up to $20,000. Many valuable energy and water reduction ideas have been implemented yielding hundreds of thousands of dollars in energy, water, and carbon reduction savings.

Employees from central staff to the plant level have objectives to reduce energy and water intensity, and their performance to these goals are evaluated mid-year and at year-end. Recognition of achievement can be monetary if enhanced variable pay is activated by GM meeting various other goals, at which time allocation of rewards is also dependent on attainment of individual goals, e.g. meeting energy and water intensity goals.

### *8.6.2 External Recognition*

A number of external recognition programs exist that recognize successful energy management achievements as shown in Fig. 8.10.

- EPA Energy Star® plant and building certifications
- EPA Energy Star® Challenge for Industry recognition
- EPA Energy Star® partner of the year award
- DOE Better Buildings Better Plants
- Dow Jones sustainability Index
- CDP disclosure and performance indices
- Association of Energy Engineer (AEE) recognition awards.

As recognition is embedded in the Energy Star® energy management model, EPA has developed many recognition awards for exemplary energy management performance. Similar to certifications for laptops and appliances, Energy Star® has developed certifications for buildings and many industrial plants. Facilities that are in the top 75th percentile of performance and meet other criteria requirements are able to display the Energy Star® label.

For manufacturing facilities without an EPI, Energy Star® developed the Challenge for Industry program that recognizes industrial facilities that achieve at least a 10 % energy intensity reduction within a five-year period. The most

**Fig. 8.10** External recognitions from various organizations

prestigious of their recognition programs is the partner of the year award for energy management that recognizes exemplary practices and performance.

In 2015, GM has been recognized for its energy management and other sustainability programs as follows:

- (11) buildings Energy Star® certified
- 73 plants met Energy Star® Challenge for Industry at least once with others meeting it multiple times
- Energy Star® Partner of the Year for the fourth year in a row with the last three as Sustained Excellence
- Included in the DJSI index
- CDP Disclosure Leadership Index.

Energy management is an important part of the business and for fiscal environmental responsibility requires a robust plan to be effective. Integrating energy management into company's business plan along with other aspects of the business is an effective and sustainable method for continuous improvement. With top level company support, dedicated resources of people and money, armed with available toolkits, energy management can provide a positive return on investment for a company.

## 8.7 Exercise

1. Based on Fig. 8.3 and the GHG Protocol, for a typical automotive manufacturer, classify these emissions into the correct "Scope" categories 1,2, or 3:

   (a) Traveling on commercial airline on business
   (b) Electricity to operate factory
   (c) Natural gas to heat office building

(d) Shipping vehicles to dealerships'
(e) Customers driving auto manufacturer's vehicles
(f) Steel used in stamping doors
(g) Dealer's facility operations.

2. Which budget method, (IPMVP or ABEA) is appropriate for these operations?

   (a) Battery plant with 2 % increase in production next year and the factory does not have any interval meter data, monthly only energy invoices.
   (b) Assembly plant changing from 1 shift per day, 5 days per week, to 3 shifts per day and 6 days per week and has hourly sub-meter data available.
   (c) Engine machining plant is opening up new next year and is built similar to other plants but has different shift operating plans.

3. According to Fig. 8.6, what is the approximate energy reduction from 1$^{st}$ shift operations and downtime period in percentage?
4. Rank these energy and carbon reduction projects by the best to worst simple payback:

   (a) Replace lights in a factory at a cost of $1 M that saves 5,000 MWh. The average electrical rate is $100/MWh.
   (b) Install 500 kW of solar power with an efficacy of 15 % and an installation cost of $2/W, offsetting $100/MWh utility electricity.
   (c) Convert a boiler from coal to natural gas at a cost of $3 M with carbon savings of 50,000 tons. The market price to sell carbon credits is $20/ton.

5. Assume that you are ready to budget next year's energy cost and use for a factory. If you have the following information available, what is missing?

   - Historical monthly energy, production units, climate data (HDD, CDD)
   - Ten-year average climate data
   - Future performance goals (year-over-year reduction)
   - Future manual adjustments due to special circumstances
   - Historical and future energy rates and cost.

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# Chapter 9
# Energy Efficiency Accounting to Demonstrate Performance

**Abstract** An important method to reduce Greenhouse gas and energy is through energy efficiency projects. To gain top-level support and funding, a systematic approach is best using data and benchmarking other companies. Explaining why support and funding is required is the first step toward selling the need. To compete with other internal funding needs—product programs, asset sustainment, and maintenance…, a strategic approach is required utilizing company's standard business practices for energy savings projects. A long-term plan including energy use forecasting, business as usual, the gap to meet the company's goals, and the spending and savings for multiple years demonstrates a strategic plan to meet the objective. Based on the available funds, prioritize projects based on return on investment, $CO_2$e reduction, and probability of success. Tracking each project throughout the planning and implementation process demonstrates accountability. Additionally, having a list of shovel ready projects and the status of each can provide an opportunity to gain more funding if it becomes available. Reducing next year's operating budget by the savings is a good method to sustain the funding year over year. Standardized measure and verification methods provide confirmation to customers and management that energy efficiency efforts really reduce the bottom-line cost and provide an attractive return on investment.

## 9.1 Selling the Need to Fund Projects

When an energy efficiency project is need, a company should begin a sales strategy with WHY the energy efficiency project needs long term funding. When energy management is included in the business plan or is consistently applied, the company will need to expand the number of available energy efficiency projects to meet reduction goals. Demonstrate the need with lots of data of past performance if available. If the company has public goals, compare progress to the goals and forecast for the future to identify the gap. In the early years of implementing energy

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S.-C. Oh and A.J. Hildreth, *Analytics for Smart Energy Management*,
Springer Series in Advanced Manufacturing, DOI 10.1007/978-3-319-32729-7_9

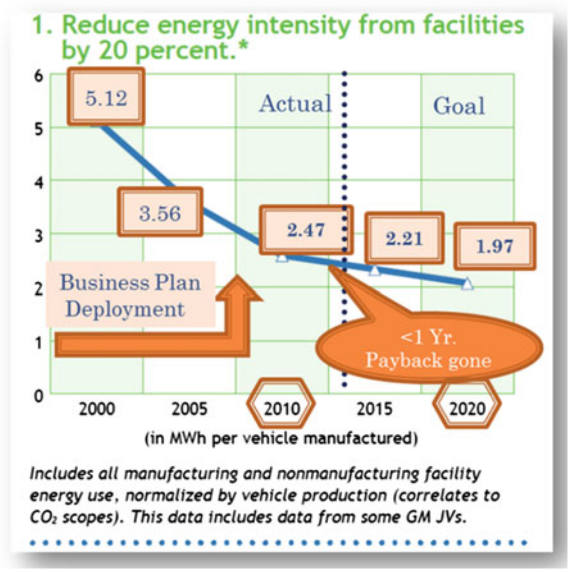


**Fig. 9.1** GM energy goals and performance (Hildreth 2014)

efficiency, the reduction percentage should be large as quick payback projects provide large savings. As time goes on, similar to the law of diminishing return, the reductions will require more investment, a higher level of technology, and generally get more difficult to keep up the large year over year reductions. The example in Fig. 9.1 shows GM's progress to its public energy intensity goal. From 2000 to 2010, the intensity reduction was greater than 40 %; whereas, performance to date and goals were reduced to 20 % for the next 10 years based on a high level of achievement and integration of energy into our business plan during the first ten years. Although new technologies can cause drastic improvements over current performance, looking at 2030 where the forecasted slope goes to zero, indicates difficulty in obtaining further savings.

