ELECTRICAL AND PRODUCTION LOAD FACTORS

A Thesis

by

TAPAJYOTI SEN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2009

Major Subject: Mechanical Engineering

ELECTRICAL AND PRODUCTION LOAD FACTORS

A Thesis

by

TAPAJYOTI SEN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Approved by:

Chair of Committee,	Warren Heffington
Committee Members,	Michael Pate
	Sarel Lavy
Head of Department,	Dennis O'Neal

December 2009

Major Subject: Mechanical Engineering

ABSTRACT

Electrical and Production Load Factors. (December 2009)

Tapajyoti Sen, B.S., Texas A&M University

Chair of Advisory Committee: Dr. Warren Heffington

Load factors are an important simplification of electrical energy use data and depend on the ratio of average demand to peak demand. Based on operating hours of a facility they serve as an important benchmarking tool for the industrial sector. The operating hours of small and medium sized manufacturing facilities are analyzed to identify the most common operating hour or shift work patterns. About 75% of manufacturing facilities fall into expected operating hour patterns with operating hours near 40, 80, 120 and 168 hours/week.

Two types of load factors, electrical and production, are computed for each shift classification within major industry categories in the U.S. The load factor based on monthly billing hours (ELF) increases with operating hours from about 0.4 for a nominal one shift operation, to about 0.7 for around-the-clock operation. On the other hand, the load factor based on production hours (PLF) shows an inverse trend, varying from about 1.4 for one shift operation to 0.7 for around-the-clock operation. When used as a diagnostic tool, if the PLF exceeds unity, then unnecessary energy consumption may be taking place. For plants operating at 40 hours per week, the ELF value was found to be greater than the theoretical maximum, while the PLF value was greater than one,

suggesting that these facilities may have significant energy usage outside production hours. A PLF value of between 0.75 and 1.0 is typically considered good. About 40% of plants that operate 80, 120 or 168 hours per week had a PLF value between 0.75 and 1.0. However, this drops to 13% for plants operating at 40 hours per week. Such a significant drop would suggest that such facilities perhaps present the most opportunities for energy conservation. The data for the PLF, however, is more scattered for plants operating less than 80 hours per week, indicating that grouping PLF data based on operating hours may not be a reasonable approach to benchmarking energy use in industries. A one way analysis of variance test was also conducted and revealed there was significant difference between the different mean values of ELF and PLF that were calculated for shift classification. The test was important as the number of plants in each category was different.

This analysis uses annual electricity consumption and demand along with operating hour data of manufacturing plants available in the U.S. Department of Energy's Industrial Assessment Center (IAC) database. The annual values are used because more desirable monthly data are not available. Monthly data are preferred as they capture the load profile of the facility more accurately. The data there comes from Industrial Assessment Centers which employ university engineering students, faculty and staff to perform energy assessments for small to medium-sized manufacturing plants. The nation-wide IAC program is sponsored by the U.S. Department of Energy.

To my parents

ACKNOWLEDGEMENTS

I am extremely grateful to my advisor, Dr. Heffington, for not only giving me the opportunity to work at the Industrial Assessment Center (IAC) as an undergraduate but for allowing me to come back and continue in graduate school. I express my sincere gratitude to him for his guidance, understanding, encouragement, patience and support. I also thank him and Jim Eggebrecht for their hard work in making the IAC the successful program that it is.

I would like to express my thanks to the directors and assistant directors of the other IAC centers for their valuable comments and interest in my research. I extend my gratitude to the other committee members, Dr. Pate and Dr. Lavy.

I also thank my friends for their encouragement and support during my graduate career and for making my time at Texas A&M University a memorable experience. The appreciation is extended to all my colleagues at the IAC for their support, invaluable discussions and well wishes.

I am deeply indebted to my parents for their love as well the tremendous support and encouragement they provided all my life. I am thankful to my brother for being there whenever I needed him. I am also especially grateful to the Roy family in California for their encouragement and love throughout my time in the United States and for providing me a home away from home.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

INDUSTRIAL ENERGY EFFICIENCY BENCHMARKING

The use of energy benchmarking has been a common practice in commercial buildings for many years [1]. However, the use of energy metrics or energy indices is fairly new for the industrial sector. Energy indices such as electric and natural gas level (kWh/sq ft and Btu/sq ft), occupancy load factor, people load factor and electrical load factor have been used as a preliminary decision tool to decide if a building is energy efficient when compared to other buildings and if a detailed study should be performed to facilitate energy conservation measures [2]. For industries, the indices relate energy consumption in a particular type of facility to a number of measurable quantities such as production units, annual sales and plant area [3]. The benchmarking information, when readily available, can be used by facilities to evaluate its current performance with respect to similar industries.

Load factors are important simplifications of energy use data and indicate the uniformity with which electrical energy is used. When reviewed periodically, they serve as a good performance metric for use by facility managers. They also provide vital information for effective demand control and energy conservation strategies. This is

---

This thesis follows the style of Energy

important as successful demand control can result in substantial cost savings and is easier to implement than some other cost cutting opportunities [4]. They can also be used as key performance indicators designed to measure the success of key elements in an energy management plan and provide energy managers with timely "nuggets" of information they need to ensure success [5]. Ranges of load factor developed for various hours of operation can be used as an energy efficiency tool for industrial energy benchmarking. A plant can use its own load factor data to evaluate its current performance with respect to plants in the similar industry or operational characteristics and set performance goals for future energy management. It is important to note that in addition to these metrics being useful to the facility, the act of plant personnel going through the process of creating them and composing the related reports can also be of benefit, as it causes them to start thinking in terms of plant energy reduction [6].

The process of developing benchmarks is important for setting energy efficiency targets and this type of measurement and performance evaluation is a fundamental part of corporate energy management. Energy costs form a major part of operational expenses for manufacturing industries and in a 2006 census of American manufactures, the percentage of companies including energy management in their strategic practices jumped from 16% in 2005 to 24% in 2006 [7]. The industrial sector accounts for more than 30% of energy consumption in the United States, the largest among all sectors [8]. Therefore, the inherent potential for significant savings is high in this sector.

There are several examples of energy benchmarking tools that have been developed. A few examples would be the programs developed at the Lawrence Berkeley

National Laboratory (LBNL), the US Environmental Protection Agency (EPA) and the US Dept. of Energy (DOE). The Benchmarking and Energy water Savings tool or BEST program developed by the LBNL provide a way for individual wineries to evaluate their energy efficiency compared to a similar hypothetical winery that employs best practices and which is used as a benchmark [9]. The program, based on Microsoft Excel, takes into account different characteristics of the winery and produces a meaningful energy intensity index, which is the ratio of the winery energy intensity to that of the benchmark winery. Additionally, the tools also provide an estimate of possible electrical energy savings that could be generated if improvements in energy efficiency are implemented.

Energy indices have been also implemented in programs such as QuickPEP, a web based tool developed by the DOE [10]. QuickPEP, which stands for Quick Plant Energy Profiler, is a tool that requires a plant's various forms of utility data to be entered along with general production information. Any energy management policies and steps taken by the undertaken to reduce energy are also considered and the program provides approximate results on potential energy savings that could be generated from particular energy conservation steps. The energy savings calculation is based on general industry specific energy consumption data and therefore may cause the actual savings to vary from the predictions made by the program. This is because the energy consumption of the plant being surveyed may not be similar to the general energy consumption data. There is much variability in industrial energy consumption data [6].

In 1992, the Energy Star program was started as result of the joint effort between the EPA and the DOE [11]. The Energy Star program is a voluntary program designed to identify and promote energy-efficient products as basic pollution prevention opportunities. In 2002, this opportunity was extended to identify energy efficient production in manufacturing facilities through the development of the Energy Performance Indicator (EPI).

The EPI is a energy management statistical benchmarking tool for specific industries that provides a ‘‘birds-eye’’ view of plant-level energy use via a functional relationship between the level of energy use and the level and type of various production activities, material input’s quality, and external factors [11]. The program was created using information based on non-public US Census Bureau data and by working with plant managers in specific industry. It was developed using a statistical regression model and provides the distribution of energy efficiency across the industry. This is important as it answers the hypothetical question “How would my plant compare to everyone else in my industry, if all other plants were similar to mine?” [11]. Therefore, the program can be used by facility energy managers to evaluate energy efficiency performance of their portfolio of plants. The program is currently limited to auto assembly, corn refining, cement, pharmaceuticals, food processing, and glass manufacturing but will be eventually available to a wide range of manufacturing plants. The program was first released for the automobile manufacturing industry and has been incorporated by many companies into their energy management program. For example, Toyota North America uses the EPI to not only monitor progress against the competition but also as verification steps for any internal metrics they are using. The Energy Star system is very precise in its benchmarking, using process specific evaluations. This enables it to avoid some of the pitfalls of using very broad data.

