Short-term Load Forecasting Using Neural Network For Future Smart Grid Application

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University of Denver

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SHORT-TERM LOAD FORECASTING USING NEURAL NETWORK FOR FUTURE SMART GRID APPLICATION

A Thesis

Presented to

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Master of Science

by

Jason Jixuan Zheng

March 2014

Advisor: David Wenzhong Gao
Abstract

Short-term load forecasting of power system has been a classic problem for a long time. Not merely it has been researched extensively and intensively, but also a variety of forecasting methods has been raised.

This thesis outlines some aspects and functions of smart meter. It also presents different policies and current statuses as well as future projects and objectives of SG development in several countries.

Then the thesis compares main aspects about latest products of smart meter from different companies.

Lastly, three types of prediction models are established in MATLAB to emulate the functions of smart grid in the short-term load forecasting, and then their results are compared and analyzed in terms of accuracy. For this thesis, more variables such as dew point temperature are used in the Neural Network model to achieve more accuracy for better short-term load forecasting results.
Acknowledgements

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Chapter One: Introduction

Short-term load forecasting of power system has been a classic problem for a long time. Not merely it has been researched extensively and intensively, but also a variety of forecasting methods has been raised. In the modern world, with the high development of electricity market and rapid expansion of power system, short-term load forecasting is becoming an important factor of power system operation scheduling. Thus, how to improve the accuracy of short-term load forecasting has always been the focus of load forecasting study.

Power grid is the electrical system that consists of electrical generation, electrical transmission, electrical distribution and electrical consumption. For the traditional power grids, electrical power is delivered from a few central generators to a large number of load centers with electricity users or customers [1]. A smart grid (SG) is a novel type of power grid under development, which allows unconventional power flow and two-way information flow to create an advanced automatic and distributed energy delivery network. Table 1.1.1 shows a brief comparison between the existing grid and the smart grid (SG).
Table 1.1.1 Comparison between the existing grid and the SG [1]

<table>
<thead>
<tr>
<th>Existing Grid</th>
<th>Smart Grid</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electromechanical</td>
<td>Digital</td>
</tr>
<tr>
<td>One-way communication</td>
<td>Two-way communication</td>
</tr>
<tr>
<td>Centralized generation</td>
<td>Distributed generation</td>
</tr>
<tr>
<td>Few sensors</td>
<td>Sensors throughout</td>
</tr>
<tr>
<td>Manual monitoring</td>
<td>Self-monitoring</td>
</tr>
<tr>
<td>Manual restoration</td>
<td>Self-healing</td>
</tr>
<tr>
<td>Failures and blackouts</td>
<td>Adaptive and islanding</td>
</tr>
<tr>
<td>Limited control</td>
<td>Pervasive control</td>
</tr>
<tr>
<td>Few customer choices</td>
<td>Many customer choices</td>
</tr>
</tbody>
</table>

Smart meter is one of the most important devices implemented in the smart grid (SG). With smart meters, electrical data such as voltage and frequency are measured and real-time energy consumption information is recorded. Smart meter supports bidirectional communications between the meter and the central system. Also, the smart meter has the built-in ability to disconnect and reconnect certain loads remotely, which can be used to monitor and control the users’ devices and appliances so as to manage demands and loads within the “smart-buildings” in the future. Figure 1.1.1 shows comparison of conventional energy meter and smart meter.
The rest of the thesis is organized as follows. Section II presents the theories and methods of the short-term load forecasting in the electrical power system; section III outlines various functions of smart meters and their practical benefits, also shows two kinds of typical technologies for smart meter communication and related research; section IV discusses current situations in several countries and the future policies and objectives of relevant governments in detail, also compares main aspects about latest products from different smart meter manufactures; section V presents three different kinds of short-term load forecasting methods by using the software of MATLAB.
Chapter Two: Theories and Methods of Short-Term Load Forecasting in The Electrical Power System

2.1 Research and practical significance of short-term load forecasting

Short-term load forecasting is based on historical data of the load power, temperature and date type to explore the intrinsic link between the short-term load and associated factors and to seek the future load prediction based on historical data. A load research program aims to deal with the past and future load conditions so as to achieve the specified accuracy and ultimately to predict the load effectively. High-precision short-term load forecasting provides a foundation for electricity operator to make the right decisions and to develop best power generation planning, scheduling and other activities. It is important to study the recent growing trend of the short-term load forecasting method and master relevant advanced technology, which are beneficial for improving the accuracy of short-term load forecasting.

2.2 Types of load forecasting

Under normal circumstances, according to the forecasting period and purposes, load forecasting can be classified as long-term load forecasting, medium-term load forecasting, short-term load forecasting, and ultra short-term load forecasting. Usually, the load and power consumption can be predicted by adopting these different time-scale forecasts.
The long-term load forecast period is generally 10 to 15 years or even longer. The prediction target is usually the regional load capacity or the annual electricity consumption. The prediction purpose is to provide the base data for the power grid planning that help determine the grid operation mode and annual maintenance plans. The main factors affecting long-term load forecasting are national economic development, population, industrial restructuring and national tariff policy and so on. Currently, mature prediction methods comprise the trend extrapolation and various types of relevant prediction methods taking into account main factors, such as regression analysis, running average, exponential smoothing and grey prediction.

The medium-term load forecast period is generally 5 or 6 years. The prediction target usually is the load capacity of a region or the monthly electricity consumption. The forecast data generally indicates cyclical growth and each month of one year consists with the similar growth pattern. The prediction purpose is to arrange monthly maintenance plan, operation mode, reservoir operation plans and coal transportation plans. The main factors affecting medium-term load forecasting come from production planning from large users, weather conditions, industrial restructuring situations and national tariff policy and so on. Currently, the mature prediction methods are trend extrapolation based on the historical data of the same month and the time series prediction methods based on the yearly data.

The short-term load forecast period is generally 24 or 48 hours or even one week. The prediction target usually is the load capacity of a region or the daily and weekly electricity consumption data. The forecasting data generally indicates daily or monthly
periodicity and the same date type of one year that follows the similar periodic pattern. The prediction purpose is to arrange day forecast for power generation projects as well as suspending or restarting power plans. The main factors affecting short-term load forecasting are week type, weather conditions and national tariff policy and so on. Currently, the mature prediction methods are the trend extrapolation based on the historical data of the same day and the artificial neural network based on the daily data.

The ultra short-term load forecast period is generally within 24 hours. The prediction target is usually the load capacity of several hours after the current moment. The forecast data generally has the similar change of instantaneous rate with the data a few days ago. The prediction purpose is mainly used for real-time security analysis, real-time economic dispatch, automatic generation control (AGC). There are few factors that can influence the ultra short-term load forecasting. However, only in summer the temperature can be regarded as a main impact factor contributing to the change on the predicted results. Currently, the mature prediction methods are trend extrapolation allowing for the instantaneous variation rate during the same time interval of previous several days, such as linear extrapolation and exponential smoothing methods.

2.3 Concept and classification of electrical load

Electrical load refers to the amount of power consumption. The amount of power demand refers to the rates of change of the consumed electric energy over time, known as the power. For power grid, the grid’s load is assumed as the workload at a particular moment. For the power user, the user's load refers to the consumed electricity by all
electrical equipment at a moment. This thesis focuses on the load forecasting at the users' side.

1. Industrial electricity

Industrial electricity mainly refers to the various industrial enterprises responsible for the industrial production of electricity. If the production is a cross-industry production, it should be classified into mining and manufacturing according to their main product types. In view of the current situation, the industrial load occupies the most important portion of the total power consumption. Its main feature is that the industrial load operation remains stable in the case of no accident taking place, but this stability situation does not take into account the seasonal production. Otherwise, these stability issue needs to be considered thoroughly. In terms of one month, it is normal for electricity consumption of industrial load to maintain relatively low level at the early stage of the month. However, for the full loaded industry, the electricity consumption of industrial load at the end stage of the month is higher than that at the middle stage of the month or at the early stage of the month. The power consumption at the early stage of the month is still the lowest part. But, in terms of one day, there will be three peaks and two troughs within it. Considering the industry features, the industrial electricity load consumption is usually relatively lower in the evening than that in the daytime. In addition, the industrial load is also affected by environmental conditions. Especially for industrial loads in some particular areas, they fluctuate subject to sunlight and air temperature change.

2. Urban and rural residential electricity
Actually, urban and rural residential electricity mainly refers to the household electricity. This consumption pattern has some prominent features such as stable growth, and is affected by seasonality. The difference between residential and industrial electrical load is that the residential one is influenced by the residents’ living habits. The impact of peak load on the system is primarily due to the seasonal fluctuations. As to the size of impact, it is not artificial but mainly depend on its proportional size relative to the total power system load. Generally speaking, compared with industrial electricity, the residential electrical load is secondary in terms of the proportion of the total electricity.

3. Commercial electricity

Commercial electricity mainly refers to the commercial electricity load in the operating time. Its basic characteristic is that the coverage area is larger than others. More importantly, the growth rate is relatively more stable. And this type of load is not likely to be affected by the seasonal fluctuations. In comparison with the other electricity load, the commercial load belongs to a relatively small part of the total power system load. Additionally, the period of time occupied by the commercial lighting load coincide with that of the peak electrical load. Lastly but not least, the commercial electricity load is usually impacted due to holidays.