As more customers desire to reduce their overall carbon footprint, they will look to their suppliers for carbon reductions. In 2014, the Automotive Industry Action Group (AIAG) issued guidance from seven Automakers on sustainability to their supply chain (Automotive Industry Action Group 2014): "We endeavor to achieve excellence, innovation and performance in a sustainable manner. People and the environment are the automotive industry's most important resources. For this reason, we are working together to attain the highest standard in business integrity and in the social and environmental performance of our supply chain. …Such a comprehensive approach includes but is not limited to:

- Reducing energy and water consumption
- Reducing greenhouse gas emissions".

### *9.1.1 Strategic Plan*

Developing a strategic plan for energy reduction is essential for gaining support for funding and project implementation. Determining forecasted energy with business as usual is the first step. Chapter 8 discusses some simple tools to forecast energy using multi-variable regression analysis with either Microsoft Excel or various third party software as a service as well as an hourly activity based forecasting model. Most use historical climate, energy, production information and future production and average climate data to forecast future energy use.

Whatever method used, the future energy forecast provides a basis to compare to the company's targeted reductions to identify the gap revealing the required energy efficiency. Figure 9.2 shows an example of a gap analysis with column G from regression analysis—energy use in future years, Column D as the goal, and column F is the gap, which is the energy savings needed from efficiency projects. The data for years 2008–2013 are actual and 2014–2020 are forecasts.

After identifying the gap, the next step is to determine an acceptable payback based on company's hurdle rate or appetite for carbon reduction (Energy Conservation Measures). Hurdle rates are developed based on expected rates of return including a risk factor. As energy projects have a low risk factor, a lower hurdle rate or higher payback should be acceptable for energy and carbon reduction projects. For example, new manufacturing technology cost savings projects have some risk that they will not deliver savings; however, more efficient lights or motors will always reduce energy with little risk. An additional benefit of energy projects is

| B | C= G/H | D (22% goal-10 Yrs.) | E = D-C | F = E x H | G | H | I | J |
|---|---|---|---|---|---|---|---|---|
| Year | Energy per unit | Target, MWh/Unit | Gap to Target, MWh/Unit | MWh needed to meet target | Energy, MWh | Production | HDD, �F | CDD, �F |
| 2008 | 0.29 | [redacted] | | | 7,702,979 | 26,605,870 | 613,259 | 235,431 |
| 2009 | 0.25 | | | | 6,116,575 | 24,594,036 | 598,741 | 244,984 |
| 2010 | 0.23 | | | | 7,359,206 | 32,270,483 | 624,604 | 274,562 |
| 2011 | 0.23 | | | | 7,573,172 | 33,328,819 | 604,179 | 261,784 |
| 2012 | 0.22 | | | | 7,764,343 | 34,979,192 | 582,712 | 271,215 |
| 2013 | 0.22 | | | | 7,756,037 | 34,962,019 | 614,107 | 255,546 |
| 2014 | 0.23 | 0.21 | (0.02) | 637,455 | 8,211,253 | 36,010,880 | 606,267 | 257,254 |
| 2015 | 0.23 | 0.20 | (0.02) | 806,611 | 8,395,276 | 37,091,206 | 606,267 | 257,254 |
| 2016 | 0.22 | 0.20 | (0.03) | 980,023 | 8,584,819 | 38,203,942 | 606,267 | 257,254 |
| 2017 | 0.22 | 0.19 | (0.03) | 1,157,864 | 8,780,049 | 39,350,060 | 606,267 | 257,254 |
| 2018 | 0.22 | 0.19 | (0.03) | 1,340,318 | 8,981,136 | 40,530,562 | 606,267 | 257,254 |
| 2019 | 0.22 | 0.18 | (0.04) | 1,527,568 | 9,188,256 | 41,746,479 | 606,267 | 257,254 |
| 2020 | 0.22 | 0.18 | (0.04) | 1,719,806 | 9,401,589 | 42,998,873 | 606,267 | 257,254 |
| | | | | | Multiple Variable regression analysis | Business plan | long term average Climate | |

**Fig. 9.2** Example—enregy forecast, targeted reduction and gap analysis (Hildreth 2014)

**ENERGY CONSERVATION MEASURES**

**TYPICAL PAYBACK PERIODS ***

| COMMERCIAL ENERGY CONSERVATION MEASURES (ECMS) | SIMPLE PAYBACK PERIOD (YEARS) | EQUIPMENT LIFE EXPECTANCY |
|---|---|---|
| Energy Management System - new | 1 to 4 | 20 |
| High Efficiency Motors & VFDs | 1 to 4 | 20 |
| Steam Trap - replacement / repairs | 1 to 5 | |
| Lighting Lamp & Ballasts - retrofit and controls | 2 to 5 | 20 |
| Energy Management System - replacement | 2 to 6 | 15 |
| Manufacturing Process - heat recovery | 2 to 5 | 15 |
| Chiller - replacement | 5 to 12 | 25 |
| Boiler - replacement | 8 to 30 | 35 |
| Rooftop Unit HVAC - replacement | 9 to 15 | 20 |
| Building Insulation - addition | 10 to 15 | - |
| Roof Insulation - addition | 20 to 30 | - |
| Windows - replacement | 15 to 50 | 40 |

**Fig. 9.3** Typical paybacks from energy efficiency (Energy Conservation Measures, Available online: http://www.think-energy.net/ecm_payback.htm)

the potential of obtaining utility incentives to reduce cost, sale of carbon credits in some countries, and reduced carbon taxes, where applicable.

From the gap data in Fig. 9.2 column G, and an average payback in years from Fig. 9.3, the amount of spending by year can be determined as follows:

$$\begin{aligned}&\text{Spending needed to meet the gap}(\$)\\&\quad = \text{MWh } \$ \times \text{average rate}(\$/\text{MWh}) \times \text{payback}(\text{years})\end{aligned} \tag{9.1}$$

Average energy rates ($/MWh) assumptions can be determined by repeating the historical trend for locations for future years, using forecasted consumer price indices, or from predictions from third parties, US DOE Energy Information Agency, or the International Energy Agency.

