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On the Prediction of the Peak Demand of Electrical Energy Use

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By

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Abstract

Prediction of electricity peak demand is an integral part in any electrical utility. Many models were previously proposed for prediction, ranging from short-term, intermediate to long-term prediction. Prediction of electricity peak demand is crucial in avoiding unneeded expenses to upgrade the electrical power supply. It is a continuous process that is still in need of study and improvement. University of Northern Iowa is an educational institution with 10,380 undergraduate students, 66% of whom reside in university housing and 59% of the total electricity demand is purchased from Cedar Falls utilities. The university utilizes a model based on computerized live reading of previous demand that undergoes continuous short-term, intermediate and long-term prediction. The model has succeeded in reducing peak demand. The purpose of the present research is to review the currently used modeling system at UNI, and to test the impact of temperature, humidity, and time variables on peak demand prediction through a Multiple Linear Regression (MLR) short-term model. The MLR model was tested three times, including in each different number of variables, ranging from two to four, with most significant results occurring when four weather and time variables were used.

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Introduction

Electrical utilities experience fluctuations in the amount of energy needed by the customers. These fluctuations depend on several factors, such as business hours of commercial or industrial customers and weather conditions. Generally speaking, peak demand is a period of strong consumer demand. This is met by peak load, a period when electrical energy is expected to be provided over a sustained period at a significantly higher than average level of supply. Peak demand may occur for a utility on a daily, monthly, or seasonal basis. Individual customers may have individual peak demands. The peak demand affects the size of generators, transmission lines, transformers and circuit breakers (Brown, 2009).

If the peak demand exceeds the maximum power that a utility can generate, it leads to power outage. The customers are instructed to decrease their use to a non-peak level during the peak load period. Encouraging the customer to use less energy during high demand hours is called Demand Side Management (DSM). This does not decrease the total energy consumption, but reduces the need for investing in new transmission networks or power plants.

Prediction of daily peak demand is very important for decision making in the electricity sector. Decision making in this sector needs planning, but this planning is under condition of uncertainty. The demand of electricity is the basis for power system planning, power security and supply reliability. This involves finding the optimal day to day operation of a power plant and even strategic planning for capacity expansion. Therefore, it is important to estimate or project the peak demand in order to avoid the costly consequences of underestimation or overestimation (Di Cosmo et al, 2014).

A. Statement of the Problem

Prediction of energy consumption is an integral part of the work of an energy facility. There are several factors that interplay to give the energy demand at a certain point in time, especially consumer habits and weather conditions. Proper planning depends on scientific prediction. This is the goal of the Physical Power Plant in University of Northern Iowa, being a utility that supplies 41% of offices and residential electricity services on a continuous basis, with the remaining 59%, being purchased from the utility of Cedar Falls (University of Northern Iowa Website, 2015). The present model utilized by the university has succeeded in predicting and reducing peak demand to reach a minimum billing requirement. Reviewing of this model and studying the effect of other variables in a prediction is warranted as continuous improvement and planning is needed in order not to exceed the purchased power limit from the utility.

B. Statement of Purpose

The purpose of this research paper is to review the mechanism and outcome of electricity demand forecast implemented at University of Northern Iowa, and to study the significance of temperature and humidity factors, on demand prediction using Multiple Linear Regression (MLR).

C. Statement of Need/Justification

The justification for the proposed research is the importance of the electricity demand forecast in supplying electricity economically and efficiently to the university facilities through the university's power plant. It may help to keep the electricity billing prices at a minimum level, as the university purchases 59% of the electricity demand from Cedar Falls local utility.

D. Research Questions to be answered

1) Does the currently used electricity demand forecast model in the University of Northern Iowa reduce the peak demand significantly?

2) What is the significance of the use of a short-term MLR Model, utilizing from two to four variables; including humidity, temperature, duration of study of input factors, and type of day (weekday); on electricity demand prediction in UNI?

Literature Review

Electricity-supply planning requires efficient management of existing power systems and optimization of the decisions concerning additional capacity. Demand prediction is an important aspect in the development of any model for electricity planning. The form of the demand depends on the type of planning and accuracy that is required; hence it can be represented as an annual demand (GW), a peak demand (MW), or load duration curves occurring daily, weekly or annually (Taylor et al., 2006).

Since the electricity market has also been deregulated dating from the 1990's (Joskow, 2008), thus offering the customer the choice of his/her energy supplier, the need for electrical demand forecasting has become more evident. Load prediction allows for effective regulation of energy supply. Scientific prediction may require the use of software programs and modeling.

For electricity demand forecasting, physical-technical economic (PTE) models have been largely used. In creating a model, a hypothesis is drawn about the causal factors and the outcome of their interaction. It is often beneficial to design the model so that it can be manipulated computationally. This may require the feedback to be applied by sequential repetition of a hierarchical set of data that represent the system. There are different frameworks of theories and models, each tackling a single or multiple sets of factors influencing energy use. These factors may be related to economics, engineering, sociology, anthropology, and psychology.

Models for electricity demand forecast include the classical and functional time-series methods, which focus on future expectations of electricity use based on previous values. Classical models include neural networks, and regression methods. Functional time series models have recently gained momentum by including the effect of electricity demand on electricity spot pricing (Liebel, 2013), even for the short-term minute-by-minute demand (Shang, 2013). Buys et al. (2015) have created a model to represent the complex multi-factorial relationship between energy demand and supply. They stressed on the importance of including multiple factors that affect the supply-demand framework of the electricity system, and to include human behavior not just technical factors. One factor might affect the others, whether the studied factor was physical-technical, economical, or social. They used system dynamic modeling in order to study the interacting elements within a complex system.

Sigauke and Chikobvu (2010) have used a multivariate regression model for daily prediction of electrical power use, called Multivariate Adaptive Regression Splines (MARS). This model focused on an important weather factor that leads to variable electricity use, which is temperature. Yang (2012) has discussed the use of demand modeling in forecasting peak demand in Korea. Verster et al. (2013) have used a modeling of the electricity use on the same day of the week in South Africa by using Generalized Paretto-type distribution in predicting excess electricity demand. Nark (2015) suggested using energy management platforms for commercial buildings that consume about 40% of the total energy in the U.S. The companies would understand how the energy is being used in order to plan for periods of peak demand.

Customers have been encouraged to cooperate during periods of high demand. Fenrick (2014) have surveyed the customer cooperation attitude in the peak demand period when a dynamic pricing program was used. Simshauser and Downer (2012) have reported on dynamic pricing in Australia. The United States Government Accountability Office (GAO) has reported on the customer response to 'demand response activities', when the customer was asked to reduce electricity use in peak periods. Di Cosmo et al. (2014) have also discussed the customer response in Ireland, when a variable tariff based on Time-of Use pricing was used to reduce consumption during peak demand.

Consumers are making irrational decisions regarding electricity use. Understanding of all technical and social factors that affect electricity at demand time is required. Peak demand is important to study because it has been growing much faster than average demand in a manner that challenges utilities to supply electricity need in a cost-effective way. Attempts to change consumers' electricity use behaviors have incorporated in complex socio-technical models (Crosbie, 2006).

Supply must equal demand at all times, and failure to do this results in power outages and load shedding causing some customers to lose supply, which is a challenge to industry. In extreme cases, electricity network could be destabilized leading to widespread blackouts.

