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Manufacturing Energy Consumption and Assessment for Us Small and Medium Sized Manufacturers

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MANUFACTURING ENERGY CONSUMPTION AND ASSESSMENT FOR US SMALL AND MEDIUM SIZED MANUFACTURERS

by

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ABSTRACT

MANUFACTURING ENERGY CONSUMPTION AND ASSESSMENT FOR US SMALL AND MEDIUM SIZED MANUFACTURERS

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U.S. Manufacturing sector consumes remarkable amount of energy while the energy efficiency is quite low. Energy consumption of CNC machines is significant and various empirical models have been developed to model the Specific Energy Consumption (SEC) of CNC machines. However, most of the models are developed for specific machines, hence have limited applications in manufacturing industry. In this research, a general empirical SEC model for milling machine at certain power level is developed based on actual cutting experimental data. In this model, stand-by power and spindle power are used in the SEC model for the first time. The Material Removal Rate (MRR) is used to represent cutting parameter. The proposed model is fitted by regression analysis and validated using experimental data. Results show that the proposed model can be applied on various milling machines with an average absolute residual ratio of 6%. The model is also validated through a series of cutting experiments on a machine center, with an accuracy of 91.5%, for the SEC calculation.

Compressed Air Systems (CAS) are the 3rd energy source in industrial facilities and has a significant impact on the energy efficiency of manufacturing systems. This thesis provides an overview of all typical energy conservation measures (ECM) for CAS as well as all the energy savings calculations methods. To provide a simple guideline for decision maker, an economic benchmark analysis is presented for typical ECMs using the baseline conditions from Technical

Reference Manuals (TRM) of multiple States in the US. Due to the ECMs correlate with each other, the comprehensive savings from multiple ECMs is not the simple summation of each individual measure. An integrated model is proposed to investigate the interrelationships of all measures and obtain combined savings. Meanwhile, the dryer's impact to the other ECMs is included for the first time in the proposed model. CAS is a dynamic system with changing load, operations, and specifications etc. Therefore, the savings is a variable depending on system situations. The reliabilities of the ECMs are analyzed to obtain their dynamic characteristics. The optimization of the ECMs is discussed to demonstrate the interrelationships and dynamic of the savings mechanisms.

While the above studies focus on the energy modeling and savings of important system of manufacturing activities, it is important to have an overall understanding of the energy efficiency and saving potentials. Energy intensity is commonly used as an indicator for the energy efficiency. Encourage the implementation of proposed ECMs is the main strategy for energy efficiency improvement programs to influence the plant's energy intensity. Study the trends of energy intensity of SMEs and the acceptance of proposed ECMs could draw outlines of the changes of energy usage, understand the flavor of plant managers towards energy savings projects and reflect the shift of technologies in the past decades. This thesis found that the industry structure of SMEs had limited effects on the energy usage while the fluctuation of producing activities and improvement of energy efficiency were the main contributors over the past three decades. Compared with the manufacturing plants with best energy efficient practices, an average of 15.71% of electricity and 14.51% of natural gas could be saved. However, the saving potentials of each subsectors varies dramatically due to the differences of production processes and energy use strategies. This discrepancy also reflected on the implementation of ECMs. Special planning and stimulations should be developed to accommodate the unique saving demands for different industries, ECM types and regions.

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Chapter 1 Introduction

The projected primary energy consumption of the United States will have a 5% growth from the 2016 level by the year of 2040, especially in the consumption of natural gas[1]. The use of fossil fuels has contributed to a great amount of greenhouse gas (GHG) emissions, which is blamed for the global climate change[2]. The increase of primary energy consumption and associated environmental concerns have driven public attention to the improvement of energy efficiency of the industrial sector (manufacturing, agriculture, construction and mining) [3]. As shown in Figure 1, the industrial sector is historically the largest energy consumer of United States, in which the manufacturing sector alone consumed 19.6% (19,045 trillion BTU) of U.S. primary total energy and generated more than 1.2 billion metric tons of greenhouse gas in 2014[1, 4]. However, as illustrated in Figure 2, only half of the energy that entered the manufacturing sector were used to support production processes. Improving energy efficiency by end-users has been an emerging and inevitable research trend.

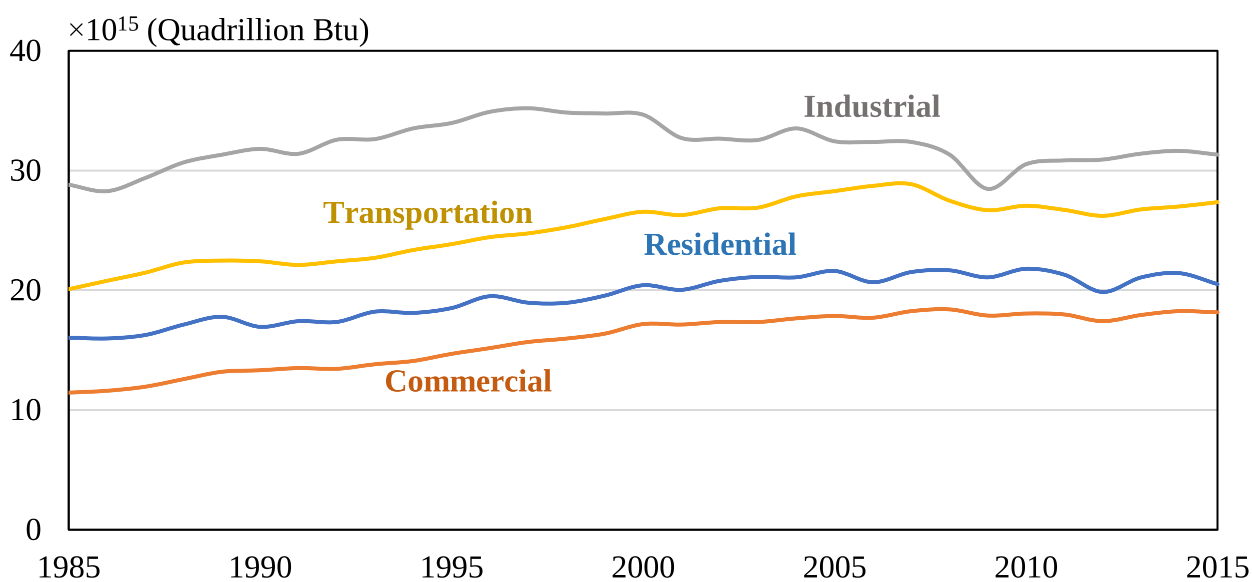


Figure 1 Energy Consumption by U.S. Sector (1985-2015)[1]

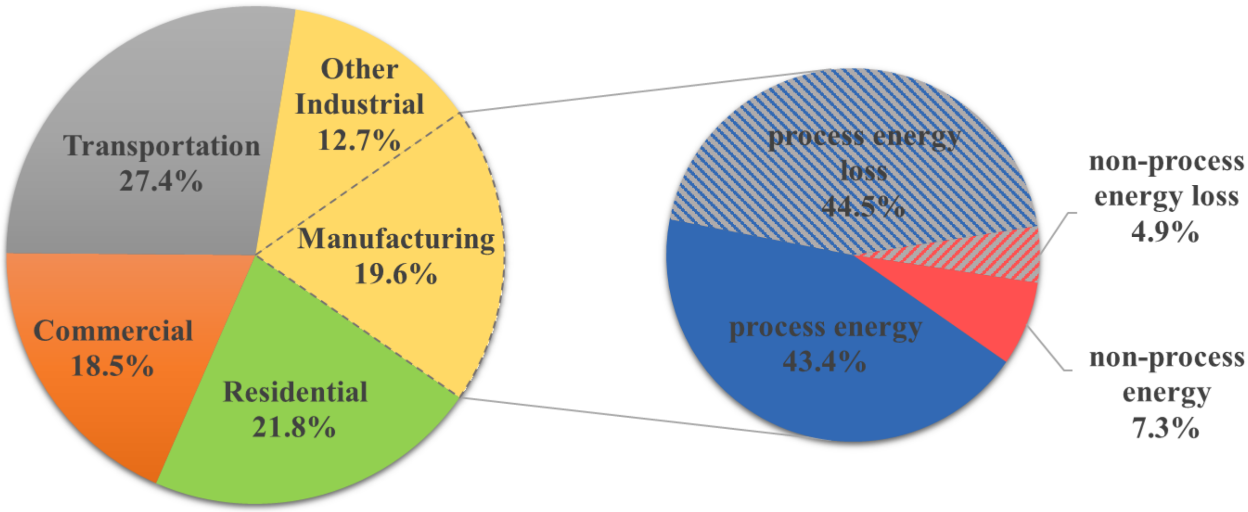


Figure 2 Energy Consumption by Sector and Manufacturing Energy End Usage[1, 4]

Manufacturing system is not isolated and comprises complex activities. Herrmann et al.[5] pointed out that measures on single production units is not sufficient to improve the efficiency of the organization. An integrated methodology to evaluate the process chain was proposed to help improve energy efficiency of manufacturing companies and solve potential conflicts of objectives. Apostolos et al.[6] proposed a bottom-up structure to study the energy efficiency of manufacturing companies and divided the analysis into process level, machine level, line level and factory level. The paper analyzed the factors that may have impacts on energy efficiency with emphasis at process- and machine- level and discussed the inter-level interactions. Duflou et al.[7] proposed similar strategies to improve energy efficiency and focused on the effectiveness of available techniques and measures. To achieve the overall goal of effective manufacturing, efforts should be put into each layer of activities.

The basic organization structure of manufacturing plants is a pyramid as shown in Figure 3, which includes unit processes, manufacturing/auxiliary systems, and factories. This thesis aims to select a representative object in each level to thoroughly analyze the energy characteristic of the manufacturing facility from micro to macro. Unit processes and individual devices are the foundation for manufacturing production. Understanding the energy consumption per process can better support engineering designs and production planning. Since the machine tool is the most common processing unit in industrial facility, its energy use will be modeled to provide a powerful tool to estimate the unit process energy consumption. Besides the machining processes, the daily operations of a plant consist of various manufacturing and auxiliary processes. Optimization of manufacturing/auxiliary systems can help to manage energy flows and maximize the cooperation between systems. Compressed air system (CAS) is one of the major auxiliary energy consumers in manufacturing facilities [8]. This thesis will build an integration model to evaluate the energy saving potentials in CAS. Further towards to factory level would require more investigation of the barriers and drivers to improve the effectiveness of industry facilities in manufacturing sector. This research will study the energy use, efficiency, and savings potential of the small and medium sized manufacturers based on Industrial Assessment Center Data.

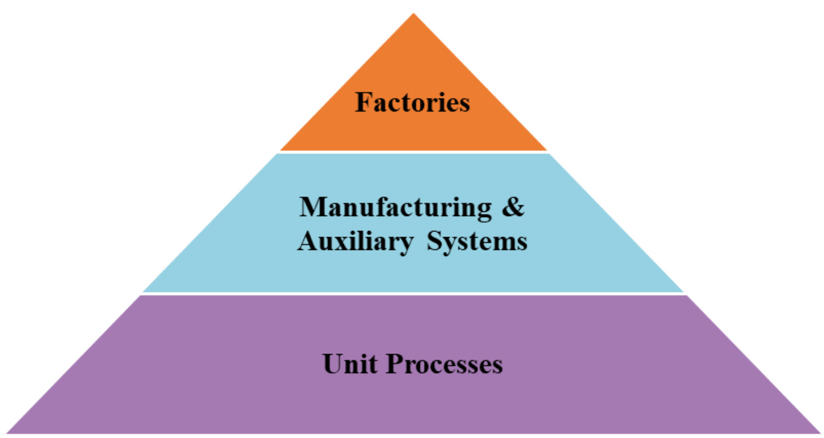


Figure 3 Manufacturing System Structure and Research Scheme

1.1 Energy Consumption Models for CNC Machines

Machine tools serve as basic equipment in most manufacturing plants and are one of the major electricity consumers[9]. Although electricity is a relatively clean energy to use for end-users, it is not generated and transmitted in sustainable ways in most of U.S.[10]. A 22kW machine tool under main shift could result in more GHG emissions than 61 SUVs per year[9]. The concerns for the environmental impact of manufacturing processes and the desire for sustainable manufacturing keep increasing in recent years. Meanwhile, the rising energy price and growing production demands have greatly increased the utility costs for manufacturing enterprises[11]. It is another strong motivation for manufacturers to reduce the energy costs and pursue more energy efficient machine tools. On the other hand, the machine tools that are commonly used for typical manufacturing processes such as milling and turning usually have low energy efficiency[12]. Therefore, there exist tremendous opportunities for potential energy and cost savings in manufacturing plants[13].

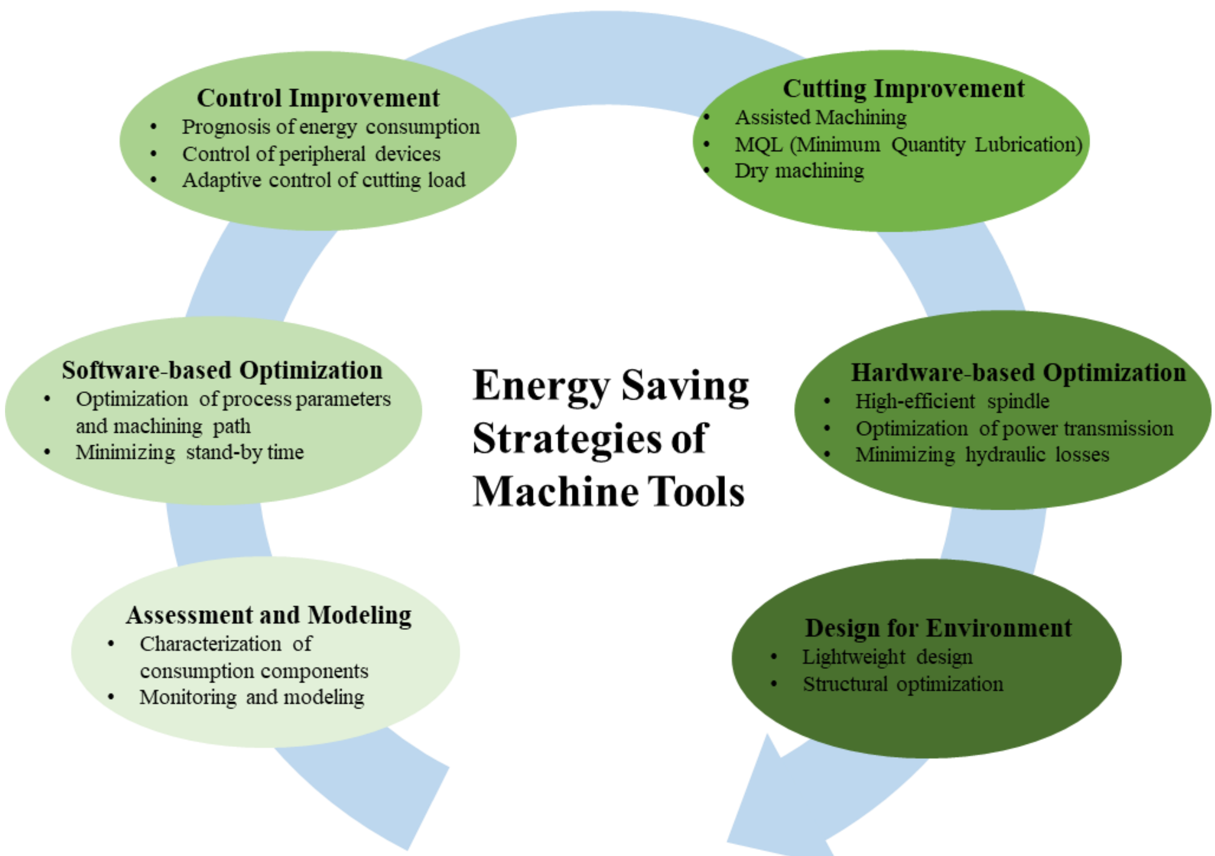


Figure 4 Energy Saving Strategies of Machine Tools for Manufacturing Processes[14]

Various energy saving technologies and strategies have been developed and proposed to improve the efficiency of manufacturing processes. Yoon et al. [14] reviewed state-of-the-art energy saving technologies and summarized 6 hierarchical approaches for machine tools to achieve energy saving goals during manufacturing processes. As shown in Figure 4, understanding and monitoring the energy consumption of machine tools would be the first and essential step towards more energy-efficient machine tools. The characteristics of the machine tool could be revealed by modeling its energy consumption during machining processes. Factors that would affect the energy usage of the machine tool, such as cutting conditions and machining states, are studied and analyzed at this level. The knowledge obtained by energy modeling at this approach not only could provide quantitative information of energy consumption; but also assist the following steps such as cutting parameter optimization and stand-by time minimization and eventually help manufacturers to improve energy efficiency, reduce energy costs and associated emissions. Accurate prediction of energy consumption can also improve manufacturers' understanding of facilities' efficiencies and products' energy intensities. Hence more efficient and economical production plans can be made accordingly [9].

Many efforts have been made to develop accurate energy consumption models for machine tools. In literature, various empirical models were proposed to predict the energy consumption during machining processes. Zhou et al. [9] summarized the essential methods of developing energy consumption models into three categories (linear model, detailed parameter correlation model, process oriented model). Table 1 lists the divisions of energy modeling methods and relative common model expressions. It is important to note that the boundaries among each modelling category are not rigid, so as the emphases of the applications for each modelling method. Some research may use one or more methods at the same time to obtain a satisfactory accuracy.

During energy modelling, Specific Energy Consumption (SEC, J/mm^3) is usually used to express the energy consumption level of machine tools. It is defined as the energy required to remove unit volume of material. Material Removal Rate (MRR, mm^3/s) is the volume of material removed by machine tool per unit time. Together with SEC, they can represent the energy intensity of the machine tool and their relation is commonly utilized in energy modelling methods.

Table 1 Energy Consumption Model Categorization for Machining Process

Types of Energy Model	Reference	Basic Model Equation		Notes
Energy Model base on MRR	Kara et al. [2]	$SEC = C_0 + \frac{C_1}{MRR}$	(1)	Models are consisted of a constant part and a variant part, which is represented as a function of material process rate.
	Gutowski et al. [15]	$SEC = \frac{P_0}{MRR} + k$	(2)	
	Li et al. [16]	$SEC = C_0 + \frac{C_1}{MRR} + \frac{C_2 \times n}{MRR}$	(3)	
Detailed Parameter Correlation Model	Rodrigues et al. [17]	$SEC = \frac{v_c}{V_{chip}} \int_0^{t_c} \left(F_x^2 + F_y^2\right)^{\frac{1}{2}} dt$	(4)	Models are proposed based on tool wear, cutting force or cutting parameters, etc. The machine characteristics are not considered.
	Guo et al. [18]	$SEC = \frac{C_1}{v_c \cdot f \cdot a_p} + C_0 \cdot v_c^{\alpha} \cdot f^{\beta} \cdot \alpha_p^{\gamma} \cdot D^{\varphi}$	(5)	
Process Oriented Model	Mori et al. [19]	$E = P_1(T_1 + T_2) + P_2(T_2) + P_3(T_3)$	(6)	Models are established according to machine tool's movements or part processing routes. The models consider the comprehensive production processes.
	Aramcharoen et al. [20]	$E = P_b \cdot t_b + P_t \cdot t_t \cdot n_t + P_s \cdot t_s + \sum_{i=1}^{m} \int_{t_{st}}^{t_{en}} P_{feed}\, \mathrm{dt} + P_c \cdot t_c + P_f \cdot t_f$	(7)	
	Budinoff et al. [21]	$E = P_0 \Delta t + k \left(\frac{h}{h_r}\right)^a \Delta V$	(8)	

Kara et al. [2] proposed a SEC model solely with respect to MRR in Eq. 1 of Table 1, where C_0 and C_1 are machine specific coefficients. The coefficients are subject to change for each different machine. The test results on multiple turning and milling machine tools indicated that this model format could generally predict the specific energy consumption under various cutting conditions with different types of workpiece material and cutting methods. Their paper also pointed out that in wet cut scenario when extra energy costs were required for coolant or lubricant, adjustments on coefficients were necessary to keep model accuracy, especially for C_1 coefficient, which could reflect the stand-by power consumption of machine tool. Gutowski et al. [15] tracked the energy transformation of various processes from raw material producing through the final product processing with consideration of manufacturing efficiencies. Their paper provided generalized energy consumption trends for common manufacturing processes. Based on their analysis, the material process rate is one of the main factors that would impact the specific energy consumption. In other words, processes working with finer dimensions and smaller scales would result in lower process rate, longer process time and larger specific energy consumption. Their theory-based model followed the similar format in this category with two coefficients. Besides MRR, some other cutting or machine related parameters are also frequently used for modeling the specific energy consumption. Li et al. [16] proposed an improved SEC model with respect to MRR and spindle speed *n* as in Eq. 3. Their model had a 96% prediction accuracy for various cutting conditions. To better understand the model, the paper clearly defined the model coefficients where C_0 is the specific cutting energy requirement that depends on cutting method, workpiece material and cutting parameters; C_1 is the specific coefficient of spindle motor and C_2 is the constant coefficient of tested machine tool.

Rodrigues et al. [17] proposed a SEC model utilizing cutting speed, removed chip volume, and cutting forces along cutting surface. Their paper compared the SEC and the surface roughness with different tool edge geometries at conventional and high cutting speed. Guo et al. [18] pointed out that the cutting tool characteristics and cutting parameters should be considered together to estimate the cutting energy consumption using Eq. 5, where D is the cutter's diameter, and v_c, f, a_p are the cutting parameters. The coefficients in related models can be determined easily by numerical analysis with experiment data. Since multiple tool and cutting parameters are considered in those models, it is usually used to analyze the tool wear conditions, material surface quality and cutting parameters optimization. Mori et al. [19] divided the machining process into three segments and calculated the total energy consumption through stand-by power P_1, machining power P_2, feeding/air-cutting power P_3 as shown in Eq. 6. Based on the proposed model, a new control method was proposed to minimize the energy consumption. Aramcharoen et al. [20] decomposed the total energy consumption into several key components: basic, tool change, cutting fluid pump spindle, feeding and cutting power. This process-oriented model is excellent at the optimization of toolpaths during cutting process. Energy consumption can also be predicted based on theoretical analysis. Branham et al. [12] proposed potential approaches to calculate minimum work required for material removal processes. However, the results from theoretical models are commonly deviated from actual manufacturing process due to the lack of prediction on auxiliary processing energy consumption. Thus, those models are less accurate than empirical models and may only account for a small amount of actual energy consumption. To obtain sufficient accuracy, empirical modeling method is adopted in this research.

The development and validation of each energy consumption model is time-, cost- and labor-consuming due to the complexity of experimentation for data collection. However, our literature review shows that most existing energy consumption models are tied to specific CNC machine tools and lack versatility. Since there are a large number of different machine tools being used in manufacturing sector, developing a general and accurate energy consumption model that can be applied to various machines is imperative. This research focuses on the energy consumption modeling in CNC milling machines during metal-cutting processes. A general SEC model which is applicable to a range of machine tools for milling processes will be proposed.

1.2 Energy Savings in Air Compressor System

Compressed air is a form of stored energy that can be used to operate machinery, equipment, or processes. It is widely used throughout manufacturing industries, due to its cleanness, availability, and ease to use. Compressed Air System (CAS) plays a strategic role in achieving better energy efficiency in industrial field due to its large diffusion, low efficiency and high energy intensity [22, 23]. CAS typically accounts around 10% or more of an industrial facility's total electricity consumption [24].

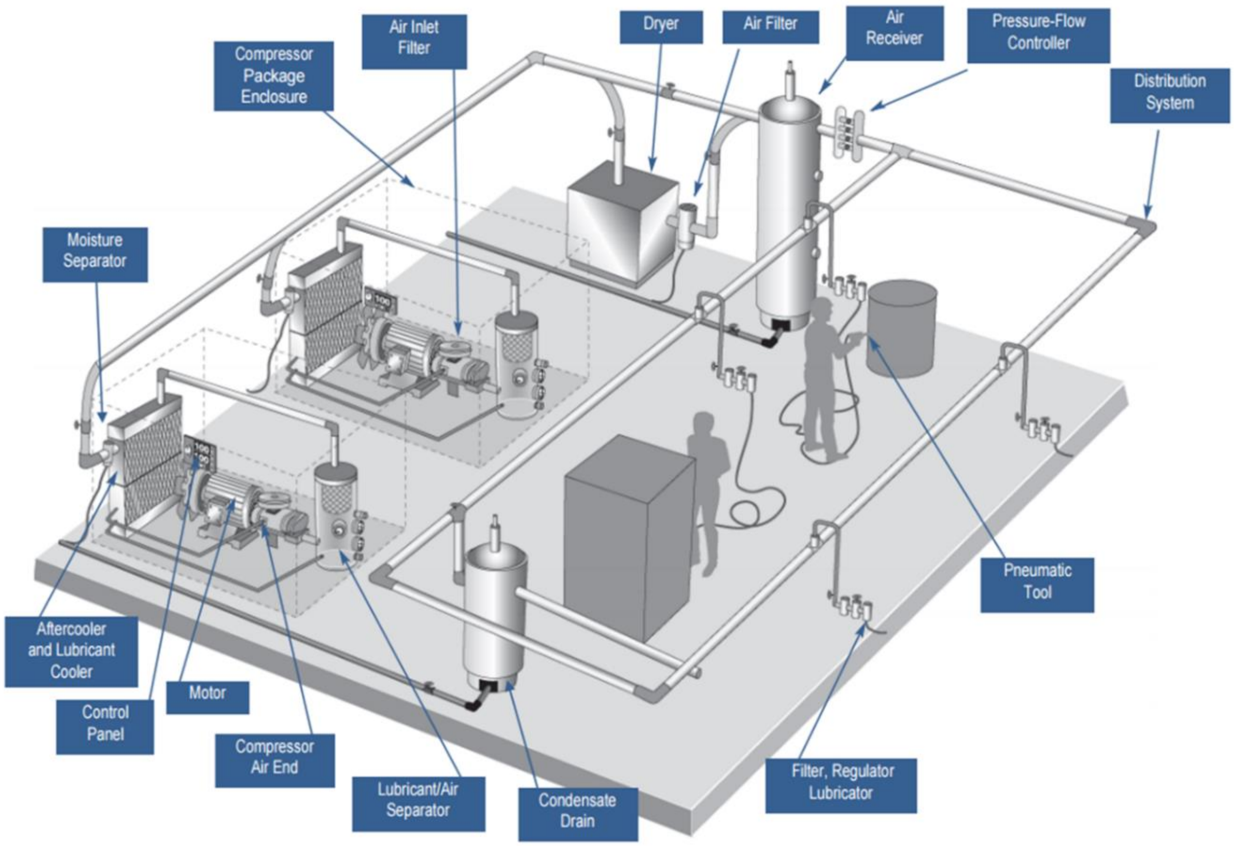


Figure 5 Typical Compressed Air System [25]

CAS typically includes of various components, such as air compressors, air dryers, filters, pipes, valves, nozzles, air tools, regulators and controllers etc. as shown in Figure 5. There are potential energy losses in the form of flow or pressure loss for all the components. Energy savings opportunities have been found in nearly all the CAS during energy assessment. The distribution of popular energy saving opportunities for CAS is illustrated in Figure 6 [26]. The top three recommendations contribute 88.3% of overall opportunities for CAS. In the IAC database, three of the top five recommendations are about compressed air system, which are: eliminate leaks in inter gas and compressed air lines/valves (rank #2), install compressor air intakes in coolest locations (rank #4), and reduce the pressure of compressed air to the minimum required (rank #5).