2.4 Characteristics and influencing factors of short-term load forecasting

2.4.1 Short-term load forecasting features

The objective of short-term load forecasting is to find out the load variation trend and predict future development by using correct prediction methods.
The characteristics of short-term load are as follows:

1. Uncertainty
   It is uncertain to know the future development of the load because the changes are related with a lot of factors that are also constantly developing and changing. Although several of these factors can be predicted, the remaining are difficult to predict, which makes our prediction results uncertain.

2. Conditionality
   The future load change occurs under the necessary conditions and the assumed conditions when predicting it. The necessary condition is the ability to predict the essential rules of change in load, and prediction results obtained in this case are usually effective. In many cases, the load change in the future is difficult to determine. That is why the assumed conditions exist. Assumed conditions are based on some certain research and obtained through repeated analysis. Therefore, some prerequisite are given prior to our predicting outcomes.

3. Temporality
   The short-term load forecasting is conducted by applying scientific prediction method during a certain period of time scale, such as minutes, hours and days. In this way, the temporality is one important feature of the short-term load forecasting.

4. Multi-scheme
   In various environments, sometimes it is necessary to predict the future load trends according to the uncertainty and conditionality of the short-term load forecasting. Thus, a variety of short-term load forecasting method is developed. The load forecasting is
conducted based on the real-time data. The short-term load forecast model might fail to fulfill its function while the load characteristics change over time. Therefore, to ensure an accurate prediction during the change in load characteristics, it is necessary to choose an appropriate short-term load forecasting methods and make corresponding adjustments based on the previous short-term load forecasting model.

2.4.2 Influencing factors of short-term load forecasting

The system load is complicated and diverse since it is affected by different social and natural conditions. These social factors include energy utilization, agricultural structure, national policy, the rate of economic growth, population growth, social conditions, national holiday system, development level of science and technology. Natural factors consist of the complex and diverse changes in the weather, natural disasters, season changing and so on.

Since the short-term load forecast has a shorter time interval during the prediction, the main factors, including the level of social progress, national policies, the use of energy and the changing of the seasons and other natural factors, has less impact on the short-term load forecasting. Usually there are four main factors that can impact the short-term load forecast.

1. Meteorological condition

It includes many aspects like season, wind, pressure, temperature, humidity and sunshine and many other conditions. With the people's living standards improvement and the social economics development, an increasing number of household electrical
appliances are put into daily use, such as refrigerators and air conditioners. All those electrical devices make residential load become an increasing component of the total power load. Since the impacts of changes from the season, temperature and other meteorological factors have been increasingly imposed on the load, it is necessary to consider their impact on human comfort and psychological indices due to meteorological factors within the acceptable levels. For the detailed short-term load forecasting, the associated meteorological factors are carefully selected in combination with the historical data of the actual power system load sequence so as to make more accurate prediction.

2. Holidays

Typically, holidays such as Christmas and weekend usually poses a certain impact on the load changes of power system. This is mainly because during the holidays, the power consumption is considerably reduced by most enterprises and other high-power industrial load. On the contrary, the main component of the power system load includes the service industries, such as residential electricity consumption, commercial electricity, catering industry. So, the overall power consumption level is dramatically reduced.

3. Emergencies

Several urgent factors cause the interference of the power load, such as: unexpected incidents, unplanned overhaul, large electricity load fluctuations and limitation of electricity consumption. Therefore, it is useful to conduct the corresponding processing about the historical load data.

In short, the short-term load forecasting accuracy level is the outcome of the combined effect of a variety of influencing factors. For short-term load forecasting, the
right technology must be applied to address those associated influencing factors in order to achieve the precise and scientific short-term load forecasting. However, the impact that influencing factors have on the future load change are usually difficult to be defined by using a specific function expression. Meanwhile, the impact of short-term load forecasting factors may be correlated with each other. All of these conditions undoubtedly increase the difficulty of short-term load forecasting.

2.4.3 The basic procedures of load forecasting

1. Drawing up the prediction scheme

There are some basic characteristics for the load forecasting. For example, target must be established to be clear; and the method should be closed to the reality and the actual method should be properly selected. So, some additional requirements should be taken into account as follows:

1) To set up an explicit time scale and then make a prediction for loads during a certain period of time.

2) To use the reliable data source, the data quantity and the data collection methods.

3) To compare various prediction methods in terms of the load forecasting according to the experience.

2. Investigation and selection of data

For the information collection, a multidimensional feature is necessary when the raw data are either from the power company's internal or external, or even derived from some economic collection sector.

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For the data selection, it should be completed based on the serviceability and the reliability. The data should be selected in a useful, reliable and up-to-date way with a direct correlation. This part of the work plays a vital role for the next steps of the forecasting in the future. If it can be accomplished in accordance with the desired effect, it means that the results of the follow-up can enhance reliability of prediction.

3. Data compilation

To analyze these data, three steps are demanded including auditing, processing and handling. Its purpose aims to service the resulting prediction and ensure its quality. To achieve this purpose, the integrity, the accuracy and the completeness of the collected data must be guaranteed for each period. More importantly, these materials must reflect the normal level of the data and make sure no exception item exists as well. For those abnormal data, it musts be pre-processed accordingly.

The data modification method is described as follows.

1) Horizontal processing [3] [4] [5]

First, a variation range is fixed for dataset. For a specific time point, if the data exceeds this range, it is regarded as bad data and it should be replaced by using the method of average value:

If \( |L(d, t) - L(d, t - 1)| > \alpha \) or \( |L(d, t) - L(d, t - 1)| > \beta \), then \( L(t) \) be adjusted as:

\[
L(d, t) = \frac{1}{2}[L(d, t - 1) + L(d, t + 1)]
\]

Where \( L(d, t) \) represents the load value at the \( d \) day and \( t \) moment.
\( \alpha, \beta \) represent the upper threshold and the lower threshold values of the maximum variation range of the data, respectively.


The electricity load features the characteristic of periodicity. Load values of the same date among different weeks should be considered during the data processing. The value fluctuates in a certain range. If the data exceeds a certain range, it should be adjusted by using the method as follows:

If \(|L(d, t) - \bar{L}(t)| > \delta(t)|\), then \(L(d, t)\) should be adjusted as:

\[
L(d, t) = \begin{cases} 
\bar{L}(t) + \delta(t) & \text{if } L(d, t) > \bar{L}(t) \\
\bar{L}(t) - \delta(t) & \text{if } L(d, t) < \bar{L}(t)
\end{cases}
\]

Where \(L(d, t)\) represents the loading value at the \(d\) day and \(t\) moment.

\(\bar{L}(t)\) represents the average value of the same date type at \(t\) moment.

\(\delta(t)\) represents the threshold value.


Due to the collection of huge data, data at certain moment is likely missing. Thus these data need to be restored. For example, the data at 5pm on a certain Monday is lost, so it can be restored based on the 5pm data on other Mondays. We can calculate the weighted average values with the supplemental data of the same date type:

\[
L(d, t) = \rho_1 L(d_1, t) + \rho_2 L(d_2, t) + \ldots + \rho_n L(d_n, t)
\]

Where \(L(d_i, t)\) (\(i = 1,2,\ldots,n\)) represents the load value which the same as \(d\) date with the same date type.

\(\rho_n\) (\(i = 1,2,\ldots,n\)) represents the weight of \(i\) period, the closer to the \(d\) date it is, the bigger the weight is.
4) Building forecasting model

Forecasting model is built based on the general characteristics of the internal structure of empiric data. This model aims to obtain the value of similar structure. The structure mentioned above refers to results obtained from historical observation values. Under these conditions, the prediction result is the desired reasonable ones.

There are many load forecasting models as a result of research and development. For specific information data, the first thing is to choose the appropriate model. It is a critical step for the whole work. The inappropriate model selection will likely cause a large error. We need to change the model and do the forecasting by repeating the previous steps. Two models can be adopted for computation to ensure the successful work under normal conditions. When it comes to more complicated conditions, the respective advantages of two or more different kinds of methods can be combined to achieve accurate results during the prediction.

5) Determining forecast results

For the choice of forecasting techniques, we must make sure it is appropriate for the condition. First, a forecasting model needs to be established to obtain the predicted values. Based on this model, a comprehensive analysis, comparison and evaluation should be conducted for the new trends and future developments. Finally, the initial predictions must be modified for the forecasting purpose, which results from the uncertainty of the prediction. Since the rule of future load development will change as time goes by, new factors and new predictive factors should be analyzed. More accurate
predicted value can be acquired only if appropriate adjustment can be achieved according to our load forecast model.

2.4.4 Load Forecasting Error Analysis

Reasonable prediction results should stay within acceptable range, which accuracy is measured by the error. The larger the error is, the lower the accuracy becomes, and vice versa. From the above analysis, it is very important to study reasons why the error occurs and how to calculate the error.

1. The causes of error

1) For the general prediction model, major factors are usually considered while other minor ones are neglected. Especially for those relatively strong nonlinear models, the load model and the actual load cannot match each other very well. If this prediction model is still used in the analysis, it will generate unexpected errors.

2) The factors affecting the load are always changing. The forecasting method is not unique and related requirement is various. A problem that emerges is to choose a more suitable approach among a number of prediction methods. Improper selection of prediction and relevant parameters will result in an error as a direct consequence.

3) For data collections, its accuracy and completeness cannot be fully guaranteed. And also many potential factors that could affect the load may not be taken into account. This will inevitably result in errors.
4) If there is an unpredictable event occurring during the load forecast or the prediction conditions suddenly change, these will likely cause errors.