Up till the present, there is no definite predictive tool or intervention. This is to be expected as electricity exists within a very complex network formed of many components interacting at the same time, thus it is difficult to be represented by a simple explanation (Buys et al., 2015). Even factors like weather and human behavior are liable to change and cannot be present in the same month, season, or year, in the form of a replica of what occurred previously.

Models differ in selected duration of study for input factors, the type of factors whether single or multiple, and the duration of forecast. The multiple factors models are more related to what happens in reality from interaction between several factors at any given point in time to give the outcome of energy use at this point. Regarding the duration of prediction of energy use, models are divided into: short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF). The duration of LTLF is longer than one year, while there were several definitions of short-term period, versus medium-term. For example, Feinberg & Genethliou (2005) defined STLF duration as one hour to one week, MTLF as one week to one year; while Aslan et al. (2011) described STLF duration as half an hour to one week, MTLF as one day to several months. El-Naggar et al. (2007), on the other hand, identified LTLF as one to ten years ahead at monthly and yearly values, and STLF as one day to one month ahead hourly and daily values. Rothe et al. (2009) described STLF as minutes to several hours ahead.

Short-term Load Forecast (STLF)

Accurate prediction of daily peak demand helps to create a consistent and reliable supply schedules during peak periods. The accurate short term daily forecasts will enable effective load shifting between transmission substations, scheduling of startup times of peak stations, and load flow analysis.

STLF models are needed in unit commitment, maintenance and economic dispatch problems (El-Naggar et al., 2007). These predictions are required as inputs to scheduling algorithms for the generation and transmission of electricity load forecasts. They help in determining which devices to operate in a given period, so as to minimize costs and secure demand even when local failures may occur in the system (Rothe et al., 2009). That is why these types of forecasts are important. They are generally more frequently used than the medium and the long-term types of models.

Some prediction techniques take into consideration only one factor of change (univariate), while others take multiple factors (multivariate). Univariate and multivariate models are used in short-term prediction. Taylor et al. (2006) reported that in shorter lead times, a univariate model is sufficient, especially if the lead time is less than 6 hours. That was the recommendation in places where there is lack of readily available weather forecasts as in Brazil. On the other hand, Rothe et al. (2009) used a mutivariable regression, namely MLR, characterized by being in common use due to its flexibility. The authors predicted the coming hour demand of electricity; after using weather data (temperature, wind, and cloud cover) in 3 readings (current, previous one, and previous 2 hours).

Taylor et al. (2006) compared four sophisticated methods for prediction of electricity demand. Two of them were widely applied; the seasonal Autoregressive Integrated Moving Average (ARIMA) and the neural network. Two double seasonal exponential smoothing and the Prinicipal Component Analysis (PCA) were newly designed and specifically used for high frequency load series. Electrical demand data were taken hourly and half-hourly to show weekly and daily seasonal patterns. The exponential smoothing method was proved to be successful, besides being the easiest and simplest to implement out of the four methods.

In both Taylor et al. and Rothe et al., the weather variables were investigated. The prediction was done on daily and weekly patterns and on hourly pattern in the latter. Weather related variation is certainly critical in predicting electricity demand for lead times below or beyond a day-ahead.

Weather is defined as the atmospheric conditions existing over a short period in a particular location. It is usually hard to predict and can vary significantly even over a short period. Climate also varies in time: seasonally, annually and on a decadal basis. Weather variability is short-term and, climate variability is long-term. Both have a major impact on the generation, transmission and demand for electricity.

Electricity demand depends on parameters such as changes in ambient temperature, wind speed, humidity, precipitation and cloud cover. Every hour demand depends on these important dynamic parameters, temperature, wind speed, and cloud cover; more than others. Future electricity demand is also forecasted using previous demand. Many variables can be used in electricity forecasting using MLR, but error factor is from 8 to 10 %. Computing the error factor between forecasted demand and actual demand and applying correction accordingly to the results of electrical forecasting by MLR method reduced error to 1 to 3% (Rothe et al., 2009).

Tuaimah and Abdul Abass (2014) also used the MLR method for short-term load forecasting (up till 24 hours) of the Iraqi Power Plant. MLR method is suitable for offline forecasting, as it requires many external variables that cannot be introduced in online algorithm. Two different models were used, one for summer and one for winter. The errors that the authors faced in implementation of load forecasting stemmed from modeling error, errors in the system as load shedding and irregular intervals, and errors of temperature forecast.

Medium-Term Load Forecast (MTLF)

Medium-term forecasting that covers a span of up to one year is an important category in electric load forecasting that serves outage, maintenance planning, and load switching operation. Abu-Shikhah et al. (2011) used multivariable regression on hourly readings of the previous year's loads, to predict hourly demands of the coming year. Thus, the peak electrical demands that are expected to be reached in the coming year are predicted. The authors investigated three regression models: the linear, the polynominal, and the exponential power on the Jordanian power system. Results have shown that the performance of the three models was close with 90% accuracy.

Long-term Load Forecast (LTLF)

Long-term load forecasting is applied in expansion planning, inter-tie tariff setting, and long-term capital investment return problems. Since the time horizon for long-term forecasting could extend to several years, difficulties arise from uncertain nature of forecasting process over a planning period of this length. There is a large number of influential factors that characterize and either directly or indirectly affect the underlying forecasting process; most of which are uncertain and uncontrollable (El-Naggar et al., 2007).

Many classic approaches have been proposed and applied to long-term load forecasting to estimate model parameters, including static and dynamic state estimation techniques (Tripathy, 1997; Beccali et al. 2014). Least error square (LES) technique has been the most widely used conventional static estimation technique and has been the preferred technique for optimum estimation in general. Some limitations, however, are associated with this approach; as for example, when the data set is contaminated with bad measurements, the estimates would be inaccurate unless a large number of data points are used. Al-Hamadi and Soliman (2005) proposed a static method based on noniterative least absolute value technique, which has the advantage of detecting bad data.

For dynamic techniques, Kalman Filtering and the least absolute value filtering algorithms; are powerful examples. The dynamic filters are recursive algorithms. This is unlike static approaches, where the whole set of data is used to obtain the optimal solution. In recursive filters, the estimates are updated using each new measurement. Dynamic filters are well suited to on-line digital processing as data are processed recursively. They had been used extensively in estimation problems for dynamic systems (Amjady, 2001).

Dynamic filters are suitable where measurements change with time. Methods based on artificial intelligence such as artificial neural networks (ANN) and expert systems have been also used with promising results (Kandil et al., 2001). Support vector machine (SVM) has proven to be an attractive tool for load forecasting. SVM is a form of machine learning method which is developed from statistical learning theory. Like ANN, the SVM has the problem of network parameter selection (Singh & Singh, 2001).

Heuristic search methods like genetic algorithms (GA) were also used in electrical load forecasting; based on the mechanism of natural selection and natural genetics (Senjyu et al., 2001). Hybrid methods using ANN, GA, SVM were also proposed (Hsu & Chen, 2003).

Most of the demand forecasting is done through programs that are specifically designed to make data analysis and demand forecast easy. Those programs consume less time to calculate the data, make decision making faster and more efficient. One example of a program that is used for such prediction is IBM – SPSS (Field, 2013).

