

5-2016

Manufacturing System Energy Modeling and Optimization

Lujia Feng

Clemson University, lujiarf@g.clemson.edu

Follow this and additional works at: https://tigerprints.clemson.edu/all_dissertations

Recommended Citation

Feng, Lujia, "Manufacturing System Energy Modeling and Optimization" (2016). *All Dissertations*. 1648.
https://tigerprints.clemson.edu/all_dissertations/1648

This Dissertation is brought to you for free and open access by the Dissertations at TigerPrints. It has been accepted for inclusion in All Dissertations by an authorized administrator of TigerPrints. For more information, please contact kokeefe@clemson.edu.

MANUFACTURING SYSTEM ENERGY MODELING
AND OPTIMIZATION

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Automotive Engineering

by
Lujia Feng
May 2016

Accepted by:
Dr. Laine Mears, Committee Chair
Dr. Joachim Taiber
Dr. Kumar Venayagamoorthy
Dr. Paul Venhovens

ABSTRACT

World energy consumption has continued increasing in recent years. As a major consumer, industrial activities uses about one third of the energy over the last few decades. In the US, automotive manufacturing plants spends millions of dollars on energy. Meanwhile, due to the high energy price and the high correlation between the energy and environment, manufacturers are facing competing pressure from profit, long term brand image, and environmental policies. Thus, it is critical to understand the energy usage and optimize the operation to achieve the best overall objective. This research will establish systematic energy models, forecast energy demands, and optimize the supply systems in manufacturing plants.

A combined temporal and organizational framework for manufacturing is studied to drive energy model establishment. Guided by the framework, an automotive manufacturing plant in the post-process phase is used to implement the systematic modeling approach. By comparing with current studies, the systematic approach is shown to be advantageous in terms of amount of information included, feasibility to be applied, ability to identify the potential conservations, and accuracy. This systematic approach also identifies key influential variables for time series analysis. Comparing with traditional time series models, the models informed by manufacturing features are proved to be more accurate in forecasting and more robust to sudden changes. The 16 step-ahead forecast MSE (mean square error) is improved from 16% to 1.54%. In addition, the time series analysis also detects the increasing trend, weekly, and annual seasonality in the energy consumption. Energy demand forecasting is essential to production management and

supply stability. Manufacturing plant on-site energy conversion and transmission systems can schedule the optimal strategy according the demand forecasting and optimization criteria. This research shows that the criteria of energy, monetary cost, and environmental emission are three main optimization criteria that are inconsistent in optimal operations. In the studied case, comparing to cost-oriented optimization, energy optimal operation costs 35% more to run the on-site supply system. While the monetary cost optimal operation uses 17% more energy than the energy-oriented operation. Therefore, the research shows that the optimal operation strategy does not only depends on the high/low level energy price and demand, but also relies on decision makers' preferences. It provides not a point solution to energy use in manufacturing, but instead valuable information for decision making.

This research complements the current knowledge gaps in systematic modeling of manufacturing energy use, consumption forecasting, and supply optimization. It increases the understanding of energy usage in the manufacturing system and improves the awareness of the importance of energy conservation and environmental protection.

ACKNOWLEDGMENTS

First of all, I'd like to thank CUICAR. It's a great and unique department, where I learned so much from my instructors and colleagues. It provides me a wonderful research and study environment. The people and activities in CUICAR inspired me deeply and will keep influencing the rest of my life.

Second, I'd like to thank Prof. Laine Mears. He mentored me on the projects, papers, and dissertation writing. He cares about our lives and respects our ideas. It is my honor to work with him closely in the past three years. I'd like to thank my dissertation committee, Dr. Taiber, Dr. Vehnovens, and Dr. Kumar. Thank you for the valuable suggestions on my research directions. I'd like to thank my wonderful colleagues – Farbod, Matthew, Abram, Jamie, Brand, and many others who were in the manufacturing team. Thank all the classmates and friends. In our friendly competition and joyous conversations, I found the power to move forward.

I would also like to thank BMW teams for their generous support throughout my PhD life. From the projects we worked together, I know this is a company that really cares about innovation and the environment.

Last but not the least, I'd like to thank my family. My parents' unconditional love and understanding make my life and study in the USA a terrific experience. Thank my fiancé – Qilun Zhu. He first introduced me to automotive engineering and infused me with passion. Now, his vision becomes my passion, and his support becomes my commitment to this research work.

TABLE OF CONTENTS

	Page
ABSTRACT.....	ii
ACKNOWLEDGMENTS	iv
LIST OF TABLES.....	vii
LIST OF FIGURES	ix
CHAPTER	
1. CHAPTER ONE BACKGROUND INTRODUCTION.....	1
1.1 Objective.....	1
1.2 Background Introduction	1
1.3 Motivation.....	5
1.4 Research Questions.....	7
1.5 Research Scope	7
1.6 Chapter One References	8
2. CHAPTER TWO SYSTEMATIC MODELING.....	10
2.1 Research Question Restatement.....	10
2.2 Background and Knowledge Gap Introduction	10
2.3 Modeling Approach	45
2.4 Case Study	51
2.5 Chapter Summary	85
2.6 Chapter Two References.....	88
3. CHAPTER THREE FORECASTING.....	91
3.1 Research Question Restatement.....	91
3.2 Background and Knowledge Gap Introduction	91
3.3 Proposed Approach.....	111
3.4 Case Study	113
3.5 Chapter Summary	147
3.6 Chapter Three References.....	148

Table of Contents (Continued)

	Page
4. CHAPTER FOUR ENERGY SUPPLY OPTIMIZATION	150
4.1 Research Question Restatement.....	150
4.2 Background and Knowledge Gap Introduction	150
4.3 Approach.....	158
4.4 Case Study	166
4.5 Chapter Summary	191
4.6 Chapter Four References.....	192
5. CHAPTER FIVE BROADER IMPACTS	196
5.1 Broader impact of research questions	196
5.2 Three RQs relationships.....	221
5.3 Chapter Five References	223
6. CHAPTER SIX INTELLECTUAL MERIT AND FUTURE WORK	225
6.1 Intellectual Merit and Contribution	225
6.2 Future Work	228
APPENDICES	232

LIST OF TABLES

Table	Page
Table 2.1: Correlation Analysis of Fuel.....	19
Table 2.2: Correlation Analysis of Electricity	19
Table 2.3: Model Evaluation Table	45
Table 2.4: Meter ID Logging Table for Energy Distribution	62
Table 2.5: Meter Log Table	78
Table 2.6: Test Plant of Pilot Study	81
Table 2.7: Proposed Modeling Approach Evaluation Results	84
Table 2.8: Model Criteria Comparison	86
Table 3.1: Paint Shop Building Original Setpoint	118
Table 3.2: Summary of Three Scenarios.....	121
Table 3.3: ARMA Model Test Results	139
Table 3.4: ARMAX Model Test Results	143
Table 4.1: Purchased Energy Indicator Assignment.....	171
Table 4.2: 2012 South Carolina Electricity Emission Profile.....	173
Table 4.3: Natural Gas Emission Profile	173
Table 4.4: Landfill Gas Emission Profile	174
Table 4.5: Coeff matrix.....	176
Table 4.6: Lower and Upper Bound	178
Table 4.7: Optimization Results	179
Table 4.8: Effects of Demand on Energy Supply	181

List of Tables (Continued)

Table	Page
Table 4.9: Energy Unit Price Range	183
Table 4.10: Multi-objective Optimization Results.....	190
Table 5.1: Experimental Design and Results of HVAC Energy in Clear-coat Booth	198
Table 5.2: Correlation Analysis	205
Table 5.3: Linear Regression Coefficient Analysis	206
Table 5.4: Water ARMA Model Test Results	211
Table 5.5: Water ARMAX Model Results.	213
Table 5.6: Energy Emission Indicator	214
Table 5.7: Electricity Price Rate of Duke Energy Industrial Service.....	218

LIST OF FIGURES

Figure	Page
Figure 1.1: World Primary Energy Consumption Trend	2
Figure 1.2: World Primary Energy Consumption Per Million Cap	2
Figure 1.3: 2011 End-Use Sector Share of Total Energy Consumption.....	3
Figure 1.4: United States Industrial Electricity Average Retail Price.....	4
Figure 1.5: United States Industrial Natural Gas Average Retail Price.....	4
Figure 2.1: Energy System in Temporal Framework.....	12
Figure 2.2: Energy System in Special/Spanning Organizational Framework	13
Figure 2.3: Section Hierarchy	15
Figure 2.4: Section Hierarchy – High Level Models.....	16
Figure 2.5: Natural Gas Signature Fitting.....	21
Figure 2.6: Electricity Signature Fitting	21
Figure 2.7: Section Hierarchy – Low Level Models.....	23
Figure 2.8: Plant Building HVAC Sketch	35
Figure 2.9: Section Hierarchy – Statistical Models	36
Figure 2.10: Machine Power Load at Working Mode	37
Figure 2.11: Assembly Line Power Load	38
Figure 2.12: Section Hierarchy – Systematic Models	40

List of Figures (Continued)

Figure	Page
Figure 2.13: Embodied Product Energy Supply Chain Scheme.....	41
Figure 2.14: Flowchart of Energy Modeling	49
Figure 2.15: Energy Flow Sketch in Studied Automotive Manufacturing Plant.....	52
Figure 2.16: Manufacturing Plant Meter/Data System Framework	53
Figure 2.17: Database Format Example.....	54
Figure 2.18: Framework Guided Systematic Approach Scheme of Studied Case.....	55
Figure 2.19: Purchased (a) Natural Gas, (b) Landfill Gas, and (c) Electricity (Normalized).....	57
Figure 2.20: Fitted (a) Natural Gas, (b) Landfill Gas, and (c) Electricity (Normalized)	58
Figure 2.21: New Year Data with Fitted Model – Natural Gas Example	59
Figure 2.22: Regression Model of a) Natural Gas and b) Electricity.....	60
Figure 2.23: Energy Demand Distribution.....	62
Figure 2.24: Energy Distribution to Departments.....	63
Figure 2.25: Painting Booth (Basecoat) Air Supply Flow Sketch.....	65
Figure 2.26: Energy Supply and Demand Models Sketch.....	66
Figure 2.27: Action and Knowledge Input Flow Chart	67
Figure 2.28: Air Supply Energy Consumption Flow Chart	69
Figure 2.29: Heat Exchanger Sketch	73

List of Figures (Continued)

Figure	Page
Figure 2.30: Water Heat Capacity and Fitted Polynomial Plot	75
Figure 2.31: Model Inputs and Outputs Sketch	76
Figure 2.32: Structure of a Water Cooling Coil.....	76
Figure 2.33: Chilled Water Coil Process	77
Figure 2.34: Baseline Heating Validation.....	79
Figure 2.35: Baseline Cooling Validation	79
Figure 2.36: Temperature Set point Adjustment Study (Heating)	81
Figure 2.37: Temperature Set point Adjustment Study (Cooling).....	82
Figure 3.1: Flowchart of Energy Modeling in Plant (Bottom-Up Strategy Highlighted in Red)	112
Figure 3.2: Flowchart of Energy Modeling in Studied Case (Bottom-Up Strategy Highlighted in Red).....	114
Figure 3.3: Three Major Components of Energy in Plant	115
Figure 3.4: Painting Spray Booth Feedforward System	117
Figure 3.5: Building Feedback System.....	117
Figure 3.6: Effect of Constant Temperature Set Point on Annual Building Total Energy Consumption	119
Figure 3.7: Separate Air Inlet Flow Route.....	119
Figure 3.8: Building to Booth Air Flow Route	120
Figure 3.9: Effect of Building Temperature Set point on Annual Booth Total Energy Consumption	121

List of Figures (Continued)

Figure	Page
Figure 3.10: Effect of Building and Booth Temperature Set point on Combined Energy Consumption.....	123
Figure 3.11: Outlier Example	125
Figure 3.12: Annual Seasonality in Observed Data.....	126
Figure 3.13: Weekly Seasonality	127
Figure 3.14: Historical Data Plot	128
Figure 3.15: Small Data Set Decreasing Trend	129
Figure 3.16: Diverged Forecasting Results.....	129
Figure 3.17: Time Series Modeling Procedure	130
Figure 3.18: Training Data ACF.....	131
Figure 3.19: Training Data PACF.....	132
Figure 3.20: New Data Series Y_t	135
Figure 3.21: New Data Series Y_t Expectation Values.....	135
Figure 3.22: New Data Series Y_t Covariance Values.....	136
Figure 3.23: ACF of Y_t	137
Figure 3.24: PACF of Y_t	137
Figure 3.25: ARMA Model Comparison	140
Figure 3.26: Model Forecasting Results Comparison.....	143
Figure 3.27: Scatterplot of Residuals.....	144
Figure 3.28: Residual Normally Distributed.....	145
Figure 3.29: ACF of Residuals	146

List of Figures (Continued)

Figure	Page
Figure 3.30: PACF of Residuals	146
Figure 4.1: Manufacturing Plant Energy System.....	151
Figure 4.2: On-site Energy Conversion and Transmission System.....	168
Figure 4.3: Energy Center Input-Output Schema	168
Figure 4.4: Cogeneration System Sketch.....	169
Figure 4.5: Effect of Landfill Gas Unit Price on Purchased Energy	183
Figure 4.6: Combined Effect of Electricity and Landfill Gas Unit Price on Purchased Energy	186
Figure 4.7: Combined Effect of Electricity and Landfill Gas Unit Price on Cogeneration Operation.....	186
Figure 4.8: Combined Effect of Electricity and Landfill Gas Unit Price on Overall Energy Cost	186
Figure 4.9: Objectives in Decision Space	189
Figure 4.10: Objectives in Criteria Space	190
Figure 5.1: Spot Welding Schedule	201
Figure 5.2: Normalized Water Plot in Time	208
Figure 5.3: ACF of Training Water Data.....	209
Figure 5.4: PACF of Training Water Data.....	210
Figure 5.5: De-Trend Training Data Series ACF.....	210
Figure 5.6: De-Trend Training Data Series PACF	211
Figure 5.7: Selected Forecasting Results Plot.....	212
Figure 5.8: ARMAX Model Forecasting Results Plot.....	213

List of Figures (Continued)

Figure	Page
Figure 5.9: Flat Rate Example	216
Figure 5.10: Tiered Rate Strategy Example.....	216
Figure 5.11: TOU Example.....	217
Figure 5.12: Real Time Pricing Example	218
Figure 5.13: Energy System Sketch in Studied Case.....	221
Figure 5.14: Research Question Relations.....	223
Figure 6.1: Sensitive Variable Sharing	229

CHAPTER ONE

BACKGROUND INTRODUCTION

1.1 Objective

The objectives of this research are to

- 1) test the hypothesis that systematic energy modeling approach based on manufacturing layer concept can improve the model accuracy, provide more information, identify the significant inputs, and target improvement implementations;
- 2) apply and augment forecasting methods from the mathematical domain to understand the energy use in the manufacturing domain;
- 3) investigate the optimal energy operation strategies in manufacturing plant.

1.2 Background Introduction

All aspects of human activity – transportation, industrial, residential and commercial activities — require support from energy. World energy consumption kept increasing in the past decades (as Figure 1.1), and the energy amount of per capita increased about 60% in the past fifty years (as Figure 1.2).

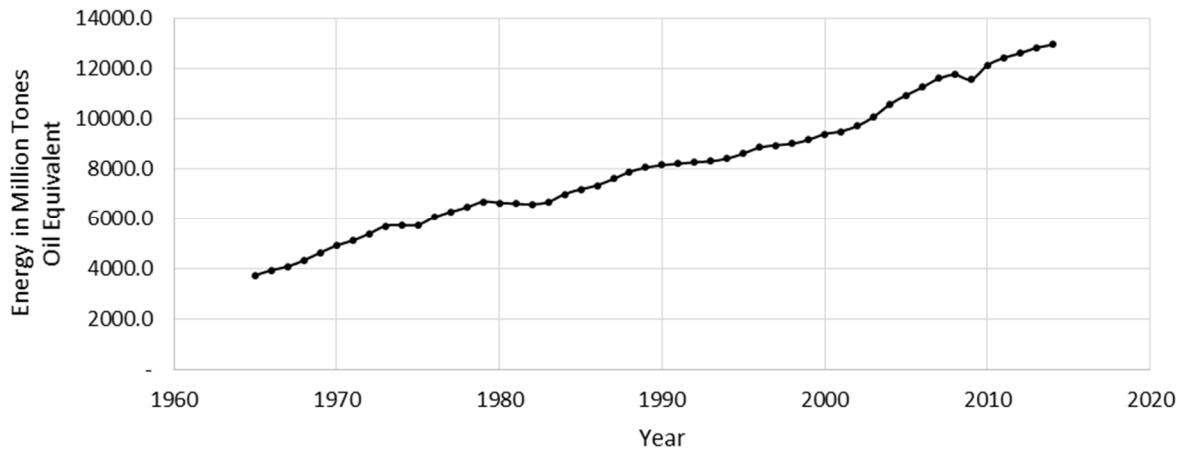


Figure 1.1: World Primary Energy Consumption Trend [1.1]

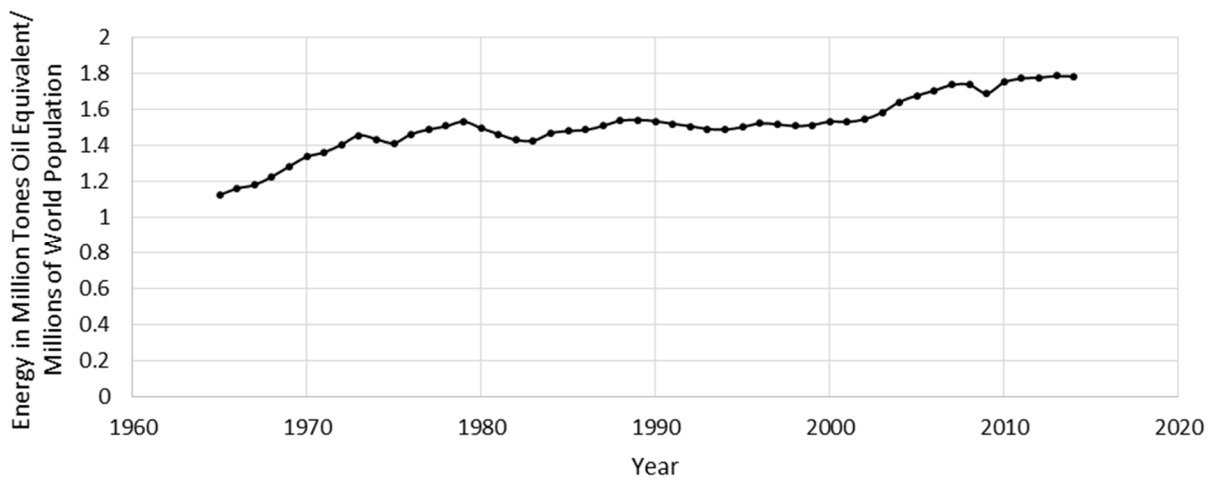


Figure 1.2: World Primary Energy Consumption Per Million Cap [1.1, 1.2]

Although energy is fundamental to human development, energy could also be harmful and restraining to our sustainability. High expenses, unbalanced distribution, and environmental pollution leave energy a potentially notorious source of environmental depletion.

Among the four end sectors (industry, commercial, residential and transportation sectors), industry is the biggest energy consumer in USA over the past sixty years. More than 30% of total energy is used in the industrial activities (as Figure 1.3) [1.3].

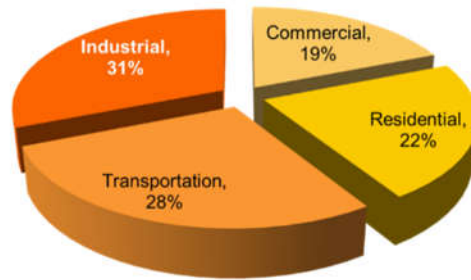


Figure 1.3: 2011 End-Use Sector Share of Total Energy Consumption [1.3]

As an important part of industrial activities, manufacturers consume a significant amount of energy every year. According to the data from US Census Bureau, the automobile assembly plants – automobile manufacturing (NAICS code 336111), light truck and utility vehicle manufacturing (NAICS code 336112), and heavy duty truck manufacturing (NAICS code 33612) plants, spent \$782 million US Dollars on electricity and fuels in 2011, which is \$45 million more compared to year 2010 [1.4].

Manufacturers are facing pressures from three main sources – instant cooperation profit, long-term brand image, and policies.

First, electricity and fossil fuels are the two major traditional energy forms used by automotive manufacturers. Data from the U.S. Energy Information Administration shows the price of electricity has continued increasing over the past 15 years (as Figure 1.4), while the price of fossil fuels (mostly natural gas) are fluctuating (as Figure 1.5). Considering the energy prices, types of vehicles produced, and various technologies used in the production

processes, the energy cost can range from \$38/vehicle to \$93/vehicle [1.5 – 1.7]. Shrinking market profit requires the cooperation to cut spends on every aspects including the utility bills.

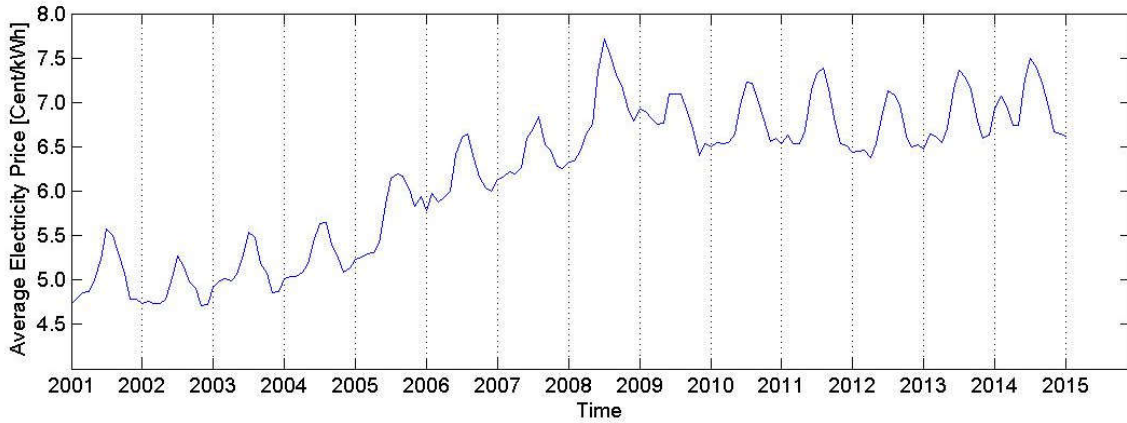


Figure 1.4: United States Industrial Electricity Average Retail Price [1.6]

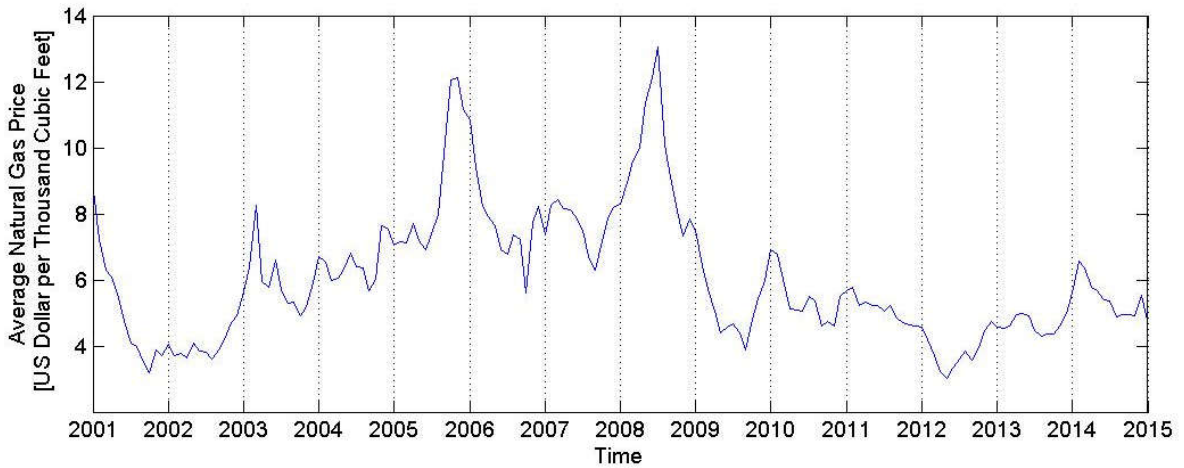


Figure 1.5: United States Industrial Natural Gas Average Retail Price [1.7]

On the other hand, the correlation between the energy consumption and environmental degradation is well known. Acid rain, deforestation, greenhouse effect,

particle matter pollution, and many other environmental pollution sources are all related to energy consumption. In order to maintain a positive brand image, the plants not only need to use less, but also use wisely. Choosing more renewable energy than the electricity and fossil fuels seems to be jeopardizing the instant profit due to the high initial investment, but it could build a positive, environmental friendly brand image among the customers, which in long term profits the company.

Finally, the standards, regulations, and laws force the manufacturers to improve their energy efficiencies. Early in 1970s, energy efficiency and conservation have become critical subjects to address the energy problem. Recently, more countries and areas participated the in discussion on policy initiation and implementation [1.8]. Policies are mainly from three aspects: 1) perspective policies for equipment efficiencies, process regulations, management, and negotiated agreements; 2) economic policies, including taxes, financial incentives, cap and trade schemes, and energy pricing; 3) supportive policies to identify the energy efficiency opportunities, cooperate measures, and train and educate.

1.3 Motivation

The previous section introduced the background of energy dilemmas and their influences on the manufacturers, especially on the automotive manufacturing plants. In this section, the incentives that initiated this research will be discussed.

It is inappropriate to discuss any energy conservations techniques without acquiring the knowledge of where and how the energy is used in the manufacturing system. Energy

models are the knowledge summary of the manufacturing energy system. Establishing systematic energy models is not only the process of quantifying the energy usage on production lines and departments, it is also a procedure to seek the answers to compensate the limitations of the current plant. From systematic models, decision makers are more informed and conservation implementations are more efficient. However, how to construct holistic models within the plants where thousands of production processes where interacted is a challenging question. To solve this problem, a systematic modeling hierarchy with levels of models serving layers of organizational managers and technicians is the key. Starting from the general manufacturing plants, the proposed approach should be repeatable across various systems. As a typical representation of many manufacturing systems, the automotive assembly plant with complex production procedures can be used as a special case to test the approach feasibility and demonstrate the approach implementation procedures.

After gaining knowledge in the current energy usage of the manufacturing plants, studying the trends and patterns of the energy consumption and making predictions based on historical data is another topic for investigation. This is because energy forecasting is essential to 1) intelligently schedule the production and manage the working conditions, 2) further realize the situational intelligence (integrated historical and real-time data to implement near-future situational awareness), 3) guarantee energy supply stability, and 4) create deeper knowledge on how the manufacturing plants affect the local energy distribution.

Thanks to the prevailing trend of renewable energy and decentralization of the energy generation and manufacturers' demand on multiple energy carriers, on-site energy conversion and transmission systems are more popular. "How to manage the on-site energy system? How to optimize the operation? What to optimize?" are key questions. The answers to these questions lies in the discussions of the tradeoffs of optimal energy supply strategies based on various objectives – minimum energy, minimum monetary cost, and minimum emissions to the environment.

1.4 Research Questions

Research Question One: How to use the manufacturing temporal and organizational framework (layer concept) to drive energy model building at functional and detail levels?

Research Question Two: What is the most effective approach to augment mathematical forecasting tools for the best applicability in the manufacturing domain?

Research Question Three: What are the tradeoffs of optimal energy operation strategies in a manufacturing plant?

1.5 Research Scope

In this research work, we focus on the post-process phase plant, on its factory and lower levels (a detailed manufacturing temporal phase and organization level definition can be found in Section 2.2.1). The limitations of the three research questions are as below.

1. The research proposes a general manufacturing modeling approach and demonstrates the approach through a studied case of an automotive assembly plant. The studied case does not exhaust the production processes or devices in plant. Instead, it exemplifies the methodology through model establishments on the typical energy consumers.
2. The research conducts the forecasting model based on historical data of a post-processing plant and assumes the future energy consumption will repeat the historical trend(s) and pattern(s). Therefore, the model cannot be used to predict the energy consumption when there are major changes in the plant, such as a new production line engagement.
3. The research optimizes the on-site energy supply system based on the current existing facility. Operation strategy suggestions are made without introduction of new equipment or devices, such as new energy storage systems.

1.6 Chapter One References

[1.1] S. Dale, "BP Statistical Review Of World Energy," *BP Global*, 2015.

[1.2] United Nations, "Total Population (Both Sexes Combined) By Major Area, Region And Country, Annually For 1950-2100 (Thousands)," *Population Division*, <http://esa.un.org/unpd/wpp/DVD/>, Accessed: Sep. 2015.

[1.3] USA EIA "U.S. Energy Information Administration Monthly Energy Review -- Energy Consumption By Sector," *Energy Information Administration*, 2015.

[1.4] USA Census Bureau, "General Statistics: Statistics for Industry Groups and Industries: 2011 and 2012," *Annual Survey of Manufactures*, https://www.census.gov/manufacturing/asm/historical_data/, Accessed: Sep. 2015.

[1.5] G. A. Boyd. "Estimating The Changes In The Distribution Of Energy Efficiency In The U.S. Automobile Assembly Industry," *Energy Economy*, **42**, pp. 81-87. 2014.

[1.6] USA EIA, "Average Retail Price Of Electricity," *Energy Information Administration*, 2015.

[1.7] USA EIA, "United States Natural Gas Industrial Price (Dollars Per Thousand Cubic Feet)," *Energy Information Administration*, 2015.

[1.8] K. Tanaka. "Review Of Policies And Measures For Energy Efficiency In Industry Sector," *Energy Policy*, **39 (10)**, pp. 6532-6550. 2011.

CHAPTER TWO

SYSTEMATIC MODELING

2.1 Research Question Restatement

Research Question One: How to use the manufacturing temporal and organizational framework (layer concept) to drive energy model building at functional and detail levels?

2.2 Background and Knowledge Gap Introduction

This section will begin with the introduction to the framework concept of the manufacturing system, followed with a critical review on previous efforts made by researchers on model construction for manufacturing energy usage, including models at different levels and systematic models in the post-process phase. Then at the end of this section, the knowledge gaps of energy modeling are identified and the hypothesis that a manufacturing layer concept can be efficiently used (in terms of information amount, flexibility to apply in similar systems, feasibility to current plants, sensitive analysis capability, improvement identification, and accuracy) to guide the systematic modeling approach is posited.

2.2.1 Framework of a Manufacturing System

The manufacturing system is a complex system containing a potentially large number of sub-systems. It is important therefore to clarify the scale of discussion pertinent to the efforts of this work. Fortunately, a rich systematic classification has been recently

described. In 2010, C. Reich-Weiser, A. Vijayaraghavan, and D. A. Dornfeld [2.1] started from the methodologies for product life-cycle assessment, and proposed four levels in spanning the organizational domain and four levels in the temporal domain (as shown in Figure 2.1). The four organizational levels include:

1. the **product feature level**, which defines specific process execution steps;
2. the **machine/device level**, which performs unit processes;
3. the **facility/line/cell level**, which acts in series or parallel to execute specific activities; and
4. the **supply chain level** which consists of all facilities in the network.

The four temporal phases include:

1. the product design phase when the product is designed;
2. the process design phase when the manufacturing processes are designed to cope with the product;
3. the process adjustment phase when basic manufacturing process is fixed but small changes on process parameter selection and optimization; and
4. the post-process phase when the product is in production.

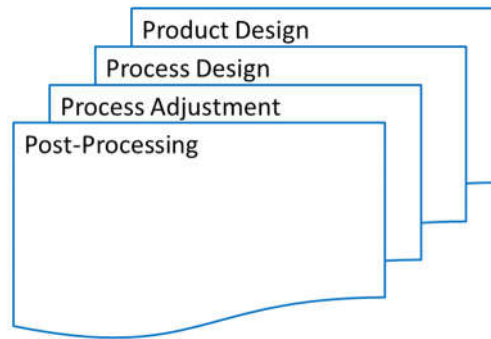


Figure 2.1: Energy System in Temporal Framework (after [2.1])

This framework started from a product standpoint and divided the manufacturing system into the described four by four orthogonal matrix.

In 2012, J. R. Duflou *et al.* [2.2] further developed the system into five levels in the organizational domain (Figure 2.2). They proposed

1. the **device/unit process level**, which performs unit processes;
2. the **line/cell/multi-machine system level**, which acts in series or parallel to execute specific activities;
3. the **facility level**, which organizes as distinct physical entities;
4. the **multi-factory system level**, which gathers with different facilities proximity to each other; and
5. the **enterprise/global supply chain level**, which consists of all facilities.

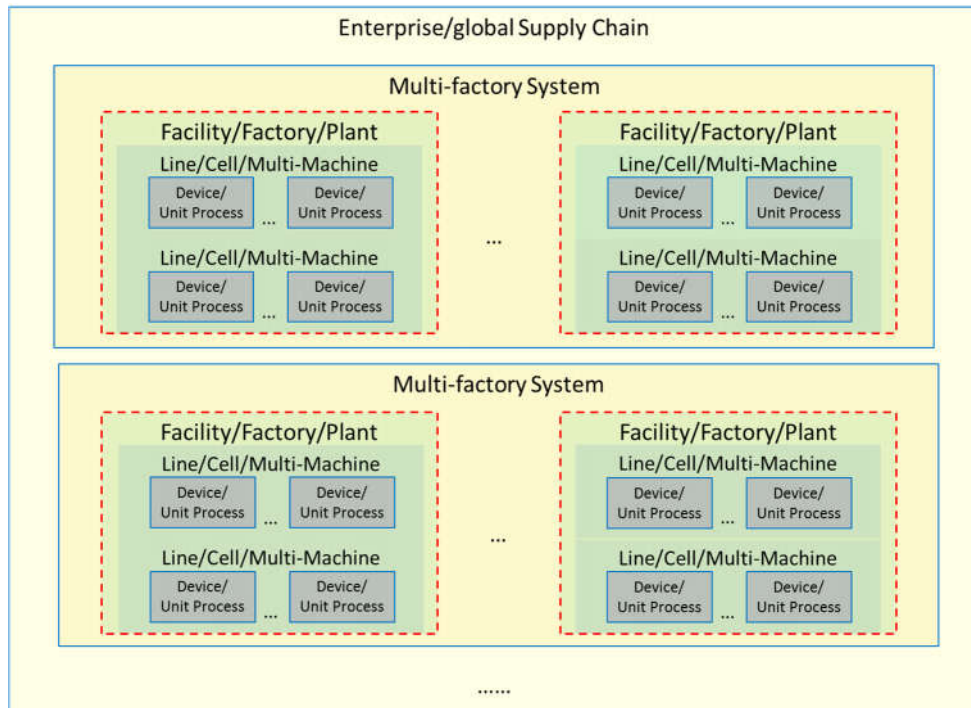


Figure 2.2: Energy System in Special/Spawning Organizational Framework (after [2.2])

Unlike C. Reich-Weiser’s team starting from the product life cycle standpoint, Duflou’s team investigated from the viewpoint of the production process system. Duflou eliminated the product level, and expanded the facility/line/cell into three sub-systems (level 2, 3, and 4).

With the temporal phases from C. Reich-Weiser and organizational layers from J. R. Duflou, the whole manufacturing system can be separated into a four-by-five orthogonal framework.

This research focuses on the energy use within the manufacturing plant. In terms of **temporal** framework, this research is at the post-process phase. It means the modeling is based on the current plant situation, where the production line built, tested and in use.

Therefore, the models have to consider the current situation of the plant, including facilitated metering and data system, production schedule, and possible equipment degradation. In terms of **organizational** framework, this research concentrates on the plant and below layers. It means any energy consumption within the plant.

From this section forward, *high level* and *low level* terms are used to refer to the energy used at the factory level and any beneath levels respectively, *i.e.*, the high level refers to the facility/factory/plant layer, and low level is the combination of line/cell/multi-machine layer and device/unit process layer as Duflou's definition. The reason that the line/cell/multi-machine layer and device/unit process layer are combined is that the energy consumption in the manufacturing plant generally requires multiple individual devices to cooperate together to perform a task and the energy consumption of these individual devices are usually highly related. High/low level terms are used in the rest of this dissertation.

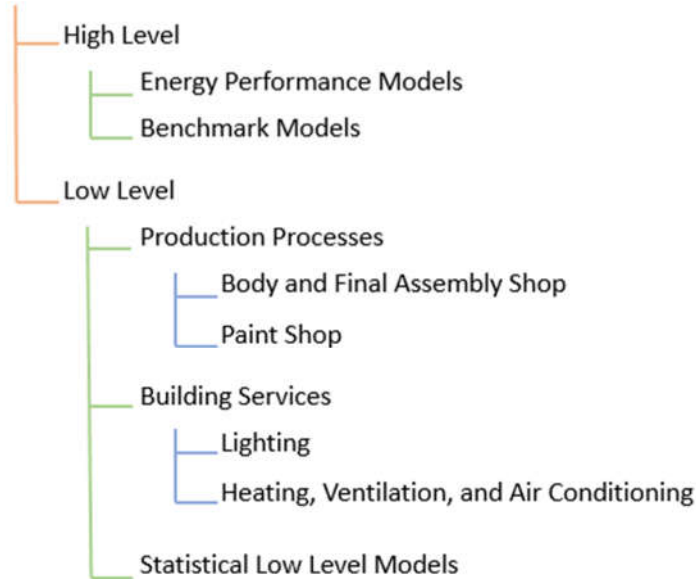
2.2.2 Manufacturing Energy Models Review

Efforts made by researchers on model establishment for manufacturing energy usage will be critically reviewed here.

Guided by the framework, publications from different levels in the post-process phase within the scope of this research is organized as Figure 2.3.

Manufacturing Energy Models

Levels of Models



Systematic Models



Figure 2.3: Section Hierarchy

Levels of Models

Models from different levels is reviewed here.

High Level

The manufacturing plant is a relatively independent entity which performs certain tasks to fabricate a product. Plant level energy modeling studies the plant as a system.

There are two branches in the high level – energy performance models and benchmark models (as Figure 2.4).

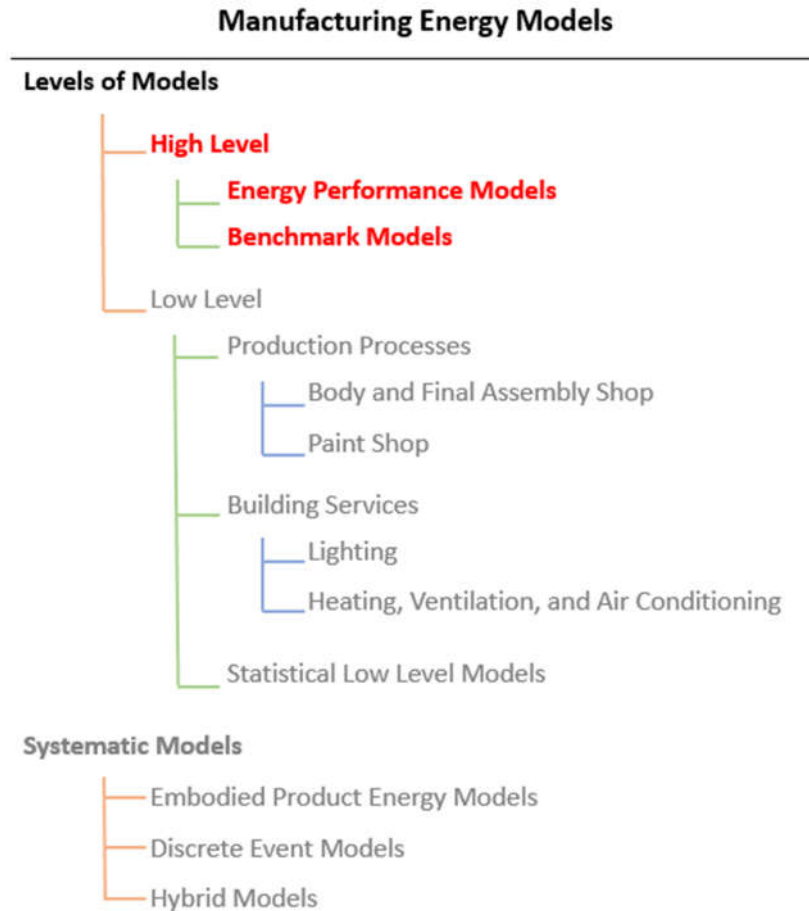


Figure 2.4: Section Hierarchy – High Level Models

Energy Performance Model

Energy performance models study the plant energy consumption per vehicle. One typical model for energy modeling of automotive assembly plant is from Gale A. Boyd's work in 2005 [2.3]. Boyd developed a performance-based indicator known as the Energy

Performance Indicator (EPI) to score energy performance in megawatt hour energy used per vehicle produced.

The EPI score can be seen as the goodness of energy consumption compared with similar plants in the automotive industry based on the source data from 35 plants within the 3 years (1998 - 2000). Corrected ordinary least squares (COLS) regression models were established to relate the energy consumption (E and F) with the productivity (number of vehicles produced annually, Y), product information (measured through the vehicle wheelbase, WBASE), plant utilization information (plant utilization rate Util, *i.e.*, the production line operation speed over its designed speed), and weather information (cooling degree days – CDD, heating degree days – HDD). Gale Boyd divided the energy within the plant to be two major energy carriers – electricity and fossil fuels out of the consideration of divergent usage. Electricity is believed to be used for both heating and cooling the working environment and manufacturing processes besides powering the robots and other equipment. On the other hand, fossil fuels are treated without the ability of cooling. These reflect in his work results shown in Equation (2.1) and (2.2). However, it neglects the fact that absorption chiller can use thermal energy (hot water, steam, exhaust gas) from fossil fuel as the energy source to reduce the temperature of cold water. In this way, the usage of fossil fuel and electricity can no longer be distinguished as indicated in Boyd's work.

$$E_i / Y_i = A + \beta_1 \text{WBASE}_i + \beta_2 \text{HDD}_i + \beta_3 \text{HDD}_i^2 + \beta_4 \text{Util}_i + \beta_5 \text{CDD}_i + \beta_6 \text{CDD}_i^2 + u_i - v_i \quad (2.1)$$

$$F / Y_i = A + \beta_1 \text{WBASE} + \beta_2 \text{Util} + \beta_3 \text{Util}^2 + \beta_4 \text{HDD} + \beta_5 \text{HDD}^2 + u_i - v_i \quad (2.2)$$

In these two equations, the E and F stands for total site electricity uses in kilowatt hours (kWh) and fossil fuels use in British thermal unit (Btu) respectively, WBASE is the production information (wheelbase), and Util represents the plant utilization rate (vehicle output/production capacity). And in these two equations, v is the normal distributed random error and u reflects the energy inefficiency. β s are the coefficients.

Plant level modeling is clear in correlations of the energy consumption with major impact factors. It is inexpensive and convenient in comparison of one plant with other similar automotive manufacturing factories – the EPI score represents energy performance of the plant through the percentages. For example, EPI score 90 stands for the achievements of 90% better than the other plants in the survey. Also, the energy consumption in megawatt hour per vehicle is valuable information in product Life Cycle Assessment (LCA). However, it also suffers several problems. First of all, this indicator/model does not include the impact from technologies. As mentioned earlier, the use of absorption chiller for chilled water production, which used in plant environment control and process cooling is no more different from the electricity. Second, this tool/model is intended to motivate the change of the automotive plants, but the ambiguous system boundary of factory plant fail to acknowledge the plants that make effort on the on-site energy supply system. For example, cogeneration system uses one energy input to create two energy outputs (usually power and heat, also called CHP – combined heat and power system), and is believed to be

promising in improving energy efficiency and is encouraged to be applied in industry. But this model fails to discuss how to give credit to the plants that are using the energy efficient on-site energy supply system. Third, clean energy, such as landfill gas is also neglected. The application of clean energy general meaning more capital investment and sometimes expensive operation maintenance cost. These procedures and cost expenses are not appreciated in the EPI tool. Last but not the least, the selection of the regression variables is obscure. Author use these variables through subjective discussions with the plant managers instead of scientific analysis. Are these variables reasonable? Are there any other ones can better describe the target factors? Below Table 2.1 and Table 2.2 are the correlation analysis of the fuel and electricity used in our studied case. The results show some of the variables included in the EPI model have no correlation with fuel and electricity consumption. Therefore, the EPI model is proved to be not accurate in describing the plant level energy.

Table 2.1: Correlation Analysis of Fuel

	F / Y
F / Y	1.00
$WBASE$	0.00
HDD	0.83
HDD^2	0.84
$Util$	-0.09
$Util^2$	-0.12

Table 2.2: Correlation Analysis of Electricity

	E / Y
E / Y	1.00

<i>WBASE</i>	0.00
<i>HDD</i>	-0.63
<i>HDD</i> ²	-0.56
<i>Util</i>	-0.77
<i>CDD</i>	0.87
<i>CDD</i> ²	0.93

Benchmark Models

Benchmark models are intended to establish references across a group of similar organizations. Yogesh Patil *et al.* developed a Lean Energy Analysis (LEA) method, which models electricity and natural gas usage in the automotive manufacturing plants [2.4]. The main contribution of this paper is the generation of *energy signatures*, defined as the *basic shape of statistical regression*. It is used to represent the baseline of energy use in each plant. This paper reported that the energy signature is represented by the manufacturers' unique energy equations derived from their own independent variables. The most straightforward example is the two-parameter (2P) energy signature equation (as Equation (2.3)).

$$Eng / day = Yint(eng / day) + RS(eng / unit) \times P(unit / day) \quad (2.3)$$

In Equation(2.3), *eng* stands for energy, *Yint* stands for the y-intercept during the regression analysis, *RS* is the regression slope, and *P* is the production of the day. Thus, the two parameters are the intercept and coefficient slope. According to the authors, these two parameters are unique to every plant. There are other energy signature equations in

this paper, but they all share the common questions – are these energy signature unique, are they necessary different from other plant?

It is interesting that the authors pointed out the concept of the energy signature, which is unique to every plant, according to the paper. However, the claim that the model can be used for comparison is questionable due to its oversimplified multivariable regression with only inputs from energy consumption of the day and production data. Will the slope and intercept vary according to the amount and types of products produced in one day? Do they change seasonally? How about non-production days? If the signature changes accordingly, do they still stand unique? Authors did not answer these questions well. In addition, the accuracy of the model is also in question. Figure 2.5 and Figure 2.6 are the two plots based on the 2P signature energy model. These figures show a poor fitting in the energy.