Errors resulting from the above reasons can be shown together. Each reason above can make forecasting results fail to meet the accuracy requirement. Thus, it is necessary to discover the fundamental cause and make the further improvement.

2. Prediction error analysis

Several common error index formulas are described as follows.

1) Absolute error and relative error [6]

Assuming the actual value is $Y$, the predict value is $\hat{Y}$, then $E = Y - \hat{Y}$ is the absolute error, and $e = \frac{Y - \hat{Y}}{Y} \times 100\%$ is the relative error.

2) Mean absolute error [7]

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |E_i| = \frac{1}{n} \sum_{i=1}^{n} |Y_i - \hat{Y}_i|$$

Where $MAE$ represents the mean absolute error; $E_i$ is the $i$th error between the predicted value and the actual value. In order to avoid the prediction error offset by positive and negative value, it is desirable to calculate the average absolute error level, which is a comprehensive index of error analysis.

3) Mean squared error [8]

$$MSE = \frac{1}{n} \sum_{i=1}^{n} E_i^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2$$

Where $MSE$ represents the mean squared error; by this equation, negative value is avoided being generated.
4) Root-mean-square error [9]

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} E_i^2} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Where RMSE represents the root-mean-square error; since the $E$ value is squared, the error value is amplified as an essential indicator to make this error more obvious.

5) Standard error [10]

$$S_y = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n - m}} (i = 1, 2, \ldots, n)$$

Where $S_y$ represents the standard error; $n$ represents the number of historical data; $m$ represents the number of variables.

2.5 Requirements and procedures of short-term load forecasting

2.5.1 Requirements of short-term load forecasting

High-precision short-term load forecasting usually needs to satisfy five requirements:

1. Rationality of the selected data

The objective of short-term load forecasting is to obtain accurate and reasonable predictions. The core point of the short-term load forecasting is to establish the corresponding mathematical model based on the historical data to express the developments and changes of the short-term load.

2. Availability of the historical data
Conflicting data obtained through different channels needs to rely on historical data for effective analysis and trade-offs, rejecting the unreasonable data to retain good historical data available. Unreasonable data exists mainly due to the errors caused by human factors and different statistical errors. But both of these unreasonable data are easy to be fixed. It is noted that unexpected past events will impose serious impact on the data due to some special reasons. These affected data are usually referred to as “abnormal data”. Its existence will lead to a great random interference on normal historical load sequence, which could affect the accuracy of the prediction results. It will cause the inaccuracy of the prediction model if there are many “abnormal data”. Thus, the adverse effects of the “abnormal data” to the short-term load forecasting should be eliminated.

3. Comprehensiveness of the statistical analysis

An objective and comprehensive statistical analysis is conducted based on a large number of historical data. Forecasting personnel can better make preparation for prediction by selecting the historical data.

4. Advancement of the forecasting method

The advancement of the forecasting method has two meanings: one is the advancement of the selection of forecasting tools and the other is the advancement of the short-term load forecasting theory. For statistical analysis and short-term load forecasting, the computer application will make the cumbersome prediction job much easier than manual calculations. For the advancement of the short-term load forecasting theory, the short-term load forecasting can achieve the desired accuracy level by
employing latest forecasting method and drawing the successful forecasting experience from other research areas.

2.5.2 Procedures of short-term load forecasting

Short-term load forecasting is usually divided into the following eleven steps.

1. To determine the prediction objective

Different short-term load forecasting is suitable for the power grid with different voltage levels. Specific requirements of short-term load forecasting are different for the same power grid during the different time intervals. Thus, it is necessary to determine the most effective and feasible short-term load forecasting objective.

2. To collect the short-term load forecasting historical data.

Widely collect the data of short-term load forecasting according to specific requirements of the short-term load forecasting. The collected data should meet the comprehensive, coherent, systematic and accurate requirements. In addition, these data should include economic and weather-related ones that influence the load variation.

3. To analyze the basic data.

A comprehensive analysis based on the collected information is conducted to select the typical, highly reliable and highly available information as the basic data for the short-term load forecasting. The effective analysis is carried out to sort, remove the unreasonable data as well as finally make the appropriate trade-offs and corrections.

4. To predict and obtain the relevant influencing data of the short-term load forecasting.
The power system is not a stand-alone system, which is usually influenced by the economic and social development as well as the seasonal change. These data affecting the future variation trend can be obtained from relevant organizations.

5. To select the short-term load forecasting method.

Based on the short-term load forecasting objective, the local environmental conditions and load data need to be taken into account to realize appropriate short-term load forecasting method.

6. To model the short-term load forecasting.

The predicted object should be effectively analyzed based on the historical data and the local environmental conditions, so that a reliable and reasonable mathematical model is built accordingly. Typically, some mature forecasting models are chosen in this step.

7. To preprocess the historical data.

If necessary, the selected historical data is preprocessed by using the appropriate method suitable for the specific short-term load forecasting model. This step is necessary in some short-term load forecast model, such as the data normalization of short-term load forecasting based on Support Vector Machine (SVM).

8. To select the parameters of short-term load forecasting model.

With the short-term load forecasting model proposed, parameters of short-term load forecasting model can be identified based on forecasting experience and knowledge.

9. To evaluate the short-term load forecast model to verify the significance of the model.
According to the hypothesis testing principle, it is necessary to decide whether the short-term load forecast model is reasonable. If the model is not appropriate, it should be discarded and replaced by the other prediction models following the steps 6-8 once again.

10. To predict by using the application of the model.

Based on the model presented previously, predictions for a specific time period are achieved.

11. To analyze and evaluate the results of the short-term load forecasting model.

Different types of short-term load forecasting models can be chosen in conjunction with the prediction model parameters. Then, results obtained from different models are compared and analyzed so as to decide which model is the best for prediction.
Chapter Three: Smart Meter

3.1 Smart meters benefits

Smart meter is an advanced energy meter that obtains information from the end users’ load devices and measures the energy consumption of the consumers and then provides additional information to the utility company and/or system operator for better monitoring and billing. Several sensors and control devices, supported by dedicated communication infrastructure, are utilized in a smart meter. Smart meters’ data is the combination of the unique meter identifier, the data timestamp, electricity consumption values and other values. Smart meter can collect diagnostic information and data about the distribution grid and home devices, and measure electricity consumption from them to distinguish the parameters and then transfer the data to utilities, and utilities finally send the command signals back to smart meters in order to optimize the customer’s bill and power consumption accordingly. Sometimes, a smart meter can also communicate with other smart meters.

From the consumer’s perspective, smart meters are offering a number of potential benefits: for example, consumers are able to estimate bills based on the collected information and thus manage their energy consumptions aiming to reduce their electric bills.

From the utility’s perspective, they can utilize the information collected from smart meters to realize real-time pricing. In this way, the companies can limit the maximum
electricity consumption and encourage users to reduce their demands during the periods of peak load as much as possible. System operator can terminate or re-connect electricity supply to any customers through proper mechanism remotely in order to optimize the power flows according to the information sent from demand sides.

3.2 Smart meter functions and benefits

3.2.1 The typical function of smart meter

Commonly, smart meter is expected to have the following functions:

1. The two-way communication function
2. The data collection function
3. The data recording function
4. The data storing function
5. The load control function
6. The programming function
7. The security function
8. The display function
9. The billing function

Figure 3.2.1 shows an actual model of a smart meter.
Figure 3.2.1 An actual model of a smart meter [11]

3.2.2 Smart metering system benefits

The benefits for installing smart meters are numerous for many different stakeholders in different aspects of the smart grid system.

- **Smart metering value proposition for the utilities:**
  1. It saves a lot of money by improving the remote area reading and billing system.
  2. It gives utility the ability to better manage during peak load times.
  3. It makes more efficient use of energy and grid resources.
  4. It offers new tariff model in the electricity market.
  5. It improves the transformer load management for the transmission line.

- **Smart metering value proposition to consumers**
1. It shows customer data about their electricity usage habit.

2. It gives customer more accurate and timely electrical billing.

3. It helps customer to better use the electrical equipment during the expensive hours.

4. It facilitates customer to switch/delay their electrical equipment with significant consumption to less expensive hours.

- **Smart metering value proposition for governments**

  1. It stimulates the economy by investing in smart metering networks.

  2. It improves the environmental condition by reducing CO2 emission.

  3. It leads to reduction of consumption by increasing the awareness of consumption pattern.

  4. It helps better load forecasting for power grid and prevent large-scale black out.

  5. It gives data for improving efficiency and reliability of service.

### 3.3 Smart meter technologies

Smart Meter Systems are varied in technology and design but operate through a simple overall process [12]. Smart Meters collect data from the end consumers and transmit this data information through the Local Area Network (LAN) to the data collector. This transmission process can be executed every 15 minutes or as infrequently as once a day based on the requirement of the data demand. After that the collector retrieves the data and then transmits it. The utility central collection points further processes the data by using the Wide Area Network (WAN). Since the communications path is two-way, signals or commands can be sent directly to the meters, customer
premise or distribution device [12]. Figure 3.3.1 shows the basic architecture of Smart Meter System operations.

