A NOVEL APPROACH TO FORECAST AND MANAGE ELECTRICAL MAXIMUM DEMAND

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I am grateful to my family, who supported me emotionally and financially. Special thanks to my parents for encouraging me in all of my pursuits and inspiring me to follow my dreams. I always knew that you believed in me and wanted the best for me. And special thanks to my twin brother for his boundless mental, and emotional support during my hard work.

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SYMBOLS

ϵ	aggregated stationary, white noise
X	demand pattern
q	demand variation
α_0	intercept of the linear regression line for MDD vs DD
β_0	intercept of the linear regression line for MDD vs P
γ_0	intercept of the linear regression line for MDD vs Ox
k	iteration index
I	noise component
T	normal component
α_1	regression coefficient for MDD vs DD
β_1	regression coefficient for MDD vs P
γ_1	regression coefficient for MDD vs Ox
$\alpha_1^{`}$	regression coefficient for $MDD_{Sub-system}$ vs DD
$\beta_1^{`}$	regression coefficient for $MDD_{Sub-system}$ vs P
$\gamma_1^{`}$	regression coefficient for $MDD_{Sub-system}$ vs Ox
$\alpha_{Sub-system}$	regression coefficient for MDD vs $MDD_{Sub-system}$
$\beta_{Sub-system}$	regression coefficient for MDD vs $MDD_{Sub-system}$
$\gamma_{Sub-system}$	regression coefficient for MDD vs $MDD_{Sub-system}$
S	seasonal component

ABBREVIATIONS

ARC	Adaptive-Rate-of-Change
CDD	Cooling degree-day
DD	Degree-day
HDD	Heating degree-day
HVAC	Heating ventilation and air conditioning
LD	Load diagram
LTLF	Long-term load forecasting
MDD	Maximum daily demand
MDM	Maximum demand management
MTLF	Medium-term load forecasting
Ox	Occupancy
P	Production
ROC	Rate-of-Change
STLF	Short-term load forecasting
VSTLF	Very short-term load forecasting

ABSTRACT

Amini, Amin M.S.M.E., Purdue University, August 2017. A Novel Approach to Forecast and Manage Electrical Maximum Demand. Major Professors: Ali Razban and Jie Chen.

Electric demand charge is a large portion (usually 40%) of electric bill in residential, commercial, and manufacturing sectors. This charge is based on the greatest of all demands that have occurred during a month recorded by utility provider for an end-user. During the past several years, electric demand forecasting have been broadly studied by utilities on account of the fact that it has a crucial impact on planning resources to provide consumers reliable power at all time; on the other hand, not many studies have been conducted on consumer side. In this thesis, a novel Maximum Daily Demand (MDD) forecasting method, called Adaptive-Rate-of-Change (ARC), is proposed by analysing real-time demand trend data and incorporating moving average calculations as well as rate of change formularization to develop a forecasting tool which can be applied on either utility or consumer sides. ARC algorithm is implemented on two different real case studies to develop very short-term load forecasting (VSTLF), short-term load forecasting (STLF), and medium-term load forecasting (MTLF). The Chi-square test is used to validate the forecasting results. The results of the test reveal that the ARC algorithm is 84% successful in forecasting maximum daily demands in a period of 72 days with the P-value equals to 0.0301. Demand charge is also estimated to be saved by $8,056 (345.6 kW) for the first year for case study I (a die casting company) by using ARC algorithm. Following that, a new Maximum Demand Management (MDM) method is proposed to provide electric consumers a complete package. The proposed MDM method broadens the electric consumer understanding of how MDD is sensitive to the temperature, production,

occupancy, and different sub-systems. The MDM method are applied on two different real case studies to calculate sensitivities by using linear regression models. In all linear regression models, R^2s calculated as 0.9037, 0.8987, and 0.8197 which indicate very good fits between fitted values and observed values. The results of proposed demand forecasting and management methods can be very helpful and beneficial in decision making for demand management and demand response program.

1. INTRODUCTION

The position of the electric consumers in the power systems operation has been change due to a couple of reasons. First, upgrading the electrical power systems infrastructure have been truly expensive and in some cases temporarily, to meet the consumers high demand. Moreover, implementation of competitive electricity markets causes the consumers to play an active role in power systems. Electric demand is a large portion (usually 40%) of electric bill in residential, commercial, and manufacturing sectors (residential sector gets charge in some states). It also has a crucial impact on planning resources for utilities to provide consumers reliable power at all time. Peak demand forecasting and management would not only cut down demand charges costs on end-user sides, but also would help the utilities to keep up with their current infrastructure for a longer period of time without having a significant investment on increasing capacity. Referring to sustainability definition as being able to be maintained at a certain level, demand forecasting and management can maintain/decrease the electric infrastructure owned by consumers and utilities [1]. Furthermore, by decreasing spikes on electric demand, generation would be more efficient with less carbon footprints.

In chapter 1, some definitions in electric systems have been defined along with literature survey in load forecasting. Chapter 2 proposes a novel maximum daily demand forecasting algorithm, called ARC algorithm, for residential, commercial and manufacturing sectors. The algorithm is proposed by analysing demand trend data and incorporating moving average calculation as well as rate of change formularization to develop an electrical maximum demand forecasting algorithm. Moreover, a new method for maximum daily demand management has been proposed in chapter 2 by understanding the impacts of number of degree-days, number of occupants, number of productions, and sensitivity of maximum daily demand to different sub-systems. In chapter 3, the ARC algorithm and management method have been applied on three different real case studies. Results of case studies have been verified in chapter 4. Chapter 5 is the conclusion and future works for this dissertation.

1.1 Definitions

Electric bills for industrial and commercial customers break down into two major parts, energy consumption and demand. In this section, electric parameters used in this dissertation such as electric demand, maximum demand, demand factor, diversity factor, and load factor have been defined by using IEEE Std 141-1993, IEEE recommended practice for electric power distribution for industrial plants.

1.1.1 Electric Demand

Electric demand is defined as "the electric load at the receiving terminals averaged over a specified interval of time" (IEEE Std 141-1993). Note that electric demand is expressed in kilowatts (kW), kilovoltamperes (kVA), amperes (A), or other suitable units. The unit is based on the particular utilitys demand rate structure and the way that the utility provider charges the costumer. The interval of time is generally 15 min, 30 min, or 1 h, based on utilitys demand metering interval [2].

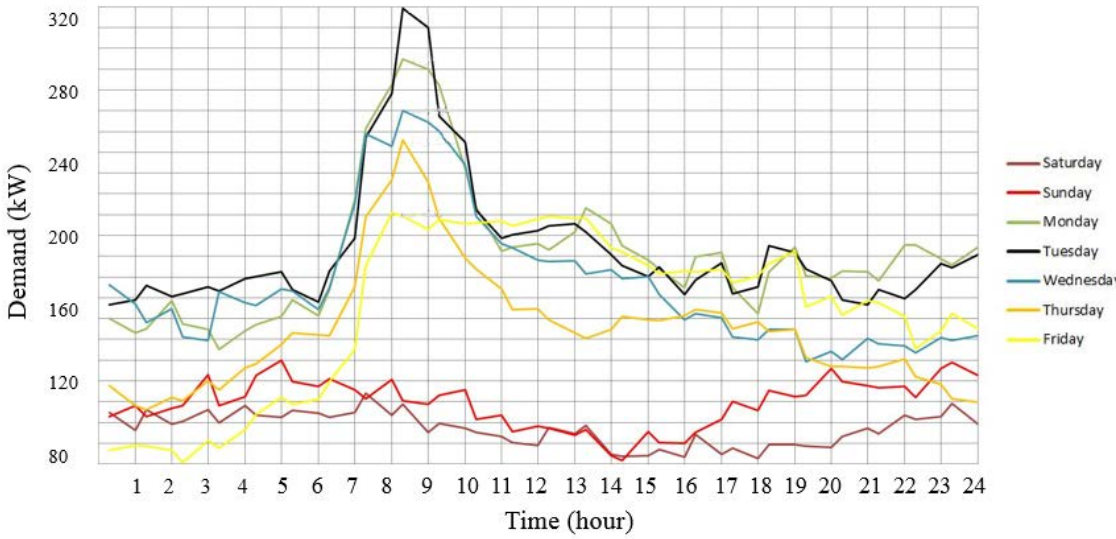
1.1.2 Load Diagram

Load diagram (or load profile) is the curve showing the electric demand of an electric system against time, on a daily, weekly, or monthly basis. This representation can be in 2D or 3D as it is shown in Fig.1.1. Figure1.1(a) is color-coded based on the day for 24hr in the period of one week, while Fig.1.1(b) is color-coded based on the magnitude of electric demand for 24hr in the period of 40 days. As it is shown in Fig.1.1(a), on Saturday and Sunday, the company has no production and the load is at the lowest, indicated by red and purple. This load diagram also reveals the base-load of $80kW$ for this facility. The base-load of about $200kW$ has been shown in Fig.1.1(b) in that period except on March, 5^{th}, 2015 which the end-user experienced power outage for 2 hours.

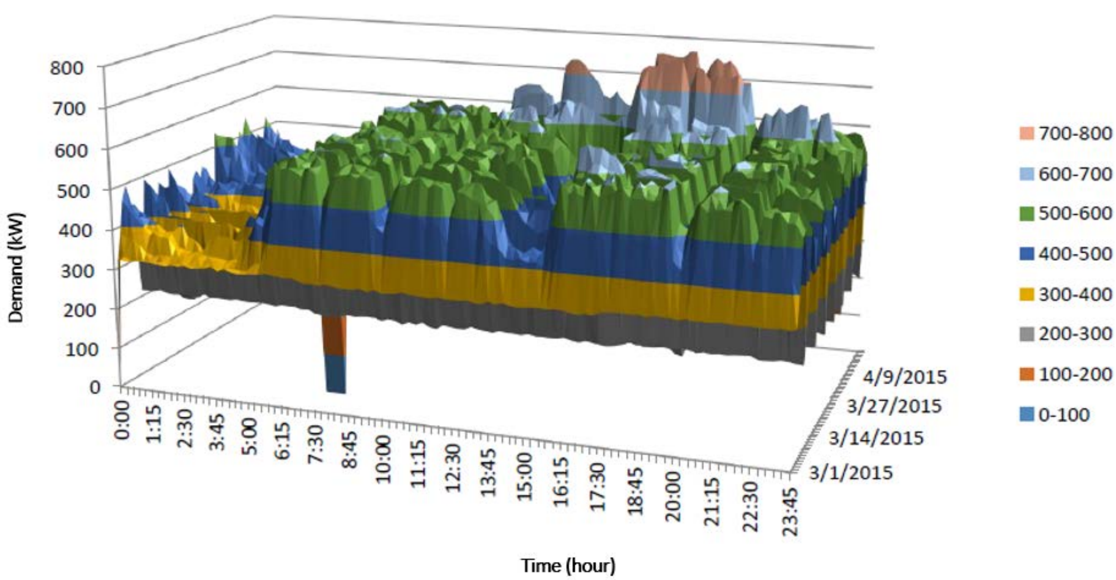
Load profile is like the finger print for an electric consumer. In other words, it is a distinctive characteristic for each consumer. Load profile alone can reveal a great deal of information, and it is a function of multiple parameters, such as hours of operation, base-load, maximum demand, number of shifts, onset of occupancy, occupied period, specific procedure to start-up at the beginning of the day/shifts, etc. Figure 1.2 shows a typical and a non-typical load diagram. A typical load diagram has a specific pattern while a non-typical diagram does not have a specific pattern. In other words, a typical load diagram is repetitive through out different working days for a company. Lacking a routine procedure/number of productions in a company would cause a non-typical (non-repetitive) load diagram.

1.1.3 Maximum Demand

Maximum demand is defined as "the greatest of all demands that have occurred during a specified period of time such as one-quarter, one-half, or one hour" (IEEE Std 141-1993). It is worth to mention that for utility billing purposes the period of time is generally one month. Therefore, utility provider monitors the costumers electric load at the receiving terminal, which is called behind-the-meter, averaged over a specified interval of time and then records the maximum of the electric loads in a month as the maximum demand. Each facility will get charged for the maximum demand every month along with electric energy consumption [2]. Using the definition, the Maximum Daily Demand (MDD) is defined as the greatest of all demands that have occurred during one day.



(a) 2D load diagram

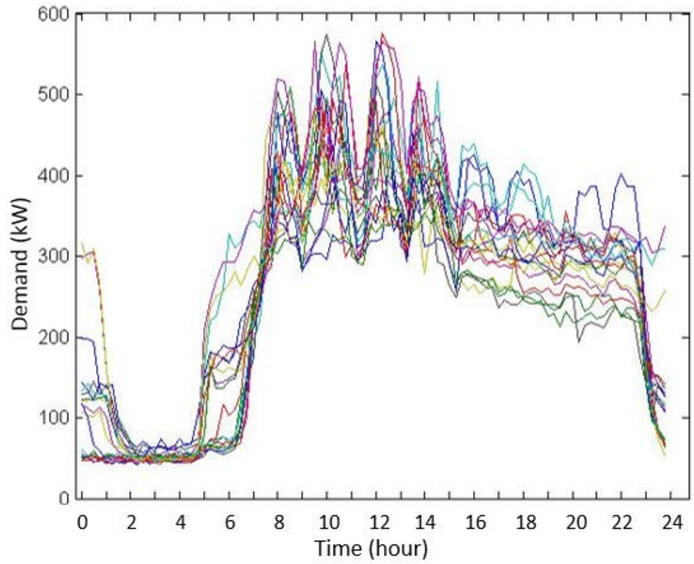


(b) 3D load diagram

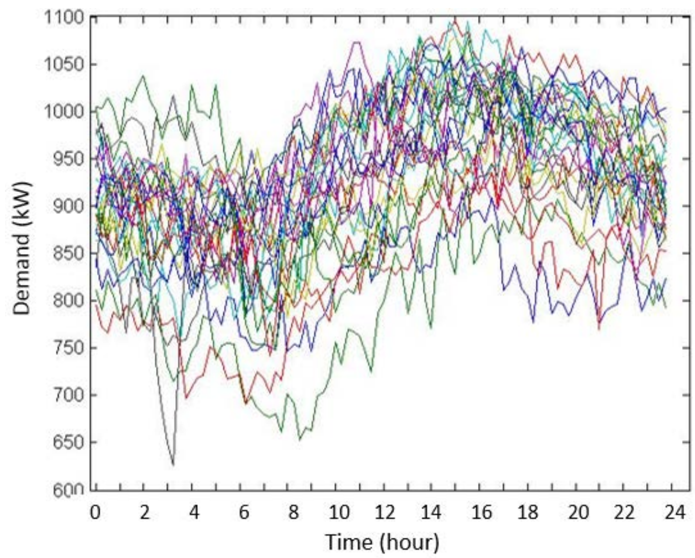
Fig. 1.1. 2D and 3D representation of Load Diagram

1.1.4 Demand Factor

Demand factor is “the ratio of the maximum coincident demand of a system, or part of a system, to the total connected load of the system, or part of the system,



(a) A typical load diagram



(b) A non-typical load diagram

Fig. 1.2. Typical & non-typical Load Diagrams

under consideration" (IEEE Std 141-1993). The resultant is always between 0 to 1.00. Demand factor usually varies from 0.8 to 1; however, for some plants with very low diversity it goes down to 0.15 to 0.25 [2].