Benchmarking each step of the strategic plan provides direction on the best practices within industry. CDP Climate Change reporting reveals that a dedicated fund for emissions reduction is the most used method (51 %) based on the Global 500 companies reporting to CDP (Carbon Disclosure Project 2013). GM has been successfully using this method as a primary means of continuous improvement in energy efficiency, along with employee engagement, utility incentives, product programs, and energy performance contracting for total spending representing about 10 % of our annual spend for utilities. To ensure successful implementation of the strategic plan and minimize risk, select projects that have a proven success rate

- Lighting is an easy, reliable energy savings initiative and LED retro-fits and new fixtures are now offer reasonable energy payback compared to other lighting systems

- Inefficient application of motors for pumps and fans have efficiency improved with Variable Frequency Drives (VFD), pump or fan replacements, or retrofits.
- Heating, Ventilation, and Air Conditioning (HVAC) can be a major opportunity with continuous commissioning or even retro-commissioning
- Steam elimination with more efficient direct fired gas heat for manufacturing plants—(30–40 % savings)
- Process energy use can be large (60 %) with lots of continuous improvement opportunities.

The best method to state the project's business case, or cost benefit analysis, is to use financial models similar the company's internal models. Typically, for short-term evaluation, less than 2 years, many companies use simple payback (Spend divided by savings per year) and set a maximum level, e.g. 1–2 years for funding as many of these are operating expense. For longer term, capital investments, discounted cash flow and return on investment models are common using an internal rate of return or hurdle rate, e.g. 12–20 %.

### 9.1.2 Accountability

To ensure long-term sustainability of energy and carbon reduction funding, accountability for results is essential. Integrating energy efficiency spending and savings into company's long term business plans provides multi-year planning and ensures a high probability that funding will occur on a regular basis. Along with this benefit comes a need for accountability. The Strategic Plan section describes the methodology to quantify the required savings to meet company's goals. Robust systems to regularly track and plan performance to these goals, similar to other business systems provides accountability and sustainment of the process.

### 9.1.3 Data Systems

Credible data is paramount to accountability and drives decision making for robust energy management systems. As an example, GM uses two systems that interact with each other to provide both real-time, interval energy use, data and monthly information for energy, water, and greenhouse gas (Hildreth 2014). Energy OnStar is a dashboard system that provides not only hourly, daily, and weekly energy use information, but also monitors the effectiveness of heating ventilating and air conditioning (HVAC) systems in manufacturing operations. Sometimes referred to as continuous commissioning, this approach provides real-time feedback on the operating efficiency of one of the major users of energy, HVAC, and provides identification of inefficient operations and projects for continuous improvement from an individual HVAC unit, to a plant, and at the enterprise level. Figure 9.4 shows a snapshot of GM Energy OnStar.

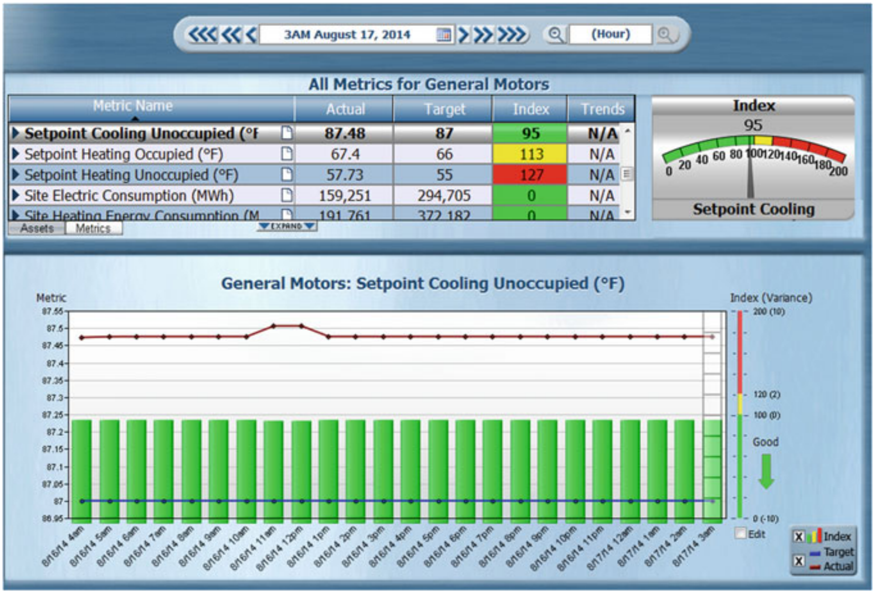


**Fig. 9.4** Energy OnStar—real-time energy dashboard and HVAC continous commitioning (Hildreth 2014)

| Production Days - MWH/Unit | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Electric | | Heat | | Total | | Production |
| Date | Actual | Target | Actual | Target | Actual | Target | Count |
| 08/11/2014 | 0.55 | 0.52 | 0.48 | 0.46 | 1.03 | 0.97 | 1091 |
| 08/12/2014 | 0.53 | 0.52 | 0.50 | 0.46 | 1.03 | 0.97 | 1064 |
| 08/13/2014 | 0.50 | 0.52 | 0.52 | 0.46 | 1.03 | 0.97 | 1107 |
| 08/14/2014 | 0.50 | 0.52 | 0.56 | 0.46 | 1.06 | 0.97 | 1108 |
| 08/15/2014 | 0.53 | 0.52 | 0.63 | 0.46 | 1.16 | 0.97 | 984 |

**Fig. 9.5** Energy OnStar—daily report (Hildreth 2014)

An additional benefit of real-time dashboard energy systems is the visual management on a daily basis regarding status of energy use and performance to goals. Waiting for a month end report is too late to make corrections to meet energy goals, so daily reports as shown in Fig. 9.5, provide immediate feedback on performance to plants and facilities.

Understanding a company's carbon footprint, including the energy drivers as shown in Fig. 9.6 is an important step to developing a strategic energy reduction plan. The cost of utilities and quantity of carbon emissions not always align as shown in Fig. 9.6, as the cost per megawatt hour and carbon intensity per MWh for electricity is much greater than other utilities. Tracking energy usage, cost, and

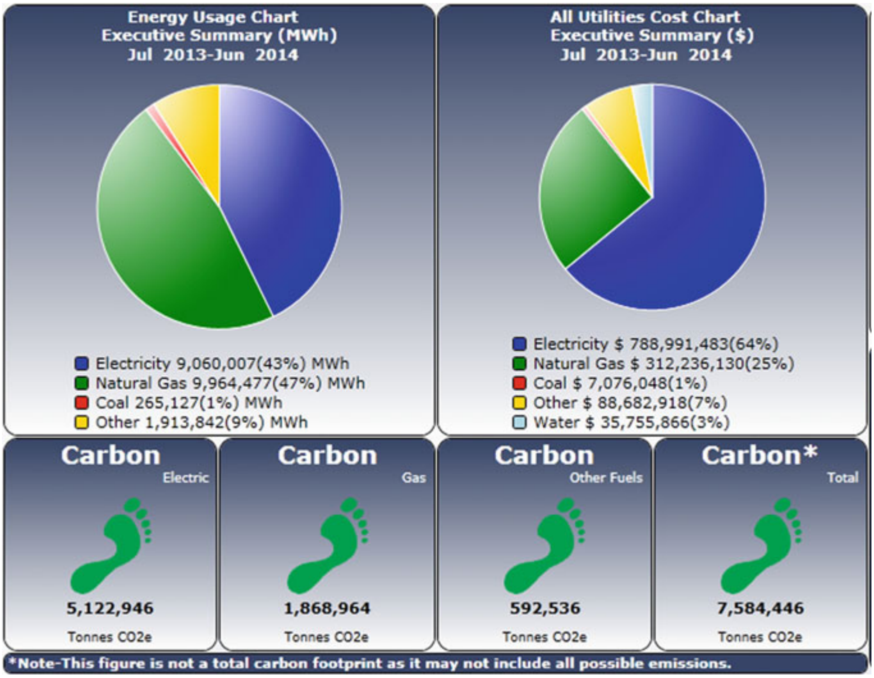


**Fig. 9.6** GM's global utility information database called GM 2100 (Hildreth 2014)

carbon emissions provides a complete picture of a company's carbon footprint and is useful to determine which reduction strategies will be most effective from a fiscal and environmental basis.