![Diagram of Smart Meter System operations](image)

**Figure 3.3.1 The basic architecture of Smart Meter System operations [12]**

There are two basic types of smart meter system communication technologies: Radio Frequency (RF) and Power Line Carrier (PLC). In smart grid applications, there are different advantages and disadvantages associated with them. The utilities choose the best technology based on their business profits. Making the right decision to choose which technology requires a thorough evaluation and analysis of the existing needs and the future benefits of business.

There are factors that impact the selection of the technology, such as [12]:

1. Evaluation of existing infrastructure;
2. Impact on legacy equipment, functionality, technical requirements as well as the economic impact to the utility’s customers.

**3.3.1 Radio Frequency – RF**

Smart meter collects the measurement data from the end consumers and then transmit the data by the wireless radio from the meter to a data collector. Then, the data is
processed and delivered by several methods to the utility data systems at a central collection location. The utility billing, outage management, and other systems use these data for operational and business purposes. There are two different types of RF technologies:

- **Mesh Technology:**

  The smart meters talk to each other to form a LAN cloud at the collection point. The collector transmits the data using various WAN methods to the utility central location [12].

  1. The mesh RF technology has some advantages, such as the large bandwidth, the acceptable latency and the typical operation frequency is at 915 MHz.

  2. The mesh RF technology also has some disadvantages, such as the proprietary communications, the topography and long distance issues for the remote areas.

Some research has been conducted in the mesh RF area. Parag Kulkarni *et al.* [13] propose a mesh-radio based solution which is an enhanced version of the RPL (Routing Protocol for Low-Power and Lossy Networks (LLN)) protocol and exhibits self-organizing characteristics. Parag Kulkarni *et al.* [14] also propose a mesh radio based solution with self-organizing characteristics, which has the ability to enhance the RPL protocol, a connectivity enabling mechanism for low power and lossy networks currently being standardized by the IETF ROLL working group. Daniel Geelen *et al.* [15] present and evaluate a real-life implementation of a new routing protocol for use in smart-metering mesh-network grids which is designed with both technological constraints and legislative requirements. Hamid Gharavi *et al.* [16] present a multi-gate mesh network
architecture that has been developed to ensure high performance and reliability under emergency conditions when a system expects to receive power outage notifications and exchanges. They take into account both the hop-count and the queue length of each mesh node to introduce a back-pressure based scheduling algorithm. Bill Lichtensteiger et al. [17] describe the system architecture and the performance evaluation of a Radio Frequency (RF) mesh based system for smart energy management applications in the Neighborhood Area Network (NAN). Arjun P. Athreya et al. [18] propose the resilient and survivable hierarchical communication architecture for the smart grid that mirrors the hierarchy of the existing power grid. Also analytical models are proposed to study the performance of the flattened architecture as a function of outage area, smart-meter density and smart-meter’s neighborhood size.

- **Point to Point Technology:**

  In this technology, smart meters talk directly to a collector, usually a tower. The tower collector transmits the data using various methods to the utility central location for processing [12].

  1. Point to Point RF technology has some advantages, such as large bandwidth, little or no latency, direct communication with each endpoint, better throughput, and can cover longer distances.

  2. Point to Point RF technology also has some disadvantages, such as the topography and long distance issues for the remote areas, the proprietary communications, and less interface with Distribution Automation (DA) devices.
Some research has been conducted in the point to point RF area. Sebnem Rusitschka et al. [19] propose a Peer-to-Peer (P2P) network of homes with low-cost digital electricity meters which consists of off-the-shelf hardware and existing communication infrastructure. Asma Garrab et al. [20] propose an AMR solution with enhanced end-to-end application. It is based on an energy meter with low-power microcontroller MSP430FE423A which includes an energy metering module ESP430CE1 and the Power Line Communication standards. Rahman, M.M. et al. [21] provides an overview of the characteristic of smart meter, associated communication standard and bandwidth and investigates the propagation delay of smart meter via Ethernet devices using the OPNET IT Guru to ensure efficient operation of a smart meter network. According to the problems such as the imperfect smart electricity meter’s detection item, heavy detection task, high working intensity and so on, Cen Wei et al. [22] has researched an advanced smart electricity meter automatic detection technology.

### 3.3.2 Power Line Carrier – PLC

The data collected by smart meter can be transmitted from the meter to the utility central collection point by using the utility power lines. And then the delivered data is further processed and analyzed. The utility utilizes these data for operational purposes and predict the future benefits of business [12].

1. PLC technology has some advantages; e.g., it can improve cost-effectiveness for rural lines, and make it possible to work for the remote area or over long distances.
2. PLC technology also has some disadvantages; e.g., it has longer data transmitting time than wireless, less bandwidth and higher cost in cities.

Some research has been conducted in the PLC area. Rakesh Rao et al. [23] present a method for identifying outliers among a set of smart meters by measuring the power line carrier (PLC) signal strength between the communication node (transformer) and residential smart meters. The PLC signal is used as a predictor of transmission problems to proactively avert local power outages. Four metrics are presented based on the distribution of signal strengths, with each metric identifying a class of outliers. Mojtaba Rafiee et al. [24] propose a practical smart metering approach which can be used for both type of automatic meter reading (AMR) and advanced metering infrastructure (AMI) by using combination of PLC and WiFi protocols. Liang Dong et al. [25] present the noise characteristic and transmission characteristic of the power line channel at first, then establish the basic power line channel model according to measured data.
Chapter Four: Current Policies and Product in Different Countries

4.1 Current development in different countries

4.1.1 France

France is a little different from other country in that the electricity and gas markets are dominated by Electricité De France (EDF) and Electricité Réseau Distribution France (ERDF), so these two big companies have the power to decide the activities on the smart meter field. But the French government promulgated a government decree in August 2010 which mandates the installation of electronic meters from January 2012 on and have at least 95% coverage by the end of 2016.

The EDF identified four areas in which smart meter will make great contribution to provide improvements within the energy field in 2006. The four areas are:

1. The billing and customer service
2. Grid operation and monitoring
3. Remote connecting and disconnecting
4. The accounting

For the ERDF, they plan to provide some new services for their energy suppliers by improving their existing processes with the rising potential of smart metering or to install completely new information and data management systems instead.
There are also some other policy objectives for the introduction of smart metering, such as [26]:

1. From January 2012, every new electricity meter installed must be a smart device.
2. By the end of 2014, 50% of all meters must be connected to an automated meter management (AMM) system.
3. By the end of 2016, 95% of the meters must be connected to an AMM system.

4.1.2 Germany

The Germany government follows a policy driven by customer demand which means to liberalise the metering service market. From the beginning of 2010, the national legislature requires the contractor to install smart meters in new buildings and the buildings that are refurbished significantly. Since the legal situation is unclear, the investment from the major metering service companies is very small. There are only about 15 out of 800 utilities offering smart metering products in the early 2010. Also the smart meters will lead to additional costs for customers. As a result, only the customers with high consumption are likely to install the smart meter and may benefit from it.

There also some other policy objectives for the introduction of smart metering, such as [26]:

1. By the end of 2010, the metering operator has to arrange smart meter that shows the timetable of use and the real consumption of energy.
2. From the beginning of 2008, the customer has the right to receive a monthly, quarterly, biannual or annual bill.
3. From 2011 on, utility companies are required to provide load-variable or time-of-use tariffs.

### 4.1.3 Netherlands

The Netherlands is one of the front runners and most positive promoter in Europe in the smart meter area. Dutch government allows citizens to install the smart meter voluntarily and can choose between four legal options of different degrees alternative smart meters (from keeping conventional meters to full AMM, to be discussed later) from November 2012. In order to ensure this development, the government issued two major policies:

1. The smart meter will only allow to be read once every two months in the standard situation.

2. The consumer will have the option of refusing the smart meter. This means that the consumer has the right to keep his or her traditional meter.

The four legal options of different degrees alternative smart meter for the consumers are [26]:

1. The first option is to allow the consumers to refuse the installation of a smart meter and to keep their ‘traditional’ meter.

2. The second option is to allow the utilities to install the smart meter, but never allow sending the consumers’ meter readings automatically. It means that the smart meter functions as a traditional meter, and still needs a meter reader.

3. The third option is to allow the utilities to install the smart meter, but with a set of limited capabilities of automatic meter reading for some important information;
for example, only allow the meter to be read once every two months in the
standard situation or once a year for annual billing.

4. The fourth option is to allow the utilities to install the smart meter and with full
function of automatic smart meter reading.

4.1.4 Norway

In Norway, the government has already deregulated the control of the power supply
system. Currently, the hourly smart metering is only required for large customers. This
means that most end customers are free to choose their power suppliers from many of the
retailers with different electrical energy tariffs. So the self-reading of the meter has been
the most common application for the smaller customers in Norway. Despite the lack of
Automatic Meter Reading (AMR) in the second quarter of 2010, there are still 55% of the
end customers holding an energy contract related to the market price.

The government only requires the customers whose yearly consumption is larger
than 100,000 kWh to install the hourly reporting smart meter. In 2007, there are 100,000
hourly reporting smart meters around the whole country constituting only 4% of the total
metering points in Norway, but more than 60% of the total yearly consumption are taken
by these large customers.

Smart metering has been a hot topic in Norway for several years and the government
has already made some proposal to encourage the smart meter field [26]:

1. In 2002, the government proposed that the new technology of AMR smart meter
should be an offer to all end customers.
2. The proposal of introducing the new type of smart metering has not been taken seriously until 2007.