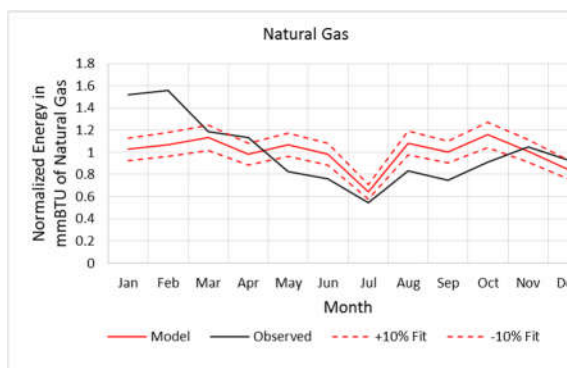


Figure 2.5: Natural Gas Signature Fitting

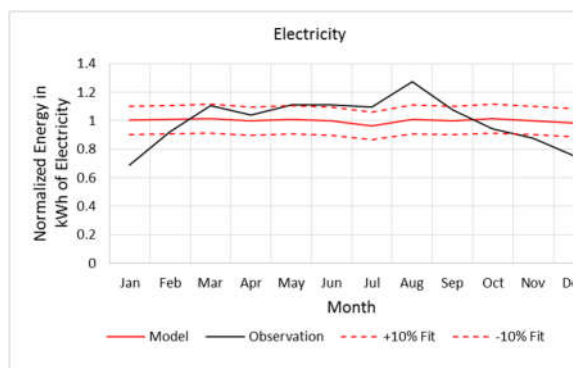


Figure 2.6: Electricity Signature Fitting

In the reviewed benchmark models, the relatively straightforward statistical regression approach was used. This makes them flexible to be applied to similar manufacturing plants. Also, due to the limited amount of input data required, these models are inexpensive and feasible to use. Nonetheless, also due to their insufficient consideration in the various technologies used in the plants, the consumption among the similar plants is hardly deemed comparable. Finally, the fundamental purposes of building an energy model is to seek conservation opportunities by identifying potential improvements and to be conscious of the amount of energy used. The reviewed works did not serve these two purposes well.

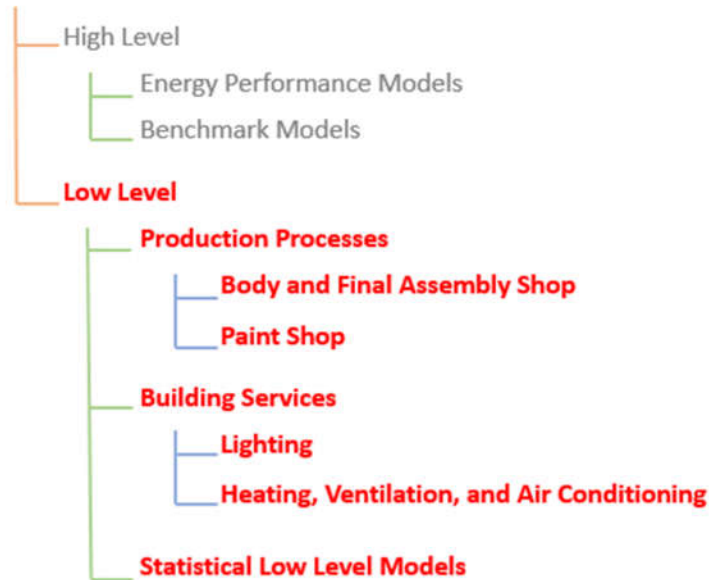
Low Level

In contrast, low level models are great in identifying potential improvements and quantify the energy consumption.

As show in Figure 2.7, low level models can be classified into three main categories: 1) production process related; 2) building serves related; and 3) data driven statistical models. The production process models including physical models for vehicle body and final assembly processes and painting processes. Building serves including lighting and building heating, ventilation and air conditioning (HVAC). Finally, despite the energy end users, the statistical models are data driven models simulate the machine/device power load during various working condition. In this section, low level models in the three categories will be reviewed and typical energy models will be exemplified.

Manufacturing Energy Models

Levels of Models



Systematic Models



Figure 2.7: Section Hierarchy – Low Level Models

Production Processes

The three main departments in the automotive assembly plant include:

- 1) body shop where the stamped panels are welded together to form a vehicle body-in-white;
- 2) paint shop where the electrocoat, paint and sealant are added to the vehicle body for an attractive and corrosion-resistant appearance; and

- 3) final assembly shop where all the components of the vehicles are assembled together to make the vehicle functional.

Body and Final Assembly Departments

Body shop, which has evolved to have a high level of automation, is responsible for the forming and joining of stamped panels to vehicle body structure. Final assembly departments marry the vehicle body to power chain, interiors and other components to make the car functional. Both body and final assembly departments contain many assembly processes and share many common aspects, such as material handling and joining.

Material Handling – Robot

Material handling in the plant can involve both human operators and robots, especially in handling dashboards, cockpit modules, engine blocks and other heavy components. Such components require both precise and rapid handling. Robots are used to carry the weight of heavy parts, while human operators could assist the secondary assembly operation, like inserting fasteners and manually connecting harnesses. Various types of material handling robots are used related to the size of handled parts, position of installed, and human ergonomics. Despite the difference in the shape and specific tasks, general material handling energy consumption is related to the weight of parts, robots design, distance of moving, time of moving and efficiency of the robot.

$$E_{handling} = \left[L \times (m_{part} + m_{grip} + \eta \times m_{robot}) \times v \right] / (\eta_{motor} \times t_{handling}) \quad (2.4)$$

Equation (2.4) indicates the energy consumption of the robot handling material, and the variables involved in this equation are the length of the moving material (L), speed of moving (v), weight of the part (m_{part}), weight of the gripper ($m_{gripper}$), robot specifications such as the weight of the robot arm (m_{robot}) and the angle of the robot arm (η), as well as the motor efficiency (η_{motor}) and handling time ($t_{handling}$).

The Equation(2.4) of energy in material handing gives a clear picture of the influential factors. It provides information to identify the improvements for energy conservation. For example, the equation has a positive correlation between the energy consumption and distance of material moved. To minimize the energy, an optimized route with minimum distance moved could be one of the potential measurements for conservation. However, Equation(2.4) is just a theoretical calculation without considering the possible auxiliary energy needed for the material handling process. Most of the time the handling robots are in their idle stage, which requires small amount of energy to maintain its position or keep the auxiliary system (*e.g.*, lubrication system) running. But the idle stage could last a long time in a low productivity time. In a situation when the productivity runs low for a long time, the idle energy could be a large share. In summary, the robot busy model is good in identifying the potential improvements through sensitivity analyses of each variable involved, but it is not sufficient to calculate the overall energy used in this process. It is also not feasible to measure all parameters in the idle stage for a holistic physical model. Specific models for each type of material handling robot would likely be expensive.

Material Handling – Conveyor

The conveyor is another tool used for parts and bulk materials handling. It transforms electricity into mechanical energy to move the materials and parts.

$$E_{Conveyor} = \int P dt = \int (F \cdot v) dt \quad (2.5)$$

The energy consumption of a conveyor is highly related to its power and time of use. As an example, the energy of the belt conveyor can be calculated as in Equation(2.5). In this equation, the power of the conveyor (P) is calculated as the function of conveyor speed v and the driving force F , which is related to the conveyor slope angle, resistance force, and weight of the parts transported. Conveyor efficiency can be improved through the use of a higher efficiency idler, drive system, and belt/chain.

Joining

Steel and aluminum are the two main production materials used in automotive manufacturing plants [2.5]. As the standard of fuel economy is increasing, more lightweight materials are used on the vehicle, which makes the joining techniques more varied. In addition to traditional spot welding, automotive manufacturing plants are deploying joining technologies such as laser beam welding, metal inert gas/metal active gas (MIG/MAG) welding, riveting and screwing.

Spot welding is one of the traditional joining technologies used in the automotive manufacturing plant. J. D. Cullen *et al.* studied the energy use in the spot welding specifically in the automotive industry [2.6]. They used the artificial intelligence approach to correlate the energy consumption of the automotive spot welding with welded material type, material thickness, number of weld, weld nugget size, and tip width. The artificial intelligence method used in the paper is beneficial to understand the relations between the energy use and other variables during the welding process, but it did not give out physical explanations of why they are correlated and how the adjustment can be made to save energy. The paper does not include information from the welding idle stage, which as discussed could be a large share during the low productivity time. Hai Liu and Qianchuan Zhao modeled the energy consumption of the welding process as two parts – energy consumed in generating welding spot and welder idle (shown as Equation (2.6)) [2.7].

$$E_{weld} = E_{ps} N_{spot} x + (1 - \alpha) P_{idle} T \quad (2.6)$$

Considering the energy consumed in generating one spot could be different according to the operation procedures, the statistical data average energy of one welding spot (E_{ps}) is used. N_{spot} is the number of welding spots per product, x is the number of products to be produced, α is the ratio of welding engaged time to the total uptime, P_{idle} is the no-load power when the welder is in idle stage, and T is the total uptime.

Laser beam welding is another popular technology used in automotive manufacturers. For laser welding CO₂, excimer, and the Nd: YAG (neodymium in yttrium

aluminum garnet) lasers are used. A further development of laser welding leads to the introduction of remote laser welding (RLW), which uses large focal length optics, high-power laser sources and mirrors to translate the laser beam into a large 3D working volume at high speeds [2.8]. Laser welding is beneficial for its short processing time, high quality and ability to process multiple materials. Unlike laser beam welding which use the laser as heat source, gas metal arc welding forms an electric arc between the wire electrode and work piece, by using the inert or active gas as the heat source. Both welding techniques join the materials through metal melting. The theoretical energy of metal melting can be calculated as Equation (2.7).

$$E_m = (vS)\rho \left(\int_{T_0}^{T_m} cdT + H \right) \quad (2.7)$$

In this equation, S is the area of weld cross section, v is the welding speed, ρ is the material density, T is the temperature, T_m is the melting point temperature, T_0 is the ambient temperature, H is the latent heat of melting and c is the specific heat. The energy of welding also depends on the efficiency of energy conversion from primary energy (*e.g.*, electricity, gas chemical energy) to thermal energy. M. Gao and his colleagues introduced a series of CO₂ laser-gas metal arc (GMA) hybrid welding experiments on the mild steel [2.9]. They discussed how the laser power, arc current and the distance between laser and arc can affect the melting energy. All these models are great in calculate the theoretical energy demand, but they are also cumbersome to apply considering the different joining

techniques, equipment used, and the time and monetary cost in measuring all the variables need for inputs.

Paint Shop

Paint provides the appearance as well as corrosion resistance to a vehicle. This area is responsible for vehicle painting and sealing, consumes as much as 60% [2.10] of total plant energy utilization.

Typically, there are several major procedures in paint shop. The first procedure is pretreatment, where a galvanized steel substrate with a thin (internal sections only) crystalline tri-cation phosphate layer. Then an electrocoat is given to provide corrosion resistance. After the electrocoat is cured, the lower panels of the vehicle body are protected with a thick antichip layer in sealer booth to protect it from gravel. At last, the final steps apply actual paint to the vehicle body through several booths and ovens – primer with anti-corrosive pigments, followed by the basecoat which gives the vehicle color, and clearcoat protects the paint from UV and gives a glare looking [2.11].

In this section, energy consumption of each main painting process will be discussed, major energy usage models will be provided to illustrate the modeling approaches.

Pretreatment

Pretreatment is a procedure for vehicle body to remove the oil and grease from stamping and body shop. And the phosphate coat during the procedure will make the body adhesion for the e-coating (electrocoat) and corrosion resistance. Pretreatment procedure

includes several repeated steps of pre-clean, rinse, activate, phosphate, passivate, rinse, and drain. The chemical reactions in the phosphate coating procedure require the maintenance of solution in the tanks at certain temperature (135°F for phosphate step). Energy is used for pumping and heating water.

$$P_{pump} = \frac{FR_{water} \cdot H}{\eta_{pump} \cdot \eta_{motor}} \quad (2.8)$$

$$E_{water} = \frac{FR_{water} \cdot C_{p,water} \cdot (T_{Hot} - T_{Cold})}{\eta_{Hex-Water}} \quad (2.9)$$

Power of pumping water to the tank is represent in Equation (2.8). It is directly related to the water flow rate (FR_{water}) and pumping water head (H), and inverse proportion to the pump (η_{pump}) and motor (η_{motor}) efficiencies. There may be several pumps in the pretreatment procedure; the total electricity consumption is the additive of all the pump powers multiply by the total hours of working. Natural gas is usually used for water heating (Equation (2.9)). The natural gas used is the energy absorbed by the water divided by the efficiency of heat exchange from gas to water/solution ($\eta_{Hex-Water}$).

E-Coat

E-coat, short for electrocoat, is a procedure provides corrosion protection for the vehicle body. Direct current is applied to the solution.

$$P_{ECoat} = P \cdot \eta_{rate} \quad (2.10)$$

Steps in E-coat include repeated electrocoat dip and rinse. The energy used in electrocoat step can be calculated as Equation (2.10), which related to the electrical duty (P) and production rate (η_{rate}). Also, in order to keep the solution concentration constant and even, pumps (Equation (2.8)) and a recirculation system are needed in all of the tanks in both pretreatment and E-coat procedures.

At the end of E-coat, the vehicle body needs to be cured/dried before transportation to the next procedure. Ovens are used to cure the paint, and can be modeled as

$$P_{oven,booth} = \frac{\Delta P \cdot FR_{air}}{\eta_{motor} \cdot \eta_{blower}} \quad (2.11)$$

$$E_{air} = \frac{FR_{air} \cdot C_{p,air} \cdot (T_{HotAir} - T_{ColdAir})}{\eta_{Hex-Air}} \quad (2.12)$$

In Equation (2.11), $P_{oven,booth}$ represents the power of oven or booth, ΔP is the input electricity power, FR_{air} is air flow rate inlet to the oven or booth, and η_{motor} and η_{blower} are efficiencies of motor and blower respectively. In Equation (2.12), E_{air} represents the space loading air energy, $C_{p,air}$ is the heating capacity of air, T_{HotAir} and $T_{ColdAir}$ are the temperatures of hot and cold air, $\eta_{Hex-Air}$ is the heat exchanger efficiency.

Air is heated before introduction to the oven. Natural gas is used to heat the air and electricity used to blow the air.

Seal and Paint Spray

In the sealing and painting spraying processes, robots that spray the sealant or paint can be simulated as the part handling/moving energy. Depending on the technology, some painting and sealing procedures need to be separated into smaller booths with controlled the temperature and humidity. This part of energy consumption is detailed in the Case Study section.

Paint Shop Summary

Regarding paint shop energy modeling, Roelant *et al.* studied the cost and environmental impact from automotive painting shop by creating a mathematical model to simulate the processes [2.12].

In their study, Ford Motor Company Michigan Truck Plant was used as a case study and data source. Thermodynamic theories, empirical assumptions, and equipment specifics from Ford are used to validate the models process by process.

Roelant claimed that their model is capable to 1) identify the major energy-consuming units; 2) calculate the economic metrics and environmental performance indices; 3) determine the sensitivity of the energy model; and 4) identify the potential heat recovery opportunities [2.12].

According to sensitivity analyses of Roelant's model, the major energy consumer in the paint shop is the booth air conditioning, followed by the coating ovens. Energy can be saved through the extra investment for heat exchanger hardware. However, Roelant's

model requires specific painting processes with tremendous amount of variable and parameter inputs; it is inflexible to apply to other plants.

Technical Building Services

In addition to the energy consumption related to the production processes, building services of the manufacturing plant also account for a big portion of the overall utilization. Some of these are detailed below.

Lighting

In an automotive manufacturing plant, lighting is believed to constitute approximately 15% of the total electricity consumption [18].

There are two lighting systems in the plants: high bay lighting and low bay lighting. High bay lighting is generally a portion of building energy to provide a bright environment for the building, whereas low bay lighting is concentrated alongside the workstations. Usually, high and low bay lighting have the same lighting fixture within the same system. Thus, the energy consumption of the lighting system can be calculated as in Equation (2.13).

$$E_{Lighting} = E_{High} + E_{Low} = N_{High} \times P_{High} \times t_{High} + N_{Low} \times P_{Low} \times t_{Low} \quad (2.13)$$

In Equation (2.13), $E_{Lighting}$ is the energy used for lighting fixtures, E_{High} and E_{Low} represent the high bay and low bay lighting energy, calculated through the number of lighting fixtures (N), power of lighting (P), and time of usage (t).

The number and power of the lighting fixtures are highly related to the building structure, availability of daylight, and working environment lumen requirements. Energy efficient buildings have sufficient daylight available to allow shorter artificial lighting time, while fine components assemblies have high lumen requirement that necessitates a higher lighting requirement. Besides the daylight availability, the lighting time also depends on the control system design. Automatic control systems with light or motion sensors are proven to be more efficient than manual controls [18].

Heating, Ventilation and Air Conditioning (HVAC)

The HVAC function is another big energy consumer in an automotive manufacturing plant. In order to maintain a good working environment, conditioned air is constantly exchanged with outdoor air. Some manufacturing plants also control the air temperature and humidity of the department 1) to make sure proper ambient working conditions exist for the workers, 2) to protect the weather-sensitive equipment, and 3) to guarantee a high quality product. The energy used for HVAC can originate from electricity, natural gas, hot water/steam, or chilled water. Electricity is mostly used to power the ventilation fans and motors. If hot water/steam and chilled water are available for direct use, they are used to heat and chill the inlet air through heat exchangers. Otherwise, natural gas and electricity are used to run the burner and chiller to generate hot/steam and chilled

water on-site. Ivan Korolija *et al.* developed regression models to predict the building annual heating and cooling demand [2.13]. According to their research, the building heating/cooling energy is related to the amount of heat gains and losses such as the transmission heat gains/losses through building envelope, solar gains, internal heat gains (such as manufacturing processing heat), and heat gains/losses in through the heat exchanger and air ventilation (as Figure 2.8).

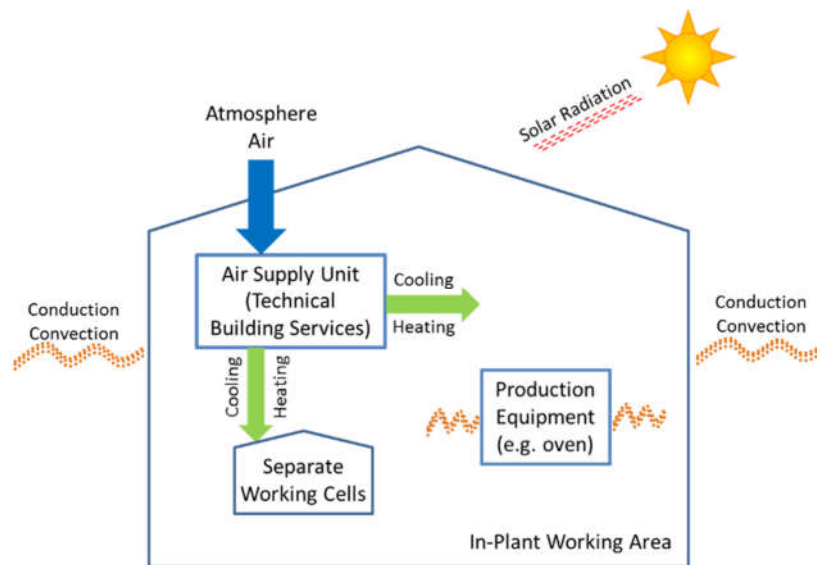


Figure 2.8: Plant Building HVAC Sketch

A detail HAVC model for plant building is studied in Section 3.4.1.

We have now covered the high level and deterministic models in low level approaches, so now turn our attention to statistical models in low level approaches.

Statistical Models

Statistical models in the studied hierarchy is shown in Figure 2.9.

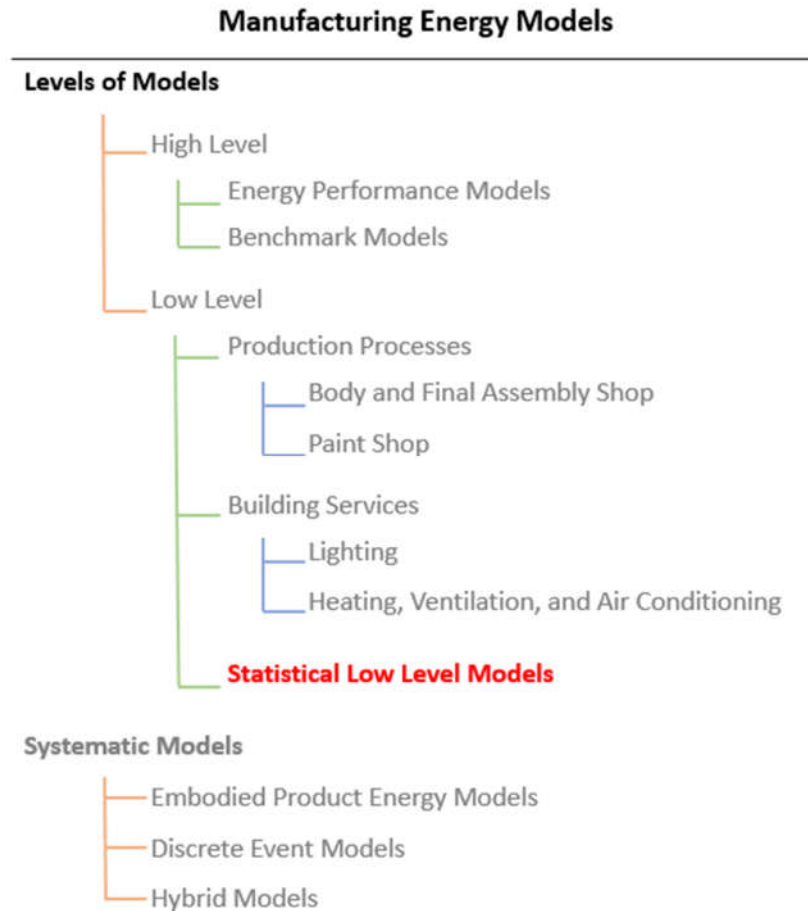


Figure 2.9: Section Hierarchy – Statistical Models

Unlike the physical models which need to be specified according to the equipment specifications, statistical modeling is a more direct and easier method to apply. Statistical model of electricity power is used as example to illustrate the modeling approach.

Many devices use electricity as the power input. The load characteristics of the device can be measured during different tasks of the device to determine the power load at each stage of the machine.

An example machine power load working model (shown as Figure 2.10) without break and pauses is a series of similar cycles according to the certain operations carried out.



Figure 2.10: Machine Power Load at Working Mode [2.14]

However, the same machine could have slightly different loads depends on the current operating conditions of human operator and variations in the operating of machines. The model of the machine with this function should include information of peak load value and average power consumption. Statistical models can be used for load description.

A production line with multiple machines/devices could have the line power load character which combines all the components contains in that line (as Figure 2.11).

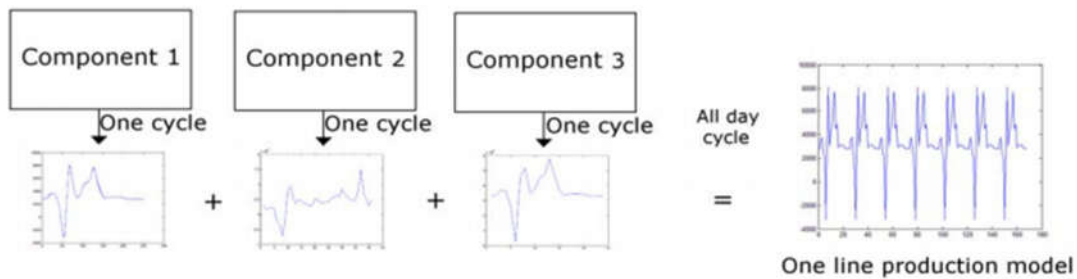


Figure 2.11: Assembly Line Power Load [22]

Once the machine power load character has been determined, the total energy used to perform the tasks can be calculated as the integration of the power over time which determined by the production line speed.

Multi-machine and single machine level modeling is great in providing detail information of the low levels. The models describe the detail machines, production cells or lines energy consumption principles, which can be easily used for sensitivity analysis to extract influential factors, and for improvement identification. However, the detail modeling of each machine in a complex plant is time intensive, and requires expensive support from meters and sensors, which do not consider the current status of most manufacturing plants. Besides, the detailed modeling on the production main lines could cause the problem of auxiliary energy consumption neglecting which could be a significant in overall consumption, especially during the low productivity period. The simple summation of the device/machine level model to picture a holistic plant energy usage is not only infeasible but also insufficient.

Systematic models

Models in different levels provide detail modeling approaches for energy usage within the manufacturing plant, but when it comes to the holistic perspective on energy utility of the plant, they are incompetent in information interaction among levels. An ignorant combination of the current levels of models either loses the comprehensive picture of the plant, or lacks accuracy and detail. Therefore, the simple compilation of levels of models, could cause problems in decision making and information dissemination. Systematic modeling in compensating for disadvantages caused by levels of modeling is summarized here. Systematic models in the section hierarchy is highlighted in Figure 2.12.

Manufacturing Energy Models

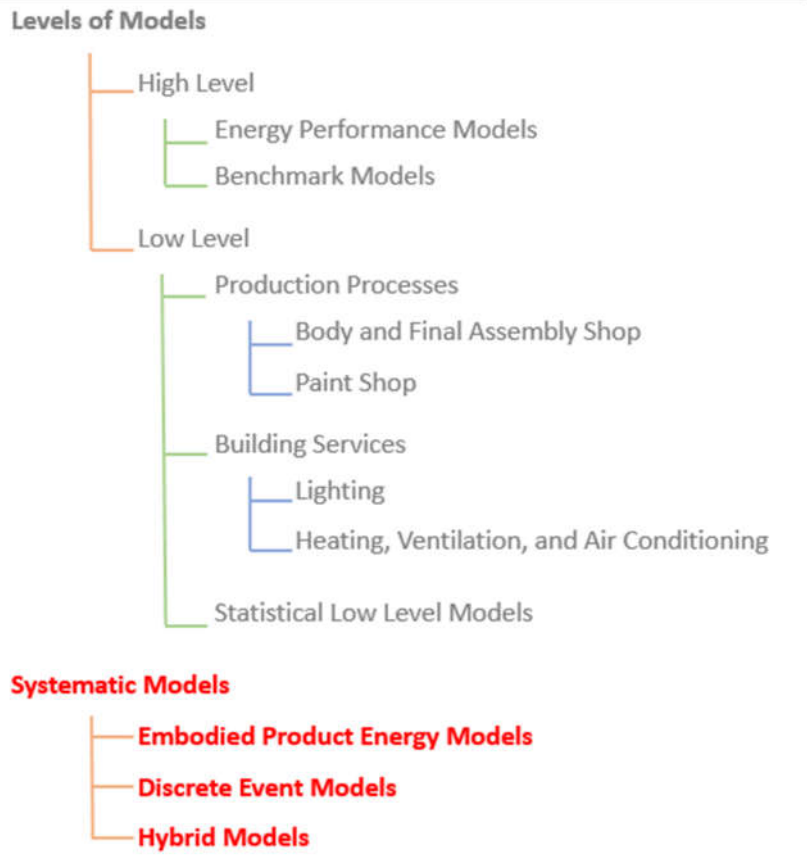


Figure 2.12: Section Hierarchy – Systematic Models

Embodied Product Energy Model

S. Kara and S. Ibbotson [2.15] started from the life cycle analysis point of view, proposing the methodology in assessing the embodied product energy (*EPE*). They used two roofing systems (fiber composite and galvanized steel roof systems) as demonstration examples, and developed 10 different manufacturing supply chain scenarios, and considered the embodied energy of raw materials supplied. The supply chain scenarios considered the transportation types (*e.g.*, road, rail and ship) and distances, and the raw

material embodied energy includes the amount of energy used in previous manufacturing processes. This work including the multi-factory and facility levels (as Figure 2.13). It is good in understanding the embodied energy in the whole product life and the energy consumption in the product's different life stage.

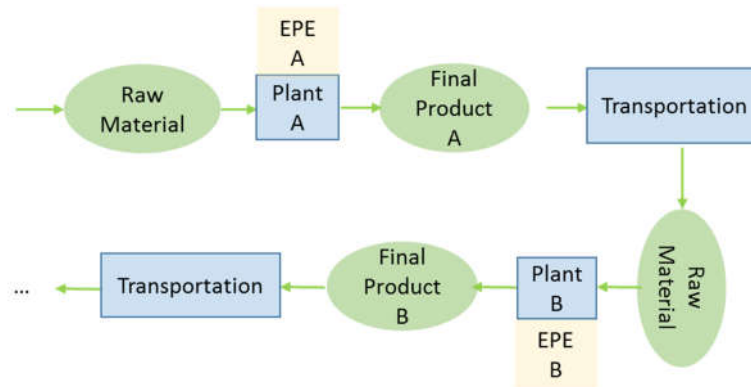


Figure 2.13: Embodied Product Energy Supply Chain Scheme

However, like many other life cycle assessment methodologies, it is criticized by its inaccuracy, large variety range in the same product and lack of detailed description of the production procedures.

Discrete Event Models

Discrete models have the energy consumption in “numbers of product”, and usually assume the energy consumption of one product has no significant difference from another product. Evolved from the traditional *EPE* models, discrete event simulation models [2.16, 2.17] took this concept one step further by describing the production procedures. They modeled the energy from two aspects – direct energy (*DE*) and indirect energy (*IE*). *DE* is

defined as the energy used directly in the manufacturing process (*e.g.*, welding, machining); *ID* is defined as the energy consumed to maintain the working environment (*e.g.*, lighting, heating and ventilation). *DEs* were modeled by using physical models of multi-machine and single machine levels, while *IEs* were calculated as the average energy consumption over the time and number of products stayed in different production zones.

Their model provides better understanding on the production lines and involved the factory, multi-machine and single machine levels, but it simply sums all the energy in levels without giving it a deep analysis on the influential factors, nor showing the interaction among levels of models to compensate the disadvantages of each other. This approach is no more than the compilation of the multi-machine and single machine level models. Besides all the advantages in levels of modeling strategy, this method makes the models cumbersome in application. Furthermore, even though the automotive assembly plants process a discrete manufacturing procedures, the energy utility in the plants is both discrete and continuous. The discrete event modeling approach proposed in reviewed paper neglects the continuous nature of the *DE* and *IE*, and the interaction between these two.

Hybrid Models

The importance of the building shell itself, and the interaction between the production process and its environment was addressed in [2.18] and [2.19]. In these papers, the energy consumption of technical building services are taken into consideration. They illustrate how it is used to ensure the production conditions in terms of temperature, moisture and air purity through heating, cooling and conditioning of the air; and how it is

affected by the local climate of the production site and machine waste heat. Unlike the previous EPE and discrete event simulation models, these models also suggested a hybrid approach (combined discrete event and continuous simulation) considering the involvement of continuous building energy and discrete product production. Unfortunately, the involvement of the building energy consumption into the production process was only discussed theoretically. Both papers did not provide the modeling approaches, nor quantification of energy consumption from the building heating, ventilation and air conditioning (HVAC). Also, because both papers still concentrated on the specific simulation models for certain processes instead of system modelling approaches, they also suffered the problem of inflexibility and infeasibility in industrial applications.

2.2.3 Knowledge Gap Summary

As previous reviewed work and framework have illustrated, the manufacturing plant is a complex system containing many main procedures and auxiliary processes. How to include the maximum **amount of information** without jeopardizing the **flexibility to apply** in similar systems is a challenge worthy of study.

The current status of the plants makes this research even more challenging. Energy models without the valid data inputs do not make a difference to other general models, nor help in quantifying or understanding the usage within the system. It is critical to have valid data inputs for model establishment and validation. However, it is common for manufacturing plants to have an incomplete data system which can only satisfy part of the modeling requirements. Actually, the plants install meters based on measurement

requirement, the compatibility with current system, database storage space and cost limitations [2.20]. To guarantee an efficient model construction process, and the reproducibility and repeatability of proposed modeling approach, the current obsolete status of the energy monitoring system needs to be taken into consideration at the very beginning of the modeling work – **be feasible to current plant**.

Many facilities have only plant level energy meters installed by the utility companies to monitor the energy purchased from the suppliers. Until recent years, more facilities show a trend of installing fewer metering systems [2.21]. Comprehensive meters for every device and machine in the production line is infeasible and unlikely in the near future. The combination of statistical and physical models are a foreseeable choice – physical detail models where the low level meters are equipped, and statistical description models where there are only high level meters installed. In the meantime, it is important to have interaction between the levels of models. How to use the information from low level models, and to have a relatively simple but robust and informed high level model is another topic worth to be studied.

Finally, as an energy model, it would be preferred that the models are **accurate** and can point out further **improvement** potentials.

Based on these requirements, the reviewed models are summarized and evaluated here from their 1) amount of information provided, 2) flexibility to apply, 3) feasible to the current plants, 4) potential to identify the improvement, and 5) accuracy. According to their

fulfillment on each of the criteria, they were given zero to one scores, where zero for not fulfilled at all, and one for completely fulfilled.

Table 2.3: Model Evaluation Table

Comparison Criteria Evaluated Models	Information Amount	Flexibility to Apply in Similar Systems	Feasibility to Current Plants	Improvement Identification	Accuracy	Average Score
	1	2	3	4	5	
Energy Performance Model	0.4	0.8	0.8	0.2	0.2	0.5
Benchmark Models	0.4	0.8	0.8	0.2	0.2	0.5
Multi-Machine and Machine Level Physical	0.6	0.2	0.2	0.8	0.8	0.5
Multi-Machine and Machine Level Statistical	0.5	0.5	0.5	0.2	0.8	0.5
Embodied Product Energy Models	0.7	0.2	0.2	0.5	0.2	0.4
Discrete Event Models	0.7	0.2	0.2	0.5	0.5	0.4
Hybrid Models	0.9	0.2	0.2	0.9	N/A	0.6
Average Score	0.6	0.4	0.4	0.5	0.5	

Table 2.3 shows the score of fulfillment of each type of models. These high and low levels' models are highly unbalanced. They are great models in serving the modeling purpose of their high score criteria, but insufficient in others. The combination of these models is not an option, because when they were build they do not consider the information sharing in different levels. The systematic models are either at the concept stage, or require the support of expensive data systems.

2.3 Modeling Approach

This research is to compensate the knowledge gaps by using a well-known manufacturing framework to guide systematic modeling approach. The scope of the models

is to explore the energy consumption at plant, multi-machine, and machine levels during the post-process phase of manufacturing plants.

During the post-process phase of the manufacturing plants, products are continuously produced to cater the market demand. The product and corresponding production procedures are designed, built, tested and in use. Modeling at this phase should be based upon the current production state of the plants, and installed metering and data systems.

At the organizational scale, models in different levels can be built separately while considering the interactions. The facility level contains all the energy usage within a manufacturing plant. At this level, energy directly or indirectly used by the production procedures needs to be included. From the angle of energy supply to stratify all the consumption demand, energy purchased from the utility companies, and generated onsite through renewable generation technologies such as solar panel, wind turbine and cogeneration system. Energy models at this level are usually built as data driven statistical models as reviewed in the previous section 0. Though well known for their flexibility in applying to similar plants, the current plant level models suffer the problems of inaccuracy, limited information, and vulnerability to external changes.

Multi-machine level models consist of more than one machine working in series or parallel to execute specific activities. The scale of the multi-machine level can range from a small production cell (*e.g.*, basecoat painting spay booth) to a complex department (*e.g.*, paint shop in automotive assembly plant). Based on the available data of the studied system, energy models at this level can be built as either data driven statistical model, or detailed

physical models. This level models are intended to include more technical details of the production processes and machines, and provide more information comparing with the facility level models.

Single machine level, also known as the device/unit process level models, involves only one machine or device. Various machines could have thousands of different tasks in a manufacturing plant. Examples of typical single machine models, such as material handling robot and water pumps, can be found in the previous section. Many ultimate theoretical energies in these typical tasks share the same models, but specifying the ultimate energy into secondary energy for each machine asks for inputs from designs of machines and procedures in completing the tasks. Without doubt, the single machine level models embroil many inputs as well as outputs information. Exhaustive models for every single machine in a complex plant is cumbersome and infeasible. A top-down method in screening critical machines is necessary in a systematic approach.

A systematic approach is key to efficient modeling (“efficiency” is defined in the model evaluation criteria, *i.e.*, information amount, flexibility to apply in similar systems, feasibility to current plants, ability of sensitivity analysis, improvement identification and accuracy), and to constructing the models at different levels. Unfortunately, the current systematic models reviewed are not sufficient to satisfy these requirements (see section 0).

Meanwhile it is noticeable that the disadvantages of high level models (energy performance models and benchmark models) are the advantages of low level models (Multi-machine and machine models). How to use the manufacturing system framework

to build models in different levels while considering the ability to interact to each other, as well as the flexibility and feasibility, is the key contribution of this proposed approach.

There are two main approaches to interface the models at different levels – top-down and bottom-up. Top-down defines building models at a high level first, and then drive the detail down to sub-systems like multi-machine and single device levels. Especially in a complex manufacturing plant, such as for automotive assembly, where the exhaustive low level models of the comprehensive plant is infeasible, the top-down method can be used to wisely select the critical energy components in the low level consumption. Therefore, the top-down method is useful in helping selectively spend money and time in establishing models. Bottom-up defines using the information from low level to feedback the high level models, and make high level models more intelligent and robust, while keep the advantages of feasibility and flexibility. In this chapter, detail top-down approach will be discussed and case study of top-down will be provided. The bottom-up method will be discussed in the next chapter.

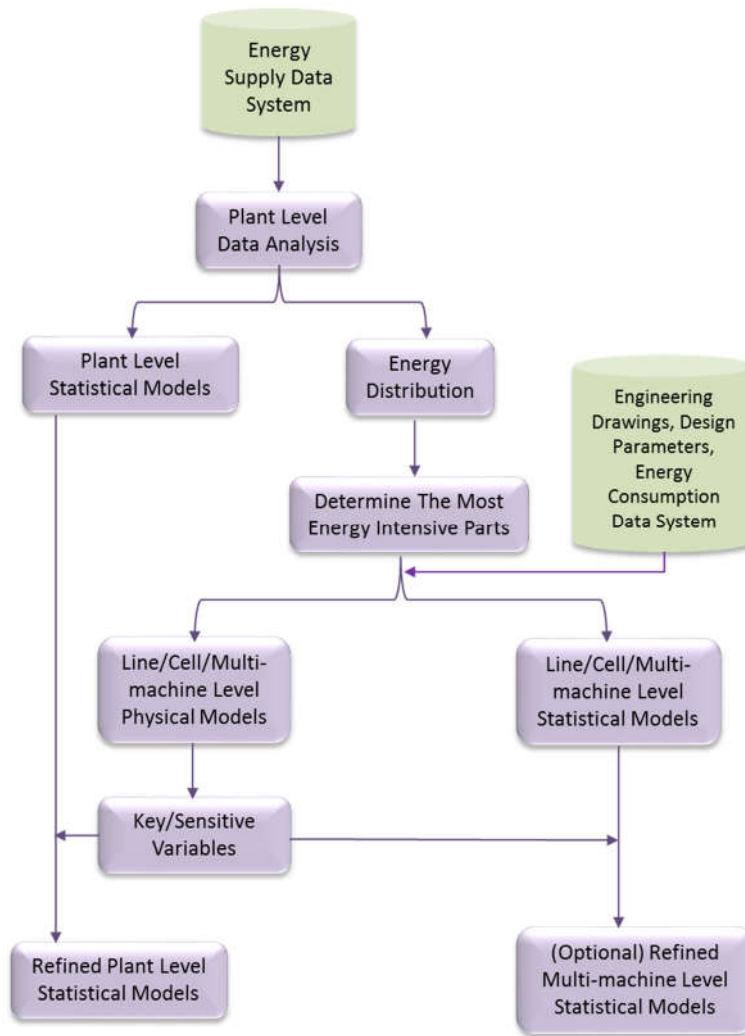


Figure 2.14: Flowchart of Energy Modeling

A general energy modeling and analyzing approach is described in Figure 2.14. Usually, a manufacturing plant has a high level energy supply data system to help understand how much energy is used in total. The first step is to understand the data system. “Are all of the energy sources purchased? Where are the meters that recording the data located? Are there any branches?” Questions of the metering and data system need to be made clear before modeling. For plants that lack data systems, either install feasible meters

for data collecting, or use utility bill information instead. Data from the main meters or utility bills need to be collected and pretreated to get rid of outliers caused by aberrant sources such as meter malfunction. In this stage, plant level statistical models can be built. Regression models correlating the energy consumption with the weather information and productivity, or simple time series models with historical data are both good choices in presenting the correlations and studying time patterns. Energy distribution analysis to the departments is a critical part in determining the next level modeling focus. Energy modeling can be processed in parallel. However, in most situations, considering the time and resources required. One area needs to be focused to proceed to the next level model. In this step, meetings, interviews, surveys, and if available meter readings in the multi-machine, production lines can be used to determine the concentration of next step work. After the focusing area is narrowed down, detailed physical models or statistical models can be built based on the data availability. Sometimes, in a case of no meters in supporting the models, extra feasible meters may have selected to help further validate the model results before any other improvement implementation. Key sensitive variables can be determined through the model analysis. These sensible parameters can be feedback to the high level statistical model, or optionally build statistical model with extra exogenous inputs to make it more robust. The same procedures can be reproduced in different lines.

2.4 Case Study

In this section, a case study from BMW Spartanburg Automotive Assembly Plant will be used to illustrate how the proposed modeling approach can be implemented, and how it fulfills the knowledge gaps.

2.4.1 Studied Case Introduction

The studied case is the BMW Automotive Assembly plant in Spartanburg, South Carolina, which assembles BMW X-series vehicles from stamped panels and many other sub-assembled components. The plant is obviously interested in energy conservation and sustainable manufacturing processes, but needs to carry these plans out in a cost effective way.

Spartanburg plant purchases electricity, natural gas from the utility companies, as well as landfill gas from local supplier. Electricity is used to power the equipment. Natural gas is mostly used for space heating and paint curing. Landfill gas is used on two on-site hot water and electricity generators (CHP, combined heat and power). Main energy conversion and transmission happens at the *Energy Center*. In the Energy Center, purchased energy from the utility companies will be converted to the energy forms (hot water, chilled water, compressed air, and so on) and amounts the main production area needs. (as Figure 2.15).

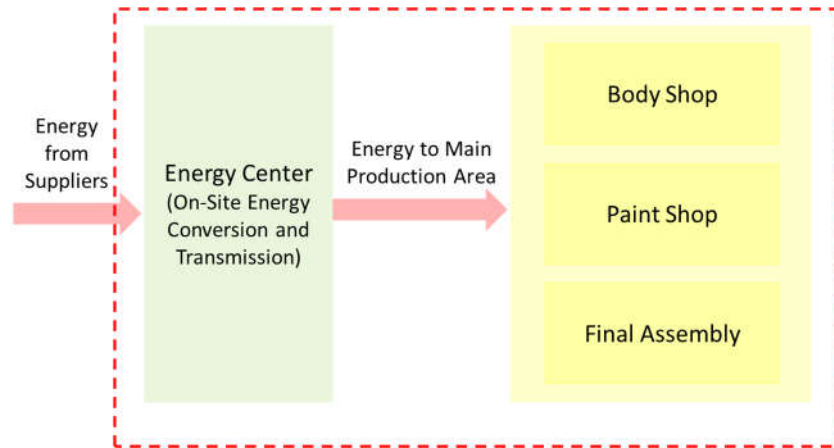


Figure 2.15: Energy Flow Sketch in Studied Automotive Manufacturing Plant

The studied plant can be split into two major parts – the energy supply system and the energy consumption system. Energy supply system is located in the *Energy Center*, where all the on-site energy conversion and transmission is processed. The efficiency of energy supply system and how to optimize the operations inside *Energy Center* is discussed in Chapter Four. The energy consumption system contains all the energy used in the major production departments, which is also the focus of energy modeling approach discussed in this chapter.

2.4.2 Data and Energy Management System

Machines and devices on the production lines are generally connected with many different meters/sensors/transducers to make sure they are functioning well. These meters measure the parameters like temperature, power load, flow rate and all various ones that can be used for energy modeling. The data measured through these meters are then loaded

to the data acquisition system, and saved in the data server. They can be accessed through an intranet connected desktop or laptop. A simplified framework is shown in Figure 2.16.

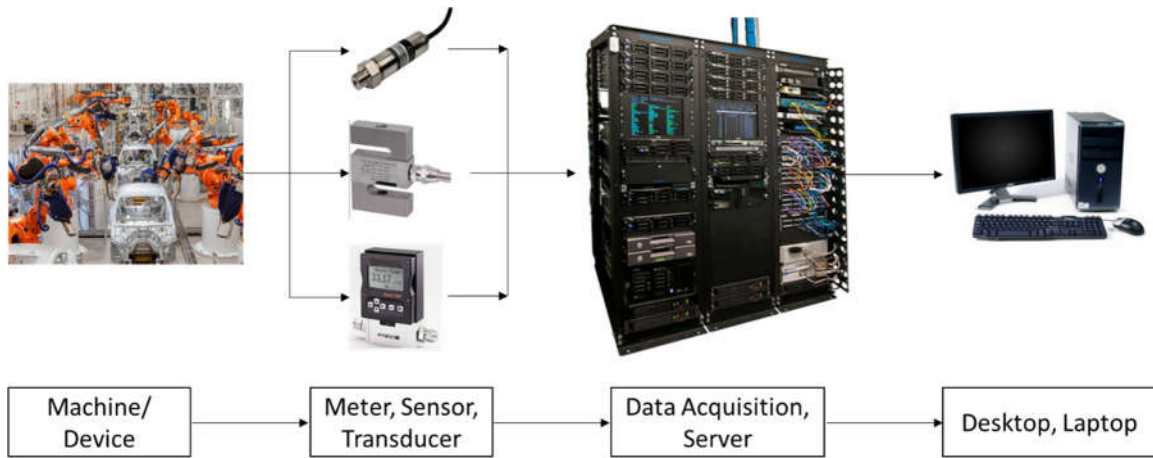


Figure 2.16: Manufacturing Plant Meter/Data System Framework

The data saved are assigned an ID to distinguish each signal, with a brief description of the data and sometimes the unit of the data. A typical database format is given as Figure 2.17. Based on the meters used, the data are stored in different frequencies. One needs exact IDs to access the certain meters.

Data
Meter ID
Timestamp
Meter Brief Description
Unit
Value

Figure 2.17: Database Format Example

The equipment metered and data stored in the database usually serve the purpose of process monitoring, instead of energy monitoring. In other words, they were installed for the proper operation of the plant, not for energy modeling. So it is common there are no sufficient data or meters for the detail energy modeling. Thus, understanding the available meters and data before modeling, and selecting modeling method accordingly are critical to successful modeling.

Except for the dynamic data recorded through the monitoring system, there are many static data, such as the design data from engineering drawings, and test data during the process adjustment phase. This information is also critical in helping determine the energy consumption.

Meanwhile, the information from workers and specialists are another kind of valuable knowledge data. Formal and informal meetings, conversation, and discussions are good methods to find out the possible hidden knowledge not covered in the database or documents.

2.4.3 Framework Guided Systematic Approach

The framework guided systematic approach is applied to this case study. An updated scheme specific to the plant is shown in Figure 2.18.