Research Methods

The research activities followed the following steps:

1. Review and study of the forecasting technique implemented at the University of Northern Iowa (UNI);
2. Study the peak demand management at UNI;
3. Investigate the significance of short-term prediction, using temperature, humidity, duration of study of input factors, and type of day (weekday/weekend) as variables in MLR model

1. Prediction Methods currently used at UNI

UNI uses a program from Schneider Electric that is connected to all the electric meters operating at the university, and displays their readings. The readings show power parameters, like active power, apparent power, power factor, frequencies, etc. This program shows two types of forecast, The Sliding Window Demand, and The Trending and Forecasting (Schneider Electric Reference Guide, 2009).

a) Sliding Window Demand

The Sliding Window Demand module (SWD), as shown in Figure 1, computes the demand values by using the sliding window averaging (or rolling interval) technique. It divides the demand interval into subintervals, and the demand is measured electronically based on the average load level over the most recent set of subintervals. The module can be internally or externally synchronized. External synchronization requires the use of a digital input module as a sync pulse. The module automatically predicts the value that each sliding window demand parameter will attain when updated at the start of the next interval.

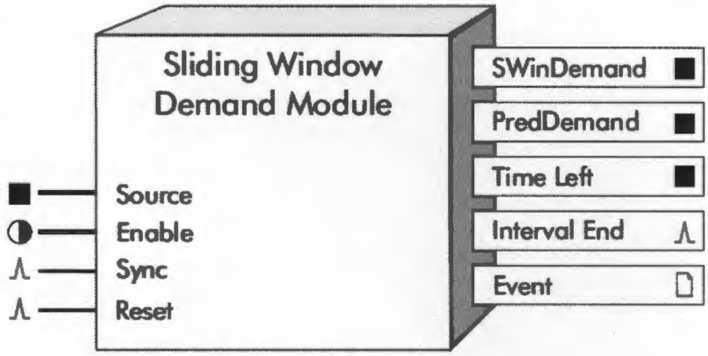

Figure 1: Sliding Window Demand Module, obtained from Schneider Electric Reference Guide (2009)

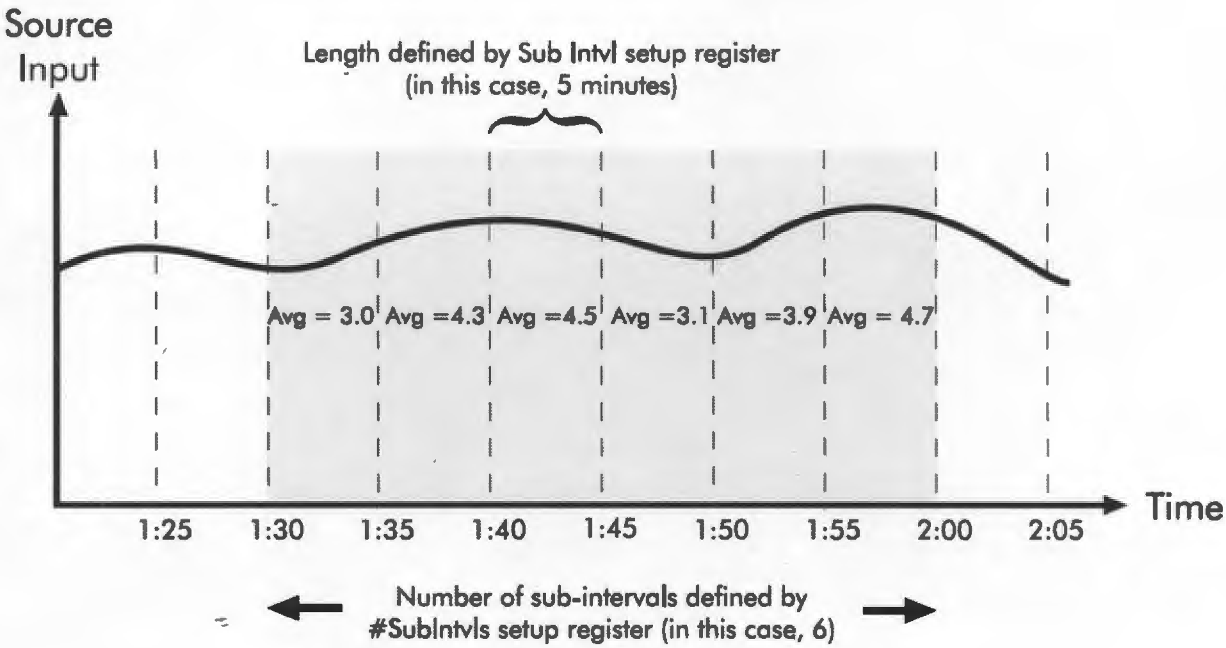

Figure 2: Sliding Window Demand Calculation, obtained from Schneider Electric Reference Guide (2009)

SWinDemand is a numeric register that contains the accumulated sliding window demand. Figure 2 illustrates how the SWD module calculates the value in the SWinDemand output register. The average demand for each of the six previous subintervals is calculated and these values are averaged across the number of subintervals (specified by the subintervals setup register). For example, the value in the SWinDemand output register from 2:00 to 2:05 is:

$$\frac{3.0 + 4.3 + 4.5 + 3.1 + 3.9 + 4.7}{6} = 3.92$$

The SWD module predicts changes in demand based on the following formula:

$$\frac{(\text{Thermal Avg} \times \text{Time Left in subinterval}) + (\text{Accumulated Value in Period}) + (\text{Prev SWD} \times (\text{\# of subintervals} - 1) \times \text{subinterval length})}{\mathit{Total\ Sliding\ Window\ Demand\ Period}}$$

The module automatically calculates the Thermal Average value used in the above formula. The Thermal Average starts at 0 when the Sliding Window Demand module powers up, and gets calculated every second based on the following formula:

$$Thermal\ Avg = \frac{Thermal\ Avg \times (PredBase - 1) + Source}{PredBase}$$

$$\text{Where } PredBase = \frac{100 - PredResp}{100} \times SubIntvl$$

The rate at which the Thermal Average responds to demand changes depends directly on the sensitivity of the demand prediction, which is programmed into the Pred Resp setup register. Pred Resp specifies the speed of the predicted demand response. It ranges is from 0 (slowest prediction) to 99 (fastest prediction). It is recommended to have a value between 70 and 99 for reasonably fast response.

b) The Trending and Forecasting

The Trending and Forecasting module is capable of recording and analysis of long-term changes in data, allowing for forecast of demand values in order to better manage things such as demand charges and time-of-use billing rates. Trend analysis is also useful for predictive maintenance, by revealing changes in load and power quality.

Average, minimum, maximum and standard deviation of the data that resemble actual electricity use, are logged for the source at the intervals of every hour for the last 24 hours, every day for the last month, every week for the last 8 weeks, and every month for the last 12 months. These data are used to graph trends and calculate forecasted values.

Below is an overview of how the trending data are accumulated:

- At the end of a 1-second interval, the present value of the source is added to a running sum of the current minute. The value is only added if it is valid; it is valid as long as the source input is not N/A for that 1-second interval.
- At the end of a 1-minute interval, the values accumulated within the last 60 seconds are averaged if there are more than 30 valid samples (at least 50% of the samples were valid during the 60 second interval). This average is then included with the 1-minute averages for the most recent 60 minutes. The 1- second data is then reset.
- At the end of the hourly, daily, weekly and monthly intervals, the averages accumulated within that interval are averaged. This average is then included with the existing averages for the interval; for example, the hourly average is added to a data structure containing averages for the last 24 hours. The interval average is only valid if at least 50% of the values used to calculate the average are valid. For example, 30 or more minute values must have been valid for an hourly average to be valid and added.
- An algorithm is used to calculate forecasted values for the next four intervals; for example the next four hours if it is an hourly graph.