3. The government suggested that the AMR smart meter should be fully deployed by the end of 2012.

4. After several delays, the government changes their suggestion to fully deploy the AMR smart meter by the end of 2017.

4.1.5 UK

For the UK government, their objective is to mandate promotion for larger customers to install the smart meters for electricity and gas by the end of 2014, and mandate promotion for domestic to install the smart meters for electricity and gas by the end of 2020.

The government estimated that it would cost at least about £340 for each household and the total cost for installing 26 million houses with smart meter would eventually cost about £8.6 billion by the end of 2020. However, by installing these smart meters, there would be more than £14.6 billion of compensatory savings in the operational costs of energy companies, and eventually would lower the bills for customers.

There are also some other policy objectives for the introduction of smart metering, such as [26]:

1. To mandate the larger or medium businesses to install the advanced meters by the end of 2014.

2. For the industrial and commercial sites, to require half-hourly metering or daily-read metering respectively
3. For the residential meters, to replace 27 million smart meters by the end of 2020.

4. For the small or medium business, to install 2.2 million smart meters by the end of 2020.

5. For the commercial and industrial customers, to install 168,000 smart meters by the end of 2014.

4.1.6 The United States

Smart meters will eventually be prevalent everywhere all over the world over the next few decades. In 2008, only less than 4% of the electricity meters in the world were the smart meters. But by 2012, the percentage grows to over 18% and it is expected to rise to 55% by the end of 2020.

But the interesting thing is that, the installations of smart meters will actually suddenly decrease over the next two years in the US. “According to research, the shipments of smart meter in the U.S. will drop by a significant 42 percent between 2011 and 2013, and after 2014 will start to gradually rise again” [27].

There are several reasons to cause this result [27].

1. One reason is because utilities in California which is the leading state to install smart meters in the US will complete many of their installation projects of the smart meter that were started a few years ago.

2. Pacific Gas and Electric Company (PG&E) has already installed almost 9 million meters by year end 2011, and they would finish the deployment by the middle of 2012.
3. Southern California Edison has already installed 4.3 million smart meters in the middle of 2012 and tries to finish all of the planned installations by the end of 2012.

4. The Department of Energy (DOE) released billions of dollars to the utilities for their smart meter installation programs in 2009, most of which would be finished in near future.

In 2010, 20,334,525 advanced ("smart") metering infrastructure (AMI) installations were completed throughout 663 U.S. electric utilities, out of which about 76% were Investor Owned utilities; and about 90% out of the total installations were for residential customers [28]. Table 4.1.1 shows the current distribution of smart meters in the US.

Table 4.1.1 The distribution of smart meters in the United States [28]

<table>
<thead>
<tr>
<th>Type of Utilities</th>
<th>Number of Utilities</th>
<th>Residential</th>
<th>Commercial</th>
<th>Industrial</th>
<th>Transportation</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investor Owned</td>
<td>108</td>
<td>13,880,141</td>
<td>1,452,929</td>
<td>24,728</td>
<td>36</td>
<td>15,357,834</td>
</tr>
<tr>
<td>Cooperative</td>
<td>342</td>
<td>3,416,336</td>
<td>323,082</td>
<td>27,542</td>
<td>0</td>
<td>3,766,960</td>
</tr>
<tr>
<td>Municipal</td>
<td>184</td>
<td>278,198</td>
<td>44,757</td>
<td>2,471</td>
<td>0</td>
<td>325,426</td>
</tr>
<tr>
<td>Public &amp; State</td>
<td>29</td>
<td>795,233</td>
<td>84,215</td>
<td>4,826</td>
<td>31</td>
<td>884,305</td>
</tr>
<tr>
<td>Totals</td>
<td>663</td>
<td>18,369,908</td>
<td>1,904,983</td>
<td>59,567</td>
<td>67</td>
<td>20,334,525</td>
</tr>
</tbody>
</table>

4.2 Latest product

Many companies have produced smart meters on the basis of market demand. According to the different application purposes and voltage ratings, these meters are
categorized into two application types: residential smart meters and commercial & industrial smart meters. In the following, some major smart meters are described.

4.2.1 General Electric (GE) Company

The GE has been offering two standards smart meters, which are the ANSI standard (American National Standard Institute) and the IEC standard (International Electrotechnical Commission). For each standard, it has some series products designed for residential and commercial or industrial purposes.

- For the ANSI standard smart meter:
  - The I-210 series residential meters:

    The GE’s I-210 series is the single phase electronic meters which includes 3 models: I-210+c, I-210+, I-210. This series cover almost all the metering needs from the basic electronic energy-only meters to the highly-flexible smart meters.

    The GE I-210 series have some key benefits, re-stated here from GE official website [29]:
    1. Reliable and accurate cash register for utilities.
    2. AMR/AMI Plug-n-Play functionality.
    3. Multiple communication technologies tied to AMI systems to provide reliable data in a timely manner.
    4. Smart Grid metering functions such as Time of Use demand metering and service switch capabilities.
    5. Demand side management through pre-payment and demand limiting features.
6. Table 4.2.1 shows the main parameters between the GE I-210 series meters.

Table 4.2.1 Main parameters for GE I-210 series meters [29]

<table>
<thead>
<tr>
<th>Product Characteristics</th>
<th>I-210+c</th>
<th>I-210+</th>
<th>I-210</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating Voltage</td>
<td>120 V-240 V</td>
<td>120 V-240 V</td>
<td>120 V-240 V</td>
</tr>
<tr>
<td>Rating Frequency</td>
<td>50 Hz or 60 Hz</td>
<td>50 Hz or 60 Hz</td>
<td>50 Hz or 60 Hz</td>
</tr>
<tr>
<td>Typical Starting Voltage</td>
<td>5.0 V</td>
<td>5.0 V</td>
<td>5.0 V</td>
</tr>
<tr>
<td>Typical Voltage Losses</td>
<td>0.7 V</td>
<td>0.7 V</td>
<td>0.7 V</td>
</tr>
<tr>
<td>Typical Accuracy</td>
<td>Within +/-0.2%</td>
<td>Within +/-0.2%</td>
<td>Within +/-0.2%</td>
</tr>
<tr>
<td>Operating Voltage Range</td>
<td>+/-20%</td>
<td>+/-20%</td>
<td>+/-20%</td>
</tr>
<tr>
<td>Operating Temperature Range</td>
<td>-40°C to +85°C</td>
<td>-40°C to +85°C</td>
<td>-40°C to +85°C</td>
</tr>
<tr>
<td>Communication Type</td>
<td>AMR, RF Mesh, PLC, Cellular</td>
<td>AMR, RF Mesh, PLC</td>
<td>AMR</td>
</tr>
</tbody>
</table>

- **The KV2c series commercial and industrial meters:**

  The kv2c has the function of five demand measures, real-time pricing, and real time data monitoring, which offers easy and powerful functional upgrades to meet the metering needs. There are 2 models (KV2c and KV2c+) in the GE kv2c product family which provides more choices for applications including a polyphase option for a voltage of 600V.

  The GE KV2c series have some key benefits, re-stated here from GE official website [29]:

  1. AMR/AMI Plug and Play designed to accommodate: RF, PLC, Cellular (GPRS/CDMA), Ethernet.

  2. Complete range of S-base and A-base forms.
3. 4-quadrant industrial or substation measures.

4. Powerful functional upgrades provide 4-channel 64 kb, 20-channel 192 kB, or 20-channel 384 kB recording for voltage, current, energy, apparent power, reactive power, distortion power, power factor, THD, TDD, DPF.

5. Per phase AC instrumentation (amps, volts, and frequency).

The GE kV2c+ offers the following benefits in addition to those offered with the kV2c [29]:

1. Enhanced power supply to support a variety of AMI technology.
2. 57-120V auto-ranging power supply for low voltage applications.
3. Ability to serve 600V applications.
4. Revenue Guard option preserves billing integrity when a phase voltage is lost.
5. Available in Switchboard form (Z base).

Table 4.2.2 shows the main parameters of the GE KV2c series meters.

**Table 4.2.2 Main parameters for GE KV2c series meters [29]**

<table>
<thead>
<tr>
<th>Product Characteristics</th>
<th>KV2c</th>
<th>KV2c+</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating voltage</td>
<td>120 V-480 V</td>
<td>57 V-120 V, 600 V</td>
</tr>
<tr>
<td>Rating frequency</td>
<td>50 Hz or 60 Hz</td>
<td>50 Hz or 60 Hz</td>
</tr>
<tr>
<td>Typical accuracy</td>
<td>Within +/-0.2%</td>
<td>Within +/-0.2%</td>
</tr>
<tr>
<td>Operating voltage range</td>
<td>+10% to -20%</td>
<td>+10% to -20%</td>
</tr>
<tr>
<td>Operating temperature range</td>
<td>-40°C to +85°C</td>
<td>-40°C to +85°C</td>
</tr>
<tr>
<td>Communication type</td>
<td>AMR RF Mesh PLC Cellular</td>
<td>AMR RF Mesh PLC Cellular</td>
</tr>
</tbody>
</table>
For the IEC standard smart meter:

- **The SGM3000 series smart meter:**

  The GE’s SGM3000 series is the most popular meter series comprise of advanced capabilities. It contains eight meters in the series for both residential and commercial demand, including single phase, polyphase, dual-element and CT metering.