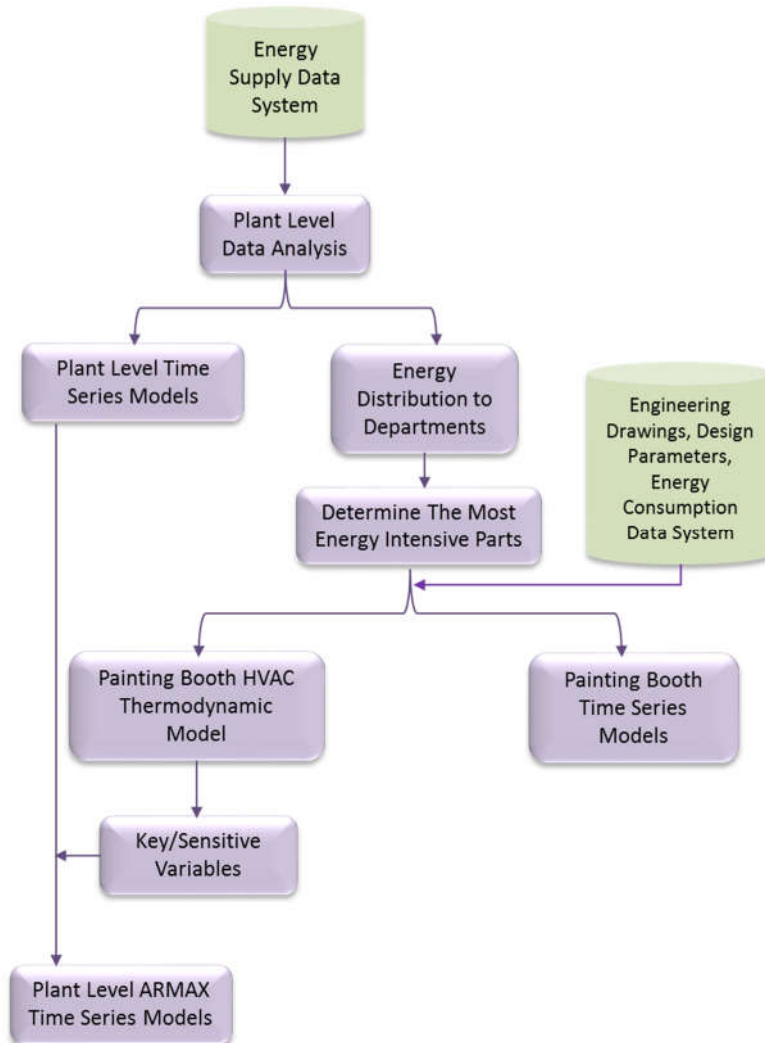


Figure 2.18: Framework Guided Systematic Approach Scheme of Studied Case

First, the plant level models were built to help understand the trends and patterns in energy purchased from the supplier. Linear regression and time series approaches were

used at the outset to give a general knowledge on the energy consumption of the whole plant. To efficiently (in terms of cost and time) establish low level models, plant energy data were further analyzed to determine the energy distribution. Specifically speaking, energy distribution to each production department and low level multi-machine processes were investigated to help decide which parts of the plant is the most critical ones (top-down). Together with the information from production specialist and lower level modeling requirement, low level models were established. With the information from low level models, information can be feedback to high level models to make informed time series models (detailed in Chapter Three).

All the data used in this research are normalized to protect the confidentiality of plant.

Plant Level

Monthly energy costs from the utility supplier is the most available data at the plant level. One year of monthly energy bill data were collected. Figure 2.19 is the monthly plot of the three energy forms purchased from utility companies. Each of them were normalized to monthly average values.

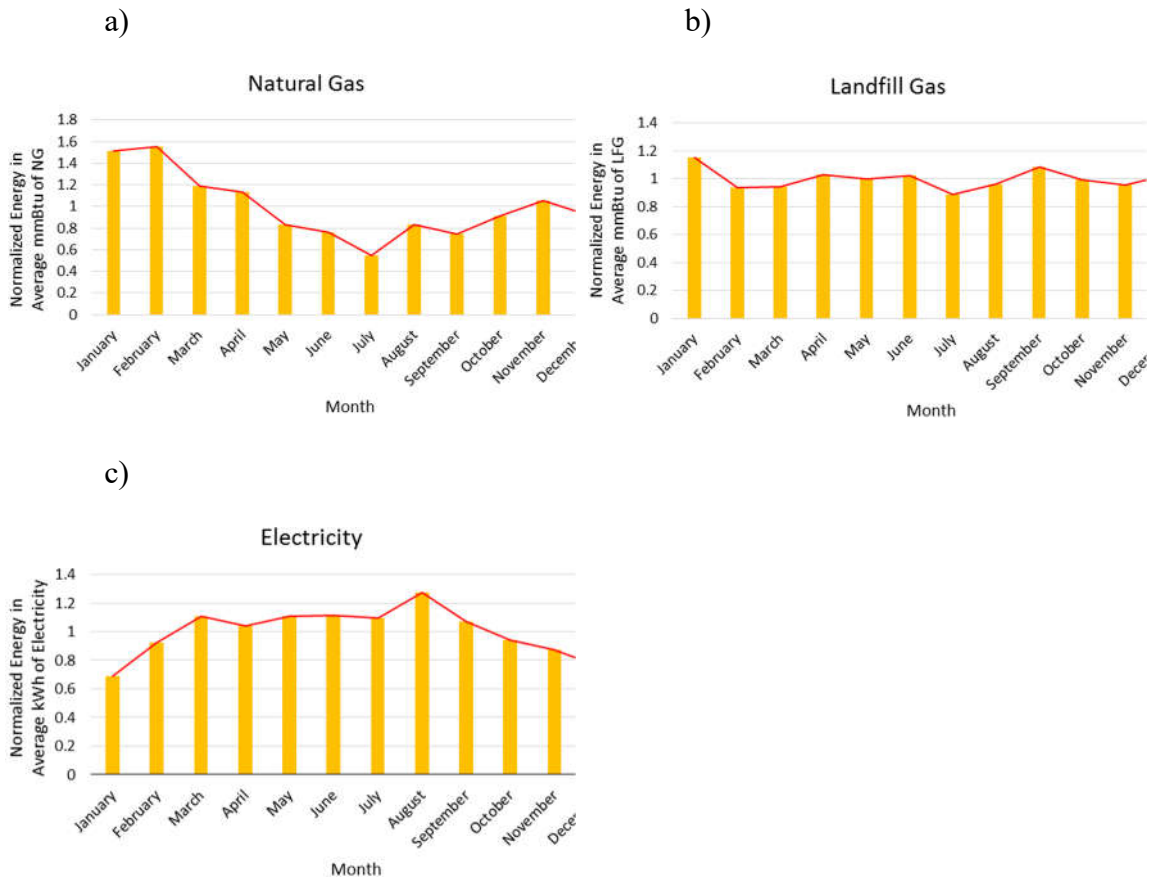


Figure 2.19: Purchased (a) Natural Gas, (b) Landfill Gas, and (c) Electricity (Normalized)

From Figure 2.19, it's obvious to observe the natural gas relationship is concave second-order; while the electricity relationship is convex second-order; and the landfill gas trend is relatively stable over a one-year timeframe. According to the observed shape, quadratic and linear models were fitted as Figure 2.20.

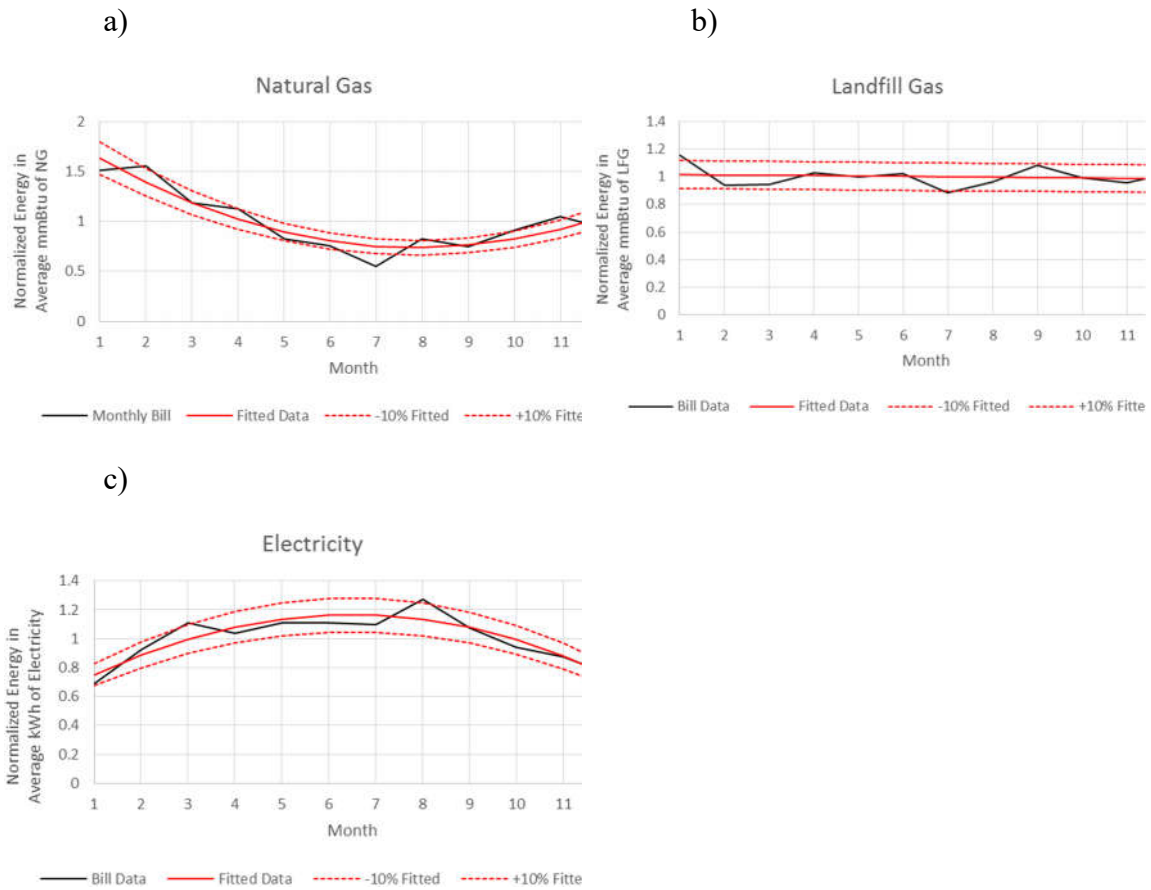


Figure 2.20: Fitted (a) Natural Gas, (b) Landfill Gas, and (c) Electricity (Normalized)

Though Figure 2.20 shows a good fitting in the modeled twelve months, the model shows a poor accuracy in the next year data (as Figure 2.21). Also, the fitted models do not provide any information explaining the reasons of energy curves, nor any constructive suggestions on energy savings.

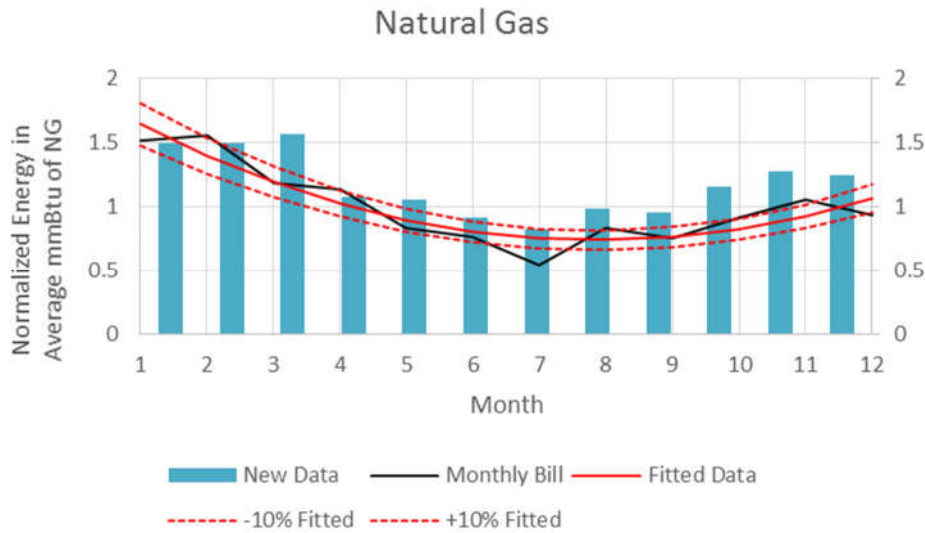


Figure 2.21: New Year Data with Fitted Model – Natural Gas Example

The manufacturing plant environment is controlled through an HVAC system. For the most part, heating energy is provided through hot water from natural gas and cogeneration system, and cooling energy is provided through chilled water, mainly from electricity. One of the main causes of fluctuation in the monthly purchased energy is local weather changes seasonally. In the summer months when the weather is hot, the heating energy (hot water) for the plant building is at bottom, but chilling energy (chilled water) for spacing cooling is at peak. In contrast, during the winter months, electricity used for generating chilled water is at bottom, but the natural gas for hot water is at peak. This is one of the reasons natural gas and electricity shows a seasonal trend as in Figure 2.19. It is also known that the landfill gas only feed to the gas turbine, which runs the onsite cogeneration system at its full capacity year round. This is the reason why the landfill gas show a stable linear trend in the studied twelve months.

To include the weather information in the regression model is a good idea to make the model more informed and robust. However, direct including of monthly average temperature is not adaptable, since it averages out the weather changes that represent the demand for heating and chilling. Heating degree days (HDD) and cooling degree days (CDD) can be used. Heating degree days represent the summation of degrees above the 65°F in a month, while cooling degree days represent the summation of degrees below the 65°F in a month. These two variables are widely used in building energy calculation. Figure 2.22 illustrates the modeling results.

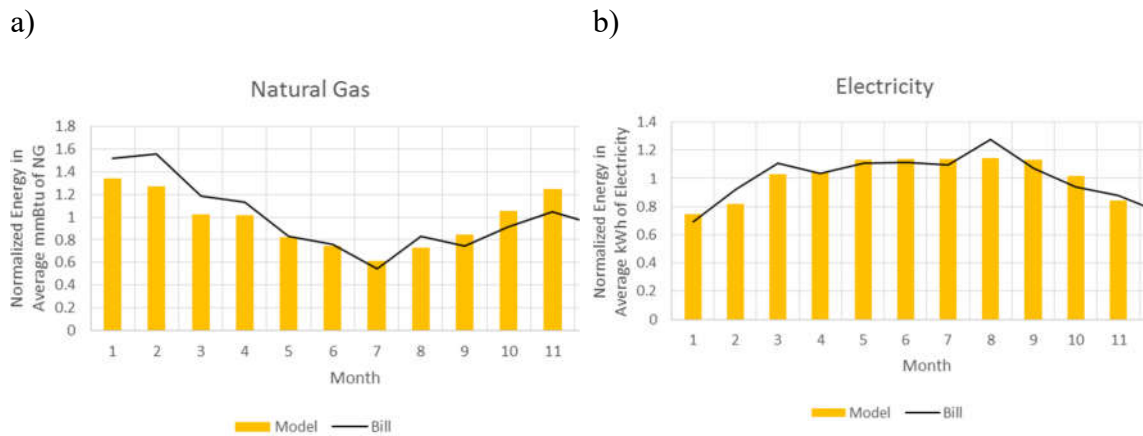


Figure 2.22: Regression Model of a) Natural Gas and b) Electricity

The regression model of the natural gas and electricity correlated purchased energy with weather information (HDD and CDD).

$$E = c + a_1 \times CDD + a_2 \times HDD \quad (2.14)$$

As Equation (2.14), the E represents the natural gas or electricity, c is the constant value, a_1 and a_2 are the parameters. However, unlike expected previously, the electricity has negative parameters with both HDD and CDD, *i.e.*, $a_1 < 0$, $a_2 < 0$ while E is the purchased electricity.

Though regression models can be used to describe the energy at plant level, it cannot provide any information on the reasons of why inputs affected the energy.

Another statistical models can be used to simulate the energy trend and pattern in plant level is time series models. Detail description of time series models were given in Chapter Three.

Energy distribution at the trunk level is a good method to help select critical parts in the plant, and make the low level modeling and analysis more efficient.

Through the energy supply data system, total energy for each department was analyzed in different forms of energy carriers. The energy forms include: hot and chilled water for building and process environment control; natural gas for building and process heating and paint curing; compressed air, and electricity for power equipment and tools. To protect the confidentiality of the studied case, the approximate percentages of each energy form is shown in Figure 2.23.

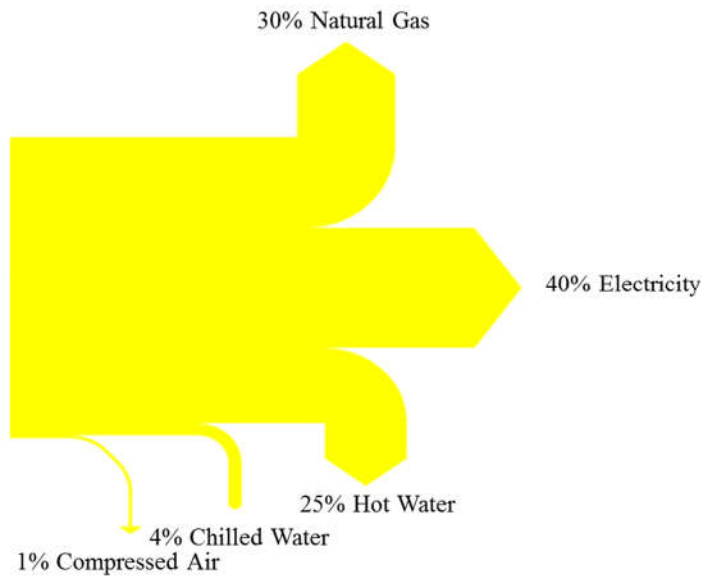


Figure 2.23: Energy Demand Distribution

All these five forms of energy were distributed to three departments. To determine the amount of energy to each department, meters of each energy forms are required. The following table can be used to record the meter IDs and energy distribution results.

Table 2.4: Meter ID Logging Table for Energy Distribution

	Natural Gas	Electricity	Hot Water	Chilled Water	Compressed Air
Body Shop					
Paint Shop					
Final Assembly					
Auxiliaries					

In the cases of direct energy meters not being available, several meters together can be used to help determine the energy amount. For example, the hot water energy can be calculated through the temperature difference and water flow rate. Therefore, three meters

need to be logged – hot water supply temperature, hot water return temperature, and hot water flow rate in the closed loop.

Again, to protect the confidentiality of the plant, the four-by-five energy distribution matrix cannot be shown here. Instead, the approximate percentages of total energy to each department is given in Figure 2.24.

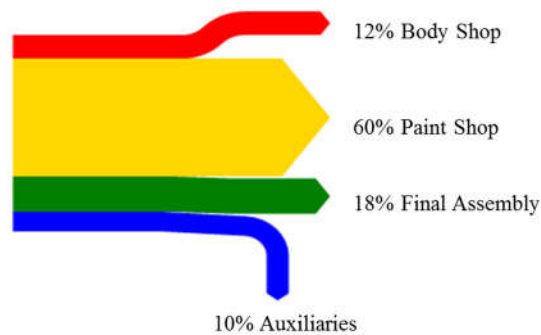


Figure 2.24: Energy Distribution to Departments

The distribution results indicate the most energy intensive department is paint shop. Further discussions and investigations were developed inside of the paint shop. Potential energy saving suggestions were made for implementation (detail improvement suggestions can be found in Appendix A). Later on, the improvement areas were decided based on holistic consideration of time, monetary cost, and influential on the production and workers. The painting booth responsible for the basecoat painting spray was selected for further study.

Low Level

Painting spray booths are the small separate rooms isolated from the painting building to prevent particle matters and gases like VOCs (Volatile organic compounds) from paint to release into the working environment. Meanwhile, the painting spray processes require controlled temperature and humidity to provide a high quality finish. It needs certain amount of air blowing from the roof of the booth to collect the sprayed paint and prevent residuals from affecting the next coming vehicles. It is known that the energy used in air conditioning to maintain the booth environment is huge.

In the air supply units to paint spray booth, recycled air from the scrubber is reused and fed back to the booth. The scrubber is implemented to remove the toxic gas and paint particles from the pass-through air by using chemical solutions of reagents or using dry absorbent. The scrubbers using chemical solutions are termed *wet*, and those with dry absorbent are termed *dry* [2.22]. Air through the dry scrubber is relatively stable in humidity, recycled air from wet scrubbers absorbs moisture from the chemical solutions, and increases the amount of vapor in the air, thereby raising the humidity. The dry scrubber-equipped booth is the study subject of this research.

A typical air flow route for the paint shop booth is given in Figure 2.25.

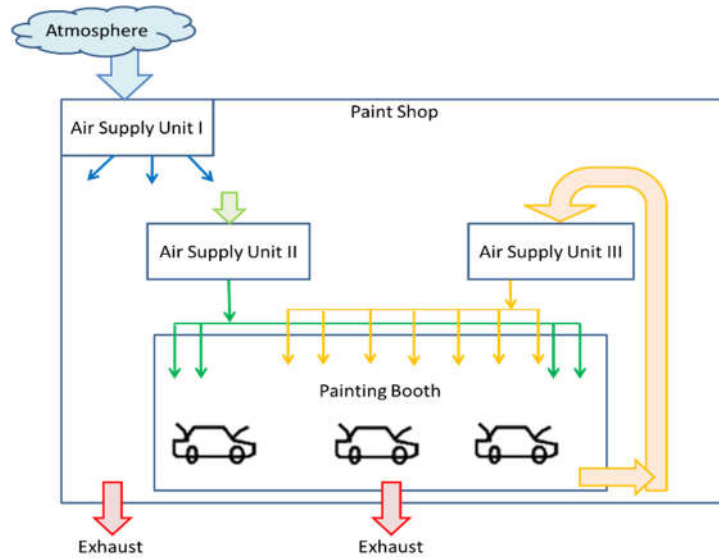


Figure 2.25: Painting Booth (Basecoat) Air Supply Flow Sketch

Fresh inlet air will be first treated in the paint shop building supply unit (as Air Supply Unit I in Figure 2.25) to the building set point temperature. This will maintain a comfortable working environment for the worker and to protect the weather sensitive equipment. Then the building air will be reused in the booth air supply unit (as Air Supply Unit II in Figure 2.25). Finally, the booth air will be recycled in Air Supply Unit III as Figure 2.25. Both temperature and humidity need to be controlled in the painting booth to guarantee the quality of paint. The studied case uses a feedforward system. Booth temperature and humidity are controlled through the air released from the top of the booth roof. Regardless of the production rate – speed of vehicles inlet into the booth, the flow rate of the blow air, and its humidity and temperature are controlled to be constant. At steady state, the booth condition is equivalent to the inlet air. Thus, by control the air inlet into the booth, the booth condition is controlled.

Several devices and energy forms were involved in this process. The main devices include air fans, heat exchanger, chiller, and dehumidifier. The fans use electricity which is assumed to be constant due to constant rate of air flow. Heat exchanger, chiller, and dehumidifier are the three main devices need to be modeled. The main energy forms are the thermal energy of air, hot water and chilled water. Thus, the thermodynamic models of heating and cooling energy of these equipment are typical single-machine and multi-machine level models as described in the organizational framework.

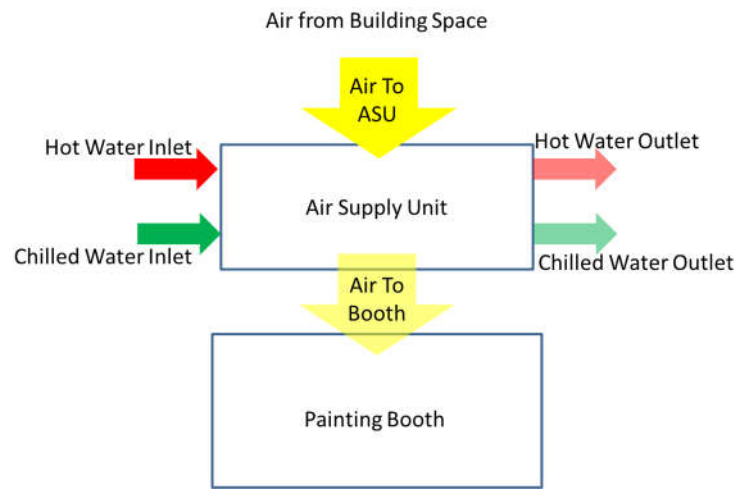


Figure 2.26: Energy Supply and Demand Models Sketch

Further analysis paint spray booth environment control system, energy models can be established in two aspects – energy supply from hot water and chilled water, and energy demand from the air status change (as Figure 2.26). Energy demand in the air temperature and humidity change between the inlet and outlet is generally known as the *Space Load*;

energy supply in the hot water and chilled water is known as *Secondary Equipment Load* [2.23].

In this case, the multi-machine and machine level models were established, validated and put into practice. The procedure is summarized in Figure 2.27.

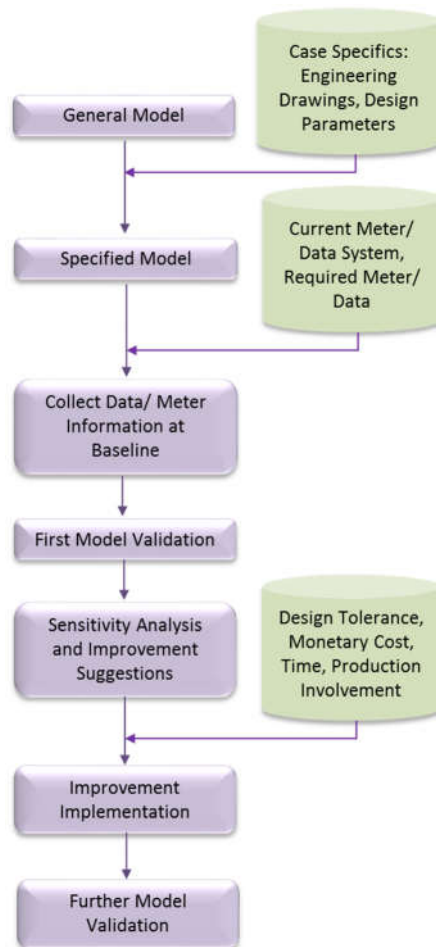


Figure 2.27: Action and Knowledge Input Flow Chart

In Figure 2.27, the square boxes indicate the actions in model establishment, validation, and implementation; the circular columns show where extra knowledge and

information inputs are needed. First, establish general models of space loading, and secondary equipment loading. Then, to make the model specified to the studied case, extra information, such as the engineering drawings of air supply house and paint spray booth, and their design parameters, is required to specify the model. Third, according to the specified model, meters and sensors to validate the model are listed. Compared with the current metering system on-site, extra meters may or may not be needed. The booth and its air supply house will run under the current the production status to give data on the baseline of specified model. First model validation is based on the baseline data. Once the model is validated, sensitivities on the model inputs can be analyzed, and improvement suggestions can be provided. At this stage, the design tolerance of the system, monetary cost, time, the possible involvement on the production procedures need to be taken into consideration to give further directions on which improvement can be proceeded. Final two steps are to implement the selected improvement and further validate the model.

The below sections detail how the models were established, validated and implemented.

Model Establishment

The energy model was built for both space load energy demand and secondary equipment load supply.

Space Load Energy Demand

In the studied case, building air is the inlet air to the air supply unit (as Figure 2.26). The building air of plant is controlled on this temperature, but not humidity. The Air supply

unit need to adjust the inlet air to its designed temperature and humidity through heat exchange with hot water and chilled water.

The flow chart of the model can be found in Figure 2.28.

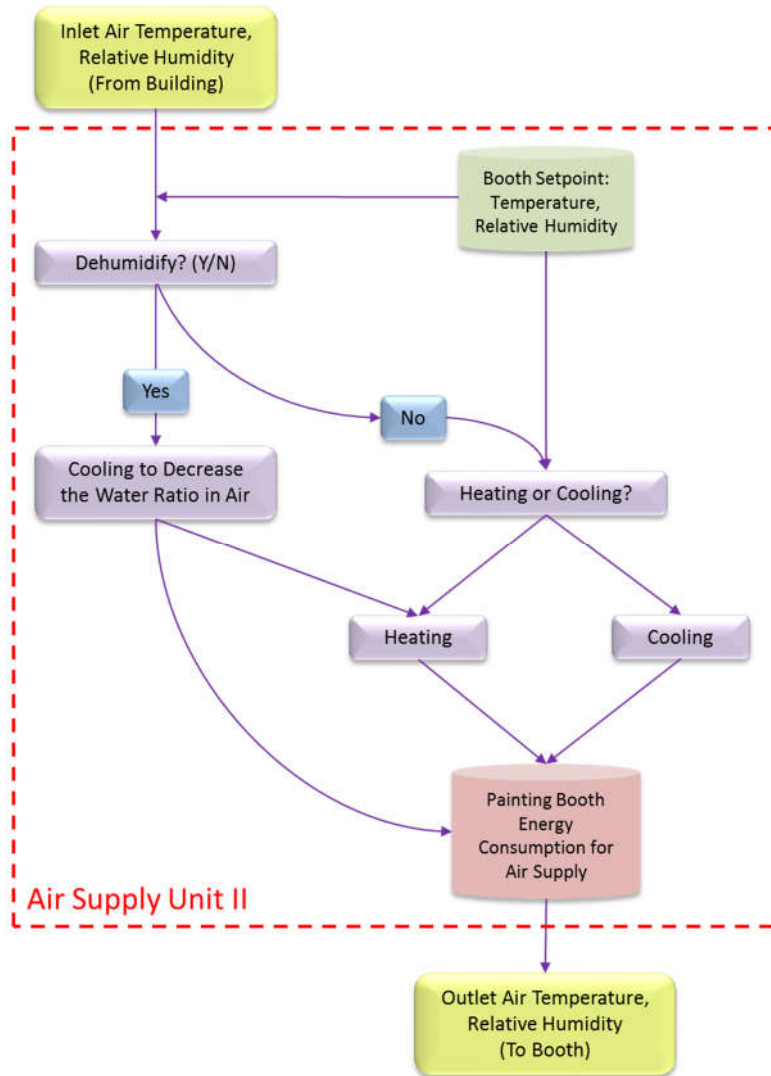


Figure 2.28: Air Supply Energy Consumption Flow Chart

The air from the building will be used as the inlet air of Air Supply Unit II, the sensors in the unit will measure the temperature and relative humidity of the inlet air. Inlet air temperature and humidity is not always exactly the same as the plant. For example, when the air inlet location is on the penthouse of the plant building, the outdoor environment temperature could cause the air temperature to drop or increase depends on the thermal conductivity of the building shell and temperature difference between the building air and outdoor environment. Another more common example is the heat from the fans. Fans use the electricity to blow the air from building to air supply unit. During this process, the air will go through the high speed fans and gain heat from the fans. Generally, the air temperature will increase two degrees Fahrenheit per fan. The measured temperature and humidity will be used to compare with target parameter. Controllers will tell the system, if the air need to be dehumidified, heated or cooled. Directly heating and cooling process is straightforward. The air goes through the heat exchanger (hot water heat exchanger for heating, or chilled water heat exchanger for cooling) to reach the target temperature. Humidity is controlled through a wet wall or nozzles to increase water content. The dehumidification process is more complex. Desiccant is widely available in the market, but it is expensive and it is not feasible to use it in a system with restricted humidity control which requires constant replacement. The studied case uses a cooling process for dehumidification. Before discussing the detail dehumidification process, there are several concepts that need to be clarified.

Generally, the air has two parts – dry air and vapor in the air. Dehumidification process decrease the amount of vapor in certain amount of dry air, *i.e.*, decrease the

absolute humidity through condensation. *Absolute humidity* can be represented in kilogram of water in kilogram of dry air. At certain temperature and pressure, the maximum amount of water can be absorbed in the air is called *saturate*, which is defined as 100% *relative humidity*. From here, the *relative humidity* (rH) can be calculated through the ratio of water amount in air (W) to water amount in saturate air (W_s) (as Equation (2.15)).

$$rH = \frac{W}{W_s} \quad (2.15)$$

rH : relative humidity [%]
 W : humidity ratio [kg/kg dry air]
 W_s : saturate humidity ratio [kg/kg dry air]

Constant pressure is assumed throughout the research work. At constant pressure, air with higher temperature can absorb more water. In other words, lower temperature air has lower saturate humidity ratio. The dehumidification process decreases the humidity ratio through a cooling process. When the saturated water ratio at temperature T_2 is smaller than the water ratio at temperature T_1 ($W_{s,T_2} < W_{T_1}$), water will be condensed and removed, and air humidity ratio decreases. This process requires a large amount of cooling energy. On the other hand, temperature T_2 to condense the water from air is usually a very low temperature, much lower than the booth target temperature. Thus, heating energy is required after the dehumidification process.

The energy demand at every process can be calculated through enthalpy (as Equation (2.16)) change in two statuses of air – before and after the heat exchanger.

$$h = C_{p,a}T + W(C_{p,w}T + h_{w,e}) \quad (2.16)$$

h : enthalpy of moist air [kJ/kg];
 $C_{p,a}$: air specific heat capacity [kJ/kg · °C];
 $C_{p,w}$: water specific heat capacity [kJ/kg · °C];
 T : temperature [°C];
 $h_{w,e}$: evaporation heat of water [kJ/kg].

The space loading energy is the summation of energy at every process. In the scenario when the air need to be dehumidified, space loading energy demand is the summation of enthalpy change in cooling process and enthalpy change in heating process (as Equation (2.17)). In a scenario when air only need heating, space loading energy demand is the enthalpy change before and after the hot water heat exchanger (as Equation (2.18)). While in a scenario when air only need cooling, space loading energy demand is the enthalpy difference before and after the chilled water heat exchanger (as Equation (2.19)).

$$E_{dehum} = \Delta h_{overchill} + \Delta h_{reheat} \quad (2.17)$$

$$E_{heat} = \Delta h_{heat} \quad (2.18)$$

$$E_{cool} = \Delta h_{cool} \quad (2.19)$$

E_{dehum} : space loading energy demand at dehumidification scenario [kJ/kg]
 $\Delta h_{ovechill}$: enthalpy change of moist air in dehumidification process [kJ/kg]
 Δh_{reheat} : enthalpy change of moist air after dehumidification heating process [kJ/kg]
 E_{heat} : space loading energy demand at heating scenario [[kJ/kg]
 Δh_{heat} : enthalpy change of moist air in heating process [kJ/kg]
 E_{cool} : space loading energy demand at cooling scenario [[kJ/kg]

Δh_{cool} : enthalpy change of moist air in cooling process [kJ/kg]

The overall energy during a certain period of time can be calculated through the flow rate and integration over time (as Equation (2.20)).

$$E_{space} = \int E(t) \cdot Q(t) dt \quad (2.20)$$

E_{space} : space loading energy demand at certain period of time [kJ]

$E(t)$: space loading energy demand at certain point of time [kJ/kg]

$Q(t)$: air flow rate at certain point of time [kg/s]

t : time

Secondary Equipment Load Supply

The energy of space loading is provided through the secondary equipment – heat exchangers in this case.

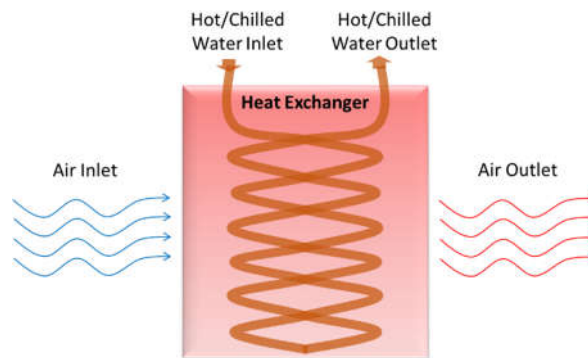


Figure 2.29: Heat Exchanger Sketch

In a closed recirculating system, hot water goes through the heat exchanger, and uses the temperature between the water and air to heat the cold inlet air. By control the flow rate of the hot water, air can be heated to different temperature. The energy of secondary equipment load energy supply can be calculated as Equation (2.21). So is the chilled water for cooling process.

$$E_w = \dot{m} \cdot C_w \cdot \Delta T \quad (2.21)$$

E_w : space loading energy [kJ/s]

\dot{m} : hot water or chilled water flow rate [kg/s]

C_w : water heat capacity [kJ/(kg · °K)]

ΔT : water temperature difference between inlet and outlet [°K]

Generally, the water heat capacity is constant at standard condition ($T = 25 \text{ }^\circ\text{C}$, $p = 101\text{kPa}$), but when the water temperature variation is large, the variation of C_w cannot be ignored. A look up table of C_w at different temperature can be found in Appendix B. C_w can also be calculated through fitted model (as Figure 2.30) in certain temperature range ($C_w = f(T)$).

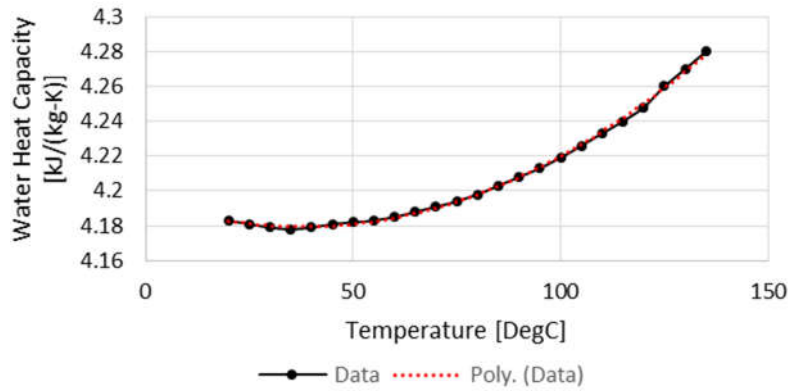


Figure 2.30: Water Heat Capacity and Fitted Polynomial Plot

Thus, in a certain period of time, the energy can be calculated as Equation (2.22).

$$E_w = \int m(t) \cdot C_w(T) dT dt \quad (2.22)$$

In this equation, the water flow rate is written as a function of time ($m(t)$), and water heat capacity is written as a function of temperature ($C_w(T)$). Both heating and cooling process can be calculated as Equation (2.22), but the polynomial fitting at different temperature could result to different functions. Thus, the function of water heat capacity should be modelled differently according to temperature range variation.

Model Validation

General models were established as section 0. According to the general models, inputs and outputs of the models are summarized as Figure 2.31.

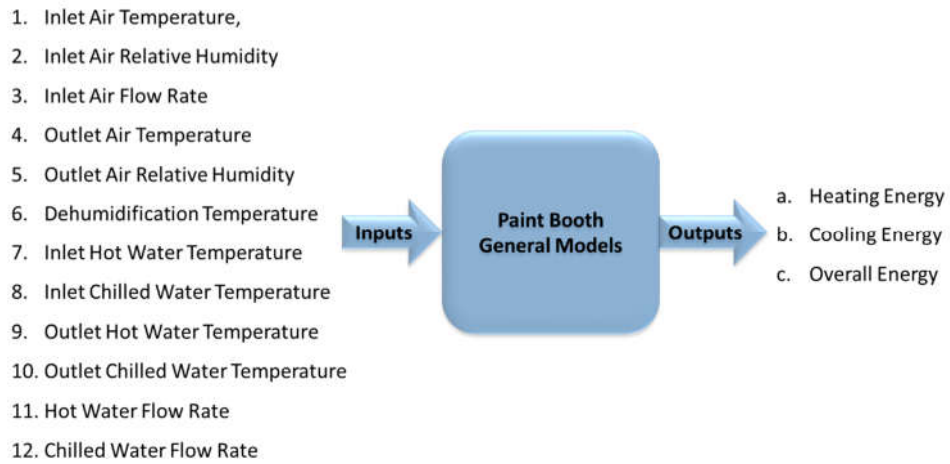


Figure 2.31: Model Inputs and Outputs Sketch

Every input of the twelve ones listed in Figure 2.31 needs to be specified for the studied case.

Inputs 1, 2, 4, 5, 7, 8, 9, and 10 are monitored through the meter and data system. Input 3 is determined through the designed parameter on engineering drawings. Inputs 6, 11, and 12 are not monitored. Flow rate meters for water is installed for model validation purpose. Avoiding the interference with the production activities, clamp-on meters were selected. However, the quantification of dehumidification chilling temperature is complex.

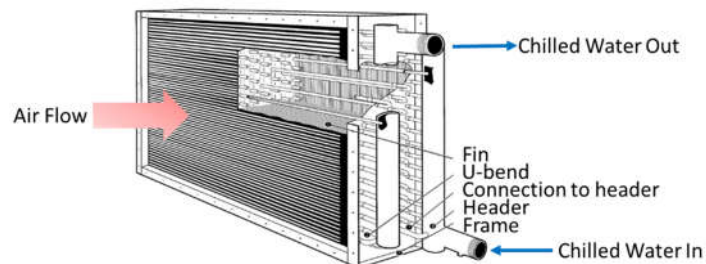


Figure 2.32: Structure of a Water Cooling Coil

Figure 2.29 is a simplified sketch of heat exchanger. In this case of dehumidification, water cooling coil is used (as Figure 2.32). In a typical water cooling coil, chilled water went inside of the header, cool the air go through the coil. When the warm humid air reaches the chilled coil and the fins around it, heat is exchanged between them. The air was chilled and humid will condensed out and form water drops on the surface of fins. When the weight of the drop is heavy enough, it falls into the drain pain at the bottom of coil. Figure 2.33 is the illustration of a chilled water coil process.

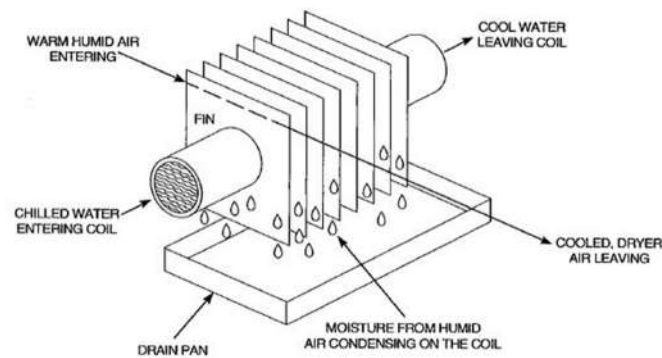


Figure 2.33: Chilled Water Coil Process

In a cooling coil, there are many rows of coils. According to the different locations of the coils, the surface temperatures of the coil are different. Therefore, the amount of water condensed from each row of coils are different. The paper [2.24] discuss how the design of cooling coils can affect the dehumidification process, and how the temperature of the dehumidification can be simulated based on the different design of the coils. Unfortunately, the design parameters of the dehumidification cooling coils in our studied

case is not available for further simulation of this process. Single dehumidification was assumed and estimated through both the space loading and secondary equipment models.

Table 2.5: Meter Log Table

Meter Description	Meter ID	Unit	Status
Inlet Air Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Inlet Air Relative Humidity		Percentage [%]	Equipped
Inlet Air Flow Rate		Cubic Feet per Minute [CFM]	Looked up through Design
Outlet Air Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Outlet Air Relative Humidity		Percentage [%]	Equipped
Dehumidification Temperature		Fahrenheit Degree [$^{\circ}F$]	Estimated
Inlet Hot Water Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Inlet Chilled Water Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Outlet Hot Water Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Outlet Chilled Water Temperature		Fahrenheit Degree [$^{\circ}F$]	Equipped
Hot Water Flow Rate		Gallon per Minute [GPM]	Installed Temporally
Chilled Water Flow Rate		Gallon per Minute [GPM]	Installed Temporally

With all the inputs data metered or got from model and design drawings (Table 2.5 can be used to log the meter information), certain period of the production day were selected as the test time for baseline to validate the model accuracy.

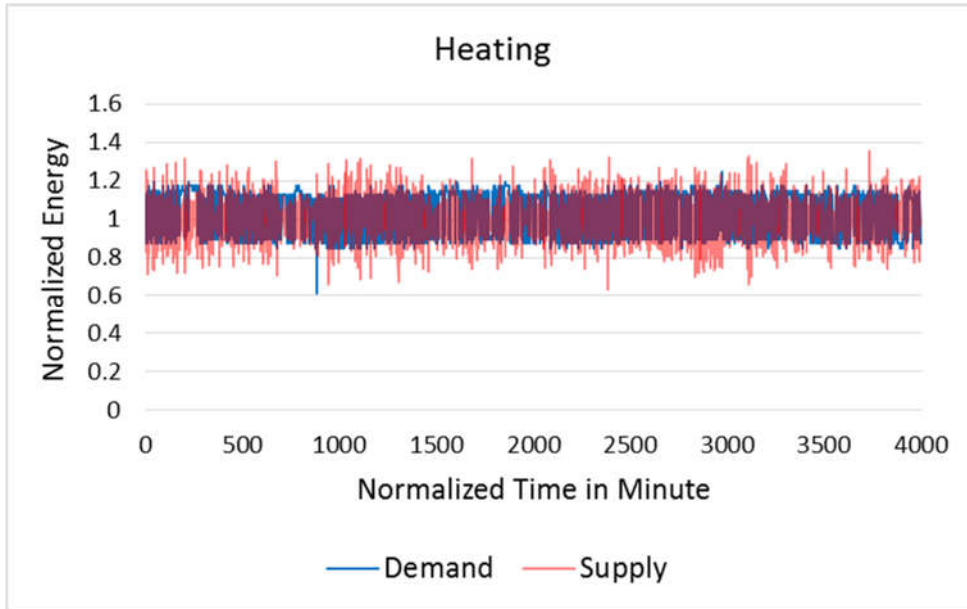


Figure 2.34: Baseline Heating Validation

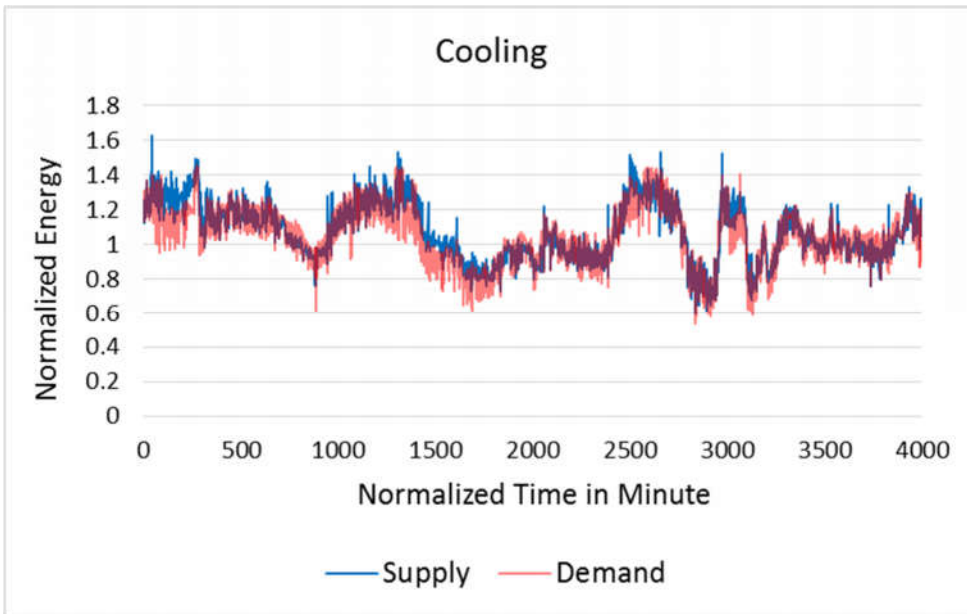


Figure 2.35: Baseline Cooling Validation

Figure 2.34 and Figure 2.35 show the model outputs from space loading demand and secondary equipment supply of heating and cooling energy. The data given in the two

figures are normalized to protect confidentiality of the plant. Before normalized, the supply energy is a little higher than the demand energy. The blue lines are the supply energy, and the red 50% transparent lines are the demand energy. The trend of the two lines in each figure follow each other well (relative standard deviation $RSD = \frac{S}{\bar{X}} \times 100\%$ for heating is 1.1% and cooling is 0.6%). This indicates a good accuracy in the models. Further look into the inputs of the models, the temperatures of the inlet air are relatively constant comparing with the humidity change, since the indoor only control the temperature. This explains the big variations in cooling energy, because most of the cooling energy was used on dehumidification process; while the heating energy is used for air heating up after the dehumidification process.