2. Peak Demand Management at UNI

Figure 3 shows the electrical actual peak values yearly for the past 18 years. The yearly peak demand usually occurs at the end of August or at the beginning of September, when the University starts the New Year and the weather is still hot. Due to the weather and the academic considerations, students would be consuming a lot of electricity, besides the daily use of other electronic devices such as computers, laptops, televisions, hair dryer, etc.

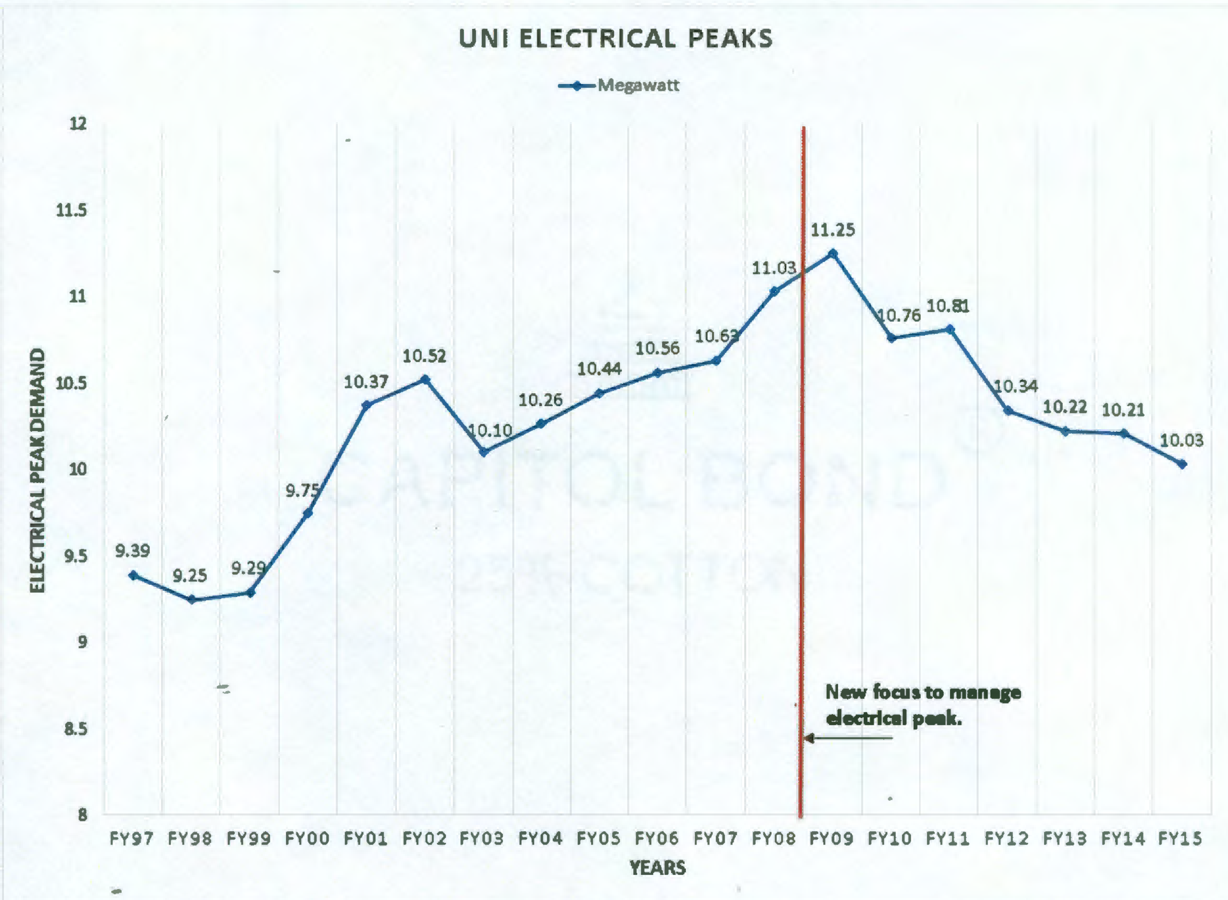

Figure 3: University of Northern Iowa Electrical Peak Demands – Old and New Management (Energy Management Department Documents)

Every year, the demand of UNI for electricity is set between late August and October, and the charge for this demand is paid monthly throughout the whole year. The level of demand establishes the billing rate. That is why UNI started to take in consideration yearly peak demands starting from 2009. The university seeks the help of students to reduce electricity use during time of predicted peaks. After 2009, it is evident that the peak demands took on a decreasing pattern nearly every year.

3. Short-term Prediction using MLR Model from IBM-SPSS

Multiple Linear Regression (MLR) model from IBM-SPSS, was chosen as the program to use for the prediction in this research. SPSS software is a widely used program for statistical analysis in social science. It is also used by market researchers, health researchers, survey companies, government, education researchers, marketing organizations, data miners, and others. In addition to statistical analysis, data management (case selection, file reshaping, creating derived data) and data documentation (a metadata dictionary was stored in the datafile) are features of the base software (Field, 2013).

4. Overview of the Modeling Procedure

The factors that were taken into consideration to be studied were temperature, humidity, duration of study of input factors (1 to 24 hours), and type of day (weekday/weekend). The process of data investigation extended from June 1 to June 14, 2015. The data were collected manually. Data were collected on a daily basis as the main load in the university consistently occurs during working hours.

Three models were created depending on which factors were included in each model. First model included the humidity and the temperature. Second model included the time, the humidity and the temperature; while the third model included the pervious factors in addition the type of the day. The goal was to check which factors affected the electrical demand significantly, in order to create the most suitable model for peak demand prediction.

Results

The multivariate MLR short-term models yielded the following results depending on the number and type of variables used in each model form.

- First Model:

In the first model, the variables that were used were the humidity and the temperature. The goal was to see the significance of the variables on the total power demand.

Table 1: First Model Variables

Model	Variables Entered	Variables Removed	Method
1	HumidityPct, Temp F[b]	.	Enter

a. Dependent Variable: Total (KW)

b. Independent Variables: humidity, temperature

Table 1 shows the variables that were used in this attempt.

Table 2: First Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.606[a]	.367	.364	659.649

a. Predictors: (Constant), HumidityPct, Temp F

This table shows what % of variability in the dependent variable is accounted for by all of the independent variables together (it's a multiple R-square).

Table 3: Analysis of Variance (ANOVA[a])

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	95896615.231	2	47948307.615	110.191	.000[b]
	Residual	165351832.706	380	435136.402		
	Total	261248447.937	382			

a. Dependent Variable: Total (KW)

b. Predictors: (Constant), HumidityPct, Temp F

Table 3 shows an F-test to determine whether the model is a good fit for the data.

According to this p-value, temperature and humidity have a significant effect on the results of prediction.

Table 4: First Model Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	3463.615	505.044		6.858	.000
	Temp F	50.859	5.256	.553	9.677	.000
	HumidityPct	-3.129	2.457	-.073	-1.273	.204

a. Dependent Variable: Total (KW)

The beta coefficients (β) are shown—one to go with each predictor. The "unstandardized coefficients" are used because the constant [beta zero] is included. Based on this table, the equation for the regression line is:

$$Y = \beta 1X1 + \beta 2X2 + \cdots + \beta$$

$$Y = 50.859(Temp\ F) - 3.129(HumidityPct) + 3463.615$$

In this model, the temperature is shown to be significant, but the humidity is not.