As well as having credible data to show how much spending the project needs, a project leader still needs to be able to tell upper management **WHY** he needs to spend money. Following is a summary of some suggestions that have been effective reasons why energy management and carbon reduction spending is needed in business.

- Energy conservation is integrated into our business plan and does not provide enough continuous improvement to meet our targets
- We have to meet our public goals
- History of performance shows efficiency projects are needed
- Law of diminishing return
- Positive business plan—ROI with low risk
- Savings will assist to fund future year's projects
- Demonstrates leadership in sustainability (CDP Performance Leadership Index at ~4 % savings to total carbon emissions)
- Our customers are demanding energy and carbon reductions
- Meets our Environmental Sustainability objectives.

## 9.2 Developing Energy Efficiency Projects

Energy efficiency projects implemented using the company's standard project delivery process provide the best results, but need some additional steps due to the fact that savings that is anticipated. Since energy efficiency projects propose to save energy, carbon, and money, proper tracking of the projects is a necessary requirement for sustainability of the process. Energy consumers have many new, emerging technologies available that promise improved energy efficiency that need to be properly evaluated and applied to ensure that the cost, energy, and carbon reduction savings are realized.

### 9.2.1 *Energy Project Tracking*

Project tracking through all phases—concept, planning, approvals, implementation, and closeout, enhances the accountability of the process and can allow for quick response to opportunities for additional spending.

Regardless of the number of projects a company has in queue, tracking them is critical to demonstrate accountability of spending and energy, carbon, and cost reduction savings.

Although standard project tracking programs may be adequate, an example from GM that modified an existing workflow program, from Reliance, to track energy project status, cost, savings, and energy reduction (MWh) provides the necessary steps to ensure success of energy savings projects. This provides accountability for every project, as well as aggregation at an enterprise level. Having this level of detail not only shows the status of performance, but also quickly identifies the potential for additional projects in the event that more funds become available. It is best to be prepared to be first in line for additional spending. Figure 9.7 shows a snapshot of GM's energy project tracking system.

This workflow project tracking system provides a means for multiple energy engineers to develop project concepts and allow review by subject matter experts and financial managers throughout the various phases of the projects.

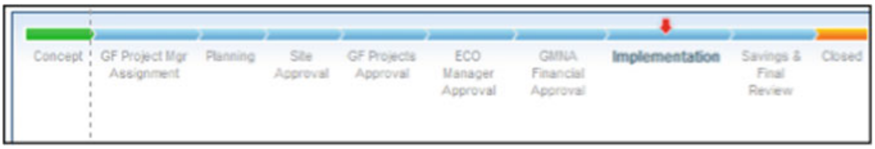


**Fig. 9.7** GM's energy project tracking system (Hildreth 2014)

- Concept
- Assignment of project managers and engineers
- Project planning
- Plant, management, financial approvals
- Implementation
- Project closeout.

The concept phase allows many stakeholders to input ideas and concepts for energy, water, and carbon reduction projects and initiatives. Based on high-level project cost and potential savings, management can assign project managers and engineers to further develop the projects or possibly decide that they are not feasible and close them out. Project planning by energy or water subject matter experts provides engineering estimates of cost and savings for projects as well as the details of project delivery for further evaluation. Based on the planning phase information all stakeholders can review and approve the project including financial approval to spend the money. Planned savings and cost determine the return on investment for the project to ensure it meets company requirements. During the implementation phase, tracking updates and changes is accomplished in the final closeout and savings review module. This process tracks the final savings and cost of the project that is useful in budgeting, forecasting, and to report to external stakeholders.

Transparency in the process is a key success factor to ensure that all stakeholders —plants, energy experts, central management, and finance are able to provide input review and approval. With a large amount of analytical calculations to justify the savings, an online system works best for large enterprise business; however, using spreadsheets and emails can perform equally as well for small businesses.

Whatever the method used to track projects, it is important to identify the amount of actual savings achieved for internal accountability and external reporting, if applicable. As an example to sustain the funding each year, GM deducts the savings from next year's utility budget.

External reporting, e.g. Carbon Disclosure Project (CDP) and others, inquire about energy reduction initiatives, so tracking by categories is helpful:

- Behavioral
- Energy efficiency (Process, Building)
- Low carbon (fuel switching, renewable…)
- Transportation
- Product.

Overall, having lots of project and initiative data, from the ones in the queue to final completion provides an accounting of efforts in energy and carbon reduction. When severe climate conditions cause more energy use, knowing how much was reduced is beneficial while explaining an increase in energy due to other factors. Also an online database of energy efficiency projects can be used to share best practices amongst plants and regions globally.

### 9.2.2 *Energy Project Technology*

A threefold strategy to reduce energy and carbon is by energy efficiency and conservation, using less carbon intensive fuels, and promoting the use of renewable energy.

The most effective approach is to reduce use of energy by conservation, but the law of diminishing return shows that other methods are needed. As an example, GM uses a combination of actions—designing efficiency in new facilities and processes, applying leadership in energy and environmental design (LEED) principles to new construction, evaluating existing operations for reduction opportunities using a dedicated budget and Energy Performance Contracting.

**Example of Fuel Switching**

- Steam elimination or reduction using direct fired gas, in-lieu of coal
- Convert boilers to eliminate coal
- Purchase steam from renewable energy sources, landfill gas and waste to energy.

Examples of the types of projects that GM utilizes:

**Energy Efficiency in Process**

- 3 wet paint process eliminates an oven
- Downsize paint booth for small vehicle
- Use 90 % recirculation of air in paint booths
- Optimize booth set-points for energy
- Dehumidify cupola hot blast air
- Redesign furnace heating elements.

**Energy Efficiency in Buildings**

- Lighting from HID/T12/T8 to T5/LED
- HVAC controls upgrades

  Variable frequency drives on motors
  Steam elimination
  Heat recovery
  Free cooling during winter months
  Install construction walls

- Compressor controls.

**Energy Conservation**

- Reduced light levels based on updated Illuminating Engineering Society of North America (IESNA)
- Right sized HVAC for occupancy and process
- Lighting controls as well as weld and paint systems, that are mostly automated and can operate “in the dark”
- Demolish unused building—consolidation
- Repair steam and air leaks.