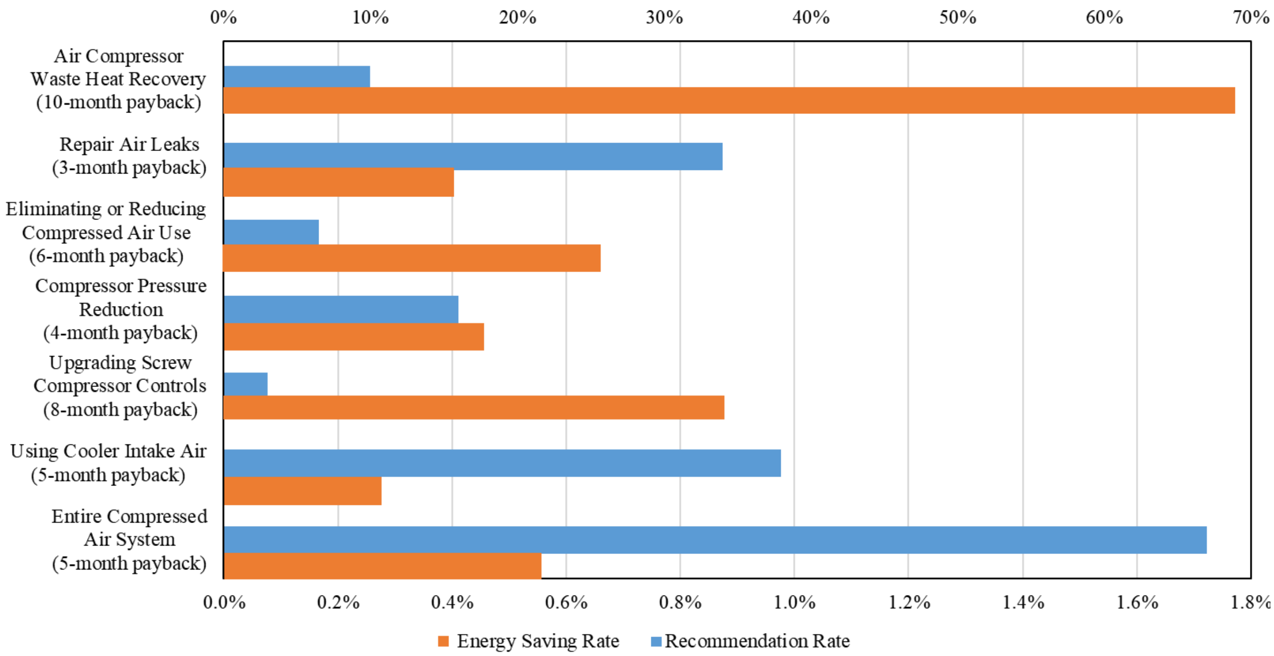


Figure 6 Recommendation and Saving Rate for Air Compressor System

Since energy saving opportunities are presented everywhere in CASs, it is relatively easy to identify where energy can be saved [23, 27]. There are several low cost or even no cost measures. Repair air leak, as the most popular recommendation for the compressed air system, has the highest implementation rate 83.5%. The simple payback period is less than 4 months according to the implementation data. Air leak detection and repair are suggested to be done every year in many energy savings programs[28]. The potential cost savings is a dynamic value related to control type, system pressure, storage size, leakage percentage and dryer type etc. However, the energy waste due to air leak was evaluated statically in many literatures [29, 30]. This thesis aims to capture the dynamic feature of air leaks through integrated calculation with other measures. Another key ECM is to reduce system operation pressure [31]. The maintenance person can set the pressure to the lowest level required by the production process. Apparently, reducing set pressure requires no investment and is a no-cost measure to save energy. Most of the CAS has to be set at a relatively high pressure for special reasons, such as high pressure drop in the air filter, insufficient of air storage, high instant demand etc. Thereby, there are many energy savings measures related with system pressure other than reducing set pressure, such as replacing air filter and installing pressure/flow controller. To achieve reducing pressure in the most effective way, both quality and quantity impacts of all the pressure related measures need to be unbiasedly compared. The best measure-candidate for reducing pressure can be obtained through optimization research.

Some of the ECMs require higher capital investment, for instance, installing extra air tank, applying VFD air compressor, and use efficient dryer etc. In the past, the rule of thumb for air tank size is 1 gal/cfm to 3gal/cfm, which is mainly derived based on reciprocating compressors. This guideline is already out of date for load/non-load (LNL) rotary screw air compressor or more advanced CAS because of the different partial load characteristics. Nonetheless, many air tanks in CAS are still sized following this rule. The inappropriate size of air receiver has a negative impact on system efficiency. The energy savings of using larger tank was estimated based on experiment data [32] without the consideration of system pressure and control details.

To evaluate the energy savings, data collection and analysis are essential, which typically requires a specific CAS energy audit. A comprehensive energy audit will collect necessary data, identify energy wastages, evaluate energy savings opportunities, propose ECMs and provide economic analysis. AIRMaster+ is a systematic software developed by U.S. Department of Energy

(DOE) to simulate performance of CAS. Its algorithm is designed based on one-hour time interval, which restricts its accuracy [33]. The energy savings from dryer or dryer related measures are not well include in the simulations. AirSim from Dayton can capture more dynamic behavior of CAS benefited from its lower time interval and specific data calibration capability [34]. Nonetheless, both software is modeled for supply side and lacks the modules for end use side.

Literature review shows the ECM for CAS is well researched through audits, experiment and simulations. It takes concerted efforts to ensure that these ECMs can be correctly evaluated and maintained. Many independent studies aim at ranking the saving potential of different measures, to address main criticalities of CAS [35]. The industry lacks reliable economic benefit comparison of all the measures during practice. Most of the researches only focused on air compressor and distribution line. The impact of dryer hasn't been comprehensively integrated. Meanwhile, the savings was evaluated separately in the literatures. Due to the interrelationship among all the measures, the combined savings effect is not the simple summation of the individual measures. The calculation of integrated savings from multiple ECMs is missing. Because of the continue changing status of the CAS, the savings from the same measure is subjected to change in various scenarios. The dynamic characteristic of the savings hasn't been researched to the author's best knowledge. Therefore, a benchmark for each measure will be presented to compare their economic benefits. A new integrated energy savings calculation model will be proposed and analyzed to address the interaction of ECMs and their dynamic characteristics.

1.3 Energy Characteristics Analysis of U.S. SMEs

Improving energy efficiency is an important strategy to mitigate the energy depletion and a promising approach to tackle environmental problems to ensure sustainable use of energy for end-use entities[36]. Efficient use of energy not only benefits manufacturing plants financially but also on other features. For instance, higher production capacities and improved customer satisfaction were reported after using more efficient process lines[37]. The industrial sector consistently consumes more than 30% of the total U.S. energy usage based on Figure 7, in which the manufacturing sector is the largest end-user. A strong boost towards the reduction of energy consumption is needed.

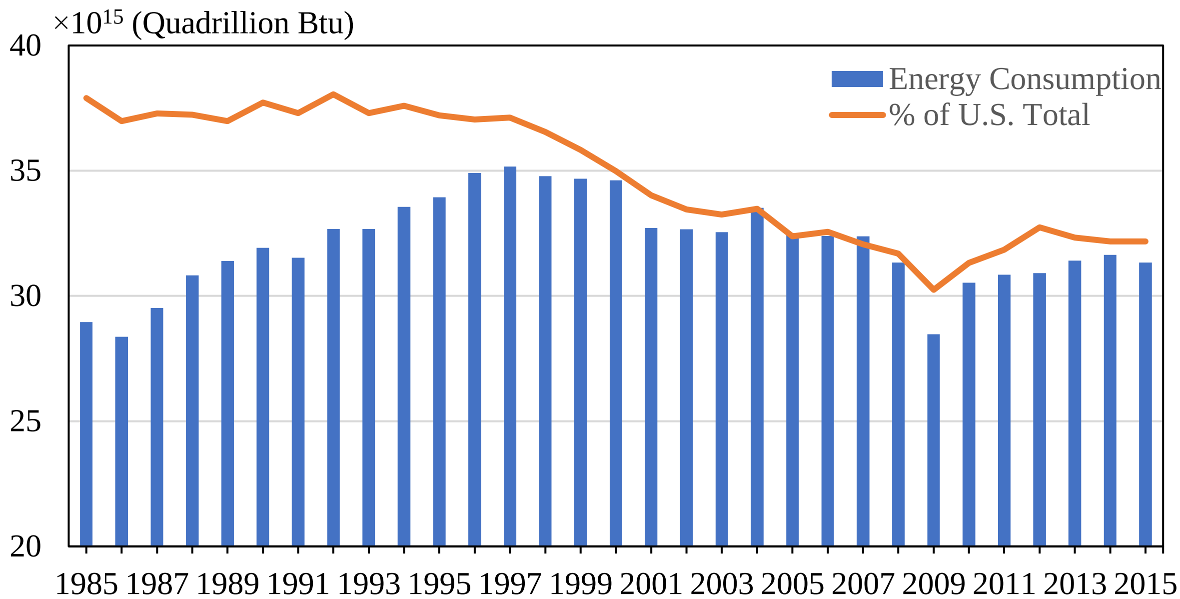


Figure 7 Industrial Sector Energy Consumption Trend (1985-2015) [1]

To better analyze energy efficiency and achieve energy savings, the existing energy consumption situation and possible energy conservation measures are two key aspects. Energy intensity is widely used to measure the industrial energy efficiency[38]. It is typically computed as the energy consumed per dollar of gross domestic product (GDP)[39]. Although the underlying influences of technical advancement, policy support or other factors may not be clearly explained, energy intensity is a simple and straightforward indicator to reflect the changes of energy-use structure. Hasanbeigi et al.[40] analyzed influences of different factors on energy usage and output of 17 manufacturing subsectors in California between 1997 and 2008 by decomposition analysis.

The energy intensity reduction and structural effects are concluded as the most important factors that affect the energy use demand. 18-26% of the total industrial energy consumption could be saved by adopting best practice commercial technologies [41]. Small- and medium- sized manufacturers/enterprises (SMMs or SMEs) are a vitally important part to achieve this goal.

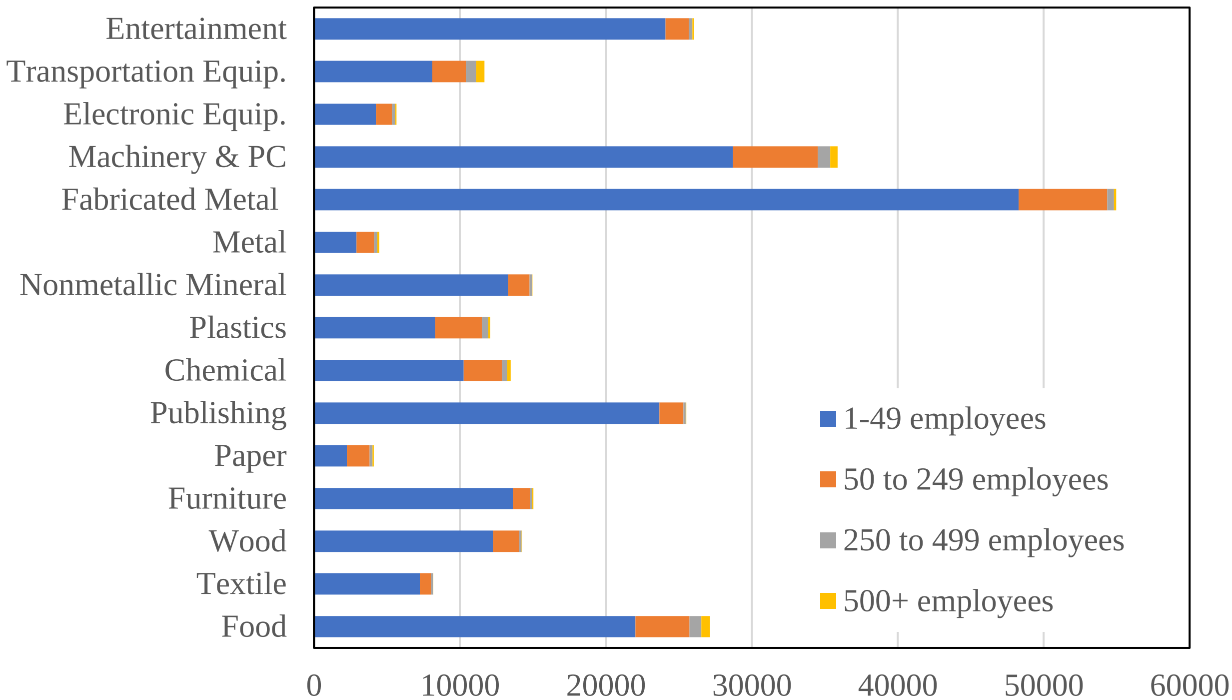


Figure 8 Manufacturing Establishments by Employment Size [42]

The definition of SMEs varies between organizations. To qualify a SME defined by IAC, the facility must be within the manufacturing sector, employ less than 500 staffs, have no on-site energy management personnel, spend between $100,000 and $2.5 million per year on its utility bills and make no more than $100 million annual sales of its products. The employment size is a popular criterion as it is easy to assess and track. As shown in Figure 8 [42], SMEs operate in every manufacturing subsectors and are account for more than 90% of establishments in U.S. manufacturing sector and 50% of the energy use [43, 44]. Addressing the special needs for SMEs to improve energy efficient could make a big difference on the energy profile of manufacturing sector. However, SMEs have unique and significant internal barriers to adopt energy efficient improvements. Trianni et al. [45] explored the barriers and drivers for SMEs of various countries. The results indicated that the economic concern is the most common barrier in SMEs, followed by the awareness issues. Financial support and energy efficiency promotion from different forms and through different channels were suggested. Bunse et al. [46] studied "energy efficiency implementation gap" between the available sustainable solutions and the actual implementations in end-users. To encourage the implementation of energy efficiency features, measurable and accurate key performance indicators (KPIs) should be identified and developed. Kissock et al. [33] pointed out that accurate measurement of energy savings could enhance the management's confidence during decision-making process and guide the selection of future projects.

There exist a variety of policies and programs to encourage the improvement of energy efficiency in the manufacturing sector. Compared with other sectors, the facilities of manufacturing sector are usually larger and more energy-intensive. As such, there exist great energy and cost saving potentials in the manufacturing facilities. However, the energy use strategies vary significantly between facilities, even within the same industry. This feature challenges the development and implementation of energy saving measures, as well as the policy and program makers for energy efficiency programs. Tanaka [41] reviewed over 300 energy efficiency policies across the world and proposed assessment criteria to evaluate the effectiveness of various policies. The paper also summarized the key features for industrial owners to implement energy efficiency measures. Thollander et al. [47] evaluated a Sweden energy efficiency program that focused on manufacturing SMEs and discussed the barriers to adopt energy efficiency measures among the companies. The results affirmed the positive influence of energy programs on improve industrial energy efficiency. Various programs that provided technical or financial assistances are available for manufacturing enterprises. The U.S. government has provided more than 600 billion dollars through 2003 for energy development in R&D funding, regulations, taxation, direct incentives and other related activities[48].

The Industrial Assessment Center (IAC) Program is initialized by the Department of Energy (DOE) and has been focused on improving the energy efficiency of SMEs for over 40 years. Students and energy engineers trained by this program have conducted thousands of energy audits to firms and facilities that couldn't afford on-site energy management staff and averagely proposed 7.6 assessment recommendations per visit. Among all those recommendations, the ones that emphasize on reducing the energy consumption of the facility buildings, the manufacturing systems and production processes could be concluded as energy conservation measures (ECMs). The follow-up interviews by IAC staffs indicate that more than half of the proposed measures are successfully implemented. By the year of 2015, the adopted ECMs have saved more than 230 million dollars and 16 million MMBTU of energy for participated companies.

To achieve energy and cost savings for SMEs, identifying potential savings opportunities is only the first step. How to break the internal barriers and difficulties and attract plant managers to implement the ECMs would be an important follow-up step. Anderson et al. [49] analyzed the adoption rates of energy efficiency projects at manufacturing plants. Various factors, such as payback period, implementation costs, capitol savings and energy price, were identified to have influence on decision making. Fleiter et al. [50] evaluated cases of an energy audit program in German and examined various self-assessed reasons that hurt the adoption of efficiency measures. Lack of capital was found to be the biggest barrier to adopt energy-efficiency measures. The paper also found that the quality of the energy audits would affect the final decisions on ECM adoption. Alhourani et al. [51] used IAC data to analyze the factors that affect the implementation rates of proposed recommendations. The paper found out that the payback period would greatly impact the company's willingness to adopt the recommendation and different industries have different patterns towards the proposals. It also pointed out that the production capacity could influence the implementation rate.

Based on the literature and program reviews, most of the energy efficient programs are neutrally designed without consideration of difference between industries. Programs primarily aim to achieve calculated savings, while lack the necessary feedback from the implementation side. The general factors that impact the decisions of ECM adoption remain unclear. Therefore, this thesis proposes to analyze the trend of the energy intensity and the key factors that affect the implementation of ECMs in the industrial field. The interaction between the changes of energy intensity and the preference of ECMs will be analyzed for the first time. The results will provide some insights to the policy makers for the design of the program and prediction of energy savings.

Chapter 2 General Energy Consumption Model of CNC Machines

2.1 Energy Model for Milling Machines

The objective of this study is to investigate the general relationship between SEC and other machining related parameters. Based on the investigations of various manufacturing processes, Gutowski et al. [15] proposed a general power consumption model for all machining processes as shown in Eq. 2 in Table 1, where P_0 is the idle power, MRR is the rate of material removal rate and k is a coefficient that related to the material and physics of the cutting processes. For a specific cutting process on a specific machine and a specific material, P_0 keeps the same, while MRR varies with different cutting processes and materials. Based on this theory, the SEC was modeled as a function of MRR in some research work [2, 52]. Such empirical models are usually established for a specific machine based on a series of scientifically designed experiments. As shown in Eq. 1, C_0 and C_1 are coefficients obtained from experimental data analysis and are unique for each machine. The model's accuracy could reach above 90% in some cases. However, this model only considers MRR variable and lacks machine-related parameters. Comparing with the modeling process of Eq. 2, the machine related parameter P_0 and material related parameter k are not explored. Theoretically, it is possible to improve the modeling accuracy or utilization range by better interpreting additional process parameters. Li et al. [16] observed the linear relationship between spindle speed and air cutting power and brought in spindle speed as another parameter to modify the model as Eq. 3, where n is the spindle speed (rpm), C_0 C_1 and C_2 are coefficients. In the modified model, the accuracy has been improved to about 97%. The results show the possibility of improving the traditional SEC model by further investigating the essential parameters. Similarly, Budinoff et al. [21] proposed a general material-based energy prediction model in Eq. 8, where

$(\frac{h}{h_r})^a$ is a material related function to capture the dependence of k on average chip thickness. This model was validated with over 97% accuracy when tested with several materials.

Inspired by the above work, this paper aims to introduce new parameters into the traditional MRR based SEC model to develop a general energy consumption model that can be used for various machines. Similar with the material related function in material-general energy model, parameters that can be used to distinguish different machines should be included in the machine-general model. Therefore, the power consumption characteristic of the machining process is analyzed to identify the key factors.

Figure 9 shows the typical power consumption profile of a machining process. Depending on the machining stages, the power can be divided into three sections: stand-by power, air-cutting power and machining power. Each section represents a stage of machining process and includes the powers of different components.

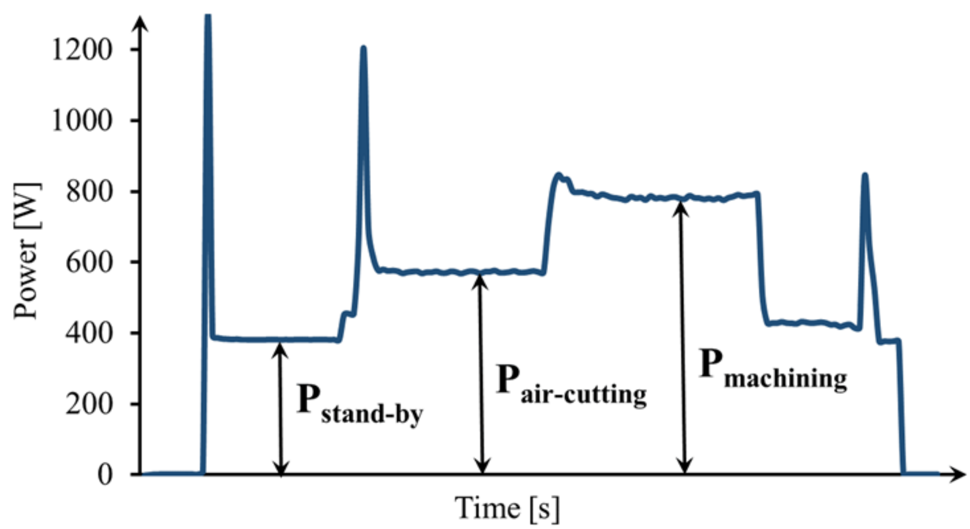


Figure 9 Power Profile of a 5.5 kW Machine Center (Sharp SV2414-SE)

The total energy consumption includes machine-based constant power and processing-based variable power. The proportions of each part are remarkably different among different machine tools[53]. The stand-by power is a portion of constant power consumption and includes the power required by the servo motor, control units, lighting and other auxiliary power consumption related to specific machining process. It ensures the operational readiness of the machine. A Highly automated machine tool tends to include more functions such as work handling, automation controls, etc. As a result, its total power consumption of a machining process could be dominated by the stand-by power, especially at lower production rates[54]. Therefore, the stand-by power is a key parameter to represent the automation level of a machine tool and would be unique for each machine. The air-cutting power is the operational power of the machine before its real engagement in cutting materials, which include idling spindle power and optional tool change power. Spindle power is the major addition of the air-cutting power compared with stand-by power. Since the nameplate power rating of the spindle motor is often used as the nominal power rating of the machine tool, it can also be used to represent the size or capacity of the machine for its energy level. A machine with a higher nominal power rating consumes more energy but is capable to process larger MRRs, which in turn will reduce its energy intensity. Hence, the power rating of the spindle motor (P_s) is a key factor to determine the power consumption level of a machine. The machining power is the total power consumed during the cutting process, which equals to air cutting power plus tool tip power and unproductive power, which depends on cutting parameters (MRR in this thesis). The machining power varies dramatically with different cutting parameters.

Based on the above analysis, the stand-by power, power rating of spindle motor and cutting parameters are three key factors that decide the total power consumption. Therefore, they are all considered in the development of a new machine-general energy consumption model in this thesis. In this thesis, machines with different nameplate power rating of spindle motors are categorized for their energy capacity levels and analyzed separately. The actual energy consumption of each machine tool is varying with the actual operating conditions and is measured in this study. In order to demonstrate the influence of different P_s, the machine tools with two different power levels of P_s (5.5 kW and 11 kW) are analyzed in this study. Since the stand-by power varies with the automation level and the power capacity of the machine, a parameter, the stand-by power ratio (R_s), is introduced here to consider this effect. R_s is defined as the ratio of the stand-by power and the nominal power rating of the machine tool. As a result, the proposed method is to use MRR and R_s as parameters to predict SEC for different sizes of machine tools.