1.1.5 Diversity Factor

Diversity factor is "the ratio of the sum of the individual non-coincident maximum demands of various subdivisions of the system to the maximum demand of the complete system". The diversity factor is always 1 or greater. Note that the term diversity, as distinguished from diversity factor is defined as the percent of time that a machine, piece of equipment, or a facility has its maximum load or demand (i.e., a machine with 50% diversity operates at its maximum load level 50% of the time that is turned on).

1.1.6 Load Factor

Load factor is "the ratio of the average load over a designated period of time to the peak load occurring in the period" (IEEE Std 141-1993). Securing the connecting power is always a crucial requirement for electric utility providers. This requirement translated into sizing and installing needs adequate supply cable and securing capacity for the supply transformer. Whether the equipment will work at full capacity all the time, part time, or no time at all, installation must be sized to the full capacity of connected device. Therefore, demand charge can always be a large portion of the total electric bill. It usually ranges from $1/3^{rd}$ to $2/3^{rd}$ of the total electric bill depends on the tariff, type of facility, number of shifts, production rate, weather, occupation rate, and occupant behaviors.

1.2 Load Forecasting

Electric demand forecasting plays a pivotal role in power system management, especially for ensuring economic and reliable operation in power systems. To achieve this end, electric utilities use load forecasting models, to ensure the load factor of one occurs at any time which means that the supplied electric energy meets the loads plus the energy lost in the power system. Adjusting the supply-demand balance in the electric system at any time requires utilizing different models for load forecasting on a variety of time horizons. Moreover, demand forecasting can be a very strong tool on the costumer side. Load forecasting is categorized based on the time scale and these could be listed into: very short-term load forecasting (VSTLF), short-term load forecasting (STLF), medium-term load forecasting (MTLF) and long-term load forecasting (LTLF) [3]. Very short-term load forecasting (VSTLF) is mostly used for load-frequency control and detecting contingencies in power system [4–6].

VSTLF method forecasts the loads from an hour to several hours into the future in a moving window manner based on real-time data collected from an electric consumer. The forecasting is in steps of a few minutes (i.e., usually equals to utility monitoring time-interval for demand). A great number of methods have been used for VSTLF. Existing methods are extrapolation, time series, fuzzy logic, and neutral networks (NN). Effective forecasting is usually very difficult in VSTLF on account of the fact that data includes a lot of noise and load features is usually complicated [7]. In section 2.1, more obstacles in VSTLF have been discussed.

STLF is utilized from an hour-ahead to a day-ahead forecasting in power system operation. Short-term load forecasting methods include conventional techniques, i.e., multiple regression [6, 8–11]], similar day approach, time series [4, 5, 12]. Artificial intelligent based approach that is more reliable has been proposed in the last couple of years, which result more accurate predictions in comparison to conventional techniques [13, 14]. Some of AI methods are used for forecasting are genetic algorithms [15], neural networks [16–18], and fuzzy system [19].

Medium-term load forecasting and long-term load forecasting are ranged respectively from one week to one year, and one year to decades. The short-term load forecasting has been extensively studied in the literature during last decade [20–23]. Instead, a few studies have been conducted about MTLF in [1, 24, 25] and LTLF in [25–27].

As system complexity increases, the results are not always reliable to make important decisions such as ceasing the production or turning off major equipment for a specified period. The results of the forecasting methods would be the input for preliminary decisions on Demand Response program. Equation (1.1) shows the probability of forecasting the monthly maximum demand for a facility working 24/7 with 100% accuracy by assuming the demand time interval as 15 min.

$$P = \frac{15min}{30days \times 24hrs \times 60mins} \times 100\% = 0.347\% \tag{1.1}$$

As it is shown in equation (1.1), assuming confidence limits of 100%, the probability of forecasting the maximum demand in a month is only 0.347%. Therefore, proposing a validated method with reliable results would be a great help to manage the demand.

1.3 Demand Response

The position of the electric consumers in the power systems operation has been change due to a couple of reasons. First, upgrading the electrical power systems infrastructure have been truly expensive and in some cases temporarily, to meet the consumers high demand. Moreover, implementation of competitive electricity markets causes the consumers to play an active role in power systems [28].

The term *demand-side load management* is the result of planning processes used by utilities in the late 1980s. The most widely accepted definition of demand-side management is by Gellings (1989): "Demand -side management is the planning, implementation, and monitoring of those utility activities designed to influence customer use of electricity in ways hat will produce desired changes in the utility's load. Utility programs falling under the umbrella of demand-side management include: load management, new uses, strategic conservation, electrification, customer generation, and adjustments in the market share" [29].

Any program intended to influence the costumer's use of energy is considered demand-side management. One of the most prominent practices of demand-side management is Demand Response (DR) program. This program has been very prominent in recent years. Demand Response is the ability to reduce electric usage at a facility in the event the utility or Independent System Operation (ISO) calls upon to do so. Electricity demand response is considered an effective way that can help manufacturers reduce electricity consumption, power demand, carbon footprints, and overall energy cost in a carbon-constrained world. By participating in the DR program, the electric consumer will get paid money based on the amount of energy usage which they are able to reduce under conditions when the power grid is stressed. In some states, like New York, the revenues are very high. As a matter of fact, the rate for the revenue is usually five times higher than the charging rate [30].

Although demand response program has a great number of benefits for consumer and utility, making decisions upon the call and implementing DR program in a facility is not easy on account of the fact that in most cases the electric consumer will be notified only a couple hours (or in some cases only 30 minutes) prior to start of each DR hours. In a nutshell, having a systematic approach in Demand Response program is crucial; a program which puts specific electricity consuming devices in priority or deferral to be allowed to run.

1.4 Literature Survey

This section offers an extensive yet concise review of current demand forecasting methods. It also covers current practices for demand management; i.e., demand response to provide a framework for the present study. There are a great number of reasons why conducting a review of relevant literature is useful for the purpose of the present study: It informs a summary of load forecasting methods on utility side and costumer side, the strategies that are developed to facilitate demand cost saving, and the gaps in the literature. At the conclusion of this section, the current gaps in demand forecasting and its applications are presented.

A great deal of work and research have been done in electricity demand forecasting and demand response program for electric power systems on both utility side and costumer side. A survey of these researches is presented in Table 1.1 at the end of this chapter. Most of the studies propose the concept and necessity of demand forecasting, a technique for load forecasting, pros and cons, verification of the method, and its application in the real world. However, maximum demand forecasting is usually the result of load forecasting in these literatures. In other words, most of the work has been done in forecasting the load pattern as the first step, instead of predicting the maximum demand itself. Predicting the maximum demand (and not the load pattern) will require less calculation, less data as input, and will take let time to be done.

Furthermore, most existing studies regarding demand forecasting and demand response have been conducted on utility side. In comparison, forecasting the maximum demand on the costumer side, known as behind-the-meter, can be as hard as doing so on utility side on account of the fact that having a much lower load, compare to utility load, makes the load profile more sensitive to electricity-consuming devices (such as chillers, HVAC, lights, etc.) while the impact of these sub-systems are indeed negligible in power system load forecasting. More gaps in the existing studies have been pointed out at the end of this chapter.

A thorough survey and literature review has been done on present techniques used in electricity demand forecasting by [17, 18, 31, 32]. Authors focused on summarizing the electricity demand forecasting techniques, their applications, and the reliability of each technique.

A large variety of mathematical methods have been developed for load forecasting in [4–6, 8–10, 12, 33]. Feinberg et al. (2003) apply econometric approach, which integrate statistical methods and economic theory when forecasting demand for electricity. They point out that the main advantage of econometric approach is that it can explain why demand can either increase or decrease in the future. Main drawback is that electricity cost changes have to remain the same for upcoming time.

Kandil et al. (2001) categorize forecasting methods as qualitative and quantitative methods. They used classical long-term forecasting time-series methods, i.e., straight line, logistic, gompertz, exponential, and polynomial to model the utility load and then compared the results with stochastic models, exponential smoothing, decomposition model, and casual method. Moreover, they proposed a new model of load forecasting for fast growing power system, which has taken into account the different levels of maximum temperature and some levels of social activity.

Hippert et al. (2001) emphasizes the importance of neural networks and fuzzy system in modeling automatically complex nonlinear inputoutput relationships through learning process using a database of load and explanatory variables. This method shows better accuracy in VSTLF and STLF compare to MTLF and LTLF. Main drawback is the complexity of the method which requires more inputs.

Kiartzis et al. (2000) tested their proposed fuzzy expert system for peak load forecasting by using historical load and temperature data of the Greek interconnected power system. Test results show that the fuzzy expert system can forecast future loads with an accuracy comparable to that of neural networks.

Sun et al. (2016) consider HAVC system and manufacturing system as dependent systems by considering the temperature as a function of manufacturing operation to find an optimal demand response strategy [34]. This strategy is very suitable in some specific industrial processes where temperature plays a critical role in the manufacturing quality and production (e.g., paint shop). However, the drawback of this method is that in most of the manufacturing facilities these two sub-systems are independent and can play role in maximum demand independently.

A great number of researches have been conducted in commercial section. On e of the most important factors in this section is occupant behaviors. Results of a questionnaire conducted by Nisiforou (2012) revealed in [35] that while employees are willing to engage in energy saving methods, "they are not willing to sacrifice their own personal satisfaction for these measure".

Table 1.1.: Summary of the literature survey in electricity demand forecasting and demand-side management

Research Characteristics	**Methodology Used**	**Results Obtained**	**Author Name (year)**
Discuss motivations as well as pros and cons of electricity demand forecasting techniques	Present techniques used in electricity demand forecasting to increase the efficiency of power system	Survey and summarize the electricity demand forecasting techniques and their applications.	Alkhathami et al.(2015) [31] Suganthi et al. (2012) [32]
Load forecasting methods for power system management	Load forecasting techniques can be classified as follows: • Economic approach • Multiple regression • Exponential smoothing • Adaptive load forecasting • Time series	Main advantage of Econometric approach is that it can explain why demand can either increase or decrease in the future. Main drawback is that electricity changes have to remain the same. Although the times series approach is still widely used, newer techniques offer a lot of promise for developing the methodology used for load forecasting.	Feinberg et al.(2003) [4] Hyndman et al.(2014) [5] Kandil et al.(2001) [6] Chikobvu et al.(2012) [9] Amjady et al.(2001) [10] Sigauke et al.(2010) [12] Fan et al.(2014) [15]

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Table 1.1.: *continued*

Research Characteristics	**Methodology Used**	**Results Obtained**	**Author Name (year)**
Recent techniques for load forecasting	Recent load forecasting methods: • Neural Networks • End-use Models • Genetic Algorithm • Fuzzy system • Artificial Intelligent Techniques	Over the last few years, the most active research in load forecasting has been neural network. Neural networks and fuzzy system can model automatically complex nonlinear inputoutput relationships through learning process using a database of load and explanatory variables. Genetic Algorithms includes impression, non-linearity, robustness, and uncertainty in the process of computing. Artificial intelligent has proven itself as one of the most reliable techniques.	Islam(2011) [16] Kalogirou(2000) [17] Hippert et al.(2001) [18] Li et al.(2013) [21] Feinberg et al.(2003) [4] Abdel-Aal(2006) [13] Amin-Naseri et al.(2008) [14] Fan et al.(2014) [15]

continued on next page

Table 1.1.: *continued*

Research Characteristics	**Methodology Used**	**Results Obtained**	**Author Name (year)**
Demand-side management/Demand Response techniques	Particle swarm optimization (PSO)	HAVC system and manufacturing system are dependent systems by considering the temperature as a function of manufacturing operation to find an optimal demand response strategy.	Sun et al.(2016) [34]

1.4.1 Research Needs

After conducting a review of relevant literature, it appears that there are several important gaps in the literature that the method proposed as part of the present study paper addresses. The gaps are both in demand forecasting part and demand management part:

- Boroojeni et al. (2017) and many others (see [4,10,16,20–23,33]) focus on maximum demand forecasting as a result of load forecasting; consequently, most of the work has been done in forecasting the load pattern as the first step, instead of predicting the maximum demand itself. Predicting the maximum demand (and not the load pattern) will require less calculation, less data as input, and will take let time to be done. The present study proposes a novel maximum demand-forecasting algorithm from very short-term to short-term horizon, called Adaptive Rate of Change (ARC), which predicts maximum demand as the first and primarily result.

- Most of the existing studies regarding demand forecasting and demand response have focused on utility side [6, 9, 12, 13, 25]. In comparison, forecasting on the electric consumer side can be challenging as utility side since the load profile of the facility is more sensitive than a larger power system. Moreover, forecasting the electric demand on the costumer side would play a very crucial role for planning the electric infrastructure in the utility side. The application of the method proposed in this study is more applicable to the consumers; however, the application for the lager power systems can be investigated.

- Sun et al. (2014) find an optimal demand response strategy using particle swarm optimization (PSO) by considering HVAC system and manufacturing system as two dependent systems, while these two systems are independent in most of the cases. Furthermore, HVAC system and manufacturing system have been studied as a single unit; therefore, the study would not provide the costumer the impact of each sub-system on the maximum demand. The present study directly investigates these gaps in research by measuring the impact of specific electricity-consuming device/devices (e.g., chillers, HVAC unit, lights, etc.) as sub-systems individually on maximum demand.

- Powell et al. (2016) and many others assume HVAC load is a function of number of occupants and they have not considered the influence of occupants behavior itself in maximum demand forecasting. While in a great number of cases as Nisiforou (2012) revealed, occupant behaviors, and not necessarily the number of occupants, can have a crucial impact on demand saving by sacrificing their own personal satisfaction. The present study investigates not only the impact of the number of occupants in Maximum Demand, but also the occupant behaviors implicitly.

1.5 Research Goals

This section discusses the research goals of this dissertation. The purpose of the study described in this paper was first to provide the electric consumer a tool to forecast the maximum daily demand. Residential, commercial, and manufacturing sectors have been considered in this study. The second purpose was to provide a method for decreasing the forecasted peak demand by understanding the impacts of number of degree-days, number of occupants, and number of productions. It also identifies the sensitivity of maximum daily demand to different sub-systems, such as HVAC, boiler, furnace, lighting, air compressor, etc. Finally, it identifies conditions for and magnitude of cost savings associated with maximum daily demand management.

2. METHODOLOGY

In this section, the methodology of a novel maximum demand forecasting and management method have been proposed. In section 2.1, after Rate-of-change method explanation, a novel maximum demand forecasting algorithm, denoted as Adaptive-Rate-of-Change (ARC) has been proposed in detail. The ARC algorithm is applicable to very short-term and short-term forecasting methods to predict Maximum Demand one or several hours into the future. In section 2.2, a new method for Maximum Demand Management (MDM) has been proposed. The MDM method helps the end-user to understand out how temperature, production, and occupancy affect Maximum Demand (MD). In section 2.2.4, a novel MDM approach is proposed to manage the maximum demand by defining a specific electricity-consuming device (or devices) as sub-system in a manufacturing facility or a commercial building.

2.1 Adaptive-Rate-of-Change (ARC) Algorithm

This section presents the proposed Rate-of-Change (ROC) methodology, denoted as Adaptive Rate of Change (ARC). The algorithm uses the historical demand data as the only input which is provided by utility provider. This method does not intend to forecast the magnitude of the electric demand but rather predicts the time that the maximum demand would occur. The ARC algorithm consists of two phases. In the first phase the algorithm uses historical demand data to calculate the rate of change with respect to each time interval and then determines how many positive ROCs of the trend are involved in the development of a local maximum demand. After determining the reference ROC, the algorithm starts to monitor real-time demand data in the second phase to calculate moving standard deviation. At the end, the result of the algorithm would be an alert for an upcoming spike which meets two specified criteria.