The use of indicators for industrial energy efficiency has been studied in other countries as well. The International Energy Agency has recently published a major new analysis of trends in industrial energy use and energy efficiency [12]. The indicators developed account for industrial energy use and CO_2 emissions based on units of production. The advantage of these indicators is that they examine the driving force behind energy use (such as technology) and account for structural differences in industries between countries, therefore allowing for a fair comparison of energy efficiency performance [12]. More importantly, the IEA's work provides a basis for documenting current energy use, analyzing past trends, identifying technical improvement potentials, setting targets and better forecasting of future trends [13]. Considerable progress has been made in this field due to the various workshops organized by the IEA, comprehensive analysis and review of available data and dialogue with experts in different industries. It is difficult to develop a single indicator of energy for an industry and therefore, a number of indicators need to be used to provide a fairly accurate picture of energy intensity levels.

The approach developed by the IEA is useful for comparing performance in sectors with multiple products. This is based on the concept of performance benchmarks such as best available technology (BAT) or best practice technology (BPT). Countries are compared on a the basis of an energy efficiency index (EEI), which is calculated as the ratio of the energy that would be used if the specific energy consumption for each product were equal to that achieved by the BAT or BPT, divided by the actual energy use in the industry [13]. Subtracting the EEI from unity indicates available potential for improvement. One advantage of this method is that the specific production related energy consumption data is not required. The use of the IEA indicator approach has been used to gain insight into the energy efficiency of various manufacturing industries in countries such as India in the cement, petrochemical, paper and steel sector [13].

Typically, the uses of energy indices for energy benchmarking are based on statistical methods. However, model based approaches for energy intensive industrial process, such as the glass furnace and ceramic industry, have also been developed [14, 15]. In an example glass furnace case, a simulation model was developed using mass balance and energy heat loss equations, along with empirical equations based on operating practices. The model was compared with field data from industrial furnaces and a simulation program was developed that could be used for energy performance calculation for a given furnace design. Such a model based benchmarking approach for complex industrial process can also be extended for other industrial processes, and provides a rational basis for energy performance improvement [14].

The use of energy indicators as benchmarking tools, however, has to be used with caution. For example, a study conducted on the use of energy use indices that normalizes energy use by dividing by the building area resulted in extremely large variations [6]. The study analyzed major industry categories for electricity and natural gas consumption in small and medium-sized manufacturing plants. A similar trend was also obtained by doing an analysis based on production units instead of plant area. The results obtained, however, improved when the analysis was refined to narrow the type of plants in a specific category. Therefore, the prediction of energy use by multiplying EUI data with plant area or production may be inaccurate. The large scatter also showed that there is no single accurate indicator of energy for a particular industry and this can be due to several reasons. Various products in single category of industry may have considerably different amount of energy requirements for production. Other reasons may include system boundary and allocation issues. For example, the energy intensive parts of production can be outsourced, thereby making the apparent use of energy by particular facility seem relatively low [13].

Characterizing the operating hour patterns or shift work patterns also became necessary for this study and a literature search revealed very little useful data. There have been surveys carried out by the Bureau of Labor Statistics on proportion of shift workers in various types of industries [16]. The Bureau of Labor Statistics also maintains a comprehensive online database containing information on productivity, hours, employment and earnings. However, the information is geared more towards the individual level (i.e., the average number of hours worked by an employee in the manufacturing sector) as opposed to an industrial level (how many hours on average does a paper mill operate). The need therefore arose to analyze the current operating hours of the manufacturing facilities in the IAC database and identify common patterns.

MOTIVATION

The main purpose of this paper is to develop ranges of load factors, a form of benchmarking, for use as diagnostic tools for effective energy management for small and medium-sized manufacturing plants in the United States. A hypothesis is that ranges of electric load factors can be associated with various levels of hours of operation characterized by certain shift patterns. This hypothesis finds support in the use of load factors in the block structure of utility tariff schedules. Utility providers such often use a block system for their electrical energy rates where the energy charge (kWh) is dependent on a combination of the facility's actual energy consumption and its electrical demand [17, 18]. From a utility company's point of view, high load factors represent more desirable customers, since they will be buying more electrical energy for a given amount of investment in generation and distribution equipment [19].

Load factor is defined as the average energy consumption rate (average demand) for a facility divided by the peak energy consumption rate (peak demand) over a period of time. The most common period of time corresponds to a utility billing period. The average demand for a period of time simply is determined by dividing the electrical energy consumed in that period by the length of time in that period. The most common and widely recognized load factor is the electrical load factor, ELF, defined in Equation 1 below [1]:

$$ELF = \frac{E}{D_p \times L_{bp}} \qquad (1)$$

where E is the electrical energy consumption in kWh and D_p is the peak demand in kW during the billing period L_{bp} measured in hours. Peak demand is measured with a meter that records the average rate of energy use during the time interval of maximum consumption. Industrial plants are often shut down during a portion of the billing period, for example, during nights and weekends. The ELF increases with the length of time a facility operates and theoretically has a maximum value of unity. Such a value would indicate the optimum use of electrical energy, i.e., use of electrical energy at the peak demand rate throughout the billing period.

Another load factor is defined based upon the operating hours of a plant and is called production load factor or PLF. For a plant with operating hours L_{oh}, the PLF is given in Equation 2 as [20]:

$$PLF = \frac{E}{D_p \times L_{oh}} \tag{2}$$

The ratio of ELF to PLF for the same period of energy use yields the fraction of operating hours in the period. A PLF value over one clearly indicates energy consumption outside operating hours and may be an indication of waste [20]. However, because not all equipment may be needed or can be used at maximum potential during the production hours, exceeding some lower PLF value may be an indicator of waste.

The energy consumption E in Equation 1 will vary with production level and operating hours. Therefore, characterizing the operating hour patterns or shift patterns is necessary and especially so because a review of the literature led to little information practically useful for this study.

CHAPTER II

BACKGROUND

IAC DATABASE

The data used in this analysis is obtained from the database maintained by the IAC field manager's office located at Rutgers University for the US Department of Energy [21]. The database contains publicly available assessment and recommendation data that has been collected through energy assessments done by the various IAC centers around the nation mostly on small to medium-sized manufacturing plants. This resource is available in web-based or downloadable MS Excel spreadsheet. Presently, the IAC program guidelines for participation by small to medium-sized plants specify that each plant will meet three of the following four criteria: under $100 million in gross annual sales, fewer than 500 employees, no in-house energy expertise, and utility cost between $100,000 and $3 million per year [22]. As of April, 2009, the IAC database contains more than 14,204 assessments and 105,889 recommendations [21]. The assessment and recommendation information in the database can be searched by a variety of parameters such as the industry type (SIC and NAICS classification), energy costs, products and location of plant or the IAC center. Table 1 summarizes the universities and locations of the individual centers used in this study. The centers listed have not been operational for the same length of time with some being relatively new compared to others. A few of the centers are now defunct.

Table 1: Summary of IAC Centers

IAC Designation	University Name	City	State
DS	South Dakota State University	Brookings	SD
ME	University of Maine	Orono	ME
WI	University of Wisconsin	Madison	WI
MA	University of Massachusetts	Amherst	MA
SU	Syracuse University	Syracuse	NY
IC	University of Illinois	Chicago	IL
UM	University of Michigan	Ann Arbor	MI
ND	Notre Dame University	Notre Dame	IN
IA	Iowa State University	Ames	IA
CO	Colorado State University	Fort Collins	CO
LE	Lehigh University	Bethlehem	PA
BD	Bradley University	Peoria	IL
WV	West Virginia University	Morgantown	WV
NV	University of Nevada	Reno	NV
UD	University of Dayton	Dayton	OH
UU	University of Utah	Salt Lake City	UT
HO	Hofstra University	Hempstead	NY
OR	Oregon State University	Corvallis	OR
MO	University of Missouri	Columbia	MO
KU	University of Kansas	Lawrence	KS
UL	University of Louisville	Louisville	KY
SF	San Francisco State University	San Francisco	CA
TN	University of Tennessee	Knoxville	TN
NC	North Carolina State University	Raleigh	NC
OD	Old Dominion University	Norfolk	VA
OK	Oklahoma State University	Stillwater	OK
MS	Mississippi State University	Starkville	MS
AR	University of Arkansas	Little Rock	AR
GT	Georgia Tech	Atlanta	GA
LM	Loyola Marymount	Los Angeles	CA
SD	San Diego State University	San Diego	CA
LL	University of Louisiana	Lafayette	LA
TA	University of Texas	Arlington	TX
UF	University of Florida	Gainesville	FL
AM	Texas A&M University	College Station	TX
KG	Texas A&M Kingsville	Kingsville	TX
AS	Arizona State University	Tempe	AZ
MI	University of Miami	Coral Gables	FL

IAC assessment visits generally take one day and are conducted by teams of university students professionally led by a university engineering faculty or staff member. The assessment consists of an in-depth evaluation of the plant site, its equipment, buildings, services and manufacturing operations. The assessment activities mainly deal with identifying opportunities for energy efficiency improvements but waste minimization, pollution prevention and productivity improvement may also be considered. The activities also include requesting and analyzing 12 months of energy consumption data for major energy sources used by the plants. The most common sources are electricity and natural gas. The energy consumption data is supplied as copies of the most recent original monthly bills. For cases when 12 months of data are not available, the annual consumption is estimated based on the current operation and consumption.