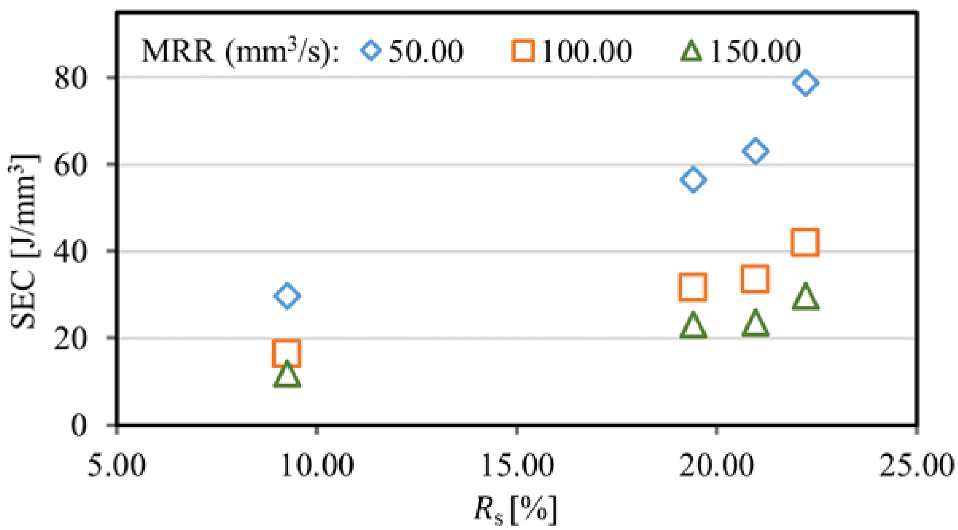


Figure 10 SEC Trend for Machine Tools with 11 kW Spindle Motor at Different MRR

A proper relationship among all key parameters is needed to establish the new SEC model. Due to the well-known connection between MRR and SEC in a specific machine, the only work left is to discover the relationship between SEC and R_s. When MRR is set at three levels, a clear quadratic relationship between R_s and SEC is observed in experiments, as shown in Figure 10, which is from four selected machine tools with 11 kW rated spindle power, data presented in Table 2. Similar relation is observed for machines with other sizes of spindle power. This quadratic relationship cannot be observed using the traditional SEC model as shown in Eq. 9, in which, the

SEC would be constant if the MRR is constant. To integrate the quadratic impact of R_s into the SEC mode, the constant parameter C_1 in Eq. 1 needs to be changed to a polynomial function. Therefore, a new energy consumption model is proposed as:

$$\mathrm{SEC} = \frac{(\mathrm{a} \times R_s{}^2 + b \times R_s + c)}{MRR} + d \tag{9}$$

where, a, b, c, d, and e are coefficients and will be determined by experimental data analyses.

2.2 Machine Modeling Case Study

Two case studies at two rated spindle power levels are carried out in this study to validate the proposed model. The experimental data of eight machine tools are used to fit the proposed model. To ensure adequate application range of the regression model, machine tools (vertical milling machines or vertical machine centers) from low-end to highly automated are all considered. According to the sizes of the spindle motors, we categorized the selected machines into 2 power levels (5.5 kW and 11 kW). The detailed specifications of the selected machine tools are listed in Table 2. The cutting material used in the experiments were assorted carbon steel with HB hardness ranging from 120 to 220. The stand-by power ratio R_s, MRR and SEC were obtained either directly from experimental data or from the energy models in literature.

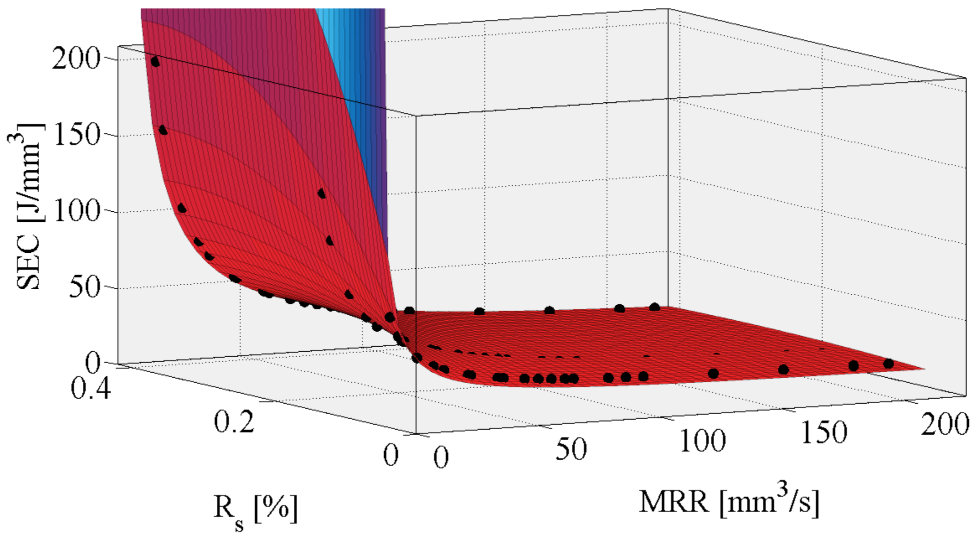
Table 2 Specifications of Selected Machine Tools

Reference	Machine Model	Rated Spindle Power (kW)	Stand-by Power (kW)	R_s (%)
Campatelli et al. [55]	NMV 1500 DCG	5.5	2.20	40.0
Li et al. [16]	Hurco BMC-20LR	5.5	0.41	7.4
Diaz et al. [52]	NV 1500 DCG	5.5	0.92	16.7
Li et al. [56]	PL700B	5.5	0.60	10.9

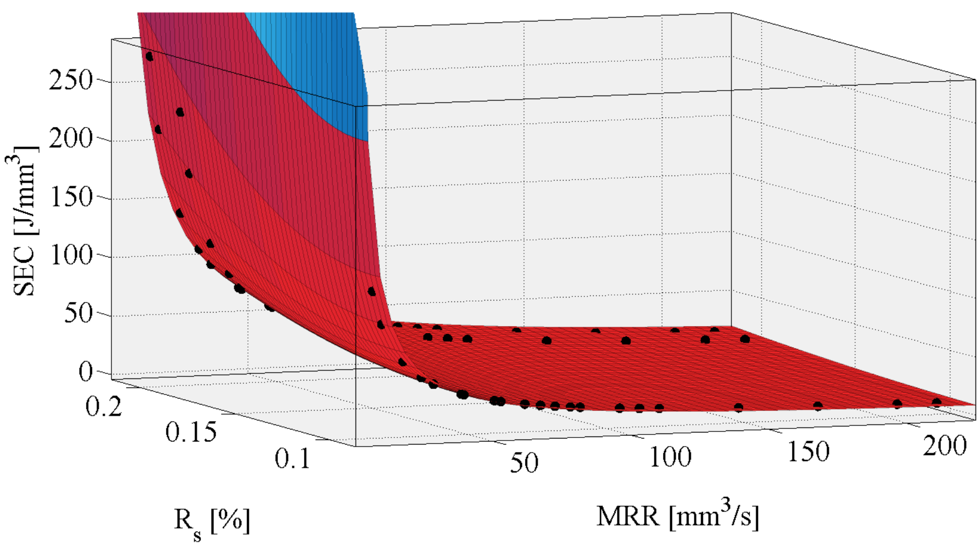
Kara et al. [2]	Mori Seiki 5100	11	1.02	9.3
Aramcharoen et al [20]	Hitachi Seiki VG45	11	2.44	22.2
Li et al. [57]	VGC1500	11	2.31	21.0
Yoon et al. [58]	Hyundai WIA F400	11	2.13	19.4

Table 3 Modelling Data from Previous Research

MRR [mm^3/s]	SEC [J/mm^3]					
	NV1500 DCG	Hurco BMC-20LR	NMV1500 DCG	Hyundai WIA F400	VGC1500	Mori Seiki 5100
11.00	138.31	67.22	199.04	233.04	273.45	125.01
14.33	107.00	54.23	153.92	180.38	210.72	96.60
22.00	71.00	39.30	102.04	119.82	138.59	63.92
28.67	55.34	32.81	79.48	93.49	107.22	49.71
33.00	48.56	30.00	69.70	82.07	93.63	43.56
43.00	38.12	25.67	54.66	64.52	72.72	34.09
44.00	37.34	25.34	53.54	63.20	71.16	33.38
55.00	30.61	22.55	43.84	51.88	57.67	27.27
57.33	29.51	22.10	42.26	50.04	55.47	26.27
66.00	26.12	20.69	37.37	44.33	48.68	23.19
71.67	24.34	19.95	34.81	41.35	45.12	21.58
77.00	22.91	19.36	32.75	38.94	42.26	20.28
82.50	21.63	18.83	30.90	36.78	39.69	19.12
86.00	20.90	18.52	29.85	35.56	38.22	18.46
100.33	18.44	17.50	26.31	31.42	33.30	16.23
107.50	17.45	17.10	24.89	29.76	31.32	15.33
114.67	16.59	16.74	23.65	28.31	29.60	14.55
143.33	14.01	15.67	19.93	23.97	24.42	12.21
172.00	12.29	14.95	17.44	21.07	20.97	10.64
200.67	11.06	14.44	15.67	19.00	18.51	9.53
215.00	10.57	14.24	14.96	18.18	17.52	9.08



(a) Customized Fit for 5.5 kW Machines



(b) Customized Fit for 11 kW Machines

Figure 11 Curve Fitting Results from Matlab

Based on past research, it is known that the SEC of a machine tool dramatically decreases with the increase of MRR at low MRR region. The decrease trend transits smoothly and becomes flat around the middle and high MRR regions. To study the full characteristic of the SEC profile, an appropriate range of MRR needs to be investigated to include all the transition stages. The selected range of MRR in this study is listed in Table 3, as well as the associated SEC for all the selected machines used for regression.

In this study, the custom equation fitting in Matlab Curve Fitting application was used to fit the proposed SEC model with selected MRR range. The results are shown in Figure 11 for machines with 5.5 kW and 11 kW spindle motors separately. It is clear that most of the data points are scattered closely around the fitting surface, which means the quadratic relation within the proposed model is capable of explaining the SEC distribution among various machines. Table 4 lists the corresponding fitting coefficients for each spindle size, and the results confirm that the proposed model could approximate most of the data points quite well.

The experimental data of the fourth machine in each power level was used to validate the fitted model. Additional experimental SEC data of the other three machine tools for each power level was also used in the model validation. Finally, the experimental data was compared with the calculated data. The residual ratios are presented in Figure 12. The results show that:

a) The overall accuracy of the developed model is confirmed as the residual ratios for all tested machines are within 20%. The average absolute residual ratio is around 6%.
b) The characteristic of the residual ratios is highly related to the stand-by power ratio. The average residual ratios of highly automated machines are more likely to be positive, while the average residual ratios of the less automated machines are negative. The prediction for middle level machines seems to present the best accuracy. The reason is: the highly automated machines are usually more energy intensive and have higher SEC. When fitting the model for various machines, it may compromise the accuracy of the machines at both higher and lower ends to develop a general adaptive model. Therefore, employing

more types of machines and more experimental data will be useful to improve the reliability of the proposed model.

c) The average residual ratio of the machine with the highest R_s at the rated spindle power level of 11 kW has a dramatic drop (-12%). All residual ratios for this machine are negative despite the machine being the most energy intensive. It is because the experimental data used for this machine was high cutting speed testing data with the average testing MRR around 560 mm^3/s, which is much higher than the MRR range values that were used to fit the model. Since the SEC trend has been predicted to be steady within high MRR range (above 220 mm^3/s), it may underestimate the decrease of SEC at high MRR range and predict a high SEC at that range. In future work, larger MRR range should be considered to include all possible conditions during machining processes.

Table 4 Fitted Coefficient Values

Coefficient	5.5 kW	11 kW
a	-13380	112300
b	10530	-19960
c	21.74	2.192
d	6.701	4.383
R-square	0.995	0.999

To illustrate the advantages of the proposed general model, here the applications of the traditional SEC models are presented using a benchmark analysis. NV 1500 DCG and Hurco BMC-20LR are both machine centers with 5.5 kW spindle motor. Diaz et al.[52] and Li et al.[16] proposed SEC models for those machines with accuracy of around 90%. However, when their models were used to predict the SEC for the other machines, much larger residual ratios were observed. For instance, the SEC for Hurco VMC-20LR was significantly over-estimated with an average residual ratio of -125% when using the proposed model for NV 1500 DCG. Likewise, the predicted SEC for NV 1500 DCG shows an average residual ratio of 43%. Therefore, it is clear the traditional SEC models are not interchangeable among machines.

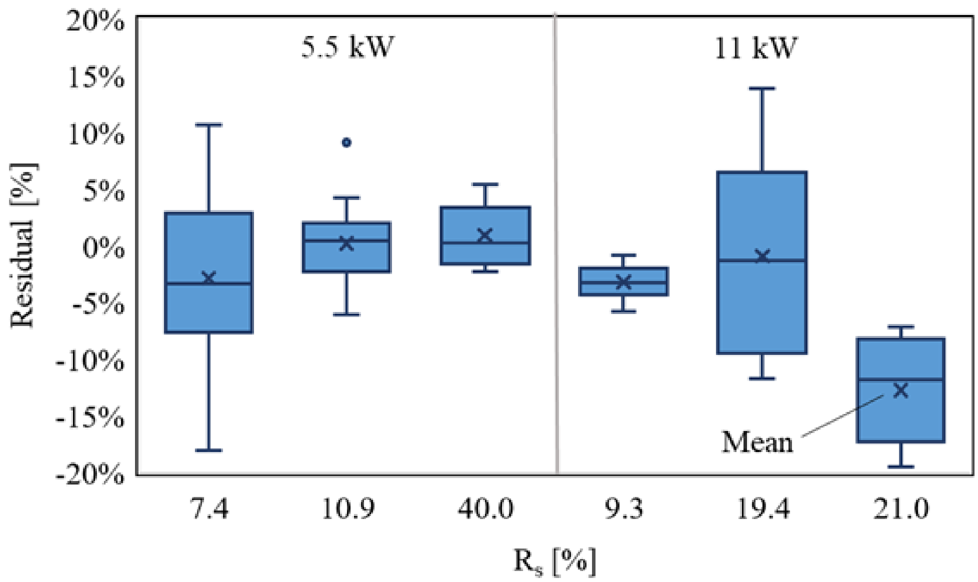


Figure 12 Comparison of Residual Ratios for Selected Machines

2.3 Experiment Validation

The validation experiment was performed on a CNC machine center (Sharp SV2414-SE) with a 5.5 kW spindle motor. Three cutting tools with 2 flutes carbide inserts were used to face-cut a medium carbon steel blank (AISI 1045). A portable power cell (PPC3) power meter was used to monitor the power consumption in real time. The DI-149 data logger manufactured by DATAQ was used to record the data gathered by power meter. This data collection system can continuously record the power consumption situation at a 0.1s sampling interval.

As shown in Figure 9, the power consumption of the machine center (Sharp SV2414-SE) during milling process was measured. The pre-experiment readings show that the average stand-by power of the machine center, which includes the control units, lighting and servo, was around 380 W. The power profile was similar for each process with variable machining power. The machining power consisted of the constant power consumption of the machine center and the variable power consumption during the milling process with respect to the planned cutting parameters. As shown in Table 5, the cutting parameters were selected to obtain a similar range of MRR compared with previous research. During the experiment, each cutting tool travelled along positive y direction nine times with assorted depth of cut and feed rate. The experimental SEC, which is the ratio of the measured energy consumption and associated MRR for each process, was then compared with the estimated SEC using the proposed model in Figure 13.

Table 5 Cutting Parameters and Levels

Parameters	Level 1	Level 2	Level 3
Depth of Cut (mm)	0.84	1.68	2.54
Feed Rate (mm/min)	50.80	101.60	152.41
Tool Diameter (mm)	6.35	12.7	19.05

The accuracy of the proposed model is about 91.5%. To test the difference between the experimental and calculated data, a paired t-test was carried out. The null hypothesis of the t-test is that there is no difference between the two groups of data. To reject the null hypothesis for a t-test, the calculated t value need to be equal to, or greater than the critical t value [57]. The test results are listed in Table 6. Since $t_{calculated} = 2.03$ is less than $t_{critical} = 2.05$, the result fails to reject the null hypothesis, which means that the proposed SEC data has no significant difference with the experiment data and obeys similar tendency, as shown in Figure 13. Since the sample size of this experiment was only 27, we believe that the P-value of 0.053 would improve with an increased sample size. Since there is no rational to pursue normality of the differences of two data sets, Wilcoxon test can also be performed. It is the nonparametric equivalent to the paired t-test. The P-value from Wilcoxon test is 0.167, which also validate the reliability of the prediction from proposed model. Therefore, it is safe to state that the proposed model can successfully predict the energy consumption of milling processes for tested machine center.

Table 6 Paired t-Test Results for Experiment and Calculated Data

	Mean	St Dev	SE Mean	t	P-value	t critical
Experiment	49.56	41.83	8.05	2.03	0.053	2.05
Estimation	47.42	8.23	7.36			
Difference	2.14	5.49	1.06			

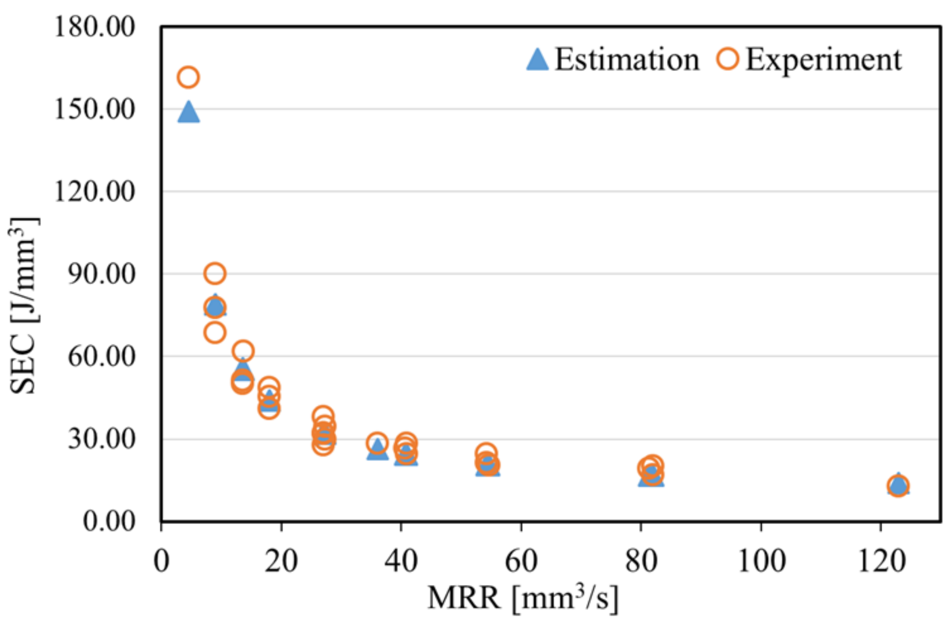


Figure 13 Comparison of Calculated and Experimental SEC Results

Observations from Figure 13 shows that the experimental data scattered around the calculated data with slightly higher residuals around the lower MRR region. The experimental data points distribute around the calculated data evenly within the middle and higher MRR regions. On average, the experimental SEC data is higher than the calculated data by 8%. Comparing with the

MRRs of previous research, 20% more MRRs of the tested machine center are under 60 mm^3/s. Also, the MMR range (0-120 mm^3/s) is smaller than those of previous research (0-215 mm^3/s) due to the limitation of the tested machine center. The concentrated data points around lower MRR range could cause the higher SEC during the test.

Chapter 3 Energy Savings in Compressed-Air System

Energy Savings for single ECM was well researched in literatures. Typical ECMs for each category are listed in Figure 14. In this chapter, an integrated CAS modeling method will be introduced to systematically evaluate the energy savings opportunities. There are three main classifications of compressors: reciprocating, rotary screw, and centrifugal. According to audit experiences, rotary screw compressor dominates the small and medium sized applications. Its market share is more than 45% of the global revenue generation in 2015 [59]. Therefore, this thesis will focus on the energy savings opportunities of small size rotary screw air compressors.

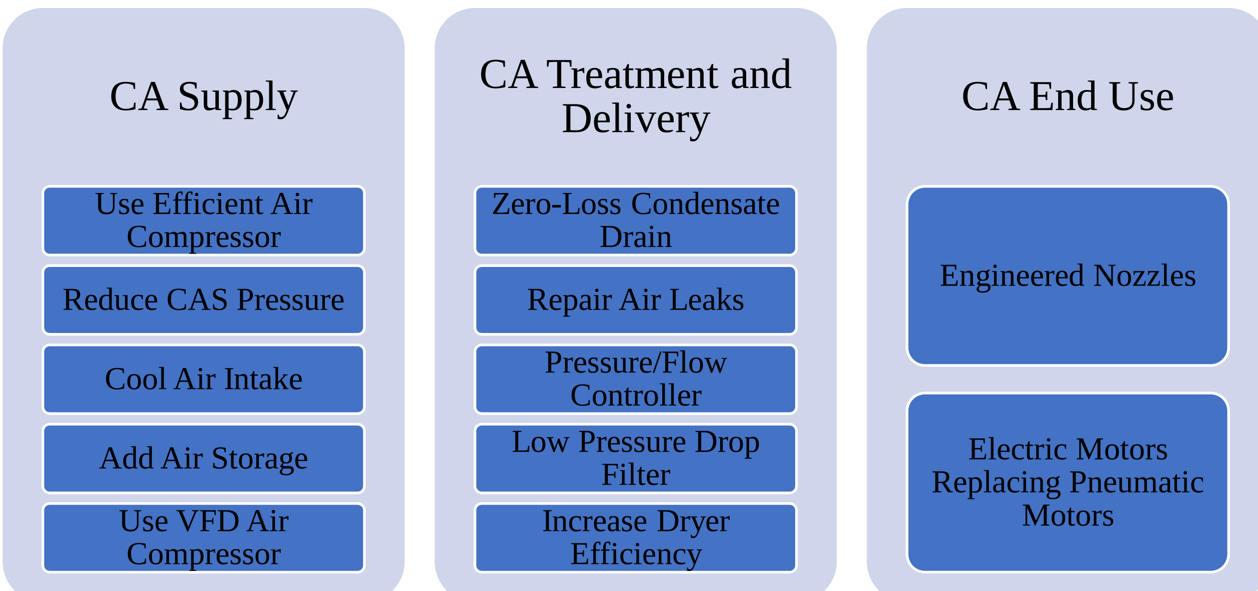


Figure 14 Typical ECMs in CAS

3.1 Modeling Methodology

At first, the detailed mathematical formulations for major ECMs will be established. Necessary key parameters for each ECM will be identified. The interaction of the ECMs and their dynamic characteristics will be concluded. A generic calculation method will be proposed for all ECMs to obtain an integrated model to evaluate the CAS as a whole.

3.1.1 Energy Savings Calculation Methods

Repair Air Leaks

There are two typical methods to calculate the air leaks and following possible energy savings by repairing the air leaks. First, the overall air leak percentage can be estimated by logging the load/unload time during non-production time for load/unload controlled air compressor. The compressor will load and unload because of the air leaks. The total leakage percentage can be calculated by the following equation:

$$\mathrm{LP} = \frac{t_{load} \times 100}{t_{load} + t_{unload}} \tag{10}$$

where, LP is leakage percentage, t_{load} is load time (minute), t_{unload} is unload time. For the air compressor with other control types, the total air leak can be measured by air flow meter during non-production time.

Table 7 Air leak Size Lookup Table [60]

Decibel Readings vs. CFM					
	Pressure (PSIG)				
Digital Reading (dB)	100	75	50	25	10
10	0.5	0.3	0.2	0.1	0.05
20	0.8	0.9	0.5	0.3	0.15
30	1.4	1.1	0.8	0.5	0.4
40	1.7	1.4	1.1	0.8	0.5
50	2.0	2.8	2.2	2.0	1.9
60	3.6	3.0	2.8	2.6	2.3
70	5.2	4.9	3.9	3.4	3.0
80	7.7	6.8	5.6	5.1	3.6
90	8.4	7.7	7.1	6.8	5.3
100	10.6	10.0	9.6	7.3	6.0

Second, the location, size and number of air leaks can be detected by ultrasonic air leak detector. The volume of air loss in a minute through a leak can be estimated according to Table 7. Because most air leak surveys in the industry use the ultrasonic air leak detector, the lookup table method is utilized in the proposed model.

Cool Air Intake

Compressors have to work harder to compress hot air because air expands at higher temperatures. The amount of work done by an air compressor is proportional to the temperature of the intake air. Therefore, the energy savings from using cool air intake can be calculated by:

$$F_s = \frac{T_i - T_f}{T_i + 460} \tag{11}$$

where, F_s is fractional savings, T_i is initial air intake temperature, T_f is final air intake temperature. It is worth to mention that the cool air intake measure is only applicable for lubricant free air compressor. The air will be warmed up to the lubricant temperature in lubricant flooded air compressor, which results the invalidation of cool air intake effect.