## 9.3 Prioritization of Projects

The usual occurrence is to have more efficiency projects available than monies available. A method to prioritize projects based on company’s values and goals is needed to systematically allocate funds to the most important projects. A common method to prioritize is payback or return on investment, but other factors should be considered also:

- Will the energy project allow the facility to meet the benchmark?
- Are there additional benefits from the project—quality or maintenance improvements
- Probability of success or low risk projects should have higher ranking
- Carbon reduction does not always correlate to payback, so if company’s goal is $CO_2e$, use it as a deciding factor
- Availability of utility or government incentives.

### *9.3.1 Energy Use*

Understanding which processes in a manufacturing business consume the most energy and have the potential for the largest reduction, is an important aspect of prioritization. Examples include the type of operations by product line and the specific manufacturing operations within the product line. Figure 9.8 shows an example from GM of the breakdown within product lines of energy consumption.

Vehicle assembly operations account for the majority of the energy and water use and are the primary target for efficiency improvements. Further breakdown of the assembly operations shows that painting vehicles accounts for 50–70 % of the assembly plant energy and is thus the major focus for energy reduction activities. As shown in Fig. 9.9, providing conditioned air to paint booths similar to a clean

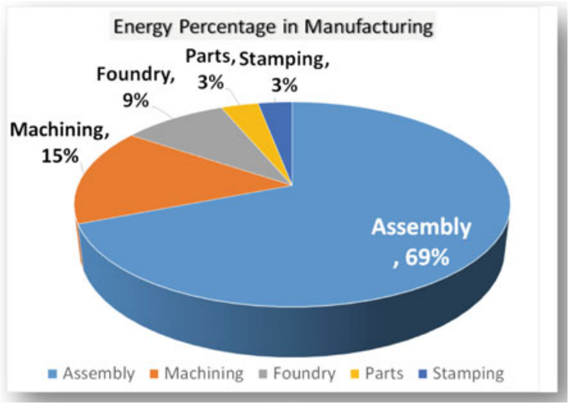


**Fig. 9.8** GM's energy use by business unit for manufacturing operations (Hildreth 2015)

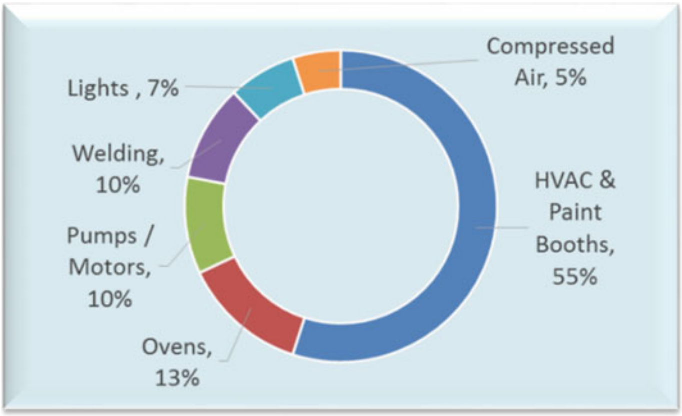


**Fig. 9.9** GM's energy use estimate for assembly plant by process/type (Hildreth 2015)

room is a major energy user (55 %), requiring methods to reduce energy in the booth to be evaluated: recycling air to automated booth zones, cascading air from building to booths, as well as designing in efficiency in fans and pumps, using the most energy efficient painting process (3 Wet paint process eliminates the prime oven), and automating shutdown activities. Reducing process energy use is most difficult since both quality and productivity must be maintained, but focusing on the most energy intensive prioritizes the effort.

As priorities are established for energy efficiency projects using the qualitative and quantitative methods described in Sect. 9.3, detailed plans can be developed to close the gap to benchmark and implement cost-effective energy efficiency projects.

## 9.4 Closing the Gap to Benchmark with Energy Efficiency

Energy benchmarking, as described in Chap. 8, is used as a basis to determine the gap to the benchmark and can be a deciding factor in the prioritization of energy projects.

An example of a GM Warehouse shows a gap in the Energy Star® score of 72/75 or 1614 MWh of heat and electricity to meet the benchmark. Projects were identified to close the gap along with ROI and rebates to prioritize the efforts to close the gap for this facility. Based on the payback, it was decided to use an energy performance contract for lighting and steam elimination.

As shown in the project description section of Fig. 9.10, lighting projects alone just barely close the gap to benchmark at the warehouse; however, eliminating steam provided the additional energy efficiency to ensure the facility will meet the benchmark.

### 9.4.1 *Energy Drivers*

Quantifying the effects of each independent variable in an EPI is an important qualifier for consideration of the prioritization of energy efficiency projects. In the example in Fig. 9.11 of an Automotive Assembly plant, the variables from a baseline plant are compared to variations of the energy drivers of climate, productivity, and vehicle size. The EPI model score results are translated to MWh/Vehicle variances to allow for comparison to industry standard intensity units. For example, a plant with similar utilization and size of vehicle that has a

| Metric | Baseline (Dec 2012) | Current (Apr 2015) | Target* | Median Property* |
|---|---|---|---|---|
| ENERGY STAR score (1-100) | 73 | 72 | 75 | 50 |
| Source EUI (kBtu/ft²) | 93.1 | 106.0 | 100.8 | 149.6 |
| Site EUI (kBtu/ft²) | 47.5 | 59.5 | 56.7 | 84.0 |
| Source Energy Use (kBtu) | 177,249,688.3 | 201,766,669.9 | 191,961,860.4 | 284,782,072.2 |
| Site Energy Use (kBtu) | 90,469,217.1 | 113,363,692.7 | 107,854,807.9 | 160,006,345.1 |

Gap to Benchmark: 5,509,000 kBtu = 1,614,529 KWh

| Description | Investment | Material $ | Labor $ | Savings $ | KWH's | Rebate | Payback |
|---|---|---|---|---|---|---|---|
| Replace 150 Watt HPS Light Fixtures | $4,327 | $2,287 | $2,040 | $1,359 | 12,802 | $430 | 2.87 |
| Replace 250 Watt HPS Light Fixtures | $141,610 | $24,010 | $117,600 | $43,231 | 523,950 | $13,034 | 2.97 |
| Replace 8' T12 Light Fixtures | $140,191 | $15,631 | $124,560 | $51,465 | 623,747 | $0 | 2.72 |
| Replace 2900 Interior Light Fixtures | $1,466,751 | $772,431 | $694,320 | $234,387 | 2,840,713 | $57,860 | 6.01 |
| Replace Plant Heating System | $1,290,000 | | | $401,603 | 7,491,988 | $270,601 | 2.54 |