  The GE SGM3000 series have some key benefits [29]:

  1. Improved energy efficiency from the utility to the house.
  2. Advanced co-generation applications using configurable, full quadrant measurements.
  3. Modular communications with field replaceable options.
  4. Extensive relay and multi-element configurations for application flexibility.
  5. Scalable, future-proof metering with ample embedded resources.

- **The SGM1100 smart meter:**

  The GE’s SGM1100 meter is the single phase smart meter which was designed for residential and small commercial energy customer. In this meter, PLC AMI communications based on the Powerline Intelligent Metering Evolution (PRIME) standard and DLMS/COSEM protocol [29] are available.

  The GE SGM1100 has some key benefits, re-stated here from GE official website [29]:

  1. Dual pole relay for old residential infrastructure resulting in a more secured and safe service disconnection.
2. Remote upgradable firmware and meter configuration via PLC communications to reduce on-site visits for service and maintenance.

3. Designed to facilitate quick and easy installations in difficult environments.

4. Integrated PRIME PLC modem; providing, reliable and interoperable communications with PRIME compliant data concentrators.

5. Local communications via an optical port, enabling local configuration, firmware updates, and diagnostics as needed.

Table 4.2.3 shows the main parameters of the GE SGM3000 series and the SGM1100 meters.

Table 4.2.3 Main parameters between the GE SGM3000 series and SGM1100 meters [29]

<table>
<thead>
<tr>
<th>Product Characteristics</th>
<th>SGM3000 series</th>
<th>SGM1100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage Rating</td>
<td>220 V, 230 V, 240 V</td>
<td>230 V</td>
</tr>
<tr>
<td>Frequency Rating</td>
<td>50 Hz, 60 Hz</td>
<td>50 Hz</td>
</tr>
<tr>
<td>Current</td>
<td>10 A</td>
<td>10 A</td>
</tr>
<tr>
<td>Operating voltage range</td>
<td>+/-20%</td>
<td>+/-20%</td>
</tr>
<tr>
<td>Typical accuracy</td>
<td>Within +/-0.2%</td>
<td>Within +/-0.2%</td>
</tr>
<tr>
<td>Single phase</td>
<td>SGM3011, SGM3013, SGM3022, SGM3023</td>
<td>SGM1100</td>
</tr>
<tr>
<td>Three phase</td>
<td>SGM3030, SGM3031, SGM3033, SGM30C2</td>
<td></td>
</tr>
<tr>
<td>Operating temperature range</td>
<td>-40°C to +70°C</td>
<td>-25°C to +70°C</td>
</tr>
<tr>
<td>Communication type</td>
<td>RF Mesh, Cellular, WiMAX, ZigBee</td>
<td>PLC</td>
</tr>
</tbody>
</table>
4.2.2 Itron Company

Itron’s smart residential meters deliver the two-way communications due to customers need to build their advanced metering infrastructure. Itron's smart meters are built upon industry standards and provide unprecedented interval data storage, remote upgradeability and configuration changes, and the gateway to consumer smart devices.

- **The Itron CENTRON OpenWay meter:**

  The Itron’s OpenWay smart meter system provides an enhanced security and a reliable approach to data collection and communications between the smart meter and the network system.

  In the Itron advanced smart meter the usage data can be calculated within the meter instead of insert a network communication card into a standard meter. This designed smart meter can allow utilities to leverage time-base rates, demand response, home networking and many other smart grid applications.

  OpenWay smart meter is unique and offers the following distinguishing features [30]:

  1. Time-of-use and critical peak pricing data.
  2. A two-way, unlicensed RF module and adaptive-tree radio frequency local area network architecture.
  3. ZigBee radio for interfacing with home area networking and load control devices.
  4. A remote service switch with load limiting capabilities to support many new services, such as prepaid metering.
5. Tamper detection including meter inversion, meter removal and reverse energy flow.

- **CENTRON Bridge Meter:**

The CENTRON Bridge smart meter is the first meter available with compatibility between the Itron’s CENTRON OpenWay network and the Itron’s ChoiceConnect mobile environment. It is the bridge between Itron communication architectures that enable AMI and smart grid functionality. The meter’s adaptability allows it to be incorporated along with the existing Itron smart meters with a mobile collection system, delivering advanced metering benefits associated with interval data, remote service switch and demand reset. This revolutionary capability is perfect for customers that require advanced metering functionality in a mobile environment today.

Table 4.2.4 shows the main parameters of the Itron OpenWay and Bridge meters.

**Table 4.2.4 Main parameters between the Itron OpenWay and Bridge meters [30]**

<table>
<thead>
<tr>
<th>Product Characteristics</th>
<th>OpenWay</th>
<th>Brudge</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage Rating</td>
<td>120 V, 240 V</td>
<td>120 V, 240 V</td>
</tr>
<tr>
<td>Frequency Rating</td>
<td>60 Hz</td>
<td>60 Hz</td>
</tr>
<tr>
<td>Starting Current</td>
<td>20 mA, 5 mA</td>
<td>20 mA, 5 mA</td>
</tr>
<tr>
<td>Battery Voltage</td>
<td>3.6 V</td>
<td>3.6 V</td>
</tr>
<tr>
<td>Operating voltage range</td>
<td>+/-20%</td>
<td>+/-20%</td>
</tr>
<tr>
<td>Operating temperature range</td>
<td>-40°C to +85°C</td>
<td>-40°C to +85°C</td>
</tr>
<tr>
<td>Communication type</td>
<td>RF Mesh ZigBee</td>
<td>RF Mesh ZigBee</td>
</tr>
</tbody>
</table>
4.2.3 Sensus Company

Sensus's iCON smart meter make consumers (residential, commercial and industrial) deliver the accurate and reliable results between customers and energy companies. Combined with the FlexNet advanced meter infrastructure, electricity supplies can install and upgrade the iCON meter’s electricity management platform for significant efficiency.

- **iCON A residential meter:**

  The Sensus iCON A smart meter with the SmartPoint integrated display is one of the most reliable and efficient Advanced Metering Infrastructure (AMI) smart meters available. An optional remote disconnect switch allows operators to disconnect or reconnect services by using the Regional Network Interface (RNI) software.

  The FlexNet communications network is approved by FCC for operation on an unshared primary-use licensed spectrum. It offers a reliable, simple, and an economical way for meter deployments, strategic deployments, and rural applications.

  The iCON A has some key benefits [31]:

  1. Integrated FlexNet™ AMI on display board
  2. Power Quality reporting
  3. Time-of-Use
  4. Remote configuration and meter firmware downloads
  5. Accuracy exceeds ANSI C12.20 (Class 0.2)

- **iCON APX commercial and industrial meter:**

  Although the traditional iCONAPX Commercial and Industrial meter provides stability in the fluid landscape of the developing smart grid, it lags behind contemporary
social requirement of a smart metering device with the flexibility to balance a wide
variety of ever changing factors and service quality demands. Combined with the FlexNet
advanced meter infrastructure, electricity supplies can install and upgrade the iCONAPX
meter’s electricity management platform for significant efficiency.

The iCON APX has some key benefits [31]:

1. Accuracy exceeding ANSI C12.20 (Class 0.2)
2. Reliable, unbreakable one-piece cover
3. Complete DC immunity
4. Inversion-proof
5. Advanced user-friendly configuration software-iCONFig

Table 4.2.5 shows the main parameters of the Sensus iCON A and iCON APX
meters.

Table 4.2.5 Main parameters between the Sensus iCON A and iCON APX meters

<table>
<thead>
<tr>
<th>Product Characteristics</th>
<th>iCON A</th>
<th>iCON APX</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage Rating</td>
<td>120 V, 208 V, 240 V</td>
<td>120 V to 480 V</td>
</tr>
<tr>
<td>Frequency Rating</td>
<td>60 Hz</td>
<td>50 Hz, 60 Hz</td>
</tr>
<tr>
<td>Starting Voltage</td>
<td>5 V</td>
<td>5 V</td>
</tr>
<tr>
<td>Operating voltage range</td>
<td>+10% to -20%</td>
<td>+10% to -20%</td>
</tr>
<tr>
<td>Typical accuracy</td>
<td>Within +/-0.2%</td>
<td>Within +/-0.2%</td>
</tr>
<tr>
<td>Operating temperature range</td>
<td>-40°C to +85°C</td>
<td>-40°C to +85°C</td>
</tr>
<tr>
<td>Communication type</td>
<td>RF Mesh, ZigBee</td>
<td>RF Mesh, ZigBee</td>
</tr>
</tbody>
</table>

[31]
Chapter Five: Load Analysis and Forecasting in MATLAB

5.1 Load analysis

For the load analysis, the historical data of the Denver area hospital energy consumption in 2004 is applied in this work [32-34]. The dataset mainly contains the hourly energy consumption of the Denver area hospital, hourly air temperature and hourly dew point temperature variation of the Denver centennial area for the whole year of 2004. The dataset is created in the Microsoft Excel Worksheet as shown in the Figure 5.1.1.

![Figure 5.1.1 Partial of input dataset](image)

First of all, a MATLAB script code ‘powerinput’ is created to import the Excel data into MATLAB, then the diagram is generated between hour and power by using ‘PLOTS
scatter’, as shown in the Figure 5.1.2. It is seen that the large amount of power consumption appears between 6:00-18:00 (the working hours).