- Second Model:

In the second model, the duration of study of input factors was added up to the other variables. This Time variable extended from 1 to 24 hours. The goal was to see test the significance of the model after adding this variable.

Table 5: Second Model Variables

Model	Variables Entered	Variables Removed	Method
1	Time (CDT)[b]	.	Enter
2	HumidityPct, Temp F[b]	.	Enter

a. Dependent Variable: Total (KW)

b. All requested variables entered.

Table 6: Second Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.362[a]	.131	.129	771.901
2	.617[b]	.381	.376	653.062

a. Predictors: (Constant), Time (CDT)

b. Predictors: (Constant), Time (CDT), HumidityPct, Temp

Table 7:ANOVA[a]

Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	34236514.985	1	34236514.985	57.460	.000[b]
	Residual	227011932.953	381	595831.845		
	Total	261248447.937	382			
2	Regression	99608594.806	3	33202864.935	77.851	.000[c]
	Residual	161639853.132	379	426490.378		
	Total	261248447.937	382			

a. Dependent Variable: Total (KW)

b. Predictors: (Constant), Time (CDT)

c. Predictors: (Constant), Time (CDT), HumidityPct, Temp F

Table 8: Second Model Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	6235.901	81.411		76.598	.000
	Time (CDT)	43.292	5.711	.362	7.580	.000
2	(Constant)	3457.396	500.006		6.915	.000
	Time (CDT)	15.760	5.342	.132	2.950	.003
	Temp F	47.205	5.348	.513	8.826	.000
	HumidityPct	-2.237	2.452	-.052	-.912	.362

a. Dependent Variable: Total (KW)

In second model, results show that humidity is not significant, but the temperature and the time are significant.

- Third Model:

In the third Model, the weekend variable is added up to the variables. The goal is to see if adding this variable would affect the total significance of all the variables.

Table 9: Third Model Variables

Model	Variables Entered	Variables Removed	Method
1	WeekDay[b]	.	Enter
2	Time (CDT)[b]	.	Enter
3	Temp F	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).
4	HumidityPct	.	Stepwise (Criteria: Probability-of-F-to-enter <= .050, Probability-of-F-to-remove >= .100).

a. Dependent Variable: Total (KW)

b. Independent Variables: humidity, temperature, time, weekday.

Table 10: Third Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.384[a]	.148	.145	764.493
2	.529[b]	.279	.276	703.853
3	.756[c]	.571	.568	543.558
4	.761[d]	.579	.575	539.145

a. Predictors: (Constant), WeekDay

b. Predictors: (Constant), WeekDay, Time (CDT)

c. Predictors: (Constant), WeekDay, Time (CDT), Temp F

d. Predictors: (Constant), WeekDay, Time (CDT), Temp F, HumidityPct

Table 11: Third Model ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38573289.616	1	38573289.616	65.999	.000[b]
	Residual	222675158.321	381	584449.234		
	Total	261248447.937	382			
2	Regression	72993022.610	2	36496511.305	73.669	.000[c]
	Residual	188255425.327	380	495409.014		
	Total	261248447.937	382			
3	Regression	149271059.837	3	49757019.946	168.408	.000[d]
	Residual	111977388.101	379	295454.850		
	Total	261248447.937	382			
4	Regression	151372567.516	4	37843141.879	130.190	.000[e]
	Residual	109875880.422	378	290676.932		
	Total	261248447.937	382			

a. Dependent Variable: Total (KW)

b. Predictors: (Constant), WeekDay

c. Predictors: (Constant), WeekDay, Time (CDT)

d. Predictors: (Constant), WeekDay, Time (CDT), Temp F

e. Predictors: (Constant), WeekDay, Time (CDT), Temp F, HumidityPct

Table 12: Third Model Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.
		B	Std. Error	Beta		
1	(Constant)	6227.031	78.026		79.807	.000
	WeekDay	732.261	90.136	.384	8.124	.000
2	(Constant)	5684.435	96.943		58.637	.000
	WeekDay	734.001	82.986	.385	8.845	.000
	Time (CDT)	43.408	5.208	.363	8.335	.000
3	(Constant)	2160.482	231.745		9.323	.000
	WeekDay	838.094	64.414	.440	13.011	.000
	Time (CDT)	14.106	4.416	.118	3.194	.002
	Temp F	54.826	3.412	.596	16.068	.000
4	(Constant)	1125.784	448.242		2.512	.012
	WeekDay	888.388	66.572	.466	13.345	.000
	Time (CDT)	15.495	4.410	.130	3.513	.000
	Temp F	63.096	4.573	.686	13.797	.000
	HumidityPct	5.670	2.109	.132	2.689	.007

a. Dependent Variable: Total (KW)

$$Y = 888.388(WeekDay) + 15.495(Time\ (CDT)) + 63.096(Temp\ F) + 5.670(HumidityPct) + 1125.784$$

In this model, all the variables were significant.

Figure 4 shows the two forecast methods, IBM-SPSS and UNI Sliding Window Forecast, in comparison to the actual power values. It is evident that the UNI forecasting aligns closely with the actual values. Although IBM-SPSS is a less sophisticated method of forecasting with a manual collection of data, yet the values in the figure show a close pattern to the actual power data.