Pressure

The thermodynamic process happens in a rotary screw air compressor is similar to an isentropic compression. The work done by the process equals to:

$$W = \frac{nRT_1}{n-1}\left(\left(\frac{P_2}{P_1}\right)^{\frac{n-1}{n}} - 1\right) \tag{12}$$

where, W is work, n=1.4 is isentropic index, R is ideal gas constant, T_1 and P_1 are the initial temperature and pressure, P_2 is the final temperature and pressure. Based on this equation, it can be seen that lowering the pressure of the compressed air will reduce the power requirement during the compression process. The power deduction at the air compressor can be expressed as followed equation where P_i, P_{in}, P_f are initial pressure, inlet pressure, and final pressure respectively.

$$\mathrm{PR}_w = \frac{\left(\frac{P_i}{P_{in}}\right)^{0.286} - \left(\frac{P_f}{P_{in}}\right)^{0.286}}{\left(\frac{P_i}{P_{in}}\right)^{0.286} - 1} \tag{13}$$

Energy savings from simply reducing system pressure, flow controller and low pressure drop filter can all be calculated based on the same equation. Flow controller, also called demand valves or pressure controller, is basically a precision pressure regulator that allows the airflow to fluctuate while maintaining a constant pressure to the plant's air distribution piping network. The installation of a flow controller on the downstream side of an air storage receiver allows the creation of a pressure differential entering and leaving the vessel, which generates system storage to compensate for high, random air usage and avoid the need to increase the entire system pressure. In this way, the set pressure at the air compressor end can be reduced. Similar energy savings can be achieved through using low pressure drop filter. In most air compressor system air filtration is needed for proper operation. The filter removes oil mist from the supply air of lubricated compressor to protect the distribution and end-use devices. However, there is obvious pressure drop through the filter. The low pressure drop filter operates with longer life and lower pressure drop than standard coalescing filters. Typically, the baseline of standard filter is 3psid (psid is pressure drop in psi) at new and 10psid at end-of-life. The drop in efficient condition is 1psid when new and 3psid at end-of-life. Therefore, the average pressure drop can be reduced by 4.5psi. Last but not the least, lower pressure also means less artificial demand, which helps to reduce the waste from air leak. The corresponding air leak reduction can be expressed by:

$$LR = 1 - \frac{P_f}{P_i} \tag{14}$$

where, LR is leak reduction, P_f and P_i are final and initial pressure respectively.

Add Air Storage

The frequent cycling caused by short of storage is a waste of energy. The fixed speed compressor will load/unload in certain period of time when working at part load. The load/unload mode transform causes cycling loss. The main reasons are: first, blowdown will waste the compressed air between compressor outlet and the check valve, which will be released to atmosphere. This volume is usually about 2 ft^3; second and the most important loss is the loss because of partial load during blowdown time. The blowdown time is typically 30 s to 90 s, the compressor doesn’t produce compressed air but consume even more energy than that consumed during absolutely unload period. Figure 15 shows the cycling current of compressor. Research has shown short cycling time will cause significant loss. Cycling loss percentage of a 15HP air compressor was simulated by Maxwell et al. [61], as shown in Figure 16. The cycling loss is less than 2% when the cycling time is longer than 5 minutes. It can be as high as 25% if the cycling time is less than 1 minute.

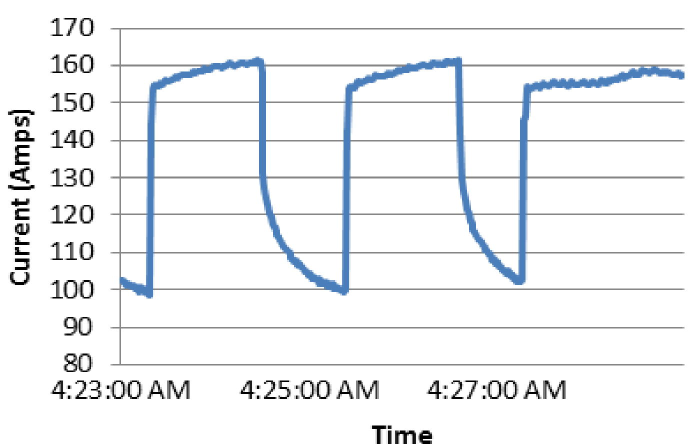


Figure 15 Cycling Current of Air Compressor

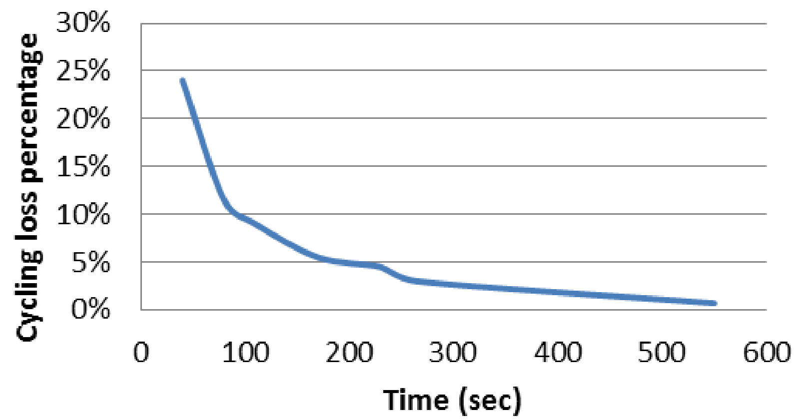


Figure 16 Cycling Loss Percentage During Different Cycling Time

Installing big enough air storage is an effective way to reduce the cycling loss. Storage can be divided into dedicated, off-line and general storage based on its location in the CAS. Dedicated storage is typically installed near specific applications to ensure their sufficient flows or pressures. Off-line storage needs to be maintained at high pressure to support special event such as peak demand reduction. General storage is the air tank installed between air compressor and main deliver line to improve the pressure and flow of the whole system. Therefore, the storage mentioned in this thesis is mainly the general storage or air tank. The amount of compressed air available in a tank depends on both tank size and the pressure difference between the tank pressure and the system's minimum acceptable target pressure, as shown in Equation:

$$V_{gas} = V_s \times (P_s - P_{atm})/P_{atm} \tag{15}$$

where, V_{gas} is usable compressed air in storage, V_s is the storage tank size, P_s is pressure in air tank, P_{atm} is the atmospheric pressure. The typical effects on the power consumption of the LNL compressor with different sizes of air receivers is shown in Figure 17.

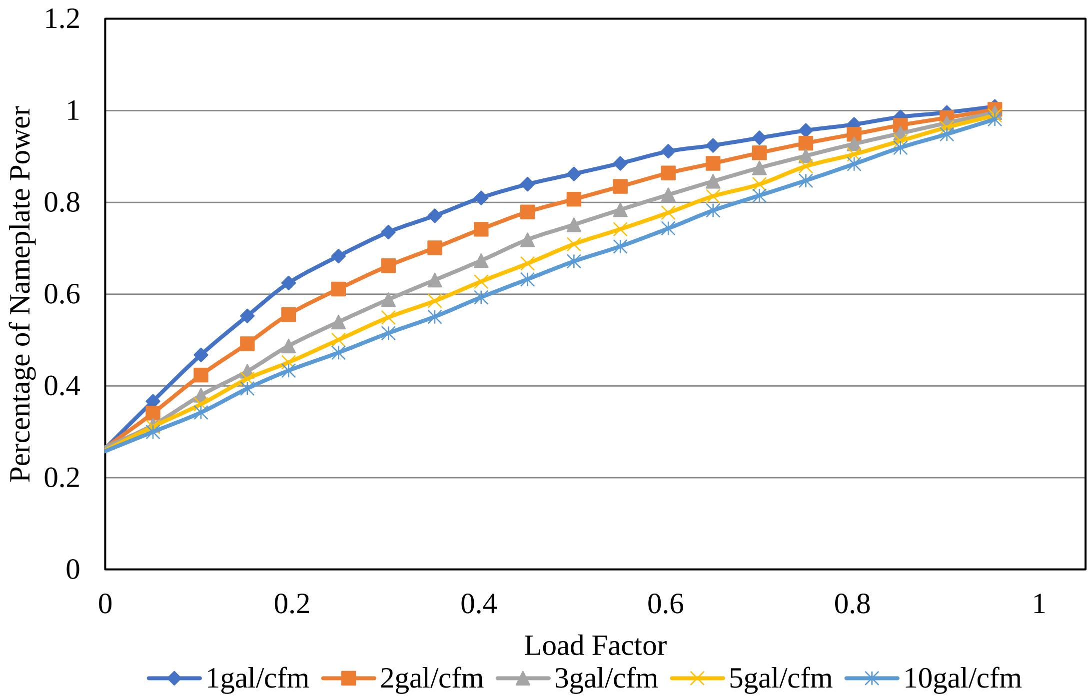


Figure 17 Effect of Air Receiver on LNL Controlled Air Compressor [32]

Table 8 Percentage Power Calculations for Different Tank Sizes

Percentage of Nameplate Power (PNP)	Tank Size (gal/cfm)
$\mathbf{-0.9366LF^2 + 1.6054LF + 0.3111}$	1gal/cfm
$\mathbf{-0.5008LF^2 + 1.2463LF + 0.2599}$	3gal/cfm
$\boldsymbol{-0.3333LF^2 + 1.0861LF + 0.2518}$	5gal/cfm
$\boldsymbol{-0.1802LF^2 + 0.9373LF + 0.251}$	10gal/cfm

It can be seen that the power consumption is almost linear with the load factor (LF) when the receiver size is 10gal/cfm. When using 1gal/cfm receiver, the percentage is much higher in low LF scenarios. These relationships can be mathematically expressed through regressions [34] as shown in Table 8.

Use Efficient Controls

The power characteristics of air compressors are primarily determined by the types of compressor controls, which include modulation, load-non-load (LNL), variable displacement and VFD etc. In modulation mode, the air compressor adjusts the inlet valve to the air compressor, allowing more air to flow into the compressor when more compressed air is needed, and less when less is needed. It is the least efficient control strategies for an air compressor. Air compressor in modulation typically draws about 70% of its rated power even at no load. Some modulation-controlled air compressors have blowdown function, which helps to increase the no load efficiency. LNL controlled air compressor can meet the air demand by loading/unloading the air compressor. According to survey from CAGI data, the typical unload power is about 25% of the rated power of the air compressor. This unload energy waste is made worse since most of the air compressors are oversized. Lower LF results longer unload time and larger idling loss for LNL air compressor. Variable displacement and VFD are capable to adjust the speed of air compressor according to the air demand at the end use. In this way, the air compressor only runs at optimized speed without idling power loss. The comparison of power consumption pattern of all air compressors is shown in Figure 18. The regression expressions are shown in Table 9.

Table 9 Regression Equations of PNP at Various Conditions

Control Type	Percentage of Nameplate Power (PNP)	LF Ranges
Modulating	0.3LF+0.7	
Modulating w/Blow down	0.3LF+0.7	LF≥0.4
	1.425LF+0.25	LF<0.4
Variable Displacement	0.77LF+0.23	LF≥0.5
	0.15LF+0.54	0.5>LF≥0.4
	0.875LF+0.25	LF<0.4
VFD	0.872LF+0.128	

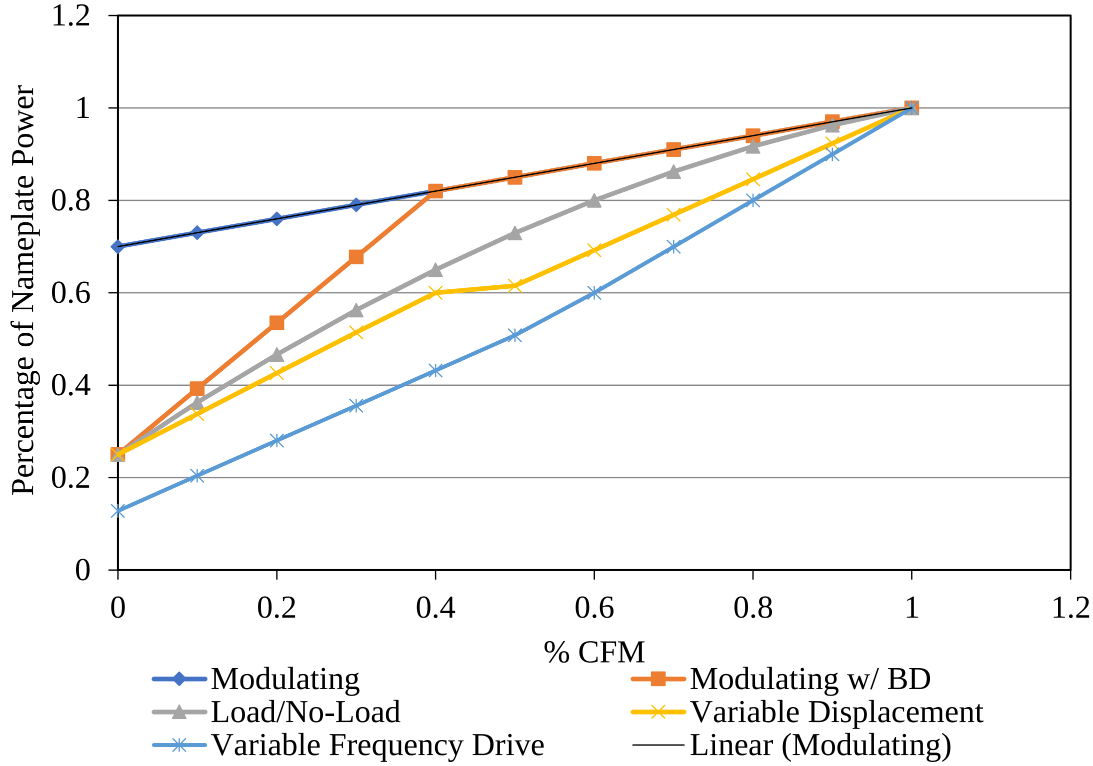


Figure 18 Percentage of Nameplate Power for Various Air Compressors

Increase Dryer Efficiency

Air dryer in CAS is needed to prevent condensate from being deposited in the supply lines of a facility. Based on the operation dew point temperature, the dryer can be divided into refrigerated dryer and desiccant dryer. A refrigerated dryer removes moisture from the lines by using a heat exchanger to cool the air so the water vapor condenses into liquid water. A non-cycling refrigerated air dryer runs at full load consistently which wastes energy during partial load time. A cycling refrigerated air dryer will vary the refrigeration compressor load with regards to the compressed air demands, resulting in energy savings. The cycling dryer includes thermal mass dryer, variable speed dryer and digital scroll dryer. The power consumption of the refrigerated dryers at various LFs are shown in Table 10 [62].

Table 10 Regression Equations of PNPD at Various Conditions

Dryer Types	Percentage of Nameplate Power of Dryer (PNPD)	LF Ranges
Non-cycling Refrigerated	0.238LF+0.762	N/A
Thermal Mass Refrigerated	$-0.928LF^2+1.8751LF+0.0715$	N/A
VFD Refrigerated	LF	LF≥0.5
	0.1048LF+0.4476	LF<0.5
Digital Scroll Refrigerated	0.9094LF+0.0906	N/A

Desiccant dryers are used when air needs to be dried to a lower dew point (-20°F or below) than refrigerated-type dryers can provide (37°F). A desiccant dryer consists of two towers containing a desiccant medium. One of the towers dries the air, while the other purges compressed air to regenerate the desiccant medium. The towers swap functions when the drying tower is saturated. This regeneration can be accomplished by several different mechanisms: heatless compressed air, heated compressed air or heated blower air. Due to the inefficiency of compressed air generation, energy can be saved through replacing heatless dryer by heated dryer or blower purge dryer, which reducing compressed air consumption by heater or blower. The key energy related parameters are concluded in Table 11 according to air compressor survey.

Table 11: Desiccant Dryer Power Consumptions

	Heatless Desiccant	Heated Desiccant	Blower Purge Desiccant
Purge CA Demand Percentage	15%	7%	0
Heater Power (kW/cfm)	0	0.012	0.019
Blower Power (kW/cfm)	0	0	0.003

Dew point control is another important energy savings method for desiccant dryer. For instance, heatless desiccant dryer uses fixed amount of purging compressed air to regenerate the desiccant towers, regardless of the LF of the CAS. This situation leads to energy wasting over-purging, which increases compressed air consumption and system LF. Similar phenomenon exists for other type of dryers in the form of wasting energy for heating or blowing. Installing dewpoint-dependent switching control will monitor the dewpoint within the dryer and only regenerate when necessary. The power consumption of the dryer with dew point control is proportional to the LF of air compressor.

3.1.2 Integration Process

Despite the diversity of the savings calculations, most of the energy savings is ultimately related to either load reduction or efficiency improvement as shown in Table 12. With necessary key parameters known, the system energy consumption can be purely decided based on load and efficiency. Therefore, it is proposed to evaluate the impacts of all ECMs on those two key factors to model the integrated energy savings.

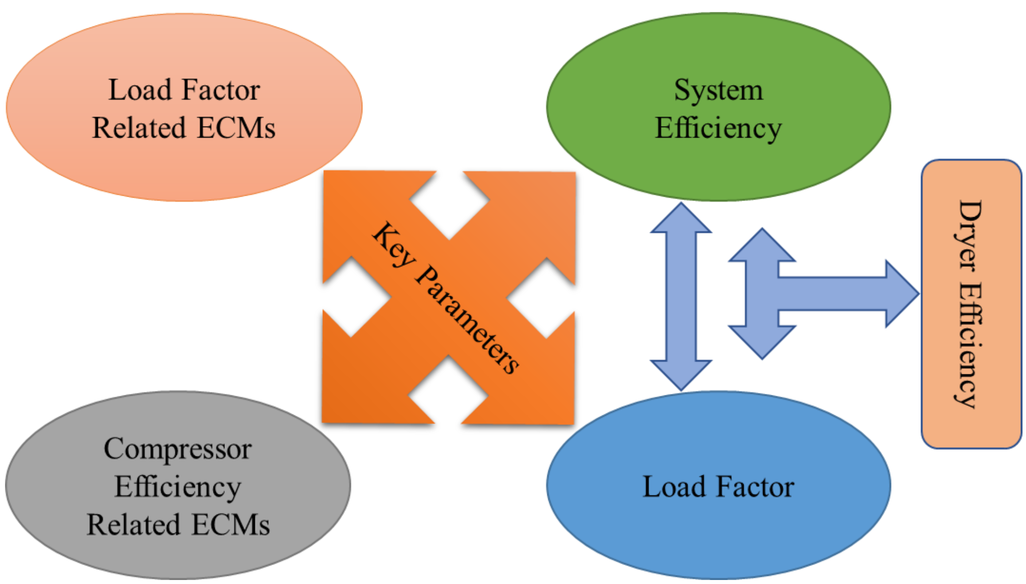


Figure 19 Interaction of the Calculation System

There are three interaction mechanisms among the calculation system as shown in Figure 19. First, direct impact of key parameters. Although the savings calculations of many ECMs are simple and only require limited information per the proposed equations, the realized savings greatly depends on or influences key parameters. The change of key parameters will hence impact the savings from the other ECMs. For instance, repairing air leaks will reduce load factor. The savings can be evaluated through leakage calculation. However, the realized savings from the corresponding load reduction also depends on the power consumption curve of the air compressor, which is related to all the key parameters. In the meanwhile, most of the efficiency related ECMs directly influence key parameters and hence impact the savings from repairing air leaks. Such as adding air tank is capable to reduce cycling loss due to larger storage size, and pressure/flow controller can help to reduce pressure because of the better flow control.

Table 12 Key Impacts of ECMs

ECMs	Key Impacts
Repair Air Leak	Reduce Load Factor
Engineered Nozzles	Reduce Load Factor
Electric Motors Replacing Pneumatic Motors	Reduce Load Factor
Zero-loss Condensate Drain	Reduce Load Factor
Cool Air Intake	Increase Compressor Efficiency
Reduce CAS Pressure	Increase Compressor Efficiency
Pressure/Flow Controller	Increase Compressor Efficiency
Low Pressure Drop Filter	Increase Compressor Efficiency
Add Air Storage	Increase Compressor Efficiency
Use VFD Air Compressor	Increase Compressor Efficiency
Use Efficient Air Compressor	Increase Compressor Efficiency
Replace Non-Cycling Refrigerated Dryer	Increase Dryer Efficiency
Replace Heatless Desiccant Dryer	Increase Dryer Efficiency or Reduce Load Factor
Desiccant Dryer Dew Point Demand Control	Reduce Load Factor

Second, relevancy of LF and system efficiency. In most cases, the change of LF will indirectly impact CAS efficiency. Such as, using engineered nozzles in an LNL CAS will reduce LF. However, the system efficiency will also be reduced due to the lower LF. Meanwhile, the increase of system efficiency quite possibly reduces the overall LF. For instance, flow/pressure control will increase system efficiency, with the "co-product" of reducing artificial demand, which reduces LF. Therefore, all the ECMs are interrelated with each other through this mechanism.

Third, interaction between dryer and air compressor. Dryer energy consumption depends on the operation status of CAS. For example, reducing LF will enhance the savings effect of replacing non-cycling refrigerated dryer because of the lower cycling numbers. Replace heatless desiccant dryer can save compressed air but increase the direct electricity consumption of the dryer. The savings of installing dew point control on heatless desiccant dryer depends on both LF and system efficiency due to its savings comes from compressed air consumption reduction. On the other hand, the measures for dryer will also impact the ECMs for air compressor through their impacts to the CAS load factor.

Based on the analysis above, an integrated energy savings evaluation method is proposed as shown in Figure 20. At first, the energy savings from single ECM is calculated based on initial baseline situation. The algorithm is established for each single measure separately. In this step, the impacts of all the measures on key parameters, LF, and system efficiency needs to be concluded, which is necessary for the following integration. For instance, Pressure/Flow Controller can help to reduce system operation pressure, which is key parameter. The system efficiency will be increased and the improvement can be calculated based on Eq. 13. Because of the lower line pressure, the artificial demand will be reduced, which influences LF. All those key characteristics are recorded to facilitate the interaction analysis afterwards.

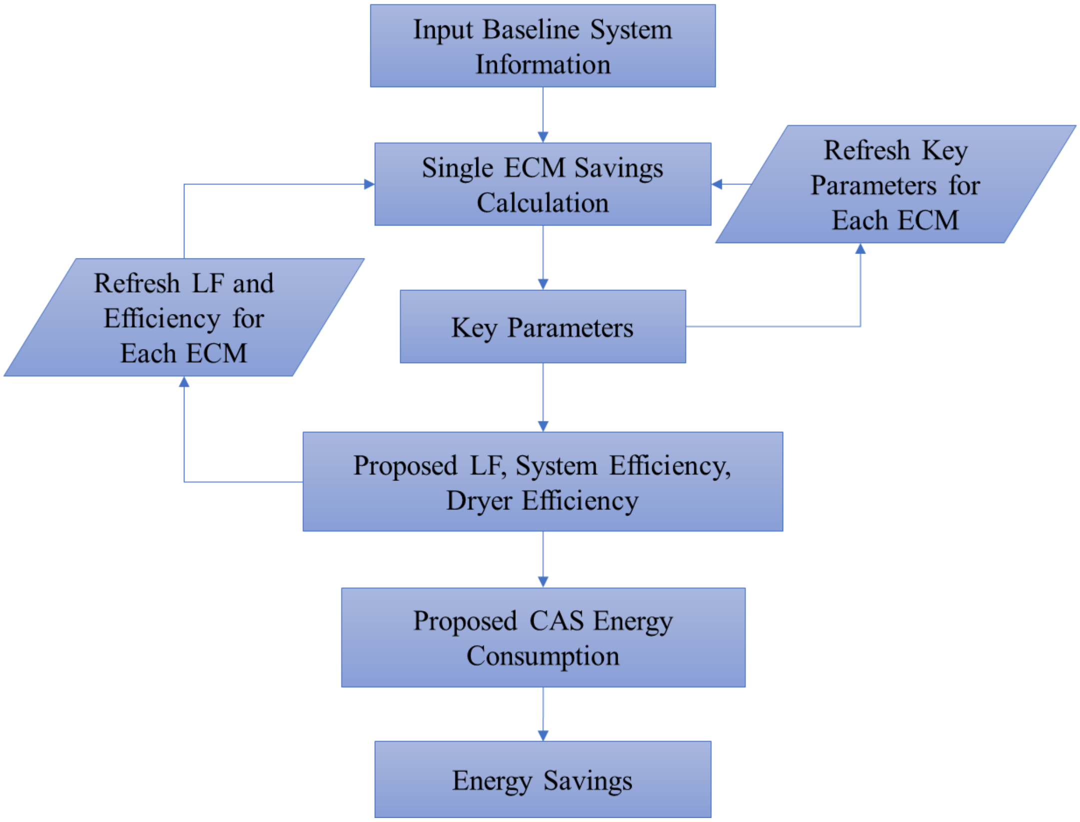


Figure 20 Basic Modeling Flow Chart

Second, integrate all calculations together to address all the interactions and finish necessary iterations due to the close loop feedback in the proposed model. Such as, Desiccant Dryer Dew Point Demand Control can cut back the purged compressed air demand and reduce LF when the air compressor is at partial load. In the meanwhile, the reduced LF will provide more room for the decreasing of purged air consumption. Therefore, it is critical to evaluate this close loop effect and ensure more accurate savings calculation. During integration, similar measures will be grouped together to simplify the integration. For example, all the pressure related measures have similar savings mechanism, therefore are evaluated in the same equation. Another two groups are direct system efficiency improvement group and load reduction group.

At last, evaluate the proposed LF, system efficiency and dryer efficiency and calculate the final the energy savings by comparing existing and proposed CAS energy consumption. Based on all the final key parameters and the integrated savings calculation algorithm, the proposed LF, System Efficiency and Dryer Efficiency can be obtained. By changing the combination of ECMs, the integration effect can be investigate based on the savings difference.

3.2 Results Analysis

3.2.1 Benchmark Analysis

Due to the difficulty of treating every single project separately and doing thoroughly energy audit, many states or programs have prescriptive measures for CAS. This section aims to evaluate the economic benefit of each measure and provide a benchmark reference for developers.