Included in the database are annual cost and consumption for both electrical energy and electrical demand. Monthly values of energy consumption and peak demand are not available. Other information includes the annual hours of operation, SIC and NAICS classifications, annual energy costs, plant area as well as identification of the center that performed the assessment and the date that the facility was visited. The SIC and NAICS are codes that represent the principal product of the manufacturer [23]. Further discussion on this can be found in the Methodology section.

The three parameters used for the analysis of load factors are the annual electrical demand, energy consumption and hours of operation. The hours of operation are open to interpretation by those entering data into the database. It is not specified to be the hours of operation of the main production area, of the production area with the largest hours or to be some average. The Texas A&M IAC typically uses the hours of the main production area. The Texas A&M IAC consulted with the other 25 IAC's and found that 25% of them used the operating hours pertaining to the main production area while 8% used the area of the plant with the largest operating hour. However, it is very typical for the production department to have the largest number of annual operational hours. The annual operating hours also may not include shutdowns or period of holidays and this is further exemplified from the operating hours distribution chart in the next section.

LOAD FACTOR

In order to understand the impact of load factor on facility's electricity charges, it is important to understand the concept of electrical demand. Electrical utility bills typically consist of usage charge (kWh), a fuel adjustment charge that allows utilities to account for seasonal and other changes in fuel costs, a demand charge and a possibly a power factor charge [24]. Demand is the rate at which electrical energy is consumed and can vary hourly, daily or monthly for a facility. Therefore, the utility provider must have equipment such as generating capacity, power lines and transformers to provide the maximum or peak demand for any customer at any time. The peak demand is measured with a meter that records the average rate of energy use during a predetermined the time interval (typically 15, 30 or 60 minutes) of maximum consumption [1]. The time interval usually is short to capture the maximum rate, but long enough to avoid influence by relatively brief events that do not have an unanticipated impact on the sizing of infrastructure. Examples of such brief events are motor starting, shorts, and lightning strikes. A separate charge for demand is thus representative of the investment necessary to meet the plant's maximum power requirement and can be an important part of the electricity cost. Demand is not always a separate charge on utility bills but usually appears on the bills for small and medium-sized plants.

The demand measured can be billed a number of ways such as contract demand, coincident peak demand (CP), non coincident peak demand (NCP) and actual demand [3, 25]. The demand may also be ratcheted, meaning that if an unusually large demand value is measured, the customer will pay some fraction (e.g., 75%) of that value for a succeeding period of time, usually 11 months. Ratchet pricing is usually in the form of a percentage of the peak demand that occurred within a set number of previous months [3, 25]. Another rate mechanism is the time-of-day rates which separates the pricing of electricity (usage and demand) into different periods of the day or year. This is essential to the utility as an increased demand during the peak demand places an added burden on the utility while an increased demand during off-peak period allows the utility to produce a larger portion of the annual load with generation equipment that is underutilized and perhaps, more efficient. [24].

The first step towards conducting a load analysis is to collect demand data over a period of time, so that seasonal patterns and peak demands can be identified [3]. One method for analyzing the variation in demand is to monitor the load factor, which is the ratio of average demand to peak demand for a given period of time. The load factor depends on the number of hours a facility is in operation and a higher number generally indicates better utilization of the connected equipment and purchased energy. However, this will be applicable only when the energy is providing useful work. From a utility company's point of view, high load factors represent more desirable customers, since they will be buying more electrical energy for a given amount of investment in generation and distribution equipment [19]. Some utility companies such provide incentives for high load factor through a load factor credit program for facilities that have large electrical demand [26].

The load factor analysis however only provides a starting point for evaluating load management options and does not provide meaningful data to indicate what loads are causing the elevated demands [25]. Regular monitoring is one of the first steps towards creating an effective load management or demand control strategy. Load management can be defined as any action taken by the customer and/or the electricity supplier to change the load profile to reduce total system peak load, increase load factor and improve utilization of valuable resources such as fuels or generation, transmission and distribution capacity [27]. Such actions may consist of process rescheduling, thermal energy storage, use of backup generation, automation, etc.

Each option depends on a number of factors such as the electrical rate system and schedule and constraints in the production process. Industrial load management strategies can be very complex and can range from real time demand side energy management that allows for immediate notification of deviation from dynamic energy targets to a linear programming based formulation for load scheduling [28, 29]. However, the implementation of an effective load management program has generated significant cost savings for various types of industries in not only the United States but also in Europe and Asia [27].

An improvement in load factor can lead to significant potential savings for heavy users of electricity. This is because a good load factor implied a more constant rate of electrical use, as the demand is held to a minimum relative to the overall use. Typically, a reduction of 24-26% in the overall cost of electricity ($/kWh) can be achieved if the load factor is increased from 0.35 to 0.65 [30, 31]. From a utility's point of view, the cost, C, per unit energy delivered can be expressed by the equation:

$$C = C_{\text{var}} + \frac{C_{amm}}{LF} \tag{3}$$

where C_{var} is the variable cost per unit energy related to fuel, labor, etc, C_{amm} is the amortized cost which generally varies with equipment size and capacity measured in kW needed to recover the investment and LF is the electrical load factor. The equation illustrates the remarkable impact of investment cost on the cost of energy produced as plant utilization varies [32].

CHAPTER III

ANALYSIS OF OPERATING HOURS

Load factors depend on operating hours (Equation 1) and so the first part of this study was to define common shift patterns and the second was to analyze the load factors. For the purposes of this work, one shift is defined as eight to ten consecutive production hours. In order to identify the most common ranges of operating hours per week, the operating hours of more than 13,000 plants from the IAC database were normalized from an annual to weekly basis by dividing by the number of weeks in a year. All resulting weekly operating hours are rounded to whole numbers.

Figure 1 is a histogram that represents the resulting operating hours per week and their relative frequency. As expected, the histogram has a multimodal characterization. An initial class width of 1 hour was chosen for the histogram generation. This is a small value, given the large number of data points being studied, but it was chosen in order to study spikes that were expected at nominal values such as 40 hours/week or 168 hours/week. These correspond to a single shift, five days per week and a three-shift, seven days per week operation, respectively. Different class widths were tested and larger class widths were more likely to hide the multimodal nature of the dataset.

As seen from the graph, five ranges can be identified that appear to have comparatively high relative frequencies. These ranges match nominal work-week length values of 40, 80, 120, 144 and 168 hours per week. An interesting feature in Figure 1 is the bimodal peak near each of the nominal values. A peak is located at the nominal value of the weekly operating hours and there is another peak in each case indicating slightly shorter operating hours. This seem to indicate that some personnel included holidays and shutdown period in the operating hours when inserting them in the database, while others may have not.

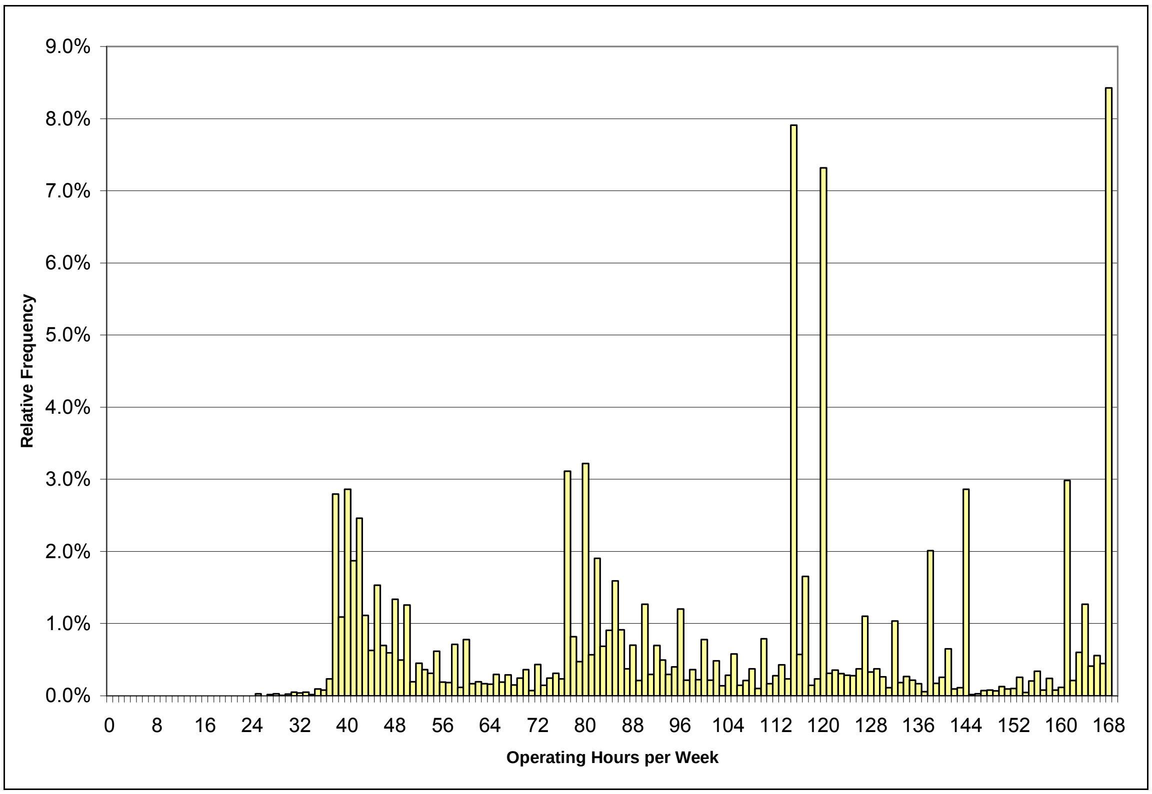

Figure 1: Relative Frequency of Operating Hours for Small and Medium-sized Plants