**Fig. 9.10** GM warehouse, Energy Star® building portfolid manager output and GM gap analysis (Hildreth 2015)

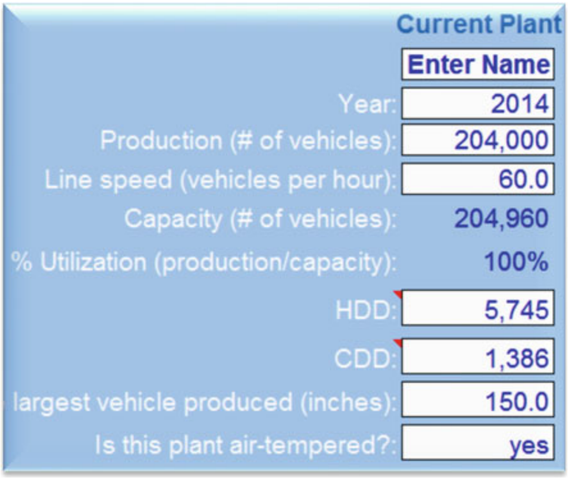


**Fig. 9.11** Energy start EPI—automotive assembly plant model input (Hildreth 2015)

60 % lower climate effect or Heating Degree Days (HDD) will have a 28 % lower Energy Intensity for a benchmark. Explaining the benchmark system with simple examples provides a better understanding and acceptance for the system. Readers are recommended to read previous studies (Oh et al. 2011; Oh and Hidreth 2013, 2014) to learn details about data and model-driven energy models for automotive assembly plant.

As the model outputs a score and energy intensity, it can be used to determine the required energy drivers to meet a score of 75 in units of energy intensity or "MWh/Vehicle".

Figure 9.12 shows the effect of energy drivers, climate or HDD, productivity or utilization, and vehicle size or wheelbase. Therefore, the effect of these energy drivers can be quantified into energy intensity for a better understanding of their

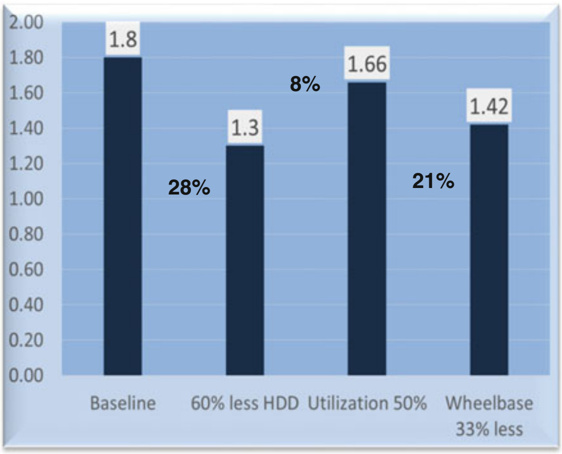


**Fig. 9.12** Comparison of the effect of independent variables to the output of EPI model in MWh/vehicle (Hildreth 2015)

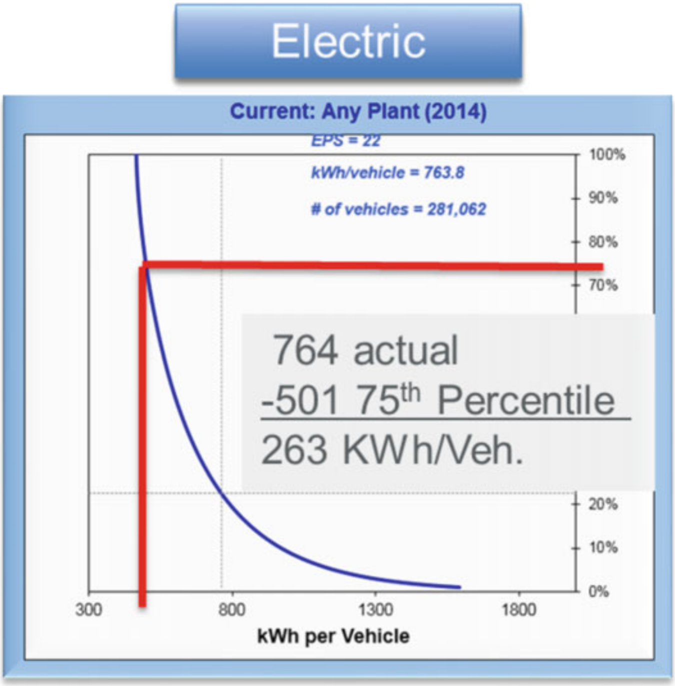


**Fig. 9.13** GM example assembly plant, electric output, kWh/vehicle by percentile (Hildreth 2015)

effect on the benchmark. For example, an auto assembly plant in a climate region with 60 % less heating degree days would have about 28 % lower energy intensity than the baseline plant. Of the three energy drivers, utilization or productivity is the only one that the plant has control of as the climate region is fixed and typically the vehicle size is also.

Figures 9.13 and 9.14 show the EPI output graphically derived from example data for a typical auto assembly plant. Dividing the benchmark into electric and heat is helpful to see where the gap originates from so that corrective measures can be planned. As the gap to benchmark is large in this example, the process of closing the gap is more difficult as a 29 % reduction in intensity is needed. As the gap for the electricity portion of the benchmark is the largest it will be the focus of reduction activities.

As shown in Fig. 9.15, Beginning with some standard energy conservation measures (ECM)—Lighting, Heating Ventilation, and air conditioning (HVAC), Variable speed drives (VSD), and shutdown performance improvement, we can plan to close the gap by only about 60 % and have to find other innovative reduction methods for the remainder.

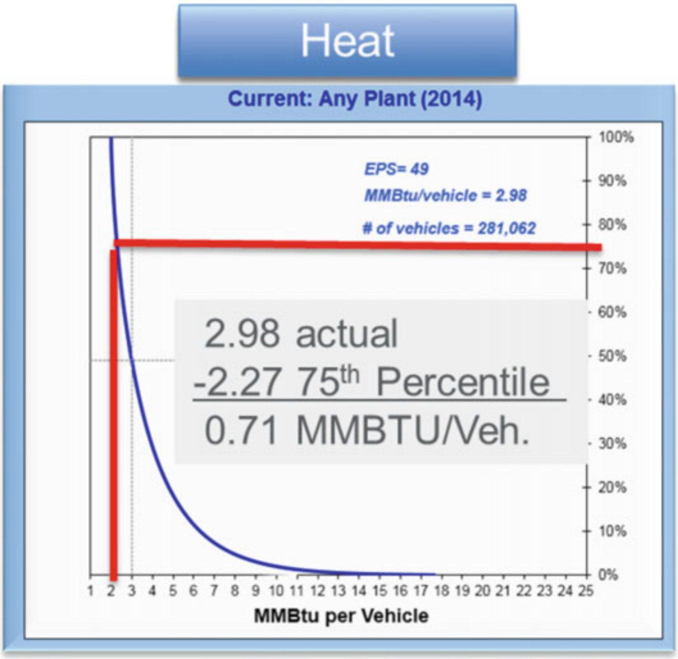


**Fig. 9.14** GM example assembly plant, heat output, kWh/vehicle by percentile (Hildreth 2015)

**Fig. 9.15** GM example assembly plant, gap closure methods (Hildreth 2015)

| ECM | Potential Reduction | % of Total | Energy Savings |
|---|---|---|---|
| Lights T8 to LED | 25% | 7% | 2% |
| HVAC Optimization | 15% | 55% | 8% |
| VSD on pumps | 10% | 10% | 1% |
| Improve shutdown | 20% | 20% | 4% |
| Other | | | 14% |

## *9.4.2 Design Energy Efficiency into New Processes and Facilities*

The greatest opportunity for a business to affect energy reduction is to design energy efficiency into the new processes and facilities that are built. Establishing a goal to meet Energy Star® EPI's or other benchmarks for new buildings and manufacturing operations is important since the investment is occurring for other reasons and can be optimized for energy savings. This is difficult to manage if it is not measured throughout the life of the project development and calibrated afterwards using an energy model. As an example GM, as paint shops are approaching end of life, has a plan to upgrade or replace them in the future.