Model Implementation

Based on the model and available techniques, suggestions were made to the studied plant for energy conservation.

Also, during the information exchange with energy and production specialists, it is found that the painting spray booth allows the fluctuation of temperature between 68 and 86 °F. Based on the temperature tolerance range, suggestions on temperature set point change were also given. Further validation on the model and the suggestion were made during the nonproduction days to avoid product quality issues.

The same inputs data are required. During the non-production period, the painting spray booth temperature set point was adjusted according to the suggestions.

Table 2.6: Test Plant of Pilot Study

Normalized Time	Temperature Setpoint [°F]
0-88	70
89-170	78
170-330	76.5
330+	72

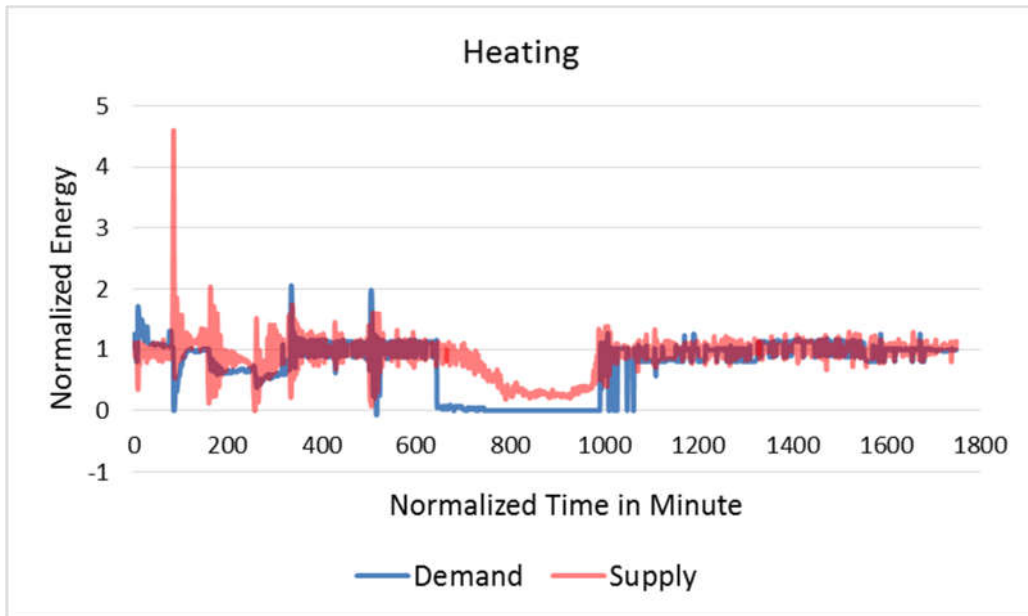


Figure 2.36: Temperature Set point Adjustment Study (Heating)

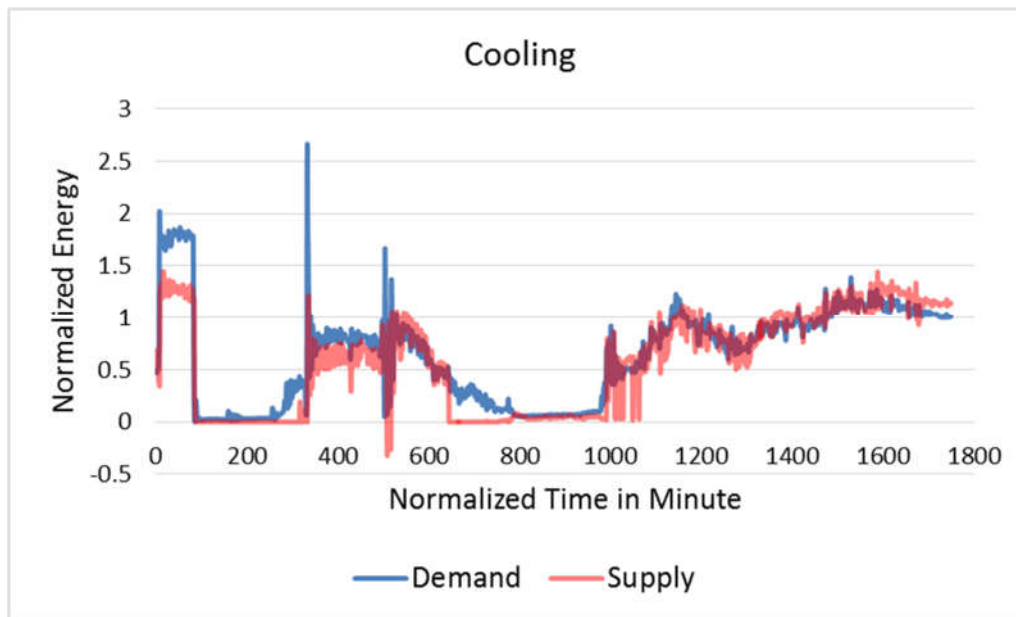


Figure 2.37: Temperature Set point Adjustment Study (Cooling)

Figure 2.36 and Figure 2.37 show the model outputs of the pilot study on the temperature set point adjustment. During the pilot study (test plan of pilot study is shown in Table 2.6), the set point of paint booth was changed. For example, during the normalized time range of 0 to 88, the booth temperature was change from 72°F (baseline) to be 70°F; during the time range from 89 to 170, the set point was controlled to 78°F; when normalized time is from 170 to 330, the set point was 76.5°F; after that the temperature was adjusted back to the original baseline 72°F. It is noticeable during the pilot study: the supply energy has a delay, and it takes some time to be stable. Also, there are several overshoot and data fluctuation. Otherwise, the two models align with each other, and can be used for suggestions on energy conservation. It worth to pay attention that the minimum energy consumption time is from 650 to 1010. During this period of time, the weather is very dry, which lead to low humidity in the building, also the inlet air to the air supply unit of

painting booth. Due to the low humidity of inlet air, there is no need for dehumidification process and re-heating up, the only energy is used to control the temperature of the air.

It is proved that the local weather and booth set point booth will affect the energy consumption tremendously. Final suggestions were giving to the plant. According to the ability of the control system, single optimal set point and real time set point based on the historical weather information, can be chosen.

After the pilot study, the models can be used off-line to predict the least energy consumption set points for the painting booth. Based on the booth current running condition and the historical weather information, models come up with two set point adjustment suggestions – single set point and variable set points. Single set point will adjust the booth temperature to the optimal one value all year which minimize the energy consumption. Variable set points adjust the temperature according the inlet air. This require the air supply house to set logic based on the inlet air temperature and humidity sensor, and adjust the temperature set point accordingly. Booth strategies require less energy than the current setting. Annual energy conservation is estimated to be range from the approximately 30% to 80%, for single and variable set points respectively. According to the model suggestions, the adjustment can be made during the production time slowly to achieve the final goal of energy saving.

Though the model was built on the post-process phase in the temporal framework, the whole energy model establishment, validation and implementation reviewed the process design and went through the process adjustment phase.

2.4.4 Case Study Summary

BMW Spartanburg Automotive Assembly Plant is a typical automotive manufacturing plant. In section 2.4, energy modeling examples were provided to illustrate how the proposed systematic modeling approach can be used for energy modeling. An evaluation on the degree of model criteria fulfillment of this approach is provided in Table 2.7.

Table 2.7: Proposed Modeling Approach Evaluation Results

Model Criteria Evaluated Models	Information Amount	Flexibility to Apply in Similar Systems	Feasibility to Current Plants	Improvement Identification	Accuracy
	1	2	3	4	5
Proposed Approach	0.9	0.9	0.9	0.9	0.9

In section 2.4, a typical automotive manufacturing plant with three department – body shop, paint shop, and final assembly shop was used as an example to show how the top-down method could be used to extract information on 1) what are the most energy intensive department and production processes; 2) how is the energy used in these major energy consumers; and 3) what could be done for energy conservation based on the model built. In the implementation of this approach, the model at high and low levels are built based on the available data and minimum inputs. Through the validation test, the model of low level is also proved to be accurate enough in predicting the real energy consumption. Also, improvement suggestions were made and tested to be effective in the studied case.

Comparing with the models in the literature review, this top-down method uses the high level models to guide the direction of low level models. The energy models were more efficiently applied to capture the main energy consumers. Thus, monetary cost and time are more efficiently spent. Besides, this approach takes consideration of the metering and data system on-site. Therefore, the models are built based on this foundation, and it benefits the later model validation, and improvement implementation.

2.5 Chapter Summary

In this chapter, the manufacturing system temporal and organizational framework were introduced to guide the understanding on various levels and systematic energy models (section 2.2.1). Through the literature review of the works done in this area, the automotive manufacturing processes were introduced (section 2.2.2). Knowledge gaps were defined through the comparison of current available models (section 2.2.3). Based on the knowledge gap, we proposed a systematic modeling approach (section 2.3), and use a case study from BMW automotive assembly plant to illustrate how the approach can be applied to fulfill the knowledge gaps (section 2.4).

2.5.1 Chapter Broader Impact

The modeling approach can be further used in many other areas. For example, the HVAC model built for painting basecoat booth can also be applied to clear coat booth, ovens, and buildings in the plant. For another example, the approach of establishing lower level models based on higher level analyses and copes with the plant current condition can

also be implemented to other departments, such as body shop and assembly shop. Last but not the least, the top-down approach guided the modeling to be more efficient and conversely will enhance the bottom-up models to be more accurate and robust by providing key influential variables to through sensitivity analysis.

More detail of the broader impacts of is shown in Chapter Five Section 5.1.1.

2.5.2 Chapter Contribution

This chapter addressed Research Question 1: *How best to use the temporal and organizational framework (layer concept) of a manufacturing system to drive energy use model building at different functional and detail levels.* Compared with other available models, the proposed approach is improved over competing approaches in terms of the amount of information provided, feasibility to implement in current plants, flexibility to be applied, ability to identify the improvements, and accuracy (as Table 2.8).

Table 2.8: Model Criteria Comparison

Comparison Criteria Evaluated Models	Information		Flexibility to Apply in Similar Systems	Feasibility to Current Plants	Improvement Identification	Accuracy
	Low Level	High level				
Proposed Model	0.9	0.9	0.9	0.9	0.9	0.9
Energy Performance Model		0.4	0.8	0.8	0.2	0.2
Benchmark Models		0.4	0.8	0.8	0.2	0.2
Multi-Machine and Machine Level Physical	0.6		0.2	0.2	0.8	0.8
Multi-Machine and Machine Level Statistical	0.5		0.5	0.5	0.2	0.8
Embodied Product Energy Models		0.7	0.2	0.2	0.5	0.2
Discrete Event Models		0.7	0.2	0.2	0.5	0.5
Hybrid Models		0.9	0.2	0.2	0.9	N/A

In addition, the contributions of this chapter work are also from following aspects.

- 1) The work quantified the energy distribution to three main departments of automotive assembly plants. It provides essential information for decision making.
- 2) The work quantified the energy carriers' demand in automotive production processes. It provides critical information of energy supply.
- 3) The work identified the energy intensive consumers in department level, and within the paint shop, through the top-down approach. It suggested detail improvement implementations, and proved to be effective.
- 4) This chapter and the later broader impact work in Chapter Five proved the energy consumption is sensitive to local weather, productivity, and production schedule.
- 5) Although this work did not compare the energy consumption among the similar plants, the approach of quantifying the distribution and identifying the intensive components makes the energy usage more comparable. Because the work established models on different layers and considered the technology difference, the energy consumption comparison is more attractive and fair.

2.6 Chapter Two References

- [2.1] C. Reich-Weiser, A. Vijayaraghavan, and D. Dornfeld, "Appropriate Use Of Green Manufacturing Frameworks," *UC Berkeley: Laboratory for Manufacturing and Sustainability*, 2010.
- [2.2] J. R. Duflou, J. W. Sutherland, D. Dornfeld, C. Herrmann, J. Jeswiet, S. Kara, M. Hauschild, and K. Kellens. "Towards Energy And Resource Efficient Manufacturing: A Processes And Systems Approach," *CIRP Annual – Manufacturing Technology*, **61 (2)**, pp. 587-609. 2012.
- [2.3] G. A. Boyd, "Development Of A Performance-Based Industrial Energy Efficiency Indicator For Automobile Assembly Plants," *US Environmental Protection Agency, Office of Atmospheric Program*, 2005.
- [2.4] Y. Patil and J. Seryak, "Benchmarking Approaches: An Alternative Method To Determine Best Practice By Examining Plant-Wide Energy Signatures," *ACEEE on Energy Efficiency in Industry*, **6**, pp. 127-138, 2005.
- [2.5] J. Gediga, H. Beddies, H. Florin, R. Loser, M. Schuckert, H. G. Haldenwanger, and W. Schneider, "Process Modeling In The Life Cycle Design - Environmental Modeling Of Joining Technologies Within The Automotive Industry," *SAE Technical*, pp.1-6, 1998.
- [2.6] J. D. Cullen, N. Athi, M. A. Al-Jader, A. Shaw, and A. I. Al-Shamma'a, "Energy Reduction For The Spot Welding Process In The Automotive Industry," *Journal of Physics*, **76**, pp.1-6, 2007.
- [2.7] Hao Liu, Qianchuan Zhao, Weihua Cao, Ningjian Huang, and Xiang Zhao. "Simulation Based Evaluation And Optimization For Energy Consumption Of A Typical Welding Shop," *Proceeding of 2011 IEEE Automation Science and Engineering (CASE)*, 2011.
- [2.8] G. Michalos, S. Makris, N. Papakostas, D. Mourtzis, and G. Chryssolouris. "Automotive Assembly Technologies Review: Challenges And Outlook For A Flexible And Adaptive Approach," *CIRP Journal of Manufacturing Science and Technology*, **2 (2)**, pp. 81-91. 2010.
- [2.9] M. Gao, X. Y. Zeng, and Q. W. Hu, "Effects Of Welding Parameters On Melting Energy Of CO₂ Laser–GMA Hybrid Welding," *Science and Technology of Welding and Joining*, **11(5)**, pp. 517-522, 2013.
- [2.10] C. Galitsky and E. Worrell, "Energy Efficiency Improvement And Cost Saving Opportunities For The Vehicle Assembly Industry -- An ENERGY STAR Guide For Energy And Plant Managers," *Ernest Orlando Lawrence Berkeley National Laboratory*, 2008.

- [2.11] D. A. Ansdell, "Chapter 4. Surfacer," in *Automotive Paints and Coatings*, Weinheim, Germany: Wiley-VCH Verlag GmbH, pp. 118, 2008.
- [2.12] G. J. Roelant, A. J. Kemppainen, and D. R. Shonnard, "Assessment Of The Automobile Assembly Paint Process For Energy, Environmental, And Economic Improvement," *Journal of Industrial Ecology*, **8**, pp. 173-191, 2004.
- [2.13] I. Korolija, Y. Zhang, L. Marjanovic-Halburd, and V. I. Hanby. "Regression Models For Predicting UK Office Building Energy Consumption From Heating And Cooling Demands," *Energy Building*, **59**, pp. 214-227. 2013.
- [2.14] M. Fratzczak, T. Klopot, J. Czeczot, and M. Bregulla. "Representative Vector Method For Modeling Of Energy Consumption For The Assembly Line," *Proceeding of 2013 18th International Conference On Methods and Models in Automation and Robotics (MMAR)*, 2013.
- [2.15] S. Kara and S. Ibbotson. "Embodied Energy Of Manufacturing Supply Chains," *CIRP Journal of Manufacturing Science and Technology*, **4(3)**, pp. 317-323. 2011.
- [2.16] Y. Seow and S. Rahimifard. "A Framework For Modelling Energy Consumption Within Manufacturing Systems," *CIRP Journal of Manufacturing Science and Technology*, **4(3)**, pp. 258-264. 2011.
- [2.17] S. Rahimifard, Y. Seow, and T. Childs, "Minimising Embodied Product Energy To Support Energy Efficient Manufacturing," *CIRP Annals - Manufacturing Technology*, **59**, pp. 25-28, 2010.
- [2.18] J. Hesselbach, C. Herrmann, R. Detzer, L. Martin, S. Thiede, and B. Ludemann, "Energy Efficiency Through Optimized Coordination Of Production And Technical Building Services," *Conference Proceedings of LCE2008 - 15th CIRP International Conference on Life Cycle Engineering*, Sydney, Australia, pp. 624-628, 2008.
- [2.19] C. Herrmann, S. Thiede, S. Kara, and J. Hesselbach. "Energy Oriented Simulation Of Manufacturing Systems – Concept And Application," *CIRP Annual Manufacturing Technology*, **60(1)**, pp. 45-48. 2011.
- [2.20] A. F. A. Aziz, S. N. Khalid, M. W. Mustafa, H. Shareef, and G. Aliyu. "Artificial Intelligent Meter Development Based On Advanced Metering Infrastructure Technology," *Renewable and Sustainable Energy Reviews*, **27**, pp. 191-197. 2013.
- [2.21] E. O'Driscoll and G. E. O'Donnell, "Industrial Power and Energy Metering: A State-Of-Art Review," *Journal of Cleaner Production*, **41**, pp. 53-64, 2013.

[2.22] B. R. Kim, D. H. Podsiadlik, D. H. Yeh, I. T. Salmeen, and L. M. and Briggs, "Evaluating The Conversion Of An Automotive Paint Spray-Booth Scrubber To An Activated-Sludge System For Removing Paint Volatile Organic Compounds From Air," *Water Environment Research*, **69 (7)**, pp. 1211-1221, 1997.

[2.23] Donald M Eppelheimer, Robert A. Parsons, and Adele J. Brandstrom, ASHRAE Handbook. Georgia: Atlanta, I-P Edition, 1997.

[2.24] M. K. Mansour and M. and Hassab, "Thermal Design Of Cooling And Dehumidifying Coils," in *Heat Exchangers -- Basics Design Applications*, pp. 367-394, 2012.

CHAPTER THREE FORECASTING

3.1 Research Question Restatement

Research Question Two: What is the most effective approach to augment mathematical forecasting tools for the best applicability in the manufacturing domain?

3.2 Background and Knowledge Gap Introduction

Given the specific parameters from the equipment and machines, physical models can be established to calculate the energy usage within certain period of time. It is also possible to forecast the energy demand over the time horizon with appropriate inputs and models. However, when a system is as complex as a manufacturing plant, it is impossible to build specific models for each and every machine in the system. In other words, it is infeasible to use physical models for energy forecasting at the plant level. On the other hand, the energy at high level (plant layer) is monitored through meters and recorded in time series; therefore, time series analysis is a good approach to deal with plant level energy data for the future prediction.

This section will begin with the research review on time series models including the time series analysis mathematical background, and research undertaken to augment the mathematical forecasting tool into the energy forecasting area. At the end of this section, knowledge gaps of augmenting the mathematical forecasting tool to the manufacturing domain will be determined.

3.2.1 Mathematical Background

Basic Statistical Concepts

Here some basic statistical concepts are listed for the reference of later discussion.

Take a probability density function f of a random variable x . The statistical mean and variance can be calculated as Equation (3.1) and (3.2)

Mean

$$\mu = E[x] = \int_{-\infty}^{+\infty} xf(x)dx \quad (3.1)$$

Variance

$$\sigma^2 = \text{var}(x) = E[(x - \mu)^2] = \int_{-\infty}^{+\infty} (x - \mu)^2 f(x)dx = E[x^2] - E[x]^2 \quad (3.2)$$

Covariance and correlation are two other important statistical concepts, given as Equation (3.3) and (3.4) respectively. They can be calculated through the mean and variance values.

Covariance of x and y

$$\text{cov}(x, y) = \sigma(x, y) = E[(x - E(x))(y - E(y))] \quad (3.3)$$

where x and y are random variables.

Correlation of x and y

$$\rho_{x,y} = \text{corr}(x,y) = \frac{\text{cov}(x,y)}{\sqrt{\text{var}(x)\text{var}(y)}} \in [-1,1] \quad (3.4)$$

where x and y are random variables.

The process $\{Z_t\}$ is said to be white noise, written

$$\{Z_t\} \square WN(0, \sigma^2) \quad (3.5)$$

if and only if $\{Z_t\}$ has zero mean, and a covariance function as

$$\gamma(h) = \text{cov}(x_s, x_t) = \begin{cases} \sigma^2, & \text{if } h = 0, \\ 0, & \text{if } h \neq 0. \end{cases} \quad (3.6)$$

where lag $h = t - s$, t and s are time indexes.

Time Series Model

A time series is a set of observations x_t , recorded at a specified time t . Each observation x_t is a realized value of a certain random variable X_t . The time series $\{x_t, t \in T_0\}$ is a realization of the family of random variables $\{X_t, t \in T_0\}$ [3.1]. Here, typical time series models are introduced.

$\{X_t\}$ is a moving-average process of order q ($MA(q)$), if

$$X_t = Z_t + \theta_1 Z_{t-1} + \dots + \theta_q Z_{t-q}, \quad (3.7)$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and $\theta_1, \dots, \theta_q$ are constants.

$\{X_t\}$ is an auto-regressive process of order p ($AR(p)$), if

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \dots + \phi_p X_{t-p} + Z_t \quad (3.8)$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and ϕ_1, \dots, ϕ_p are constants.

The process $\{X_t\}$ is said to be an auto-regressive moving average $ARMA(p, q)$ process if $\{X_t\}$ is stationary and if for every t ,

$$X_t - \phi_1 X_{t-1} - \dots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \dots + \theta_q Z_{t-q} . \quad (3.9)$$

It is noticed that $MA(q)$, $AR(p)$, and $ARMA(p, q)$ have no inputs.

The autoregressive moving average model including exogenous variances, ARMAX (p, D, q) is described by:

$$X_t = \sum_{i=1}^p \phi_i X_{t-i} + \sum_{k=1}^r \beta_k U_{t-k} + Z_t + \sum_{j=1}^q \theta_j Z_{t-j} . \quad (3.10)$$

where $\{Z_t\} \sim WN(0, \sigma^2)$ and ϕ s, θ s and β s are constants, and U_t are exogenous variables.

For time series, the variance and correlation are calculated within the same data series in time lag h , called the auto-covariance ($\gamma(h)$), and auto-correlation respectively ($\rho(h)$).

$$\gamma(h) = \text{cov}(X_{t+h}, X_t) \quad (3.11)$$

$$\rho(h) = \frac{\gamma(h)}{\gamma(0)} \quad (3.12)$$

Stationary and Model Decomposition

The time series $\{X_t, t \in \mathbb{Z}\}$ is said to be strictly stationary if the joint distribution of $(X_{t_1}, \dots, X_{t_k})'$ and $(X_{t_1+h}, \dots, X_{t_k+h})'$ are all the same for all positive integers k and for all

$t_1, \dots, t_k, h \in \mathbb{Z}$. This is very difficult to prove. Instead, time series analysis requires only weak stationarity.

$\{X_t\}$ is called weakly stationary, if 1) $E[X_t] = \mu$ does not depend on time t ; and 2) $\text{cov}(X_{t+h}, X_t) = \gamma(h)$ does not depend on t . The stationarity of classes of time series models can also be tested through the fitted parameters, such as Equation (3.13) for the ARMAX model. The series is stable if the roots of the characteristic equation lie outside of the unit circle, where the characteristic equation of ARMAX model can be written as

$$\phi(L) = L^p - \phi_1 L^{p-1} - \phi_2 L^{p-2} - \dots - \phi_p L. \quad (3.13)$$

Thus, the stationarity of a time series can be checked through the simple data plot and later fitted model unit circle test, *i.e.*, the data plot does not show a trend nor obvious change in variance, and the roots of the fitted model characteristic equation are larger than one.

Correct selection of suitable mathematical models (or a class of models) for the data series is an important step in analyzing a time series. However, many mathematical models for time series require the data series to be stationary. When the data series is not stationary, there are many methods to make the data be stationary. Data decomposition is a method most commonly used.

Typically, a time series can be written as (3.14).

$$X_t = m_t + s_t + Y_t \quad (3.14)$$

where m_t represents the trend, s_t represents the seasonality, and the Y_t is new stationary series. There are many methods in getting rid of trending and seasonality. Polynomial fitting, pattern recognition, and many other techniques can be applied here to quantify the trend and seasonality directly. Simply by subtracting them, a new stationary data series can be calculated:

$$Y_t = X_t - m_t - s_t . \quad (3.15)$$

However, there is more direct way to get a stationary data series. Differencing is one method that can be easily applied. In this method, the difference operator ∇ is defined as

$$\nabla X_t = X_t - X_{t-1} = (1 - B)X_t \quad (3.16)$$

where B is the backward shift operator,

$$BX_t = X_{t-1} \quad (3.17)$$

While the power of ∇ and B is defined as

$$B^j(X_t) = X_{t-j} \quad (3.18)$$

$$\nabla^j = \nabla(\nabla^{j-1}(X_t)). \quad (3.19)$$

The polynomial of ∇ and B are manipulated as the polynomial functions of real variables. For example

$$\begin{aligned} \nabla^2 X_t &= \nabla(\nabla X_t) \\ &= (1-B)(1-B)X_t \\ &= (1-2B+B^2)X_t \\ &= X_t - 2X_{t-1} + X_{t-2} \end{aligned} \quad (3.20)$$

Starting the series with trend,

$$X_t = m_t + Y_t \quad (3.21)$$

where trend m_t is any k -degree polynomial

$$m_t = \sum_{j=0}^k a_j t^j \quad (3.22)$$

and Y_t is stationary with zero mean.

The k^{th} degree difference can reduce the original series to a constant and stationary series,

$$\nabla^k X_t = k!a_k + \nabla^k Y_t \quad (3.23)$$

where $k!a_k$ is the mean value of stationary series $\nabla^k X_t$.

To deal with series with trend and seasonality as Equation (3.14), the difference operator ∇_d at lag d is introduced here.

$$\nabla_d X_t = X_t - X_{t-d} = (1 - B^d)X_t \quad (3.24)$$

For seasonality s_t , it is defined

$$s_t = s_{t+d} \quad (3.25)$$

where d is the season period length.

Apply the difference operator ∇_d at lag d to the series

$$\begin{aligned} \nabla_d X_t &= \nabla_d m_t + \nabla_d s_t + \nabla_d Y_t \\ &= (m_t - m_{t-d}) + (s_t - s_{t-d}) + (Y_t - Y_{t-d}) \\ &= (m_t - m_{t-d}) + (Y_t - Y_{t-d}) \end{aligned} \quad (3.26)$$

The new $\nabla_d X_t$ is a series with only trend component ($m_t - m_{t-d}$) and stationary series ($Y_t - Y_{t-d}$). To get the stationary series, further apply the previous differencing method as Equation (3.21) to (3.23).

Model Establishment and Parameter Estimation

Once the stationary data is acquired, different classes of models can be established.

Trial and error is one way to find the best-fit model. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are two additional functions that can be used for model suggestions. ACF and PACF can help identify the autocorrelations at different time lags (given respectively as Equation (3.27) and (3.28)).

$$\rho_x(h) = \frac{\gamma_x(h)}{\gamma_x(0)} = \text{corr}(X_{t+h}, X_t) \quad (3.27)$$

$$\alpha(h) = \text{Corr}(X_{t+h} - P_{t,h}(X_{t+h}), X_t - P_{t,h}(X_t)) \quad (3.28)$$

Here, $P_{t,h}(X_t)$ is the projection of X_t onto the space spanned by the sub-series between the time $(t+1)$ and $(t+h-1)$.

Stationary data should have a fast-decaying value in both ACF and PACF. Through the ACF and PACF, the data internal correlation can be identified. A dominant ACF

indicates an autoregressive model, while a dominant PACF indicates a moving average model; large values of ACF and PACF at lag h indicate the order of potential models.

Once the model class is selected, parameters of the model can be estimated.

There are many methods can be used for parameter estimation. Three main estimation techniques are introduced here.

Yule-Walker

For a p^{th} order autoregressive model, the auto-covariance and parameters can be written as Equation (3.29).

$$\underbrace{\begin{pmatrix} r_1 \\ r_2 \\ \dots \\ r_{p-1} \\ r_p \end{pmatrix}}_{\mathbf{r}} = \underbrace{\begin{pmatrix} r_0 & r_1 & r_2 & \dots & r_{p-2} & r_{p-1} \\ r_1 & 1 & r_1 & \dots & r_{p-3} & r_{p-2} \\ & \vdots & & & \vdots & \\ r_{p-2} & r_{p-3} & r_{p-4} & \dots & r_0 & r_1 \\ r_{p-1} & r_{p-2} & r_{p-3} & \dots & r_1 & r_0 \end{pmatrix}}_{\mathbf{R}} \underbrace{\begin{pmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_{p-1} \\ \phi_p \end{pmatrix}}_{\boldsymbol{\Phi}} \quad (3.29)$$

In short,

$$\mathbf{R}\boldsymbol{\Phi} = \mathbf{r} \quad (3.30)$$

The auto-covariance $r_0 = 1$, and the \mathbf{R} is square coefficients matrix. \mathbf{R} is full-rank and symmetric, thus invertible. The parameter vector can be estimated as

$$\hat{\Phi} = \mathbf{R}^{-1} \mathbf{r}. \quad (3.31)$$

Innovation Algorithm

For a q^{th} order moving average model, define the innovation estimates $\hat{\theta}_m, \hat{v}_m$ for $m = 1, 2, \dots, n-1$, by the recursion relation $\hat{v}_0 = \hat{\gamma}(0)$. The parameters can be estimated through Equation (3.32) and (3.33).

$$\hat{\theta}_{m,m-k} = \hat{v}_k^{-1} [\hat{\gamma}(m-k) - \sum_{j=0}^{k-1} \hat{\theta}_{m,m-j} \hat{\theta}_{k,k-j} \hat{v}_j], \quad k = 0, 1, \dots, m-1 \quad (3.32)$$

$$\hat{v}_m = \hat{\gamma}(0) - \sum_{j=0}^{m-1} \hat{\theta}_{m,m-j}^2 \hat{v}_j \quad (3.33)$$

Maximum Likelihood

In this case, the maximum likelihood estimation technique (see Equation (3.34) and (3.35)) is used to estimate the parameters for different ARMA models.

The Gaussian likelihood for an ARMA process can be written as

$$L(\phi, \theta, \sigma^2) = \frac{1}{\sqrt{(2\pi\sigma^2)^n r_0 \dots r_{n-1}}} \exp\left\{-\frac{1}{2\sigma^2} \sum_{j=1}^n \frac{(X_j - \hat{X}_j)^2}{r_{j-1}}\right\} \quad (3.34)$$

Maximum likelihood estimators:

$$\hat{\sigma}^2 = n^{-1}S(\hat{\phi}, \hat{\theta}) \quad (3.35)$$

where $S(\hat{\phi}, \hat{\theta}) = \sum_{j=1}^n (X_j - \hat{X}_j)^2 / r_{j-1}$, and $\hat{\phi}, \hat{\theta}$ are the values estimated through the minimization of $l(\phi, \theta) = \ln(n^{-1}S(\phi, \theta)) + n^{-1} \sum_{j=1}^n \ln r_{j-1}$, and $r_t = E \left[(X_{t+1} - \widehat{X}_{t+1})^2 \right] / \sigma^2$.

Additional estimation techniques can be found in [3.1].

3.2.2 Augmentation of Time Series Analysis in Energy Forecasting

Time series analysis and forecasting methods are widely used in many fields, such as finance [3.2] and marketing [3.3]. Recently, they have been applied to energy study.

Researchers from Lebanon studied the electric energy consumption in their country, which has had several intermittent power outages and increasing demand during the studied period [3.4]. In their study, they established three univariate models, namely, the autoregressive (AR) model, autoregressive integrated moving average (ARIMA) model, and combination process from AR(1) and highpass filter. According to their test results, they claimed the AR(1)/highpass filter model yields the best forecasting results for their particular data. Authors used electric energy consumption data from January 1970 to May 1999. In this period of time, the country went through the civil war (1975-89), several economic outbursts, and substantial demand increasing. By comparing the mean absolute errors (MEA) and mean square errors (MSE), the author claimed the AR(1)/high-pass was

best models among the three classes. However, the modeling processes did not consider any other possible influential effects on the electricity usage. Even though the fitted model performed well in the selected period of time, it is delicate to the disturbance and uncertainty in electricity consumption. Neither the fitted model considers or explain the influences from the war or economic outbursts.

In 1996, R. E. Abdel-Aal and A. Z. Al-Garni used the univariate Box-Jenkins time-series analysis to model and forecast the domestic electric energy monthly consumption in the East Provinces of Saudi Arabia. Though data plotting, ACF and PACF analysis, the authors came up with a multiplicative combination of seasonal and non-seasonal autoregressive integrated moving average (ARIMA) models (as Equation (3.36) and (3.37)) to forecast the sixth year's energy consumption based on the previous five years data.

$$(1 - \phi_1 B)(1 - \phi_{12} B^{12})w_t = a_t \quad (3.36)$$

$$w_t = (1 - \theta_1 B)(1 - \Theta_{12} B^{12})a_t \quad (3.37)$$

In Equation (3.36) and (3.37), ϕ and θ are the ARIMA parameters, B is the backward shift operator as defined in (3.17), w_t is the observed series, and $a_t \sim IID(0, \sigma^2)$. Authors also compared the results with regression and additive network machine-learning models. According to their results, they proved that the ARIMA models require less data, have fewer coefficients, and are more accurate [3.5].

Time series with multiple seasonal patterns were discussed in [3.6]. In this paper, authors built a state space model and used innovation approach to explicit models for multiple seasonal cycles. Authors used the utility demand data, and observed both daily and weekly seasonality in the series. Holt-Winters (HW) method was used to decompose the data y_t in two four parts – noise ε_t , level ℓ_t , trend b_t and seasonal component s_t .

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \quad (3.38)$$

where $\varepsilon_t \in IID(0, \sigma^2)$, and

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t \quad (3.39)$$

$$b_t = b_{t-1} + \beta \varepsilon_t \quad (3.40)$$

$$s_t = s_{t-m} + \gamma_\omega \varepsilon_t \quad (3.41)$$

where α , β and γ_ω are the smoothing parameters for the level, trend and seasonal terms respectively. In general, HW method, it can only include one seasonal term. The paper observed two seasonal patterns in the data series, and developed HW methods into multi-seasonal models (for number of seasons/cycles r smaller than the number of sub-cycles k). First of all, a set of dummy variables based on r shorter cycles was defined

$$x_{it} = \begin{cases} 1 & \text{if time period } t \text{ occurs when sub-cycle } i \text{ is in effect;} \\ 0 & \text{otherwise.} \end{cases} \quad (3.42)$$

Let $\mathbf{x}_t = [x_{1t}, x_{2t}, x_{3t}, \dots, x_{rt}]'$ and $\mathbf{s}_t = [s_{1t}, s_{2t}, s_{3t}, \dots, s_{rt}]'$. Then general multi-seasonal models can be written as

$$y_t = \ell_{t-1} + b_{t-1} + \sum_{i=1}^r x_{it} s_{i,t-m_1} + \varepsilon_t \quad (3.43)$$

$$s_{it} = s_{i,t-m_1} + \left(\sum_{j=1}^r \gamma_{ij} x_{jt} \right) \varepsilon_t \quad (i = 1, \dots, r) \quad (3.44)$$

where noise ε_t , level ℓ_t , trend b_t are the same as the general HW model. In the paper, the authors used examples from utility loads and traffic flows to illustrate how the method can be used to include both hourly and daily patterns, and the forecasting results show the actual values are within the 80% confidence intervals.

The previous three papers [3.4 – 3.6] indicate that the time series models can be used on energy modeling and forecasting. Though the models may need to be adjusted according to the data series (*e.g.*, adjust model to include multiple seasonal cycles as [3.6]), time series models are claimed to be **more accurate, require smaller data set, and have less coefficients/parameters need to be estimated**. However, these papers did not consider the energy consumption deviation from exogenous factors, nor addressed the

problem of over-fitting. Their application to a longer period of time forecasting is suspicious.

The overfitting problem should be avoided to guarantee an accurate forecasting. S. Sp. Pappas and his team use the time series approach to model the national electricity demand load in Greece [3.7]. They de-seasonalized and fitted an autoregressive moving average model by minimizing the Akaike Corrected Information Criterion (AICC) (as Equation (3.45)).

$$AICC = \log|\hat{R}_\theta| + \frac{2(p+q+1)n}{n-p-1-2} \quad (3.45)$$

where n is the sample size, (p, q) is the model order, and \hat{R}_θ is a maximum likelihood estimation (in many other publications written as \hat{L}_θ). AICC gives a penalty to the models with higher order, therefore to avoid the problem of overfitting. In this paper the model selection through AICC is not only based on the accuracy of data fitting (guaranteed by maximum likelihood estimation \hat{R}_θ), but also considers the problem of higher order model over-fitting through penalty $(\frac{2(p+q+1)n}{n-p-1-2})$. The main contribution of this work was 1) it proved the electricity loads in the power market can be modeled by an ARMA process, and 2) it addressed the problem of overfitting by comparing model order selection criteria under the presence of noise.

Besides the problem of overfitting, sudden changes in the data training series and forecasting periods also call attention from researchers. The sudden changes are the descent or ascent impulses in data series. Researchers are eager to find the scientific explanations to the causes behind these impulses. Once the reasons are found, these influential factors are introduced into the time series model as exogenous inputs.

C. E. Asbury studied how the weather affects the electric demand [3.8]. The heat sensitive portion of the load is separated from base load. The author established an energy model utilizing a summer weather load model, which takes into account the probability variation of weather factors. Historical information was used to establish the system load characteristics and process the regression analysis of electric load and weather information. This model can be used for intermediate forecasting, ranging from 3 to 10 years, but cannot be used for short term prediction in hours or days, because the historical data acquired were in low time resolution (monthly data).

Another challenge is from uncertainty. The power generation from solar and wind sources is difficult to predict because of their high uncertainty. Yanting Li and his colleagues use the time series to analyze the power output of a photovoltaic system [3.9]. The photovoltaic system uses the solar energy as the source energy input, which highly depends on the weather condition. Due to the high uncertainty, the authors introduced multiple exogenous inputs into the traditional time series model to increase the model accuracy. The authors also use the Bayesian information criterion (BIC) to avoid the problem of over-fitting. As a result, the ARMA model with exogenous inputs (ARMAX) of daily average temperature, precipitation amount, insolation duration and humidity is

believed to be the most accurate model compared with many other models. Thus, the ARMAX is shown to be efficient in modeling processes with high uncertainties.

As to short term energy forecasting with exogenous inputs, a Spanish group discussed the short-term (one day) electricity load forecasting of Spanish system operator [3.10]. In their model, the exogenous inputs like weather information and special days are incorporated with the electricity consumption seasonality and trend. The authors assumed the model is in additive logarithms (as Equation (3.46)).

$$\ln C_t = p_t + s_t + CSD_t + CWEA_t + U_t \quad (3.46)$$

where p_t denotes the trend, s_t denotes part of the seasonality, CSD_t as the contribution of special days, $CWEA_t$ as the contribution of meteorological variables, and u_t is a stationary disturbance that may display some short-term, transitory dynamics. The authors further separated the model into two parts – basic consumption BC_t (as Equation (3.47)) and joint contribution of special days and weather variables (as Equation (3.50)).

$$\ln BC_t = \ln C_t - CSD_t - CWEA_t = p_t + s_t + u_t \quad (3.47)$$

$$\phi(L)\Delta(L)\ln BC_t = \theta(L)a_t \quad (3.48)$$

There are strong trend and weekly seasonal patterns recognized when plotting the data series. Thus, authors specify the $\Delta(L)$ as $\Delta\Delta_7 = (1-L)(1-L^7)$. Authors further specified

the multiplicative form of Equation (3.47), in to a stationary ARIMA model with annual seasonal factor. The Equation (3.47) can be written as Equation (3.49).

$$\phi(L)\phi_7(L^7)\phi_{365}(L^{365})\Delta\Delta L_7 \ln(BC_t) = \theta(L)\Theta_7(L^7)\Theta_{365}(L^{365})a_t \quad (3.49)$$

The joint contribution of special days and weather variables in Equation (3.50) can be further expressed as Equation (3.50).

$$CSD_t + CWEA_t = \sum_{i=1}^m \alpha_i(L)SD_{i,t} + \sum_{j=1}^n \beta_j(L)WEA_{j,t} \quad (3.50)$$

where $SD_{1,t}, SD_{2,t}, \dots, SD_{m,t}$ are m dummy variables that define the different classes of special days; $WEA_{1,t}, WEA_{2,t}, \dots, WEA_{m,t}$ represent n transformations of the observed meteorological variables; and $\alpha_i(L), \beta_j(L), i = 1, \dots, m,$ and $j = 1, \dots, n$ are lag polynomials. Authors compared the developed method with other two benchmarks, and claimed that the proposed time series models were more accurate in terms of mean absolute percentage errors (MAPE).

3.2.3 Knowledge Gap Summary

Though the mathematical background of the time series analysis is well studied, and the application of mathematical method to energy usage is developed, its application

to manufacturing plant energy modeling is rare. How to apply the time series analysis to manufacturing plant energy consumption is a question that has never been studied.

On the other hand, the manufacturing plant energy consumption has known (*e.g.*, scheduled production volume), predictable (*e.g.*, weather condition), and has uncertain variables (*e.g.*, unexpected production line breakdown). The question of how to introduce the influential factors into time series model, and what influential factors should be included are the other two questions worth to be studied.

Finally, because of the recent attention to the energy consumption on the manufacturing plant, as well as the quick development in metering/sensor and data system, a tool to deal with a large energy database system is urgent. Time series analysis is deemed as the solution to deal with large scale energy database [3.11]. However, how much data is required in model training to guarantee an accurate forecasting, while not sacrifice the efficiency of parameter estimation, is another question explored in this research work.

3.3 Proposed Approach

In the previous chapter, energy modeling approach is proposed (as Figure 3.1), and the top-down strategy is demonstrated (as the purple elements in Figure 3.1). In this chapter, the refined statistical model will be established.

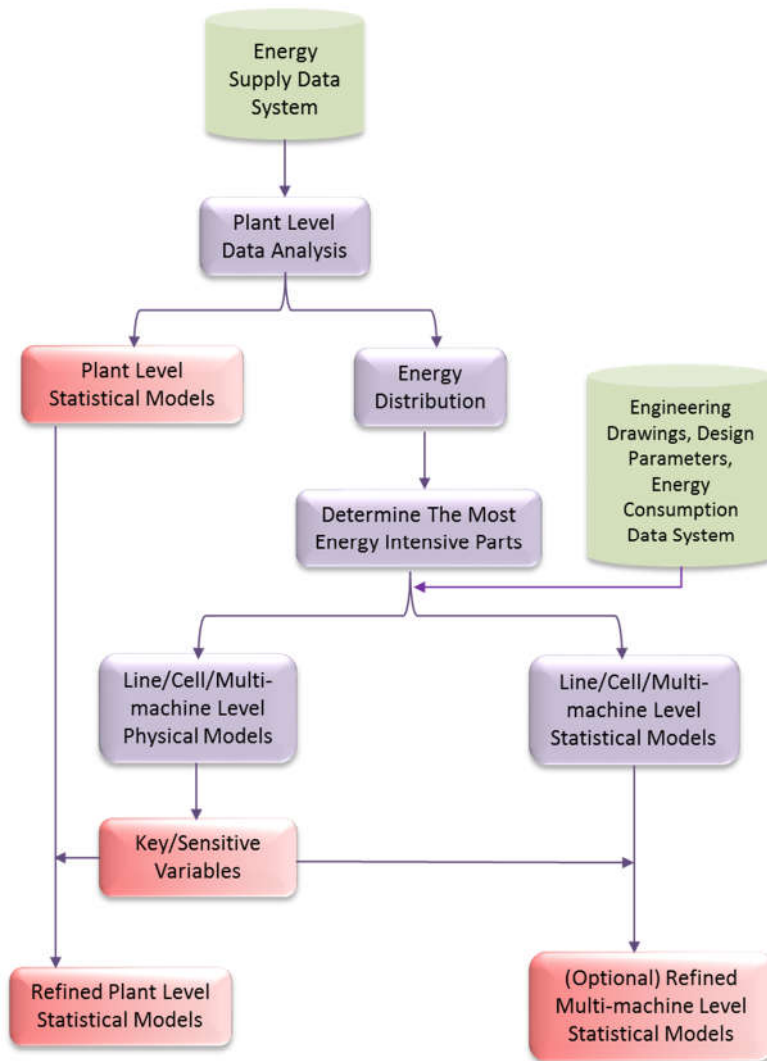


Figure 3.1: Flowchart of Energy Modeling in Plant (Bottom-Up Strategy Highlighted in Red)

First the statistical model at high or low level models can be established simply based on the metering data. However, as mentioned previously, the simple statistical models suffer from the problem of inaccuracy. Thus, a more robust model needs to be established.

Sensitive/key variables from lower level models can be identified through the physical models. With these key influential variables, the second step is to introduce them into the previous simple statistical models. Depending on the levels of models, sensible variables can vary.

In time series models, the simple statistical models are the traditional ARMA model. The key influential variables can be introduced through the exogenous inputs of ARMAX model. Therefore, establish refined models with high robustness. This process is illustrated as the red elements in Figure 3.1.

Since the exogenous features are from the physical energy model of low level in the plant, they are different from the national electricity, or any other energy consumption, and are unique to the manufacturing plants. Sensitivity analysis can be applied to all the variables, while only the key features should be included in the final model(s). Acquired data can also be separated into larger and smaller sets to help decide the size of training data set.