Based on Figure 1, five interval ranges were initially defined to analyze the data, with each range representing the five nominal values. The lower limit for each range was calculated assuming 10 federal holidays, which account for 4% of non-weekend days [33]. The five ranges then used for the load factor analysis are:

- 40 hours per week: equivalent to an 8 hour/5 day, single-shift operation. The upper limit for this range was chosen to be 50 hours, assuming a single 10-hour length shift operation. The lower limit was set to 40 hours less 4% or 38 hours to account for any holidays.
- 80 hours per week: equivalent to a 16 hour/5 day, two-shift operation. The upper limit is 100 hours, assuming a maximum of 10 hours per shift while the lower limit was set to 80 hours less 4% or 77 hours to account for any holidays.
- 120 hours per week: equivalent to a 24 hour/5 day, three-shift operation or a 20 hour/6 day, two-shift operation. The lower limit was therefore chosen to be 120 hours less 4% or 115 hours while the upper limit is 120 hours.
- 144 hours per week: equivalent to an 8 hour/6 day, three-shift operation or 20 hour/7day, two-shift operation. The lower limit was therefore chosen to be 140 hours less 4% or 134 hours while the upper limit is 144 hours.
- 168 hours per week: equivalent to a 24 hour/7 day, three-shift operation. The upper limit was set to the maximum possible value of 168 while the lower limit was set to 161 hours, assuming a 4 % reduction from a regular 8 hour shift.

The ranges that were developed were found to have encapsulated the bimodal peak near each of the nominal values. Each peak for the shorter operating hours is at values of 38, 77, 115, 138 and 161 hours per week, respectively. These values correspond to the lower limits of the five interval ranges that were defined to analyze the data. This leads to the conclusion that an assumption of 4% for non-weekend holidays was fairly reasonable and accurate for this analysis.

Table 2 below summarizes the intervals for each work-week length, along with the relative frequency with which each appears. The interval range corresponding to 144 hrs/week appeared only 6% of the time and was not included. Almost 60% of the plants operate 40, 80 or 120 hours per week. Including around-the-clock operations of 168 hours per week covers almost 75% of the plants.

Table 2: Interval Ranges of Operating Hours

Operating hours/week			Shift pattern deduction [S=shift, D=days/week]	Relative frequency, %
Nominal work-week length	Lower limit	Upper limit		
40	38	50	1S/5D	19
80	77	100	2S/5D	22
120	115	120	3S/5D or 2S/6D	18
168	161	168	3S/7D	15
			Total	74

Each nominal work-week length was also analyzed further by grouping the data with the first two digits of their standard industrial classification (SIC) industrial code and is shown is Figure 2. This was done to study the relative frequency of each industrial group within a particular range of operating hours. The IAC database has SIC data from 1981 [21]. In 2002 data based on the North American Industrial Classification System (NAICS) began to be included. However, the number of plants that could be considered under the NAICS system was small and therefore the analysis was carried out using the SIC classification system. Table 3 summarizes the major SIC codes used in this analysis and their NAICS counterparts [21].

Table 3: SIC and NAICS Code Description

NAICS Code	SIC Code	Description
-	20	Food and Kindred Products
311	-	Food Manufacturing
312	-	Beverage and Tobacco Product Manufacturing
313	22	Textile Mill Products
315	23	Apparel And Other Finished Fabric Products
321	24	Lumber And Wood Products, Except Furniture
337	25	Furniture And Fixtures
322	26	Paper And Allied Products
323	27	Printing, Publishing, And Allied Industries
325	28	Chemicals And Allied Products
324	29	Petroleum Refining And Related Industries
326	30	Rubber And Miscellaneous Plastics Products
327	32	Stone, Clay, Glass, And Concrete Products
331	33	Primary Metal Industries
332	34	Fabricated Metal Products, Except Machinery And Transportation Equipment
333	35	Industrial And Commercial Machinery And Computer Equipment
-	36	Electronic And Other Electrical Equipment And Components, Except Computer Equipment
334	-	Computer and Electronic Product Manufacturing
335	-	Electrical Equipment, Appliance, and Component Manufacturing
336	37	Transportation Equipment
-	38	Measuring, Analyzing, Controlling Instruments; Photographic, Medical, Optical Goods; Watches
339	39	Miscellaneous Manufacturing
511	-	Publishing Industries (except Internet)

The number of plants under each SIC classification for every nominal work-week length period is different, as shown in the relative frequency chart in Figure 2. This chart was assumed to be a representative sample of small and medium-sized industries as the figure shows data pertaining to the various assessments carried out by the different IAC center over many years.

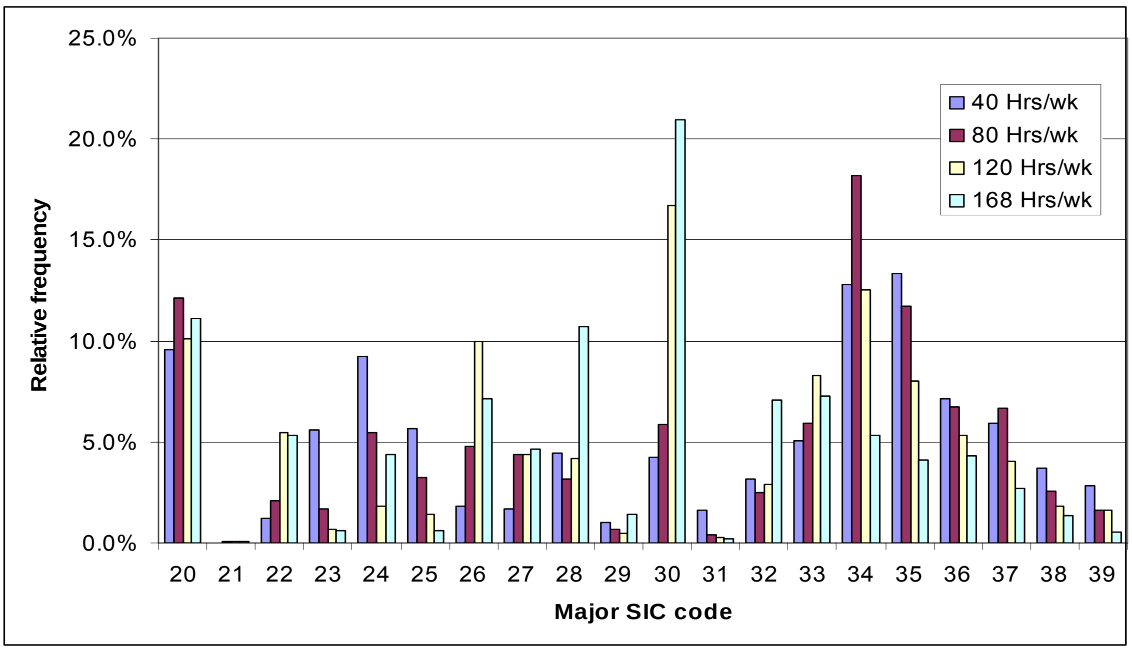

Figure 2: Relative Frequency of Plants for Each SIC Classification

CHAPTER IV

ANNUAL LOAD FACTORS ANALYSIS

Using the annual electrical energy consumption E_{an} and annual demand D_{an} from the IAC database, the annual electrical load factor or ELF_{an} was calculated using Equation 4 below for each interval defined above in Table 3.

$$ELF_{an} = \frac{E_{an}}{\frac{D_{an}}{12} \times 8760} \tag{4}$$

where E_{an} and D_{an} are in kWh and kW·mo, respectively.[1] A majority of the plant entries in the database were missing electrical demand information and therefore were excluded from this analysis. Other data points that were excluded are plants with ELF_{an} greater than one or less than 0.1. This was done to eliminate extreme outliers, as the ELF can have a maximum value of one and plants with one shift operation tend to have ELF's greater than 0.1 [19, 25]. The maximum theoretical ELF for any given nominal work-week length is the ratio of the operating hours per week to the maximum number of hours in a week, i.e., 168. This yields a theoretical maximum of 0.24, 0.48, 0.72 and 1.0 for nominal work-week lengths of 40, 80, 120 and 168 hours, respectively.