In section 3.1 the ARC algorithm has been applied on two case studies. The results of the algorithm have been verified in section 4. At the end of section 2.2, the results of the ARC algorithm has been used with MDM method to present a systematic approach for planning and decision making.

Representing the electric demand pattern as a time series is generally accepted [36]. A time-series is a sequence of data points, usually consisting of consecutive measurements occurred over a time interval [3]. Such time series function takes into account one or more factors which affect Maximum Demand (MD); i.e., time, social, economic, temperature, and noise component. Interference noise component is a crucial factor in very short-term forecasting methods since the forecasting is based on real-time data collected for an electric consumer or a specified system in the facility. Noise can be generated from machinery, nearby power lines, computers, etc. Noise can be reduced by not being close to noise sources or using an insulated Faraday cage for measuring and logging data.

The temperature factor has been the focus of a great number of previous studies; however, using this factor alone is not a feasible approach for manufacturing facilities. Furthermore, time factor definitely plays a crucial role in Maximum Demand forecasting. Time is the factor which takes into account the shift start time, lunch break, number of shifts, shift duration, and indicates if a company follows a specific operating schedule or not.

The time series function for demand pattern can then be modeled as a stochastic process, representing by Gupta in [37] as:

$$X_t = T_t + S_t + I_t \tag{2.1}$$

Where T_t is the normal or trend component which represents the general shape of the demand pattern; S_t is the seasonal component which represents the temperature effect on demand, and I_t is the noise component of the peak demand. Noise plays a very crucial role when the case study is a low power system (i.e., the magnitude of the noise spike is similar to the inrush current). In the original setting the seasonal effect is a long-term seasonal stochastic influence on the curve. In our short-term real-time setting strategy, this can be viewed as the temperature/weather effect which varies throughout a daily operation as given in Eq.(2.2).

$$T_t = T_{t-1} + q_t \tag{2.2}$$

Equation(2.2) represents that the trend component is changed by the q factor at any time t. The change factor q is generated by u, which is a stationary, zero-mean as it is represented in Eq. (2.3). The noise component, I_t, can be modeled as Eq. (2.4) to be sampled from ϵ, which is a stationary, zero mean, and white noise process with an unknown variance.

$$q_t = q_{t-1} + u_t \tag{2.3}$$

$$I_t = I_{t-1} + \epsilon_t \tag{2.4}$$

Therefore, the change in the demand pattern can be modeled as Eq.2.5. This is a simplified model as the seasonal effect between two very short increments is negligible.

$$\Delta X = X_t - X_{t-1} = (T_t + S_t + I_t) - (T_{t-1} + S_{t-1} + I_{t-1}) = q_t + \epsilon_t \tag{2.5}$$

where ϵ is the aggregated stationary, zero-mean, white noise process, constituting the trending random walk and the noise random walk. In a nutshell, the change in demand is a function of change factor q and random noise processes ϵ.

As the focus in this study is forecasting maximum daily demand (MDD) for the whole residential, commercial, and manufacturing facility the noise component (ϵ_t) can be assumed much smaller than the trend component of demand (q_t). Therefore by assuming $q_t >> \epsilon_t$, Rate-of-Change (ROC) is define as follow:

$$ROC = \frac{X_t - X_{t-1}}{t_t - t_{t-1}} = \frac{q_t + \epsilon_t}{t_t - t_{t-1}} \tag{2.6}$$

then,

$$ROC = \frac{\Delta X_t}{\Delta t} \tag{2.7}$$

Owing to the fact that the rate of change for demand is a mean reverting process, the Eq.(2.7) will approach to zero when demand curve gets close to its peak. In other words, the ROC slows down when the electrical demand curve is about to revert as is shown in Eq.(2.8) [38].

$$\lim_{X_t \to peak} \frac{dX_t}{dt} = 0 \tag{2.8}$$

Figure 2.1 shows the flowchart representation of the ARC algorithm. As it is shown, the algorithm consists of two phases. The only input for the first phase is historical demand data. In this phase the ROC will be calculated for each time interval by using Eq.(2.7). The ROC would be positive if demand increases for that specific interval and would be negative if demand decreases. Next step, the algorithm would investigate each time-interval to find out if that interval has been involved in the positive increment or not. It is an incontrovertible fact that every local or global maximum demand is the last incident of a single or series of positive slopes as it is explained in Table 2.1. As it is shown in the table, in this case, a spike in demand has occurred on $13:30:00PM$ after three positive ROCs in a row. Afterward, the algorithm determines the statistical mode of the positive ROCs leading to peaks, and in the last step, it would calculate the mode of chosen ROCs (in that specific number of positive ROCs), denoted as reference ROC.

It is recommended that the historical data used in this section be chosen from the same month which the forecasting is going to be occurred on account of the fact that the similarity of the historical data to the forecasting period would be most probable due to the fact that the conditions which have effect on demand (i.e., weather, production, etc.) would be similar.

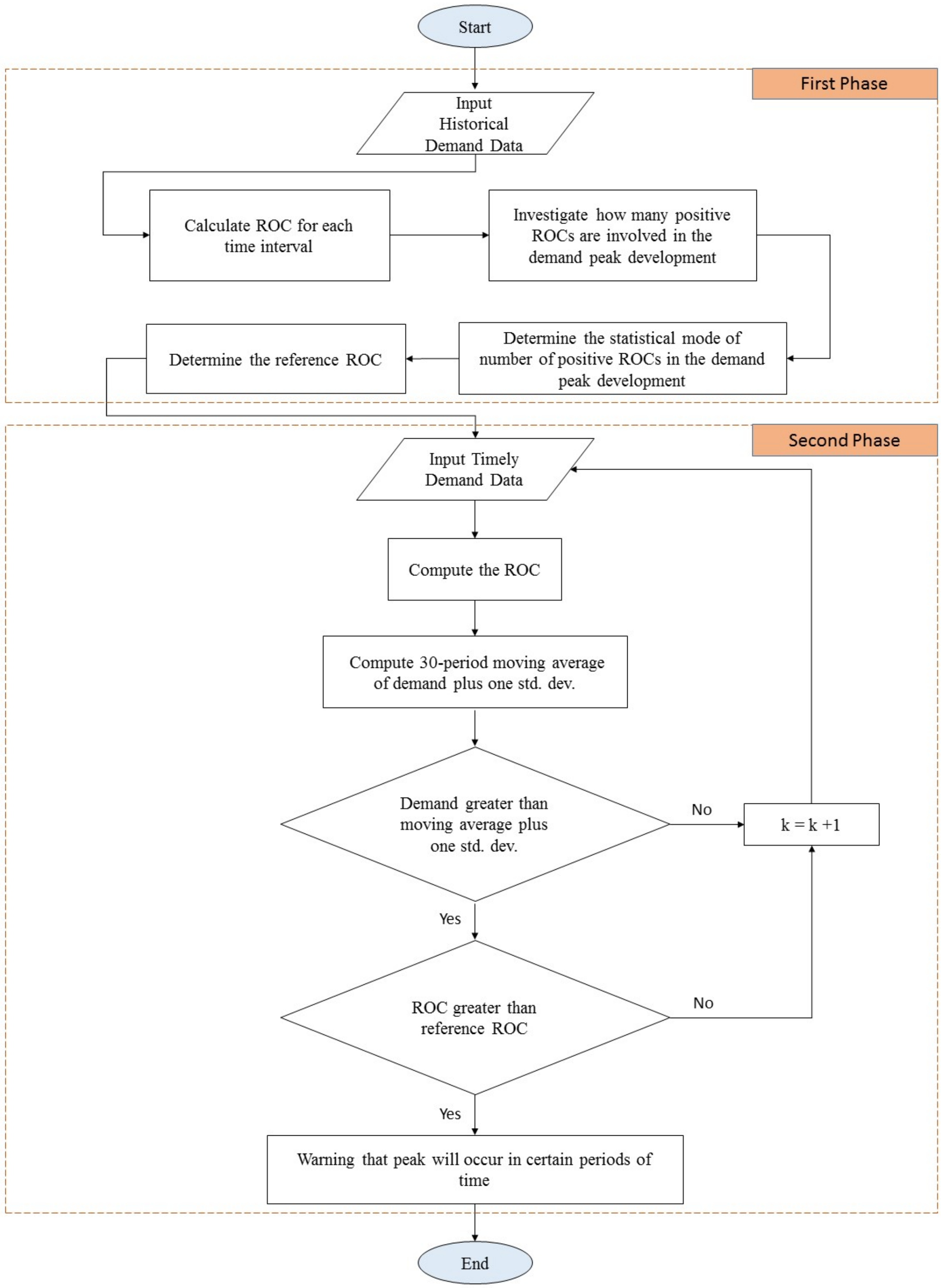


Fig. 2.1. The flowchart representation of the ARC methodology

Table 2.1.
An example of calculating number of ROCs leading to a spike in demand

	Time	**Demand(kW)**	**ROC**	**Positive?**
	12:30:00 PM	439.3		
	12:45:00 PM	428.64	-0.7107	0
	13:00:00 PM	549.96	8.0880	1
	13:15:00 PM	601.44	3.4320	1
Spike in Demand	13:30:00 PM	611.16	0.6480	1
	13:45:00 PM	571.21	-2.6633	0
Total steps involved				3

The second criteria is defined in the second phase of the algorithm. First, the method imports demand data and starts to calculate current ROC as well as the 30-period moving average plus one standard deviation. Current demand has to be greater than moving average plus one standard deviation to meet the first criteria. Moving average ha been chosen since peak demand is a real-time mean reverting process. One standard deviation makes the model insensitive to local minimums and maximums. Having a greater ROC than the reference ROC is the second criteria for a spike to be identified as an alert. Afterward, the algorithm checks the data to see if it meets both criteria. If the spike meets both conditions, the algorithm would issue a warning that the peak will occur in certain periods of time. The confidence time window for the algorithm is twice as the interval owing to the fact that only assuming one interval further as a positive increment is safe otherwise the accuracy would decrease by widening the confidence window. It is worth mentioning that this algorithm is not only a very short-term forecasting algorithm, but also it can be used as a short-term forecasting method by having the input data in longer intervals. For instance, by using maximum daily demand (MDD) as the input the results of the algorithm would be in a confident window of a day.

2.2 Maximum Demand Management

In section 2.1, a new maximum daily demand forecasting method was proposed. The results of ARC algorithm will be presented in 3.1. Once the maximum daily demand is forecasted, the user needs to take action for decreasing the load at that specific forecasted time. In this section, a new method for Maximum Demand Management (MDM) has been proposed. The focus of this study is to define a regression model which contains explanatory variables to find out how temperature, production, and occupancy affect Maximum Daily Demand (MDD). Each explanatory variables has different effects on Maximum Demand and it has been determined independently. This method can be applied in residential, commercial, and manufacturing sectors. In contrast to previous studies [6, 9, 12, 13, 25], this study is conducted on the consumer side.

In section 2.2.4, the study goes further to identify the impact of specific electricity-consuming device/devices (e.g., chillers, HVAC unit, lights, etc.) as sub-systems individually on maximum daily demand. The results of these two different methods help the electric consumers in residential/commercial sectors, with no technical background, to decrease their maximum demand. Moreover, it helps the consumers in commercial/manufacturing sectors to get a better understanding of their electric demand systems, demand-side management (i.e., by being involved in Demand Response program, etc.), and planning for on-site electric power generation, known as distributed generation (DG).

2.2.1 Temperature

Outside temperature plays a crucial role in the time and magnitude of electric demand. The electric demand for a cooling/heating load is a function of outside temperature. In a residential/commercial sector the electric demand associated with cooling/heating loads may be changed significantly throughout the course of a year to maintain the conditions of the air space within comfort zone (defined by

ANSI/ASHRAE standard 55). However, in manufacturing sector, as Sun et al. (2016) mention in [34], for a vast majority of industrial processes the temperature does not influence the production; therefore, the load on a heating/cooling system is independent from the operation of manufacturing system. Those industrial processes where temperature plays an important role in the manufacturing quality and productivity (e.g., paint shop) are out of the scope of this dissertation.

The degree-days

Degree-day is a measure of the energy requirement for heating and cooling of buildings. "The degree-days of a time interval (monthly, seasonal, and annual) are defined as the summation of the temperature anomaly between the mean daily air temperature and the base temperature" [39]. For a time interval of n days accumulated heating degree-days can be defined as:

$$HDD = \sum_{i=1}^{n} (T_{bh} - T_{meani})^{+} \tag{2.9}$$

In Eq.(2.9), T_{meani} is the daily mean air temperature, defined as $T_{meani} = (T_{maxi} + T_{mini})/2$, where $T_{maxi}(T_{mini})$ is the daily mean maximum (minimum) air temperature; T_{bh} is the base temperature and is usually defined as 10°C, 12°C, 14°C, 16°C, and 18°C [40]. Similar to HDD, CDD can be defined as:

$$CDD = \sum_{i=1}^{n} (T_{meani} - T_{bc})^{+} \tag{2.10}$$

where, T_{bc} is the base temperature and is usually defined as 18°C, 20°C, 22°C, 24°C, and 26°C [40]. In the current study T_{bh} and T_{bc} are defined as 18°C since this base is the most common in literatures. n is also consider as one in this study, since CDD and HDD will be defined for each day later on. Figure2.2 shows the load diagram for an assembly manufacturing facility with an air-conditioned space. In this facility, the energy associated to cooling/heating load is very significant compare to manufacturing load. Figure 2.2(a) is the load diagram for a week (n = 7) in the

Winter with $HDD = 28°$C. As it is indicated in the graph, the demand spikes have been occurred between $7 - 8 : 30AM$ due to the heating load during the start-up. Figure 2.2(b) is the load diagram for a week ($n = 7$) in the Summer with $CDD = 8°$C. The demand spikes have been shifted to the afternoon between $1 : 30 - 3PM$ due to the cooling load in the facility (operation schedule has been almost the same for the chosen weeks). Comparing two graphs reveals that degree-days affects the time and the magnitude of electric demand significantly throughout the course of a year. Therefore, maximum daily demand (MDD) can be written as a function of degree-day (DD):

$$MDD = f(Degree - day) \tag{2.11}$$

Degree-day (DD) can be either HDD or CDD depends on T_{mean}. When $T_{mean} > 18°C$, CDD will be considered and in case $T_{mean} < 18°C$, HDD will be considered in calculations. In days with $T_{mean} = 18°C$, $HDD = CDD = 0°C$