3.4 Case Study

BMW Spartanburg Automotive Manufacturing plant is the studied case. The assembly plant has its own onsite boilers to supply hot water for heating, and chillers to supply chilled water for cooling. How the heating and cooling energy demand affects the purchased energy supply is illustrated in Figure 2.19.

In the previous chapter, systematic energy modeling approaches were proposed, and a case study was applied to illustrate the top-down modeling strategy of the approach.

This section will illustrate how the bottom-up strategy (as Figure 3.2) could be used to make the higher level models more robust.

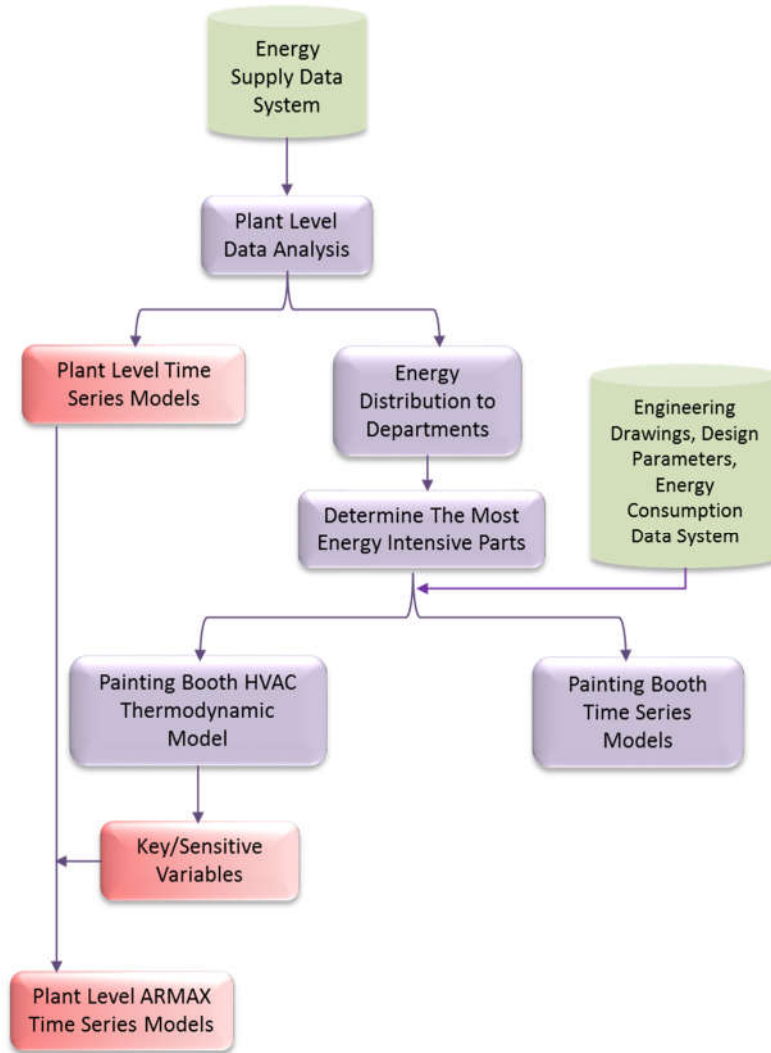


Figure 3.2: Flowchart of Energy Modeling in Studied Case (Bottom-Up Strategy Highlighted in Red)

3.4.1 Sensitive Variables

In the previous chapter, systematic energy modeling approaches were proposed, and a case study was applied to illustrate the top-down modeling strategy of the approach.

This section is going to illustrate how the bottom-up method could be used to make the higher level models more robust.

At the high level, there are three major components of energy – production process, technical building service, and building shell. These three major components in the manufacturing system are relatively independent but are also somewhat correlated (as Figure 3.3). Independent models can be established to represent the energy usage in each component. For those plants with large heating processes, the interaction between the production processes and building cannot be neglected. To simulate the correlation, internal and building heating gain or loss can be added when determine the building status in terms of temperature and relative humidity.

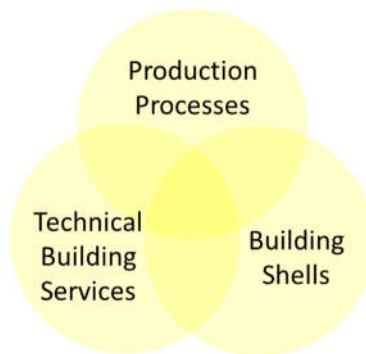


Figure 3.3: Three Major Components of Energy in Plant

In Chapter Two, Section 0, models of the HVAC system of the painting spray booth were established and validated. Further implementation of such HVAC models can be used on the plant buildings. However, unlike the paint spray booth, the building is a feedback

system that correlates the internal and external gain/loss through its monitored temperature. Figure 3.4 is the painting spray booth HVAC feed forward system. In this system, the logic process in the air conditioning unit is summarized in the right part of the figure. Air in the painting booth is used to remove the residual paint in the air and collect it through the downdraft in the scrubber. Unless there is a non-working day, the air will continuously blow to guarantee the quality of the paint. The fast air flow rate was designed to balance the moisture brought in by the moving vehicle. In a steady state, the internal air temperature and humidity is controlled in the tolerance range. In this case, a feedforward system is applied. However, in a building environment, conditioning is on and off from time to time, considering the heat gain/loss from the internal production lines/cells/equipment and external environment. The monitored building temperature and humidity state is the interconnection parameter among the air conditioning unit of the technical building service, production process and building shell. Monitored building status feed backed to the control window decides when and whether the air condition unit should be on or not. The process is summarized in Figure 3.5.

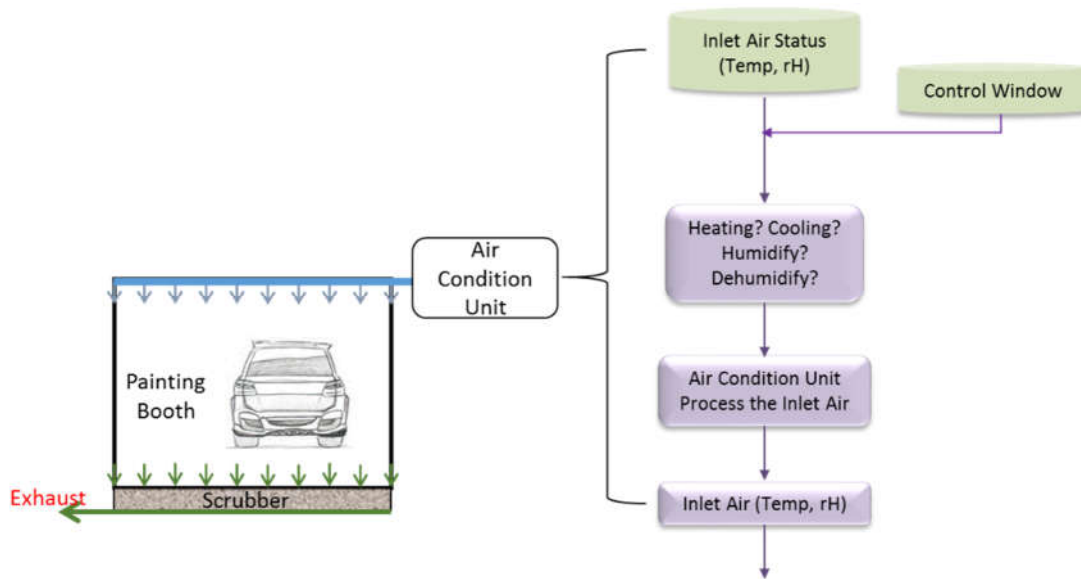


Figure 3.4: Painting Spray Booth Feedforward System

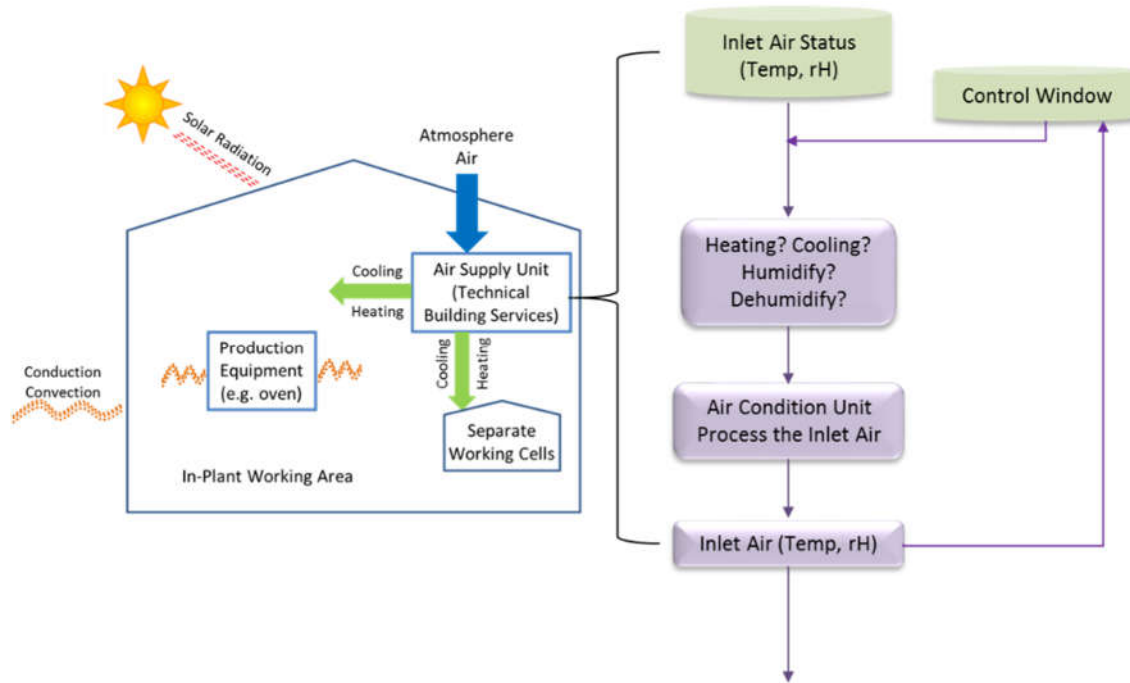


Figure 3.5: Building Feedback System

A building HVAC system consumes a great amount of energy every year. It is important to have an effective HVAC system for the plant building to guarantee a good working environment and protect the weather-sensitive equipment. The studied case has air supply houses for plant building temperature control. Unlike the painting spray booth, the building HVAC system only controls the air temperature of the building, but not humidity.

Building air supply units use the air from outdoors, and control the temperature before inlet into the building. To protect the confidentiality of the studied case, and for the convenience of further discussion, the following assumptions were made on internal/external gain, air flow rate and building temperature setpoint. Assume there is one building in the plant with building set point temperature $22^{\circ}C$, and air flow rate $650,000 m^3 / hr$ (as Table 3.1).

Table 3.1: Paint Shop Building Original Setpoint

	Setpoint	Unit
Building Temperature	22	$^{\circ}C$
Building Flow Rate	650	$1,000m^3/hr$

According to the local weather information, annual energy consumption can be calculated through a function related to the local weather, internal gain/loss, external gain/loss, setpoint, and air flow rate (as Equation (3.51)).

$$E_{building} = f(\text{local weather, internal gain, external gain, setpoint, air flow rate}) \quad (3.51)$$

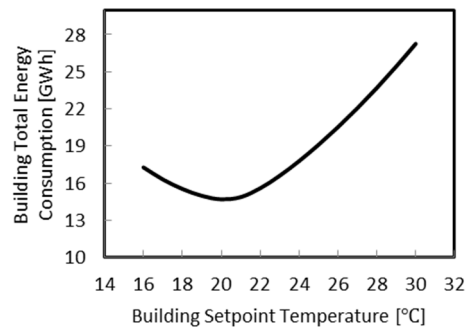


Figure 3.6: Effect of Constant Temperature Set Point on Annual Building Total Energy Consumption

Figure 3.6 shows a convex curve, with the minimum energy consumption of the point of 20°C.

In the previous chapter, the building to booth air supply concept was introduced. Figure 3.7 and Figure 3.8 are the figures to illustrate different air flow routes. In our studied case, the building to booth concept is used.

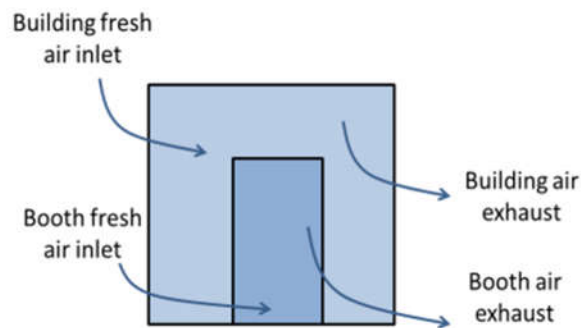


Figure 3.7: Separate Air Inlet Flow Route

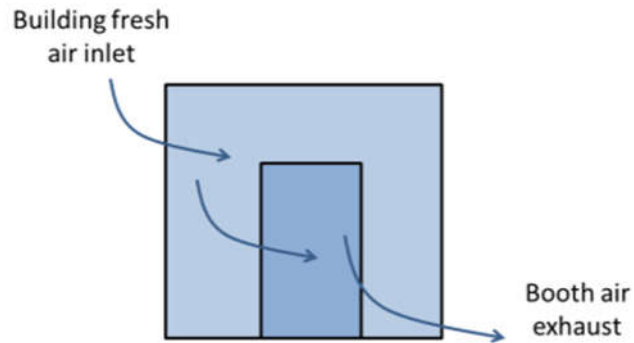


Figure 3.8: Building to Booth Air Flow Route

While keep the building $T_{bld} = 24^{\circ}\text{C}$, the set point of the booth temperature effects on the booth energy is more linear – higher booth set point means higher energy demand.

Considering the global optimum, there are three different scenarios in optimization: building temperature is smaller than the minimum booth temperature; building temperature is within the booth temperature control window; and, building temperature is larger than the maximum booth temperature. First, when the building temperature is below the minimum temperature of booth setting, only a chiller is used to condense water from air, but the heater must be turned on to heat up all the time. Second, when the building temperature is within the constraint of booth temperature window, (*i.e.*, $T_{bth_min} \leq T_{bld} \leq T_{bth_max}$ is always true) the energy used in supplying air to the booth is only used in controlling the humidity – over chill to condense water and reheat to the designed temperature. In this case, the energy difference caused in booth temperature difference is the saving of the overchill energy to dehumidify and reheat energy after the dehumidification. Third, when the building set point is higher than the booth temperature,

the chiller is constantly on, being used in both cool down and dehumidification. These three scenarios are summarized in Table 3.2.

Table 3.2: Summary of Three Scenarios

Scenarios	Chill Down	Heat Up	Over Chill and Reheat Up
$T_{bld} \leq T_{bth_min}$	-	1	1,0
$T_{bth_min} \leq T_{bld} \leq T_{bth_max}$	-	-	1,0
$T_{bth_max} \leq T_{bld}$	1	-	1,0

(1-equipment on; 0-equipment off; 1,0-either on or off)

Unlike the local optimization for building or booth only, the global optimum of building temperature set point on booth energy consumption is more complex.

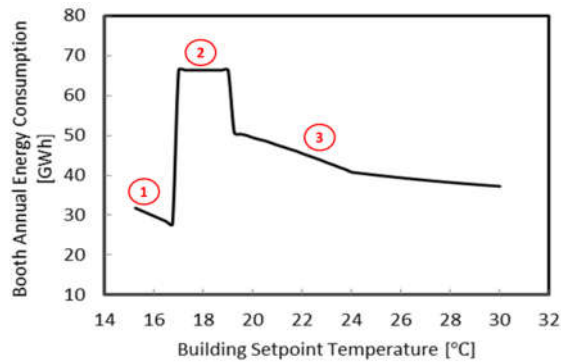


Figure 3.9: Effect of Building Temperature Set point on Annual Booth Total Energy Consumption

Figure 3.9 shows the stages in booth annual energy consumption. Stage 1 has a very low building setpoint. During this stage, the atmosphere into the building is condensed, which means the building has very low humidity ratio (W), even the condensation is not

intentional. And actually, it is so low that during this stage, no dehumidification process is needed. The air condition unit of paint booth simply consumes energy to heat the moist air to designed booth temperature. A tremendous increase in energy consumption happened when temperature increase above the 17°C. This is because during the stage 2, the over chill and reheat up is required. And the increase of vapor in dry air will also call for large amount of heating energy. And then as the temperature increases, less energy is used for heating. While the air is mixed before the air conditioning, if the temperature of mixed air is larger than the minimum point of the booth temperature (test 3), no heating is necessary. That is the reason of fast energy drop at the point around 19°C. And when the temperature of building is equal or above the booth temperature, less inlet air needs to be treated.

The energy consumption of the combined building and booth air condition is coupled together, the temperature with minimum building energy consumption does not necessarily lead to minimum combined energy consumption. And the set point for booth air to achieve the least energy demand will also vary according to different selection of building temperature. For example, if we look at the minimum energy consumption of building, Figure 3.9 shows the best result can be reach by setting $T_{bld} = 20^{\circ}\text{C}$. Then the combined energy consumption is 52GWh. However, this combination is 9GWh away from the global minimum of 43GWh within the test range. The effect of building and booth temperature set points on combined energy consumption is illustrated in the 3D plot of Figure 3.10.

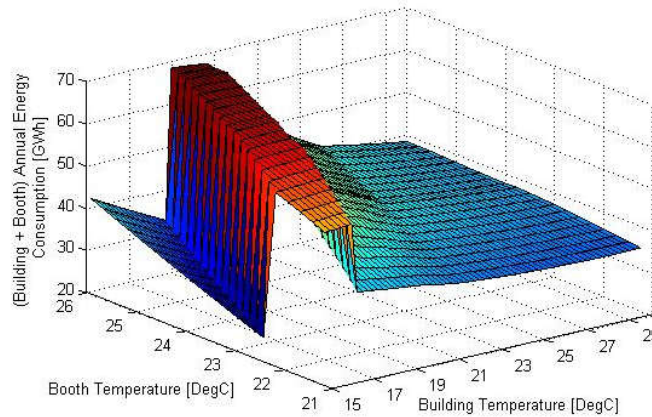


Figure 3.10: Effect of Building and Booth Temperature Set point on Combined Energy Consumption

Out of the purpose of research, we fully explore the set point range $15^{\circ}\text{C} \leq T_{bld} \leq 30^{\circ}\text{C}$, $21^{\circ}\text{C} \leq T_{bth} \leq 26^{\circ}\text{C}$. But in the real case study, energy managers need to select optimum operation strategy under the constraint of a feasible control window.

This example demonstrates how the building and process energy can be related and interact with each other. In this example, both booth and building temperature are critical in energy consumption at low level. However, when it comes to plant level energy consumption, the sensitive variables could be different. More sensitive variable analysis were developed in Chapter Five Section 5.1.1. In Chapter Five, it was concluded that the sensitive variables from the physical model include the weather information, the productivity of the plant, also the week of the days and special occasions, such as the maintenance days and national holidays. These manufacturing featured variables should be introduced into a high level model.

3.4.2 Data

The time series analysis requires a set of historical data from the past for model training.

Data Source

Because of the nature of the time series model, it requires reliable data inputs from history.

There are four main electrical feeders in the plant; the total electricity consumption of the plant is the summation of the four feeders' energy (as Equation (3.52)).

$$Electricity(kWh / Day) = \sum_{i=1}^4 Feeder_i \quad (3.52)$$

Daily data from May 28th, 2013 to July 16th, 2015 were collected. There are 780 data points in total. Occasional outliers in the data series were identified by the meter malfunction. Due to the large number of data points, outliers were directly removed from the data series without impairing the series trend and seasonality. In this particular series, the outliers were very obvious – extremely larger than the normal electricity consumption. Figure 3.11 is the plot of subset of the data series with outliers. The x-axis represents the normalized time (t) from 1 to 22, where 1 as January 22nd 2014 and 22 as February 12th 2014. The y-axis represents the electrical energy, which was normalized to protect the information of studied plant. It is obvious that there are two outliers at time 13 ($t = 13$) and 14 ($t = 14$).

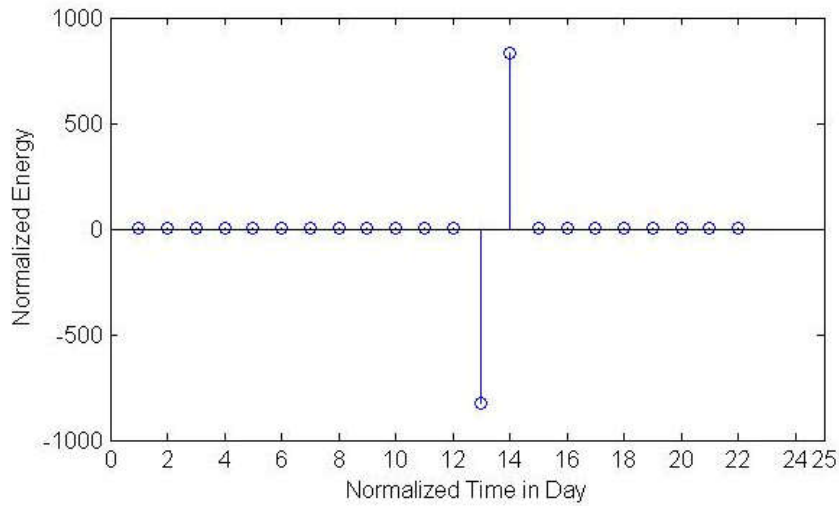


Figure 3.11: Outlier Example

There are 38 outliers in the collected series. When the sample amount is small, it is infeasible to delete the data from the series. However, in this case, the number of outlier is relatively small (38 outliers out of 780 sample, <5%). Directly removing the small set of outliers will not cause problem. After the outlier removal, there left 742 data points as later model raw data (equation (3.53)).

$$\{X_t, t = 1, 2, \dots, 742\} \quad (3.53)$$

This data series was further split into two parts, the first 726 data points for model training, and the later 16 data points for model forecasting validation.

The training data was plotted in Figure 3.14. The training data is not stationary. There are obvious increasing trend and seasonality (as Figure 3.12) in the data series. It is important to identify the trend and seasonality for later model establishment.

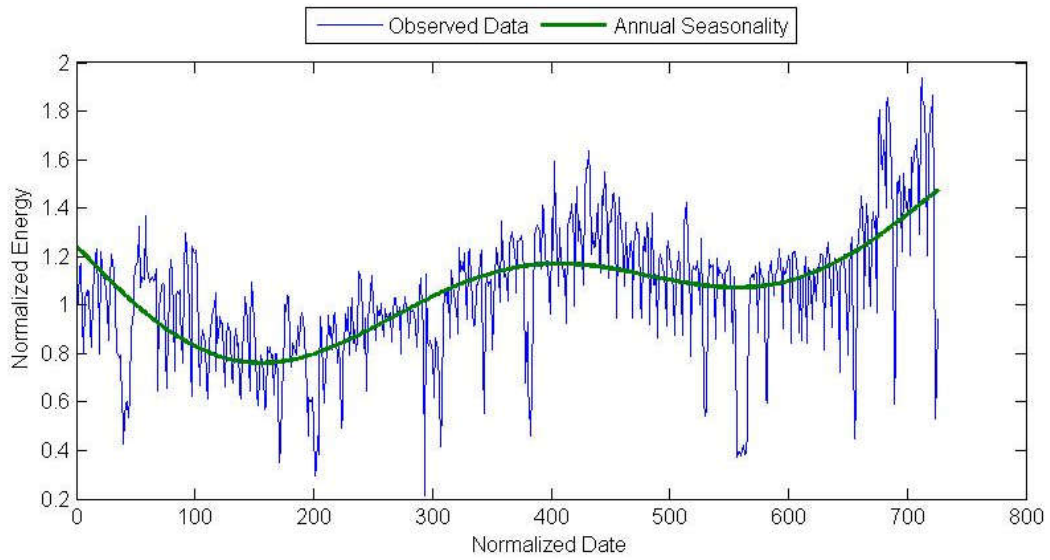


Figure 3.12: Annual Seasonality in Observed Data

Figure 3.12 shows the increasing annual trend and winter/summer seasonality. Further analyzing of the data series reveals the weekly periodicity. Figure 3.13 is the plot to typical four weeks' daily energy consumption.

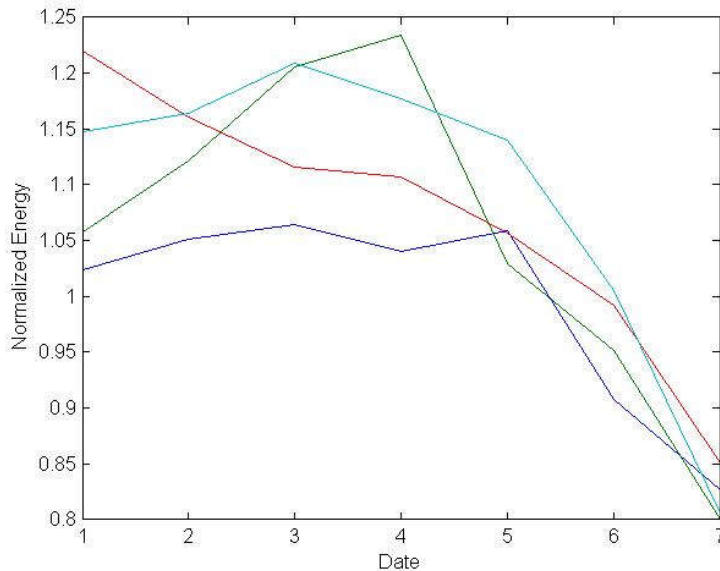


Figure 3.13: Weekly Seasonality

Figure 3.13 x-axis represent the days 1 as Monday, 2 as Tuesday, and such that. The y-axis represents the normalized energy consumption. The figure shows a relatively stable energy consumption during the weekdays, and lower energy consumption on Saturdays and Sundays.

Size of training dataset

The amount of available historical data (training data) will affect the model in two main ways. 1) Training computational time. More training data will require more computation time to estimate the model parameters. 2) Trend and seasonality. The larger the data set is, the better for trend and seasonality analysis. Take the example from our studied case. Figure 3.14 shows more than two years of data. From this figure, we can clearly visualize the increasing trend and annual seasonality in the data (see fitting

increasing trend and annual seasonality in Figure 3.12). If we zoom into weeks of data, it is also obvious to see the 7 days (weekly) seasonality (as Figure 3.13).

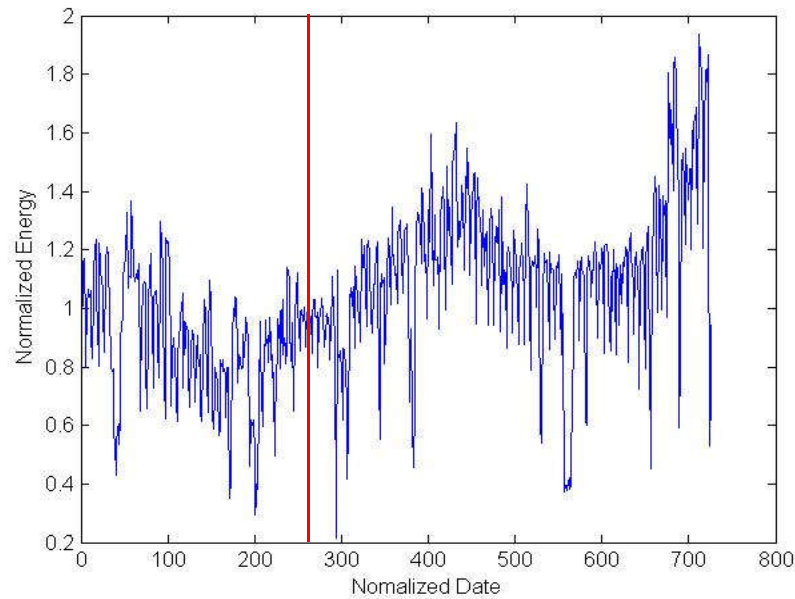


Figure 3.14: Historical Data Plot

However, if the training data set is limited to a smaller data set, these features may not be so easy to observe. If we select only part of the data (*e.g.*, smaller data set from $t=1$ to $t=150$), in this period of time, the training data set shows a linear decreasing trend. Meanwhile, since the data only includes 150 days, it is impossible to get the annual seasonality from it. Thus, when training, the model will be fitted with a simple decreasing linear trend (as Figure 3.15). The fitted model may also behave well in forecasting the next few days' results. However, if the fitted model is used in the long run (selected model class with trained parameters), the results will diverge from the observed data (as Figure 3.16).

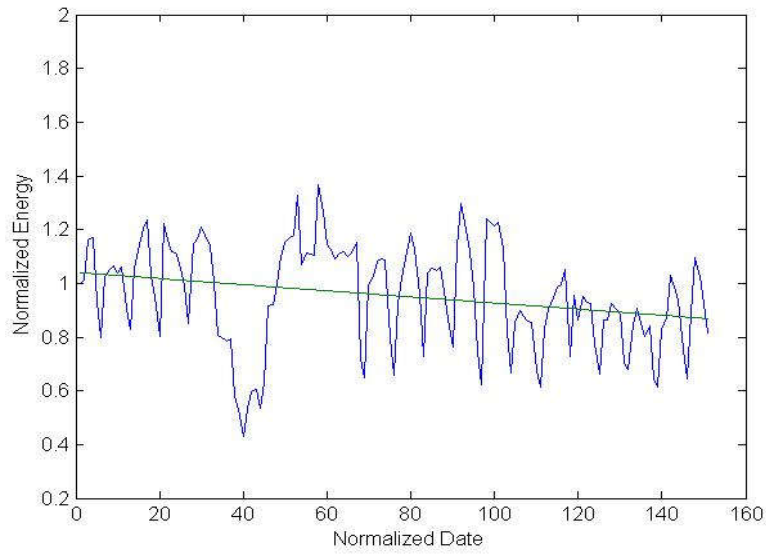


Figure 3.15: Small Data Set Decreasing Trend

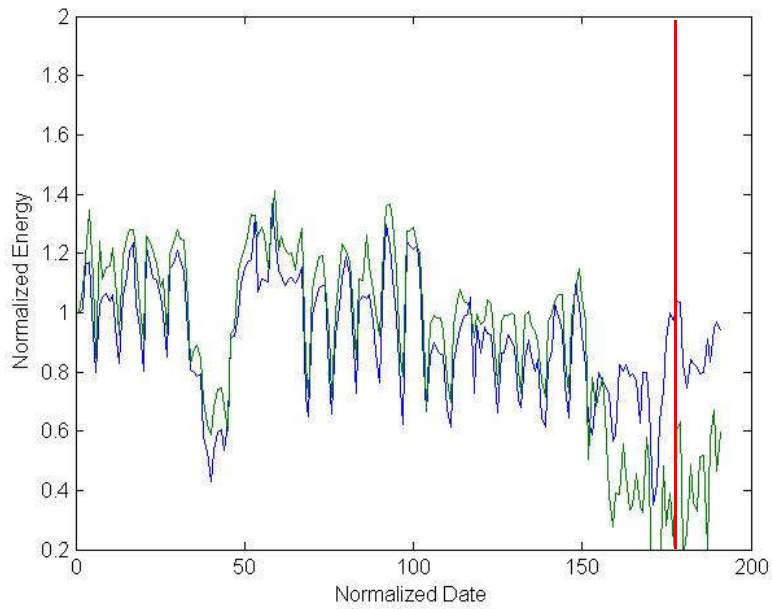


Figure 3.16: Diverged Forecasting Results

Figure 3.17 is a simplified sketch of time series modeling procedure.

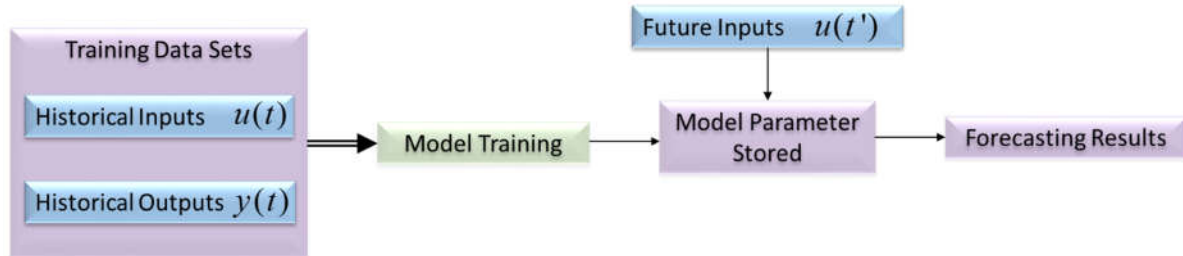


Figure 3.17: Time Series Modeling Procedure

These two problems can be solved in the future with the help of the big data system. With a big data system, it is expected to have a more efficient data fetching and computational time. Updating the stored model parameters frequently by training the model with larger data sets and more recent data inputs (*i.e.*, frequently repeat the training procedures in Figure 3.17) will make forecasting results more accurate.

3.4.3 Model

By establishing a time series model, we can reveal the energy demand variation phenomenon in the manufacturing plant; therefore, we can better understand the energy usage and plan for the next steps' energy operation and control strategy. Unlike the national electricity consumption example reviewed in the previous section, a manufacturing system is believed to have more predictable noise factors and working conditions. For example, the energy used for the automotive assembly plant is proved to be related to the weather condition. Adding the exogenous input of weather conditions into the time series model makes the forecasting result more robust and interpretable. On the other hand, the known

variables such as national holidays and vehicle production plan (*i.e.*, number of vehicles being produced) can also be taken into the model for a better understanding the phenomenon in the time series. Exogenous information is discussed in more detail in Chapter Five.

Stationary Data Series Preparation

The observed training data are plotted in Figure 3.12 and seen to be non-stationary. Before fitting the model, the data need to be transformed into a stationary series. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are two functions that help identify the autocorrelation at different time lags (given as Equation (3.27) and (3.28)).

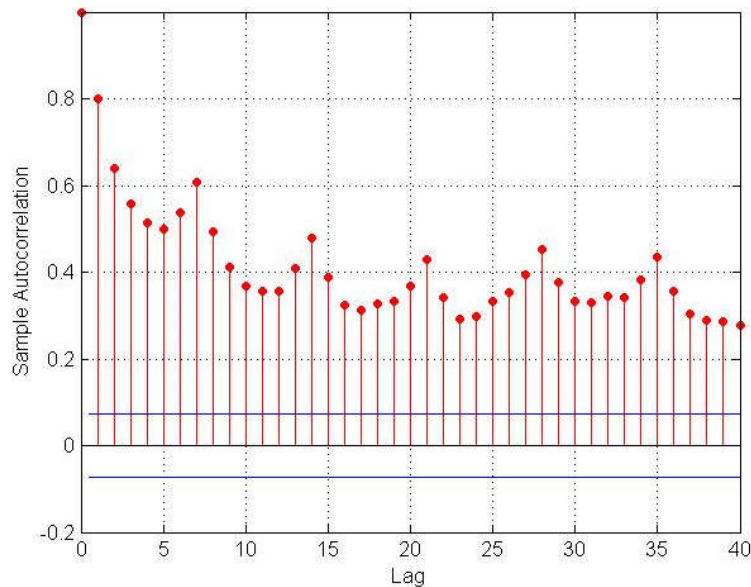


Figure 3.18: Training Data ACF

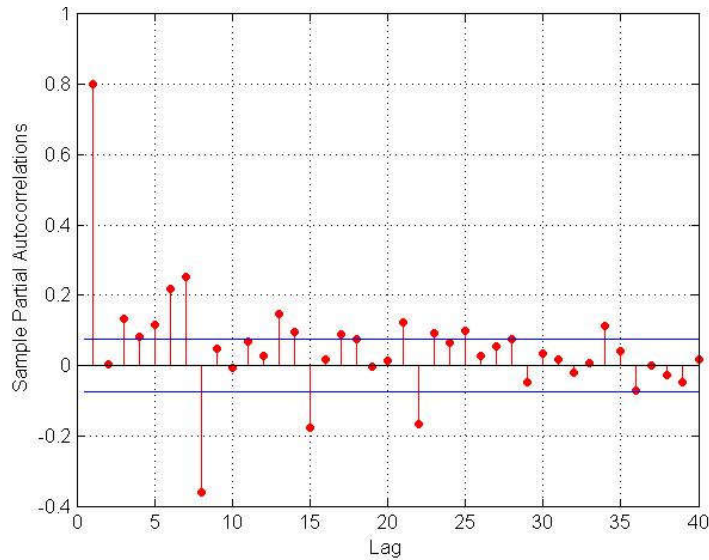


Figure 3.19: Training Data PACF

Figure 3.18 and Figure 3.19 are the ACF and PACF plot of training data respectively. Figure 3.18 shows a slow degradation trend in the ACF value, while a strong correlation at time lag 7. This verifies the previous observations on the data trend and seasonality. Figure 3.19 also supported the lag 7 seasonality.

In order to achieve a stationary time series, the trend and seasonality need to be removed from the original data series. There are many different techniques that can be applied. Here, we assume the data series can be represented as Equation (3.14). Thus the new stationary series Y_t , can be written as Equation (3.15). One of the typical methods used to get the trend and seasonality is through the regression model and least square estimation.

Linear regression

$$\hat{Y}_t = \alpha + \beta t \quad (3.54)$$

Quadratic regression

$$\hat{Y}_t = \alpha + \beta_1 t + \beta_2 t^2 \quad (3.55)$$

n^{th} order regression

$$\hat{Y}_t = \alpha + \beta_1 t + \beta_2 t^2 + \dots + \beta_n t^n \quad (3.56)$$

where the parameters α and β s can be estimated through the least square estimation:

$$\min \frac{1}{2} (Y_t - \hat{Y}_t)^2 \quad (3.57)$$

The original data series trend and seasonality can be represented in terms of regression fitting. By subtracting the best fit given through least square estimation, a new data series without trend and seasonality can be achieved.

There are many other approaches to detect and remove the trend and seasonality. Differencing is another straightforward method in de-trending and de-seasonality, given as

Equation (3.16) – (3.26). To remove the trend and seasonality, the difference as Equation (3.58) can be applied to the training data series.

$$\begin{aligned} Y_t &= \nabla_{365} \nabla_7 \nabla_1 X_t \\ &= (1 - B^{365})(1 - B^7)(1 - B)X_t \end{aligned} \quad (3.58)$$

In Equation (3.58), the first order difference is to get rid of the increasing trend, the seventh order difference is to remove the weekly seasonality, while the 365th order difference is to remove the annual seasonality.

No matter what de-trending and de-seasonality methods were use, a new stationary data series plot should not show obvious trend and seasonality. After processing, the new data series is plotted as Figure 3.20, where has no apparent trend and seasonality. Further exam the expectation and covariance values (as Figure 3.21 and Figure 3.22), the new data series is qualified as weakly stationary (weakly stationary is defined in Section 0).

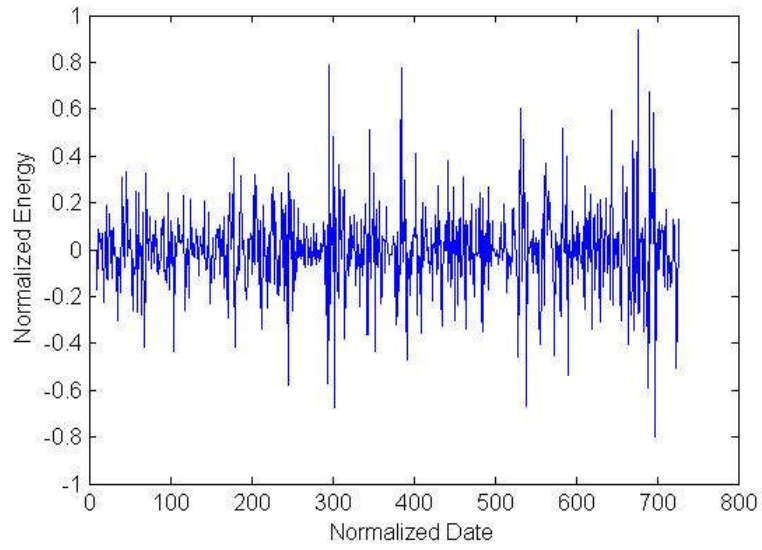


Figure 3.20: New Data Series Y_t

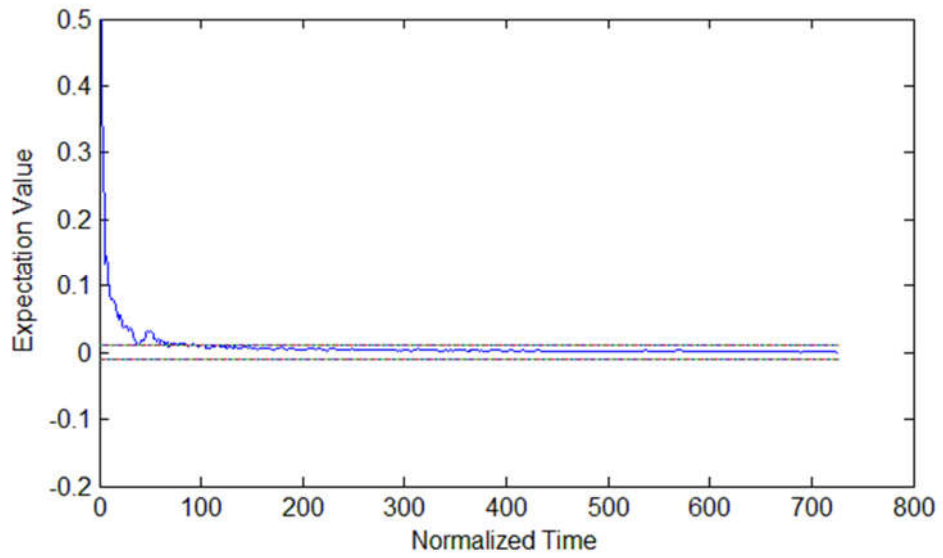


Figure 3.21: New Data Series Y_t Expectation Values

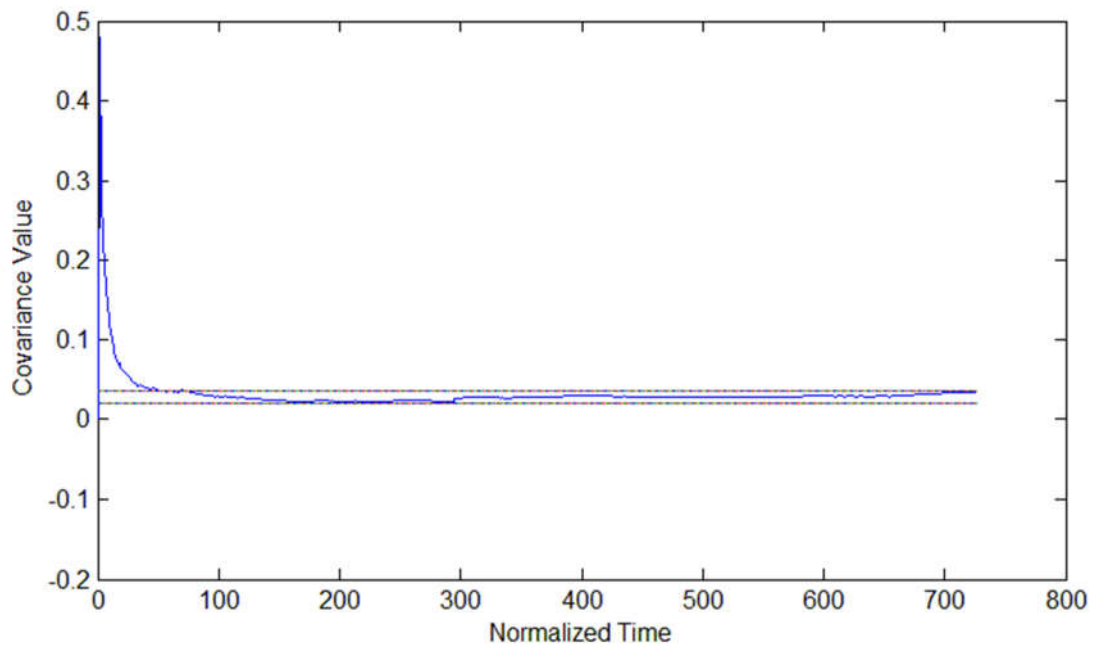


Figure 3.22: New Data Series Y_t Covariance Values

ACF and PACF can be applied to further exam the stationary data set. The new data series ACF and PACF plots are in Figure 3.23 and Figure 3.24 respectively. The fast decreasing rate of ACF and PACF suggest there is no obvious trend, but a relatively strong correlation at the time lag 7 suggests possible MA(7) or AR(7) model.

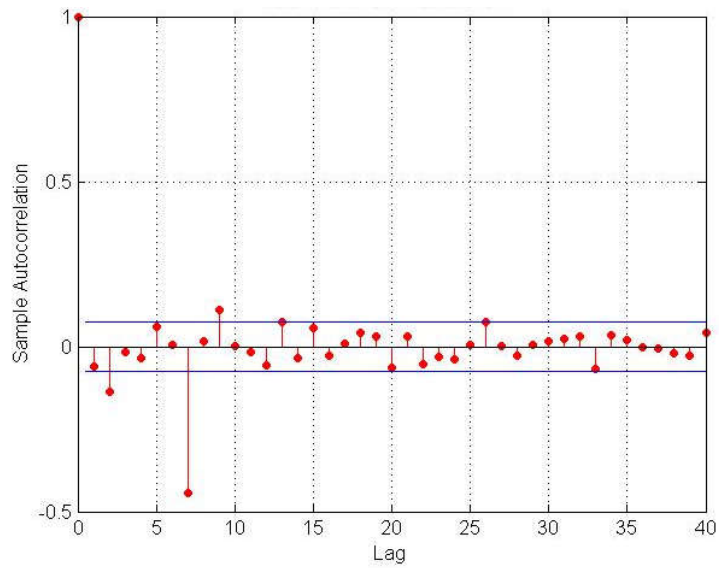


Figure 3.23: ACF of Y_t

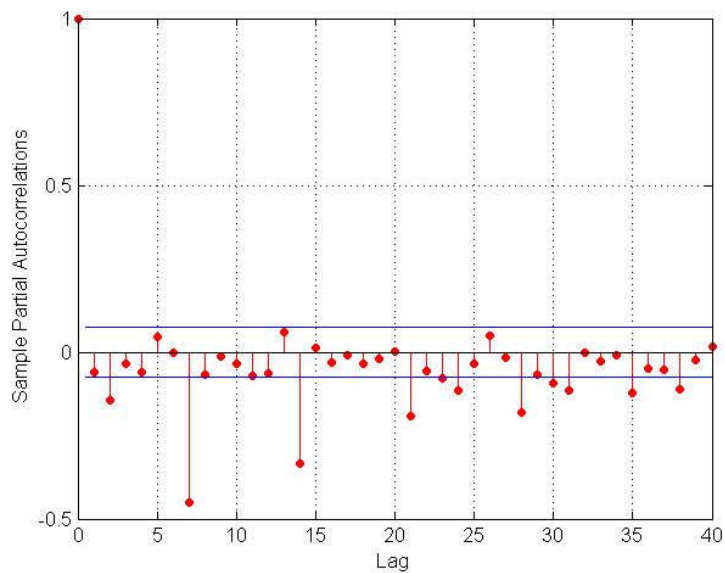


Figure 3.24: PACF of Y_t

Once the model were selected and the parameters were estimated, the unit circle method (as Section 0) can also be used to help identify if the fitted series is stationary.