The annual production load factor or PLF_{an} was calculated using the same information as before, but using operating hours from the IAC database instead of billing

[1] It is emphasized that annual values are used because more desirable monthly data are not available. Monthly data would be better because they would more accurately capture the load profile of the facility.

hours. Equation 2 was modified as shown in Equation 5 to use the annual values from the IAC database.

$$PLF_{an} = \frac{E_{an}}{\frac{D_{an}}{12} \times L_{oh,an}} \tag{5}$$

where $L_{oh,an}$ is the plant operating hours per year. The ratio of ELF_{an} to PLF_{an} yields the fraction of operating hours in the annual period, so the formula for PLF_{an} can be written as Equation 6 below

$$PLF_{an} = \frac{ELF_{an} \times 8760}{L_{oh,an}} \tag{6}$$

Therefore, the lowest possible value of PLF_{an} occurs when ELF_{an} is minimum and $L_{oh,an}$ is maximum. Since the lowest allowable value of ELF_{an} used in the analysis in 0.1 and the maximum value of $L_{oh,an}$ is 8,760 hours, a lower threshold of 0.1 was used for PLFan was well. The highest possible value of PLF_{an} occurs when ELF_{an} is maximum and $L_{oh,an}$ is minimum. This would correspond to an ELF_{an} value of one and $L_{oh,an}$ value of 1,980 hours/year (38 hours/week), yielding a upper threshold PLF_{an} of 4.5. Therefore, outliers from plants with PLF_{an} less than 0.1 or higher than 4.5 are excluded as these are highly unlikely values, perhaps indicative of data entry errors.

The implementation of the above steps coupled with discounting any plants that were missing information about electrical energy and operating hours significantly reduced the number of plants available for analysis. About 50% of the entries in the database were found to be missing electrical energy and demand information. Using the theoretical lower and upper limits to analyze the data further reduced the number of plants available for analysis by 7.5%. Therefore, of the original 13,769 plants were available in the database, only 6,485 plants or about 47% of them were evaluated. Possibly, the missing data was unique to some particular work-week length, so the frequency of occurrence of operating interval ranges was recalculated. Table 4 below shows the relative frequency for each of the nominal work-week length for the reduced number of plants. Despite removing half the data points from the database, the old and new relatively frequencies are very similar.

Table 4: Interval Ranges of Operating Hours for Plants with Complete Data

Operating hours/week			Original Relative frequency %	New Relative frequency %
Nominal work-week length	Lower limit	Upper limit		
40	38	50	19%	16%
80	77	100	22%	21%
120	115	120	18%	19%
168	161	168	15%	16%
Total			74%	72%

The calculated load factors were statistically analyzed for each interval by computing the mean, standard deviation and upper and lower quartile values. The lower quartile represents the median of the lower half or the lowest 25% of data and the upper quartile represents the median of the upper half or the highest 25% of data. The average of these two values is the median of that data set. A 95% confidence intervals for both load factors were also calculated. However, it encompassed a very small range for the ELF_{an}. Similar calculations were carried out again, grouping the data by the first two digits of their standard industrial classification (SIC) industrial code. This was done to compare the load factors for different industry types for the same interval ranges of operating hours.

A one-way analysis of variance (ANOVA) test was performed to see if the various mean values of ELF_{an} and PLF_{an} had significant differences. This was important because the number of plants in each interval range was different. The test method used in this case is the Tukey-Kramer multiple comparison procedure or T-K procedure. The T-K procedure is based on computing confidence intervals for the difference between each possible pair of mean values. In the case for the ELF's and PLF's, there will be four differences to consider for each type of load factor, since there are four mean values that were calculated. Once the confidence intervals have been computed, each is examined to determine whether it includes zero. If the interval does not include zero, the two means are significantly different from one another. The procedure was based on critical values for a probability distribution called the Studentized range distribution and carried out using a 95% level of confidence [34].

When k treatments are being compared, there will be k(k-1)/2 confidence intervals to be computed. In our case, k will be the four load factors analyzed representing work-week lengths of 40, 80, 120 and 168 hrs/week. The intervals for the difference of the entire sample means are then calculated using the procedure given by Equation 7:

$$\begin{aligned} \mu_1 - u_2 &= (\bar{x}_1 - \bar{x}_2) \pm q\sqrt{\frac{MSE}{2}\left(\frac{1}{n_1} + \frac{1}{n_2}\right)} \\ &\vdots \\ \mu_{k-1} - u_k &= (\bar{x}_{k-1} - \bar{x}_k) \pm q\sqrt{\frac{MSE}{2}\left(\frac{1}{n_{k-1}} + \frac{1}{n_k}\right)} \end{aligned} \qquad (7)$$

where μ_k represents the true mean load factor for plants operating within a particular range of operating hours, $\bar{x}_k$ is the mean load factor for any given work-week length, n is the sample size (number of plants), and q is 95% Studentized range critical value. The mean square error or MSE is the sum of the square divided by the degree of freedom.

$$MSE = \frac{SSE}{N-k} \qquad (8)$$

where N is the total number of plants (for all operating hours), N-k are the degrees of freedom given by Equation 9 and SSE is the error sum of squares given by Equation 10, with s being the sample standard deviation

$$N - K = (n_{1-}1) + (n_2 - 1) + ...(n_k - 1) \tag{9}$$

$$SSE = (n_1 - 1)s_1^{\ 2} + (n_2 - 1)s_2^{\ 2} + ...(n_k - 1)s_k^{\ 2} \tag{10}$$

The load factors presented in this report are calculated using Equation 3 and 4 and are on an annual basis. Typically, load factors are monitored on a monthly basis (Equations 1 and 2) and therefore caution should be exercised when using this information as diagnostic tools, as there may be differences between the two. In order to check if there were sufficient differences between the two, an analysis was carried out using the data collected from assessments by the Texas A&M IAC. The Texas A&M IAC has been in operation since 1986 and has completed over 500 assessments [21]. Similar to the IAC database, the data collected from the A&M assessments includes annual electrical energy, demand and operating hours. The data however, also allows calculation of monthly ELF and PLF data, which is not available in the IAC database.

After accounting for missing and invalid data, a sample of 330 plants was chosen to analyze for differences between the annual and average monthly load factors. Table 5 summarizes the absolute percentage differences between the monthly and annual load factors. On an absolute basis, about 75% of the plants had less than 15% variation with respect to the annual ELF. A similar analysis conducted on the PLF revealed that 60% of the plants analyzed had less than 15% variation with respect to the annual PLF. In fact, over half the plant in each case had 10% or less variation. The results of the preliminary analysis on the difference between monthly and annual load factors was fairly inconclusive and therefore a statistical testing approach was adopted.

Table 5: Analysis of Differences between Monthly and Annual Load Factors

Absolute Difference Annual and Monthly Load Factors	Relatively Frequency	
	ELF	PLF
< 5%	55.5%	40.3%
5%-10%	10.6%	11.8%
10-15%	10.9%	9.4%
15%-20%	6.7%	10.6%
>20%	16.4%	27.9%

A more accurate test to check for differences is a paired sample t-test [34]. In this test, the differences between the observations are calculated for each pair of ELF and ELF_{an} or PLF and PLF_{an} along with the mean and standard error of these differences. Dividing the mean by the standard error of the mean yields a test statistic, t, that is t-distributed with degrees of freedom equal to one less than the number of pairs. The paired confidence interval, I, for the difference D between two sample means of load factor is given by

$$I = \bar{D} \pm t_{\alpha/2,n-1} \frac{S_d}{\sqrt{n}} \tag{11}$$

where, t is the test statistic based on a 95% confidence interval (α=0.05), n is the number of pair being considered and S_d is standard deviation of the differences. The average difference, $\overline{D}$, is given as

$$\bar{D} = \frac{\sum \mu_x - \mu_y}{n} \tag{12}$$

where μ_x and μ_y are the monthly and annual ELF or PLF values, respectively. The standard deviation is then given as

$$S_d = \frac{\sum(\mu_x - \mu_y)^2 \frac{\left(\sum \mu_x - \mu_y\right)^2}{n}}{n-1} \tag{13}$$

The paired sample t-test is most accurate when the data is normally distributed. One of the most useful tools to assess the normality of a data set is a Q-Q plot. A Q-Q plot is a plot of the ordered residuals versus the theoretical quartile of normal distribution and reveals severe departure from the normal assumption [35].

Figures 3-4 show the QQ plot for the monthly ELF, annual ELF, monthly PLF and annual PLF, respectively. The closer the points are to the line, the more normally distributed the data looks. Points for both pairs of ELF's fall along the line, indicating the data is normally distributed. However, the same cannot be said for the pair of PLF data points, with some points showing more severe deviation.