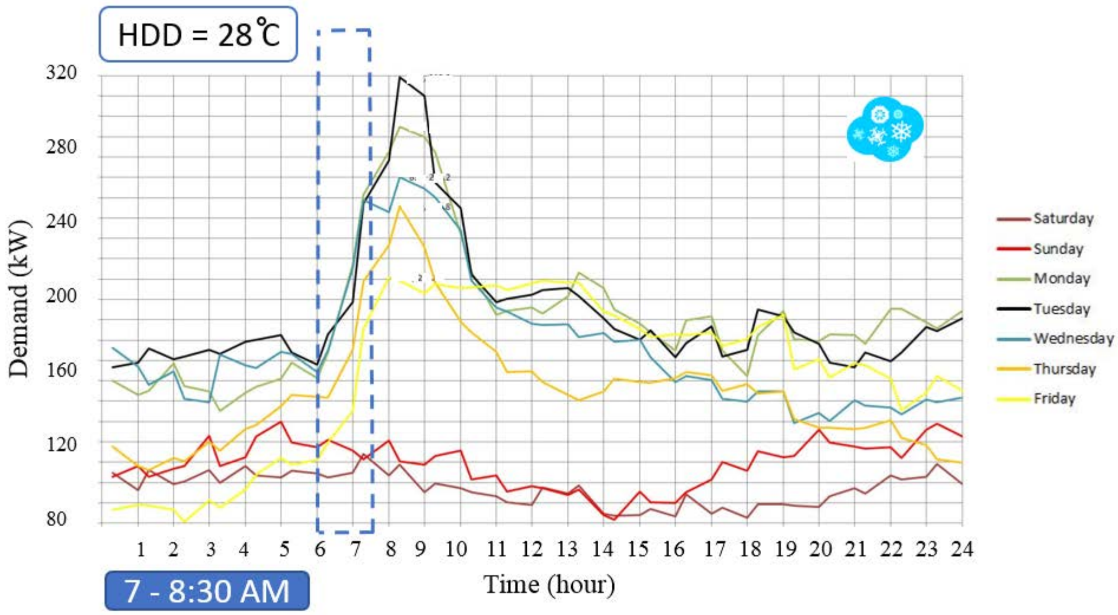
Regression Model

The regression model can be obtained by assuming the maximum daily demand (MDD) as an explained variable and the degree-days as an explanatory variable [5]. Accordingly, the model includes the days with the same number of occupants and the same occupied period for residential/commercial consumers. For manufacturing facilities, days with the same number of productions have been considered regardless of the number of occupants. Figure2.3 shows the maximum daily demand (MDD) increases as the outside air temperature increases. The parameters α_1 and α_0 determine the slope and the intercept of the line respectively:

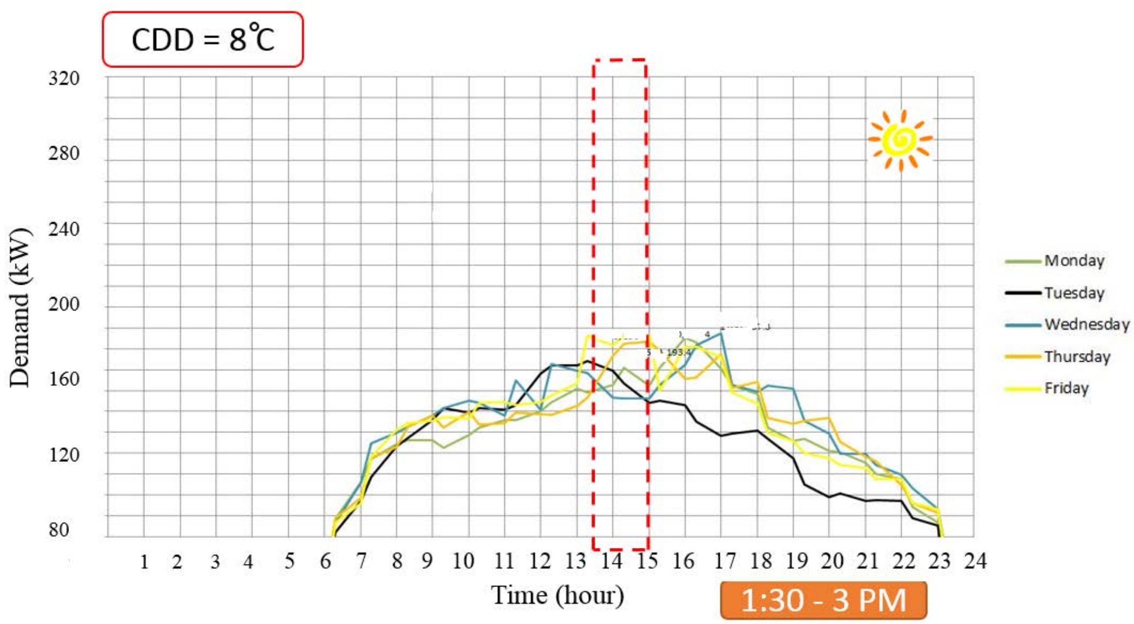
$$MDD = \alpha_0 + \alpha_1(DD) \tag{2.12}$$

The unit of regression coefficient α_1 is $kW/°C$ which describes the sensitivity of the maximum daily demand to the number of degree-days as it is defined in Eq.(2.13).

$$\alpha_1 = \frac{d(MDD)}{d(DD)} \tag{2.13}$$



(a) Load diagram in the Winter



(b) Load diagram in the Summer

Fig. 2.2. Load diagram for a manufacturing facility with air-conditioned space

It is worth pointing out that having daily mean air temperature T_{meani} instead of degree-days in the regression model will provide the same results due to the fact that Eq.(2.9) and Eq.(2.10) are linear functions.

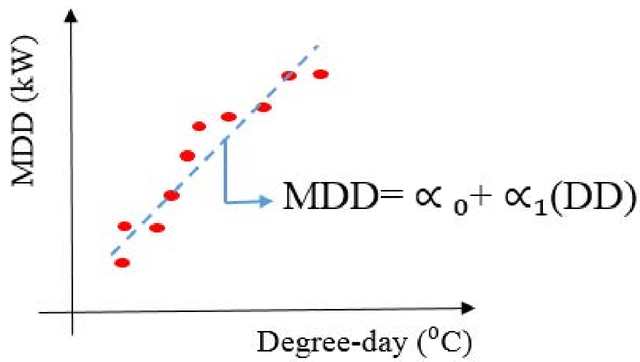


Fig. 2.3. Regression model of MDD as a function of degree-days

2.2.2 Production

Manufacturing processes dominate a large portion of maximum demand for manufacturers. Air compressor, lighting, furnace, boiler, vacuum, and grinder are just a few examples of significant electricity-consuming devices in manufacturing sector. In several cases, maximum demand is the aggregate of inrush currents during the start-ups.

For a vast majority of industrial processes the temperature does not influence the production; hence the operation of manufacturing process is independent from the cooling/heating loads. Therefore, maximum daily demand (MDD) can be written as a function of the number of production (P):

$$MDD = f(Production) \tag{2.14}$$

Regression Model

Similar to previous section, the regression model can be obtained by assuming the maximum daily demand (MDD) as an explained variable and the number of production (P) as an explanatory variable. Accordingly, the model includes the days with the same degree-days for manufacturing consumers to find out the impact of the number of production on MDD. Figure 2.4 shows the maximum daily demand (MDD) increases as the number of production increases. The parameters β_1 and β_0 determine the slope and the intercept of the line respectively:

$$MDD = \beta_0 + \beta_1(P) \tag{2.15}$$

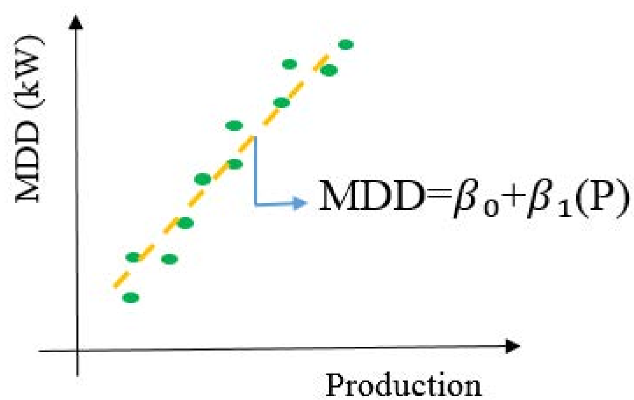


Fig. 2.4. Regression model of MDD as a function of number of production

The unit of regression coefficient β_1 is $kW/number of production$ which describes the sensitivity of the maximum daily demand to the number of production (P) as it is defined in Eq.(2.16).

$$\beta_1 = \frac{d(MDD)}{d(P)} \tag{2.16}$$

2.2.3 Occupancy

The use of appliances, lighting, and domestic hot water within a residential /commercial building varies considerably with respect to number of occupants, occupied period, and occupant behaviors. The present study investigates not only the impact of the number of occupants in maximum daily demand, but also the occupant behaviors implicitly. Occupant behaviors can have a crucial impact on electric demand by sacrificing their own personal satisfaction or consuming excess energy based on their own desirables. Therefore, maximum daily demand (MDD) can be written as a function of occupancy (Ox):

$$MDD = f(Occupancy) \tag{2.17}$$

Monitoring the occupancy in residential/commercial sectors can save a great deal of electric energy which the electric consumers do not even use. Although it is out of the scope of this dissertation, monitoring the occupancy would also reveal the idling equipment, and phantom load. Phantom load is electricity used by devices that are turned off but still plugged into an outlet.

Regression Model

The regression model can be obtained by assuming the maximum daily demand (MDD) as an explained variable and the occupancy (Ox) as an explanatory variable. Accordingly, the model includes the days with the same degree-days for residential/commercial consumers to find out the impact of occupancy on MDD. Figure2.5 shows the maximum daily demand (MDD) increases as the occupancy increases. The parameters γ_1 and γ_0 determine the slope and the intercept of the line respectively:

$$MDD = \gamma_0 + \gamma_1(Ox) \tag{2.18}$$

The unit of regression coefficient γ_1 is $kW/numberofoccupants$ which describes the sensitivity of the maximum daily demand to the occupancy (OX) as it is defined in Eq.(2.19).

$$\gamma_1 = \frac{d(MDD)}{d(Ox)} \tag{2.19}$$

In a nutshell, Table 2.2 indicates the conditions for defining regression coefficients. The conditions depend on the electric sector category (residential, commercial or

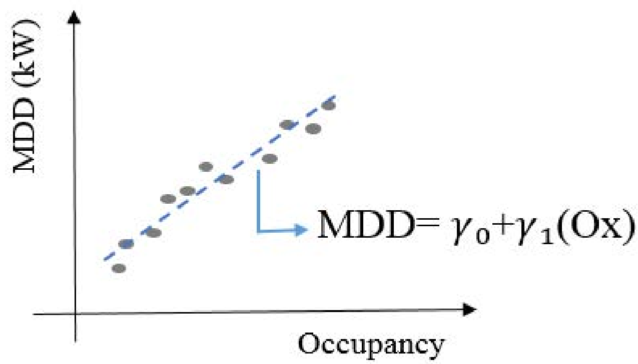


Fig. 2.5. Regression model of MDD as a function of occupancy

manufacturing). For instance, β_1 can only be defined for manufacturing sector for a period of time while number of degree-day (DD) is fixed and number of production (P) varies regardless of occupation status.

Table 2.2.
Conditions for defining regression coefficients α_1, β_1, and γ_1 in different electric sectors

Reg. Coeff.	**Resid./Commercial**			**Manufacturing**		
	DD	P	Ox	DD	P	Ox
α_1	variable	n/a	fixed	variable	fixed	n/a
β_1	n/a	n/a	n/a	fixed	variable	n/a
γ_1	fixed	n/a	variable	n/a	n/a	n/a

The results of section 2.2.1, 2.2.2, and 2.2.3 will help the electric consumer to get a better understanding of their maximum daily demand and how temperature, number of production, and occupation affect it during a specific period of time by using historical data as input to find explanatory variables. Finally, the energy manager would be able to manage the maximum demand of the facility by changing temperature or number of production. Similarly, the operation manager/householder can manage the maximum demand in commercial/residential sector by changing the temperature or the number of occupants to have the correlated saving on maximum demand.

2.2.4 Sub-system Approach

In some cases, changing temperature, number of production, or number of occupants is not a feasible solution for demand management and maximum demand (MD) has to be controlled by load-shedding. Load shedding is the action to reduce the power consumption to keep the power demand below a defined level [41]. Seeking to have demand management by load shedding come to full fruition by finding out how does each sub-system affect the maximum daily demand (MDD). Therefore, maximum daily demand (MDD) for an end-user can be written as a function of maximum daily demand of a sub-system ($MDD_{Sub-system}$):

$$MDD = f(MDD_{Sub-system}) \tag{2.20}$$

while $MDD_{Sub-system}$ itself can be a function of degree-days, occupation, and number of production. Regression coefficients for a sub-system can be defined as follows:

$$\alpha_1^{`} = \frac{d(MDD_{Sub-system})}{d(DD)} \tag{2.21}$$

$$\beta_1^{`} = \frac{d(MDD_{Sub-system})}{d(P)} \tag{2.22}$$

$$\gamma_1^{`} = \frac{d(MDD_{Sub-system})}{d(Ox)} \tag{2.23}$$

Figure2.6 shows the correlation between the total maximum daily demand (MDD) and a sub-system's maximum daily demand ($MDD_{Sub-system}$). In this case, the correlation is degree-days; however, it can be also defined based on occupants and number of production. It is worth to mention that the conditions represented in Table 2.2 are still necessary.

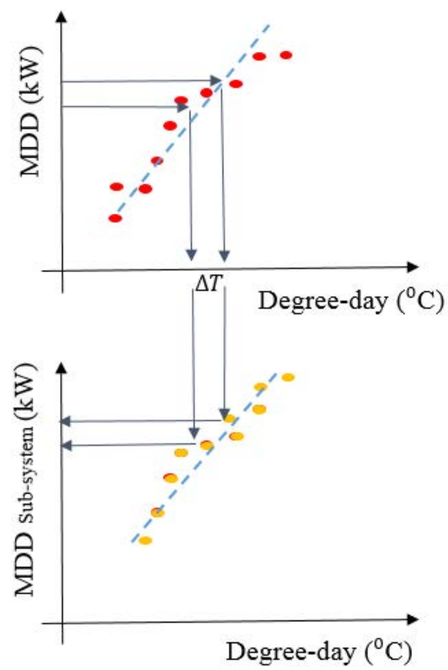


Fig. 2.6. The correlation between MDD and MDD_{Sub_system}

Consequently, by considering the relation of the total MDD with $MDD_{Sub-system}$, and using Eq.2.13, Eq.2.16, Eq.2.19, Eq.2.21, Eq.2.22, Eq.2.23, regression coefficients (corresponding factors) in this model can be defined as:

$$\alpha_{Sub-system} = \frac{d(MDD)}{d(MDD_{Sub-system})} = \frac{\frac{d(MDD)}{d(DD)}}{\frac{d(MDD_{Sub-system})}{d(DD)}} = \frac{\alpha_1}{\alpha_1^{'}} \tag{2.24}$$

$$\beta_{Sub-system} = \frac{d(MDD)}{d(MDD_{Sub-system})} = \frac{\frac{d(MDD)}{d(P)}}{\frac{d(MDD_{Sub-system})}{d(P)}} = \frac{\beta_1}{\beta_1^{'}} \tag{2.25}$$

$$\gamma_{Sub-system} = \frac{d(MDD)}{d(MDD_{Sub-system})} = \frac{\frac{d(MDD)}{d(Ox)}}{\frac{d(MDD_{Sub-system})}{d(Ox)}} = \frac{\gamma_1}{\gamma_1^{'}} \tag{2.26}$$

Nature of the load in terms of its occurrence would be an indicator for selecting a device as a sub-system. The nature of electric loads have been categorized by IEEE Std 141-1993 as follows [2]:

- Continuous

  The electric demand for such load is always greater than zero and the load diversity is slightly less than 100%. Lighting is an example of a continuous load.