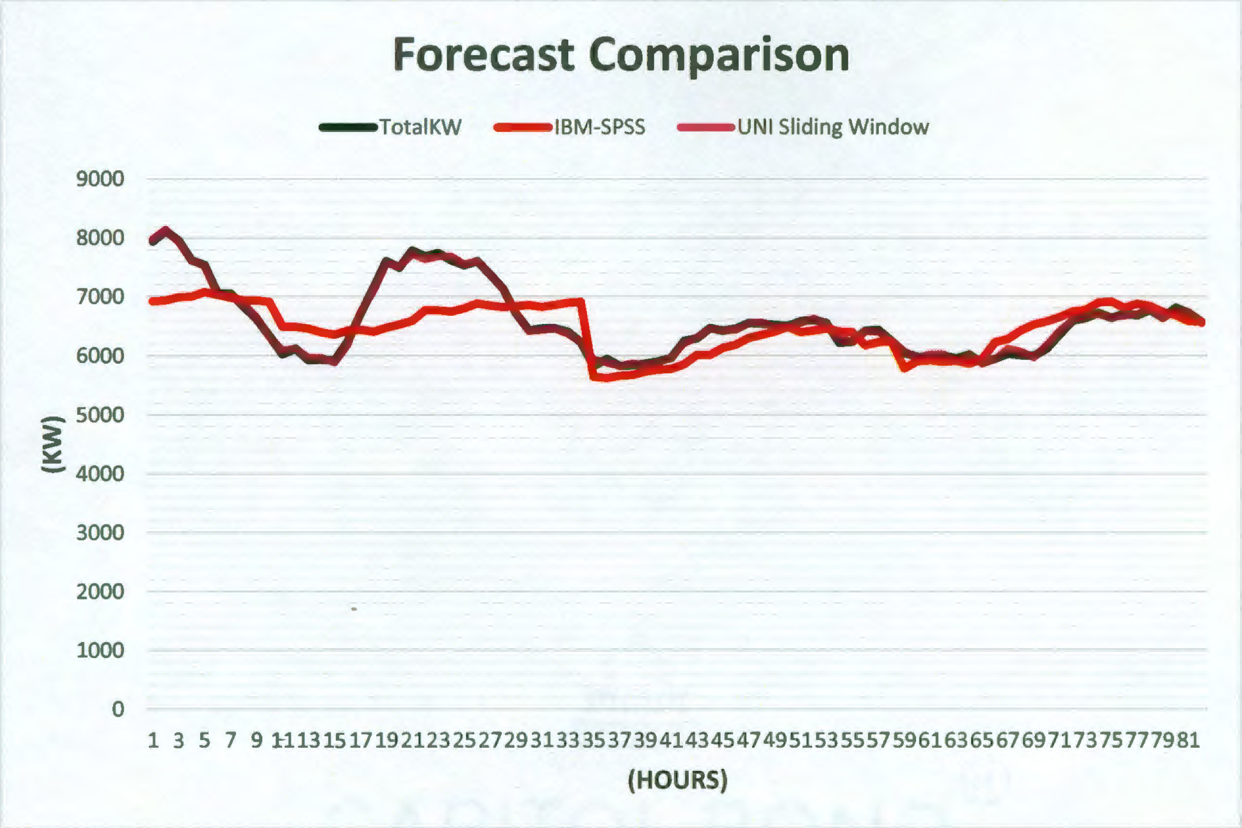

Figure 4: Predicted Values of IBM-SPSS and UNI Sliding Window in comparison to the Actual Total Power Values

Data Analysis

The weather variables, temperature and humidity, were included in the MLR short-term IBM-SPSS model as the importance of these factors in prediction was stressed in previous articles. Fahad and Arbab (2015) have stressed on the importance of weather as an independent variable in electricity peak demand forecasting. Temperature is a weather factor that can alter the conductivity of the transmission lines; besides having a significant correlation with electrical demand whether in summer or in winter. Humidity has no effect on the real temperature, but can intensify the feeling of severity of hot temperature, leading to more use of cooling appliances.

The use of multiple variables in short-term electricity prediction adds value to the significance of the prediction model. It resembles more the complex nature of many factors interplaying to ultimately give the actual electricity demand. In the current MLR model, the variables of humidity, temperature, duration of study of these variables, and the type of day were included in the model and yielded best results in comparison to the use of only two variables.

Conclusions

The following could be concluded from the present study:

- The live extraction of data used by the University of Northern Iowa proved to be less time consuming and with less error factor compared to the manual extraction of data used in the current MLR model.
- The humidity factor was the least significant factor in the short-term MLR model.
- Including more variables, weather and time related, in short-term prediction models yields better significance in prediction results.

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Appendix

Table 1: IBM-SPSS Multiple Linear Regression Data with Predicted Values

JuneDay	TimeCDT	TempF	HumidityPct	TotalKW	WeekDay	PredictedValue (KW)
1	1	50.0	77	5314	1	5621.06
1	2	48.9	77	5308	1	5567.15
1	3	46.9	80	5171	1	5473.46
1	4	45.0	82	4934	1	5380.41
1	5	46.0	79	4897	1	5441.99
1	6	44.1	82	5065	1	5354.62
1	7	48.0	83	5533	1	5621.86
1	8	52.0	71	6313	1	5821.69
1	9	55.9	57	6769	1	6003.88
1	10	59.0	51	7026	1	6180.96
1	11	62.1	44	7331	1	6352.36
1	12	63.0	41	7369	1	6407.63
1	13	66.0	42	7294	1	6618.08
1	14	66.2	46	7308	1	6668.88
1	15	69.8	40	7165	1	6877.50
1	16	71.1	41	7242	1	6980.69

1	17	71.1	36	7254	1	6967.83
1	18	70.0	36	7042	1	6913.92
1	19	69.8	38	6798	1	6928.14
1	20	64.9	45	6458	1	6674.15
1	21	60.1	55	6330	1	6443.49
1	22	57.9	60	6301	1	6348.52
1	23	55.9	60	6162	1	6237.82
1	24	55.9	60	5839	1	6253.32
2	1	55.9	60	5702	1	5896.93
2	2	55.0	62	5630	1	5866.98
2	3	53.1	69	5535	1	5802.28
2	4	53.1	71	5340	1	5829.12
2	5	54.0	72	5270	1	5907.07
2	6	50.0	86	5452	1	5749.56
2	7	54.0	80	5848	1	5983.42
2	8	55.9	77	6445	1	6101.79
2	9	61.0	75	6775	1	6427.73
2	10	64.9	70	7310	1	6660.95
2	11	66.0	65	7385	1	6717.50
2	12	68.0	61	7384	1	6836.51
2	13	69.8	60	7477	1	6959.91
2	14	70.0	57	7524	1	6971.01

2	15	72.0	53	7545	1	7090.02
2	16	73.9	48	7394	1	7197.05
2	17	73.9	48	7480	1	7212.54
2	18	73.9	48	7294	1	7228.04
2	19	71.1	51	7047	1	7083.87
2	20	69.1	57	6538	1	7007.20
2	21	66.9	61	6429	1	6906.56
2	22	64.0	70	6461	1	6790.11
2	23	62.1	75	6426	1	6714.07
2	24	61.0	78	6083	1	6677.17
3	1	60.1	78	5798	1	6264.00
3	2	60.1	78	5725	1	6279.49
3	3	59.0	83	5815	1	6253.93
3	4	59.0	83	5450	1	6269.43
3	5	59.0	83	5649	1	6284.92
3	6	59.0	83	5923	1	6300.42
3	7	61.0	81	6295	1	6430.76
3	8	63.0	78	6788	1	6555.44
3	9	64.0	75	7118	1	6617.02
3	10	66.9	73	7341	1	6804.15
3	11	72.0	66	7479	1	7101.75
3	12	75.0	62	7599	1	7283.85

3	13	78.1	60	7704	1	7483.60
3	14	77.0	60	7717	1	7429.69
3	15	80.1	58	7664	1	7629.45
3	16	79.0	58	7840	1	7575.54
3	17	79.0	60	7748	1	7602.37
3	18	78.1	60	7421	1	7561.08
3	19	78.1	58	7304	1	7565.23
3	20	75.9	62	6813	1	7464.60
3	21	73.9	66	6652	1	7376.58
3	22	71.1	73	6792	1	7255.10
3	23	68.0	87	6462	1	7154.38
3	24	64.9	93	6137	1	7008.29
4	1	64.9	90	5982	1	6634.90
4	2	62.1	96	5913	1	6507.74
4	3	62.1	93	5793	1	6506.23
4	4	60.8	94	5875	1	6445.37
4	5	57.9	93	5775	1	6272.22
4	6	57.9	93	5872	1	6287.71
4	7	62.1	96	6473	1	6585.22
4	8	64.9	90	7026	1	6743.36
4	9	70.0	81	7509	1	7029.62
4	10	73.9	73	7643	1	7245.83