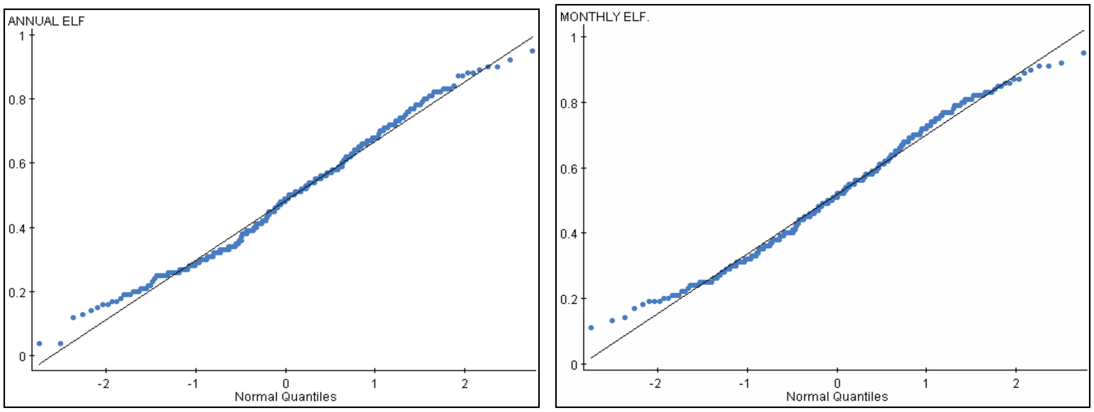

Figure 3: Q-Q Plot of Annual and Monthly Electrical Load Factors

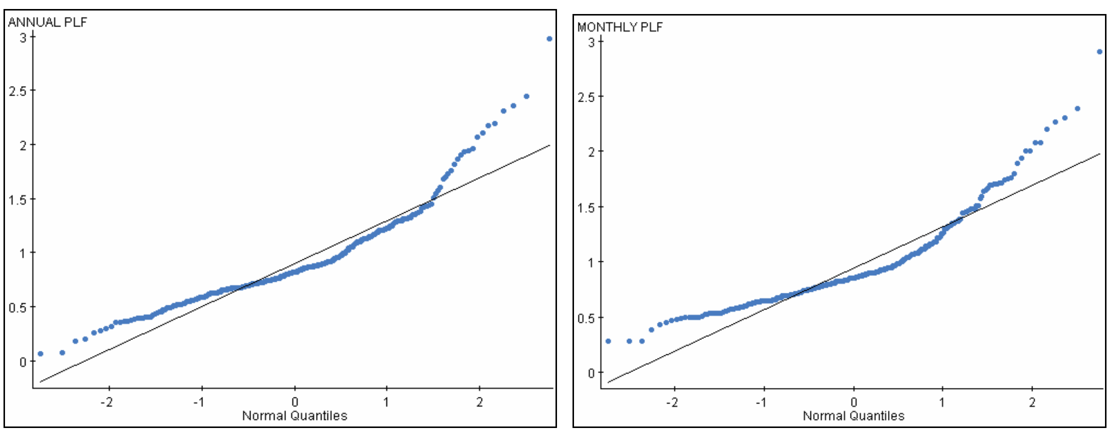

Figure 4: Q-Q Plot of Annual and Monthly Production Load Factors

Therefore, the results of the paired t-test will be fairly accurate for the ELF data but not so for the PLF data. Using equation 10-12, a 95% confidence interval for the mean difference between monthly and annual load factors is shown in Table 6.

Table 6: Average Differences between Annual and Monthly Load Factors

Difference	Sample Difference	Std. Error	DF	L. Lim	U. Lim
Monthly ELF - Annual ELF	0.036	0.005	329	0.026	0.045
Monthly PLF - Annual PLF	0.044	0.017	329	0.012	0.077

The results indicate that on the average, there is a mean difference of 0.036 for the ELF and 0.044 for the PLF. The lower and upper limit using a 95% confidence for both load factors are positive, indicating that the monthly load factor is typically higher than the annual load factor most of the time.

CHAPTER V

RESULTS OF ANALYSIS

This section summarizes the data used to draw conclusions about the average ELF_{an} and PLF_{an} values for each of the nominal values of hours per week of operation, as well as differences in variation between the different types of industries. The conclusions that can be made from this data will be presented in the next section.

Table 7 below shows the mean values of ELF_{an}, along with the lower quartile (Q1), upper quartile (Q3), standard deviation (Std. Dev) and the theoretical maximum for each of the four nominal work-week lengths. Similarly, Table 8 shows the mean PLF_{an} along with the upper and lower quartile values, standard deviation and 95% confidence interval of the mean (lower and upper limit). Typically, a PLF value of 0.75 to 0.85 is considered good for a plant and the table below also shows the percentage of plants for each nominal work-week length that operate with PLF_{an} ranging from 0.75 to 1.0 [20].

Table 7: Summary of ELF_{an} Values

Nominal work-week length, hours	Mean	Q1	Q3	Std. Dev	Theoretical Max.
40	0.36	0.28	0.43	0.130	0.24
80	0.47	0.38	0.55	0.133	0.48
120	0.56	0.48	0.64	0.130	0.72
168	0.70	0.62	0.81	0.147	1.00

Table 8: Summary of PLF_{an} Values

Nominal work-week length, hours	Mean	Q1	Q3	Std. Dev	Lower Limit	Upper Limit	0.75≤PLF≤1.0 %
40	1.43	1.09	1.73	0.521	1.41	1.47	14%
80	0.93	0.75	1.09	0.271	0.92	0.95	40%
120	0.80	0.69	0.91	0.187	0.79	0.81	55%
168	0.70	0.63	0.82	0.149	0.70	0.72	45%

Tables 9 and 10 show the mean ELF_{an} and PLF_{an}, respectively, along with the standard deviation and total number of assessments performed for all of the plants in each specific industry for each nominal value of operation hours. The industries in Table 9-10 are based on the first two digits of the plant's SIC code (Table 2). Due to an insufficient number of plants in certain categories of the SIC, the standard deviation could not be calculated.

Table 9: ELF$_{an}$ Values based on Operating Hours and SIC code

	40 Hours/week			80 Hours/week			120 Hours/week			168 Hours/week		
SIC	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev
20	107	0.46	0.16	153	0.54	0.13	114	0.59	0.12	108	0.68	0.13
21	2	0.42	0.13	1	0.48	NA	1	0.67	NA	2	0.58	0.32
22	13	0.35	0.15	20	0.46	0.11	53	0.53	0.13	41	0.71	0.14
23	42	0.33	0.08	20	0.44	0.09	6	0.56	0.10	4	0.69	0.05
24	106	0.32	0.10	82	0.45	0.11	27	0.52	0.14	35	0.65	0.18
25	69	0.32	0.07	53	0.46	0.11	18	0.53	0.12	8	0.52	0.15
26	22	0.36	0.10	63	0.48	0.13	136	0.57	0.12	78	0.73	0.13
27	15	0.35	0.15	49	0.44	0.12	48	0.55	0.13	62	0.62	0.12
28	42	0.42	0.14	39	0.55	0.15	47	0.59	0.12	115	0.77	0.13
29	9	0.24	0.08	13	0.37	0.14	8	0.56	0.14	14	0.71	0.20
30	46	0.30	0.08	82	0.43	0.14	198	0.56	0.13	237	0.74	0.11
31	22	0.33	0.06	6	0.43	0.06	1	0.50	NA	0	NA	NA
32	39	0.42	0.19	41	0.43	0.15	36	0.51	0.14	62	0.70	0.17
33	49	0.32	0.16	85	0.44	0.18	104	0.53	0.15	78	0.63	0.17
34	132	0.34	0.12	262	0.45	0.12	157	0.55	0.13	62	0.66	0.16
35	132	0.36	0.12	149	0.47	0.13	106	0.56	0.12	46	0.65	0.14
36	61	0.40	0.11	89	0.51	0.12	63	0.60	0.13	55	0.74	0.16
37	65	0.37	0.10	106	0.47	0.12	54	0.59	0.11	36	0.66	0.18
38	33	0.48	0.13	46	0.51	0.13	18	0.59	0.10	15	0.79	0.10
39	24	0.37	0.10	22	0.46	0.13	15	0.50	0.14	8	0.63	0.13