- Intermittent

  Intermittent loads occur at irregular intervals. Air compressor, roof-top units (RTUs), chillers, and refrigerators are examples of this type.

- Cyclical

  Cyclical loads occur at regular intervals with a repetitive pattern in load profile. Loads controlled by time relay circuits are in this category.

- Special or unusual loads

  There is no pattern in load profile. Such as resistance welding, arc welding, induction melting, etc.

- Combination of above

Generally, sub-system shall be chosen not only among significant electricity-consuming devices throughout an/a industrial/commercial facility, but also the loads which do not have continuous natures of occurrence. Due to the fact that such loads can cause a positive rate-of-change in demand ($dX_t > 0$ in Eq.(2.7) over a time period dt), while for continuous loads, $dX_t = 0$ (except during start-up periods). HVAC, chiller, air compressor, and pumps are among sub-systems which have significant effect on maximum demand.

Shedding is effected on a priority basis, and in accordance with load defining parameters and priorities defined by load operational levels automatically or manually sensed or entered into the overall building automation system (BAS).

3. CASE STUDY

In section 3.1, the ARC algorithm is implemented on two different case studies. In 3.1.1, the ARC algorithm has been implemented on an aluminum die casting facility to build an hour-ahead maximum demand forecaster using three weeks of historical demand data. In 3.1.2, the same forecaster has been developed for a generator manufacturer by using three months of historical demand data. In chapter 4, the results from the algorithm have shown 84% successful rate on forecasting maximum demand for case study II.

In section 3.2, the new MDM method is implemented on the same aluminum die casting company to find out the sensitivity of maximum daily demand to the air handling units.

3.1 Adaptive Rate-of-Change (ARC) Results

In this section ARC algorithm is implemented on two different real case studies to develop a VSTLF,STLF and MTLF. Case study I is an aluminum die casting company and case study II is a generator manufacturer company. Both manufacturing facilities are located in Indiana, U.S., and for both cases demand charge is a large portion of the electric bill. In case study I, only two weeks have been used to determine the reference ROC while in case study II three months of historical demand data has been used. In each case study, the use of the ARC algorithm is demonstrated by showing the results of each step represented in section 2.1. In chapter 4, the ARC algorithm has been evaluated, and superior performance of our proposed methodology is illustrated.

3.1.1 Case Study I

Case study I is a metal die casting facility, located in Shelbyville, Indiana, U.S., with a great volume of electricity consumption due to the nature of its production. The facility works 24/7 in three shifts. Shift hours is shown in Table 3.1. Demand for this facility is being recorded every 30 min and the greatest of all demands in a month will be used for utility billing purposes. Table 3.2 shows the summary of electric consumption in 2016 for this facility. As it is shown, the facility consumed 14,122,924 kWh of electricity with the highest monthly peak demand of 2,213 kW occurred on Aug. 4, 2016 at 15:00.

Table 3.1.
Shift hours for case study I

Shift	Shift starts- Shift ends
1^{st}	6:30 AM- 3 PM
2^{nd}	2:30 PM- 11 PM
3^{rd}	10:30 PM- 7 AM

Electricity rates are declared in the rate structure, provided by local utility provider. The Energy Charge is \$0.016275/ kWh and Demand Charge is \$13.08/kW. However, by considering different riders, these rates would be higher. For instance, as is shown in Fig.3.1, the electricity bill for March 2016 shows the total demand charge of \$26,243.71 which is based on \$13.08/kW. However, by considering all electric demand riders, which have been indicated by arrows, the demand rate would increase to \$23.31/kW. Table 3.3 shows the electricity analysis for 2016 including different riders. Electricity usage vs. demand in 2016 is shown in Fig.3.2. As it is shown in Table 3.4, demand cost is accounted for 58% of the total electricity charge in 2016. Therefore, maximum demand study would help the end-user to cutdown total electric charge.

Table 3.2.
Summary of electric consumption for case study I in 2016

Weekday Maximum Demand (kW)	2,213
Weekend Maximum Demand (kW)	2,059
Power Factor at Time of Maximum Demand	79.36%
Maximum Reactive Demand (kVAR)	1,728
Load Factor	0.7266
Total Energy Usage (kWh)	14,122,924
Maximum Demand (kW)	2,213
Maximum Demand Time	08/04/2016 15:00

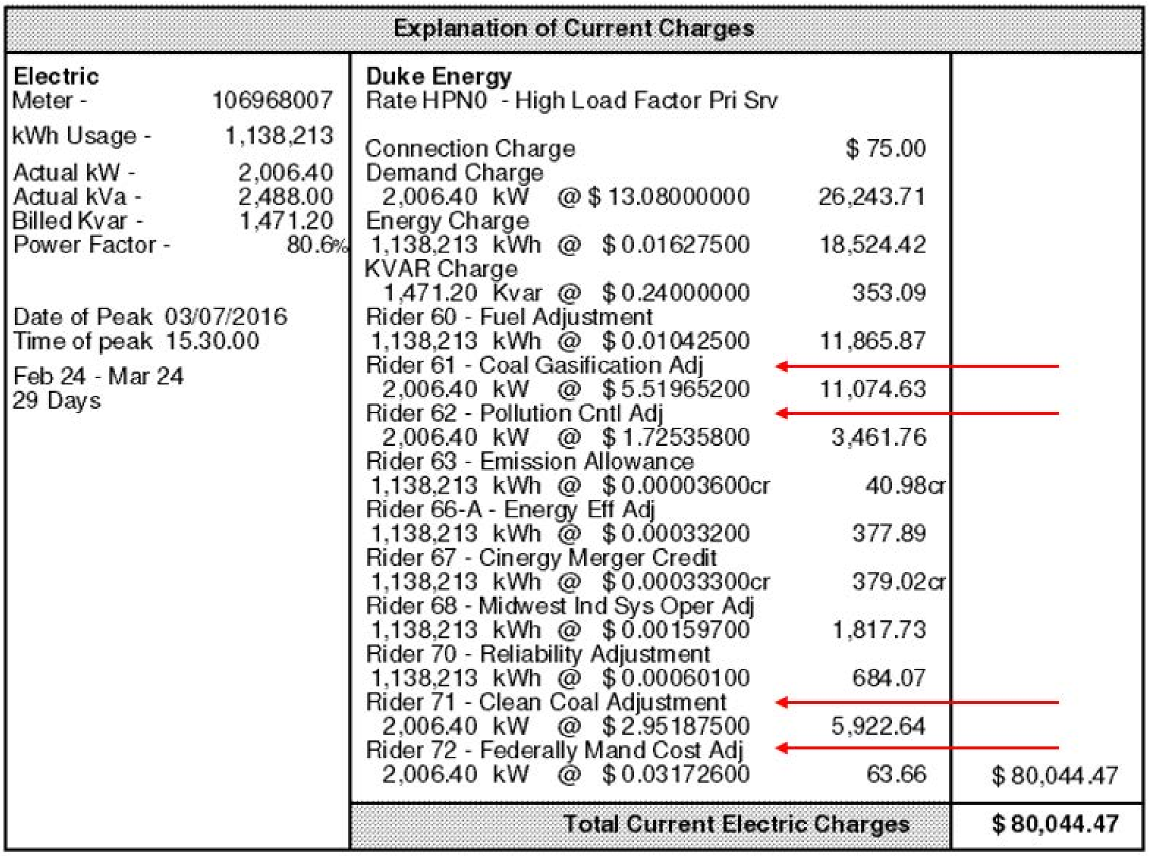
Using the method described in 2.1, the ARC algorithm will be applied on case study I to forecast peak demand for the last week in March 2016. As it is recommended in 2.1, the historical data shall be chosen from the same month which is going to be foretasted; therefore, two weeks of demand data in March 2015 have been used for the first phase of the algorithm. First the ROC will be calculated for each time interval by using Eq.2.7. Then the algorithm investigates each time-interval to find out if that interval has been involved in the positive increment or not. As is shown in Fig.3.3, throughout the historical demand data, peaks can be induced by several number of positive ROCs, among which 2 positive ROCs provides the strongest signal, which is the statistical mode.

Next step is selecting reference ROC by calculating the mode of ROCs when the number of positive ROC equals 2 steps. In this case the reference ROC is 1.5 kW/min. Therefore, peaks occur most frequently in 2 time intervals $(2 * 30min = 1hr)$ with the slope of 1.5 (kW/min) from the start point to the peak.

Once the reference ROC is determined, second phase starts by importing demand data as input. The algorithm calculates ROC for each time interval as time moves on. At the same time it computes the moving average of demand plus one standard

Table 3.3.
Electricity analysis for case study I in 2016 including all riders

Date	**Energy Usage (kWh)**	**Demand (kW)**	**Power Factor**	**Total Energy Charge**	**Total Demand Charge**	**Total Cost**
Jan-2016	1,163,114	2,004	78.6%	$32,196	$44,906	$77,866
Feb-2016	1,124,635	2,026	79.4%	$31,131	$47,214	$79,067
Mar-2016	1,138,213	2,006	80.6%	$32,850	$46,766	$80,353
April-2016	1,202,500	2,050	80.4%	$33,892	$47,773	$82,420
May-2016	1,175,501	2,078	79.4%	$33,131	$48,445	$82,339
Jun-2016	1,269,071	2,201	79.7%	$35,762	$51,298	$87,834
Jul-2016	1,300,351	2,182	79.2%	$38,812	$50,850	$90,420
Aug-2016	1,251,563	2,213	79.4%	$37,355	$51,577	$89,740
Sept-2016	1,291,336	2,136	80.3%	$38,491	$52,744	$91,982
Oct-2016	1,175,693	2,081	79.1%	$32,996	$51,381	$85,125
Nov-2016	1,107,118	1,879	78.5%	$31,071	$46,403	$78,225
Dec-2016	994,885	1,733	80.0%	$27,921	$42,788	$71378
Total	14,193,980	1,733	80.0%	$405,610	$582,143	$996,751



Explanation of Current Charges

Electric
Meter - 106968007
kWh Usage - 1,138,213
Actual kW - 2,006.40
Actual kVa - 2,488.00
Billed Kvar - 1,471.20
Power Factor - 80.6%

Date of Peak 03/07/2016
Time of peak 15.30.00

Feb 24 - Mar 24
29 Days

Duke Energy
Rate HPN0 - High Load Factor Pri Srv

Connection Charge		$ 75.00	
Demand Charge			
2,006.40 kW	@ $ 13.08000000	26,243.71	
Energy Charge			
1,138,213 kWh	@ $ 0.01627500	18,524.42	
KVAR Charge			
1,471.20 Kvar	@ $ 0.24000000	353.09	
Rider 60 - Fuel Adjustment			
1,138,213 kWh	@ $ 0.01042500	11,865.87	
Rider 61 - Coal Gasification Adj			
2,006.40 kW	@ $ 5.51965200	11,074.63	
Rider 62 - Pollution Cntl Adj			
2,006.40 kW	@ $ 1.72535800	3,461.76	
Rider 63 - Emission Allowance			
1,138,213 kWh	@ $ 0.00003600cr	40.98cr	
Rider 66-A - Energy Eff Adj			
1,138,213 kWh	@ $ 0.00033200	377.89	
Rider 67 - Cinergy Merger Credit			
1,138,213 kWh	@ $ 0.00033300cr	379.02cr	
Rider 68 - Midwest Ind Sys Oper Adj			
1,138,213 kWh	@ $ 0.00159700	1,817.73	
Rider 70 - Reliability Adjustment			
1,138,213 kWh	@ $ 0.00060100	684.07	
Rider 71 - Clean Coal Adjustment			
2,006.40 kW	@ $ 2.95187500	5,922.64	
Rider 72 - Federally Mand Cost Adj			
2,006.40 kW	@ $ 0.03172600	63.66	$ 80,044.47
Total Current Electric Charges			**$ 80,044.47**

Fig. 3.1. Electricity cost breakdown for case study I in March 2016

Table 3.4.
Cost breakdown for case study I in 2016

Demand Cost	Energy Cost	Total
$582,143	$405,610	$996,751
%58	%42	%100

deviation for the last 30-period. At this stage, a spike has to meet two conditions to be identified as a daily peak. Current demand has to be greater than moving average plus one standard deviation to meet the first criteria. It also has to have a greater

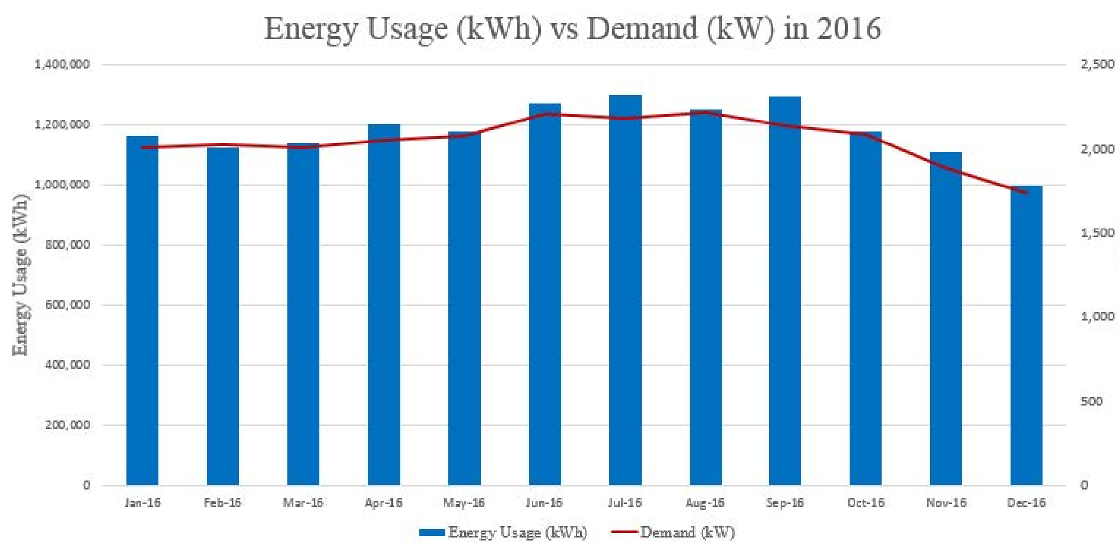


Fig. 3.2. Energy usage vs. Demand for case study I in 2016

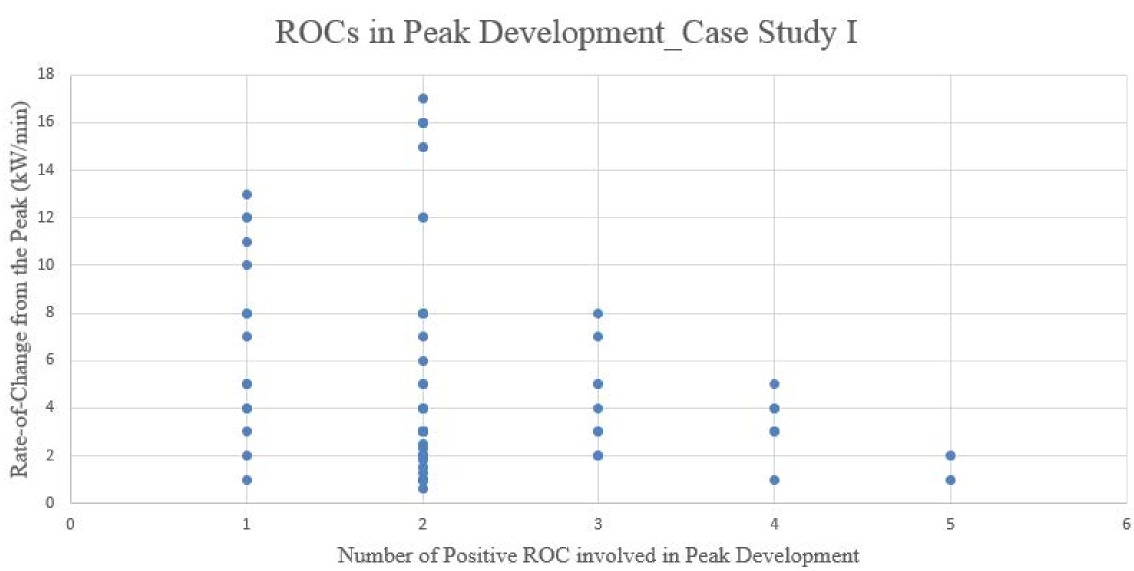


Fig. 3.3. Number of positive ROCs leading to peak in the historical data

ROC than the reference ROC. If the spike meets both conditions, the algorithm would issue a warning that the peak will occur in certain periods of time. Figure

3.4 shows the load diagram for case I from Mon., March 21^{st}, 2016 to Sun., March $27th$, 2016. One standard deviation plus average has been also calculated and showed on the graph. Being above the one standard deviation plus one moving average line is the first criteria. By applying this criteria local maximum spikes will be filtered. This condition also helps to eliminate the peaks at the beginning of- the shifts which usually have low demands.