Table 13 Key parameters and assumptions

Parameters	Values	Units
Operating Hours	5083	Hour
Nameplate HP	50	HP
Nameplate CFM Capacity	187	CFM/HP
Motor Efficiency	91.50%	N/A
Control Type	Load/No-Load	N/A
Air Storage Size	1	Gal/cfm
Max Rated Pressure	125	psi
Load/unload Pressure	110/120	psi
Intake Air Temperature	70	°F
LF	47%	N/A

To represent the majority situations, the baselines for typical CAS and operation conditions are defined based on surveys. Inlet modulation-controlled air compressor is already out of date due to its low partial load efficiency. To be conservative, the baseline air compressor in this thesis is

LNL rotary screw air compressor. The load/unload pressure at the air compressor end is 110psi/120psi, while the pressure at the end use is 85psi. According to the CAS surveys from MI and OH, the average LF is 47%. Average electricity rate of the industrial facility in the whole US is used in economic analysis [63] . Since the savings calculation algorithms for refrigerated dryer and desiccant dryer are totally different, two separate scenarios are analyzed in this section. Other essential data is obtained based on typical IAC audits. All critical parameters, assumptions and CAS audit data are listed in Table 13 and Table 14.

Table 14 Audit Data for the CAS

Air leak			
Quantity	Decibel Reading	Pressure at Leak	Reduced Load
5	70	75 psi	24.5 cfm

Engineered Nozzles					
Nozzle Size	Nozzle Number	Pressure	Flow Rate	Operation Hours	Reduced Load
1/8"	5	80 psi	16.9 cfm	1000	10

Install Zero-Loss Condensate Drain						
Drain Orifice Size	Drain Number	Pressure at Drain	Drain Duration	Drain Interval	Operation Hours	Reduced Load
1/2"	1	110 psi	5 Seconds	5 Minutes	84.7	5.9 cfm

Electric Motors Replacing Pneumatic Motors						
Motor hp	Motor Efficiency	LF of Pneumatic Motor	Efficiency of Electric Motor	Annual Operation Hours	Average Reduced Load	Extra Electricity Consumption by Electric Motor
2	39 cfm/HP	0.75	0.65	400	4.6 cfm	688.6

Annual energy savings can be evaluated for each measure with all the parameters. Simple payback and Net Present Value (NPV) are treated as major economic indexes in the analysis. When evaluating NPV, real discount rate and electricity price escalation rate from US Department of Commerce were utilized [64]. The lifetimes of the measures vary in different resources. To be conservative, 10 year was adopted for most measures. Since air leak and filter need continue maintenance, 2 year and 5 year were used respectively based on [60]. The benchmark results are shown in Figure 21 and Figure 22.

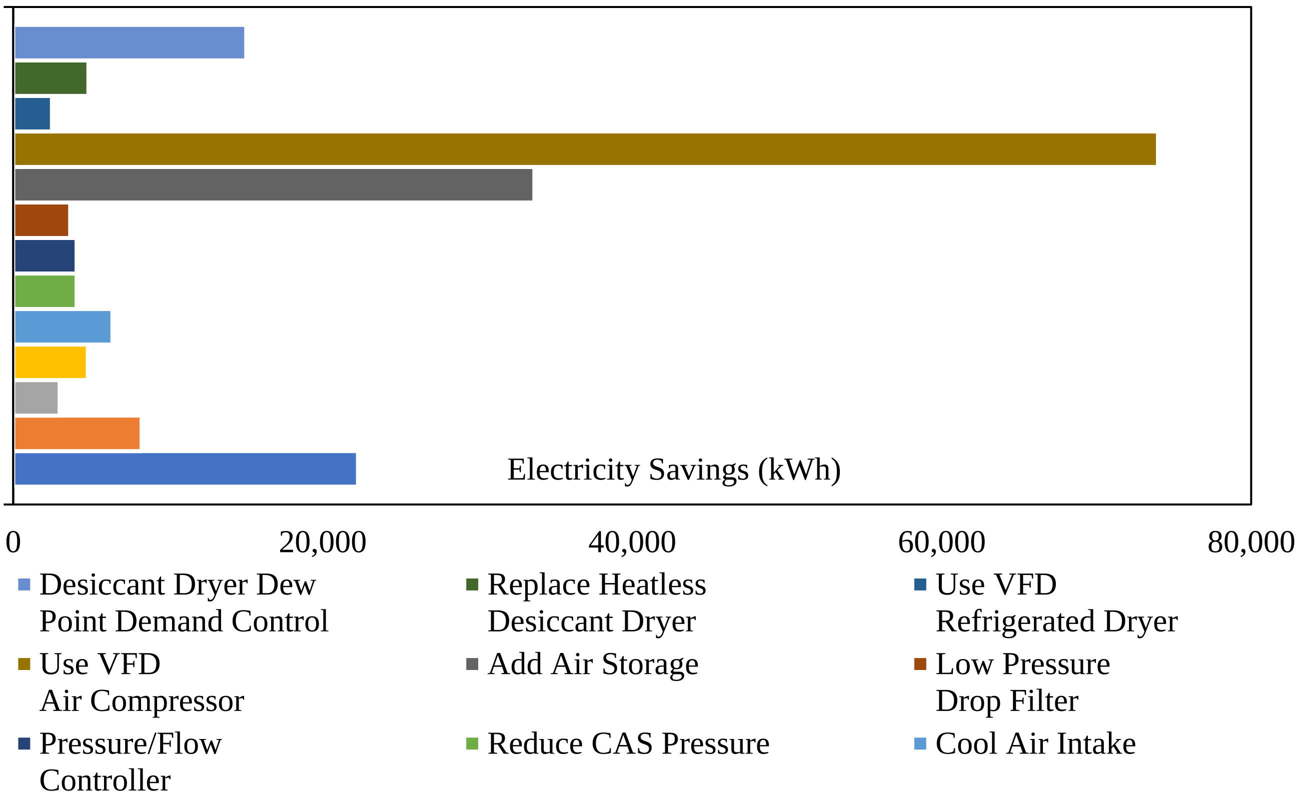


Figure 21 Annual Energy Savings of All Measures

At first, Use VFD Air Compressor and Add Air Storage have largest savings potential. In both situations, the savings is achieved by reducing system cycling loss. The system efficiencies are promoted by 43.5% and 19.8% respectively. Therefore, the partial load inefficiency is recognized as the most significant factor in the system. Use VFD Air Compressor represents the best NPV of 73,975kWh but has a relatively high simple payback period of more than four years.

In contrast, Add Air Storage provides moderate NPV and low payback, which makes it the most important measure under assumed baseline conditions. Repair Air Leak and Desiccant Dryer Dew Point Demand Control can also contribute considering savings. According to the load reduction calculation, the load is reduced by 13.1% and 9.4% respectively, which illustrates that LF also plays as a significant factor.

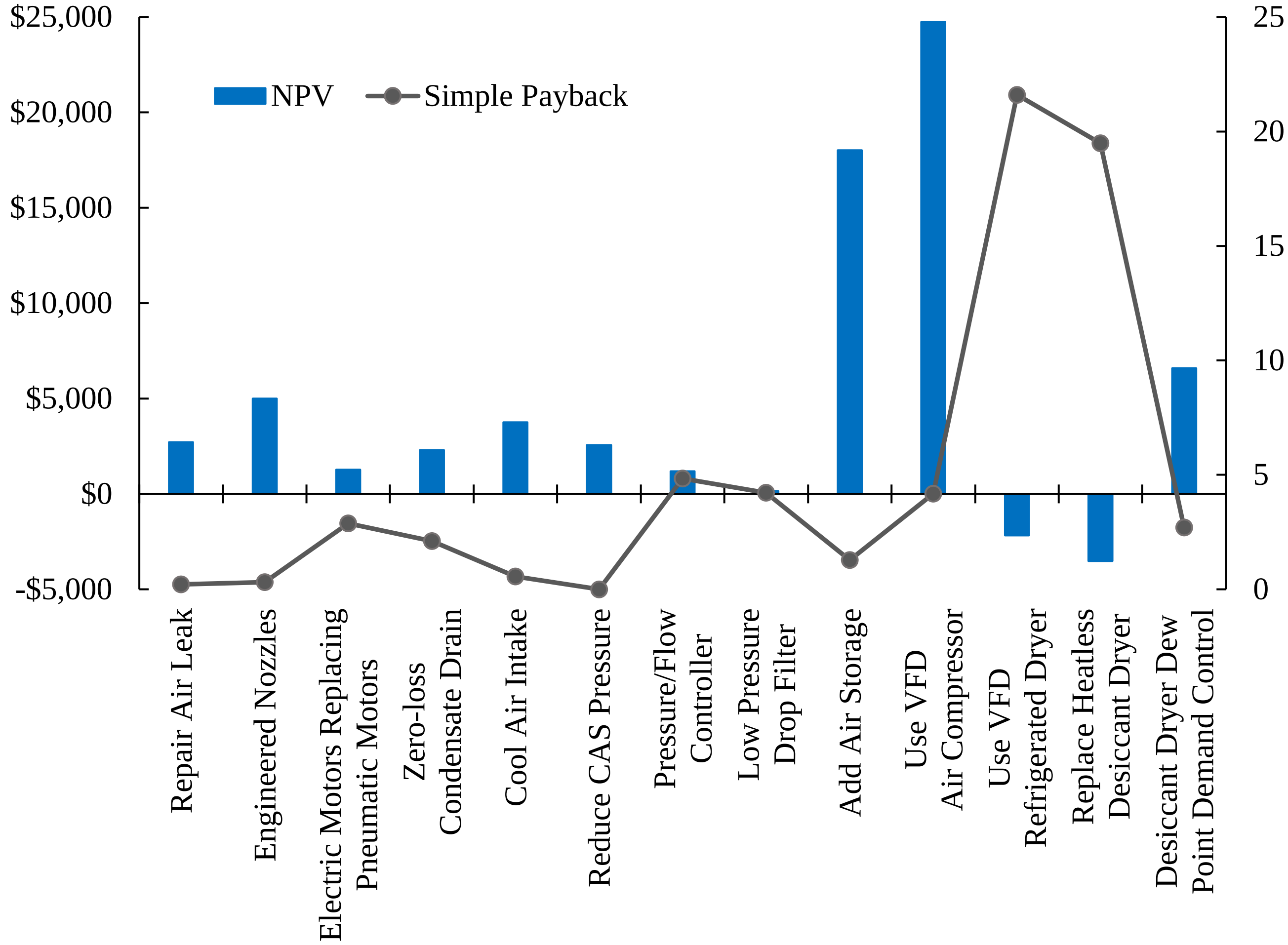


Figure 22 NPV and Simple Payback of All Measures

Second, besides of Add Air Storage and Use VFD Air Compressor, the other system efficiency related measures only provide limited savings potentials. The maximum savings are capped by temperature and pressure requirements. Load reduction measures are overall more attractive compared with system efficiency measures because of their shorter payback period.

Several measures are not recommended for early replacement project due to their NPVs. For instance, Use VFD Refrigerated Dryer and Replace Heatless Desiccant Dryer have negative NPVs. The NPV of low pressure drop filter is only $142. Therefore, only end-of-life replacement is recommended for them.

At last, the savings and economic results from the ECMs are well coincident with observations from IAC database. Repair Air Leak is recognized as the top measure due to its big savings potential and short payback period in the benchmark analysis. It is also the top recommendation in the whole IAC database. Similarly, Engineered Nozzles, Cool Air Intake and Reduce CAS Pressure have payback period of less than one year, which makes them the best options for many customers.

3.2.2 Integration Results

To better illustrate the advantage of using the integration model, this section employs the same baseline situation for single ECM and compares their savings side by side. The Difference%, which is defined as the savings difference of integration model and separation model in percentage, is used to indicate the interaction of the measures. When testing the proposed integrated model, there are thousands of combinations if every possibility is examined. Since the interaction mechanisms were already obtained in the methodology section, similar ECMs were grouped together to simplify the analysis. Because of the negative or minimal NPVs, Use VFD Refrigerated Dryers, Replace Heatless Desiccant Dryer, and Low Pressure Drop Filter are eliminated in the analysis. In practice, Use VFD Air Compressor and Add Air Storage are usually not recommended simultaneously, therefore they are analyzed separately. The final group assignments are shown in Table 15. The simulation results are shown in Figure 23.

At first, the total savings is increased by 17.7% when integrating all the load reduction ECMs, which implies positive interaction among all the load related measures. This effect can be further demonstrated by the 30.7% difference in scenario of putting Group 1 and Group 5 together. Although Group 5 is not a direct load reduction measure, it cuts the system load through the reduction of purged compressed air in the desiccant dryer. Due to its highest Difference%, the internal interaction of the load reduction is recognized as the most significant interaction in the integrated system.

Table 15 Group Assignments

Name	Group Number	Measures
Load Reduction ECMs	Group 1	Repair Air Leak, Engineered Nozzles, Electric Motors replacing Pneumatic Motors, Zero-loss Condensate Drain
Low-Cost System Efficiency ECMs	Group 2	Cool Air Intake, Reduce CAS Pressure, Pressure/Flow Controller
High-Cost System Efficiency ECMs	Group 3	Add Air Storage
	Group 4	Use VFD Air Compressor
Dryer ECM	Group 5	Desiccant Dryer Dew Point Demand Control

Second, the gradually decrease of Difference% in system efficiency groups as shown in scenarios of "Group 2", "Group 2,3", and "Group2,4" illustrates their negative internal interactions. All measures in Group 2 are Low-Cost system efficiency ECMs with relatively small savings, therefore the Difference% is only -1.3%. When Add Air Storage and Use VFD Air Compressor are included, the Difference% is decreased to -6.3% and -7.3% respectively. This is because of their higher savings potential and more significant interaction.

Third, mixed Difference% values are obtained when combining load reduction and system efficiency ECMs. Comparing scenarios of "Group 2,3" and "Group 1,2,3", the addition of Group

1 provides more negative impact, which is opposite with the results of evaluating Group 1 separately. The reason is that the lower system pressure reduces the load reduction savings. In scenarios of "Group 1,2", "Group1,3", and "Group 1,4", the absolute Difference% are less than 3% due to counteract effect of both mechanisms.

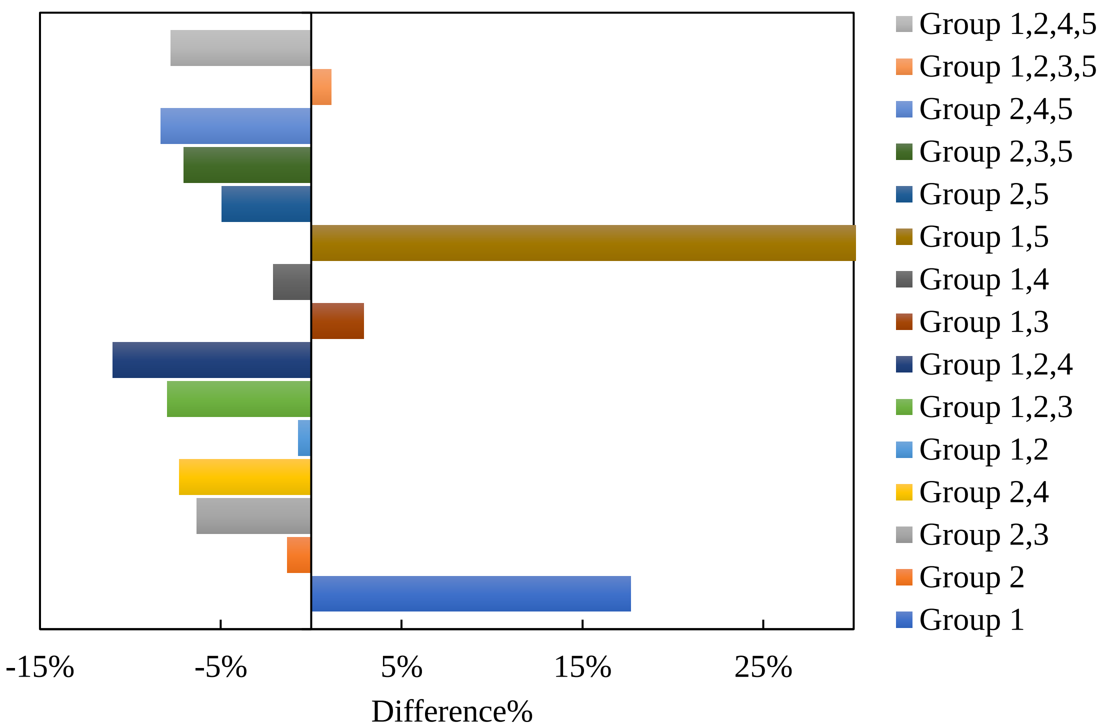


Figure 23 Savings Comparison of Integration Model and Simple Model

Forth, the negative impacts from system efficiency ECMs dominate the interaction results in most scenarios. It can be explained by its higher overall savings compared with load reduction ECMs. Dryer type is a significant factor in the CAS. The savings potential of refrigerated dryer is minimal. The dew point control of desiccant dryer not only contributes a lot to the savings, but also greatly interact with all the other ECMs during integration.

Overall, the interaction among all the ECMs are complicate and cannot be ignored. It is recommended to use the proposed integration model to accurately evaluate the savings.

3.2.3 Reliability and Optimization Analysis

The savings from the ECMs can be accumulated along the lifetime of the measures. Nonetheless, it is unrealistic to claim the same energy savings every year due to the dynamic compressed air operation conditions. The LF and operation hours may increase or decrease with the change of production plan. It is necessary to carry out reliability analysis for the savings and research the impact of CAS's dynamic characteristic.

Table 16 Load Factor Reliability Analysis

Scenarios	Annual Savings(kWh)				
	LF=40%	LF=50%	LF=60%	LF=70%	LF=80%
Group 1	51,439	42,483	33,526	24,570	15,613
Group 2	13,497	14,778	15,744	16,396	16,732
Group 2,3	44,396	45,248	43,599	39,448	32,795
Group 1,2,3	80,856	78,968	74,578	67,687	58,295
Group 1,2,3,5	107,448	100,614	91,743	80,834	67,888
Scenarios		**Difference Percentage with LF=40% as Baseline**			
		LF=50%	LF=60%	LF=70%	LF=80%
Group 1		-17.4%	-34.8%	-52.2%	-69.6%
Group 2		9.5%	16.6%	21.5%	24.0%
Group 2,3		1.9%	-1.8%	-11.1%	-26.1%
Group 1,2,3		-2.3%	-7.8%	-16.3%	-27.9%
Group 1,2,3,5		-6.4%	-14.6%	-24.8%	-36.8%

Load factor is not only the critical factor for the savings calculation, but also the most dynamic parameter which changes all the time. The annual savings from typical Groups at various LFs were analyzed to obtain their reliabilities. The Results are shown in Table 16. It can be seen the savings from Group 1 quickly decreases with the increase of LF, which means the Load

Reduction ECMs works better at low LF situations. The opposite results are observed for the Low-Cost System Efficiency ECMs. The reason is these measures increase the overall system efficiencies no matter what the LFs are. Larger LF provides higher baseline, hence greater savings. However, the High-Cost System Efficiency ECMs act differently. In the situation of "Group 2,3", the savings slightly increase at first, and decrease quickly after LF passes 50%. It is because LF is also the critical value for the savings from "Add Air Storage" and "Use VFD Air Compressor". Higher LF results lower savings opportunities of increasing partial load efficiency. Therefore, a negative impact from increasing LF is obtained for "High-Cost System Efficiency ECMs". Overall, Larger LF means less savings potentials in the integrated system as shown in the results for "Group1,2,3,5".

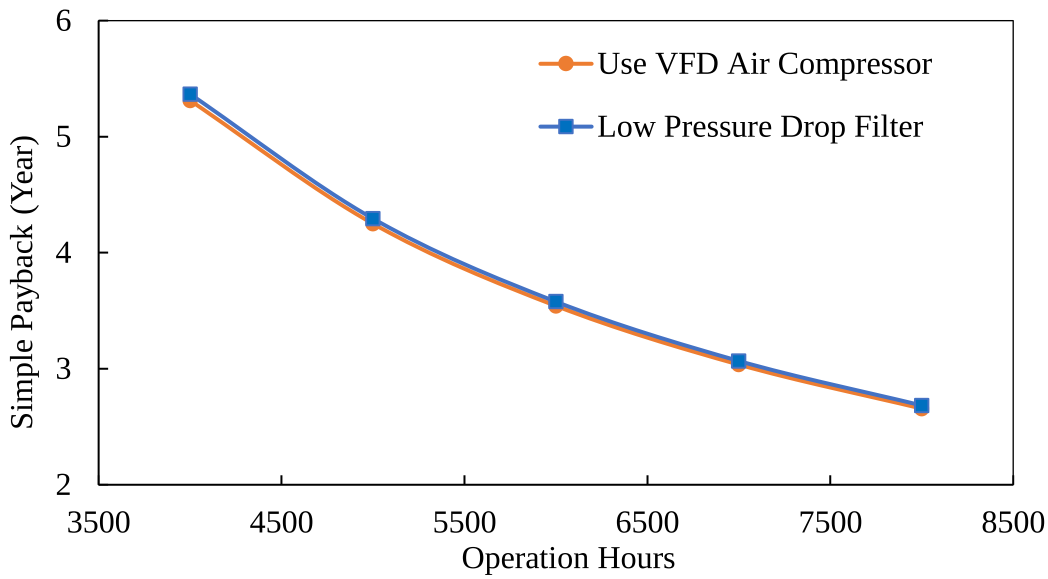


Figure 24 Relationship Between Operation Hours and Simple Payback

The influence of operation hours is straightforward. The savings is linear related to operation hours. Therefore, the simple payback will decrease at the situation of high operation hours as shown in Figure 24. It is shown the VFD air compressor will have a simple payback of less than 2.5 years when operation hour is over 8,300 hrs. It is worth to mention that Use VFD

Refrigerated Dryer has negative NPV and more than ten years simple payback even at 27/7 operation condition.

Due to the dynamic characteristic of CAS and the variation of customer's demand, there is no absolute optimized energy savings matrix for each CAS. however, several basic guidelines can be provided based on the results of proposed model.

For the scenario of high load factor, the low-cost system efficiency measures are the best options because of its better savings and shorter payback. Load reduction measures are not suggested to be adopted alone because its saving potential tends to decline with the increase of LF. For the same reason, high-cost system efficiency ECMs are not suggested in this situation either. Nonetheless, if the customer has enough budget and intend to achieve maximum NPV by installing a new VFD air compressor or air tank, the load reduction measures are highly recommended to be implemented together. It is because they are positively related to each other in this situation. For instance, the integrated savings of "Group 1,2,4" is 20% more than that of applying them separately.

For the scenario of low load factor, the load reduction measures have higher priority due to the low system overall efficiency. Comparably, the low-cost system efficiency measures can only provide less than 30% of the savings. Reduce system setting pressure is still recommended due to its zero-implementation cost, but cool air intake and pressure/flow controller should be avoided considering its low savings and negative impact on the load reduction measures. High-cost system efficiency measure is more attractive in this situation compared with that of high load factor. However, replacing pneumatic motors is not recommended if VFD air compressor is already implemented because the add-in NPV is minimal in the integrated system.

Chapter 4 Energy Characteristics Analysis of U.S. SMEs

This section aims to research the overall characteristics of the energy consumption in the U.S. SMEs. At first, the IAC data is collected and processed to obtain valid research samples. The methodologies used to study the changes of energy intensity and the ECM adoption rate of U.S. SMEs are explained. The impacts of various factors related to energy intensity and ECM adoption are exanimated.

4.1 Energy Management Strategies and Data Acquisition

The manufacturing processes and auxiliary systems interact with each other to support regular operations of industry facilities. Integrated strategies of energy assessment, improvement and management are required to achieve industrial energy efficiency [8]. Various programs and tools that aim at promoting energy efficient practices and reducing energy consumption are available in the United States. The IAC program is one of them and has been operated for more than 40 years. Thousands of energy audits for SMEs have been conducted by IAC staffs across the states. The research of this section is based on the analysis of the IAC database.

4.1.1 Energy Management Strategies for SMEs

Numerous energy efficient equipment and technologies are available in the market. While they are easy to access, there still exist challenges for manufacturing plants to achieve energy efficiency. Most of the manufacturing companies, especially the small- and medium-sized manufacturers, would not choose to replace their existing equipment for machining or auxiliary systems with more advanced and efficient devices. This kind of primary updates is usually too pricey to implement for SMEs due to the expensive equipment and labor costs. Lack of professional knowledge also prevents companies to installing efficient practices. Introducing energy conservation measures that SMEs can afford is critical for the energy efficiency improvement in this sector.

Conducting energy assessments by professional staffs are widely accepted method to help SMEs upgrade and optimize current equipment and systems with affordable capital costs. The plant will be assessed by a team of trained energy engineers during an on-site visit. Before the visit, a comprehensive data gathering process is carried out. Besides of the basic plant information like sales, employment size and the industry type, the team also collects energy usage files of the participated manufacturing companies. The annual energy usages and costs per provided utility bills are usually extracted and analyzed before the on-site audit. The energy usage profiles and the billing charges not only reveal the energy structure of the plant, but also help to identify special saving potentials in advance, such as unnecessary fee charges and abnormal peak-demand consumptions. The analysis results will be shared and discussed with plant personals before the audit to better understand the tradition and energy use structure of the plant. Additional data are also obtained during the audit by communicating with the facility managers and sub-metering critical energy consumers.

After each visit, the audit team will write an energy report to illustrate identified energy or cost saving opportunities and propose several assessment recommendations. Energy saving potentials exist in most energy systems of industrial facilities. The IAC program prepared a list of potential recommendations, which can be used as training document, as well as a great reference book to guide the team to check every possible area with saving potentials. The assessment recommendations are categorized into three main groups according to their saving objectives: to improve energy management, to minimize wastes and prevent pollutions, and to enhance productivity. The recommendations aiming to improve energy management are also known as

Energy Conservation Measures (ECMs). They are the main subjects of this research due to their predominate quantities and saving potentials as shown in Figure 25. The content of the ECMs, estimated annual energy and cost savings, and calculated payback period are all recorded in the IAC database. The database also provides the adoption status of proposed ECMs, which is obtained by follow-up survey or interview within 6 to 12 months after the on-site assessment.