Table 10: PLF_{an} Values based On Operating Hours and SIC code

	40 Hours/week			80 Hours/week			120 Hours/week			168 Hours/week		
SIC	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev	# Plants	Mean	Std. Dev
20	107	1.79	0.61	153	1.06	0.28	114	0.84	0.17	108	0.69	0.13
21	2	1.80	0.59	1	0.85	NA	1	0.98	NA	2	0.59	0.34
22	13	1.44	0.61	20	0.92	0.25	53	0.78	0.19	41	0.72	0.14
23	42	1.33	0.34	20	0.89	0.20	6	0.80	0.16	4	0.69	0.05
24	106	1.26	0.41	82	0.91	0.22	27	0.75	0.21	35	0.66	0.19
25	69	1.31	0.31	53	0.93	0.21	18	0.74	0.16	8	0.53	0.16
26	22	1.45	0.44	63	0.95	0.26	136	0.81	0.17	78	0.74	0.13
27	15	1.34	0.62	49	0.86	0.23	48	0.78	0.19	62	0.63	0.12
28	42	1.60	0.55	39	1.11	0.31	47	0.84	0.17	115	0.78	0.13
29	9	0.88	0.31	13	0.74	0.28	8	0.80	0.20	14	0.72	0.20
30	46	1.18	0.29	82	0.85	0.28	198	0.79	0.19	237	0.75	0.12
31	22	1.31	0.25	6	0.86	0.12	1	0.70	NA	0	NA	NA
32	39	1.71	0.82	41	0.87	0.31	36	0.73	0.20	62	0.71	0.17
33	49	1.25	0.61	85	0.87	0.35	104	0.75	0.22	78	0.64	0.17
34	132	1.35	0.48	262	0.89	0.24	157	0.79	0.19	62	0.67	0.16
35	132	1.39	0.48	149	0.92	0.26	106	0.80	0.17	46	0.66	0.14
36	61	1.60	0.43	89	1.02	0.25	63	0.86	0.19	55	0.75	0.16
37	65	1.46	0.39	106	0.94	0.25	54	0.85	0.17	36	0.67	0.18
38	33	1.86	0.55	46	1.01	0.29	18	0.85	0.14	15	0.80	0.11
39	24	1.47	0.42	22	0.88	0.26	15	0.71	0.19	8	0.64	0.14

Table 11 below shows the results of the ANOVA analysis for the ELF. The lower and upper limit is based on a 95% confidence interval and indicates the difference between ELF_{an} for each pair of nominal work-week length period. The range of difference between the ELF_{an} for a plant operating at 80-168 hours/week and a one operating at 40 hours/week is always positive, indicating that the former plants have, on average, a higher ELF_{an} value than those operating with a single shift operation. Similarly the range of difference between plants operating with a two-shift operation (80 hours/week) and those operating 120-168 hours/week is also positive, indicating that there are significant differences between in the ELF_{an} values. Similar deductions can be made by comparing plants operating 120 hours/week and 168 hours/week.

Table 11: Results of ANOVA Analysis for ELF_{an}

40 subtracted from		
	Lower	**Upper**
80	0.092	0.121
120	0.178	0.207
168	0.320	0.350
80 subtracted from		
	Lower	**Upper**
120	0.072	0.099
168	0.215	0.243
120 subtracted from		
	Lower	**Upper**
168	0.128	0.157

Similar to Table 11, Table 12 below shows the results of the ANOVA analysis for the PLF. The lower and upper limit is also based on a 95% confidence interval and indicates the difference between PLF_{an} for each pair of nominal work-week length period. It can be observed that the range of difference between the PLF_{an} for a plant operating at 80-168 hours/week and a one operating at 40 hours/week is always negative, indicating that the former plants have, on average, a lower PLF_{an} value than those operating with a single shift operation. Similarly the range of difference between plants operating with a 2 shift operation (80 hours/week) and those operating 120-168 hours/week is also negative, indicating that there are significant differences between the PLF values. Similar deductions can be made by comparing plants operating 120 hours/week and 168 hours/week.

Table 12: Results of ANOVA Analysis for PLF_{an}

40 subtracted from		
	Lower	**Upper**
80	-0.538	-0.473
120	-0.673	-0.606
168	-0.762	-0.693
80 subtracted from		
	Lower	**Upper**
120	-0.166	-0.103
168	-0.255	-0.190
120 subtracted from		
	Lower	**Upper**
168	-0.121	-0.055

CHAPTER VI

DISCUSSION OF RESULTS

Table 7 in the previous section shows that the ELF_{an} increases as the operating hours increase, as expected from Equations 1 and 3. The ELF value is expected to increase with operating hours because the longer a facility operates the more electrical energy it consumes. Surprisingly, the mean ELF_{an} of 0.36 is 50% greater than the theoretical maximum ELF for plants operating 40 hours/week and the value of 0.70 is 30% less for those operating 168 hours/week. This can be attributed to the fact that the operating hours in the database may not be representative for the entire facility. Some facilities may have more than one area where significant production activities occur and the operating hours of the areas may differ considerably. The standard deviation is similar for all groups, ranging from 0.13 to 0.15 with no particular trend being demonstrated. There is also some overlapping between the lower quartile (Q1) of a particular work-week length and the upper quartile (Q3) of the preceding row. Therefore, a small portion of plants have similar load factors even if they have significantly different shift patterns.

Table 8 shows that the PLF_{an} values decrease as the operating hours increase. If the energy consumed is proportional to the operating hours, then Equation 2 and 4 indicate that the PLF should be invariant with operating hours and any value greater than one indicates energy consumption outside the nominal weekly operating hours. When used as a diagnostic tool, if the PLF exceeds unity and nothing in the plant should be operating outside the plant operating hours, then unnecessary energy consumption may be taking place. The percentage of plants that operate with a PLF_{an} greater than 0.75 but less than 1.0 was found to be greater than 40% for plants that operate 80, 120 or 168 hours per week. However, this drops to 13% for plants operating at 40 hours per week. Such a significant drop would suggest that such facilities perhaps present the most opportunities for energy conservation. The 95% confidence interval of the PLF_{an} in Table 8 is the expected range of the mean PLF_{an} for all plants that operate at either 40, 80, 120 or 168 hours. Comparing the values of standard deviation in Tables 7 and 8 shows that the standard deviation is much higher for the PLF_{an} values than the ELF_{an}'s, indicating the presence of more scatter in the PLF data. However, this reduces with an increase in operating hours, indicating that there is less scatter among PLF values of plants operating on a 24/7 schedule.

The trend indicated in Tables 7 and 8 where the ELF's for the lower nominal operating hours are greater than the theoretical maximum correlates with the PLF's decrease from values greater than unity to less than unity as the operating hours increase. The mean PLF_{an} value along with the upper and lower quartile for a plant operating at 40 hours/week is greater than one, suggesting that these facilities may have significant energy usage outside production hours. The energy consumption could result from the use of facility equipment such as lights or product refrigeration which are on all the time or from operation of other departments within the facility that are not part of the main production area. This could also explain why the mean ELF_{an} is greater than the theoretical maximum for plants operating with a single shift operation.

The mean ELF_{an} for each specific industry in Table 9 were found to be comparable to the mean values calculated in Table 7. For plants that operate at 40 hours, per week, about 40% of the categories have an ELF value greater than the overall average (0.36). A similar analysis for other work-week periods yielded equivalent results. Analogous to Table 9, Table 10 shows the mean PLF_{an} for different types of plants. Almost all the categories of plant operating with a single shift operation have a PLF value greater than one. The exception to this are plants under SIC group 39, which corresponds to petroleum refining. The data also shows that almost all types plant seem to operate more efficiently when operating with two or more shifts. However, compared to Table 9, the standard deviation of the PLF data is very high for single shift operations.

In order to check if there was significant difference between the different mean values of ELF_{an} and PLF_{an}, a one way analysis of variance (ANOVA) test with the Tukey-Kramer multiple comparison procedure was carried out using a 95% level of confidence. Using this procedure, the confidence interval for the difference between each pair of ELF_{an} and PLF_{an} was calculated. None of the intervals were found to include zero, thus indicating that the mean ELF_{an} or PLF_{an} for plants operating at 40 hours per week is significantly different than the ELF_{an} or PLF_{an} of plants operating at other nominal work-week lengths. If any of the intervals were found to contain zero, it would mean that there is no statistical distinction in the load factors for that pair of plants. This test is important as the number of samples in each group is different.

The results from Table 7 and 8 shows that the standard deviation is higher for the PLF data as compared to the ELF. Figure 3 and 4, which shows the QQ-plot suggests that the PLF data does not portray a normal distribution similar to the ELF, as evident by the large number of outliers present outside the diagonal. Therefore, the data presented in Table 12, which shows the results of the ANOVA analysis for the annual PLF, will not match the accuracy of the data shown on Table 11. The large variations indicate that grouping PLF data based on operating hours may not be a reasonable approach to benchmarking energy use in industries.

There can be several sources of error that could contribute to variations in the data used for this analysis. The first of these is that the SIC codes that were used in this study often contain industries within their major groups of products that may have very different energy consumption needs. An example of this could be SIC Major Group 35, which has industries ranging from turbines to office equipment.