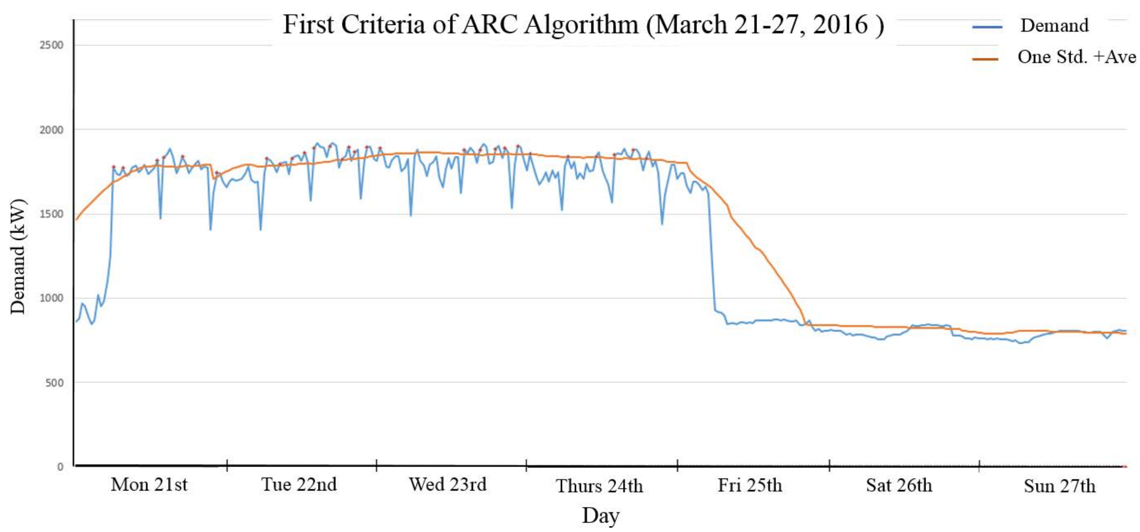


Fig. 3.4. Load diagram and one std+ave for the last week of March 2016

Figure3.5 illustrates the zoom-in of Tuesday, March 22^{nd}. Forecasted peaks have been indicated on the load diagram. All forecasted peak demands meet two conditions. They are all above the one standard deviation plus moving average line, and they all have a greater ROC than reference ROC. As it has been mentioned in previous chapter, proposed algorithm only forecasts the time and not the magnitude of upcoming peaks. Table 3.5 shows the first top six maximum demands in March 22^{nd}. It also indicates the actual time that peaks occurred and the forecasted time by the algorithm. The confidence time window for the algorithm is twice as the interval which in this case is an hour. Thus, forecasting any peak demand an hour ahead is a success for the algorithm.

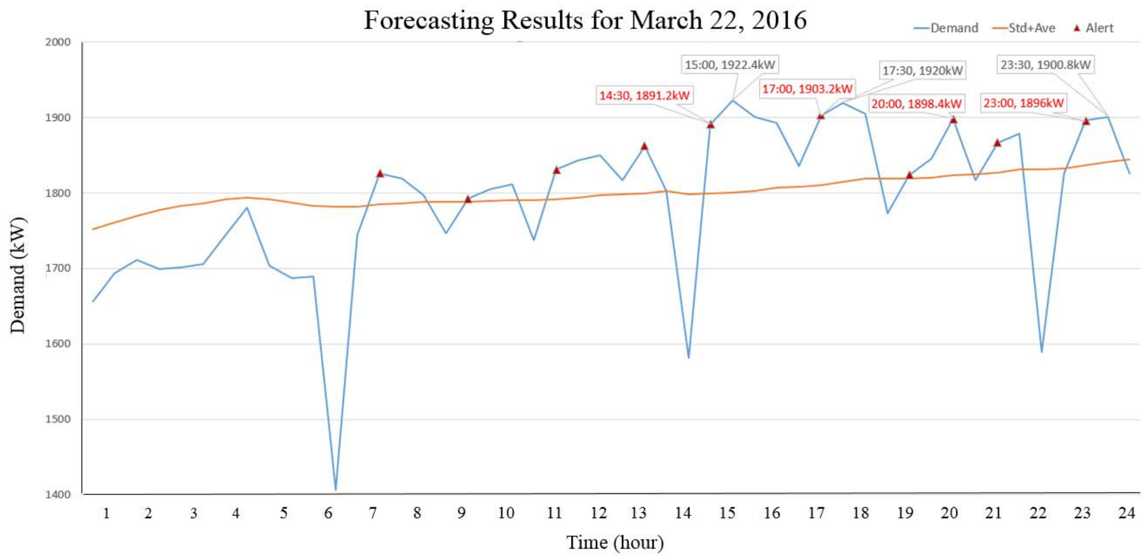


Fig. 3.5. Forecasting results for March 22,2016

Table 3.5.
Forecasting results for case study I on Mar. 22, 2016

Demand (kW)	**Actual Time**	**Forecasted Time**	**Success**
1922.4	15:00	14:30	✓
1920	17:30	17:00	✓
1905.6	18:00	17:00	✓
1900.8	23:30	23:00	✓
1898.4	20:00	20:00	✓
1893.6	16:00	—	×

As it is shown in the table, the algorithm could forecast the first top 5 maximum demands in that specific day of March 2016. However, it missed the sixth maximum demand due to the fact that this spike is located on a negative slope with a negative

ROC. Thus, this data point does not meet the first criteria of ARC to be recognized as a peak.

3.1.2 Case Study II

Case study II is a manufacturing facility produces sheet metal enclosures for generators and large motors. They also provide testing to those generators and motors. Case study II is located in Monticello, Indiana, U.S., and operates about 6,240 hours annually. The facility works Monday through Friday in three shifts. Shift hours is shown in Table 3.6. Demand for this facility is being recorded every 15 min and the greatest of all demands in a month will be used for utility billing purposes. Electricity rates are declared in the rate structure, provided by local utility provider. By considering riders, the Energy Charge is \$0.05401/ kWh and Demand Charge is \$15.27/kW. Table 3.7 shows the electricity analysis for 2014-15 including different riders. As it is shown, the facility consumed 1,708,200 kWh of electricity with the highest monthly peak demand of 633 kW occurred on March 10, 2015 at 13:45. Electricity usage vs. demand in 2014-15 is shown in Fig.3.6.

Table 3.6.
Shift hours for case study II

Shift	Shift starts- Shift ends
1^{st}	7 AM- 3 PM
2^{nd}	3 PM- 11 PM
3^{rd}	11 PM- 7 AM

This case has a non-typical load profile, as it is shown in Figure 1.2 (b); therefore, the load pattern is not repetitive which is a result of lacking a routine procedure/number of productions in this company. As it is shown in Table 3.8, demand cost

Table 3.7.
Electricity analysis for case study II in 2014-15 including all riders

Date	**Energy Usage (kWh)**	**Demand (kW)**	**Power Factor**	**Total Energy Charge**	**Total Demand Charge**	**Total Cost**
Sept-2014	107,100	574	82%	$5,712	$8,780	$14,492
Oct-2014	128,700	524	100%	$6,864	$8,009	$14,873
Nov-2014	127,800	570	84%	$6,816	$8,669	$15,485
Dec-2014	140,400	557	65%	$7,488	$8,518	$16,006
Jan-2015	146,700	551	80%	$7,966	$8,422	$16,388
Feb-2015	124,200	532	87%	$6,744	$8,133	$14,877
Mar-2015	143,100	633	86%	$7,770	$9,674	$17,444
Apr-2015	143,100	550	84%	$7,770	$8,394	$16,164
May-2015	139,500	575	84%	$7,575	$8,793	$16,368
Jun-2015	166,500	596	85%	$9,040	$9,110	$18,150
Jul-2015	164,700	568	84%	$8,943	$8,683	$17,626
Aug-2015	176,400	563	92%	$9,578	$8,587	$18,165
Total	1,708,200	6,795	84.4%	$92,266	$103,772	$196,038

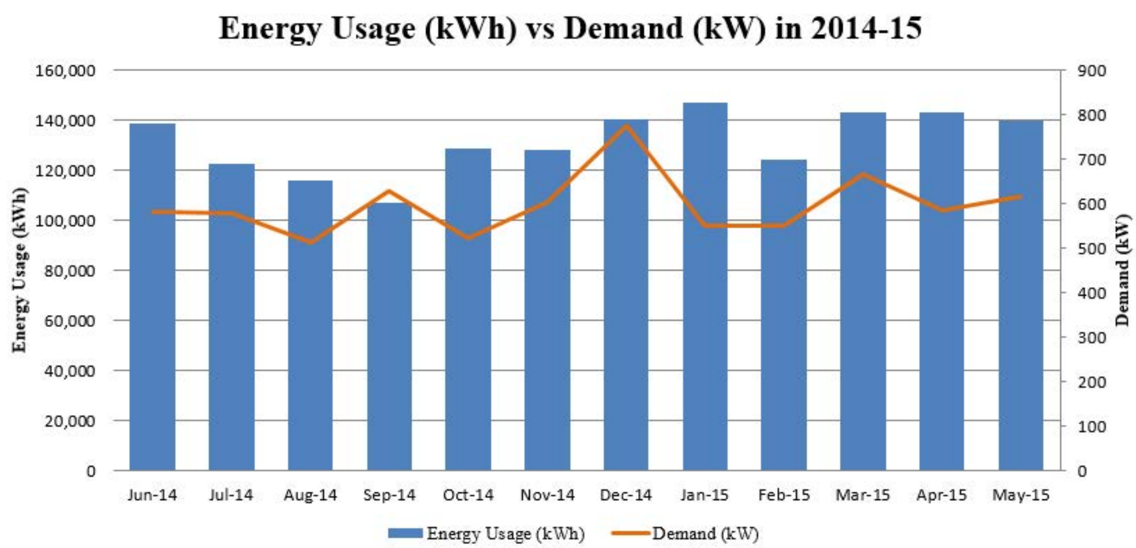


Fig. 3.6. Energy usage vs. Demand for case study II in 2014-15

is accounted for 53% of the total electricity charge in 2014-15. Therefore, maximum demand study would help the end-user to cutdown total electric charge.

Table 3.8.
Cost breakdown for case study II in 2014-15

Demand Cost	**Energy Cost**	**Total**
\$103,772	\$92,266	\$196,038
%53	%47	%100

Similar to case study I, the ARC algorithm will be applied on case study II to forecast peak demand from April, 6^{th}, 2015 to June, 26^{th}, 2015. Three month of historical demand data, from April to June 2014 have been used for the first phase of the algorithm. First the ROC will be calculated for each time interval by using Eq.2.7. Then the algorithm investigates each time-interval to find out if that interval has been involved in the positive increment or not. Similar to case study I, throughout the historical data the daily maximum demand can be induced by several numbers of positive ROCs, among which 2 positive ROCs provides the strong signals, along with a peak inducing reference ROC of 2.5 kW/min, as is shown in Fig.3.7.

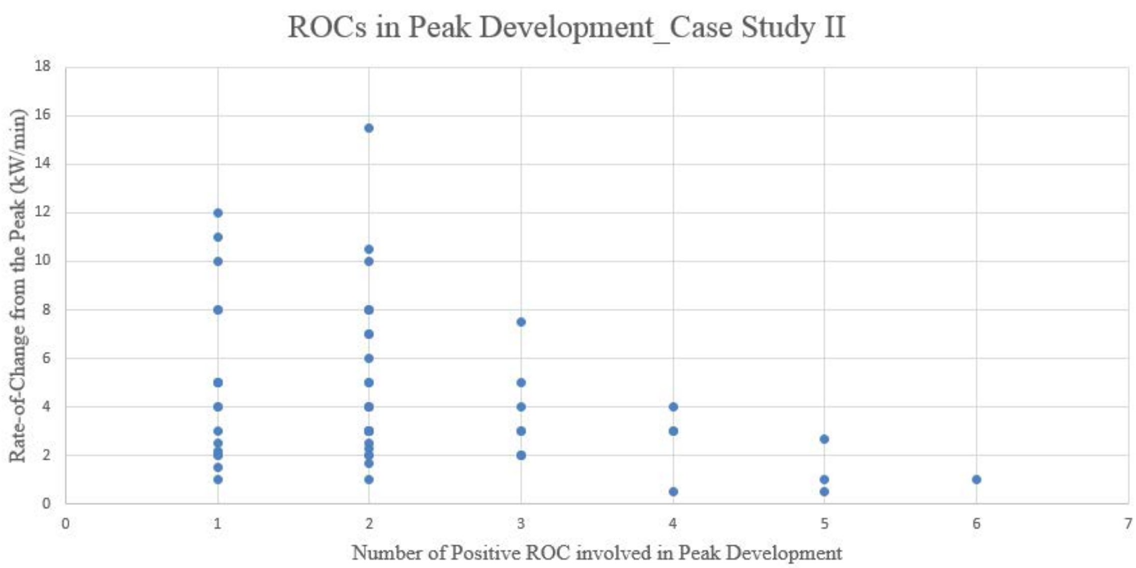


Fig. 3.7. Number of positive ROCs leading to peak in the historical data

Therefore, peaks occur most frequently in 2 time intervals ($2 * 15min = 30min$) with the slope of 2.5 (kW/min) from the start point to the peak.

Once the reference ROC is determined, second phase starts by importing demand data as input. The algorithm calculates ROC for each time interval as time moves on. At the same time it computes the moving average of demand plus one standard deviation for the last 30-period. At this stage, a spike has to meet two conditions to be identified as a daily peak. If the spike meets both conditions, the algorithm would issue a warning that the peak will occur in certain periods of time. Figure 3.8 shows the result of the ARC algorithm for 5 consecutive working days in the second week of April 2015. The forecasted peak demands, indicated by circles, are the times when the warning criteria are met. The confidence time window for the algorithm is twice as the interval (which in this case is 30min). Thus, forecasting any peak demand 30min ahead is a success for the algorithm. As shown in Fig.3.8, the method captures not only the daily maximum demand but also the secondary, and sometimes, thirdly demand spikes. This is useful for the plant manager in order to reschedule the process more efficiently to avoid high demand charges. Later in section 3.2, plant manager (or in general, the electric consumer) would get a better understanding of each sub-system's impact on maximum daily demand and its sensitivity to explanatory variables.