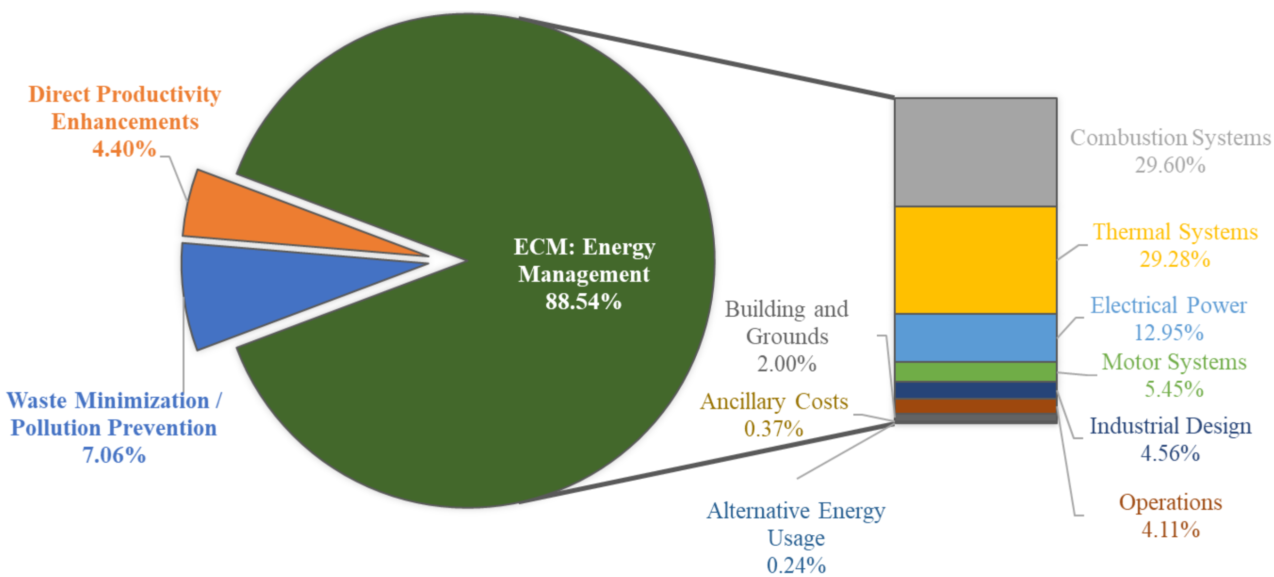


Figure 25 IAC Recommendation Frequencies per Original Database [65]

ECMs developed in the following categories are the most popular and promising during energy audits:

1. *Motor System.* Popular ECMs include to install variable speed drives for motors of various equipment; optimize motor sizes and air compressors; upgrade motor control systems.

2. *Building and Grounds.* Lighting and space conditioning are the most important parts of this category. Install energy efficient lighting sources and optimize the temperature controls contribute large amount of saving potentials.
3. *Thermal System.* The maintenances and operations of the steam system is the theme of this category. Appropriate heat recovery from various equipment could save tremendous energy for the plant.
4. *Combustion.* The furnaces, ovens and boilers can be optimized by installing ECMs in this category. Proper insulations and efficient burners are usually recommended. Regular maintenances are also encouraged best practices.
5. *Electrical Power.* Electricity demand management and thermal energy storage could benefit the plant in the long run. Maintain high power factors and use appropriate transformers usually bring instant capital benefits.

Because of the variance of energy use strategies between industries, it is important to understand the industry types before analyzing [36]. The IAC database provides both SIC (Standard Industrial Classification) and NAICS (the North American Industry Classification System) code to classify participated manufacturing establishments. However, the NAICS code is only available for assessments after the year of 1997. In order to extend the scope of research subjects, SIC code system is used in this research. Based on SIC system, the companies with codes ranging from 2000 to 3999 are categorized as manufacturing enterprises. The major manufacturing subsectors included in this research and their industry descriptions are listed in Table 17. The subsectors of Tobacco (SIC 2100 to 2199), Apparel (SIC 2300 to 2399), Petroleum and Refining (SIC 2900 to 2999), Leather (SIC 3100 to 3199) and Miscellaneous (SIC 3900-3999) are excluded due to lack of valid data points in IAC database.

Table 17 List of Manufacturing Subsectors

Industry Types	Description	SIC Range
Food	Food and Kindred Products	2000-2099
Textile	Textile Mill Products	2200-2299
Wood	Lumber and Wood Products, Except Furniture	2400-2499
Furniture	Furniture and Fixtures	2500-2599
Paper	Paper and Allied Products	2600-2699
Publishing	Printing, Publishing, And Allied Industries	2700-2799
Chemical	Chemicals and Allied Products	2800-2899
Plastics	Rubber and Miscellaneous Plastics Products	3000-3099
Nonmetallic Mineral	Stone, Clay, Glass, And Concrete Products	3200-3299
Metal	Primary Metal Industries	3300-3399
Fabricated Metal	Fabricated Metal Products, Except Machinery and Transportation Equipment	3400-3499
Machinery & PC	Industrial and Commercial Machinery and Computer Equipment	3500-3599
Electronic Equip.	Electronic and Other Electrical Equipment and Components, Except Computer Equipment	3600-3699
Transportation Equip.	Transportation Equipment	3700-3799
Entertainment	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks	3800-3899

4.1.2 Data Acquisition and Filtering Methods

The IAC program is known as one of the world's largest and best documented energy efficiency program [50]. A collection of all completed assessments and proposed recommendations since 1981 is publicly available online and updating regularly [65]. Over 18 thousand of energy assessments and 130 thousand of proposed recommendations are recorded in IAC database by September 2018. A statistically significant sample of the assessments and recommendations is obtained after cleaning the data, removing out-of-range points and excluding outliers.

Although the assessment data has been available since 1981, the records for the first several years are incomplete, and only a few assessments and ECMs are available in the database. To ensure that the selected data sets are comparable with the each other, the assessment data that are out of time frame of 1987 to 2017 are firstly excluded. The data of audits in 2018 is not included because most of the implementation status is not available by the time this thesis is composed. It is worth to mention that some non-SME companies were allowed to participate the program if obtained special approvals. Therefore, the audits for companies that are out of the ranges of SME definitions are identified and excluded since this research is focused on the energy profiles of SMEs. The annual sales and number of employees are provided as basic information of the plant. Annual costs of various energy sources such as electricity, natural gas, water and LPG are also included in the database. Although multiple types of energy sources are used in manufacturing sector, natural gas and electricity are the most common energy sources and can be used to generate other types of secondary energy sources such as steam and compressed air [66]. The electricity and natural gas are also the major saving targets during energy audits. Therefore, the total utility cost of a plant is calculated as the sum of the annual electricity and natural gas costs in the filtering processes.

The next step is to eliminate abnormal energy usage records in the rest of the database. Energy price is an important element of energy cost. Although it is not directly recorded in the database, the energy price for electricity or natural gas can easily be calculated by dividing the energy costs by the consumptions. Since the electricity demand is not recorded before the year of 1996, the average electricity price is calculated by dividing the sum of the electricity and demand cost by the electricity usage. The records that have impractical energy prices, i.e. with gas price more than \$50/MMBTU or less than \$0.5/MMBTU, or average electricity price greater than \$0.5/kWh or less than \$0.01/kWh, are eliminated from the data set. A reasonability check for proposed recommendations is also conducted. Although the payback period can be relatively long at certain circumstances, it is financially impossible for a small or medium sized company to invest on such projects. Also, the recommendation that promises to save more than 25% of the total utility costs or reduce the energy usage by half is not convincible to be a valid proposal. All the records that have above characteristics are excluded for the following analysis.

Finally, the energy intensity outliers are removed from research sample. Energy intensity is a widely used indicator for energy efficiency. To obtain the energy intensity of a participated plant, the total energy consumption of a plant uses the sum of its annual natural gas and electricity usage in terms of MMBTU. Since the gross domestic product or the value added of the plant is not listed in the database, the annual sales is considered as an alternative in this case. Considering that there exists an average of 2.93% CPI inflation during the period of 1981 to 2015 [67], the sales will be recalculated to chain to 2015 U.S. dollar value.

The interquartile range (IQR) rule is used to detect the presence of outliers. IQR can be used as a measure to describe the distribution of the data. The first quartile Q_1 includes the lowest 25% of the data points in the sample and the third quartile Q_3 includes 75% of the data points. IQR is the difference between Q_1 and Q_3, which consists of middle ranged data points. The upper fence and lower fence to identify outliers of sample can be quantified using Eq. 16 and 17. The value of coefficient k can be adjusted to suite different sampling purpose. For this work, k equals to 1.5. The upper fence is 3753 BTU/Dollar. However, the lower fence calculated in this method is invalid as it is less than zero. In order to screen abnormally low energy intensity data points, the 5%

percentile of the sample is used as lower fence, which is 172.5 BTU/Dollar. Any plants with calculated energy intensity beyond the upper and lower fences are excluded in future work.

$$\text{IQR} = Q_3 - Q_1 \tag{16}$$

$$\text{Upper Fence} = Q_3 + k \times \text{IQR} \tag{17}$$

$$\text{Lower Fence} = Q_1 - k \times \text{IQR} \tag{18}$$

Table 18 lists the number of assessments and recommendations that have been removed during the filtering processes and shows the surviving number of data records. There are 10,293 assessments conducted for SMEs of selected manufacturing subsectors during 1987 to 2017 and 68,895 ECMs proposed for energy saving purpose. Although a large amount of records are excluded in future study, this process is necessary as it ensures that the obtained sample data is compliant with research criteria without any interferences from incomplete, inaccurate data and outliers.

Table 18 Number of Assessments and Recommendations Removed in Filtering Processes

Filtering Process	Number of Filtered Assessments	Number of Filtered Recommendations
Non-ECM Filter	0	16,040
Out of Research Range (Time Frame, SIC)	1,472	9,520
Non-SME Filter	4,698	30,230
Abnormal Data Filter	106	673
Reasonability Check	0	2,028
Energy Intensity Outliers	1,851	12,201
Surviving Data Points	**10,293**	**68,895**

4.2 Analysis Method

Three data analysis methods are adopted in this thesis to research the filtered IAC database. Decomposition analysis is used to estimate the major effects on energy usage among SMEs. Data Envelopment Analysis is employed to examine the participated companies and compare the energy efficiency between regions and sectors. Logistic regression analysis is carried out to obtain the key factors that affect the adoption of proposed ECMs.

4.2.1 Decomposition Analysis

The decomposition analysis is often used to study the changes of energy use in industry [68]. While there are many different techniques to utilize decomposition analysis, the additive LMDI (logarithmic mean Divisia index) method is more preferred to interpret the changes of industrial energy consumption [40, 69]. Thus, additive LMDI method will be used herein to analyze the energy use trend among SMEs for the past three decades.

By analyzing the energy consumption changes between selected base year and target year, the decomposition method segregates the impacts on energy use changes into three main terms: aggregate activity level, sectoral structure and energy intensity. Eq. 19 to Eq. 25 [40] shows the calculation formulas used to quantify the total energy usage changes and the main effects. "E" and "Q" denote to the energy consumption and industry activity, while "S" and "I" are used for sectoral share of activity and energy intensity. The superscripts "T" and "0" represent the target (last) year and base year of selected time frame. The subscripts "*i*" indicates the different subsectors within manufacturing sector, "*tot*", "*act*", "*str*" and "*int*" are the total energy consumption and the effects caused by activity level variances, industry structure adjustments and energy intensity changes respectively.

$$\Delta \mathrm{E}_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} \tag{19}$$

$$\Delta E_{act} = \sum_i \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^0} \ln\left(\frac{Q^T}{Q^0}\right) \tag{20}$$

$$\Delta E_{str} = \sum_i \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^0} \ln\left(\frac{\mathrm{S}_i^T}{\mathrm{S}_i^0}\right) \tag{21}$$

$$\Delta E_{int} = \sum_i \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^0} \ln\left(\frac{\mathrm{I}_i^T}{\mathrm{I}_i^0}\right) \tag{22}$$

$$Q = \sum_i Q_i \tag{23}$$

$$\mathrm{S}_i = Q_i / Q \tag{24}$$

$$\mathrm{I}_i = E_i / Q_i \tag{25}$$

The IAC database provides the annual sales in dollars and production levels in physical units as the output of participated companies. However, the physical units of production levels are mixed even within the same subsector and may cause misinterpretations between subsectors as the units cannot compare with each other. A company that only manufactures thousands of motors a year may consume the same energy with the one that produces millions of nails. Thus, the annual sales are selected to represent the activity level in the following decomposition analysis. Accordingly, the energy intensity is the ratio of plants' energy usage (annual electricity and gas usage in MMBTU) and the annual sales (in million dollars). To reduce the effect of monetary inflation, all the dollar amounts are chained to the 2015 dollar-value.

The effect of activity level represents the contribution of the output (sales) fluctuation to the change of the total energy usage. The activity effect usually has direct relation with the final energy consumption as higher output would typically require more energy input. On the other hand, lower output, especially lower sales in this case, would not only decrease the demand of the company's energy usage, but also could be a driver for the management to seek for lower producing costs and lead to more energy efficient processes.

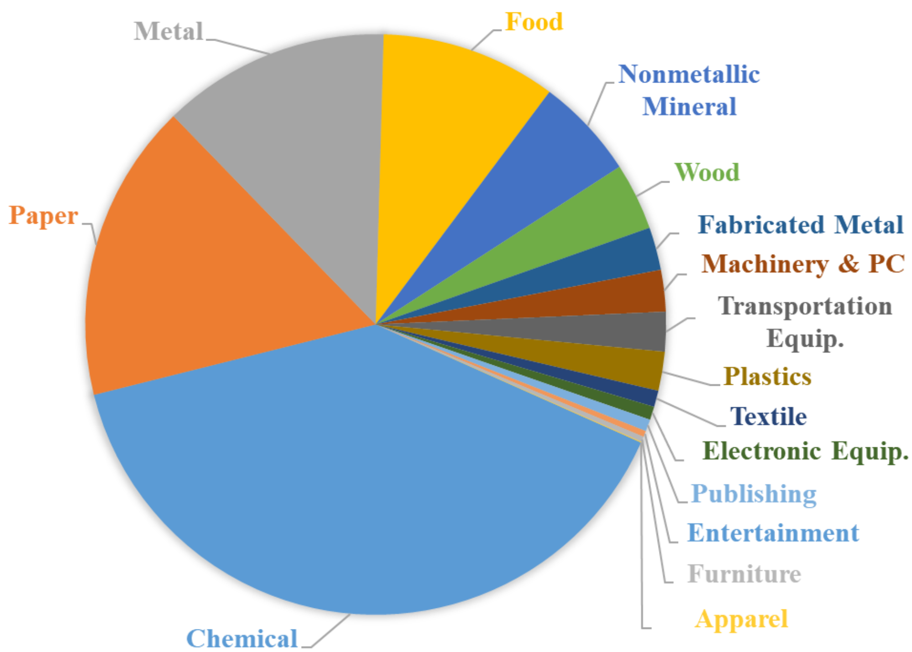


Figure 26 Energy Consumption by Subsectors (Trillion Btu) [4]

The effect of the sectoral structure should illustrate the impacts from the shifts of the industry types within manufacturing sector. The composition of the industries could highly affect the total energy consumption and energy intensity. As illustrated in Figure 26 (data retrieved from the *Manufacturing Energy Consumption Survey* of 2014), the most energy-intensive industries, subsectors of Wood (SIC group 2400), Paper (SIC group 2600), Chemical (SIC group 2800), Nonmetallic Mineral (SIC group 3200) and Metal(SIC group 3300), contribute to 32% of manufacturing gross output but use more than 80% of fuel consumption [4]. When the share of the more energy-intensive subsectors increases, the energy consumption would significantly increase and vice versa. The energy intensity reduction caused by the shifting of industries from more energy-intensive to less energy-intensive ones was five times more than the reduction via purely installing energy efficient measures for U.S. manufacturing sector from 2010 to 2014 [4, 70]. Therefore, the structure change of manufacturing sector is a key indicator to understand the energy consumption and intensity changes. Energy-related policies, regulations and programs could affect the choices of industry types, encourage the adoption of energy-efficient technologies and subsequently influence the trend of energy intensity.

The intensity effect reflects the changes in energy efficiency in the manufacturing sector that could result in changes of final energy usage. The popularization of efficient technologies and environmental awareness could help to reduce the energy intensity. However, the modernization of manufacturing processes does not always reduce the energy consumption as the new added ancillary processes requires additional energies.

4.2.2 Data Envelopment Analysis

The Data Envelopment Analysis (DEA) is a popular tool to evaluate the efficiency among a group of objectives. While the LMDI method analyzed the macro effects on the energy usage within the manufacturing sector, it is important to investigate the micro level at specific facilities to understand the variance of energy efficiency. DEA is a useful method to benchmark the energy efficiency within selected group of companies and identify the inefficient sources[71]. The techniques employed by DEA can be used to deal with large amount of objectives and multiple variables [72].

Each chosen objective company would be the decision making unit (DMU) in the analysis with multiple inputs and outputs be examined and compared. Various kinds of measures such as economic output, energy consumption, or operational cost can be involved in DEA. The peer companies with the best energy efficiency practices are identified as the output frontiers during the analysis. A relative efficiency score will then be assigned to each DMU by comparing with the frontiers. The DEA model calculates the relative efficiency of DMUs by solving the following linear programing equations [72]:

$$\max \quad \theta_k = \frac{\sum_j u_j y_{jk}}{\sum_i v_i x_{ik}} \tag{26}$$

$$\text{subject to} \quad \theta_k \leq 1 \tag{27}$$

$$u_j \geq 0 \tag{28}$$

$$v_k \geq 0 \tag{29}$$

where, k is the plant or decision making unit (DMU) in the analysis;

θ_k is the relative efficiency of company k or $\mathrm{DMU_k}$, which is at most 1 for the frontiers;

u_j, v_i are the coefficients or "weights" of inputs and outputs to calculate to obtain the optimal θ_k;

y_{jk} is the jth output of $\mathrm{DMU_k}$;

x_{ik} is the ith input of $\mathrm{DMU_k}$;

The DEA system has been extended to many different models to fit all kinds of research scenarios. Two kinds of DEA models are commonly used in literature. The CCR method was proposed by Charnes, Cooper and Rhodes in 1978 and the BCC method was then developed as an important extension by Banker, Charnes and Cooper in 1984 [73]. The difference between these two models is the assumption about the return-to-scale (RS) activities. The CCR model assumed constant RS while the assumption in BCC method is variable, which leads to piecewise efficient output frontiers [74]. The energy efficiency of manufacturing plants could be measured in multiple ways and affected by various factors. Thus the BCC method is selected to evaluate the performance of participated companies.

According to the purpose of the study, the BCC method can also be divided in to two models. The version that aims to maximize the outputs of the plant under constant inputs is called output-oriented model. On the other hand, the model that is mainly designed to minimize the inputs to the plant while keep the same output levels refers as input-oriented model. In this case, the main objective of the IAC program and many similar energy programs are primarily devoted to reducing the energy consumption and cost of manufacturing plants without sacrificing their productivity. Thus, the input-oriented BCC model suites the requirements of the study. Various tools can be used to solve data envelopment problem. MaxDEA Pro 6.6 is used in this work. MaxDEA is a powerful and professional DEA software and equips with extensive range of DEA models.

If a company satisfies $\theta_k = 1$, it is called BCC-efficient. The other companies are then BCC-inefficient and the analysis defines reference slacks for each input sources and output measures based on the BCC-efficient units. The slacks provide improvement potentials (s^{-*} or s^{+*}) to the BCC-inefficient companies. The improved activities are then BCC-efficient, as follows:

$$\theta_k^* x_k = \sum \lambda_j^* x_j + s^{-*} \quad (30)$$

$$y_k = \sum \lambda_j^* y_j - s^{+*} \quad (31)$$

The next step of DEA is to determine the input sources and output measures that would involve in the analysis. Although the DEA method is designed to analyze the performance of entities with multiple inputs and outputs, it is an important task to select suitable input and output variables that could fully represent the performance of energy utilization for the actual manufacturing processes and exclude the miscellaneous factors. The selection of the input and output variables is also dependent on the data acquisition method and data availability.

The annual consumption of electricity and natural gas is one of the most important input sources for SMEs that participated in the IAC program. Other sources such as LPG, oil, water and other charges like electric demand and fees are also available in the database. Although the DEA method could analyze the efficiency with various input types, the records for those sources are inconsistent and incomplete. For instance, the electric demand is recorded only for companies that assessed after the year of 1996 and the water consumption is only available for less than 50% of the companies despite its necessity to almost all plants. Since this study is focused on the energy usage and efficiency of manufacturing plants, other physical inputs such as raw material are not considered. Certain features of the company can also affect the final energy usage. The plant area and the employment size are among those influential features. The labor energy intensity (energy usage per employee) and the space energy intensity (energy demand per square foot of plant area) are important indictors when evaluating plant efficiency [75]. The size of the employment correlated to the electricity usage and cost, while the plant area directly impacts the gas usage and cost especially for those located in cold areas or with weak building envelop. In summary, the electricity, natural gas, size of employment and plant area were chosen to be the input factors for the analysis.

Table 19 Input Values of Selected Companies per Subsector in DEA

Manufacturing Subsectors	Average Employment Size	Average Plant Area SQ FT	Average Electricity Usage 10^3 kWh	Average Gas Usage MMBTU
Food	156	133,085	5,524	32,547
Textile	175	171,885	8,484	31,797
Wood	137	160,338	6,676	10,519
Furniture	219	216,022	3,473	13,526
Paper	129	169,283	5,630	25,963
Publishing	176	112,833	4,568	11,255
Chemical	109	134,626	6,106	28,353
Plastics	130	114,468	7,506	7,043
Nonmetallic Mineral	133	119,627	4,514	20,734
Metal	133	142,609	6,872	35,682
Fabricated Metal	153	147,112	4,246	16,955
Machinery & PC	169	136,836	3,639	11,999
Electronic Equip.	209	133,731	5,475	11,014
Transportation Equip.	212	144,373	5,468	12,020
Entertainment	207	117,397	4,662	7,234

Both annual sales and physical yearly production are valid components to measure the outcome levels for manufacturing plants. However, as discussed before, it is hard to unify the physical units of production levels and may cause misunderstanding during analysis. The utility costs consist an important part of total expenses for the plant. The costs vary between plants and may fluctuate among industries, regions and years. Analysis of the utility bills could reflect the healthiness of the energy use structure and reveal hidden or unnecessary charges by comparing with similar demand entities. Thus, the utility costs for electricity and natural gases, together with the annual sales are selected as output measures in analysis.

Since DEA analyze the internal energy efficiency of selected units and the energy usage structures may be significantly different between industries, the DEA analysis was carried out separately for each manufacturing subsectors. 150 companies of each subsector were selected randomly from the database. The average employment size, plant area and energy usage for each subsector are listed in Table 19. An energy efficiency score is provided after each analysis by comparing with the companies with best energy efficient practices in the group, as well as the estimated slack distance between inefficient and efficient units for each input factor.

4.2.3 Logistic Regression Analysis

Applying energy and cost saving projects is an important way to approach better energy efficiency. Tremendous programs and policies are devoted to promoting the best energy practices. The IAC program aims to help SMEs around United States to connect with advanced energy efficient knowledges and commercially available energy-saving technologies. One of the most important outcomes for each energy audit is the ECMs proposed by IAC staff. To ensure complete understanding and adequate adoption of the proposed ECMs would be a promising way to achieve the program objectives. While the situation of each plant and the concerns for each ECM installation are different, the implementation status of ECMs simply shows the results of "implemented" or "non-implemented". To investigate the reasons for a proposal to be adopted or not could help future IAC staffs to better serve the SME community.

Unlike the sales or costs that have continuous values, the values for the adoption of ECMs are discrete and in this case, only structured with binary outcomes. Logistic regression could statistically analyze the relationship between categorical response variable and multiple independent variables [51]. It is superior in this analysis as the adoption status of ECMs is a typical categorical variable. The model also expands the limits on other inputs or factors and could involve either continuous or discrete variables for the analysis. The response variable in the Logistic Regression is the logarithm of the ECM implementation odds ratio. The odds ratio is the probability of the response variable occurring against the probabilities of the response variable not occurring [76]. In this case, it is the probability of an ECM to be adopted versus the probability to be abandoned. A transformation function is developed to convert the categorical data to continuous values. The function used to accomplish the conversion is called the Logit function or the link function. After the transformation, the converted response variable would be linear with the independent variables. A simple Logistic Regression model is formed as the following equation:

$$Logit\ Function\ Y = \ln\left(\frac{p}{1-p}\right) = \alpha_0 + \alpha_1 X_1 + \cdots + \alpha_s X_s \quad (32)$$

where, p is the probability of an ECM to be implemented;

α_0 is the intercept;

$\alpha_1, \dots, \alpha_s$ are the regression coefficients;

$X_1, \dots, X_s$ are the independent variables.