Figure 5.1.2 Power consumption VS Hours

Using another ‘PLOTS boxplot’ command, a statistical analysis diagram is generated in a more intuitive way as shown in Figure 5.1.3. The red line represents the median value of the power consumption; the short black line represents the range of the values; the red ‘X’ represents the outlier values; the blue box represents the data values between 25% and 75%.

For example, the collected data on Fridays in the middle diagram has low range of data values and a lot outlier values. It is unsuitable to be used directly for short-term load forecasting. There are many reasons that may cause this outlier values such as inappropriate data collection and even the different living habits.
Figure 5.1.3 Power consumption versus hours, days of week, month

A MATLAB Function code 'createfigure.m' is designed, which is used to generate the diagram showing both of the relationship between ‘power consumption to hour’ and ‘temperature to hour’. Also, "zoom in" is applied to display detailed change for any short periods while "zoom out" is used to show a general variation trend for any relatively long period as shown in the Figure 5.1.4 and Figure 5.1.5, respectively.
Figure 5.1. Power, temperature versus dates

Figure 5.1.4 Power, temperature versus dates

Figure 5.1.5 A 'zoom in' picture of Power, temperature versus dates
5.2 MATLAB modeling

5.2.1 Using polynomial model

Firstly, the polynomial model is utilized to set up the dataset. In order to plot the diagram, some valid data is extracted from the whole dataset. Since the power consumption of weekend has different regularity compared with the other weekdays, in order to get more accurate performance, only weekday data is applied instead of whole week’s data. Based on Figure 5.1.3, it can be observed that the data on Friday contains a lot of outlier values. So, they are unsuitable for the training. Meanwhile, the data on Thursday has lower range of power consumption than that on the other weekdays so these data are removed accordingly.

Due to data reliability and its type of the same date, the data from Monday to Wednesday in the months from May to July are selected for forecasting. ‘ThisHour’, ‘ThisTemperature’ and ‘ThisPower’ are the new dataset extracted from the whole dataset.

These new data are inputted into the ‘Curve Fitting Tool’ and then these data are used for the parameters fitting. Finally, the best result is obtained by trial and error when the degree of X is 5 and degree of Y is 2. X and Y represent the variable of the polynomial function, respectively. The coefficients of this model are shown as follows:

Linear model Poly 52:

\[ f(x,y) = p_{00} + p_{10}x + p_{01}y + p_{20}x^2 + p_{11}xy + p_{02}y^2 + p_{30}x^3 + p_{21}x^2y + p_{12}xy^2 + p_{40}x^4 + p_{31}x^3y + p_{22}x^2y^2 + p_{50}x^5 + p_{41}x^4y + p_{32}x^3y^2 \]

Coefficients obtained from training are as follows (with 95% confidence bounds):

\[
\begin{align*}
p_{00} & = \text{value} \\
p_{10} & = \text{value} \\
p_{01} & = \text{value} \\
p_{20} & = \text{value} \\
p_{11} & = \text{value} \\
p_{02} & = \text{value} \\
p_{30} & = \text{value} \\
p_{21} & = \text{value} \\
p_{12} & = \text{value} \\
p_{40} & = \text{value} \\
p_{31} & = \text{value} \\
p_{22} & = \text{value} \\
p_{50} & = \text{value} \\
p_{41} & = \text{value} \\
p_{32} & = \text{value}
\end{align*}
\]
\[ p_{00} = 1.72 \ (0.9874, 2.453) \]
\[ p_{10} = -0.419 \ (-0.629, -0.209) \]
\[ p_{01} = -0.03384 \ (-0.05891, -0.008765) \]
\[ p_{20} = 0.06977 \ (0.04816, 0.09138) \]
\[ p_{11} = 0.0124 \ (0.005604, 0.01919) \]
\[ p_{02} = 0.0002963 \ (8.208 \times 10^{-5}, 0.0005106) \]
\[ p_{30} = -0.003797 \ (-0.004943, -0.002651) \]
\[ p_{21} = -0.001317 \ (-0.001895, -0.0007387) \]
\[ p_{12} = -0.0001039 \ (-0.0001616, -4.616 \times 10^{-5}) \]
\[ p_{40} = 6.749 \times 10^{-5} \ (3.366 \times 10^{-5}, 0.0001013) \]
\[ p_{31} = 4.446 \times 10^{-5} \ (2.485 \times 10^{-5}, 6.406 \times 10^{-5}) \]
\[ p_{22} = 9.82 \times 10^{-6} \ (5.092 \times 10^{-6}, 1.455 \times 10^{-5}) \]
\[ p_{50} = -1.435 \times 10^{-7} \ (-6.43 \times 10^{-7}, 3.56 \times 10^{-7}) \]
\[ p_{41} = -3.346 \times 10^{-7} \ (-6.606 \times 10^{-7}, -8.542 \times 10^{-9}) \]
\[ p_{32} = -2.58 \times 10^{-7} \ (-3.755 \times 10^{-7}, -1.405 \times 10^{-7}) \]

Goodness of fit:

SSE: 3.65

R-square: 0.9152

Adjusted R-square: 0.9139

RMSE: 0.06295
From the results, it can be seen that the R-square is 0.9152 and the RMSE is 0.06295, which is not perfect but good enough for forecasting of the power consumption in the future. The result diagram is shown in the Figure 5.2.1.

![Curve fitting tool screenshot](image)

**Figure 5.2.1 Curve fitting result of polynomial**

### 5.2.2 Using ‘2-order Fourier series’ model

In this section, the ‘Custom Equation’ model is used to model the dataset. The ‘2-order Fourier series’ is employed to fit into this model, the equation is as shown:

\[
f(x, y) = a_0 + a_1 \cos(wx) + b_1 \sin(wx) + a_2 \cos(2wx) + b_2 \sin(2wx) + c_1 y^2 + c_2 y
\]
Based on the MATLAB program, the data on Monday to Wednesday in the month from May to July are used. ‘ThisHour’, ‘ThisTemperature’ and ‘ThisPower’ are the new dataset extracted from the whole dataset.

These new data are inputted into the ‘Curve Fitting Tool’ and then the data is used for training. Finally, the coefficients of this model are shown as follows:

General model:
\[
f(x,y) = a_0 + a_1 \cos(wx) + b_1 \sin(wx) + a_2 \cos(2wx) + b_2 \sin(2wx) + c_1 y^2 + c_2 y
\]

Coefficients (with 95% confidence bounds):
\[
\begin{align*}
a_0 &= 1.237 \ (1.154, 1.319) \\
a_1 &= -0.2042 \ (-0.2124, -0.1961) \\
a_2 &= -0.02544 \ (-0.03258, -0.0183) \\
b_1 &= -0.1609 \ (-0.1698, -0.1519) \\
b_2 &= -0.07795 \ (-0.08449, -0.07141) \\
c_1 &= 2.934e-05 \ (1.002e-05, 4.865e-05) \\
c_2 &= -0.004525 \ (-0.007058, -0.001993) \\
w &= 0.3097 \ (0.307, 0.3124)
\end{align*}
\]

Goodness of fit:
\[
\begin{align*}
\text{SSE:} & \ 2.624 \\
\text{R-square:} & \ 0.939 \\
\text{Adjusted R-square:} & \ 0.9385 \\
\text{RMSE:} & \ 0.05318
\end{align*}
\]
Based on above results, it can be seen that the R-square is 0.9390 and the RMSE is 0.05318, which is much better than that from using the fitting of polynomial model in forecasting the power consumption in the future. The result diagram is as shown in the Figure 5.2.2.

**Figure 5.2.2 Curve fitting resulting of self-equation**

### 5.2.3 Using neural network model

The Neural Network Function Fitting is the process of training a neural network based on a set of inputs for the purpose of generating an associated set of target outputs.
Once the neural network fit the data well, it will establish an input-output relationship used to generate outputs from new inputs that are not trained previously.

This dataset can be used to train a neural network to estimate the energy consumption in terms of time and weather conditions.

To realize the fitting model, these two variables are loaded into MATLAB workspace:

Input is an 8x8785 matrix used to define eight attributes for 8785 different datasets.

1. Temperature: the hourly temperature data of Denver centennial area during the whole year of 2004.
2. Dewpoint: the hourly dew point temperature data of Denver centennial area during the whole year of 2004.
3. Hour: hour from 1 to 24. ‘1’ represents 01:00 am while ‘13’ represents 13:00 pm.
4. Dayofweek: it represents the date. ‘1’ represents Monday and ‘7’ represents Sunday.
5. Isworkingday: it represents the working day. ‘1’ means the day is a working day and ‘0’ means not.
6. PrevWeekSameHourLoad: the present hourly load data replaced by the same hour data one week ago.
7. PrevDaySameHourLoad: the present hourly load data replaced by the same hour data one day ago.
8. Prev24HrAveLoad: the present hourly load data replaced by the average data of previous 24 hour.

Target is a 1x8785 matrix of power consumption that can be estimated from the inputs.

After setting the data, the input and the target are inputted into the Neural Network Toolbox. In order to perform this training program, we need to set the training data, validate data and testing data as 70%, 15% and 15% of the whole datasets based on the experience, respectively. And then 10 hidden neurons are selected in the hidden layer for the training program. The results are shown in the Figure 5.2.3 and Figure 5.2.4.