Estimation

The estimation methods as Section 0 are applied, and results are shown in Table 3.3.

Model Selection

Once the models are fitted, different criteria can be used to evaluate the models. The Mean Square Error (MSE) can be used to measure the accuracy. Except for accuracy, the problem of overfitting can be avoid by the Akaike information criterion (AIC), Akaike information corrected criterion (AICC), and Bayesian information criterion (BIC). AIC, AICC, and BIC, as well as the MSE can be calculated as:

$$AIC = -2 \ln L \left(\phi_p, \theta_q, \frac{S(\phi_p, \theta_q)}{n} \right) + 2(p + q + 1) \quad (3.59)$$

$$AICC = -2 \ln L \left(\phi_p, \theta_q, \frac{S(\phi_p, \theta_q)}{n} \right) + \frac{2n(p + q + 1)}{(n - p - q - 2)} \quad (3.60)$$

$$BIC = (n - p - q) \ln \left[\frac{n\sigma^2}{n - p - q} \right] + n(1 + \ln \sqrt{2\pi}) + (p + q) \ln \left[\frac{\sum_{i=1}^n X_i^2 - n\bar{X}^2}{p + q} \right] \quad (3.61)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (\hat{X}_i - X_i)^2 \quad (3.62)$$

From Equation (3.59) to (3.62), $L(\cdot)$ is the likelihood of models, ϕ_i and θ_j are the parameters for auto-regressive and moving average models respectively, p and q are the orders of auto-regressive and moving average models respectively, n denotes the number of training data, X_t is the training data, and \hat{X}_t is the estimated data.

All these four criteria can be used to aid in the model selection. The lower values of these criteria, the better accuracy are, and less likely have the problem of overfitting. However, the AIC has a tendency to overestimate the p order [3.1]. The AICC and BIC has a greater penalty for large-order models; thus these two are more commonly used for model selection, AICC is used in this work.

Both AICC is used as indicators to avoid the problem of overfitting. Table 3.3 provides the AICC indicators, as well as the MSE of training data and MSE of the next 16 days' forecasting. From this table, we can see the ARMA(7, 7) model has the smallest AICC, training MSE, and forecasting MSE, so it can be selected as a stationary representation of the series.

Table 3.3: ARMA Model Test Results

	AICC	Training MSE	Forecasting MSE
AR(1)	683	1.75	0.88
AR(7)	651	7.32	2.09
MA(7)	581	1.71	0.26
ARMA(7,7)	412	0.97	0.16

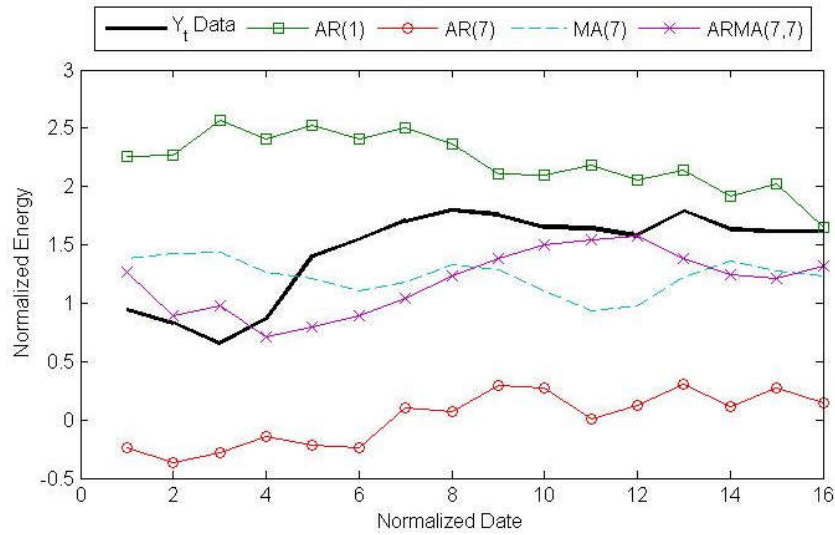


Figure 3.25: ARMA Model Comparison

Figure 3.25 compares the forecasting results from four ARMA models. As the figure shows, ARMA(7, 7) model is obviously better in following the Y_t data.

Exogenous Inputs

As stated before, the automotive manufacturing plant has many features that can be taken as exogenous inputs into the time series model to make it more robust and interpretable. From the previous lower level analysis, the sensible variables are from three main aspects – weather, productivity, and working days. These three aspects were further developed into the following representations:

$$\mathbf{u} = [\text{Weather} \quad \text{Productivity} \quad \text{Working Days}] \quad (3.63)$$

where u is the exogenous inputs/sensible variables matrix, while

$$Weather = [T_{avg} \quad T_{Max} \quad T_{Min} \quad CDD \quad HDD \quad \dots \quad rH_{Max} \quad rH_{Min}] \quad (3.64)$$

where T represents the temperature, rH represents the relative humidity, CDD the cooling degree days, HDD heating degree days; subscript avg denotes the average value in one day, Max denotes the maximum value in one day, and Min denotes the minimum value in one day.

$$Productivity = [V_{1,1} \quad V_{2,1} \quad V_{3,1} \quad \dots \quad V_{m,n}] \quad (3.65)$$

where V represents the number of vehicles produced in one day; subscript $(i,j)=\{(1,1) (2,1) (3,1) \dots (m,n)\}$ denotes the vehicle model i from department j .

$$Working Days = [D \quad NW \quad \dots \quad MT] \quad (3.66)$$

where D represents the i^{th} day in a week, NW represents the non-working/working days condition, and MT represents the maintenance condition. Other variables can also be included in the matrixes. Then the exogenous inputs in (3.63) can be written as (3.67).

$$\mathbf{u} = \begin{bmatrix} u_{1,1} & u_{1,2} & \dots & u_{1,j} \\ u_{2,1} & u_{2,2} & \dots & u_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ u_{t,1} & u_{t,2} & \dots & u_{t,j} \end{bmatrix} \quad (3.67)$$

where $u_{i,j}$ represents the j^{th} exogenous input at time t .

In this studied case, four independent variables (\mathbf{u}) were selected – CDD (CDD_i), working/nonworking days (NWD_i), total number of Vehicle Type I made in one day (VA_i), and total number of Vehicle Type II made in one day (VB_i) (as Equation (3.68)).

$$\mathbf{u} = \begin{bmatrix} CDD_1 & NWD_1 & VA_1 & VB_1 \\ CDD_2 & NWD_2 & VA_2 & VB_2 \\ \vdots & \vdots & \vdots & \vdots \\ CDD_t & NWD_t & VA_t & VB_t \end{bmatrix} \quad (3.68)$$

ARMAX with different orders were tested (as Equation (3.10)). The model with the given exogenous inputs shows improvements in AIC and MSE (as Table 3.4). The fitted models has absolute value of auto-regressive parameters smaller than 1, which means the unit roots tested to be stationary. Among all the ARMAX model, ARMAX(7, 7, 5) performs best with AIC of 21.91 and forecasting MSE of 0.0154.

Table 3.4: ARMAX Model Test Results

	AIC	Training MSE	Forecasting MSE
ARMAX(7,7,5)	21.91	0.0068	0.0154
ARMAX(0,7,5)	21.99	0.0072	0.0327
ARMAX(7,0,5)	21.92	0.0069	0.0195

Model Comparison

The models with exogenous inputs and the best fit of ARMA model are shown here for comparison.

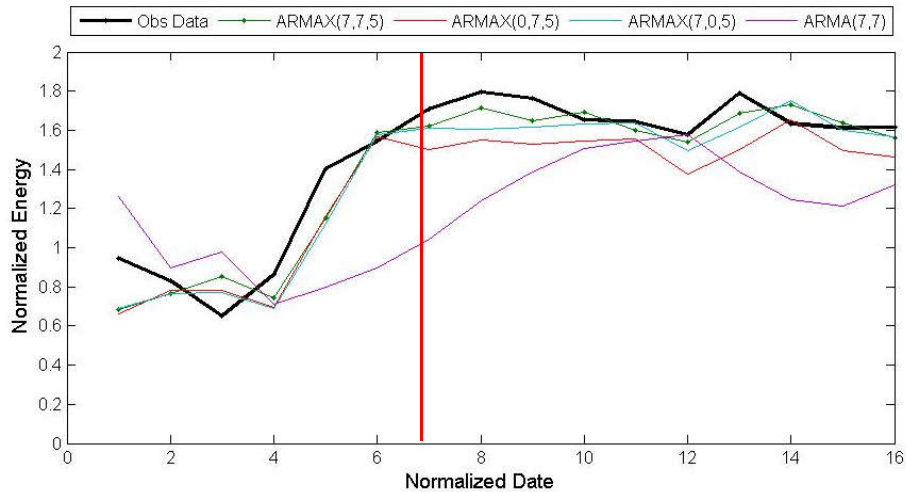


Figure 3.26: Model Forecasting Results Comparison

Figure 3.26 shows how the time series model performs better with exogenous inputs, especially in days with a sudden change with assignable cause. ARMAX is much better at forecasting $t \geq 5$. This is because, during this period of time, the plant begins to produce after a long shutdown. The ARMAX model follows the sudden energy increase right after

the shutdown ($t = 5$), while it takes ARMA(7, 7) model a longer time (after $t = 11$) to follow the increase.

It is obvious that the traditional time series models cannot quickly follow the sudden energy consumption change, nor are they more accurate than the ARMAX model. With the exogenous inputs from ARMAX model the accuracy is much improved (in terms of MSE) and more robust to the predictable and scheduled changes.

Residual Randomness

The residuals from the ARMAX(7, 7, 5) were also tested.

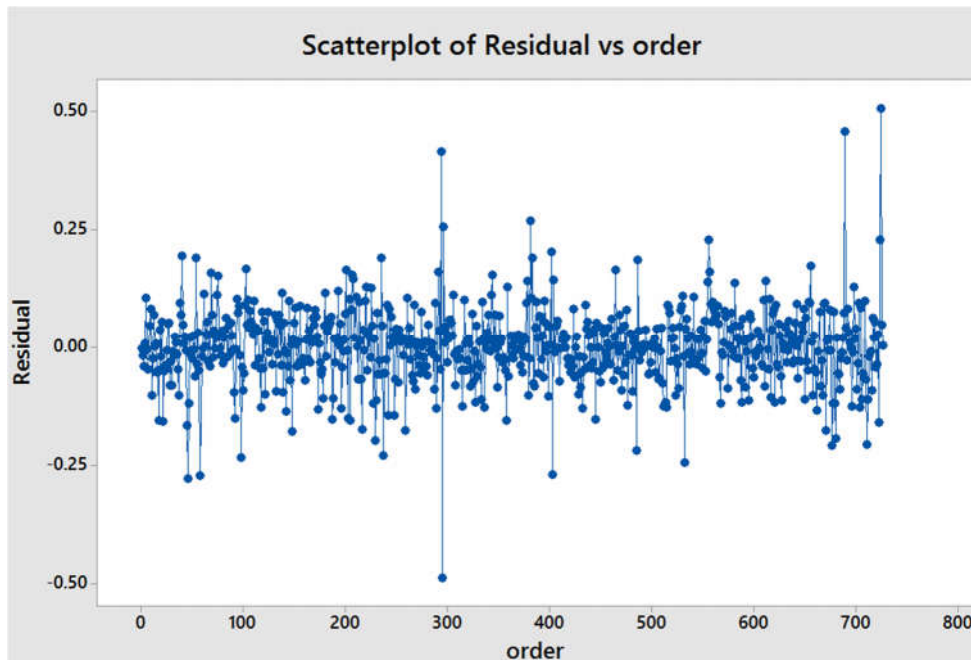


Figure 3.27: Scatterplot of Residuals

Figure 3.27 is the scatter plot of residuals. This figure does not show obvious mean and variation value change over the orders, *i.e.*, the residual values are independent on orders.

Figure 3.28 shows a histogram distribution of the residuals. It indicates the residual randomness and distribution about 0.

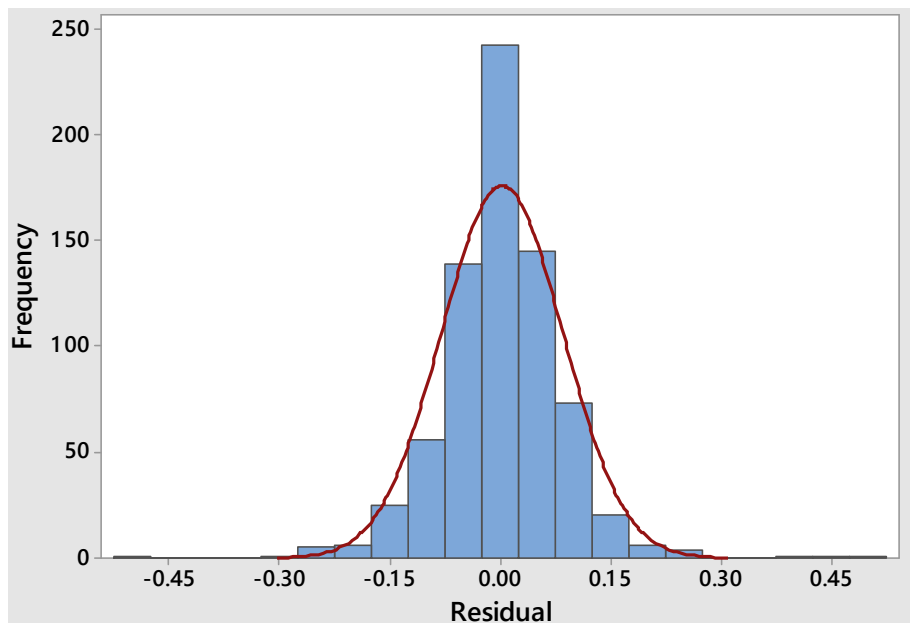


Figure 3.28: Residual Normally Distributed

Further analyses of ACF and PACF of the residuals (as Figure 3.29 and Figure 3.30) indicates no correlations among the residuals, *i.e.*, the residuals are random.

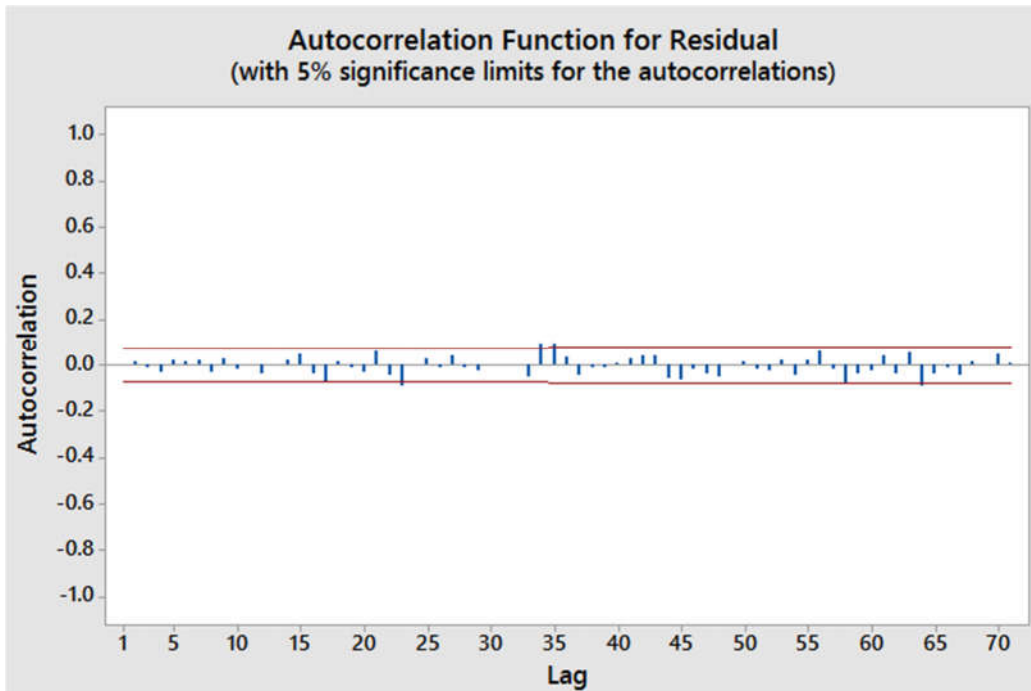


Figure 3.29: ACF of Residuals

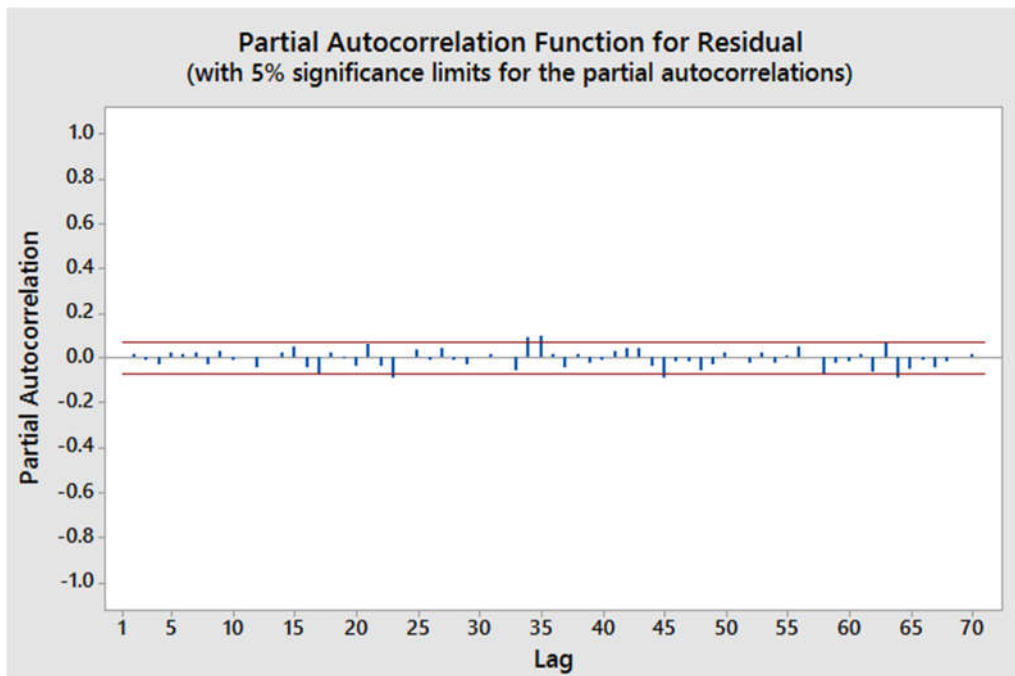


Figure 3.30: PACF of Residuals

3.5 Chapter Summary

In this chapter, time series models from the mathematical domain were introduced. Manufacturing energy consumption at the lower level was further analyzed. Sensitive features from the manufacturing systems were categorized into three classes, and introduced into time series models to illustrate the bottom-up modeling approach.

Traditional time series models and models with exogenous inputs were established for an automotive assembly manufacturing plant to illustrate the application of time series techniques into the manufacturing plant energy forecasting. Data trend and seasonality were detected, and estimations were made to the model parameters. The ARMAX models with exogenous inputs show a better accuracy in MSE and are more robust to the sudden deviation.

3.5.1 Chapter Broader Impact

The time series approach for energy consumption can also be applied to other similar plants and other resources, such as water consumption. The result of the energy consumption forecasting from the ARMAX model can be as one of the inputs for the later energy supply system optimization constraints.

Detailed broader impact can be found in Chapter Five Section 5.1.2.

3.5.2 Chapter Contribution

The contributions of the research in this chapter are as follows.

- 1) This work recognized the increasing trend, annual, and weekly seasonality in the energy consumption of automotive assembly plant.
- 2) This work introduced manufacturing featured key variables into the traditional time series models, and improved the model accuracy and robustness.
- 3) The energy demand forecasting results are essential to intelligently schedule the production, manage the working conditions, and stabilize energy supply.
- 4) This work can assist the understanding on how the manufacturing plants affect the local energy distribution.
- 5) This work is promising to be further applied into real time forecasting and its outputs can be used as constraints for on-site energy optimization.

3.6 Chapter Three References

[3.1] P. J. Brockwell and R. A. Davis, Introduction to Time Series and Forecasting. New York: Springer-Verlag, 2002.

[3.2] S. J. Taylor, Modelling Financial Time Series (Second Edition). World Scientific Publishing, 2007.

[3.3] H. Kömm and U. Küsters. “Forecasting Zero-Inflated Price Changes With A Markov Switching Mixture Model For Autoregressive And Heteroscedastic Time Series,” *International Journal of Forecasting*, **31(3)**, pp. 598-608, 2015.

[3.4] S. Saab, E. Badr, and G. Nasr. “Univariate Modeling And Forecasting Of Energy Consumption: The Case Of Electricity In Lebanon,” *Energy*, **26(1)**, pp. 1-14, 2001.

[3.5] R. E. Abdel-Aal and A. Z. Al-Garni. “Forecasting Monthly Electric Energy Consumption In Eastern Saudi Arabia Using Univariate Time-Series Analysis,” *Energy*, **22(11)**, pp. 1059-1069, 1997.

- [3.6] P. G. Gould, A. B. Koehler, J. K. Ord, R. D. Snyder, R. J. Hyndman, and F. Vahid-Araghi. "Forecasting Time Series With Multiple Seasonal Patterns," *European Journal of Operational Resource*, **191(1)**, pp. 207-222, 2008.
- [3.7] S. S. Pappas, L. Ekonomou, D. C. Karamousantas, G. E. Chatzarakis, S. K. Katsikas, and P. Liatsis. "Electricity Demand Loads Modeling Using Autoregressive Moving Average (ARMA) Models," *Energy*, **33(9)**, pp. 1353-1360, 2008.
- [3.8] C. E. Asbury. "Weather Load Model For Electric Demand And Energy Forecasting," *IEEE Transactions On Power Apparatus and Systems*, **94(4)**, pp. 1111-1116. 1995.
- [3.9] Y. Li, Y. Su and L. Shu. "An ARMAX Model For Forecasting The Power Output Of A Grid Connected Photovoltaic System," *Renewable Energy*, **66**, pp. 78-89, 2014.
- [3.10] J. R. Cancelo, A. Espasa, and R. Grafe. "Forecasting The Electricity Load From One Day To One Week Ahead For The Spanish System Operator," *International Journal of Forecast*, **24(4)**, pp. 588-602, 2008.
- [3.11] T. Samak, C. Morin, and D. Bailey. "Energy Consumption Models And Predictions For Large-Scale Systems," *Proceeding of 2013 IEEE 27th International on Parallel and Distributed Processing Symposium Workshops & PhD Forum (IPDPSW)*, 2013.

CHAPTER FOUR

ENERGY SUPPLY OPTIMIZATION

4.1 Research Question Restatement

Research Question Three: What are the tradeoffs of optimal energy operation strategies in a manufacturing plant?

4.2 Background and Knowledge Gap Introduction

The previous chapters introduced the importance of understanding energy consumption within the manufacturing plants, and how to build models to help identify the energy consumption and potential conservation opportunities. This chapter is going to study the optimization problems in the plant energy supply system, especially for the plants with on-site energy conversion and transmission systems. Generally, manufacturing plants have demand on many different energy carriers and the on-site energy supply system can be operated variously to satisfy the demand. However, “How to operate the system? What to optimize – energy, monetary cost, or emission pollutants?” are the questions discussed in this chapter.

This section will begin with the introduction of some basic concepts – energy carriers, energy conversion and transmission system, equipment efficiencies, and renewable energy methods. Then the literature of the plant energy supply optimization will be reviewed. Finally, the knowledge gaps in energy supply optimization of manufacturing plants are summarized.

4.2.1 Introduction to Energy Carriers

The energy carrier, also known as secondary energy, is a substance or phenomenon that contains energy which can be used for energy transport and further conversion to apply to manufacturing production lines. Common energy carriers include electricity, hot water, natural gas, and compressed air. In many manufacturing plants, a variety of energy carriers are employed to support the complex production system [4.1]. The schematic location for the energy carrier is shown in Figure 4.1.

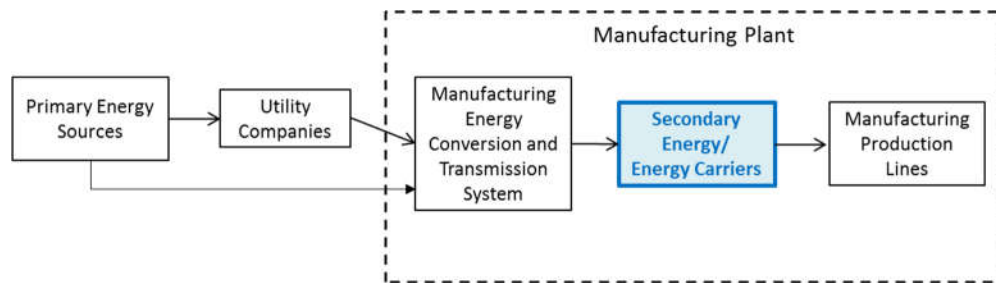


Figure 4.1: Manufacturing Plant Energy System

Electricity is one of the most general energy carriers. It is widely used to power production equipment (such as motors and pumps) and to maintain the building environment (such as lighting and ventilation). Thermal energy is another widely-used energy which can be contained in multiple carrier types such as hot water, steam and natural gas. Another popular energy carrier is compressed air, which can be easily converted to mechanical energy; however, at a higher cost.

In later sections of this chapter, we refer the primary energy sources and energy carriers from the utility companies as *purchased energy*; the secondary energy from the onsite energy conversion and transmission system as *demand energy*.

4.2.2 Energy Conversion and Transmission

Purchasing all demand energy directly from the utility company requires only a small capital investment but it is neither cost reasonable, nor pragmatic in the long term. To face the variable production conditions and changeable energy prices, plants are typically equipped with an onsite (*decentralized*) energy conversion and transmission system. While the purpose of energy transmission is only to deliver the same forms and amount to the production lines, conversion involves changes in the energy forms and quantities. Typical energy conversion forms include combustion, electricity generation, air compression and thermal energy exchange. Representative examples of the energy conversion is given here. Combustible energy (such as coal, oil and natural gas) are burned in the combustion chamber to generate steam which rotates the turbine connected with an electrical generator. In this way, the chemical energy from the primary energy is converted to electricity. Traditional fired generation systems release the exhaust gas to the atmosphere; however, a co-generation or tri-generation system will recover part of the thermal energy through heat exchange to create hot water or steam for later use. In this case, the thermal energy is also captured [4.2]. Take other examples, burners convert chemical and thermal energy and chillers convert electricity and thermal energy. Usually, a burner/boiler will be on-site to supplement hot water/steam for production or building heating [4.3]. Chilliers use

electricity to generate chilled water, used for equipment and building cooling [4.4]. In the case of air compression, air compressors use electricity as energy input to compress air to a higher pressure for carrying energy to the shop floor [4.5]. Detailed energy modeling of these traditional energy conversion and transmission systems is relatively straightforward and well-studied [4.6].

4.2.3 Efficiency and Coefficient of Performance

Efficiency is one of the key parameters to evaluate the effectiveness of energy conversion and transmission. It is usually calculated as the ratio of amount of output energy (E_{out}) to input energy (E_{in}):

$$\eta = E_{out} / E_{in} \quad (4.1)$$

The coefficient of performance (COP) is another parameter used to measure the effectiveness of energy conversion, especially in cooling processes [4.7]. The formula for calculating COP is given as follows:

$$\begin{aligned} COP &= \frac{C_{net}}{P_{in}} = \frac{\text{Net Capacity (Watts)}}{\text{Power Input (Watts)}} \\ &= \frac{(\text{Gross Cooling Capacity}) - (\text{Supply Fan Heat})}{(\text{Supply Fan}) + (\text{Compressor(s)}) + (\text{Condenser Fan(s)})} \end{aligned} \quad (4.2)$$

For a heat pump with COP=2.5, it means it can produce two and a half times as much heat than the heat equivalent of the watts input. Typically, a vapor compression chiller (e.g. centrifugal compression chiller) has a COP of 4.0, and the absorption chiller has a COP of 0.5 since it requires a tremendous amount of thermal energy input.

4.2.4 Renewable Energy

Apart from the geothermal and biomass energy, which have high requirements on the techniques and are particular to location, solar and wind generation are two relative popular renewable energy sources for the manufacturing plants. However, compared with traditional energy supplies, solar and wind are relatively unstable.

Solar energy is used to provide high temperature as a process heat source, which has seen increased use recently [4.8], or electrical power from photovoltaic (PV) solar panels, which depends on weather condition and temperature. Researchers use the MPPT (maximum power point tracker) to calculate the most power they can obtain from the sun:

$$P_s(G, \Delta T) = k_1 \cdot A_s \cdot G \cdot (1 - k_T \Delta T) \quad (4.3)$$

where A_s is the total area of the PV model (m^2), $\Delta T = T_c - T_{cref}$ the temperature difference between the cell temperature T_c and the reference cell temperature T_{cref} ($^{\circ}C$), k_T is the temperature coefficient, and k_1 is the PV module generation efficiency

[4.9]. Solar irradiation G is often described in stochastic models to solve the problem of unstable availability of the solar input.

Wind power can be captured through coupled wind towers and turbines. The available wind generator power P_{out} can be expressed as a function of wind speed V_{wind} :

$$P_{out}(V_{wind}) = \begin{cases} P_{rated} \cdot \frac{(V_{wind}^k - V_{in}^k)}{(V_{in}^k - V_{rated}^k)} & \text{if } V_{in} \leq V_{wind} \leq V_{rated} \\ P_{rated} & \text{if } V_{rated} \leq V_{wind} \leq V_{out} \\ 0 & \text{Otherwise.} \end{cases} \quad (4.4)$$

where P_{rated} is the rated power of turbine which is design specifics generally given by the turbine manufacturers, V_{in} is the cut-in wind speed, V_{rated} is the rated wind speed, V_{out} is the cut-out wind speed, k is the Weibull shape parameter. Like solar irradiation, wind speed is also commonly described by a random variable distribution function [52].

Landfill gas is another renewable energy used to replace the consumption of natural gas. Compared with natural gas, landfill gas has lower methane content and relatively low quality. Generally, landfill gas has only half heating content of natural gas. However, compared with other renewables, landfill gas is highly reliable and constant. As long as the manufacturing plant can find suppliers with landfill gas, and can have a long-term contract and by small modifications to their current equipment (usually burners), landfill gas can be used directly.

4.2.5 Plant Energy Supply Optimization

Multiple criteria need to be taken into consideration when making decisions about sustainability in energy management. Jiangjiang Wang and his colleagues reviewed the work done in energy decision making [4.10]. According to their paper, the criteria can come from techniques, economy, environment and society. They also pointed out that the decision of criteria selection could be difficult, and they came up with the principles to follow and elementary methods to apply when choosing the major criteria.

The weighting method is one of the most popular approaches when dealing with multicriteria optimization. Generally, the decision maker will assign preferential weights to different normalized criteria and force the multi-objective problem to be a single cost function. Equal weights method without prudent knowledge gives the objectives the same priority and treated equally, while rank-order weighting drives the ranking of each objective hierarchically to determine the priority in optimization. This method does not necessarily encompass deeper knowledge of the problem (such as the lexicographic optimization), but instead calls for subjective opinions [4.11].

Apart from converting to single objectives, multicriteria programming allows for solving the problem with non-dominated points called efficient or Pareto optima [4.11]. The Pareto optimal solution is a state where it is impossible to improve one objective without sacrificing at least one of the others. In planning distributed energy resources, applications of the Pareto optima approach are seen in [4.12 – 4.14] Rodriguez and his group organized a review on the multi-objective planning of distributed energy resources;

they concluded that this area is promising and will provide guidance to the future development of distributed energy sources [4.12].

D. Buoro and his team studied an industrial area where different economic sectors (e.g., food, plastics, furniture manufacturers, and so on) clustered to share an energy facility – a district heating network, small CHP systems, large centralized solar plant and a thermal storage [4.13]. In their paper, mixed integer linear programming was used to consider the influence from energy cost and carbon dioxide emission caused by the operation. The relative weights of the energy and emission minimization objectives were varied to identify the Pareto front solutions. This optimization was developed under the condition of steady state operation without considering the fluctuation caused by demand variation in different scenarios.

A. Lazzaretto and A. Toffolo took an example to discuss the energy objective in terms of exergetic efficiency in a cogeneration plant, economy in the total cost of fuel and environment effects through the conversion of pollution damage cost of multiple emission pollutants [4.14]. Their research considered the primary zone combustion temperature, combustor inlet pressure and pressure drop in the combustion chamber of cogeneration system to calculate the emission of nitrogen oxides and carbon monoxide. Single objective on each of the cost functions and multicriteria optimization with a Pareto surface was given in the paper to illustrate the tradeoff of the optimal solutions. This paper concentrated on the thermal systems design, but neglected the multiple energy demands of current manufacturing systems.

4.2.6 Knowledge Gap Summary

Besides the traditional straightforward energy supply, modern manufacturers tend to have their own on-site distributed energy generation and conversion systems to fulfill the variety energy carriers' demands over the production cycle. However, the questions of 1) how to efficiently operate on-site energy conversion and transmission systems, 2) how to coordinate the on-site system with the primary energy delivery from the utility companies, and 3) how to achieve the best results in terms of energy, cost, and emissions, have rarely been discussed before.

4.3 Approach

Although the initial investment and construction is critical, our research focuses on the post-processing stage of the energy usage and its associated effects. The main assumptions of the below-described approaches are:

- The supply system is already on-site, and there is no need for further capital investment;
- In order to achieve the optimal energy supplies, there is no need for production equipment upgrade;
- The energy inputs from the suppliers can satisfy the plant demand and can be provided in time.

4.3.1 Objectives

It is unlikely the manufacturers can rely on the renewable energy completely, purchasing energy from suppliers is most of the cases. Meanwhile the relation between environmental impact and the energy consumption is well known. While the objectives of energy cost in terms of megawatt hours, U.S. dollars or emissions do not always lead to consistent energy management strategy. It is of importance to understand the analysis and optimization objectives.

Purchased Energy in MWh

Energy consumption per unit production is one of the key parameters to evaluate the overall efficiency of the energy usage from the manufacturing plant. In 1992, the U.S. Environmental Protection Agency (EPA) launched a voluntary program (ENERGY STAR) that was intended to assist the public to save money and protect the environment. In this program, fifteen industrial foci compared and published the energy use in the same areas to encourage the best practice. Therefore, the amount of energy purchased by the plant is one of the objectives. In this chapter, we calculate the amount of purchased energy in the unit of MWh and the first objective/criterion function can be expressed as:

$$z_1 = \sum_{i=1}^m E_i = J_{1 \times m} \cdot E \quad (4.5)$$

where E_i is the amount of purchased energy in MWh; m is the number of types of energy inputs to the plant.

Cost – operation cost, purchased energy cost

The cost of the energy operation comes from two major parts –facility maintenance cost [4.15], and operation source energy consumption. While the operation source energy consumption is continuously proportional to the use of primary energy input, the maintenance cost is mostly periodic according to the scheduling [4.15].

$$z_2 = \sum_{i=1}^m CE_i + \sum_{j=1}^n (k_j \cdot CM_j) \quad (4.6)$$

where CE_i is the cost of i^{th} purchased energy; j is the index of equipment in the energy system; n is the number of pieces of equipment; k_j is the number of maintenance resources deployed during the modeling period to the j^{th} equipment; CM_j is the maintenance cost of j^{th} equipment. This is expressed in the format of the matrix

$$z_2 = J_{1 \times m} \cdot CE + J_{1 \times n} \cdot CM \quad (4.7)$$

where the ones matrix J is used for summation. CE and CM are the matrices with elements of CE_i and CF_i .

Emission – CO₂, NO_x and SO₂

Emission related to energy usage can be quantified through the emission index (also known as the *environmental coefficient*) with units of kilograms per megawatt hour. For example, the three major emissions – sulfur dioxide, nitrogen oxides and carbon dioxide from electricity in South Carolina, USA can be found in [4.16]. The pollutant effect of the emission can be used as one environment objective. Sulfur dioxide is the major component in the formation of acid rain. Nitrogen oxides can contribute to acidification and eutrophication of waters and soils; and when it exits the atmosphere, could be the reason of particle matter and ground-level ozone formation. Both sulfur dioxide and nitrogen oxide can cause health problems in the respiration system. Carbon dioxide is well known for its greenhouse gas effect, and series of impacts related to global warming. The objective in this case could be formulated as

$$z_3 = EF \cdot E \quad (4.8)$$

where EF is the emission vector for each of the emission. For example, in the latter case where the plant purchases landfill gas, natural gas and electricity. Emission objective z_3 can be constructed as

$$z_3 = EF \cdot E = \begin{bmatrix} \frac{\text{kg CO}_2}{\text{MWh Ele}} & \frac{\text{kg CO}_2}{\text{MWh NG}} & \frac{\text{kg CO}_2}{\text{MWh LFG}} \\ \frac{\text{kg NO}_x}{\text{MWh Ele}} & \frac{\text{kg NO}_x}{\text{MWh NG}} & \frac{\text{kg NO}_x}{\text{MWh LFG}} \\ \frac{\text{kg XO}_2}{\text{MWh Ele}} & \frac{\text{kg SO}_2}{\text{MWh NG}} & \frac{\text{kg SO}_2}{\text{MWh LFG}} \end{bmatrix} \begin{bmatrix} \text{MWh Ele} \\ \text{MWh NG} \\ \text{MWh LFG} \end{bmatrix}. \quad (4.9)$$

While considering several pollutants together, it is difficult to compare the impact each of them could have on the environment. Simply put, the harmfulness from one gram of carbon dioxide is not equal to the harmfulness of one gram of nitrogen oxide. Thus, straightforward summation of these parameters is not an ideal way to set one objective. In paper [4.17, 4.18], the concept of pollution damage cost was introduced. They took the emission from a district heat network and calculate the spending on heat pumps, cogeneration and/or gas furnace conversion. The monetary cost per kilogram of nitrogen oxides and carbon dioxide were calculate based on their system specifics. The revised third objective function can be expressed as:

$$z_3' = CEM \cdot EF \cdot E \quad (4.10)$$

where CEM is the pollution damage cost matrix [\$/kg].

Once the environmental impact is expressed in terms of monetary cost, the third objective is combined with the second objective to formulate the criterion of combined operational and environmental cost.

$$z_{23} = J_{1 \times m} \cdot CE + J_{1 \times n} \cdot CM + CEM \cdot EF \cdot E \quad (4.11)$$

However, the absolute values of pollution damage cost are difficult to stipulate. The reasons are complex, including but not limited to the lack of data on pollution damages, and inability to precisely measure the emissions [4.19]. For example, carbon dioxide (CO₂) is the most famous emission ostensibly causing global warming. It is also the emission gas correlated most closely with monetary cost in many countries. The amount that needs to be paid to emit CO₂ into atmosphere is called the *Carbon Price*. Basically, the carbon price is related the greenhouse gas CO₂ with the market. The largest carbon market is the European Union Emission Trading Scheme (EU ETS), in terms of market value and trading volume [4.20]. EU ETS puts limit on overall emissions from high-emitting industry sectors. Within the limit, companies can buy and sell emission allowances as needed. Therefore, the “cap-and-trade” approach gives companies the flexibility to cut their emissions in the most cost-effective way. EU ETS covers more than 11,000 power stations and manufacturing plants. In total, around 45% of overall EU emissions are limited by EU ETS [4.21]. The European Climate Exchange (ECX) is the largest carbon exchange market within the EU ETS, since its daily carbon trading volume generally accounts for over 80% of the total carbon trading volume of EU ETS [4.22]. It is reported that the variation of the carbon price is caused by institutional decisions; energy prices and weather events; macroeconomic and financial market shocks [4.23].

Multicriteria objective function

As long as the objectives in the optimization problems are more than one, the problem is called multicriteria objective optimization. In this case, three objectives are concurrently minimized:

$$\min(z_1, z_2, z_3) \quad (4.12)$$

There are many ways to deal with the different objectives. The simplest is to assign equal weights to each of the normalized objective and sum them to be one objective. In this way, the outcome will treat each of the objective as having the same preference.

$$Z = \alpha_1 z_1 + \alpha_2 z_2 + \alpha_3 z_3 \quad (4.13)$$

Programmers can also change the weights based on decision makers' preference on the objectives, or give multiple options to rank different priorities to the problem.

4.3.2 Constraint

The constraints of the optimization problem come from three aspects – equipment capacity, utility supply and production demand.

Equipment

The existing facility will have a constant number of equipment available, and the capacity of each piece of equipment is fixed in certain range. During the optimization, equipment capacity needs to be set to limit the feasible solutions. For example, if the maximum capacity of the burner is 100MWh per day and the plant owns two burners, the constraints for the burner should be set as 200 MWh per day.

Supply

Energy suppliers and the stability of renewable energy resources need to be carefully considered in an energy system. An optimal solution outside of the supply capacity is infeasible. For example, in a cloudy day, the energy outputs of solar panels cannot reach maximum due to the shortage of supply solar energy. Constraints should be set according to the availability of supply energy.

Demand

The energy demand from the manufacturing production line is one of the most important constraints needing to be satisfied. The energy demand is not constant; it depends on many factors, such as the production schedule, productivity, weather conditions, process line maintenance, and mixture ratios of the products. For example, in extreme days like very cold winter days, the energy demand on the hot water and electricity will be tremendously high. Optimization to satisfy these extremes is crucial in guaranteeing the throughput. It will be beneficial to have an energy demand forecasting model in order to

have a single day or single week prediction on the coming energy demand. Therefore, the output of forecasting results in Chapter Three can be the one of the inputs in the optimization. In that case, a dynamic optimization can be developed in everyday operations to reach the objectives.

With the on-site energy generation, conversion and transmission system, the energy demand can be calculated by the amount of purchased energy through the equipment specifics.

$$E_i = x_{i,h} \cdot ED_h \quad (4.14)$$

where h is the index of energy from production line demand; ED_h is amount of h^{th} the energy demand; $x_{i,h}$ is the facility operational parameter to convert energy demand from manufacturing processes to the plant purchased energy.

4.4 Case Study

In this section, the authors use the programming methods developed in section 3 to study an automotive assembly manufacturing system and illustrate how the approach is applied.

4.4.1 Case Study Introduction

The automotive assembly manufacturing plant production lines can be separated into three main departments – body shop, paint shop and final assembly shop. The body shop is mainly responsible for the vehicle body welding. Stamped panels and parts produced on site, or from an external supplier will be welded together to a vehicle body-in-white. In the body shop, energy is used to move the parts from one location to another, and electricity and compressed air will be used in the welding process. The vehicle body-in-white from the body shop will be transported to the paint shop.

The paint shop is reported to be the most energy intensive department in the plant [4.24]. The painting and sealing process will be deployed in this department to make the vehicle corrosion resistant and protected. The vehicle body will go through several painting and sealing process followed by oven curing. A pretreatment tank with warm phosphate solution, booth with controlled temperature and humidity, and oven with controlled air flow temperature will call for large amounts of energy. Hot water, chilled water, natural gas, and electricity are typically required in this department to support the processes.

Final assembly is the department which assembles the vehicle components and powertrain to the painted body. This department also needs energy carriers such as electricity and compressed air. Besides the energy used on the process lines, energy demand in the plant is also used on building services, mainly lighting, heating, ventilation and air conditioning [4.25].

In summary, the energy carriers' demand includes: electricity, natural gas, hot water chilled water and compressed air. The studied manufacturing plant purchases three

energy carries from the suppliers – electricity, natural gas and landfill gas. Thus, the onsite energy conversion and transmission should be modeled as a three-input, five-output system as represented in Figure 4.2.

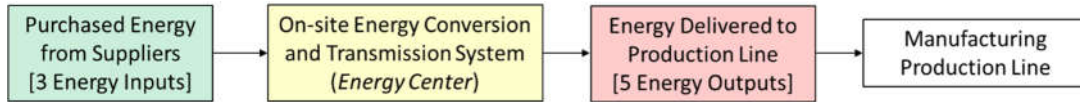


Figure 4.2: On-site Energy Conversion and Transmission System

The cluster of onsite energy conversion and transmission systems is referred to in this chapter as the *Energy Center*, and represented in Figure 4.3.

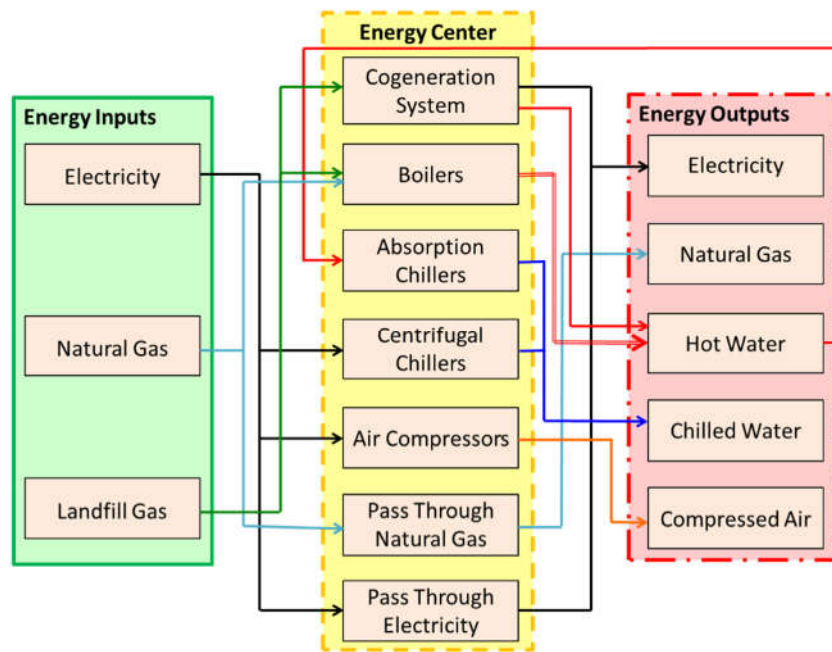


Figure 4.3: Energy Center Input-Output Schema

This figure is a simplification diagram of the case study, which illustrates a typical multiple input multiple output (MIMO) energy system. Electricity, natural gas and landfill gas are used as three energy source inputs to the Energy Center. Electricity, natural gas, hot water, chilled water and compressed air are the five outputs of the Energy Center.

The cogeneration system, which converts burnable fuel to both electricity and heat, is believed to have an average payback period of 2 – 5 years [4.26, 4.27]. In general, the combined heat and power (CHP) cogeneration system improves the energy efficiency over separate systems from traditionally 30% to an encouraging 70% (as Figure 4.4).