Dummy variables will be used if the selected factors include categorical variables. A dummy variable is an artificial variable created to represent an attribute with two or more distinct categories. Dummy variables are assigned to distinguish different groups, i.e. different ECM categories. In that case, an enormous amount of information can be packed into a single model with appropriate use of dummy variables. The values of “0” or “1” are assigned to dummy variables to indicate its membership with any mutually exclusive categories. If a parameter consists of N categories, the necessary number of dummy variables to represent this parameter is equal to $N-1$. The category with no dummy variable constructed is represented by assigning “0” to all the dummy variables of other categories for this parameter.

All possible factors that may affect the implementation of proposed ECMs will be explored and discussed. The stepwise testing procedure will be used to evaluate the selected factors and determine the best logistical regression model. A significant level of 0.05 will be used for the factors to entry or retention of the analysis. The non-significant factor is removed before adding the next factor into the analysis.

The intercept and regression coefficients are calculated by the maximum likelihood method. If all the regression coefficients are zero, the Logistic Regression fails to generate better prediction of probability of the outcome occurrence than the mean of the dependent variable [76]. If at least one of the regression coefficients is not zero, then take antilog transformation on both side of the model formula to obtain the calculated probability of the occurrence of a proposed ECM:

$$p = \frac{e^{\alpha_0+\alpha_1 X_1+\cdots+\alpha_s X_s}}{1+e^{\alpha_0+\alpha_1 X_1+\cdots+\alpha_s X_s}} \tag{33}$$

4.3 Results and Discussion

4.3.1 Results of SME Energy Usage Decomposition Analysis

Since the number of companies that participates the IAC program varies every year, we randomly selected 200 plants each year from 1987 to 2017 to study the changes of energy end usage. As shown in Figure 27, the average energy usage per plant slightly increases for the period of before 1990 and between 1997 and 2002. During all the other time interval, it steadily decreases. By 2017, the average plant energy consumption has dropped more than 10% compared with that of 1987. The decomposition analysis would indicate the main causes of those changes. Based on energy usage trend, six periods were selected to carry out the LMDI decomposition analysis: 1987-1992,1992-1997, 1997-2002, 2002-2007, 2007-2012 and 2012-2017. For each period, the last year's energy usage was compared with the base year's and the changes will be separated into three main effects.

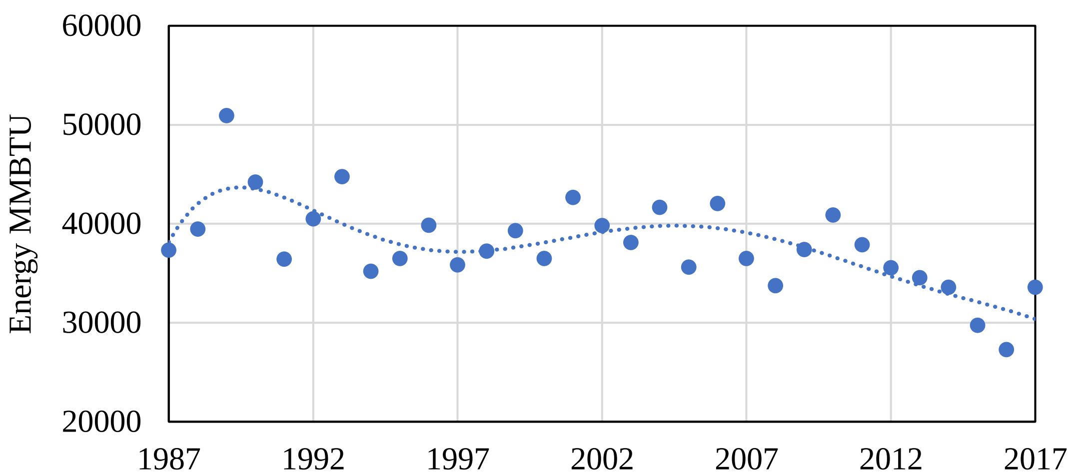


Figure 27 Average Plant Energy Usage from 1987 to 2017 of Participated SMEs

Although only 200 companies were analyzed in this study per year, all objectives were randomly selected and included all subsectors distributed across all contiguous states. The analysis of those selected companies should be able to draw the trend of SMEs' energy consumption in silhouette. Figure 28 shows the results of the LMDI decomposition analysis for the energy consumption during 1987 to 2017. The results are illustrated by four columns that represent the activity effect, the structural effect, the intensity effect and the aggregate energy use change for each time period. The structure effects are relatively small in all selected time periods, which indicates that the shares of the manufacturing subsectors retain at a steady status for the past three decades. The activity and the intensity effects are the main contributors to the energy use changes.

From 1987 to 1992, the activity effect is the main driver to the change of final energy usage. The sales of the manufacturing sector experienced an extraordinary increase from 1987 to 1992 and then constantly declined except a small bounce up during 2007 to 2012. The decrease of energy intensity at 1987-1992 period balanced the raise of activity level and finalized the total energy consumption increase at 960 trillion BTU. The other increase of total energy consumption is the period of 1997 to 2002 with a rise of 726 trillion BTU. It is worth noticing that the three main effects of these two periods have exact opposite influences. The largest energy use decrease happened during 2002 to 2007, which matched the timeline of the economic depression started early 2007. Declines on all effects were observed, especially the activity level effect. The depressed activity level stimulated the plants to transfer to lower energy intensity production. However, simply correlate the negative activity effect and the energy intensity decrease would be arbitrary. During the period of 1992 to 1997, the activity level experienced similar negative trend but the energy intensity effect is only as quarterly strong as period of 2002 to 2007. Further investigations of the differences of the behaviors of SMEs, such as the energy profiles, popular ECMs and their adoption levels in these periods, would reveal interesting facts. The energy intensity effect observed on to the period of 2007 to 2012 even with the economic recovery. It is also noticed that the aggregate energy consumption keeps the declining trend and remains at low level since then.

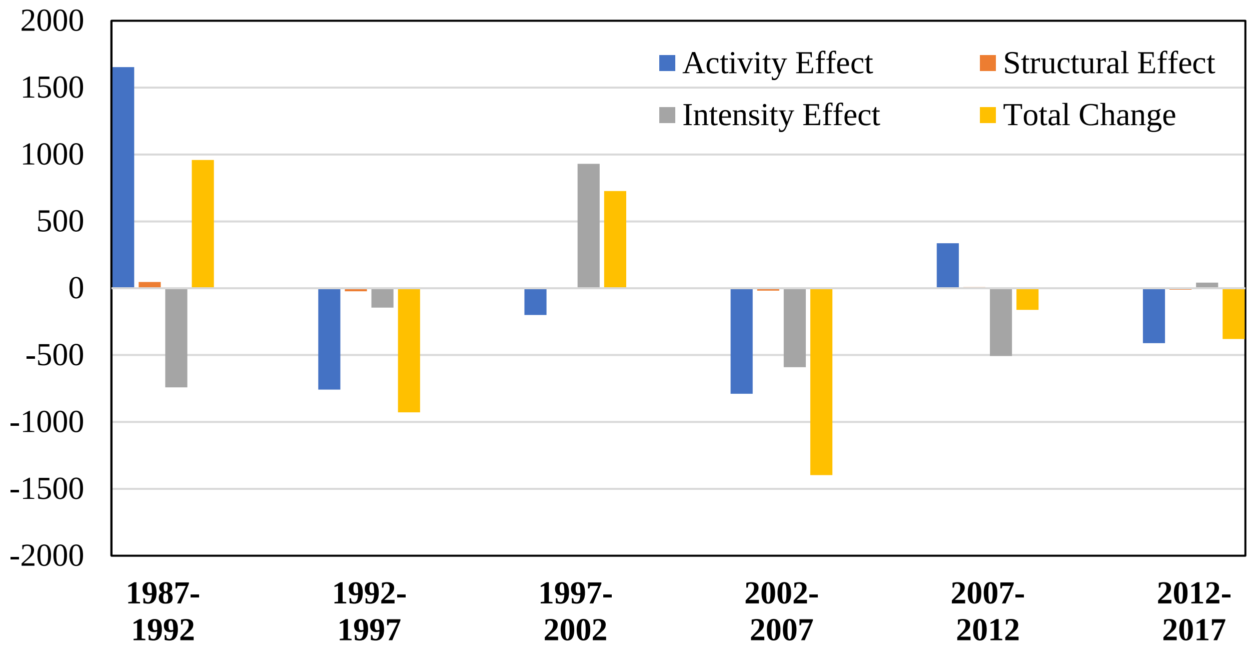


Figure 28 Decomposition Analysis Results for U.S. SMEs' Energy Use

4.3.2 DEA Results for Energy Efficiency

As revealed by the quantitative results of the decomposition analysis, the changes of energy intensity and output level could greatly affect the trend of the final energy consumption among SMEs. Improving energy efficiency is a common method to achieve higher output with lower energy consumption. The data envelopment analysis can help to understand the variance of energy use efficiency in industries and their distances to the best energy efficient practices.

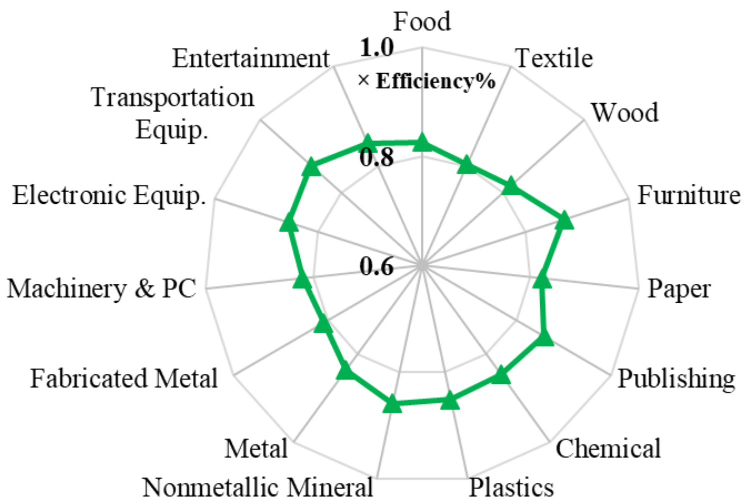


Figure 29 Average Efficiency Scores by Manufacturing Subsector

Figure 29 shows the average DEA efficiency scores per manufacturing subsector. Generally, the average efficiency score ranged between 80% to 90% for all selected subsectors. It is worth noticing that the efficiency scores under BCC model are usually higher than CCR model because the return-to-scale is variable, which means the score is estimated by comparing with the closest optimal DMUs [77]. Although the scores only reflect the relative energy efficiency among selected companies, the estimations show the similarity of energy use strategies within the same industry. The known energy-intensive industries such as Wood, Paper, Chemical and Metal have lower efficiency while the Nonmetallic Mineral is among the most efficient industries in this comparison. Furniture, Transportation Equipment and Electronic Equipment have the highest relative efficiency as they are usually highly automated in their production lines with standard procedures. The Textile and Wood industries have the lowest efficiency scores and share the largest variance within the industry, which indicates diverse and less efficient energy practices in these subsectors.

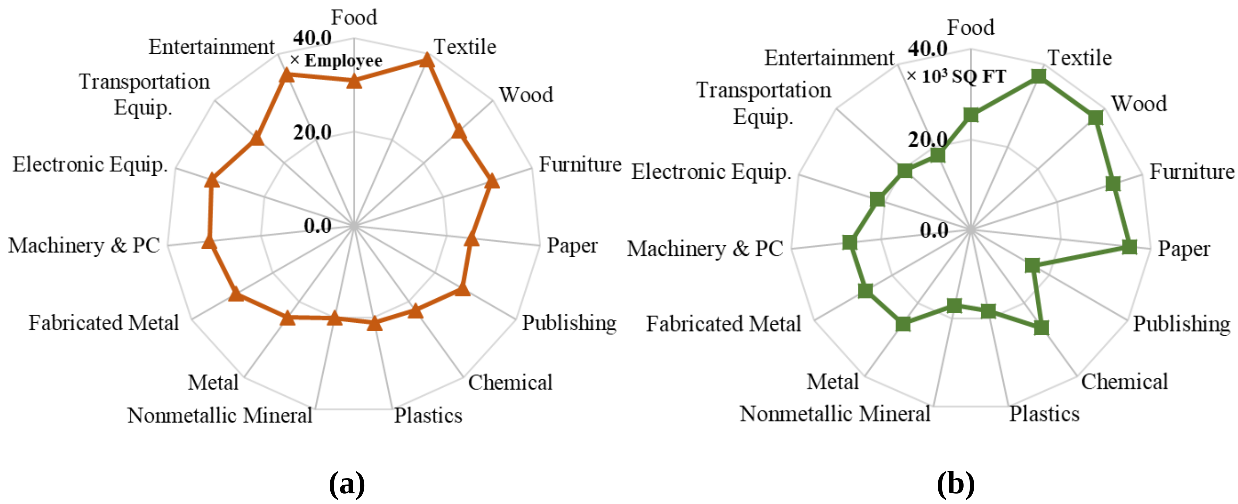


Figure 30 Calculated Improvements of Employee and Plant Area from DEA

Figure 30 shows the average suggested improvements on size of employment and plant area for each subsector to approach the optimal DMUs. It would be unrealistic to suggest companies to lay off employees or close part of their plants, but the calculated improvements for employment size and plant area indicate the saving potentials in their direct connected energy-consuming areas. For instance, more employees could mean more office areas which have additional requirements for constant lighting, room temperature, more office appliances and ancillary facilities such as lunch rooms and restrooms. The improvement under this input variable implies inefficient use of energy in non-production plant areas. The average redundant of this input is pretty similar for most subsectors, except the ones typically have smaller employment size like Metal, Plastics, Nonmetallic Mineral and Chemistry. On the other hand, the redundant plant area could lead to unnecessary cost on both electricity and natural gas. A poor insulated building could greatly increase the plant's energy costs during heating and cooling seasons. An inappropriate planning of the plant areas may cause the system to supply excessive energy to unnecessary areas such as warehouses and loading docks. Smart controls and functional zoning could help to reduce energy lost in those areas. Although the improvement potentials vary largely between industries, it wouldn't be a surprise to find more opportunities in the ones with larger average plant areas as summarized in Table 19.

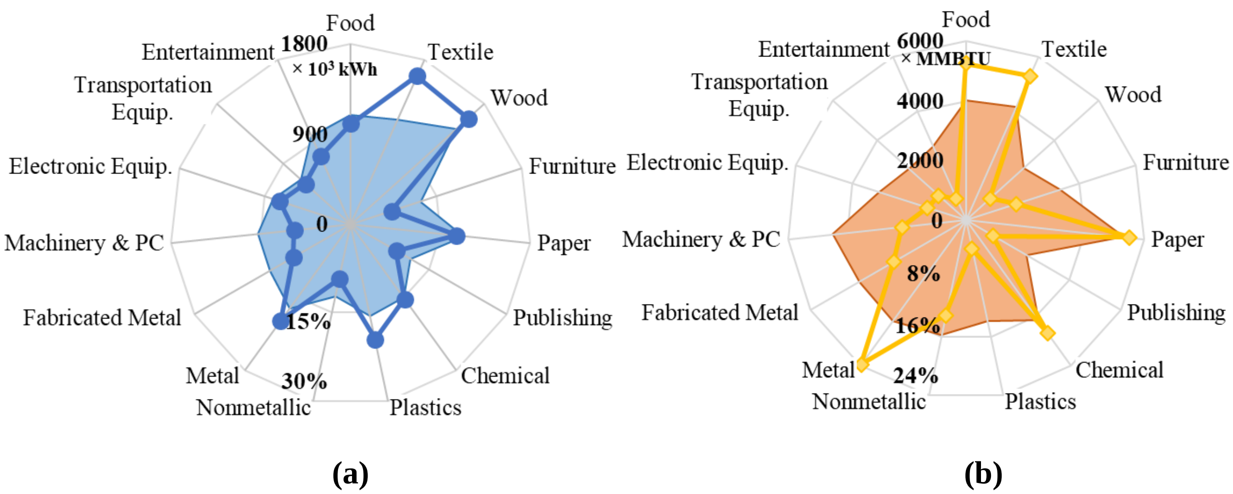


Figure 31 Calculated Improvements and Ratios of Electricity and Natural Gas from DEA

The improvement suggestions on energy sources of electricity and natural gas could reveal the potentials on energy efficient of DMUs. It is noticed that the subsectors consumed more energy per plant usually have larger saving potentials. Another parameter, the improvement ratio, is introduced to mitigate the plant-size effect and illustrate unbiased energy use efficiency of the subsector. As illustrated in the filled radar charts in Figure 31, 15.71% of electricity and 14.51% of natural gas could be saved averagely in manufacturing plants with best energy efficient practices. The Textile, Paper and Metal industries are among the most energy-intensive and lest efficient subsectors. They have the most saving potential on both the electricity and natural gas usage. The improvement ratios indicate that the Paper subsector has the worst practices on natural gas and the Wood industry uses electricity the least efficient. While the saving potentials of the Machinery and Fabricated Metal are relatively small, their efficiencies are below average on both energy input sources. Transportation and Electronic Equipment subsectors excels in efficient use of electricity and natural gas. Publishing subsector has the smallest improvement potentials and uses relatively smaller amount of energy per plant.

4.3.3 Influential Factors on ECM Adoption Rate and Logistic Regression Analysis Results

The DEA results can provide initial prediction of the possible saving areas for each industry. Together with a systematic recommendation list, the audit efficiency and accurately can be greatly improved. However, to detect the energy inefficient areas and propose energy saving measures are only the first steps. Promoting and encourage the implementation of good ECMs would be an important follow-up.

The implementation of ECMs depends on many factors. Figure 32 shows the calculated energy intensity of selected manufacturing subsectors. It is clearly stated that the energy intensity varies dramatically between industries and even between regions within the same industry. The production energy end users within the same industry may be similar, but the factors of the non-production areas could make the difference in different regions. For instance, the plants in Rocky Mountain and Great Lakes tend to be more energy intensive than other regions in many subsectors as they need to use more energy during heating seasons to keep their plants warm; on the other hand, the plants in more developed regions such as Far West and New England usually have more chances to connect with advanced efficient technologies and are more likely to adopt efficient measures, which would result in lower energy intensities. Thus, the subsector and the region would be important factors to test in analyzing the adoption rates.

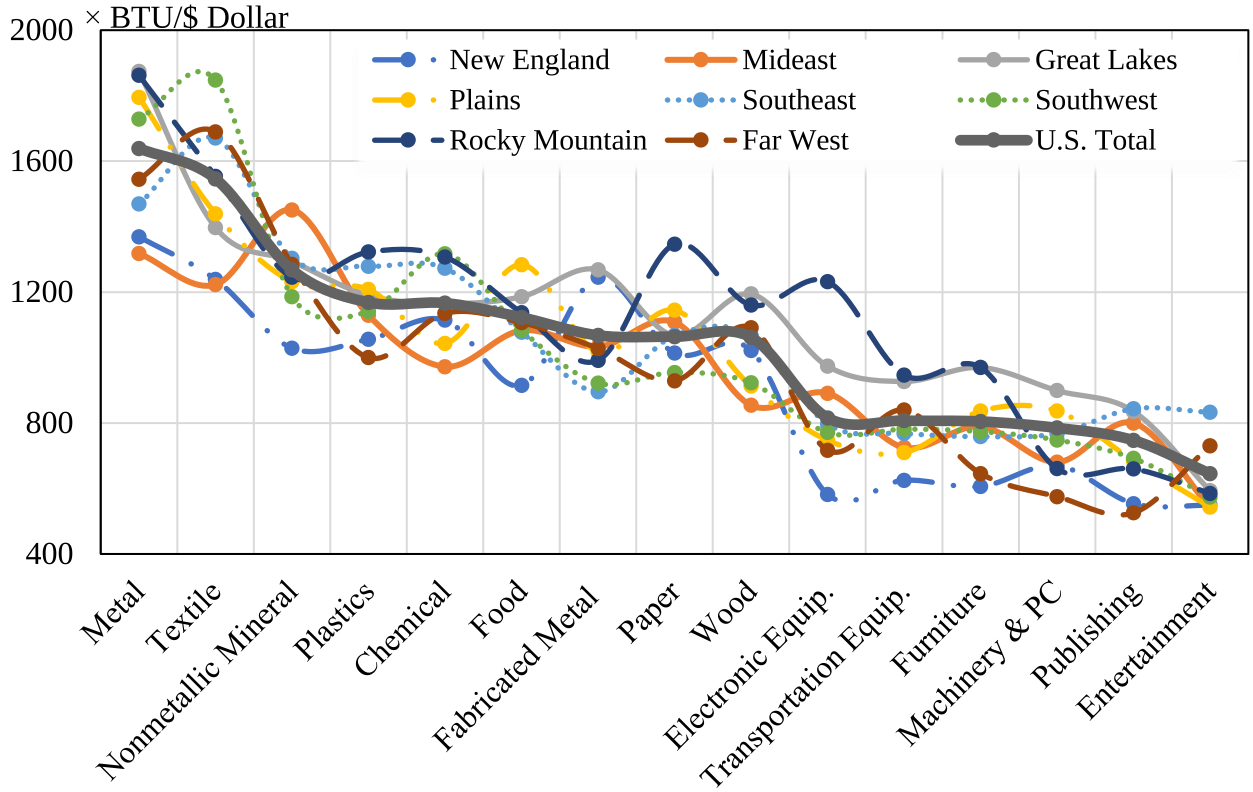


Figure 32 Energy Intensity Between Regions and Industries

The popularity and adoption level of ECM categories could be significantly different as illustrated in Figure 33. The adoption rate per category varies from 5.8% to 55.2%, while over 97% of proposed ECMs focus on the six main categories of Motor, Building, Thermal, Combustion, Operation and Electrical Power. To test whether the ECM category is a significant factor on the final adoption probability could assist the audit team in preparing more attractive recommendations to plant managers to eventually implement the ECM.

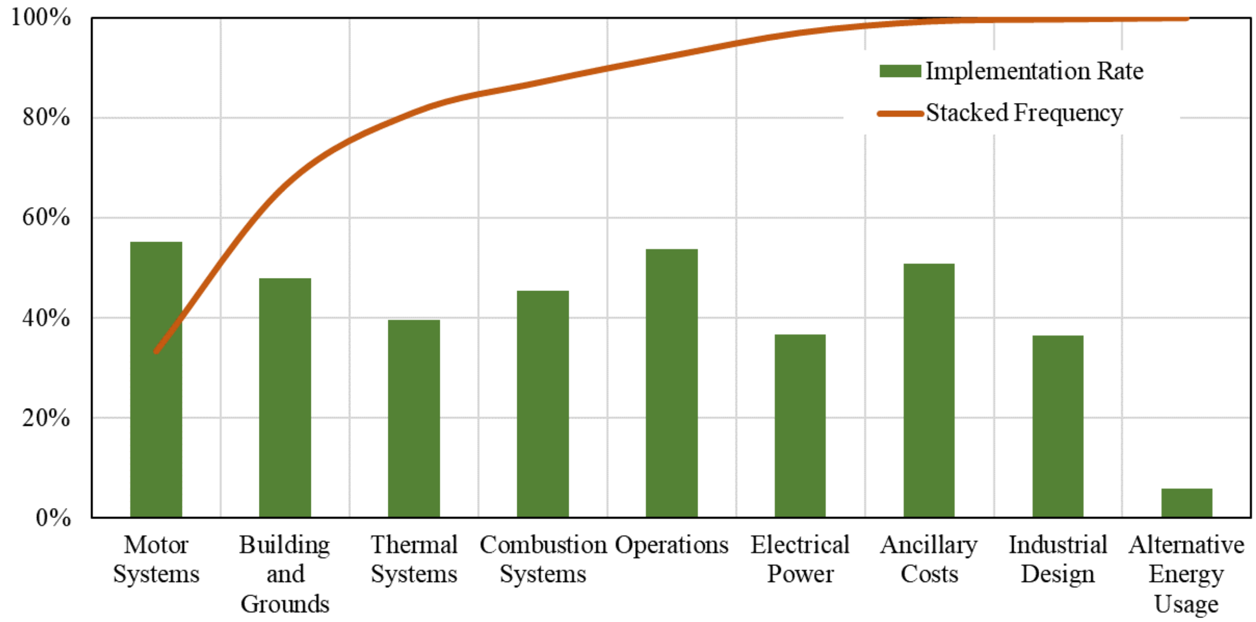


Figure 33 Stacked Frequency and Implementation Rate per ECM Category

The decomposition analysis has shown how the changes of energy intensity affect the total energy usage. The interests on different types of saving opportunities have also changed over the years. To achieve energy efficiency for existing plants is a slow process. Energy engineers have dedicated to promoting and implementing energy efficient projects for years. The first impression of a plant's energy usage situations to the energy audit team would be much different compared with those of 40 years ago, so as the plant saving potentials and management's preferences. Figure 34 shows the changes of average payback periods of the most popular proposed and accepted ECMs from 1987 to 2017. The focus of the audits has changed from short-term projects to longer ones, which could also reflect that many plants have already been operating with basic efficient practices (such as motion sensors, efficient light sources, etc.). However, a response delay to this change can be observed in the figure. The average payback for the implemented ECMs does not show a significant increase during the observation period. Overall, more than 67.3% of implemented ECMs has payback period less than one year, which is shorter than the average payback of 1.27 years for all proposed ECMs. To test the influence of the payback length and its related elements like implementation cost and cost savings could disclose the opinions of the plant decision makers towards energy saving measures.