![Figure 5.2.3 Training results](image)

Figure 5.2.3 Training results
Figure 5.2.4 Performance results

Based on above results, it can be seen that the R-square of training is 0.96032 and the MSE of training is 0.0039529, which is much better than results obtained by using both polynomial model and 2-order Fourier series model in forecasting the power consumption in the future.
In order to acquire more accurate fitting results, we increase the number of hidden neuron and retrain the program. We set 20, 30, 40 and 50 hidden neurons respectively to retrain the program, so the results are summarized in the Table 5.2.1.

**Table 5.2.1 Performance in term of different numbers of neurons**

<table>
<thead>
<tr>
<th>Sample</th>
<th>Training</th>
<th>Validation</th>
<th>Testing</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-square(10)</td>
<td>0.96012</td>
<td>0.96154</td>
<td>0.95838</td>
<td>0.96021</td>
</tr>
<tr>
<td>MSE(10)</td>
<td>0.0019529</td>
<td>0.0038829</td>
<td>0.0042506</td>
<td></td>
</tr>
<tr>
<td>R-square(20)</td>
<td>0.96763</td>
<td>0.96768</td>
<td>0.96909</td>
<td>0.96786</td>
</tr>
<tr>
<td>MSE(20)</td>
<td>0.0032235</td>
<td>0.0032981</td>
<td>0.0032101</td>
<td></td>
</tr>
<tr>
<td>R-square(30)</td>
<td>0.97007</td>
<td>0.967</td>
<td>0.96658</td>
<td>0.9668</td>
</tr>
<tr>
<td>MSE(30)</td>
<td>0.0029932</td>
<td>0.0034658</td>
<td>0.0031185</td>
<td></td>
</tr>
<tr>
<td>R-square(40)</td>
<td>0.97289</td>
<td>0.97258</td>
<td>0.9599</td>
<td>0.97467</td>
</tr>
<tr>
<td>MSE(40)</td>
<td>0.0021818</td>
<td>0.002817</td>
<td>0.0040278</td>
<td></td>
</tr>
<tr>
<td>R-square(50)</td>
<td>0.97647</td>
<td>0.96945</td>
<td>0.96372</td>
<td>0.97432</td>
</tr>
<tr>
<td>MSE(50)</td>
<td>0.0024046</td>
<td>0.0030081</td>
<td>0.0039524</td>
<td></td>
</tr>
</tbody>
</table>

It can be seen that the R-square value become increased from 0.96021 to 0.97467 as the number of neurons increases from 10 to 40. But when the number of neurons is increased to 50, the R-square will decrease to 0.97432. The best performance of training for this program is achieved when 40 is selected as the number of hidden neurons in the hidden layer.
Chapter Six: Conclusion and Future Work

6.1 Conclusion

By comparing these three modeling functions and their results, it is concluded that the Neural Network fitting tool possesses higher R-square in the result and it has the best performance in the accurate short-term load forecasting.

As to Neural Network model, there are more detailed inputs and more variables influencing the power consumption. It is a more complicated algorithm that possesses both self-directed learning and self-adaptive capabilities. For a certain group of input-output dataset, we can directly identify their mutual relationship and meanwhile obtain associated parameters without learning the specific mapping relation. Therefore, the Neural Network fitting tool is the more desirable algorithm model in the short-term load forecasting.

By using this short-term load forecasting, the data about customers’ electricity usage habit can be provided so that customers can make more efficient and economic use of electricity together with power market pricing signals from smart grid. Then the hospital can save a lot of money by making better energy management and informed usage of electrical equipment according to price signals.
6.2 Future work

Nowadays, short-term power load forecasting have become increasingly demanding. With rapid development of computer technology, computer-orientated load forecasting has been extensively applied to services provided by power system. In this thesis, one simple forecasting method was developed by using the software of MATLAB in order to simplify the short-term load forecasting. The core value of this software, which is interpreted in this article, is to integrate prediction model of temperature effect with modern computer technology. This software meets major needs of current electricity market. What’s more important, the software has a user-friendly interface and improved prediction analysis function.

However, there are many deficiencies due to the time and individual capacity. This thesis still has some future works to do, which also is the problems faced by the entire short-term load forecasting area, including: the learning and training procedures and processes of Neural Network are still relatively complex, uncertain parameters will directly lead to the different of the output results. The improvement of further development is needs to be achieved to this model. In addition, the weight factors are still need to be improved. Some uncertain factors, such as emergencies and unusual weather impact on the load forecasting are still need to be defined.
References


Conference on Smart Grid Communications (SmartGridComm), pp. 291-296, October 2011.


Appendix A

%%%  
%createfigure.m%  

function createfigure(X1, Y1, Temperature) 

%CREATEFIGURE1(X1,Y1,TEMPERATURE1)  

% X1: vector of x data  
% Y1: vector of y data  
% TEMPERATURE1: vector of y data  

% Auto-generated by MATLAB on 27-Jan-2014 06:14:24  

% Create figure  
figure1 = figure;  

% Create subplot  
subplot1 = subplot(2,1,1,'Parent',figure1,'XTick',zeros(1,0));  
box(subplot1,'on');  
hold(subplot1,'all');  

% Create plot  
plot(X1,Y1,'Parent',subplot1,'DisplayName','Power');
% Create ylabel
ylabel('Power Usage [KW]');

% Create legend
legend(subplot1,'show');

% Create subplot
subplot2 = subplot(2,1,2,'Parent',figure1,...
'XTickLabel',['Nov03';'Jan04';'Feb04';'Apr04';'Jun04';'Jul04';'Sep04';'Oct04';'Dec04';'Feb05'],...
'XTick',[731900 731950 732000 732050 732100 732150 732200 732250 732300...
732350]);

%%%% Uncomment the following line to preserve the X-limits of the axes
% xlim(subplot2,[731900 732350]);
box(subplot2,'on');
hold(subplot2,'all');

% Create xlabel
xlabel('Dates');
% Create ylabel

ylabel('Temperature [\textdegree F]');

% Create plot

plot(X1, Temperature, 'Parent', subplot2, 'Color', [1 0 0], ... 
'DisplayName', 'Temperature');

% Create legend

legend(subplot2, 'show');

% Add date ticks

datetick ('x', 'mmmyyyy', 'keepticks')

% Link axes

linkaxes([subplot1 subplot2], 'x')
Appendix B

%import data from Excel to Matlab%
%powerinput.m%

%% Import data from spreadsheet

% Script for importing data from the following spreadsheet:
%
% Workbook: C:\Users\HelloWorld\Desktop\a thesis\data for matlab\Denver
% hospital electricity and temperature 2004.xlsx Worksheet: Sheet1
%
% To extend the code for use with different selected data or a different
% spreadsheet, generate a function instead of a script.
%
% Auto-generated by MATLAB on 2014/01/30 13:51:57

%% Import the data

[~, ~, raw] = xlsread('C:\Users\HelloWorld\Desktop\a thesis\data for matlab\Denver
hospital electricity and temperature 2004.xlsx','Sheet1');

raw(cellfun(@(x) ~isempty(x) && isnumeric(x) && isnan(x),raw)) = {''};

cellVectors = raw(:,1);

raw = raw(:,[2,3,4,5,6,7,8]);

%% Replace non-numeric cells with NaN

R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),raw); % Find non-numeric cells

raw(R) = {NaN}; % Replace non-numeric cells
%%% Create output variable

data = reshape([raw{:}].size(raw));

%%% Allocate imported array to column variable names

Date = cellVectors(:,1);
Month = data(:,1);
Day = data(:,2);
Hour = data(:,3);
Dayofweek = data(:,4);
Power = data(:,5);
Temperature = data(:,6);
DewPoint = data(:,7);

%%% Clear temporary variables

clearvars data raw cellVectors R;

%%% Creat serialdates

Serialdates = datenum(2004, Month, Day, Hour, 0, 0);

%%%define X type

Term = 'short';
Appendix C

%generate three using variables for polynomial model%
%generatepoly.m%

idx = Dayofweek < 4 & ismember (Month, [5 6 7]);

ThisHour = Hour (idx);

ThisTemperature = Temperature (idx);

ThisPower = Power (idx);
Appendix D

%generate the eight variables for Neural Network Toolbox%
%generatex.m%

% Create Predictors

% Short term forecasting inputs

% Lagged load inputs
PrevDaySameHourLoad = [NaN(24,1); Power(1:end-24)];
PrevWeekSameHourLoad = [NaN(168,1); Power(1:end-168)];
Prev24HrAveLoad = filter(ones(1,24)/24, 1, Power);

% Non-business days
IsWorkingDay = ~ismember(floor(Serialdates),holidays) & ~ismember(Dayofweek,[1 7]);
% [~,~,isWorkingDay] = createHolidayDates(data.NumDate);

if strncmpi(Term, 'long', 4);
    % Long Term Forecast Predictors
    X = [Temperature DewPoint daily5dayHighAve daily5dayLowAve Hour Dayofweek
         IsWorkingDay];
    Labels = {'Temperature', 'DewPoint', 'Prev5DayHighAve', 'Prev5DayLowAve', 'Hour',
              'Weekday', 'IsWorkingDay'};
end
else

    \% Short Term

    X = [Temperature DewPoint Hour Dayofweek IsWorkingDay
         PrevWeekSameHourLoad PrevDaySameHourLoad Prev24HrAveLoad];

    Labels = {'Temperature', 'DewPoint', 'Hour', 'Weekday', 'IsWorkingDay',
              'PrevWeekSameHourLoad', 'PrevDaySameHourLoad', 'Prev24HrAveLoad'};

end