4	11	77.0	62	7941	1	7394.55
4	12	79.0	58	7999	1	7513.56
4	13	81.0	56	7928	1	7643.90
4	14	81.0	58	7837	1	7670.74
4	15	82.0	54	7700	1	7726.65
4	16	84.2	48	7743	1	7846.94
4	17	84.0	49	7807	1	7855.48
4	18	84.0	53	7568	1	7893.66
4	19	79.0	58	7446	1	7622.02
4	20	75.9	62	6984	1	7464.60
4	21	73.0	68	6977	1	7331.14
4	22	71.6	69	6806	1	7263.97
4	23	69.1	78	6707	1	7172.75
4	24	68.0	81	6306	1	7135.85
5	1	66.9	84	6024	1	6727.07
5	2	64.9	87	6085	1	6633.38
5	3	64.0	90	5996	1	6609.10
5	4	64.9	87	5899	1	6664.37
5	5	63.0	90	5824	1	6577.00
5	6	62.1	93	6126	1	6552.71
5	7	66.0	87	6616	1	6780.26
5	8	69.1	78	6996	1	6940.33

5	9	72.0	71	7628	1	7099.11
5	10	75.2	61	7759	1	7259.81
5	11	77.0	56	7958	1	7360.53
5	12	79.0	54	7803	1	7490.88
5	13	80.1	50	7714	1	7553.10
5	14	81.0	49	7728	1	7619.71
5	15	79.0	50	7719	1	7514.68
5	16	80.6	48	7811	1	7619.79
5	17	82.9	46	7719	1	7769.07
5	18	80.1	54	7292	1	7653.25
5	19	78.1	58	6923	1	7565.23
5	20	73.9	62	6494	1	7338.41
5	21	70.0	71	6500	1	7158.86
5	22	69.1	70	6592	1	7111.90
5	23	66.9	76	6485	1	7022.60
5	24	64.9	75	6151	1	6906.23
6	1	62.1	78	5860	0	5501.80
6	2	61.0	78	5836	0	5447.89
6	3	59.0	83	5830	0	5365.54
6	4	57.2	88	5768	0	5295.82
6	5	57.9	87	5704	0	5349.81
6	6	57.9	84	5781	0	5348.29

6	7	59.0	75	5839	0	5382.16
6	8	62.1	72	5886	0	5576.25
6	9	63.0	70	5919	0	5637.19
6	10	66.9	66	5827	0	5876.08
6	11	69.1	63	5921	0	6013.37
6	12	72.0	59	6091	0	6189.17
6	13	73.9	57	6198	0	6313.20
6	14	73.9	59	6227	0	6340.04
6	15	75.9	56	6304	0	6464.72
6	16	77.0	56	6372	0	6549.62
6	17	77.0	54	6433	0	6553.77
6	18	75.9	58	6443	0	6522.54
6	19	75.0	57	6362	0	6475.58
6	20	75.0	60	6008	0	6508.08
6	21	73.0	61	6025	0	6403.06
6	22	72.0	66	6251	0	6383.81
6	23	71.1	70	6366	0	6365.19
6	24	70.0	73	6222	0	6328.29
7	1	70.0	76	5845	0	5988.92
7	2	70.0	78	6059	0	6015.75
7	3	68.0	93	6023	0	5990.11
7	4	66.0	93	5961	0	5879.41

7	5	66.9	90	5983	0	5934.68
7	6	66.0	93	5961	0	5910.40
7	7	66.9	90	5940	0	5965.67
7	8	70.0	84	5863	0	6142.74
7	9	70.0	84	5925	0	6158.24
7	10	75.9	71	5926	0	6472.29
7	11	79.0	64	5870	0	6643.69
7	12	79.0	69	5966	0	6687.54
7	13	81.0	65	6568	0	6806.55
7	14	82.0	58	6577	0	6845.45
7	15	84.0	49	6607	0	6936.10
7	16	82.9	41	6596	0	6836.83
7	17	82.9	46	6631	0	6880.68
7	18	82.0	42	6527	0	6816.71
7	19	75.0	60	6699	0	6492.59
7	20	73.9	62	6580	0	6450.02
7	21	72.0	66	6589	0	6368.31
7	22	71.6	60	6495	0	6324.55
7	23	69.1	70	6464	0	6239.00
7	24	66.0	78	6303	0	6104.26
8	1	64.9	81	5962	1	6583.87
8	2	64.9	78	6017	1	6582.35

8	3	63.0	81	5866	1	6494.98
8	4	61.0	90	5900	1	6435.31
8	5	61.0	93	5741	1	6467.81
8	6	59.0	93	6131	1	6357.12
8	7	64.0	90	6709	1	6671.08
8	8	68.0	76	7326	1	6859.58
8	9	71.1	68	7929	1	7025.31
8	10	73.4	65	8139	1	7168.92
8	11	77.0	56	8181	1	7360.53
8	12	78.8	47	8268	1	7438.57
8	13	80.1	42	8087	1	7507.74
8	14	82.0	41	7922	1	7637.44
8	15	82.0	41	7854	1	7652.94
8	16	82.9	38	8205	1	7708.21
8	17	82.9	38	8069	1	7723.71
8	18	82.4	39	7777	1	7713.32
8	19	80.1	39	7441	1	7583.70
8	20	77.0	43	6982	1	7426.27
8	21	73.9	48	6815	1	7274.52
8	22	71.6	57	6708	1	7195.93
8	23	66.0	73	6678	1	6948.80
8	24	63.0	84	6357	1	6837.38

9	1	61.0	87	6020	1	6371.81
9	2	60.1	90	5958	1	6347.53
9	3	59.0	90	5843	1	6293.62
9	4	57.9	93	5814	1	6256.72
9	5	57.9	93	5736	1	6272.22
9	6	57.9	90	6193	1	6270.70
9	7	62.1	90	6753	1	6551.20
9	8	70.0	68	7130	1	6940.41
9	9	75.9	58	7716	1	7271.47
9	10	82.0	44	7975	1	7592.47
9	11	87.1	36	8152	1	7884.40
9	12	89.1	32	8176	1	8003.41
9	13	91.0	30	8197	1	8127.44
9	14	91.9	30	8153	1	8199.72
9	15	93.9	29	8146	1	8335.74
9	16	93.2	28	8098	1	8301.40
9	17	93.2	28	8202	1	8316.89
9	18	93.0	28	7958	1	8319.77
9	19	91.0	32	7586	1	8231.75
9	20	87.1	36	7246	1	8023.85
9	21	84.9	41	6889	1	7928.89
9	22	82.4	48	6950	1	7826.33

9	23	81.0	49	6743	1	7759.16
9	24	81.0	50	6438	1	7780.33
10	1	79.0	54	6197	1	7320.43
10	2	75.9	62	6143	1	7185.69
10	3	78.1	58	6020	1	7317.31
10	4	75.9	62	5936	1	7216.68
10	5	71.1	70	5973	1	6974.67
10	6	66.0	84	6357	1	6747.76
10	7	72.0	71	6783	1	7068.12
10	8	73.9	66	7397	1	7175.15
10	9	77.0	58	7955	1	7340.88
10	10	79.0	50	8079	1	7437.21
10	11	82.0	35	8170	1	7556.94
10	12	82.9	32	8360	1	7612.21
10	13	82.9	34	8232	1	7639.05
10	14	84.9	34	8300	1	7780.73
10	15	86.0	35	8414	1	7871.30
10	16	87.8	31	8133	1	7977.69
10	17	87.1	33	7891	1	7960.36
10	18	86.0	32	7707	1	7900.78
10	19	84.0	34	7618	1	7801.42
10	20	81.0	42	6956	1	7672.99