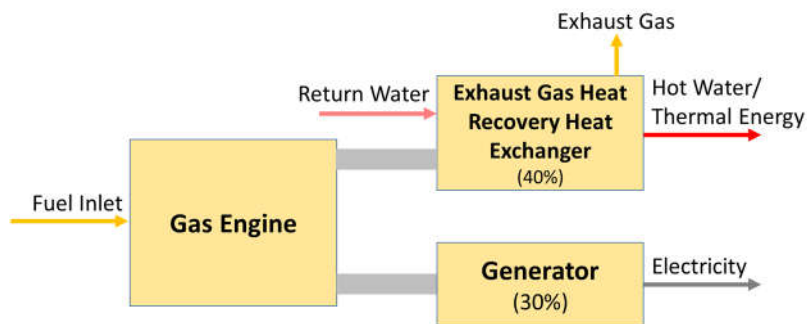


Figure 4.4: Cogeneration System Sketch

The cogeneration system can use many different energy sources, such as combustion gas, gasoline, coal, or biofuel, and depends on the equipment specifics; in our case the energy source is landfill gas, and it generates two forms of energy – electricity and hot water. Hot water can also be produced from boilers to supplement the combustion gas chemical energy to thermal energy. In this case, landfill gas and/or natural gas are used in boilers. The hot water could also be circulated back from energy outputs to the absorption chiller for chilled water production. The introduction of the absorption chiller to

cogeneration, is making the whole system even more efficient [4.28, 4.29]. In some publications, the incorporate of the absorption chiller to the CHP is called tri-generation [4.29].

Air compressors and centrifugal chillers transform the electricity into compressed air and chilled water respectively. From here we can define the energy conversion as a process of changing energy forms and qualities; energy pass-through, on the other hand is defined as a process of delivery energy in the same form and quality. Case study energy system includes both energy conversion and pass-through.

In the processes of energy conversion and pass-through, auxiliary power is unavoidable. For example, landfill gas from supplier needs to be pretreated before send to the combustion chamber of the cogeneration equipment. And during the process of pretreatment, such as gas filtration to eliminate the particle matter, electricity is used. In our model, the auxiliary procedures like the gas pretreatment of the cogeneration system are not discussed as an individual process. Instead, it is taken as a part of the cogeneration. And the electricity usage caused by the auxiliary processes is calculated as the conversion loss/inefficiency of the Energy Center.

4.4.2 Model Establishment

The Energy Center processes energy from suppliers and delivers the desired forms and amount of energy to the production line. The optimization discussed in this section focuses on the energy processed in the Energy Center.

Optimization Criteria

Three energy inputs from the suppliers need to be purchased. Here we assign an index to each of the three inputs as Table 4.1.

Table 4.1: Purchased Energy Indicator Assignment

Energy Inputs	Index i
Electricity:	1
Natural Gas:	2
Landfill Gas:	3

In this case $m = \text{number of indexes} = 3$. The energy purchase vector is:

$$E = \begin{bmatrix} E_1 \\ E_2 \\ E_3 \end{bmatrix} = \begin{bmatrix} \text{MWh Purchased Electricity} \\ \text{MWh Purchased Natural Gas} \\ \text{MWh Purchased Landfill Gas} \end{bmatrix} \quad (4.15)$$

Thus Equation (4.5) can be written as:

$$z_1 = J_{1 \times 3} \cdot E = [1 \quad 1 \quad 1] \begin{bmatrix} E_1 \\ E_2 \\ E_3 \end{bmatrix} \quad (4.16)$$

To simplify the problem, here we only consider the cost from the energy purchased, excluding the maintenance and degradation fees. Equation (4.6) in the previous section can be written as:

$$z_2 = \sum_{i=1}^3 CE_i = J_{1 \times m} \cdot CE \quad (4.17)$$

where the unit price of the three purchased energy used is represented in the price vector F_2 :

$$F_2 = \begin{bmatrix} 60 \\ 30 \\ 15 \end{bmatrix} \quad (4.18)$$

F_2 has the unit of US Dollars per megawatt hour.

The elements in the vector CE – cost of energy, and the second objective (z_2) function can be expressed as follows:

$$z_2 = (F_2)^T \cdot E \quad (4.19)$$

In terms of the environmental objective. The purchased electricity and natural gas can be converted to environmental emissions based on how the electricity was generated

and natural gas composition respectively. According to the US Environmental Information Administration, in year 2012, South Carolina has the electricity emission profile as shown in Table 4.2.

Table 4.2: 2012 South Carolina Electricity Emission Profile [4.16]

Emissions	Value [lbs/MWh]
Sulfur Dioxide	1.5
Nitrogen Oxide	0.5
Carbon Dioxide	778

Natural gas has a range for the emission profile according to the boilers used and the quality of natural gas. These values are given in Table 4.3.

Table 4.3: Natural Gas Emission Profile [4.30]

Emissions	Volumetric Mass [lbs/10 ⁶ scf] ^a	Power-Normalized Mass [lbs/MWh]
Sulfur Dioxide	0.6 ^b	0.0020
Nitrogen Oxide	32 – 100 ^c	0.11 – 0.33
Carbon Dioxide	120,000 ^d	401.39

^a The value is based on an average natural gas high heating value of 1,020 Btu/scf.

^b Based on 100% conversion of fuel sulfur to SO₂, with the natural gas sulfur content of 2,000 grains/10⁶scf.

^c Based on small boilers with <100MMBtu/hr heat input. The value range is caused by the NO_x control condition: 100 is uncontrolled, 32 is low NO_x burner with flue gas recirculation.

^d Based on 100% carbon converted to CO₂.

The emission caused by the landfill gas used is worthy of discussion. The main components in the landfill gas are methane and carbon dioxide. Additionally, there are many unstable compositions of both organic and inorganic compounds. The combustion of landfill gas will release greenhouse gases and other emissions into the atmosphere. However, the landfill gas is produced from landfill, without centralized collection and pretreatment for the later use, it would be discharged to the environment directly [4.31]. On the other hand, due to the consumption of landfill gas, the manufacturing plant does not need to purchase more electricity and natural gas, while the consumption of both energy inputs can cause environmental problem. In this case, we should consider landfill gas as a clean energy source which helps to prevent emissions by using less electricity and natural gas. Thus, when dealing with the landfill gas emissions, we will use negative values that represent the emission reduction by replacing the electricity and natural gas (as Table 4.4).

Table 4.4: Landfill Gas Emission Profile

Emissions	Through Cogeneration ^e Value [lbs/MWh]	Through Boiler ^f Value [lbs/MWh]
Sulfur Dioxide	-0.45	-0.0020
Nitrogen Oxide	(-0.21) – (-0.33)	(-0.11) – (-0.33)
Carbon Dioxide	-447.47	-401.39

^e Based on 30% efficiency in electricity, 40% efficiency in hot water, and 75% efficiency in boilers.

^f Based on the same efficiency in boilers for both gases.

If one of the three major pollutants is used as an objective, the third single objective function can be written as:

$$z_3 = (F_3)^T \cdot E \quad (4.20)$$

F_3 could be the vector with any of the emission pollutants. For example, if choose

carbon dioxide as the objective emission, $F_3 = \begin{bmatrix} 778 \\ 401 \\ -447 \end{bmatrix}$ when landfill gas is only used in

cogeneration system, with unit of pound per megawatt hour. F_3 can also be any set of combined emission factors to represent the degree of harm from each energy to the environment. For example, in paper [4.32], the authors use the unification of damage cost to combine the factors from different emission pollutants. However, in this case study, emissions from different pollutants are not combined because of the big gaps among the countries and years.

Efficiency

Equipment efficiencies and energy conversion ratios are represented as an energy-equipment coefficient and all together denoted in the 6×8 matrix *Coeff* as shown below.

$$Coeff = \{c_{i,j}, i = 1, 2, \dots, 6; j = 1, 2, \dots, 8\} \quad (4.21)$$

Consider $c_{i,j}$ to represent the coefficient of i^{th} energy carriers with j^{th} equipment. For example, the hot water produced through CHP has the efficiency of 40%. Here, i refers to the hot water generated, j refers to the CHP system, and $c_{i,j} = 0.4$ in the matrix. The matrix can be written as Table 4.5.

Table 4.5: Coeff matrix

		1	2	3	4	5	6	7	8
		CHP	Boiler use LFG	Boiler use NG	Absorption chiller	Centrifugal chiller	Air compressor	NG from pipe to production	Ele from grid to production
1	Electricity generated								
2	Hot Water generated								
3	Chilled Water								
4	Natural Gas								
5	Compressed Air								
6	Purchased Electricity								

For a specific energy supply system, the coefficient matrix can be obtained from the equipment manual or energy monitoring system.

Constraints

Energy supplied from the Energy Center to the production line can be expressed as:

$$S = TF \times [Coeff \times X] - B \times X \quad (4.22)$$

where TF is 5×6 transfer matrix; $Coeff$ – 6×8 Coefficient matrix; X – 8×1 Equipment/Energy Center consumption vector (it is processed as the form of energy, and in unit of MWh), and B is 5×8 inner loop matrix that represents the amount of energy cycling inside of the Energy Center.

Demand should be no more than the output of the Energy Center, *i.e.* $D \times S$ where D – 5×1 Energy demand vector.

Assume the optimization is developed on a daily basis. The average energy demand distribution to the three departments is shown in Figure 2.23. In order to protect the confidentiality of operational data at the OEM, a nominal representative value of daily energy demand E_D from the major plant was chosen, and all energy data can be normalized to this value.

Aside from major plant demand, constraints also come from capacities. Constraints from equipment lower bounds and upper bounds can be defined through the matrix $X : LB \leq X \leq UB$ as shown in Table 4.6.

Table 4.6: Lower and Upper Bound

[MWh]	Lower Bound	Upper Bound
Cogeneration	0	$0.70E_D$
Boiler (LFG)	0	$0.70E_D$
Boiler (NG)	0	$0.25E_D$
Absorption Chiller	0	$0.02E_D$
Centrifugal Chiller	0	$0.04E_D$
Air Compressor	0	$0.04E_D$
Pass Through Gas	0	∞
Pass Through Electricity	$0.03E_D$	∞

The lower bound is assumed as the situation when the plant is completely shut down and the only electricity consumption is to make sure the plant and its facilities are protected from damage. The upper bound is assumed as the equipment and/or supply capacity.

In addition, the transfer function T is used to transform the energy consumed by equipment to energy purchased from suppliers, as

$$\underbrace{\begin{bmatrix} \text{Ele} \\ \text{NG} \\ \text{LFG} \end{bmatrix}}_E = \begin{bmatrix} \square & \dots & \square \\ \vdots & \ddots & \vdots \\ \square & \dots & \square \end{bmatrix} \begin{bmatrix} \text{Cogeneration} \\ \text{Boiler (LFG)} \\ \text{Boiler (NG)} \\ \text{Absorption Chiller} \\ \text{Centrifugal Chiller} \\ \text{Air Compressor} \\ \text{Pass Through Gas} \\ \text{Pass Through Electricity} \end{bmatrix} = \underbrace{\begin{bmatrix} t_{11} & \dots & t_{18} \\ \vdots & \ddots & \vdots \\ t_{31} & \dots & t_{38} \end{bmatrix}}_T \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_8 \end{bmatrix}}_X$$

(4.23)

T – 3×8 Transfer matrix (transfer equipment/Energy Center consumption vector X to E);

E – 3×8 Purchased Energy vector.

4.4.3 Results

Table 4.7 summarizes the optimization result for each single objective.

Table 4.7: Optimization Results

Objective \ Result	Supply [MWh]	Cost [\$]	Emission [kg CO ₂]
Energy	E	$1.35C$	$45.38EM$
Economy	$1.17E$	C	$-EM$
Environment	$1.17E$	C	$-EM$

(E : energy in MWh; C : cost in US Dollars; EM : emission in kg CO₂.)

Table 4.7 gives out the optimization results on three objectives and also the resultant energy supply, monetary cost and carbon dioxide emission while operating the

Energy Center under each objective strategy. The minimum amount of energy is used when the objective is set to be MWh of energy; however, the cost to purchase the minimum amount of energy is 35% more than the result of monetary cost oriented optimization, while the emission is about 45.38 times of the environment oriented optimization. Likewise, the economy and environment oriented optimization gives out results with the minimum US Dollar cost and kg of CO₂ released, but has a higher result on the amount of supply energy in terms of megawatt hours. It proves the conflict among different objectives, and quantifies the differences.

It is worth paying attention to the results of the emission objective. In this automotive assembly plant, landfill gas is used as a renewable energy to generate hot water and electricity. Without the consumption of landfill gas, more electricity and natural gas will be used. In this consideration, the emission factor of landfill gas was set to be negative. Thus extra constraints need to be set to avoid the problem of misapplication the landfill gas to decrease plant emission. In the results of environmental emission as the objective, the negative result of emission will be achieved, since the system will automatically use more landfill gas over the electricity directly from the grid.

Energy Demand

A good energy demand forecasting for the next few steps (usually in days) are critical in energy operation strategy on the supply side. The traditional energy demand forecasting techniques are based only on the historical records and cannot typically satisfy the accuracy requirement. An inaccurate forecasting of the energy demand can lead to

waste in energy supply operations or supply failures, which can result in tremendous monetary loss. Energy demand of the manufacturing plant depends on many variables; some key inputs are the production rate, production schedule, working shifts, maintenance, and weather conditions [4.33]. Incorporating this extra knowledge into the traditional time series model can make the forecasting more robust and reliable. A time series model is proposed in Chapter Three to predict the energy demand for a given time horizon. By combining the energy demand forecasting and energy supply optimization, manufacturers can create a more informed strategy for the production scheduling and realize potentially high energy savings, as well as to monetary cost and carbon dioxide emission.

The original data used for demand is the plant running in a 2 shift working load (results shown in Table 4.7). It is common for the manufacturer to reduce the shifts for holidays and have fewer production planned days. However, the energy demand for half production does not usually equate to half the expected workload. If we assume the energy used in one-shift working days use about 60% of energy as a full production day, and the energy forms distribution keeps same breakdown as indicated in Figure 2.23.

Table 4.8: Effects of Demand on Energy Supply

[in E_D]	Energy		Economy		Environment	
	2 Shifts	1 Shift	2 Shifts	1 Shift	2 Shifts	1 Shift
Supply						
Electricity	44%	26%	23%	5%	23%	5%
Natural Gas	61%	37%	30%	18%	30%	18%
Landfill Gas	0%	0%	70%	70%	70%	70%

Table 4.8 shows the percentages of each energy form in terms of daily energy demand E_D (2 shifts) for normal production days. It compares the energy supply in two working load scenarios.

When the objective is to minimize the amount of purchased energy per produced vehicle, the optimization results will abandon the cheap, clean landfill gas and choose to use electricity and natural gas directly. While the optimization objective is either economy or environment, except for natural gas, electricity and landfill gas do not reduce proportionally as the demand. They use the maximum capacity of the Energy Center to achieve the different goals. For example, when the optimization objective is the environment protection, the result show the landfill gas purchase amount is the same as the 2-shift working load which lead to the small amount of electricity demand from the grid.

Except for the working load change, there are many other reasons influencing the energy demand, such as the production rate (number of vehicles produced per day), weather condition (seasonal changes and extreme weather days), and implementation of energy intensive or energy saving equipment. The model can be easily applied to test energy operation strategies according to the different reasons that cause the demand change, by changing the demand matrix accordingly.

Economy

Economy is crucial to the manufacturing plant. Lower monetary spending on the energy of the plant results in a more profitable product. However, the cost of energy is

affected by both higher and lower level – purchase energy unit price from the suppliers and energy demand from the production line.

The industrial average retail price for natural gas from Jan-2001 to Jan-2015 has ranged from \$3.02 to \$13.06 per thousand cubic feet; the heat content of NG is about 1030 BTU/ft³. The industrial average retail price for electricity from Jan-2001 to Jan-2015 has ranged from 4.71 to 7.72 cents/kWh (Table 4.9).

Table 4.9: Energy Unit Price Range

USD/MWh	Min	Max
Natural Gas	10.0	43.3
Electricity	47.1	77.2

Table 4.9 shows the energy unit price range for both natural gas and electricity.

Assume the landfill gas is the half price of natural gas.

The effect of unit price of landfill gas on the operation strategies is studied.

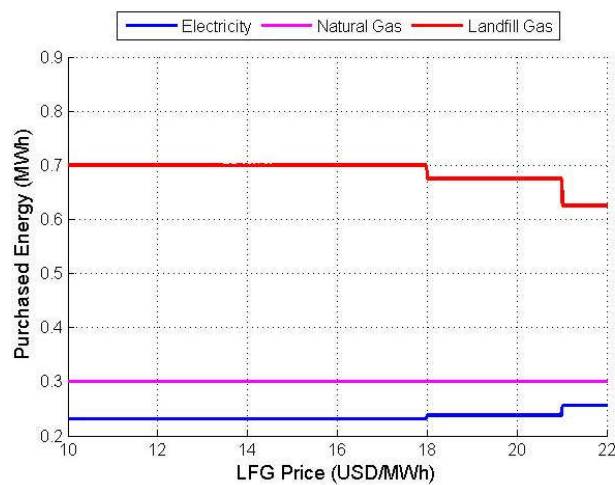


Figure 4.5: Effect of Landfill Gas Unit Price on Purchased Energy

A continuous change in the landfill gas unit price show the operation strategies change. From Figure 4.5, we can partition the landfill gas equation into three parts:

$$\left\{ \begin{array}{l} \text{LFG Price} < 18 \text{ USD/MWh} \\ 18 \text{ USD/MWh} \leq \text{LFG Price} \leq 21 \text{ USD/MWh} \\ 21 \text{ USD/MWh} < \text{LFG Price} \end{array} \right. \quad (4.24)$$

In the first partition, when the landfill gas is inexpensive, the optimization results in running the full capacity of cogeneration system, even when the produced hot water is greater than the demand from the production line. In this way the total cost is still minimized, because the cogeneration system produces the maximum amount of electricity.

In the second partition, even though the price of landfill gas increases, it still shows a high running rate. This is because using the extra hot water produced from the cogeneration system to run the absorption chiller is still less expensive than the cost of running centrifugal chiller by using grid power.

In the third partition, where the landfill gas is higher than 21 USD per MWh, the cogeneration only runs to give out enough hot water for the production line and the corresponding electricity. This is still less expensive than running the boiler and purchasing electricity from the grid.

Further examination also indicates that only when the unit price of landfill gas is larger than 33USD/MWh, operators should refrain from using the cogeneration system completely and choose to directly purchase grid power and natural gas instead. And it is

worth noting that the optimization result is highly related to the unit prices of the different purchased energies and also the efficient in energy conversion and transmission. In some cases, when the efficiencies of the equipment degrade as the time passes, the operators need to verify if the previous operation strategy still results in the desired state.

To better understand the effect from the purchased energy unit prices, analyses of electricity and landfill gas prices and how they together will affect the optimal results are given below (Figure 4.6, Figure 4.7 and Figure 4.8).

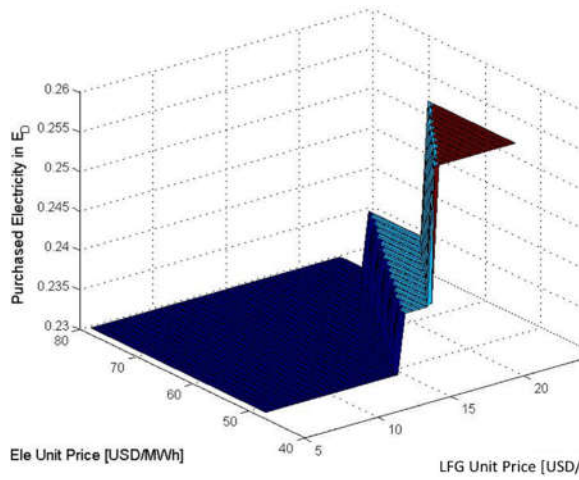


Figure 4.6: Combined Effect of Electricity and Landfill Gas Unit Price on Purchased Energy

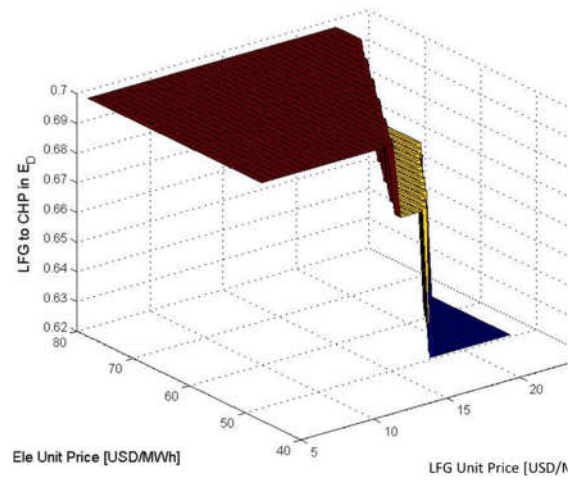


Figure 4.7: Combined Effect of Electricity and Landfill Gas Unit Price on Cogeneration Operation

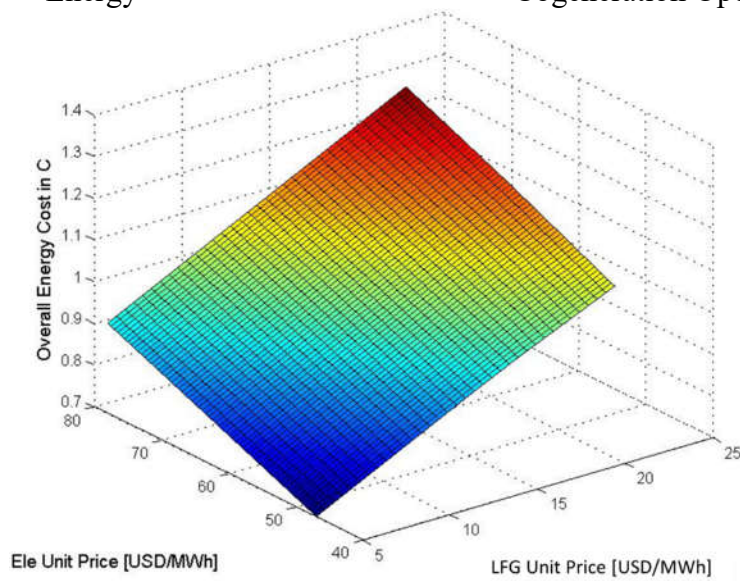


Figure 4.8: Combined Effect of Electricity and Landfill Gas Unit Price on Overall Energy Cost

Obviously the overall energy cost will increase along with the unit price of landfill gas and electricity. It worth noting that the usage of electricity and landfill gas changed

over the price. The reasons of shift from one energy to another is the same as explained in Figure 4.5.

Environment

The environmental emission is measured as the weight of the carbon dioxide in this section. The optimization results can be achieved through the single objective optimization as demonstrated in the Energy Demand and Economy. It worth to pay attention that the emission lead optimization also shows a discrete operation strategy as the adjustment of the emission parameters to each of the purchased energy. In calculating different environmental influences, changing the coefficient vector of F .

Multicriteria Optimization (MOP)

The decision makers will have multiple objectives in the real world energy management. Optimum operation strategies for the minimum energy consumption in terms of MWh do not necessary lead to the optimal result of energy cost. Multicriteria optimization is introduced in this section to illustrate how different objectives can be involved according to the priority of energy managers.

$$\min(z_1, z_2, z_3) \quad (4.25)$$

Among many MOP techniques, weighted sum scalarization technique is one widely used:

$$\min(Z) \tag{4.26}$$

where $Z = \alpha_1 z_1 + \alpha_2 z_2 + \alpha_3 z_3$, weights $(\alpha_1, \alpha_2, \alpha_3)$ are assigned to each objective as the priority in optimization.

Besides the weighted sum optimization, the ε -constraint method is another one commonly used.

$$\min(z_k) \tag{4.27}$$

Subject to $z_k \leq \varepsilon_k, k' = 1, 2, \dots, p \quad k \neq k'$, where $\varepsilon \in \mathbb{R}^p$. In this method, the energy managers can optimize the target objective to be minimal and control the other parameters low. For example, the ε -constraint method can be used to minimize the cost, while control the energy consumption and emission within the certain thresholds.

A plot of the objectives in both decision and criteria space is given below. In the decision space, the objectives are plotted in the vertical axis and the constraint is in the horizontal axis; while in the criteria space, one objective is plot in the vertical axis and the other is plotted in the horizontal axis. This method gives a better understanding on the relation between the constraint and objectives, and between two different objectives. It is only feasible when the objective is limited to two. Here, the objective of energy in MWh and cost in USD are selected for demonstration.

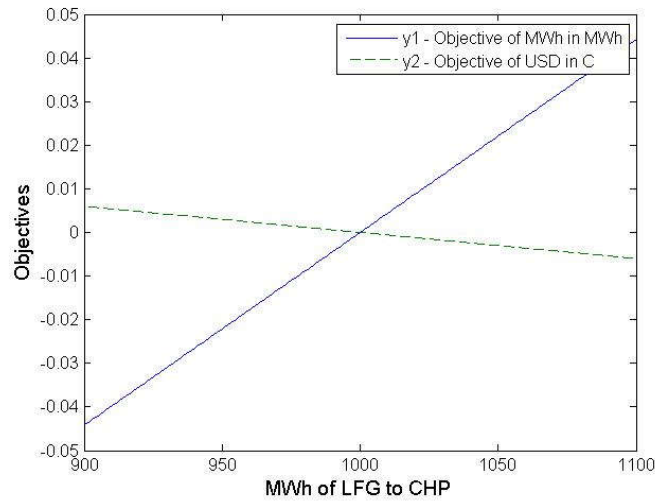


Figure 4.9: Objectives in Decision Space

By subtracting the mean values of two objectives, the decision space multicriteria optimization problem is shown as Figure 4.9. In the constraint range of X_1 , all solutions are Pareto efficient solutions for this bi-objective problem. To better understand the relationship between the two objectives, the criteria outcome space is constructed in Figure 4.10.

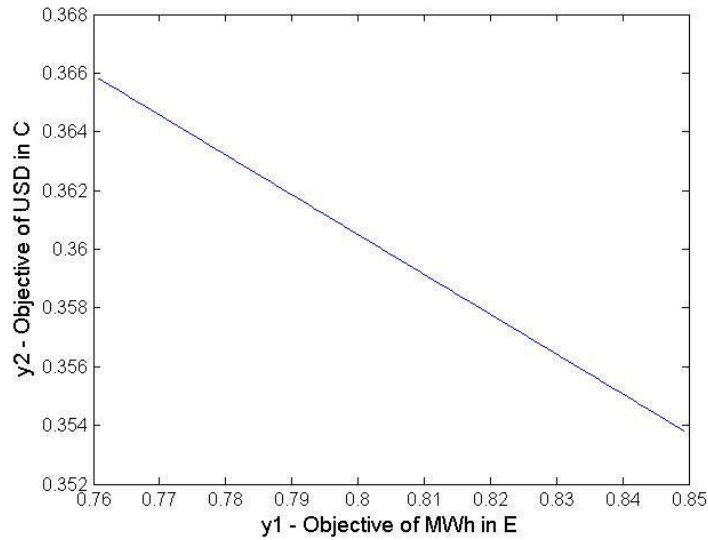


Figure 4.10: Objectives in Criteria Space

In such a case with an infinite number of efficient points, the decision makers' preference can be applied to choose a preferred solution.

Normalizing the F 's and setting different weights to each of the objectives, the result below is achieved:

Table 4.10: Multi-objective Optimization Results

	α_1	α_2	α_3	E_1	E_2	E_3
1	1	0	0	$1.48 E$	$2.04 E$	$0 E$
2	0	1	0	$0.79 E$	E	$2.25 E$
3	0	0	1	$0.79 E$	E	$2.25 E$
7	$1/3$	$1/3$	$1/3$	$0.79 E$	E	$2.25 E$
8	$8/10$	$1/10$	$1/10$	$0.85 E$	E	$2.08 E$

(E_1 , E_2 , and E_3 are normalized to value E in MWh.)

Table 4.10 gives the multi-objective optimization by giving sets of weights to each of the three objectives. It is interesting to see the discrete change in the result of purchased energy. Energy managers can select different operation strategies based on their various priorities of energy, cost and environment.

4.5 Chapter Summary

In this chapter, related studies on energy conversion, management, simulation, and optimization are summarized. Modeling approaches of plant on-site energy conversion and transmission system were given. A case study from an automotive assembly plant with a relatively complex three energy inputs and five energy outputs system was built to study the energy supply system. Both single objective and multi-objective optimizations were described in this chapter. Optimization of energy, economy and environment were analyzed.

4.5.1 Chapter Broader Impact

The research in this chapter gave example from an automotive manufacturing plants. The approach exemplified can be repeated to study many other systems with different equipment and facilities. The objectives selected in the studied case can be easily changed to other criteria and used to optimize the operation accordingly.

Detailed broader impact can be found in Chapter Five Section 5.1.3.

4.5.2 Chapter Contribution

The contributions of the research in this chapter is summarized as below.

- 1) Renewable energy is critical in affecting the operation. The renewable energy used can be taken as the traditional energy (*e.g.*, electricity and natural gas) conservation in terms of environmental emissions.
- 2) The operation strategies according to different optimization criteria – energy in megawatt hours, US Dollars, and emission pollutants are proved to be inconsistent.
- 3) The optimal energy supply need to be adjust according to both higher level (*e.g.*, energy market) and lower level (*e.g.*, production energy demand).
- 4) The decision makers’ priorities/preferences on the energy, cost, and environment directly affect the optimal operation of on-site energy supply.

4.6 Chapter Four References

[4.1] B. H. Bakken, H. I. Skjelbred, and O. Wolfgang. “Investment Planning In Energy Supply Systems With Multiple Energy Carriers,” *Energy*, **32(9)**, pp. 1676-1689, 2007.

[4.2] P. Ghadimi, S. Kara, and B. Kornfeld. “The Optimal Selection Of On-Site CHP Systems Through Integrated Sizing And Operational Strategy,” *Applied Energy*, **126**, pp. 38-46, 2014.

[4.3] R. Saidur, J. U. Ahamed, and H. H. Masjuki. “Energy, Exergy And Economic Analysis Of Industrial Boilers,” *Energy Policy*, **38(5)**, pp. 2188-2197. 2010.

[4.4] F. W. Yu and K. T. Chan. “Improved Energy Performance Of Air Cooled Centrifugal Chillers With Variable Chilled Water Flow,” *Energy Conversion and Management*, **49(6)**, pp. 1595-1611, 2008.

- [4.5] J. Zahlan and S. Asfour. "A Multi-Objective Approach For Determining Optimal Air Compressor Location In A Manufacturing Facility," *Journal of Manufacturing System*, **35**, pp. 176-190, 2015.
- [4.6] R. Vepa, *Dynamic Modeling, Simulation and Control of Energy Generation*. London, UK: Springer, 2013.
- [4.7] J. Mix, "HVAC Efficiency Definitions," *Carrier*, pp,1-7, 2006.
- [4.8] E. A. Carnevale, L. Ferrari, and S. Paganelli. "Investigation On The Feasibility Of Integration Of High Temperature Solar Energy In A Textile Factory," *Renewable Energy*, **36(12)**, pp. 3517-3529, 2011.
- [4.9] J. Li, W. Wei and J. Xiang, "A Simple Sizing Algorithm for Stand-Alone PV, Wind, Battery Hybrid Microgrids," *Energies*, **5**, pp. 5307-3523, 2012.
- [4.10] J. Wang, Y. Jing, C. Zhang and J. Zhao. "Review on multi-criteria decision analysis aid in sustainable energy decision-making," *Renewable and Sustainable Energy Reviews*, **13(9)**, pp. 2263-2278, 2009.
- [4.11] M. Ehrgott, *Multicriteria Optimization*. Berlin, Germany: Springer, 2005.
- [4.12] A. Alarcon-Rodriguez, G. Ault, and S. Galloway. "Multi-Objective Planning Of Distributed Energy Resources: A Review Of The State-Of-The-Art," *Renewable and Sustainable Energy Reviews*, **14(5)**, pp. 1353-1366, 2010.
- [4.13] D. Buoro, M. Casisi, A. De Nardi, P. Pinamonti, and M. Reini. "Multicriteria Optimization Of A Distributed Energy Supply System For An Industrial Area," *Energy*, **58**, pp. 128-137, 2013.
- [4.14] A. Lazzaretto and A. Toffolo. "Energy, Economy And Environment As Objectives In Multi-Criterion Optimization Of Thermal Systems Design," *Energy*, **29(8)**, pp. 1139-1157, 2004
- [4.15] M. S. Owayedh. "Energy Cost Based Technique For Maintenance Scheduling Of Generating Systems," *Proceeding of 7th Mediterranean at Electrotechnical Conference*, 1994.
- [4.16] US EIA "South Carolina Electricity Profile," *Energy Information Administration*, 2012.
- [4.17] V. Curti, M. R. von Spakovsky, and D. Favrat. "An Environomic Approach For The Modeling And Optimization Of A District Heating Network Based On Centralized And Decentralized Heat Pumps, Cogeneration And/Or Gas Furnace Part I: Methodology," *International Journal of Thermal Sciences*, **39(7)**, pp. 721-730, 2000.

- [4.18] V. Curti, D. Favrat, and M. R. von Spakovsky. "An Environomic Approach For The Modeling And Optimization Of A District Heating Network Based On Centralized And Decentralized Heat Pumps, Cogeneration And/Or Gas Furnace. Part II: Application," *International Journal of Thermal Sciences*, **39(7)**, pp. 731-741, 2000.
- [4.19] US EPA, "National Center for Environmental Economics -- Pollution Charges, Fees, and Taxes," *US Environmental Protection Agency*, <http://yosemite.epa.gov/ee/epa/eed.nsf/2602a2edfc22e38a8525766200639df0/e0b6a259b4e16cba8525777d000cbd0b!OpenDocument>, Accessed on May 2015.
- [4.20] Zhang, Y.J., & Wei, Y. M., "An Overview Of Current Research On EU ETS: Evidence From Its Operating Mechanism And Economic Effect," *Applied Energy*, **6**, pp. 1804-1814, 2010.
- [4.21] European Commission, "The EU Emission Trading System (EU ETS)," *EU Climate Publication*, European Union, Oct. 2013.
- [4.22] B. Zhu, P. Wang, J. Chevallier and Y. Wei, "Carbon Price Analysis Using Empirical Mode Decomposition," *Computational Economics*, **45**, pp. 195-206, 2015.
- [4.23] J. Chevallier, "Carbon Price Drivers: An Updated Literature Review," *International Journal of Applied Logistics*, **4**, pp. 1-7, Oct. 2013.
- [4.24] J. L. Rivera and T. Reyes-Carrillo. "A Framework For Environmental And Energy Analysis Of The Automobile Painting Process," *Proceeding of Procedia CIRP*, **15**, pp. 171-175, 2014.
- [4.25] Hao Liu, Qianchuan Zhao, Ningjian Huang, and Xiang Zhao. "A Simulation-Based Tool For Energy Efficient Building Design For A Class Of Manufacturing Plants". *IEEE Transactions On Automation Science and Engineering*, **10(1)**, pp. 117-123, 2013.
- [4.26] J. Zarnikau and B. Reilley. "The Evolution Of The Cogeneration Market In Texas," *Energy Policy*, **24(1)**, pp. 67-79, 1996.
- [4.27] Z. Sun. "Energy Efficiency And Economic Feasibility Analysis Of Cogeneration System Driven By Gas Engine," *Energy Building*, **40(2)**, pp. 126-130, 2008.
- [4.28] R. P. Marques, D. Hacon, A. Tessarollo, and J. A. R. Parise. "Thermodynamic Analysis Of Tri-Generation Systems Taking Into Account Refrigeration, Heating And Electricity Load Demands," *Energy Building*, **42(12)**, pp. 2323-2330, 2010.
- [4.29] S. A. Tassou, I. Chaer, N. Sugiarta, Y. Ge, and D. Marriott. "Application Of Tri-Generation Systems To The Food Retail Industry," *Energy Conversion and Management*, **48(11)**, pp. 2988-2995, 2007.

[4.30] US EPA, "Emissions Factors Chapter 1: External Combustion Sources," *US Environmental Protection Agency*, <http://www.epa.gov/ttnchie1/ap42/ch01/>, Accessed on May 2015.

[4.31] N. A. M. Rosli, N. Kamarrudin, K. H. Ku Hamid, S. Akhbar, and N. M. Yusof. "Greenhouse Gas Emission Of MSW Landfill Site," *Proceeding of 2013 IEEE Business Engineering and Industrial Applications Colloquium (BEIAC)*, 2013.

[4.32] A. Lazzaretto and A. Toffolo. "Energy, Economy And Environment As Objectives In Multi-Criterion Optimization Of Thermal Systems Design," *Energy*, **29(8)**, pp. 1139-1157, 2004.

[4.33] Yan Cheng-wen and Yao Jian. "Application of ANN for the prediction of building energy consumption at different climate zones with HDD and CDD," *Proceeding of 2010 2nd International Conference On Future Computer and Communication (ICFCC)*, 2010.

CHAPTER FIVE

BROADER IMPACTS

Three main research questions were discussed, and broader impacts of the answers to these questions were briefly discussed. In this chapter, further examples and discussions will be provided for better understanding the research intellectual merits and their potential application in other areas of manufacturing systems. At the end of this chapter, the relations between each research questions will be explained.

5.1 Broader impact of research questions

In previous chapters, the broader impacts of each research question were generally summarized. Here, detailed cases of the broader impact of each questions will be presented by example.

5.1.1 Broader Impact of RQ1

In Chapter Two, the knowledge gaps of manufacturing energy modeling were defined, and systematic approach was proposed. In that chapter, the example of an automotive assembly manufacturing plant was studied, and high and low level models were established. In this section, the application of the HAVC model to other areas of the plant will be demonstrated; other low level models will also be exemplified to show how lower level models can provide sensitive variables for later bottom-up modeling.

Further application of HVAC model to other areas in the plant

Among the different levels of models, an HVAC model of a basecoat painting spraying booth was established and validated. The HVAC model of the painting booth serves the purpose of improvement identification well by suggesting the adjustment of temperature setpoint.

Besides the implementation on the painting basecoat booth, the HVAC model can also be used in many other areas of the plant. The similar system including: 1) the painting clear-coat booth, where the clear-coat of paint was sprayed onto vehicle to give a glare look; 2) ovens in the paint shop, *e.g.*, e-coat oven, basecoat oven, clear-coat oven, sealant oven, and; 3) building areas – shop building area where the body shop and assembly lines are.

Clear-coat Booth

Like the basecoat booth, the clear-coat booth is a separate room within the building, where the clear-coat spray is applied. The energy models of the base coat booth can be directly applied into the clear-coat booth, since the clear-coat booth has the similar building-to-booth air supply system as the basecoat booth.

In our studied case, the clear-coat booth has a designed tolerance on humidity from 50% to 67%. As the required model inputs, the variables in the model are: 1) inlet air temperature, 2) inlet air humidity, and 3) outlet air humidity. Other inputs are constant, namely the air flow rate and outlet air temperature. Because of the building-to-booth air

supply system, the inlet air temperature is actually relatively stable. However, out of the research purpose, it is discussed as one of the variables.

As a previous output of the models from basecoat booth, the dehumidification process should be avoided as much as possible, due to its large energy demand in the dehumidification and reheating processes. Thus, in the clear-coat booth where the relative humidity is a variable, higher humidity could have better chance in avoiding the dehumidification process. However, the larger relative humidity (in this case 67%) in the outlet air also requires more energy for the extra moisture heating or cooling, *i.e.*, in a simple heating or cooling process, the extra moisture (the extra 17% on the original 50%) requires more energy to change temperature. Which energy demand is more dominant is a question that needs to be answered. Experiments were designed as Table 5.1 to discuss the question.

Table 5.1: Experimental Design and Results of HVAC Energy in Clear-coat Booth

No.	Inlet Air Temperature [°F]	Inlet Air Humidity [%]	Outlet Air Humidity [%]	Dehumidification or not (1-Yes, 0-No)	Normalized Energy Demand
1	68	49.8	50	0	0.476
2	68	49.8	67	0	0.478
3	68	79.1	50	1	1.803
4	68	79.1	67	0	0.478
5	72	49.8	50	0	0.204
6	72	49.8	67	0	0.205
7	72	79.1	50	1	3.109
8	72	79.1	67	1	1.247

By comparing the energy demand two by two, Table 5.1 provides great information to study how energy demands are correlated to the humidity in the outlet air. In summary,

1. if the dehumidification process is not in the control range [50%, 67%], 50% consumes slightly less energy (experiments 1 and 2, 5 and 6);
2. when both humidification and dehumidification processes are within the control range [50%, 67%], choosing a set point of 50% will consume less energy (reference Experiments 3 and 4);
3. when the dehumidification process is in the control range [50%, 67%], 67% consumes less energy (reference Experiments 7 and 8).

The test results make sense, when considering the heating/cooling process and dehumidification process. When the process does not need dehumidification, less humidity means less energy used for moisture in the air. When choosing between the process with and without dehumidification, the energy demand is always lower in a process without. When the dehumidification process is inevitable, choosing a higher relative humidity output needs less energy, since there is a lower amount of water condensed. Therefore, the best operation strategy is to set variable set points based on the inlet air condition, instead of a constant set point throughout the year.

Ovens

The automotive paint shop has many ovens in the painting process to cure the layers of paint and sealant. Generally, the vehicle in the oven will go through heating up, temperature hold, and cooling down processes. The oven is another relatively separate space from the building. Except for the temperature and humidity control inside the oven, the oven air supply houses can also control their inlet air flow rate. One of the energy

conservation strategies is to reduce the air flow rate into the oven during downtime. In this phase, the previous vehicle has left the oven, and the next vehicle has not entered the oven yet. The air supply houses adjust the airflow speed into the oven, but not shut down, to prevent dust and particulate matter from entering the oven. During this period of time, the energy can be saved from two sides – thermal energy and electrical energy. Except for the energy saving for heating and cooling, the electrical energy for fan speed reduction is also substantial.

According to the previous HVAC model established, the airflow affected the heating and cooling energy linearly. Based on the specification of the fans used, the electrical energy is also influenced. In this way, the energy of the oven is closely related to the vehicle production speed.

Other low level models

Chapter Two exemplifies the low level models of paint shop, because it is the main energy consumer. In this section, more low-level models from body shop and final assembly shop will be provided to demonstrate how the production parts/vehicles can affect the energy consumption.

Spot welding

Welding is a main process in the body shop, which joins two parts together. As Section 0, general spot welding energy consumption can be written as Equation (2.6).

$$E_{weld} = E_{ps} N_{spot} x + (1 - \alpha) P_{idle} T \quad (5.1)$$

where N_{spot} is the number of welding spots per product, x is the number of products to be produced, α is the ratio of welding engaged time to the total uptime, P_{idle} is the no-load power when the welder is in idle stage, and T is the total uptime.

Figure 5.1 shows two spot welding schedules under different production rates. The green regions are the down time, while the red regions are the welding engaged time, and yellow regions are the idle time.

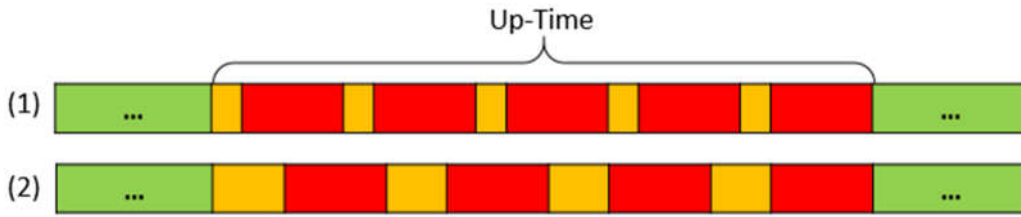


Figure 5.1: Spot Welding Schedule

These two scenarios have the same uptime, but during the uptime, the upper (1) schedule has one more part processed than the lower schedule.

Assume the production time is T , which is also the uptime for spot welding. During this period of time, x parts were processed in this particular spot welding procedure, and the average engagement time for each part is t . Thus,

$$\alpha = \frac{x \cdot t}{T} . \quad (5.2)$$

Therefore, α in Scenario (1) is larger than Scenario (2) in Figure 5.1.

If the quantity of produced parts was reduced by 20% of the original ($x' = 80\% \cdot x$), the welding engaged ratio becomes

$$\alpha' = \frac{x' \cdot t}{T} = \frac{0.8 \cdot x \cdot t}{T} . \quad (5.3)$$

Therefore,

$$\begin{aligned} E'_{weld} &= E_{ps} \cdot N_{spot} \cdot x' + (1 - \alpha') \cdot P_{idle} \cdot T \\ &= E_{ps} \cdot N_{spot} \cdot 0.8 \cdot x + (1 - 0.8 \cdot \alpha) \cdot P_{idle} \cdot T \\ &= 0.8 \cdot [E_{ps} \cdot N_{spot} \cdot x + (1 - \alpha) \cdot P_{idle} \cdot T] + 0.2 \cdot P_{idle} \cdot T \\ &= 0.8 \cdot E_{weld} + 0.2 \cdot P_{idle} \cdot T \end{aligned} \quad (5.4)$$

Let $0.2 \cdot P_{idle} \cdot T = c$, where c is a constant, we get

$$E'_{weld} = 0.8 \cdot E_{weld} + c . \quad (5.5)$$

Generally, Equation (5.5) can be further written as

$$E = c + a \cdot x \quad (5.6)$$

where the a is the coefficient, c is a constant, and x is the production rate.

It can be concluded that the welding energy is linearly related to the production ratio (*i.e.*, number of parts produced in certain uptime period).

Material handling

The production affects the energy consumption not only in terms of number of parts produced in certain period of time, but also in terms of vehicle type.

As mentioned in Section 0, heavy parts handling usually involves in robotic material handling. Generally, robot material handling energy was summarized in Equation (2.4)

$$E_{handling} = \left[L \times (m_{part} + m_{grip} + \eta \times m_{robot}) \times v \right] / (\eta_{motor} \times t_{handling}) \quad (5.7)$$

This equation indicates the energy consumption of the robot handling material, and the variables involved in this equation are the length of the moving material (L), speed of moving (v), weight of the part (m_{part}), weight of the gripper ($m_{gripper}$), robot specifications such as the weight of the robot arm (m_{robot}) and the angle of the robot arm (η), as well as the motor efficiency (η_{motor}) and handling time ($t_{handling}$).

From this equation, the energy of material handling was affected by part variation due to the different vehicle models through the parts' weights m_{part} . For a certain autonomous material handling robot, the time of handling, efficiency of the motor, handling route, speed, robot weight, grip weight and robot efficiency are all designed and constant. The equation can be simplified as

$$E_{handling} = \alpha + \beta \cdot m_{part} \quad (5.8)$$

where α is a constant, and β is the coefficient. In this case,

$$\alpha = \frac{(m_{grip} + \eta \times m_{robot}) \times v \times L}{\eta_{motor} \times t_{handling}} \quad (5.9)$$

$$\beta = \frac{L \times v}{\eta_{motor} \times t_{handling}} . \quad (5.10)$$

Notation: length of the moving material (L), speed of moving (v), weight of the part (m_{part}), weight of the gripper ($m_{gripper}$), robot specifications such as the weight of the robot arm (m_{robot}) and the angle of the robot arm (η), the motor efficiency (η_{motor}), and handling time ($t_{handling}$).