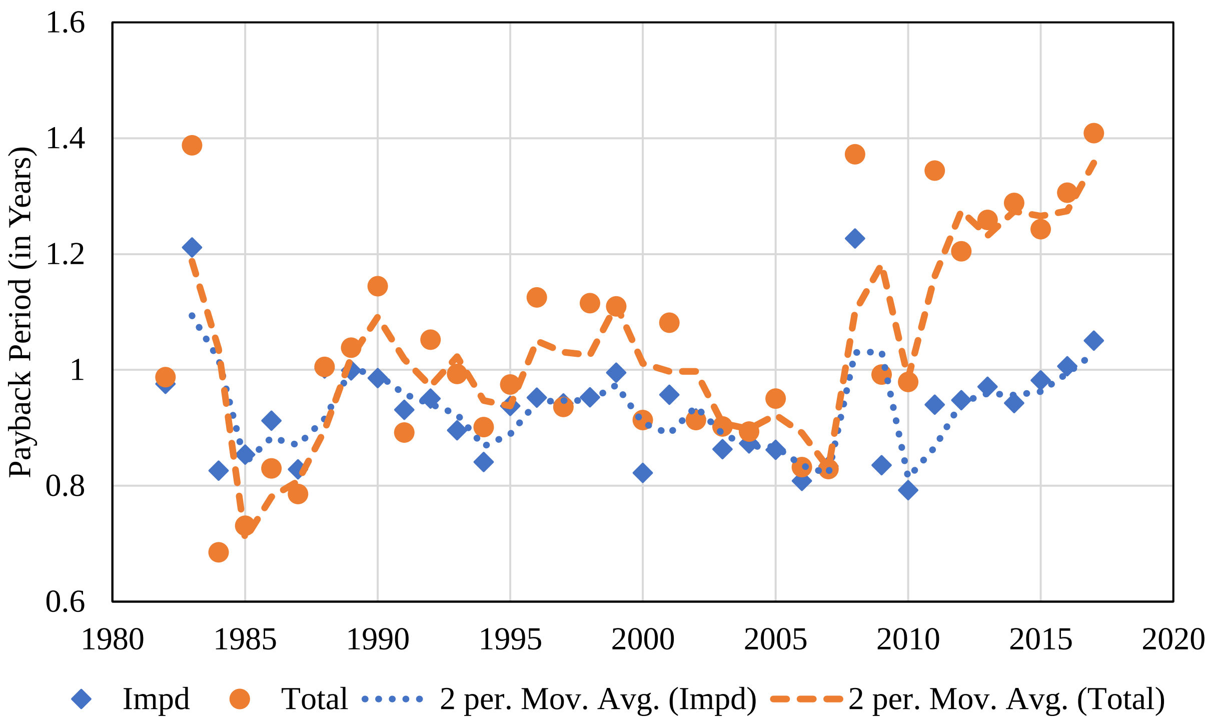


Figure 34 Average Payback of Top 25 ECM Types

Among the screened sample of ECMs, a total of 33,730 recommendations have been implemented, which makes the sample probability for an ECM to be adopted is 48.96%. The logistical regression analysis could develop a model to estimate the probability to implement an ECM according to the determined significant factors. The industry type, the located region, the ECM type, payback period, implementation cost and cost savings are evaluated.

The industry type was the first factor to enter the model. Although the p-value of this variable is less than 0.05, the odds ratio for the plant to implement an ECM keeps at 1.00, which means that the change of the industry type is not always together with change of adoption probability. Therefore, the industry type that are not significant related to the implementation of

ECMs were removed in the model. As shown in Table 20, it is found that different industries treat the saving opportunities differently. The Publishing, Electronic and Transportation industries are the most efficient industries according to DEA results, which also make them the least likely industries to accept ECMs. The subsectors of Wood, Furniture, Nonmetallic Metal and Entertainment are more open to install ECMs compared with other industries. The plants in Paper, Chemical and Metal has the lowest odds ratios to implement ECMs while they have most saving potentials. To increase the plants' interests to adopt ECMs, future recommendations should work harder to focus on the specific needs of each industry. Five industries (Wood, Paper, Publishing, Chemical, and Metal) are included in the regression model and represented by dummy variables X_1 to X_4. The Wood industry is represented by assigning "0" to all these four dummy variables.

Table 20 Significant Test for Industry Type

Predictor	Coefficient	P-Value	Odds Ratio	95% CI Lower	95% CI Upper
SIC Group		**0.028**	**1.00**	**1.00**	**1.00**
Constant	-0.0036	0.892			
Textile	0.0036	0.568	1.00	0.91	1.10
Wood	0.0914	0.028	1.14	1.05	1.23
Furniture	0.0109	0.839	1.01	0.91	1.12
Paper	-0.1249	0.011	0.91	0.85	0.98
Publishing	-0.2055	0.000	0.85	0.78	0.92
Chemical	-0.0639	0.020	0.91	0.84	0.98
Plastics	-0.0567	0.050	0.94	0.89	1.00
Nonmetallic Mineral	0.0313	0.678	1.03	0.93	1.14
Metal	-0.0577	0.034	0.92	0.86	0.99
Fabricated Metal	-0.0368	0.207	0.96	0.91	1.02
Machinery & PC	-0.0331	0.297	0.97	0.91	1.03
Electronic Equip.	-0.0548	0.184	0.95	0.88	1.02
Transportation Equip.	-0.0680	0.117	0.93	0.87	1.01
Entertainment	0.0320	0.642	1.03	0.93	1.15

The cost savings and implementation cost are not reported to have significant influence of the implementation of the recommendation. However, the length of the payback period is an important factor that greatly influence the implementation of an ECM. As illustrated in Table 21, the analysis results show that the odds ratio of the payback period is 0.82, which indicates that for every one-year increase of the payback period, the odds for the plant to implement the measure decreases by 0.18. This parameter is represented by variable X_5 in the model.

Table 21 Results of Logistic Regression Analysis

Predictor	Coefficient	P-Value	Odds Ratio	95% CI Lower	95% CI Upper
Constant	0.1092	0.016	0.02		
Payback	**-0.1925**	**0.000**	**0.82**	**0.81**	**0.84**
ECM_Group		**0.000**	**1.37**	**1.27**	**1.48**
Thermal Systems	-0.2115	0.000	0.81	0.75	0.87
Electrical Power	-0.3530	0.000	0.70	0.64	0.77
Motor Systems	0.3249	0.000	1.38	1.29	1.48
Operations	0.2030	0.000	1.23	1.12	1.34
Building and Grounds	0.1619	0.000	1.18	1.10	1.26
State_Group		**0.000**	**1.03**	**1.02**	**1.04**
Mideast	-0.1069	0.011	0.90	0.83	0.98
Great Lakes	-0.2866	0.000	0.75	0.70	0.81
Plains	0.0995	0.014	1.10	1.02	1.20
Southeast	-0.0533	0.150	0.95	0.88	1.02
Southwest	-0.0032	0.937	1.00	0.92	1.08
Rocky Mountain	0.0887	0.076	1.09	0.99	1.21
Far West	0.0259	0.529	1.03	0.95	1.11

The ECM type shows a strong relationship with the adoption of efficient measures. It shows that the plant managers are more likely to install ECMs about Motor system, Operation and Building & Ground. The odds to install an ECM about thermal system or electrical power reduce by 0.19 and 0.3 respectively. The recommendations about these topics usually involve large amount of financial inputs and have longer payback periods. However, as revealed in Figure 34, the easy and quick payback measures have been fully developed over the years, the future trend of the ECMs are the ones that have longer payback periods but would benefit the plants in the long run. Six ECM categories are explored in the model and are represented by five dummy variables X_6 to X_{10}. The situation with all "0" values in all of these dummy variables indicate the Combustion category.

The location of the plant is another significant factor. The plants located in less developed areas like the Plain, Rocky Mountain regions are more likely to install proposed ECMs. If the plant located in Southwest, Southeast and Far West regions, the adoption rates of ECMs would not be significantly impacted. However, the probabilities of the plants in Great Lakes and Mideast areas to install ECM are reduced by 0.25 and 0.10. Numerous SMEs locate in those regions and most of them consumes large amounts of natural gas during winter times, in which lies huge saving potentials as illustrated in DEA results. Special stimulations should be developed to encourage the adoption of ECMs for each region. Dummy variables X_{11} to X_{17} are used to represent the regions except New England.

The final model is expressed in Eq. 34 with complete coefficients listed in Table 22.

Table 22 Logistic Regression Coefficients

Coefficients	Values	Coefficients	Values	Coefficients	Values
a_0	0.1473	a_6	-0.2115	a_{12}	-0.2866
a_1	-0.1249	a_7	-0.353	a_{13}	0.0995
a_2	-0.2055	a_8	0.3249	a_{14}	-0.0533
a_3	-0.0639	a_9	0.203	a_{15}	-0.0032
a_4	-0.0577	a_{10}	0.1619	a_{16}	0.0887
a_5	-0.1925	a_{11}	-0.1069	a_{17}	0.0259

$$p = \frac{e^{0.1473-0.1249X_1+\cdots+0.0259X_{17}}}{1+e^{0.1473-0.1249X_1+\cdots+0.0259X_{17}}} \quad (34)$$

4.3.4 Case Study

Case studies are carried out to demonstrate the application of the proposed models in this section. A predictive evaluation with clear saving targets can help the plant to make feasible goals towards more energy efficient manufacturing. Six SMEs are random selected from the IAC database to performance the energy evaluation and set up the savings and implementation targets. The results are then compared with actual assessment recommendation savings and adoption status.

The basic information about the six companies are described in Table 23. The companies are from different industries and regions with distinct sizes of employment, plant area and economic outputs. These companies are analyzed by the input-oriented BCC models to calculate the DEA efficiency scores and input improvement values. The analysis results are listed in Table 24. The performance indicator of selected companies varies from 0.64 to 0.96.

Table 23 Characteristics of Selected SMEs

Company	Sales ($)	Employee	Plant Area (Sq Ft)	Industry	Region
C1	$91,070,493	150	220,000	Chemical	Plains
C2	$57,518,206	200	240,000	Chemical	Far West
C3	$88,443,190	375	4,539,823	Fabricated Metal	Southeast
C4	$86,277,309	425	600,000	Machinery & PC	Great Lakes
C5	$85,277,309	290	300,000	Machinery & PC	Great Lakes
C6	$64,228,664	219	523,000	Electronic Equip.	Southeast

The comparisons of electricity savings and gas savings in different scenarios are illustrated in Figure 35 and Figure 36. The “Improvement” columns indicate the estimated potential based on the DEA models. The “Proposed” columns are the identified savings during energy audits. The “Implemented” columns represent the actual implemented energy savings based on the feedbacks from customer surveys. It is shown the potential savings identified by models for both electricity and natural gas are not fully explored during energy audits with “C2” and “C3” as exemptions. Comparing the DEA score data, it is shown both exemptions are high-score customer with already decent energy efficiency. Therefore, plants with better practice of energy efficiency are more willing to explore and implement ECMs. In contrast, the implemented ECMs for low-score customer are relatively small as shown in “C1” and “C6”. Although more than enough ECMs are proposed for customer “C6”, only less than 30% of them are adopted. Last but none the least, both recommendation and implementation situations for gas related measures are far from reaching targets. The possible reason is the relatively low natural gas price.

Table 24 Energy Inputs and Calculated Improvement Values via DEA

Company	Annual Elec. Usage (kWh)	Annual Gas Usage (MMBTU)	DEA Score	Improvement (Elec. kWh)	Improvement (Gas MMBTU)
C1	7,551,960	18,549	0.700	2,263,095	5,559
C2	3,073,333	9,719	0.930	215,905	683
C3	5,800,467	10,798	0.738	1,520,285	2,830
C4	9,756,000	27,135	0.965	345,697	962
C5	4,926,321	14,245	0.758	1,192,590	3,449
C6	5,804,609	15,887	0.640	2,086,971	5,712

Overall, the savings potential prediction and comparison analysis can provide guidelines for future assessments and set up better objectives for the energy audits. For instance, more attention should be paid to low-score customers and natural gas consumption especially when it comes to implementation. It is suggested to do more education work to address the economic benefits and environmental contribution during the assessment process.

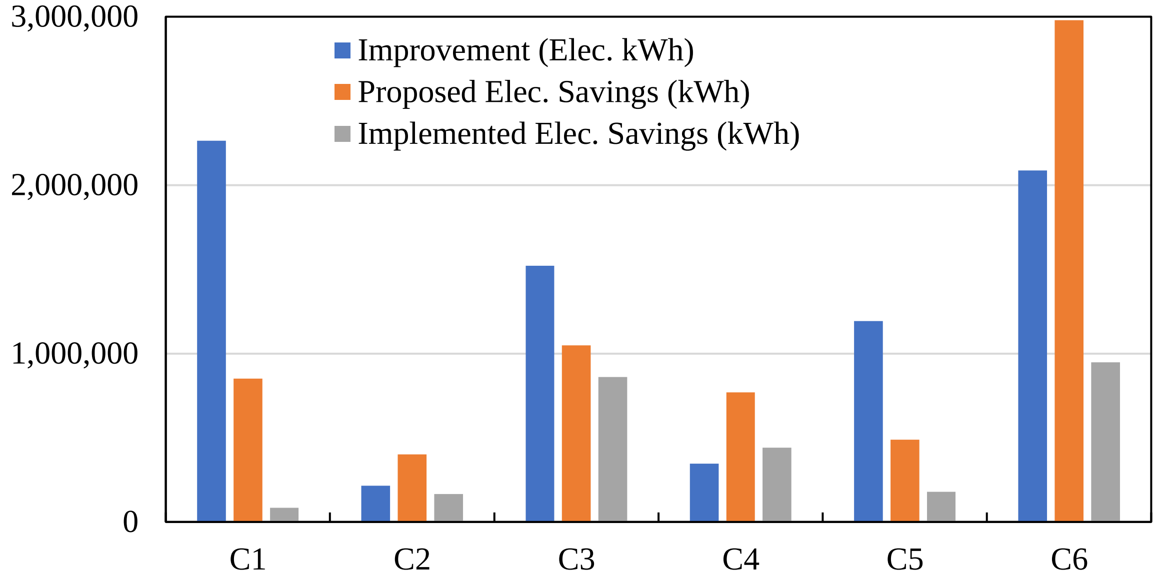


Figure 35 Electricity Savings Comparison

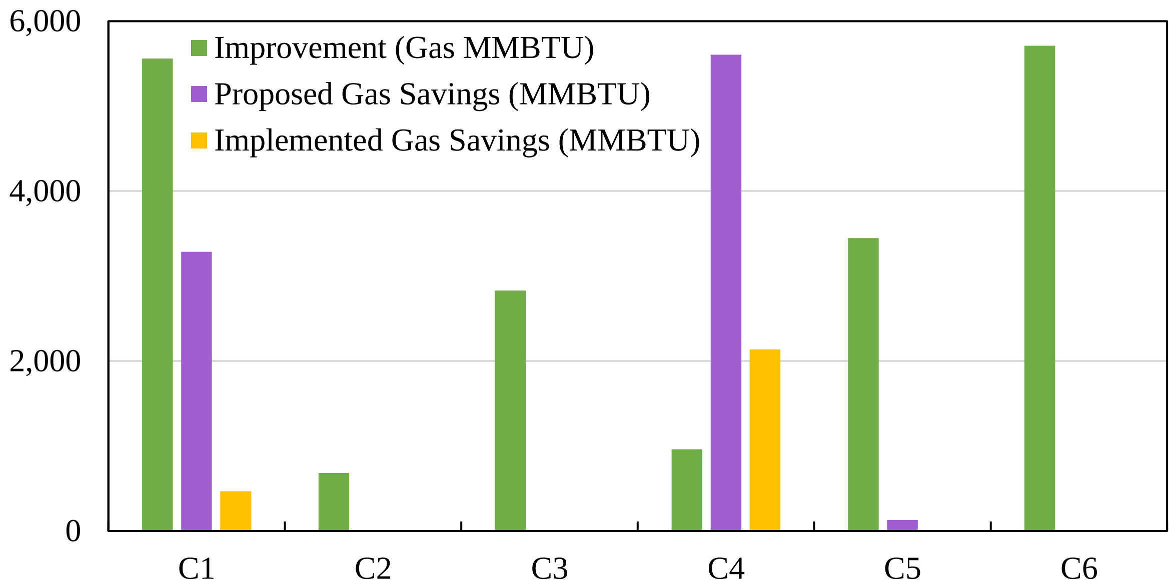


Figure 36 Natural Gas Savings Comparison

A total of 48 ECMs are proposed in the selected six energy assessments. An example of proposed ECMs and predicted implementation probability are shown in Table 25. The predicted probability of implementation is calculated using Eq. 34. The values of the four factors (payback, industries, ECM categories and regions) are substituted in to the model. Noting that only a few industries are entered in the model with constructed dummy variables. The ECM category of Combustion System and the region of New England are represented with the related dummy variables X_6 to X_{10} and X_{11} to X_{17} to be "0" values. The observed implementation status is the recorded status of proposed ECMs from each assessment. The performance of the proposed logistic regression model is assessed by comparing those two values.

Table 25 Example of Proposed ECMs and Implementation Prediction

ID	Payback	Industries	ECM Category	Region	Predicted Implementation Probability	Observed Implementation Status
C4-1	0.00	Machinery	Building and Grounds	Great Lakes	51%	I
C4-2	0.00	Machinery	Motor Systems	Great Lakes	55%	I
C4-3	0.00	Machinery	Operations	Great Lakes	52%	I
C4-4	0.23	Machinery	Motor Systems	Great Lakes	54%	I
C4-5	0.00	Machinery	Operations	Great Lakes	52%	I
C4-6	2.77	Machinery	Thermal Systems	Great Lakes	29%	I
C4-7	0.36	Machinery	Thermal Systems	Great Lakes	40%	N
C4-8	0.85	Machinery	Electrical Power	Great Lakes	34%	N
C4-9	1.43	Machinery	Combustion	Great Lakes	40%	N
C4-10	0.00	Machinery	Combustion	Great Lakes	47%	N

The classification table of the prediction accuracy is listed in Table 26. If the predicted probability is greater than 50% and the ECM is actually implemented (with status "I"), the prediction is considered to be correct; otherwise the prediction fails. A successful prediction can also occur when the ECM is not implemented and the calculated probability is less than 50%. The overall correct prediction percentage of this model is 64.6%.

Table 26 Classification Table for Prediction Accuracy of ECM Implementations

Implementation		**Predicted**		**Correct Prediction %**
		1	0	
Observed	I	11	7	61.1%
	N	10	20	66.7%
Overall Correct Perdition %				**64.6%**

Chapter 5 Conclusions

This thesis aims to draw a sophisticated picture for the energy usage, efficiency and savings for the manufacturing SMEs. Key energy characteristics are progressively investigated from micro to macro in three chapters. A general energy model for CNC machine is proposed to evaluate the energy consumption during unit machining process, an integrated model for CAS is built to investigate the energy savings potential of the whole system, IAC database is analyzed to obtain the overall energy characteristics of the SMEs in the US. The main contributions are summarized as follows:

1. This thesis built a general SEC model which can be used for multiple machines with similar power capacity level. In the proposed model, the stand-by power ratio (R_s) and the power rating of the spindle motor (P_s) are selected as factors to represent the automation level and size of the machine. The MRR is used to indicate the machining speed. A regression model is proposed based on the analysis of the relationship among R_s, MRR and SEC. The experimental and modeling data from reference papers are used to fit the regression model using Matlab.

2. In validation analysis, the results show an accuracy of over 80% for all cases. The average absolute residual ratio is about 6%, which is comparable with most of the traditional SEC models. The model was further validated through designed cutting experiments on a 5.5kW machine center. The results show the proposed model is suitable to be used for multiple milling machines.

3. A benchmark analysis for all typical ECMs in CAS was carried out to provide a basic guideline for the customer. In proposed baseline situation, Use VFD Air Compressor and Add Air Storage provide the largest savings. Load reduction related measures are more attractive because of their shorter payback. Some of the ECMs are only suggested for end-of-life replacement due to

their negative NPVs. The results from the benchmark analysis well coincident with the recommendation rate distributions of the IAC database.

4. The savings from the ECMs were evaluated at different combinations in the proposed integrated model to investigate their interactions. A Difference% of 17.7% for load reduction measures implies significant positive interactions. Mixed Difference% were obtained at various scenarios with negative interactions dominate the integrations. An optimization guideline was proposed for different load factors based on the integrated savings results.

5. Reliability analysis was carried out to investigate the savings in the changing operation conditions. Load reduction measures are extremely sensitive to the LF with a savings reduction of over 69% when increasing LF from 40% to 80%. In contrast, low-cost system efficiency measures are positively related to LF. Overall, larger LF and less operation hours mean less savings potential in most scenarios.

6. Energy usage was researched for selected SMEs in different time periods and manufacturing subsectors using decomposition analysis. The statistical data reveals that the energy intensity varies among regions and industries. For SMEs, the structure change over the past three decades has few contributions to the changes of total consumption. The economic healthiness and prosperity, together with the popularization of energy efficient measures have greatly impacted the energy usage of SME plants.

7. The energy efficiency of different manufacturing subsectors was analyzed by DEA method. The results show the variance of energy efficiency between industries and reveal the improvements that the plant need to achieve by implementing energy efficient measures. An average of 15.71% of electricity and 14.51% of natural gas can be saved if approaching energy use strategies of the manufacturing plants with best energy efficient practices.

8. Key factors that influence the decision to adopt ECM proposals was analyzed using logistic regression. The simulations show that payback period, region and ECM type are significant factors that determine the implementation of ECMs. The odds ratio for an ECM to be installed reduces 0.18 for every one-year incremental of payback period. Also, ECMs about thermal system or electrical power are less likely to be implement by 0.19 and 0.3 respectively. It also found out that the probabilities to install ECMs dropped to 0.75 and 0.90 if the plants located in Great Lakes and Mideast areas.

Future Researches

This thesis analyzed the manufacturing usage characteristics from unit process, to manufacturing system and finally the overall SMEs community to discover the energy and cost saving opportunities. Although the proposed general model can predict the SEC of multiple machines, there are some limitations with the proposed model. First, the current model is limited to predict the energy consumption of machine tools with similar or same level of power capacity. In this study, two regression analyses were carried out to obtain the models for two selected machine power levels. There is potential to include machines with various power capacity levels into one general SEC model in future research. Second, due to the experimental data limitation, the proposed model can only be effectively applied for certain range of MRRs. The accuracy and reliability of the proposed model can be improved through adding more MRR data in the future. Also, additional experiments should be carried out to further validate the versatility of the proposed model.

Although encouraging the industry to install ECMs has been a traditionary and popular objective of energy efficiency policies and programs, there has been an increasing emphasis on energy saving opportunities at other levels such as reducing production energy usage and recycling

[41]. The IAC Recommendation Code has included measures about minimizing wastes, increasing productivity and other production-related problems for a long time. As shown in Figure 37 non-ECM proposals have been popular in energy reports between 1995 and 2005, but gradually shrink into oblivion thereafter. It is worth promoting non-ECMs among SMEs as most of them cannot afford on-site energy staff and good, efficient processes would be easier to keep and pass along. A recent update of IAC has expanded the saving potential scope to explore smart manufacturing technologies and improve cybersecurity awareness. The transitions reflect the newest demand and attention from industry about energy efficiency. Future energy engineers should be closer to the trends and integrate those potential into opportunities.

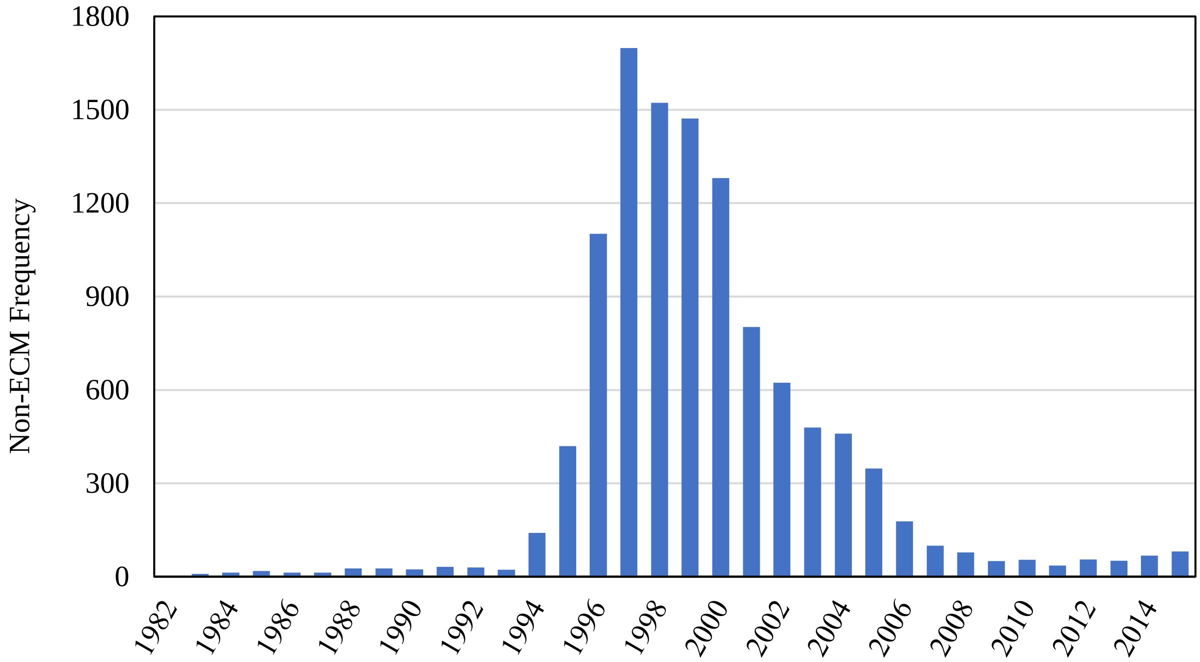


Figure 37 Non-ECM Recommendations Frequency from IAC Database

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