The first step is to establish a goal to meet EPA Energy Star® EPI for Assembly plants benchmark energy intensity, that is pro-rated for paint shops for various operating plans for the new project (Hildreth 2015). Since a method to track the progress did not exist, GM worked with contractors to develop a model to track operating energy based on installed equipment, operating hours, and shut down capabilities. This included identifying all energy use devices—motors, fans, pumps, burners, coils, compressed air, lights, hot and chilled water, and other energy uses for the entire new plant. Climate effects are included using outside conditions for the location of the new facility as well as amount of outside air for heat and process.

As the model tracks energy use during various modes of operations, it will provide an energy intensity for multiple operating shift scenarios. Figure 9.16 shows an example of the input items with various energy loads during a number of operating modes—design or nameplate, maximum load, production, production setback, maintenance and, shutdown.

Figure 9.17 shows an example of the output from the model based on a selection of production rate (jobs/hour), number of shifts, hours per shift, and hours per production shift, as well as the days of production and the annual production volume.

Figure 9.18 shows the output for three operating conditions of potential shift patterns and depicts a huge benefit for high utilization or running 3 shifts per day or 24 per day, 5–6 days per week compared to running one or two shifts only with a 35 % reduction possible for running 24 h per day during the week. The elimination of waste, as idle time, in the facility or operation provides a significant improvement in its energy efficiency performance.

| | Electric - HP | | | | | | Natural Gas - MMBTU/h | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Item | Design | Max Load | Production | Production Setback | Maintenance | Shutdown | Design | Max Load | Production | Production Setback | Maintenance | Shutdown |
| Spraybooth Fresh Air ASH | 100.0 | 82.0 | 82.0 | 82.0 | | | | | | | | |
| Basecoat Prime ASH Return Fan 1 | 75.0 | 51.0 | 51.0 | 51.0 | | | | | | | | |
| Basecoat Prime ASH Return Fan 2 | 75.0 | 51.0 | 51.0 | 51.0 | | | | | | | | |
| Basecoat Supply Fan #1 | 40.0 | 31.0 | 31.0 | 31.0 | | | | | | | | |
| Basecoat Supply Fan #2 | 40.0 | 31.0 | 31.0 | 31.0 | | | | | | | | |
| Basecoat Exhaust Fan | 75.0 | 43.7 | 43.7 | 43.7 | | | | | | | | |
| Zone 1 Filter Exhaust | 20.0 | 16.0 | 16.0 | 16.0 | | | | | | | | |
| Heated Flash off 1 Recirc Fan #1 | 60.0 | 45.4 | 45.4 | 45.4 | | | | | | | | |
| Heated Flash off 1 Recirc Fan #2 | 60.0 | 45.4 | 45.4 | 45.4 | | | | | | | | |
| Combustion Blower | 1.5 | 1.0 | 1.0 | 1.0 | | | 3.0 | 3.0 | 0.4 | 0.1 | | |
| Heated Flash off 2 Recirc Fan #1 | 60.0 | 50.4 | 50.4 | 50.4 | | | | | | | | |
| Heated Flash off 2 Recirc Fan #2 | 60.0 | 50.4 | 50.4 | 50.4 | | | | | | | | |
| Combustion Blower | 1.5 | 1.0 | 1.0 | 1.0 | | | 3.0 | 3.0 | 0.4 | 0.1 | | |

**Fig. 9.16** GM energy model for new paint shops, input module (Hildreth 2015)

| Projected MWh/Job | 0.94 | MWh/j |
|---|---|---|
| EnergyStar per Vehicle Target | 1.00 | MWh/j |
| % of Target | 93.8 | % |
| | | |
| EnergyStar Production Definition | | |
| Production Rate | 60 | Jobs/Hr |
| Number of Shifts | 2 | # |
| Hours per Shift | 8 | hr |
| Hrs of Production/ Shift | 7 | hr |
| Hours per Startup | 2 | per startup |
| Days of Production | 244 | Days |
| Annual Production | 204960 | Vehicle |
| | | |
| Annual Steady State Load | 142,675,624 | KWh |
| Annual Weather Variable Load | 49,669,861 | KWh |
| Total Annual Load | 192,345,485 | KWh |

**Fig. 9.17** GM energy model for new paint shops, output module (Hildreth 2015)

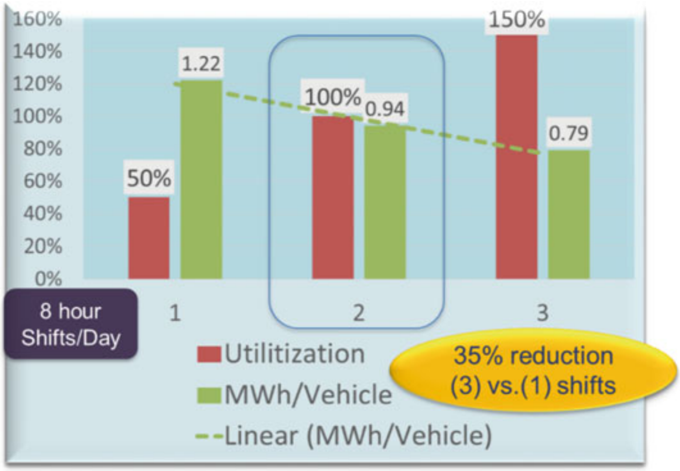


**Fig. 9.18** GM energy model for new paint shops, comparison of operating shifts (Hildreth 2015)

## 9.5 Measurement and Verification

Measurement and verification (M&V) of energy projects is a standardized process and protocol (National Renewable Energy Laboratory 2002) that is used to document and quantify savings from energy conservation measures (ECM). It is used by Utility companies to verify payments for Energy Optimization programs that pay commercial and industrial companies incentives to reduce energy. M&V is an integral part of energy performance contracts (EPC) where customers pay a supplier to provide energy reduction services. M&V also provides credibility to management for either internal or external energy efficiency projects that the planned savings has actually been realized. Similar to energy benchmarking and forecasting methods, pre-and post-measurement and verification must include normalization for energy drivers—climate, production, and other operating practices where applicable. The protocol includes methods to ensure that building indoor environmental quality is maintained and not sacrificed with the ECM. The international measurement and verification protocol (IPMVP) outlines the role it plays in M&V:

- Provides energy efficiency project buyers, sellers and financiers a common set of terms to discuss key M&V project-related issues and establishes methods which can be used in energy performance contracts.
- Defines broad techniques for determining savings from both a "whole facility" and an individual technology.
- Applies to a variety of facilities including residential, commercial, institutional and industrial buildings, and industrial processes.
- Provides outline procedures which (i) can be applied to similar projects throughout all geographic regions, and (ii) are internationally accepted, impartial and reliable.
- Presents procedures, with varying levels of accuracy and cost, for measuring and/or verifying: (i) baseline and project installation conditions, and (ii) longterm energy savings.
- Provides a comprehensive approach to ensuring that building indoor environmental quality issues are addressed in all phases of ECM design, implementation and maintenance.
- Creates a living document that includes a set of methodologies and procedures that enable the document to evolve over time.