Spot welding and material handling are two good examples to show how the number of parts produced and types of parts can affect the energy consumption. These examples provide good information in terms of influential features in plant level, and they are the foundations for the next sensitivity analysis of the key variables.

Sensitive variables

With these examples and the models in Chapter Two, it is concluded that the sensitive variables from the physical model include the: 1) **weather information**, 2) **productivity** of the plant, and 3) **days of the week and nonworking days**. These manufacturing featured variables should be introduced into the high-level model. These three types of variables can be further detailed into: 1) daily average temperature, 2) CDD, 3) HDD, 4) daily average relative humidity, 5) day of the week, 6) working and nonworking days, 7) type I vehicles produced daily, and 8) type II vehicles produced daily. Daily average temperature is important because the building air houses heat and cool the air from

the atmosphere before inlet into the plant building. CDD and HDD are the two terms used widely in building energy calculations, and especially in the case where one type of energy was used only for heating or cooling, *e.g.*, electricity is only used for cooling in our case. Relative humidity is proven to be critical in energy consumption of the paint booth, but not for the overall building HVAC. Days of the week could affect the energy in potential weekly productivity activities. Working and nonworking days are important, because main production lines will be shut down in nonworking days. Different types of vehicle have different geometry and weight, and could affect the energy consumption as shown in Section 0 and 0. Some of these seven variables are actually highly related and it is important to choose appropriate ones for further analyses. Correlation is analyzed among the output electricity consumption and eight input variables as Table 5.2.

Table 5.2: Correlation Analysis

No.	Variables	Electricity
1	Vehicle Type I	0.65
2	Vehicle Type II	0.55
3	Daily Average Temperature	0.43
4	CDD	-0.47
5	HDD	-0.35
6	Daily Average Humidity	0.08
7	Weekdays	-0.26
8	None Working Days	-0.43

Among these variables, the daily average temperature, CDD and HDD are not independent. Actually CDD and HDD are calculated directly from daily average temperature as

$$CDD = \begin{cases} 0, & \text{if } T_{average} - T_{set} < 0 \\ T_{average} - T_{set}, & \text{if } T_{average} - T_{set} > 0 \end{cases} \quad (5.11)$$

$$HDD = \begin{cases} T_{average} - T_{set}, & \text{if } T_{average} - T_{set} < 0 \\ 0, & \text{if } T_{average} - T_{set} > 0 \end{cases} \quad (5.12)$$

According to the correlation analysis, CDD has the highest (maximum absolute value) correlation with the electricity consumption, which makes sense when considering the large amount of cooling energy provided by electricity. Thus, among these three variables, only CDD was selected as the independent variable input. Apart from these variables, the daily average relative humidity and weekdays are the two variables with lowest correlation. The low value from the table suggests not including these two in later modeling.

Besides the correlation analysis, multivariable linear regression coefficient analysis was used to help determine the sensitive variables. Table 5.3 is the statistical result of the coefficient analysis on every potential input variable. The results are consistent with the correlation analysis.

Except for the daily average temperature and HDD, which were excluded due to their dependences with CDD, daily average relative humidity and weekdays are the two variables with the large P-values and small F-values.

Table 5.3: Linear Regression Coefficient Analysis

	Coefficients	t-value	P-value
Intercept	309147	12.95	0.000
Vehicle Type I	57.60	22.49	0.000

Vehicle Type II	23.07	6.26	0.000
Daily Average Temperature	124.2	1.78	0.076
CDD	-13297	-14.06	0.000
Daily Average Humidity	396	1.62	0.106
Weekdays	-2108	-1.14	0.225
None Working Days	-51562	-3.49	0.001

Table 5.3 suggests input variables – vehicle type I and II, CDD, and none working days can be selected as sensitive variables for later time series analysis.

When comparing the statistical results with the physical models built in this chapter and Chapter Two, the results are consistent. Vehicle type I and II represent the two models of vehicles greatly different in terms of weight, which could affect the energy like welding and material handling. CDD is the parameter used to represent the weather information, because the electricity is only used for cooling. Relative humidity is an important parameter in the paint spraying booth but not for the whole building, and due to the relatively small energy share in painting booth, the relative humidity is not a sensitive variable in the high level. Days of the week is not a strong variable considering its main change is already represented in the number of vehicle produced in the day (Vehicle type I and II). The non-working days are important, because main equipment and production will be shut down in a non-working day, but not necessary to consider in a low production day.

5.1.2 Broader Impact of RQ2

Chapter three gives examples of how the mathematical time series models can be used as a forecasting tool in the manufacturing energy prediction. Similarly, the same approach can also be applied to water consumption forecasting by including manufacturing

features into the time series models to make it more robust and accurate in water consumption prediction.

Like electricity and other energy carriers used in a manufacturing plant, water is widely used for production purposes. In an automotive manufacturing plant, water is mainly used on the cooling tower, chemical solution, hot and chilled water makeup, and car wash. The studied cases provide daily data of the overall water purchased from suppliers. 2014 water consumption in the first 251 days was given, and split into two parts – the first 237 data points for model training, and the last 14 data points for forecasting validation. The training data was plotted as Figure 5.2. To protect the confidentiality of the studied case, the water is normalized by an arbitrary volumetric rate value.

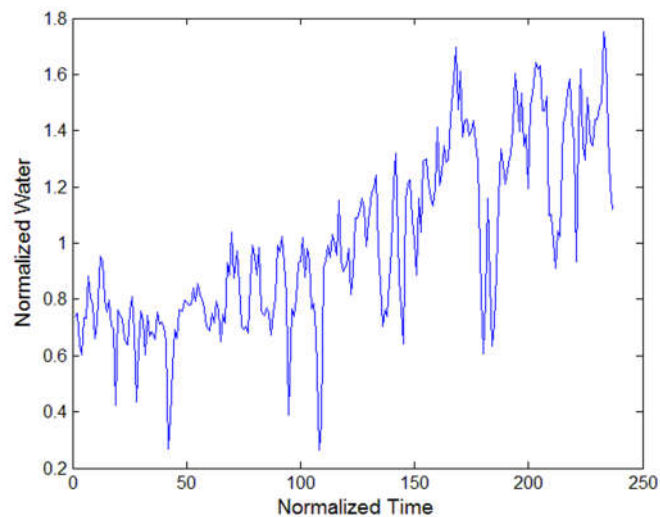


Figure 5.2: Normalized Water Plot in Time

Figure 5.2 shows the training data set of the first 237 data points in the year 2014. The x axis represents the normalized time, where 1 represents the first day of 2014, and

time lag 1 represents one day. The y axis is the water amount normalized with its mean value as

$$\text{Normalized Water} = \frac{\text{Actual Water Amount in Gallon}}{\text{Mean Value of Water Amount in Gallon}} \quad (5.13)$$

This figure shows a linear increasing trend with fluctuation. Further analyzing the data, ACF (autocorrelation function) and PACF (partial autocorrelation function) were calculated and plotted in Figure 5.3 and Figure 5.4. Figure 5.3 shows a slow degradation rate with a relatively strong 7 days pattern, which indicate a potential linear trend and possible 7 days repeated pattern. Figure 5.4 has a large value at lag 1 and fast decay while a relatively large value at lag 4. With this two figures, a trend is strongly suggested, and possible AR(7), MA(1), AM(4) or ARMA(7,1), ARMA(7,4) models should be considered.

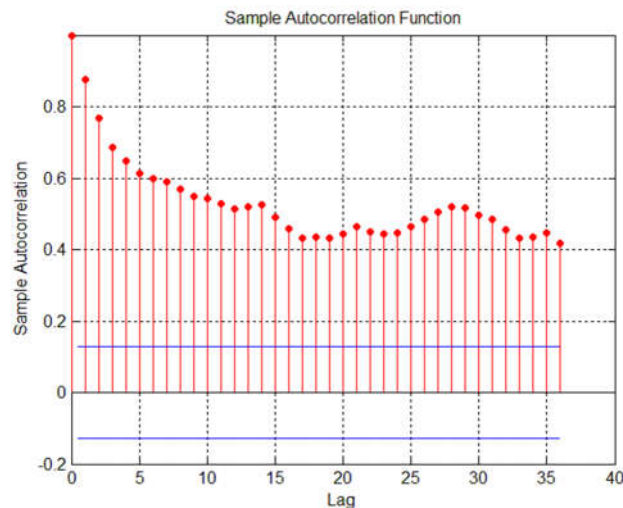


Figure 5.3: ACF of Training Water Data

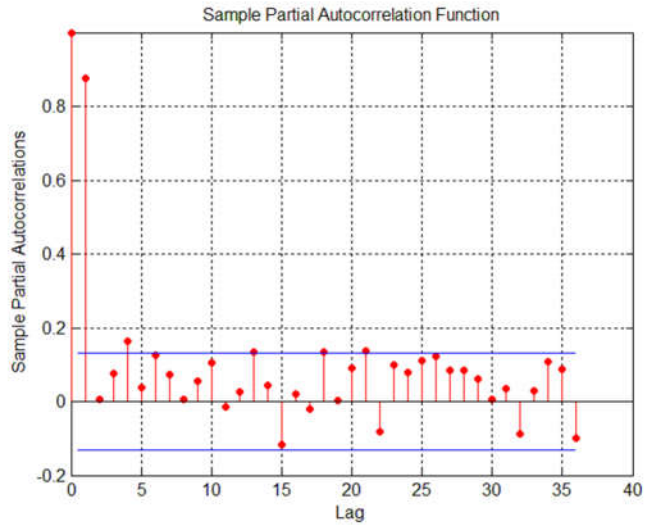


Figure 5.4: PACF of Training Water Data

As carried out in Chapter Three, Section 0 for energy forecasting, the training data of water use was also de-trended. ACF and PACF of the new data series were calculated and plotted in Figure 5.5 and Figure 5.6.

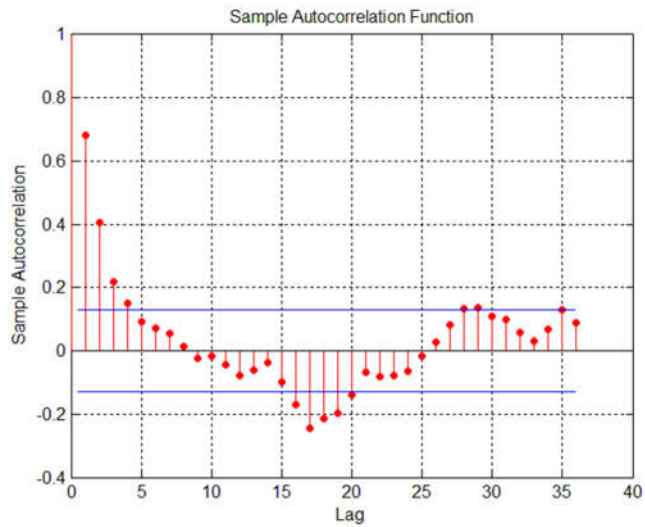


Figure 5.5: De-Trend Training Data Series ACF

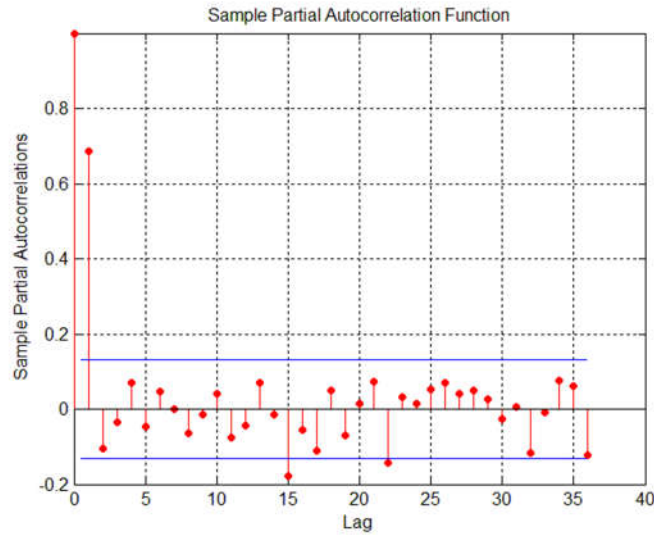


Figure 5.6: De-Trend Training Data Series PACF

The de-trended data still show a 7 days’ pattern. Different time series models as suggested were tried, as summarized in Table 5.4.

Table 5.4: Water ARMA Model Test Results

	AIC	Training MSE	Forecasting MSE
AR(1)	6017.3	0.0883	0.1631
AR(4)	6019.2	0.0829	0.1651
AR(7)	6024.3	0.0709	0.1181
MA(1)	6081.6	0.0875	0.0651
ARMA(1,1)	6017.1	0.0630	0.0376
ARMA(4,1)	6020.9	0.0823	0.0206

As in the approach in Chapter Three, the models were measured with goodness of fitting in AIC, normalized training MSE and forecasting MSE metrics. AIC and training MSE do not show a dramatic difference, which indicates no obvious overfitting problem or accuracy improvement. The best fitting result in terms of forecasting MSE is model ARMA(4,1).

The forecasting results of the models were shown in Figure 5.7. The models show different forecasting results of traditional time series models. The goodness of fitting is not acceptable.

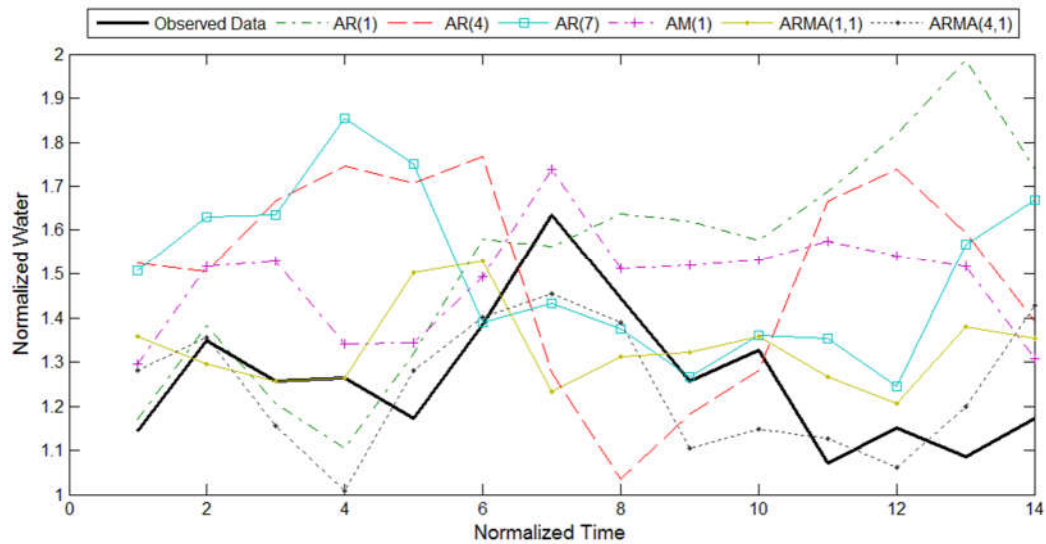


Figure 5.7: Selected Forecasting Results Plot

Like electricity forecasting, exogenous inputs can be introduced into the model to make it more accurate and robust. However, in this research, lower level water information was insufficient to establish detail models for sensitivity analysis. Therefore, the exogenous inputs were not specified for water consumption. Out of the purpose of the approach demonstration, the same exogenous inputs for electricity were used here.

Different types of time series model with exogenous inputs were tested, and the results shown in Table 5.5.

Table 5.5: Water ARMAX Model Results.

	AIC	Training MSE	Forecasting MSE
ARMAX(7,7,4)	22.41	0.0571	0.0138
ARMAX(7,1,4)	22.32	0.0581	0.0149
ARMAX(1,1,4)	22.36	0.0584	0.0152
ARMAX(4,1,4)	22.45	0.0600	0.0153

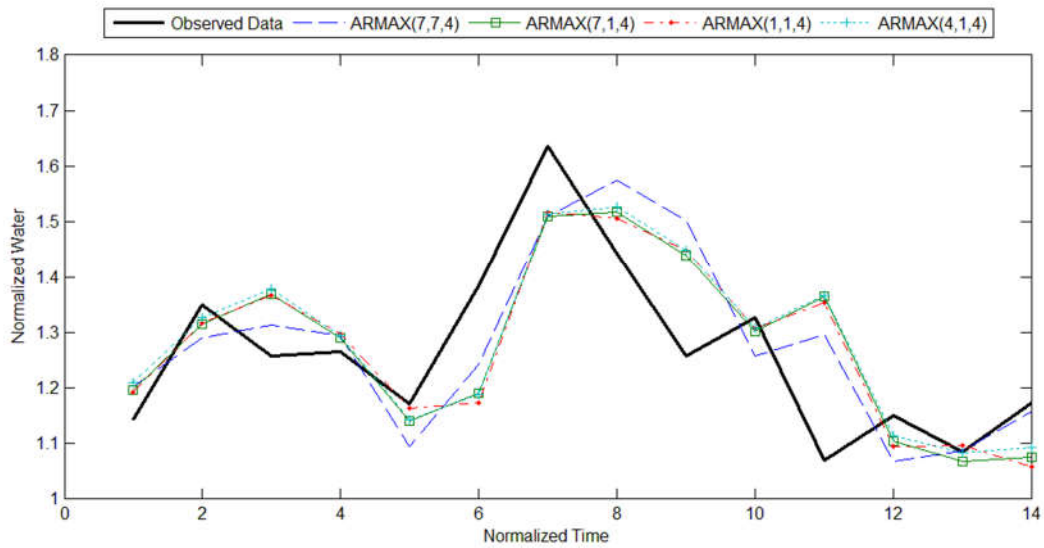


Figure 5.8: ARMAX Model Forecasting Results Plot

Even though the exogenous inputs are not specified for water consumption, the results in Table 5.5 show a great improvements comparing with the results in Table 3.3, and the goodness of fitting can also be easily observed through Figure 5.8.

5.1.3 Broader Impact of RQ3

Other emission pollutants

When answering the research question three, carbon dioxide was used as a representative for environmental emission. Actually, there are many other emission

pollutants that can be taken into consideration. The approach in Research Question three can not only reveal the conflicts between different objective criteria – energy in terms of megawatt hour, monetary cost in US dollar, and environment emission in carbon dioxide, but also used to discuss the relationships among the three different pollutants – sulfur dioxide, nitrogen oxide, and carbon dioxide. Though three of them are all indicators of emission pollution, will they be consistent in the “best” operation strategy?

The approach of research question three was applied here to answer this question. The amount of emission per energy carriers is summarized in Table 5.6.

Table 5.6: Energy Emission Indicator

[lbs/MWh]	Ele	NG	LFG
Sulfur Dioxide	1.5	0.0020	-0.45
Nitrogen Oxide	0.5	0.11 – 0.33	(-0.21) – (-0.33)
Carbon Dioxide	778	401.39	-447.47

The optimization approach in Chapter Four can still be used here, only by adjusting the coefficient vector to the emission indicators.

$$F_{SO_2} = \begin{bmatrix} 1.5 \\ 0.002 \\ -0.45 \end{bmatrix}, \quad F_{NO_x} = \begin{bmatrix} 0.5 \\ 0.11 - 0.33 \\ (-0.21) - (-0.33) \end{bmatrix}, \quad F_{CO_2} = \begin{bmatrix} 778 \\ 401.39 \\ -447.47 \end{bmatrix} \quad (5.14)$$

The optimization comes with the consistent optimal results throughout the energy emission indicator. The results suggest to use landfill gas as much as possible in the cogeneration. Taking a closer look into the emission indicators, it is not difficult to

understand the results. In Table 5.6, the emission of landfill gas is always less than the natural gas and natural gas is always less than electricity, whichever emission pollutant is chosen.

This result also further proves that whichever pollutant is chosen to represent emission, the results will be consistent. Thus, it is reasonable to only use one pollutant, *i.e.*, carbon dioxide to represent for the overall emission in the optimization calculation.

Energy pricing

In Chapter Four, energy prices were used as a constant vector for optimization. However, there are many different energy pricing agreements between the suppliers and manufacturing plants. In this section, energy pricing strategies were reviewed, and the effects of variable energy price on optimization were discussed.

Supplier

There are three interconnections in the US, *i.e.*, eastern interconnection, western interconnection, and EROCT (Electric Reliability Council of Texas) interconnection. Generally, electric power companies are monopoly utilities, *i.e.*, consumers have very limited choices for selection of the electricity supplier. However, in some states, such as Texas, customers can choose their providers from many retailers.

Prices and Pricing Strategies

Electricity prices are referred to as electricity rates or tariffs. A tariff is an approved collection of different rates that utilities offer to specific but different types of customers. For example, tariffs for industrial plants and residential customers are different. Electricity

tariffs can be affected by many factors, such as the precision of electricity usage data. The forecasting results of this research work can be used for negotiation of electricity rates and tariffs.

For many residential customers, the flat rate and tiered rate that are typical pricing strategies used by utility companies. The flat rate strategy charges customer the same rate over a given billing cycle (see example in Figure 5.9). The tiered rate strategy charges different prices on blocks of consumption (see example in Figure 5.10).

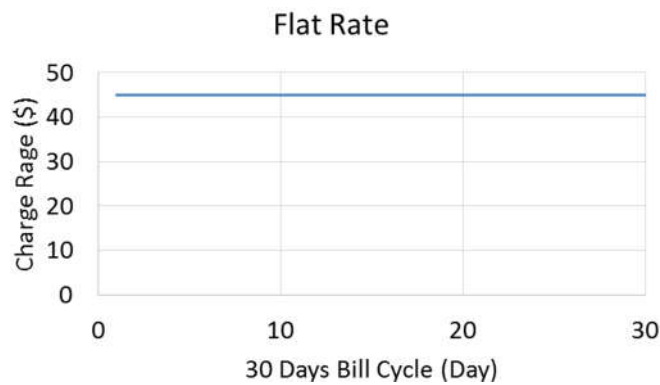


Figure 5.9: Flat Rate Example

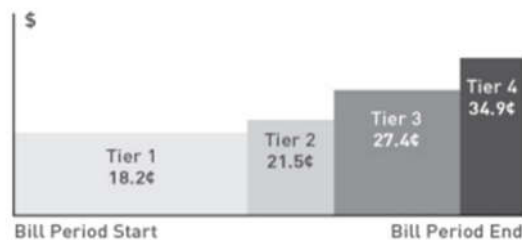


Figure 5.10: Tiered Rate Strategy Example (From PG&E [5.1])

As the development of metering systems improves, the utility companies can record electricity usage in a higher frequency. It enables newer time-based rate strategies. Here are some typical pricing strategies: 1) time of use (TOU) in which the price for each period

is determined, as shown in the example of Figure 5.11; 2) real-time pricing (RTP) in which the pricing rates varies hourly according to the usage, as shown in the example of Figure 5.12; 3) variable peak pricing (VPP) in which the off-peak periods of price are defined in advance, but on-peak price varies according to the demand and marketing; 4) critical peak pricing (CPP) in which the price of critical events period raises; and 5) critical peak rebates (CPR) in which the customers get rebates when they use less energy than expected during the critical events period [5.2].

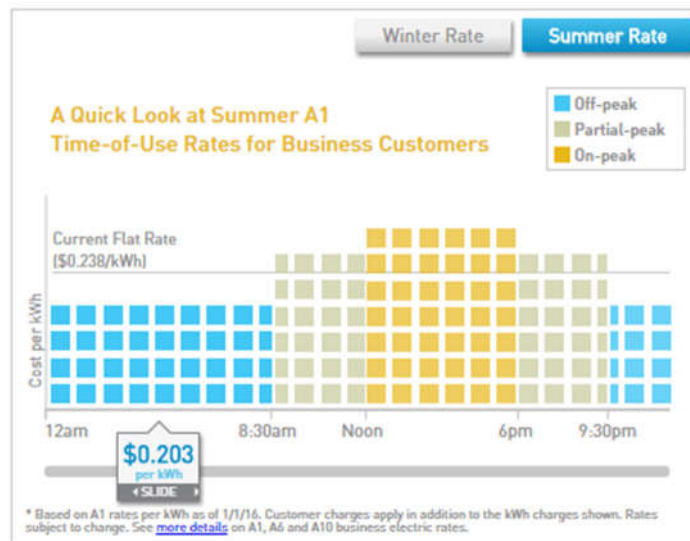


Figure 5.11: TOU Example (From PE&G [5.3])

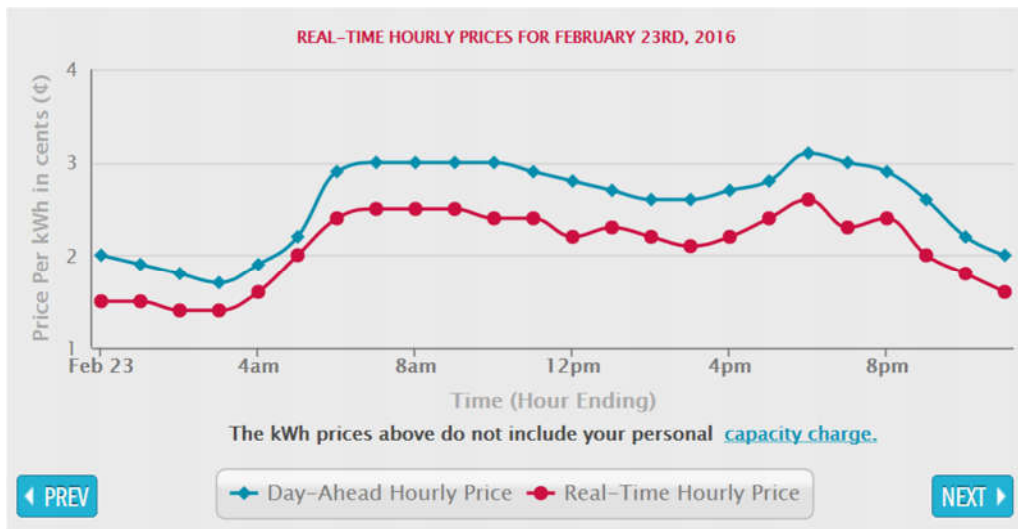


Figure 5.12: Real Time Pricing Example (From ComEd [5.4])

In South Carolina, Duke Energy is the largest provider. Its service to industrial companies follows the tiered rate strategy, except for contracting consumers. Besides the basic facility and demand charge, the pricing rate is summarized in Table 5.7.

Table 5.7: Electricity Price Rate of Duke Energy Industrial Service [5.5]

Range		Price
kWh	kWh	Cents
-	3,000	12.1838
3,000	90,000	6.3497
90,000	125,000	4.8523
125,000	265,000	6.3423
265,000	325,000	5.9169
325,000	400,000	5.3708
400,000	1,400,000	5.1770
1,400,000	1,400,000+	5.0790

Effect on Optimization Model

The main difference in the optimization model comes from consideration of the electricity pricing strategies.

For the general case, the constant price vector F_2 in the optimization (as vector in (5.15)) can be changed to a function related with amount of energy purchased.

$$F_2 = \begin{bmatrix} 60 \\ 30 \\ 15 \end{bmatrix} \quad (5.15)$$

F_2 has the unit of USD/MWh.

The first element in F_2 represents the average electricity price, which can be adjusted to equation (5.16) according to Table 5.7.

$$F_2(1) = \begin{cases} 121.84, & \text{if } P_{Elec} \leq 3,000\text{kWh} \\ \frac{63.50 \times (P_{Elec} - 3,000) + 365.51}{P_{Elec}}, & \text{if } 3,000 < P_{Elec} \leq 90,000\text{kWh} \\ \frac{48.52 \times (P_{Elec} - 90,000) + 5889.75}{P_{Elec}}, & \text{if } 90,000 < P_{Elec} \leq 125,000\text{kWh} \\ \frac{63.42 \times (P_{Elec} - 125,000) + 7588.06}{P_{Elec}}, & \text{if } 125,000 < P_{Elec} \leq 265,000\text{kWh} \\ \frac{59.17 \times (P_{Elec} - 265,000) + 16,467.28}{P_{Elec}}, & \text{if } 265,000 < P_{Elec} \leq 325,000\text{kWh} \\ \frac{53.71 \times (P_{Elec} - 325,000) + 20,017.42}{P_{Elec}}, & \text{if } 325,000 < P_{Elec} \leq 400,000\text{kWh} \\ \frac{51.77 \times (P_{Elec} - 400,000) + 24,045.52}{P_{Elec}}, & \text{if } 400,000 < P_{Elec} \leq 1,400,000\text{kWh} \\ \frac{50.79 \times (P_{Elec} - 1,400,000) + 75,185.52}{P_{Elec}}, & \text{if } 1,400,000\text{kWh} < P_{Elec} \end{cases}$$

(5.16)

In the studied case, because the optimization is established on a daily basis and industrial companies are not charged time-based, it is not necessary to consider the effects from the time based charging strategies. In the previous work, we use a constant rate for the electricity price. The only different scenario happens when the electricity consumption is at the edge of a certain range. For example, during one billing cycle, the manufacturing plant can adjust the on-site energy operation to change the amount of electricity purchased from the utility companies, and the amount purchased can fall in different ranges, such as the range from 125,000 to 265,000 kWh, and range from 265,000 to 325,000 kWh. In this case, the electricity price will be different, and actually, the average price of electricity can

be reduced by purchasing more. However, the reduction rate is too small to change the operation strategies in our studied case (Figure 4.7).

5.2 Three RQs relationships

From Chapter Two to Chapter Four, three research questions were answered. The first two questions concentrated on the energy consumption, and the third one was focused on energy supply (as Figure 5.13).

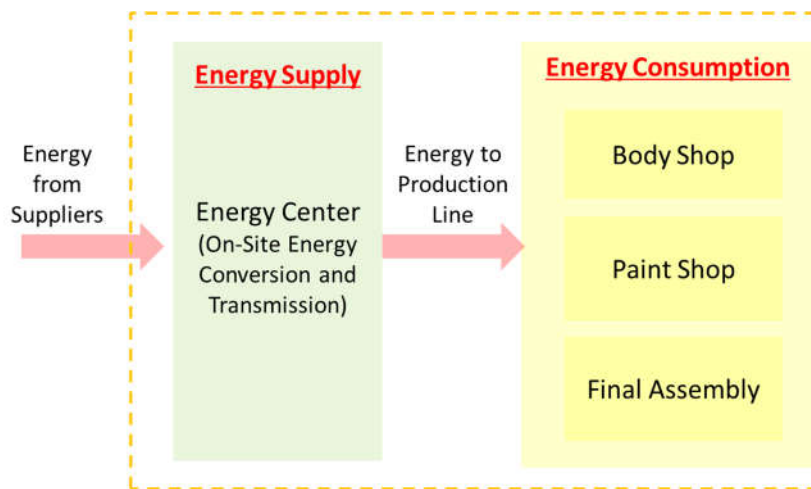


Figure 5.13: Energy System Sketch in Studied Case

In the first research question, modeling approaches of a systematic manufacturing energy strategy were proposed, and examples were provided. Top down detail models were used. Sensitivity variables were identified through the top-down modeling approach. These variables were further analyzed in Chapter Three, and some of them were selected as exogenous inputs of the time series model to make it more accurate and robust. With the sensitive variables included, time series models can predict the energy consumption in the next few days. On the other hand, the energy supply optimization is constrained to satisfy

any energy demand from the main production plant. Therefore, the result of the research question two is one of the inputs for the optimization in research question three.

With days' ahead energy forecasting, the on-site energy supply system can schedule the operation accordingly. This approach results in a guarantee of stable energy supply and increases the situational awareness (especially in days of high or unexpected variation). With the on-site energy conversion and transmission systems schedule, the optimization results also determine the amount of energy that needs to be purchased from local supplier. Thus, the demand forecasting and on-site supply optimization provides more reliable information for the local energy distribution. The combination of research question two and three provides model-based prediction of energy supply to the manufacturing plant.

In some scenarios, different energy forms are coupled together. For example, the hot water and electricity. In order to generate inexpensive electricity from the landfill gas through the cogeneration system, the hot water can be taken a byproduct of the cogeneration. In a scenario when the electricity is highly demanded but not the hot water, energy conservation actions to save hot water are not as efficient as saving electricity, even though they may have the same amount of energy in terms of megawatt hour. The optimization results of the on-site energy supply system can guide the systematic energy modeling by providing information on which energy is critical in certain situations, *i.e.*, providing more information for better decision making when spending limited time and cost for modeling and improvement implementations.

In summary, the research questions relations are illustrated in Figure 5.14.



Figure 5.14: Research Question Relations

5.3 Chapter Five References

[5.1] PG&E, "Tier Based Plan (E1) -- Together, Building a Better California," *Pacific Gas and Electric Company*, <http://www.pge.com/en/myhome/saveenergymoney/plans/tiers/index.page>, Access: Mar. 2016.

[5.2] Smart Grid, "Time Based Rate Programs," *Smart Grid Gov*, https://www.smartgrid.gov/recovery_act/time_based_rate_programs.html, Access: Mar. 2016.

[5.3] PG&E, "Time-of-Use Energy Rates," *Pacific Gas and Electric Company*, http://www.pge.com/en/mybusiness/rates/tvp/toupricing.page?WT.mc_id=Vanity_TOU, Access: Mar. 2016.

[5.4] ComEd, "ComEd Powering Lives -- Real-Time Hourly Price," *Commonwealth Edison Company*, <https://hourlypricing.comed.com/live-prices/?date=20160223>, Access: Mar. 2016.

[5.5] Duke Energy, "Duke Energy Carolinas South Carolina Electric Rates," <https://www.duke-energy.com/rates/south-carolina.asp>, Access: Mar. 2016.

CHAPTER SIX

INTELLECTUAL MERIT AND FUTURE WORK

6.1 Intellectual Merit and Contribution

The world energy consumption has been continually increasing. As an important part of the critical industrial activities, automotive manufacturing plants are affected by this increasing energy, both in terms of cost and long-term sustainability. This research investigated the energy consumption within individual manufacturing plants – the energy consumption model in the plant and lower levels, energy forecasting, and on-site supply system optimization. Instead of exhausting the subsystems in the complex manufacturing plant with a large amount of equipment and processes, this research provides modeling approaches and examples for energy analysis and optimization. By answering three research questions, the work achieved the research objectives in 1) testing the hypothesis that a systematic energy modeling approach based on the layered concept can improve the modelling in terms of improving accuracy, sharing information, identifying sensitive variables, and implementing conservation approaches; 2) applying and augmenting forecasting methods from the mathematical domain to understand energy use in the manufacturing domain; and 3) investigating the optimal energy operation strategies in manufacturing plants. Therefore, this research provides deeper knowledge in manufacturing energy usage and analysis.

The contribution of this research can be seen from the following seven aspects.

1. This research quantified the energy distribution to departments and identified key production processes. Internally, it provided information for plant energy management, and pointed out the directions for improvement implementation. Externally, it identifies additional approaches for energy consumption comparison among the similar systems. Previously, the benchmark and other comparison models have been criticized by their insufficient consideration in the variation of technologies. In this research, the energy is more comparable by partitioning the consumption into department and key processes.
2. The implementation measures can be replicated in other areas of the plant. Improvement suggestions were made through the model outputs, but the final measures taken to implement is a collective decision made based on the system design variables, production schedules, implementation timelines, and monetary cost. This research provided information for the business model of implementation and guided the measures to be taken efficiently in terms of time and monetary cost.
3. Among many variables, this research pointed out the weather, productivity, and working conditions (working days or non-working days) are three influential factors in manufacturing energy consumption. Though the research scope applies to the postproduction phase, this research result provided constructive suggestions for earlier process

design phases. For example, during the plant location selection, weather information can be incorporated for better decision making.

4. Energy consumption in the manufacturing plant was shown to be able to be modeled by time series models. Energy consumption was observed with trending and seasonal patterns. Informed manufacturing energy models were shown to be accurate in forecasting. The time series models were identified as a potential to be used further in later big data systems.
5. With accurate consumption forecasting results, the energy supply system (*e.g.*, utility companies and on-site energy supply system) can schedule the energy load accordingly. This strategy provides a more stable energy supply for local facilities and plant processes.
6. This research revealed the tradeoffs of supply in terms of energy (MWh), cost (USD), and emission (as represented by CO₂). Though these three objective criteria are correlated, the optimal operation of the on-site supply system is not consistent, especially in a complex system with renewable energy sources as might be encountered in a manufacturing plant.
7. The optimization results also demonstrated how the operation strategies could vary according to the different scenarios caused by high and low levels, such as shift and energy prices.

Though this research successfully answered three research questions, there is a clear continuing path for future work.

6.2 Future Work

The potential future work to build upon this research in different areas is shown below.

1. Establishing high level energy models including the local industrial plants, suppliers, utility companies, and landfills, *i.e.*, models on multi-factory and supply chain levels, would be interesting. In some cases, the output energy of one plant could be the energy input demand of another plant (*e.g.*, extra thermal energy used as a commodity). By establishing high level models in the local industrial areas, information and energy can be shared to better benefit each facility. If incorporating the information from the utility company and landfill, energy delivery can be better distributed; therefore, it can create a more energy stable environment.
2. Current manufacturing plants' and production lines' design and construction have not typically considered energy conservation as an objective. Establishing energy models for the design phase would be valuable in providing analysis for the balance of capital investment and long term energy savings. The design phase models can also be built in

high and low levels to investigate questions such as the location selection of plant and heat exchanger installation.

3. The results of the water forecasting model suggest the sensitive variables for electricity are also the key influential inputs of the water consumption. Is it possible the expendable resources (*e.g.*, other energy carriers, water, materials, and labor) share the same key variables? How about the variables in the similar plants, do they share the same ones? Considering the close relation between the supplier and customer, is it possible the other plants in the same supply chain system share these features (as Figure 6.1)? These are the questions worth to be studied further.

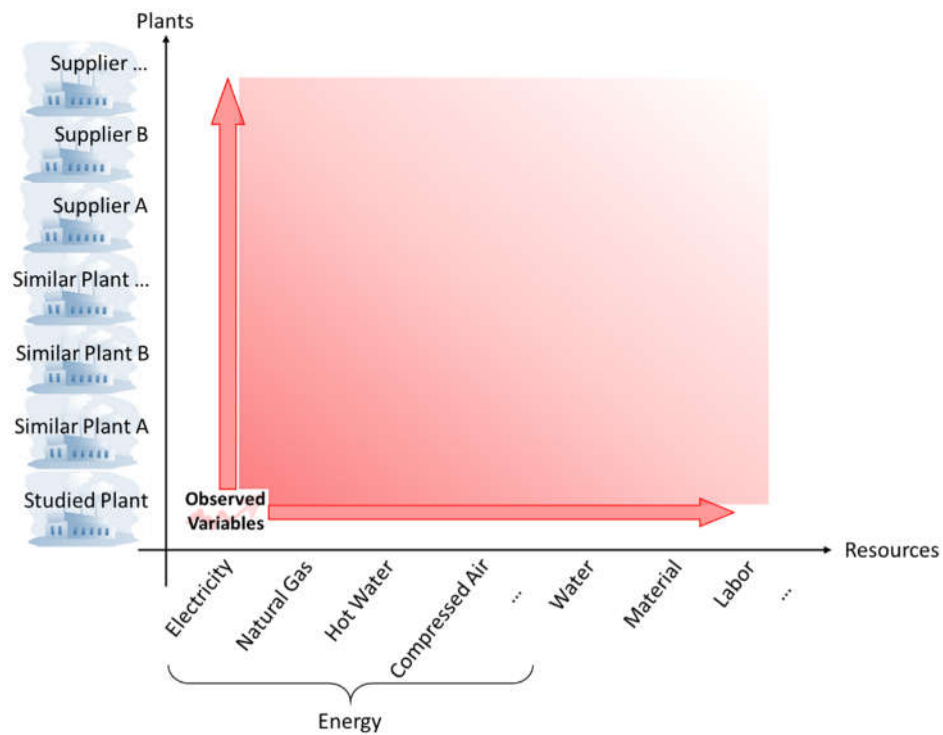


Figure 6.1: Sensitive Variable Sharing

4. Time series modeling in high time resolution (*e.g.*, in hour, minute, and second) would be interesting to observe energy consumption trends across different time scales and seasonal patterns; therefore, it could be used for better energy monitoring and analyzing in plant and lower production levels. By combining multiscale patterns with online estimation and big data techniques, the system can update the forecasting parameters frequently to provide a more accurate result.
5. Forecasting can also be applied to monitor the device and equipment operations through models for devices and equipment. Setting comparison logic between the model outputs and monitored data can be used to warn and create alarms for unusual conditions. This approach can be termed *energy health monitoring*.
6. Solar and wind energy are increasing in market use. In many countries, solar and wind energy are the main renewable energy sources for investment in the future. Including these two unstable renewable energy sources in the research would be promising. How could the uncertainty of these two energy sources affect the traditional on-site energy operation system? How could energy storage systems to be applied in such a system, and this analysis used to optimize its operation?
7. The on-site energy generation system is also known as the distributed energy generation system. How would the on-site generation system

affect and be affected by the utility company in terms of generation capacity and energy price? Would it be economically or sustainably advantageous to sell energy back to the utility companies in non-working days? If two-way communication is possible, how could the utility companies and these distributed generation system work together to reduce energy consumption overall? It would be interesting to study the effects of manufacturing plants' consumption and supply on the smart grid.

In summary, manufacturing energy is a broad topic worthy to be studied further. This research answered three main research questions and compensated current knowledge gaps in systematic modeling, consumption forecasting, and supply optimization. Increasing the understanding of energy usage in the manufacturing system and improving the awareness of the importance of energy conservation and environmental protection are the primary goals and future vision of this research work.

APPENDICES

Appendix A

Improvement Suggestions and Examples

No.	Category	Improvement Suggestions and Examples
1	Energy Management Program	<ul style="list-style-type: none">• Cooperation with utility companies• Example of Project Energy Partnerships offered by Detroit Edison• Program expanded to Daimler Chrysler, Ford and General Motors in year of 2001
2	Energy Management Program	<ul style="list-style-type: none">• Use sub-metering• Example from a Canadian plant• 3-year project• Closing windows and doors• Switch off unused machinery
3	Energy Management Program	<ul style="list-style-type: none">• Switch off lights and coolers when leaving an office• Remove superfluous lights• Prevent blockage of radiator and ventilation grids• Example from Volvo Car Company at Born (the Netherlands)
4	Energy Management Program	<ul style="list-style-type: none">• Computer-based energy management system• Set up procedures to shut down equipment during non-production periods• Ford's Edison Assembly Plant in New Jersey• Installed an energy management system that maintains control of compressed air, lighting, equipment power utilization, steam and innovative energy savings technologies
5	Energy Management Program	<ul style="list-style-type: none">• GM of Canada, Ltd.
6	CHP combined with absorption cooling	<ul style="list-style-type: none">• Absorption chillers installation• Continuous operation or for peak shaving
7	Strategic motor selection	<ul style="list-style-type: none">• Exchange 296 of its standard efficiency motors with energy efficient motors• Cummins Engine Company, Inc., MidRange Engine Plant in Indiana
8	Strategic motor selection	<ul style="list-style-type: none">• Specified new energy efficient motors for their HVAC system• Cummins Engine Company, Inc., plant in Columbus, Indiana

9	Strategic motor selection	<ul style="list-style-type: none"> • Replace five motors used in operate its furnaces with high efficiency motors • Delta Extruded Metals (UK)
10	Variable frequency drives (VFDs, ASDs)	<ul style="list-style-type: none"> • Install VFDs • Energy savings are shown to vary between 7% and 60%
11	Variable frequency drives (VFDs, ASDs)	<ul style="list-style-type: none"> • Installed VFDs together with energy management system (EMS) to control the VFDs as a unit • General Dynamics Armament Systems, Burlington, Vermont
12	Variable frequency drives (VFDs, ASDs)	<ul style="list-style-type: none"> • Application of VFDs in the pumping of machine coolant • Pressure at the pumps was reduced from 64psi to 45psi • An U.S. Engine plant, in 1989
13	Variable frequency drives (VFDs, ASDs)	<ul style="list-style-type: none"> • Computer chip controls on the electric blower motors, to regulate the motors' speeds by continuously monitoring the speed and adjusting the power to meet the speed demand • GM Fairfax Assembly Plant in Kansas City
14	Variable frequency drives (VFDs, ASDs)	<ul style="list-style-type: none"> • Use new energy management system to control VFDs • Lockheed Martin facility (Vermont)
15	Compressed Air Systems	<ul style="list-style-type: none"> • Filter cleaning periodically • Monitor pressure drop
16	Compressed Air Systems	<ul style="list-style-type: none"> • Automatic valves to separate production-line sections of the compressed air from the main supply • An U.S. automobile plant
17	Compressed Air Systems	<ul style="list-style-type: none"> • Reduce leaks in pipes and equipment
18	Compressed Air Systems	<ul style="list-style-type: none"> • Ultrasonic inspection tool to search for leaks • Repair leaks • Ford Stamping Plant in Geelong, Victoria (Australia)
19	Compressed Air Systems	<ul style="list-style-type: none"> • Replace single stage compressors with multi-stage compressors
20	Compressed Air Systems	<ul style="list-style-type: none"> • Reducing intake air temperature by using outside air
21	Compressed Air Systems	<ul style="list-style-type: none"> • Installed a computerized control system for air compressors • Land Rover's Solihull plant, in 1991
22	Boiler	<ul style="list-style-type: none"> • Improve insulation • New material with better insulation and a lower heat capacity

23	Boiler	<ul style="list-style-type: none"> • Potential material: ceramic fiber • Heating will be more rapidly. • Maintenance • To ensure that all components of boiler are operating at peak performance
24	Hot Water Distribution	<ul style="list-style-type: none"> • Improve insulation
25	Lighting	<ul style="list-style-type: none"> • Use more energy efficient lights • Automatic controlling systems
26	HVAC	<ul style="list-style-type: none"> • Electronic control • Simple as on/off switches to switched off during non-operating hours • Several U.S. industrial cases • On-off control system
27	HVAC	<ul style="list-style-type: none"> • Climate-adapted ventilation control system • Volvo Torslanda Manufacturing plant in Sweden

Appendix B

Water Heat Capacity Lookup Table

Temperature [°C]	Heat Capacity [kJ/(kg K)]
5	4.204
10	4.193
15	4.1855
20	4.183
25	4.181
30	4.179
35	4.178
40	4.179
45	4.181
50	4.182
55	4.183
60	4.185
65	4.188
70	4.191
75	4.194
80	4.198
85	4.203
90	4.208
95	4.213
100	4.219
105	4.226
110	4.233
115	4.24
120	4.248
125	4.26
130	4.27
135	4.28
140	4.29