10	21	75.0	51	6798	1	7360.94
10	22	71.1	59	6821	1	7175.72
10	23	69.1	61	6695	1	7076.36
10	24	71.1	55	6369	1	7184.03
11	1	69.8	56	6004	1	6751.29
11	2	69.1	61	6093	1	6750.97
11	3	68.0	63	5951	1	6708.40
11	4	64.9	78	5939	1	6613.34
11	5	64.0	84	5885	1	6606.07
11	6	62.1	93	6135	1	6552.71
11	7	62.1	93	6820	1	6568.21
11	8	61.0	97	7276	1	6536.98
11	9	63.0	90	7772	1	6638.98
11	10	64.4	88	7934	1	6731.46
11	11	64.0	90	8186	1	6733.06
11	12	64.9	90	8115	1	6805.34
11	13	64.0	93	7991	1	6781.06
11	14	64.9	93	8049	1	6853.34
11	15	66.0	90	7942	1	6921.23
11	16	66.2	88	8117	1	6938.01
11	17	66.9	87	7955	1	6992.00
11	18	66.0	96	7620	1	7001.74

11	19	66.9	97	7540	1	7079.69
11	20	66.0	96	7058	1	7032.73
11	21	64.9	97	7056	1	6984.49
11	22	64.0	96	6833	1	6937.53
11	23	64.0	93	6623	1	6936.01
11	24	63.0	97	6337	1	6911.09
12	1	62.1	96	6029	1	6492.25
12	2	62.1	93	6125	1	6490.73
12	3	61.0	97	5929	1	6459.50
12	4	60.1	93	5934	1	6395.53
12	5	59.0	96	5919	1	6358.63
12	6	60.1	93	6232	1	6426.52
12	7	60.1	93	6703	1	6442.02
12	8	59.0	96	7145	1	6405.12
12	9	60.1	93	7605	1	6473.01
12	10	61.0	90	7495	1	6528.28
12	11	62.1	86	7789	1	6590.50
12	12	64.9	84	7688	1	6771.32
12	13	64.9	81	7746	1	6769.81
12	14	64.0	84	7620	1	6745.53
12	15	64.9	81	7537	1	6800.80
12	16	66.0	81	7607	1	6885.70

12	17	64.9	84	7382	1	6848.80
12	18	64.0	87	7134	1	6824.52
12	19	64.0	87	6716	1	6840.01
12	20	64.0	87	6431	1	6855.51
12	21	63.0	90	6464	1	6824.92
12	22	63.0	93	6464	1	6857.42
12	23	63.0	97	6406	1	6895.60
12	24	63.0	97	6227	1	6911.09
13	1	63.0	93	5829	0	5643.64
13	2	62.1	96	5946	0	5619.36
13	3	62.1	100	5830	0	5657.53
13	4	62.1	100	5837	0	5673.03
13	5	63.0	97	5870	0	5728.30
13	6	63.0	100	5904	0	5760.80
13	7	63.0	100	5966	0	5776.30
13	8	64.0	100	6252	0	5854.89
13	9	66.9	93	6295	0	6013.67
13	10	66.9	90	6467	0	6012.16
13	11	69.1	84	6422	0	6132.44
13	12	70.0	81	6459	0	6187.71
13	13	72.0	76	6553	0	6301.05
13	14	73.0	71	6540	0	6351.29

13	15	73.9	68	6519	0	6406.56
13	16	75.2	65	6500	0	6487.07
13	17	73.0	71	6581	0	6397.78
13	18	73.0	73	6604	0	6424.61
13	19	73.0	76	6553	0	6457.12
13	20	72.0	76	6218	0	6409.52
13	21	71.1	81	6238	0	6396.57
13	22	66.2	94	6421	0	6176.61
13	23	66.9	93	6438	0	6230.60
13	24	66.9	93	6254	0	6246.10
14	1	64.9	97	6046	0	5786.20
14	2	66.9	93	5985	0	5905.21
14	3	66.9	93	5989	0	5920.70
14	4	66.0	96	6003	0	5896.42
14	5	66.0	96	5956	0	5911.92
14	6	64.9	97	6022	0	5863.67
14	7	66.0	96	5877	0	5942.91
14	8	71.1	87	5952	0	6229.16
14	9	72.0	84	6035	0	6284.43
14	10	75.0	73	6008	0	6426.84
14	11	77.0	66	6001	0	6528.84
14	12	78.1	60	6124	0	6579.72

14	13	79.0	60	6364	0	6652.00
14	14	80.1	62	6593	0	6748.24
14	15	80.1	64	6637	0	6775.08
14	16	82.0	62	6722	0	6899.12
14	17	82.0	62	6640	0	6914.61
14	18	79.0	74	6711	0	6808.86
14	19	80.1	71	6682	0	6876.75
14	20	79.0	74	6773	0	6839.85
14	21	77.0	76	6641	0	6740.49
14	22	75.2	83	6813	0	6682.10
14	23	73.0	87	6723	0	6581.47
14	24	72.0	93	6571	0	6567.89

Table 2: University of Northern Iowa Sliding Window Forecast

JuneDay	TimeCDT	Total(KW)	UNI Sliding Window forcast (KW)
11	15	7942	7982.592
11	16	8117	8145.651
11	17	7955	7931.269
11	18	7620	7623.328

11	19	7540	7524.734
11	20	7058	7038.541
11	21	7056	7023.576
11	22	6833	6882.583
11	23	6623	6654.635
11	24	6337	6321.964
12	1	6029	6092.955
12	2	6125	6120.905
12	3	5929	5970.071
12	4	5934	5966.123
12	5	5919	5883.809
12	6	6232	6178.448
12	7	6703	6728.501
12	8	7145	7097.719
12	9	7605	7566.847
12	10	7495	7518.093

12	11	7789	7722.854
12	12	7688	7635.585
12	13	7746	7683.657
12	14	7620	7686.957
12	15	7537	7550.972
12	16	7607	7609.95
12	17	7382	7384.666
12	18	7134	7126.577
12	19	6716	6730.732
12	20	6431	6416.092
12	21	6464	6433.485
12	22	6464	6459.475
12	23	6406	6367.585
12	24	6227	6234.985
13	1	5829	5931.114
13	2	5946	5886.086

13	3	5830	5822.598
13	4	5837	5872.394
13	5	5870	5849.008
13	6	5904	5881.465
13	7	5966	5972.426
13	8	6252	6211.055
13	9	6295	6307.017
13	10	6467	6454.701
13	11	6422	6423.939
13	12	6459	6435.241
13	13	6553	6550.627
13	14	6540	6561.706
13	15	6519	6480.117
13	16	6500	6479.599
13	17	6581	6552.082
13	18	6604	6624.781

13	19	6553	6533.006
13	20	6218	6273.85
13	21	6238	6245.873
13	22	6421	6412.179
13	23	6438	6403.239
13	24	6254	6250.262
14	1	6046	6073.633
14	2	5985	5968.331
14	3	5989	6028.858
14	4	6003	6030.588
14	5	5956	5906.153
14	6	6022	6019.953
14	7	5877	5868.248
14	8	5952	5940.628
14	9	6035	6121.261
14	10	6008	6070.006

14	11	6001	5970.223
14	12	6124	6184.652
14	13	6364	6419.145
14	14	6593	6602.67
14	15	6637	6676.948
14	16	6722	6699.687
14	17	6640	6647.255
14	18	6711	6671.899
14	19	6682	6702.597
14	20	6773	6785.703
14	21	6641	6627.546
14	22	6813	6762.253
14	23	6723	6738.748
14	24	6571	6543.543