### *9.5.1 M&V Baseline Plan*

Similar to comparing facility energy performance to a baseline to evaluate performance to energy target, a pre-measurement and verification baseline plan is essential to establish the operational characteristics of the facility prior to energy conservation measures to determine the true effect of energy savings initiatives.

The baseline of a facility or process's energy profile must be aligned with the energy conservation measure and its intended result. Establishing the boundaries of the savings determination provides the focus needed to identify both the energy and operating conditions prior to the implementation of the ECM. As an example for an auto assembly plant, the relevant information includes:

- energy usage specific to the ECM
- production volume, operating shifts, and line rates (jobs per hour)
- equipment inventory and operations uptime

- indoor conditions—light level, temperature set point, quantity of fresh makeup air, and indoor air quality
- outside conditions—temperature and relative humidity
- details of the timing and collection technology for the information.

It is important that the method for data collection—meters, invoices, and time-period, remain consistent between the pre-measurement period and the post retrofit period. Variables that affect energy and cost, that are outside the control of the ECM should be fixed for both the pre-and post-measurement evaluation. As an example energy rates are typically outside of the control of the ECM and therefore should remain the same for the pre-and post-measurement activities. Using independent third parties for M&V is preferred and required for utility incentive programs, to ensure that both customer and service provider support the M&V and savings determination. Measurement and verification for internally financed energy projects provides management with level of credibility that the savings has been realized.

## 9.5.2 *Post-retrofit M&V*

Post retrofit measurement and verification should focus on the energy use and facility operating characteristics relevant to the ECM. The energy conservation measure must be in full operational mode under similar operating conditions as possible as the pre-measurement period.

An example lighting retro-fit project will demonstrate the calculation methodology related to a basic M&V plan.

Figure 9.19 provides an example of a simplified lighting retro-fit project where T8 Fluorescent lamps and ballasts as well as HID fixtures were replaced with more energy efficient LED, solid state luminaires for energy, carbon, and cost savings. Following the IPMVP, the light levels remained similar to provide the same indoor

| Pre-measurement & verification | B | C | B x C / 1000 | E | D x E | G | F x G | I | F / 1,000 x I / 2,204 |
|---|---|---|---|---|---|---|---|---|---|
| Lighting: Type | Number of luminaries (lamp) | Watts / luminaire (including ballast or drivers) | KW | Operating Hours | KWh/Year | Electric Rate, USD/KWh | Annual Energy Cost, USD | Carbon Emission factor, Metric Lbs. / MWh | Carbon Emissions, CO2e (Metric tons / Year) |
| Linear T8 Fluorescent | 1800 | 32 | 58 | 5,000 | 288,000 | $ 0.08 | $ 23,040 | 1,147 | 150 |
| High Intensity Discharge (Hi-bay) | 200 | 400 | 80 | 7,600 | 608,000 | $ 0.08 | $ 48,640 | 1,147 | 316 |
| Total | | | 138 | | 896,000 | | 71,680 | | 466 |
| Post-measurement & verification | | Note: Equal light level, fix hours, rates, and carbon emission factors and ignore waste heat effect and maintenance | | | | | | | |
| Linear LED | 1800 | 18 | 32 | 5,000 | 162,000 | $ 0.08 | $ 12,960 | 1,147 | 84 |
| Engineered LED fixture | 200 | 172 | 34 | 7,600 | 261,440 | $ 0.08 | $ 20,915 | 1,147 | 136 |
| Total Post M&V | | | 67 | | 423,440 | | 33,875 | | 220 |
| **Energy, Cost and Carbon savings for ECM** | | | **71** | | **472,560** | | **37,805** | | **246** |

**Fig. 9.19** Example measurement and verification calculation—LED lighting retro-fit from fluorescent

environmental conditions for occupants. Assumptions for the M&V for simplification are as follows:

- System operating hours remain the same
- Energy rates and carbon emission factors are fixed for pre and post-measurement periods
- Maintenance cost, although favorable for LED are not included in the savings calculation.

The lighting energy use is established based on the pre-existing condition, including operating hours, energy rates, cost, and carbon emissions. The retro-fit project conditions are similarly evaluated for the same energy use, cost, and carbon emissions to demonstrate the savings for the ECM, in this case about $38,000. The customer and service provider can review the simple energy savings calculations and be assured that the savings for the retro-fit project is valid.

Energy reduction activities are a key success factor in a company's business plan for environmental sustainability. Incorporating it into a business plan requires lots of data and good salesmanship. As sustainability includes economics, sound business cases are needed to justify spending money. Begin with answering the "Why" question—have to meet goals, solid investment, customers and other demanding greenhouse reductions, and it's good for the environment too. To adequately plan energy and carbon reduction initiatives requires historical and forecasting energy, production, and climate data. As goals are established, the business as usual energy forecasts will identify the gap that the initiatives can fill. Tracking progress in all stages will provide for good accounting for future opportunities and recognition. Verification with standardized protocols provide management and customers with assurance that energy projects provide savings to the bottom-line cost of the business and aid in sustaining the process into the future. After all of this hard work, recognizing achievement becomes a necessity. People enjoy seeing the accomplishments of themselves and others publicized and recognition provides an incentive to accomplish even more.

## 9.6 Exercise

1. You have determined that the gap to next year's benchmark target is 10,000 MWh, with next year's rates for energy at a blended five cents per kilowatt hour and a limit on spending based on a two-year simple payback, how much will you have to spend and what is the amount of savings in US dollars next year.
2. In the first 10 years of operations your company successfully reduced carbon intensity by 50 %. What rationale would you use to not expect another 50 % reduction in the next 10 years? If the requirement was another 50 %, what method would you propose for carbon reduction from electricity to meet the target for the next 10 years.

3. What is the average simple payback from lighting ECM's in Fig. 9.10 in years?
4. Based on Fig. 9.18, what is the energy intensity improvement when a plant adds one shift to a one shift operation? Based on a rate of $100 per megawatt hour in a production build of 200,000 vehicles, what is the potential cost savings of adding a shift?
5. The cost of the lighting retrofit project in Fig. 9.19 is $100,000. Your company uses a price on carbon of $25 per ton. What is the simple payback in years for the combined cost savings of energy and carbon?

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