The energy use and operating hour data are also potential sources of error. The energy consumption and demand in the database should be reported on an annual basis. However, possibly reported values of energy and demand are not extrapolated properly to a twelve month basis when sufficient data is unavailable or not extrapolated at all. The operating hours in the database refer to the hours of production for the core manufacturing area. Significant energy consumption may take place outside the time of operation of the core manufacturing area. Such circumstances would lead to a high value of PLF but a low value of ELF.

Another likely source of error would be the possibility of human error involved in the incorporation of data into the database. The data is inserted by the individual centers after the report is complete. During the initial analysis, there were a significant number of electrical and production load factors calculated that were theoretically impossible.

CHAPTER VII

CONCLUSIONS

The database of the Department of Energy sponsored Industrial Assessment Center program was used to identify the most common ranges of operating hours for manufacturing facilities and develop ranges of load factors. The average ELF_{an} along with the upper and lower quartile values corresponding to nominal work-week length values of 40, 80, 120 and 168 hours/week were calculated and were found to be comparable to values published in literature [19, 25]. As expected the ELF increased with operating hours while the PLF showed an inverse trend. The standard deviation of the mean PLF_{an} values was significantly higher than the corresponding ELF_{an} values, thus indicating more variability in the results.

Plants that operated 40 hours per week were found to have a high range of PLF_{an} values, often exceeding unity. Although a PLF over one is theoretically indicative of energy waste, it may not always hold true, especially for plants that operate with a single shift. This is because such plants are more likely to have energy usage outside the nominal hours. The percentage of plants operating with a good PLF (about 0.75) were also much lower in this group as compared to plants with two or three shift operation.

The number of plants analyzed in each category was different, so checking if there were differences between the mean load factors calculated for the nominal work-week length was essential. An analysis of variance test revealed that the load factors for each corresponding shift were significantly different. As mentioned earlier, the load factors calculated are on an annual and not monthly basis. A statistical analysis on the data based on assessments done by the Texas A&M IAC alone revealed that the monthly ELF and PLF on average tends to be higher than the corresponding annual load factor. Since there may be significant differences between the two, it is advisable to use caution when using this information as a diagnosis tool. This is especially true for the PLF, as it was found to have less of a normal distribution relative to the ELF.

REFERENCES

[1] Capehart BL, Turner WC, Kennedy WJ. Guide to energy management. Lilburn, GA: The Fairmont Press, Inc.; 2006.

[2] Haberl JL, Landman JS. Monthly Indices: A procedure for energy use display creating monthly indices for comparing the energy consumption of buildings. College Station, TX: Energy Systems Lab, Texas Engineering Experiment Station, Texas A&M University, 1996. See also: <http://txspace.tamu.edu/bitstream/handle/1969.1/2166/ESL-TR-96-10-02.pdf?sequence=1> Accessed September, 2008

[3] Turner WC. Energy management handbook. 5th Ed. Lilburn, GA: The Fairmont Press, Inc.; 2006.

[4] Dacquisto JF. Beating those power demand charges. In: Ottaviano V, Ottaviano technical service. 3rd Ed. Upper Saddle River, NJ: Prentice Hall; 1988.

[5] Van Gorp JC. Using key performance indicators to manage energy costs. In: Proceedings, Industrial Energy Technology Conference, New Orleans, LA; 2005.

[6] Hanegan A. Industrial energy use indices. Thesis report. College Station, TX: Mechanical Engineering Department, Texas A&M University, 2007. See also: <http://repository.tamu.edu/handle/1969.1/85849> Accessed January, 2009

[7] Blanchard D. Census of manufacturers: What's working for US manufacturers? Industry Week 2006;255(10):49-51.

[8] Greenfield D. Energy management: First steps towards greater energy efficiency. Controls Engineering 2009; 56(1):32-35.

[9] Galitsky C, Worrell E, Radspieler A, Healy P, Zechiel S. Best winery guidebook: benchmarking and energy and water savings tool for the wine industry, Publication Number: LBNL- 3184. Berkley, CA: Energy Analysis Department, Environmental Energy Technologies Division, Ernest Orlando Lawrence Berkeley National Laboratory, University of California, 2005.

[10] US Department of Energy. BestPractices: Quick PEP – FAQ. Industrial Technologies Program. Department of Energy Efficiency and Renewable Energy, US Department of Energy. See also: <http://www1.eere.energy.gov/industry/quickpep/faq.aspx> Accessed September, 2008

[11] Boyd G, Dutrow E, Tunnessen W. The evolution of the ENERGY STAR energy performance indicator for benchmarking industrial plant manufacturing energy use. Journal of Cleaner Production 2008;16(6):709-715.

[12] IEA. Tracking industrial energy use and CO2 emissions. Paris: IEA/OECD; 2007.

[13] Dolf P, Gielen T. Indicators for industrial energy efficiency in India. Energy 2008; doi:10.1016/j.energy.2008.11.008

[14] Rangan B, Gatinode UN, Sardeshpande V. Model based energy benchmarking for glass furnace. Energy Conversion and Management 2007; 48(10):2718-2318.

[15] Ross CP. Energy benchmarking: A tool for continuing process improvement for the glass industry. In: Proceedings, Ceramic Engineering and Science, Columbus, OH; 1997.

[16] Tasto DL. Shift work practices in the United States. Cincinnati, OH: US Department of Health, Education and Welfare; 1977.

[17] CenterPoint Energy Houston Electric. Tariff for retail delivery service. Houston, TX: CenterPoint Energy, 2006. See also:

<http://www.centerpointenergy.com/services/electricity/business/tariffs/> Accessed June, 2008

[18] CPS Energy. Base commercial electrical rates. San Anotnio, TX: CPS Energy, 2008. See also <http://www.windtricity.com/Commercial/Billing_Payments/Rates/index.asp> Accessed June, 2008

[19] Beggs C. Energy: management, supply and conservation. Oxford, MA: Butterworth-Heinemann; 2002.

[20] Capehart, BL. Encyclopedia of energy engineering and technology. Boca Raton, FL: CRC Press; 2007.

[21] US Department of Energy. IAC database. Industrial Assessment Centers. Center for Advanced Studies, Rutgers University: Piscataway, NJ. See also: <http://iac.rutgers.edu/database> Accessed November, 2006

[22] US Department of Energy. Industrial Assessment Center Eligibility. Industrial Technologies program. Department of Energy Efficiency and Renewable Energy, US Department of Energy. See also: <www1.eere.energy.gov/industry/bestpractices/iac_eligibility.html> Accessed

February, 2007.

[23] US Department of Energy. IAC glossary. Industrial Assessment Centers. Center for Advanced Studies, Rutgers University: Piscataway, NJ. See also: <http://www.iac.rutgers.edu/database/glossary.php> Accessed November, 2008

[24] Eppelheimer, DM. Electrical demand control. In: Symposium on Improving Building Systems in Hot and Humid Climates, College Station, TX; 1984.

[25] Muller, TD. Basic demand control. Energy Management Series 2000;25(9): p.30-34.

[26] Pedernales Electric Corporation. PEC Rate information. Johnson City, TX: Pedernales Electric Corporation, 2008. See also: <http://www.pec.coop/Documents/RateInformation.pdf> Accessed December 2008

[27] Leonardo Energy. Electrical load management in industry. Paris, France: UIE Working Group;1996.

[28] Ashok S, Banerjee R. An optimization mode for industrial load management. IEEE Transactions on Power Systems 2001;16(4): p.879-884.

[29] Victor A, Brodkor A. Real time demand side energy management. In: Proceedings, Industrial Energy Technology Conference, New Orleans, LA; 2006.

[30] Will CF. Factors that affect your power bill. In: Proceedings, Textile, Fiber and Film Industry Technical Conference, Atlanta, GA; 1993.

[31] TVA Electric Power. Improving load factor and power factor to reduce demand. Electrical Energy Management Guideline Series, No. 102. Tennessee Valley Authority .See also: http://www.p2pays.org/ref/15/14375.pdf > Accessed July 2007

[32] Coad WJ. Energy engineering and management for building systems. New York: Van Nostrand Reinhold Co.; 1982.

[33] US Office of Personnel Management Operating Status and Schedule. 2008 Federal Holidays. US Office of Personnel Management: Washington, DC. See also <http://www.opm.gov/Operating_Status_Schedules/fedhol/2008.asp> Accessed August 2008

[34] Devore JL, Peck R. Statistics: the exploration and analysis of data. Belmont, CA: Thomson Brooks/Cole; 2005.

[35] Montgomery DC, Runger GC. Applied statistics and probability for engineers. New York: Wiley; 2003.

VITA

Name:	Tapajyoti Sen
Address:	Department of Mechanical Engineering C/O Warren Heffington Texas A&M University College Station, Texas 77843-3123
Email Address:	email@tjsen.com
Education:	M.S., Mechanical Engineering, Texas A&M University, 2009 B.S., Mechanical Engineering, Texas A&M University, 2006
Publication:	Sen, T, Heffington W. Electrical and production load factors. In: Proceedings of the 2009 Industrial Energy Technology Conference. May 2009, New Orleans