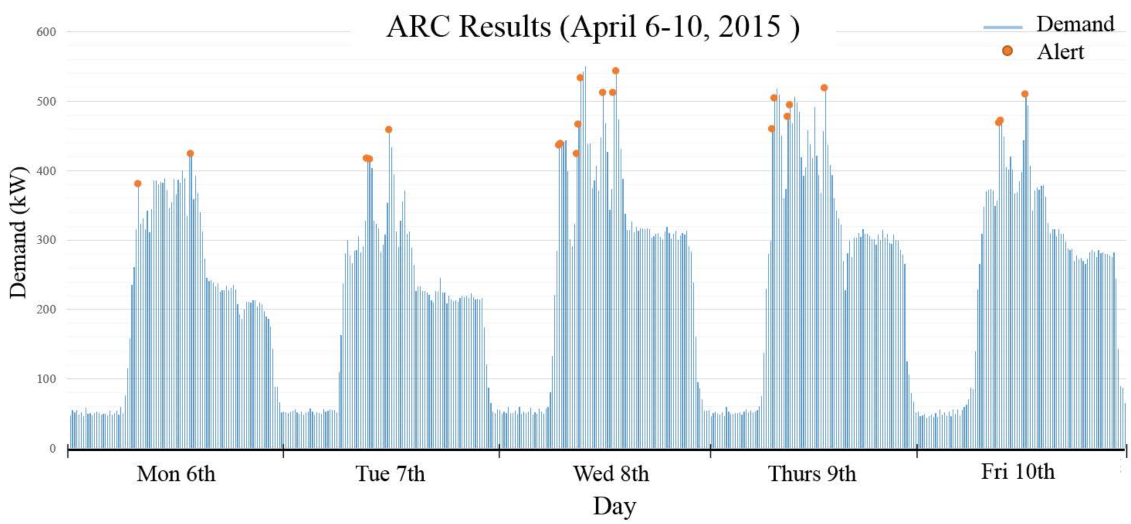


Fig. 3.8. ARC forecasting results for 2^{nd} week of April 2015

3.2 Maximum Demand Management

In this section, the same forging company and a commercial building have been chosen as case studies to apply the new MDM method proposed in 2.2. In sections 3.2.1, 3.2.2, and 3.2.3 explanatory variables are calculated to see the sensitivity of maximum daily demand to number of degree-days, production, and occupants. Later in section 3.2.4, the study goes further to see how does a sub-system affect maximum daily demand. The result of this section would be so beneficial for electric consumers to decrease their demand by changing explanatory variables or a sub-system's load.

3.2.1 Explanatory Variable α_1

In this section, the proposed MDD method is implemented on the same metal die casting company to find out the regression coefficient α_1 for October 2016. The only air conditioners systems in this facility are four York cooling makeup air systems provide cold air to this facility. The result of this study would reveal how sensitive is MDD to the temperature. As it is mentioned in section 2.2.1, the base temperature for cooling degree-days calculation is chosen as $18°C$. Maximum daily demands and CDDs have been shown in Table 3.9 for fifteen days in October 2016. These days have positive CDDs with the same number of productions as 7,820 parts per day. As it is represented in Table 2.2, number of occupants is not a factor in manufacturing sectors for defining α_1. The linear regression model is obtained by using Eq.2.11 as it is shown in Fig.3.9. The regression coefficient $\alpha_1 = 29.39kW/°C$ describes the sensitivity of the maximum daily demand to the number of cooling degree-days for this facility in Oct. 2016. In other words, in this case, cooling down the facility by $1°C$ would increase MDD by $29.39kW$. The intercept of the line, $\alpha_0 = 1,688.6$ represents the baseline of the maximum daily demand in a day with $CDD = 0$. This is the maximum demand related to all consumption in the plant, it also includes the idling power of the cooling units.

3.2.2 Explanatory Variable β_1

The same method has been approached to find out the regression coefficient β_1 for the same metal die casting company. MDD can be written as a function of production by using Eq.2.14. As it is mentioned in Table 2.2, the model shall include the days with the same degree-days for manufacturing consumers to find out the impact of production on MDD; moreover, number of occupants is not a factor in manufacturing

Table 3.9.
Days with a positive CDD and same number of production in Oct. 2016

Date	**CDD (°C)**	**MDD (kW)**
10/6/2016	9.5	1,973
10/7/2016	7.7	1,906
10/8/2016	0.2	1,690
10/11/2016	5.4	1,877
10/13/2016	5	1,846
10/14/2016	4.2	1,826
10/16/2016	7.3	1,900
10/17/2016	8	1,894
10/20/2016	4	1,812
10/21/2016	4	1,752
10/22/2016	2	1,718
10/24/2016	5.3	1,872
10/25/2016	2	1,781
10/26/2016	4.2	1,802
10/28/2016	6.7	1,899

sectors for defining β_1. The model includes 24 days in Feb. and Mar. 2016 all with zero cooling degree-days as it is shown in Fig.3.10. The result of this study would reveal how sensitive is MDD to the number of production in this case study. The linear regression model is obtained by using Eq.2.14 as it is shown in Fig.3.10. The regression coefficient $\beta_1 = 1.6488kW/(100Parts)$ describes the sensitivity of the maximum daily demand to the number of productions for this facility. For instance, increasing the production by 100 pieces would increase MDD by $1.6488kW$. It is worth to mention that on account of the fact that the company has been running all

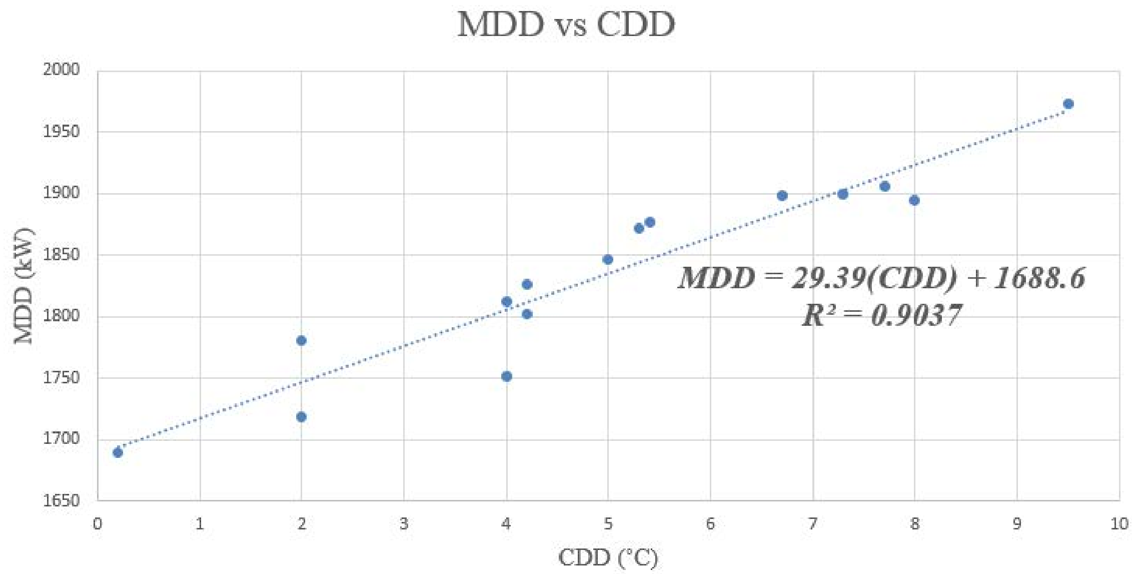


Fig. 3.9. Linear regression of MDD vs. CDD in Oct. 2016

the time during the test, $\beta_0 = 1,730.1$ shows the idling power of all manufacturing equipment in the plant when the production is zero.

3.2.3 Explanatory Variable γ_1

The same method has been approached to find out the regression coefficient γ_1 for a museum in Indiana, U.S. to see how the number of occupants would have effect on MDD. The museum is air-conditioned in the Summer and Winter by using two 300 Ton chillers and seven air handling units. This case is a commercial building; therefore, MDD can be written as a function of number of occupants by using Eq.2.17. The model can be applied on 19 days from Nov. 2015 to Mar. 2016 as it is shown in Table3.11. As it is mentioned in Table 2.2, the model includes the days with the same degree-days to find out the impact of occupants on MDD; in this case, all days have the same $HDD = 18°C$ by considering the base temperature as $18°C$ in calculations. The result of this study would reveal how sensitive is MDD to the number

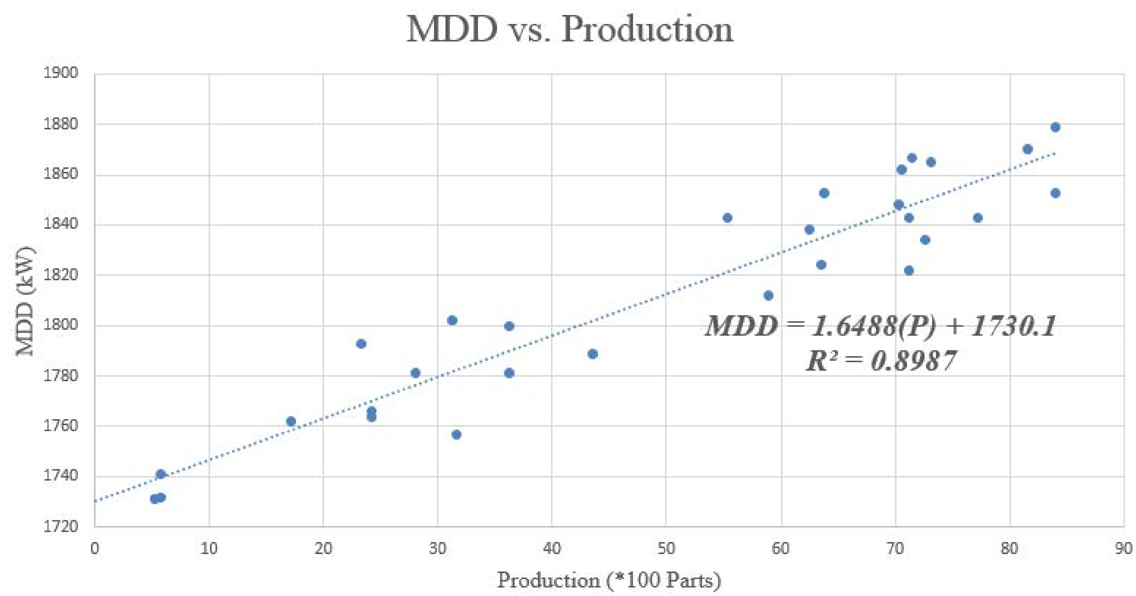


Fig. 3.10. Linear regression of MDD vs. production in Feb. & Mar. 2016

of occupants in this case. The linear regression model is obtained by using Eq.2.17 as it is shown in Fig.3.11. The regression coefficient $\gamma_1 = 0.2738kW/(10Persons)$ describes the sensitivity of the maximum daily demand to the number of attendance for this commercial building. For instance, increasing the number of occupants by 10 would increase MDD by $0.2738kW$. The museum has constraints on temperature and humidity of the building which can be a reason of not having the MDD very sensitive to the number of occupants. It is worth to mention that $\gamma_0 = 228.89$ shows the demand required mostly by air handling units to keep the temperature at $18°C$ and lighting systems in this museum.

3.2.4 Sub-system Approach

As it is mentioned in 2.2.4, in some cases, changing temperature, number of production, or number of occupants is not a feasible solution for demand management. In fact, load shedding can be a better practice for demand management which provides

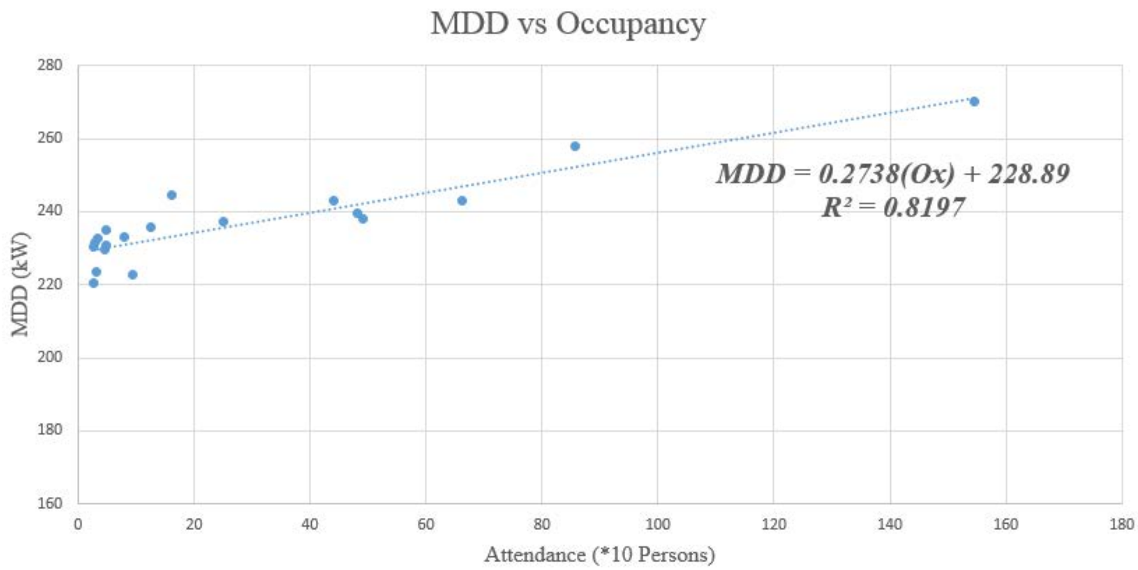


Fig. 3.11. Linear regression of MDD vs. number of occupants in Nov. 2015 to Mar. 2016

more options to end-users. Seeking to have demand management by load shedding come to full fruition by finding out how does each sub-system affect the MDD. In this section the same metal die casting company has been chosen to demonstrate the results of the sub-system approach described in 2.2.4. In this case, four AHUs have been chosen as the sub-system to see how the MDD for the whole facility is sensitive to the electric demand of the AHUs. (MDD_{AHUs}). The same time window as 3.2.1 (fifteen days in Oct. 2016) has been considered for this study. As it is defined in 2.24, first step to find α_{AHUs} is to calculate α_1. This regression coefficient has been already calculated in 3.2.1 as $\alpha_1 = 29.39 kW/°C$. Next step is finding $\alpha_1^{`}$, which is the sensitivity of AHUs to CDD as it is defined in 2.21. In order to do that, the regression model has been made and presented in Fig.3.12. $\alpha_1^{`} = 27.457 kW/°C$ means increasing CDD by $1°C$ would increase the AHUs' MDD by 27.457.

Finally, α_{AHUs} can be calculated by using Eq.3.1 and considering four AHUs as one single sub-system.

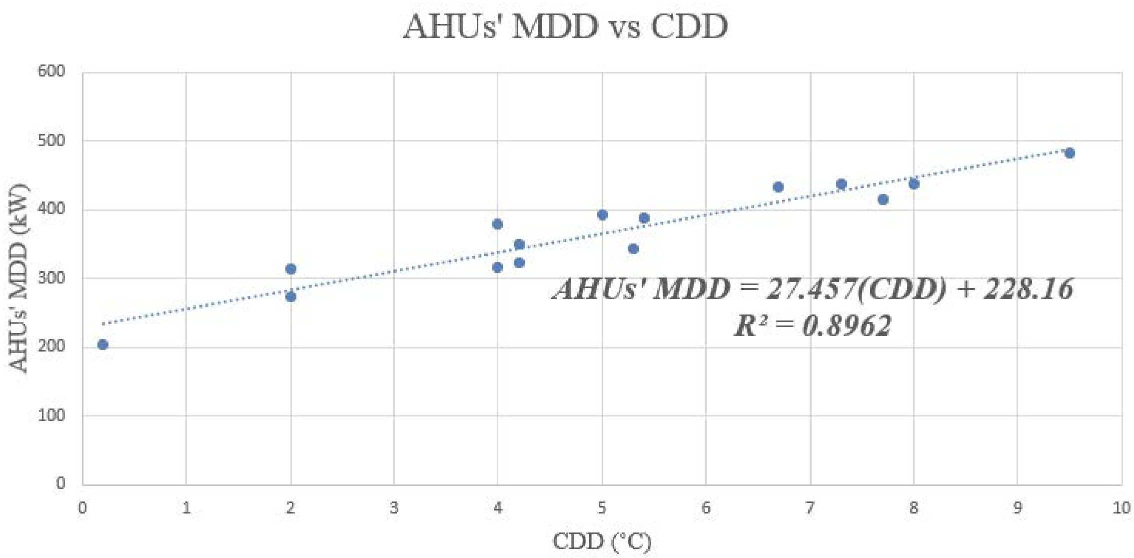


Fig. 3.12. Linear regression of AHUs' MDD vs. CDD in Oct. 2016

$$\alpha_{AHUs} = \frac{d(MDD)}{d(MDD_{AHUs})} = \frac{\frac{d(MDD)}{d(DD)}}{\frac{d(MDD_{AHUs})}{d(DD)}} = \frac{\alpha_1}{\alpha_1^{`}} = \frac{29.39}{27.457} = 1.07 \tag{3.1}$$

α_{AHUs} shows the sensitivity of total MDD of this facility to AHUs' MDD. Although α_{AHUs} is dimensionless, it is helpful for interpretation to have the same units in both numerator and denominator (kW/kW). In this case $\alpha_{AHUs} = 1.07kW/kW$ means increasing/decreasing the AHUs' MDD by $1kW$ would result in increasing/decreasing total MDD of the facility by $1.07kW$. Another way to calculate α_{AHUs} is to have MDD vs. AHUs' MDD model directly from data. As it is shown in Fig.3.13, α_{AHUs} obtained in this way is very close to α_{AHUs} calculated by using Eq.3.1. The intercept of the line shows the MDD of the facility would be $1,470kW$ once all four AHUs are turned off.

The results of the study can be very useful for plant manager to manage the MDD of the facility. For instance, this facility is enrolled in Demand Response program by the utility provider. By using the result of this study, the plant manager is aware of the sensitivity of MDD to the AHUs' MDD. If the utility calls upon to reduce the

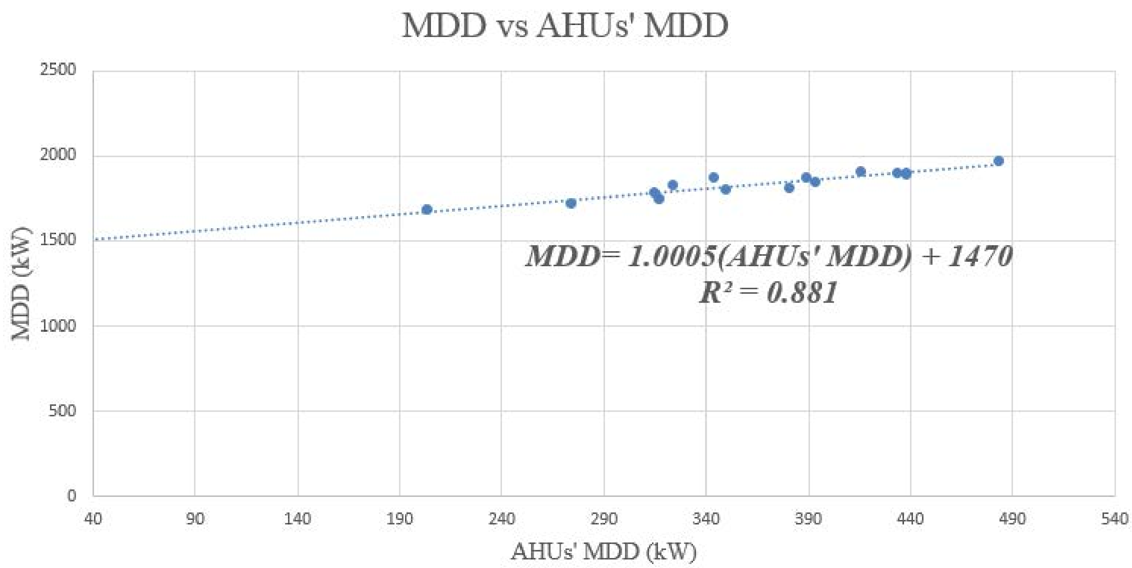


Fig. 3.13. Linear regression of MDD vs. AHUs' MDD in Oct. 2016

demand at the facility by $107kW$, the plant manager can accomplish that by reducing the AHUs' power by $100kW$ (α_{AHUs} is considered as $1.07kW/kW$).

Table 3.10.
Number of productions for 24 days in Feb. & Mar. 2016 with $CDDs = 0°C$

Date	**Production (*100 Pieces)**	**MDD (kW)**
2/5/2016	63.47	1,824
2/6/2016	81.54	1,870
2/7/2016	70.28	1,848
2/8/2016	36.25	1,800
2/9/2016	77.2	1,843
2/10/2016	73.14	1,865
2/12/2016	63.74	1,853
2/14/2016	36.25	1,781
2/15/2016	5.77	1,732
2/16/2016	84.06	1,879
2/17/2016	72.67	1,834
2/19/2016	28.08	1,781
2/20/2016	24.25	1,766
2/23/2016	17.18	1,762
2/24/2016	71.2	1,843
2/25/2016	31.19	1,802
2/26/2016	71.18	1,822
3/1/2016	5.77	1,741
3/4/2016	23.25	1,793
3/5/2016	71.47	1,867
3/6/2016	58.9	1,812
3/8/2016	5.29	1,731
3/9/2016	70.62	1,862
3/10/2016	84.04	1,853

Table 3.11.
Number of occupants for 19 days in Nov.2015 to Mar.2016 with $HDDs = 18°C$

Date	**Occupants (*10 Persons)**	**MDD (kW)**
11/22/2015	25	237.15
12/3/2015	9.5	222.6
12/4/2015	3.2	223.7
12/5/2015	8	233.1
1/2/2016	154.6	270.15
1/3/2016	49.1	238
1/4/2016	44	242.85
1/5/2016	48.1	239.7
1/6/2016	85.6	258
1/16/2016	66.2	243
1/26/2016	2.6	230.5
1/27/2016	4.7	229.7
2/4/2016	2.9	231.5
2/5/2016	4.9	235
2/6/2016	12.5	235.9
2/8/2016	3.4	232.6
2/16/2016	4.8	230.6
3/2/2016	2.6	220.35
2/4/2016	16.1	244.5

4. RESULTS ANALYSIS

4.1 Results Verification

In this section the results of the ARC algorithm have been verified by using Pearson's chi-squared test. This test is called the test of independence which assesses whether unpaired observations on two variables, expressed in a cross tabulation (contingency table), are independent of each other. The result of the case study II (a manufacturing produces metal sheets for generators) presented in section 3.1.2 is chosen for verification on account of the fact that the population is much larger compare to case study I (a die casting company). Moreover, as it is mentioned in section 3.1.2, case study II has a non-typical load profile which makes it much harder for the algorithm to forecast the MDDs; therefore, this case has been chosen as the worst case scenario for results verification. In other words, if the algorithm shows promising results for case study II, it will definitely show satisfactory results for case study I since forecasting MDD for a typical load diagram is easier than forecasting MDD for a non-typical load diagram. A standard Pearson's chi-squared test is performed by categorizing demand time series into binomial pair, 1 and 0. 1 means a maximum daily demand occurrence either in reality or prediction while 0 means the rest. As it is explained in Fig.4.1 by using IBM SPSS software, and considering demand data from April, 6^{th}, 2015 to June, 26^{th}, 2015 (72 working days), 84.72% of the actual daily maximum demands have been successfully forecasted by the ARC algorithm, and 15.28% of daily maximum demands have been totally missed. It also shows 6,724 times, when no daily peak demands have been occurred, the algorithm has not issued any warnings while the method issues undesired signals 1.70% of the time when a maximum daily demand has not been occurred in reality. Undesired signals may include local maximums throughout a day which might be beneficial for the end-user to manage the demand. For calculating the P-value, null hypothesis (H_0) is considered such that the methodology will create an unbiased result which; therefore, should catch 50% of the peaks because the test has only two categorical variables. Alternative hypothesis (H_a) is that the algorithm can catch more than 50% of MDDs. Null hypothesis will be rejected if the algorithm catches more than 50% of the MDDs throughout 72 working days. As the result of IBM SPSS software, the P-value equals 0.0301 and thus the null hypothesis is rejected.

Data vs. Prediction Cross tabulation

			Prediction		***Total***
			0	*1 (Peak)*	
Data	0	Count	6,724	116	6,840
		% within Prediction	***98.30%***	1.70%	100.00%
		% within Data	99.84%	65.54%	98.96%
		% of Total	97.28%	1.68%	98.96%
	1 (Peak)	Count	11	61	72
		% within Prediction	15.28%	***84.72%***	100.00%
		% within Data	0.16%	34.46%	1.04%
		% of Total	0.16%	0.88%	1.04%
Total		Count	6,735	177	6,912
		% within Prediction	100.00%	100.00%	100.00%
		% within Data	97.44%	2.56%	100.00%
		% of Total	97.44%	2.56%	100.00%

Fig. 4.1. Results of Pearson's Chi-squared test for ARC algorithm

Regarding the MDM linear regression models, Table4.1 shows R^2s for three different case studies. The regression models account for 90.37%, 89.87%, and 81.97% of the variance respectively for MDD vs DD, MDD vs P, and MDD vs Ox. Theoretically, if a model could explain 100% of the variance, the fitted values would always equal the observed values and, therefore, all the data points would fall on the fitted regression line. In these cases, R^2s indicate a very good fit between fitted values and observed values (R^2s are close to 100%).

Table 4.1.
R^2s for three different regression models

Model	R^2
MDD vs DD	90.37%
MDD vs P	89.87%
MDD vs Ox	81.97%

4.2 Cost Saving

Case study I in section 3.1.1 has been selected to show cost saving calculation for demand charge by using ARC algorithm. We assume the maximum demand for March 2016 has been occurred on March 22^{nd}. By using the results of ARC algorithm, the company would be able to skip the first 5 forecasted maximum demands, shown in Table 3.5. Therefore, as it is mentioned in section 3.1.1, by considering demand rate as \$23.31/kW, demand cost saving for March 2016 can be calculated as follow:

$$Saving = (1,922.4kW - 1,893.6kW) \times \$23.31/kW = \$671.3 \tag{4.1}$$

Therefore, in this case, by using ARC algorithm the potential saving in Mrch 2016 is \$671. Consequently, demand cost saving for one year can be estimated by using the same method for 12 months as follow:

$$Saving = \$671.3/month \times 12\frac{month}{year} = \$8,056/year \tag{4.2}$$

As it is shown in Eq.4.2, the demand charge saving can be very significant by using the forecasting algorithm.

5. CONCLUSION

In this thesis, a novel MDD forecasting method, called ARC algorithm, was proposed by analysing demand trend data and incorporating moving average calculation as well as rate of change formularization to develop an electrical maximum demand forecasting algorithm. This tool can be used by electric consumers in residential, commercial, and manufacturing sectors to predict upcoming peak demands in VSTLF, STLF, and MTLF windows. Then ARC algorithm was applied on two different case studies with typical and non-typical load diagrams for a period of one week and three months respectively. The results reveal that the proposed ARC method would have the following advantages:

- Prior works in electrical maximum demand forecasting have been mainly focused on the utility side while ARC algorithm is a forecasting tool which can be used on either utility or consumer sides. In this dissertation the forecasting method was conducted on consumer side.

- Prior works have been mainly focused on using seasonal effects on MDD forecasting which is not always a feasible approach for industrial manufacturing facilities. Instead, the only input for the ARC algorithm is the historical demand data which can decrease the intrinsic uncertainties associated with demand forecasting. Therefore, the proposed algorithm has the simplicity that not only needs less input but also runs faster.

- Using real-time data for calculating moving average and one standard deviation to predict the future makes the ARC algorithm very adaptive to the growing and dynamic systems such as increasing production, or expanding the electric network in the facility.

- ARC algorithm's results for case study I (a metal die casting company) reveal that the algorithm captures not only the daily maximum demand but also the local maximums. For instance, the algorithm could capture the first top 5 maximum demands in a specific day in case study I. Moreover, demand cost saving was estimated as $8,056 in a year by using the forecasting algorithm.

- The Chi-square method was used to validate the forecasting results in case study II (a manufacturing facility produces sheet metal enclosures for generators). The results of the test reveal that the ARC algorithm is 84% successful in forecasting maximum daily demands (for the period of 72 days) for a non-typical load diagram with the P-value equals to 0.0301.

The focus of this study was to help the end-users to understand how temperature, production, and occupancy affect MDDs in their facilities by using linear regression models. The MDM method was applied on three different real case studies in commercial and manufacturing sectors and the sensitivity of MDD to the number of degree-days, number of production and number of occupants was determined independently. These information broaden the electric consumer understanding of how MDD is sensitive to the temperature, production, and occupancy. Finally, the sensitivity of MDD to different sub-systems was defined and investigated. The application of proposed algorithm can help the end-user to manage the MDD by turning a specific electricity-consuming device (such as chillers, fans, lights, etc.) on or off or it can be more sophisticated to reduce the load on particular equipment without completely removing the load by using sub-systems' regression coefficients. In all linear regression models, R^2s indicated a very good fit between fitted values and observed values.

In a nutshell, the proposed method can be used to provide the electric consumer a MDD forecasting and management tool. The effective forecasting provided essential context for MDM by understanding MDD's sensitivities to temperature, production, occupancy, and different sub-systems in a facility. It can also be very helpful in decision making for demand management and demand response program.

5.1 Future Work

Future works include but are not limited to the following:

- Proposing an optimized solution for MDM by finding priorities for sub-systems. Later on by using a PLC, the scheme can offer a flexible solution suitable for a user with many sheddable loads. In this case the shedding sequence can be programmed into the PLC, and an interface allows the end-user to change the priorities of load shedding.
- Conducting a cost analysis to find out the total cost (i.e. energy and demand costs) of making a product in manufacturing sector or having an occupant in a commercial sector.
- Even though ARC algorithm results were verified by Chi-square test, a different energy modeling software can be used for result verification.

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