EEE 310: Power System

PROJECT ON

SHORT TERM LOAD FORECASTING USING DIFFERENT MODELS

Submitted By

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Objective

Load forecasting is an essential part for the power system planning and operation. In this project modeling and design of artificial neural network, regression tree, multiple linear regression and curve fitting model for load forecasting is carried out in the BUET academic and residential area. These approaches help to reduce the problems associated with conventional method and has the advantage of learning directly from the historical data. The forecasting models here have used data such as past load, weather information like dew point and temperatures. Once the models are trained for the past set of data it can give a prediction of future load. This reduces the capital investment reducing the equipment to be installed. The actual data are taken from the BUET POWER PLANT. The data of load for the year 2005 is collected for a particular region and used to create an arbitrary dataset for 20 years. The main objective is to forecast the amount of electricity needed for better load distribution in the area. The load forecasting is done for the month of **(INSERT THE DATE)** and is validated for accuracy.

Using different methods for forecasting gives the chance to compare their performances and choose the best out of them. Which leads to create an averaging model to take the best three of them and get a better result.

Another objective of this project is to learn the factors which affect the weight of load and their importance in load forecasting.

Introduction

Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Load varies very frequently on a daily basis. If the generation is not able to cope up with the demand, there is a change in frequency. If the frequency exceeds the limits, there is a loss of synchronism which affects the power system on a great scale. Practically, the change in frequency should not exceed 0.5 Hz. In order to cope up with the demand, generation needs to predict values of the load, and this requires the need of load forecasting. Also different electrical failures can be avoided by proper forecasting of load.
A large variety of mathematical methods have been developed for load forecasting. Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Some of the models are used here.

Load Forecasting

Load forecasting is a technique used by power or energy-providing companies to predict the power/energy needed to meet the demand and supply equilibrium. Load Forecasting is the process of making predictions or estimation of the future demand of energy based on past and present data or physical factors like temperature, pressure, loading on lines, losses, weather conditions etc. Future power demand is estimated on the basis of the historical load data. The generation, transmission, and distribution utilities require some means to forecast the electrical load so they can utilize their electrical infrastructure efficiently, securely, and economically. Therefore, the accuracy of forecasting is of great significance for the operational and managerial loading of a utility company. Electrical failures like blackout, faults due to unnecessary loading can be avoided if proper care can be taken to the load demands.

Load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market. In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.

Categories of Load Forecasting

The load forecasting techniques are categorized into three groups. The selection of a forecasting Method relies on several factors including the relevance and availability of historical data, the forecast horizon, the level of accuracy for weather data, desired prediction accuracy, and so forth. Accordingly, selecting the proper load forecasting approach primarily depends on the time horizon of the prediction. The categories of Load Forecasting Techniques are:

1. Short Term Load Forecasting (STLF)
2. Medium Term Load Forecasting (MTLF)
3. Long Term Load Forecasting (LTLF)

Short Term Load Forecasting (STLF)

The short-term load forecasting (STLF) represents the electric load forecast for a time interval of a few hours to a few days. The distribution and transmission planning are involved with STLF. A short-term forecast provides information to the day-ahead market, which requires a high-level of accuracy. Short term load forecasting mainly considers calendar variables, weather data, and customers’ behaviors as predictor’s variable.

Medium Term Load Forecasting (MTLF)

Medium term load forecasting covers a time span of (1week - 12 months). This type of forecasting depends mainly on growth factors, factors that influence demand such as main events, the addition of new loads, seasonal variations, demand patterns of large facilities, and maintenance requirements of large consumers. This will also help to plan major tests and commissioning events, and determine outage times of plants and major pieces of equipment.

Long Term Load Forecasting (LTLF)

Long-term load forecasting (LTLF) usually covers forecasting horizons of one to ten years, and sometimes up to several decades. It provides weekly/monthly forecasts for peak and valley loads which are important to expand generation, transmission and distribution systems. Long-term load forecasting plays a vital role for utilities and planners in terms of grid development and expansion planning. The load prediction provides a decision platform for financial or power supply planning. An overestimate of long-term electricity load will result in substantial wasted investment in the construction of excess power facilities, while an underestimate of future load will result in insufficient generation and unmet demand. The required level of accuracy in this time horizon is not high, as the decisions in the long-term are preliminary and may need significant changes in subsequent planning stages due to very uncertain input information.

Load Forecasting Techniques

The techniques used and implemented for load forecasting can be classified broadly in three major groups. These are:

1. Traditional Forecasting technique
2. Modified Traditional Technique and
3. Soft Computing Technique.

Traditional Forecasting Technique:

Traditional forecasting technique includes methods like,

a. Regression
b. Multiple Regression
c. Exponential Smoothing (Curve Fitting)
d. Iterative Reweighted Least-Squares

Modified Traditional Technique:

Modified traditional technique have methods like,

a. Adaptive Demand Forecasting
b. Stochastic Time Series
c. Support Vector Machine based Techniques

Soft Computing Technique:

Soft computing technique includes methods,

a. Genetic Algorithms
b. Fuzzy logic
c. Neural network

We have used the methods Regression, Multiple Regression, Curve Fitting and Neural Network to forecast loads. We have also created a new model named Averaging Model that takes the best three of the four models used and average them to get a better model and therefore better results.

Factors Affecting Electrical Loads

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors.

The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently.

Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short term load forecasts. Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors.

Most electric utilities serve customers of different types such as residential, commercial and industrial. The electricity usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class.

There are some other factors that influence the electrical load profile. It consists of all the other random disturbances in the load pattern that cannot be explained by the previous factors. They can be categorized as Random factors.

Considering all the cases discussed above, the factors for load forecasting can be classified in following categories:

1. Economic Factors
2. Time Factors
    a. Seasonal Effects
    b. Weekly-Daily Cycle
    c. Holidays
3. Weather
4. Customer Types
5. Random Effects

Techniques and Factors Considered

The techniques we have used in this project are:

1. Neural Network
2. Regression Tree Model
3. Multiple Linear Regression Model
4. Curve Fitting Model
5. Averaging Model

Factors used for load forecasting are:

1. Dry bulb Temperature
2. Dew point
3. Day of Week
4. Holidays

Collection Of Data

We have collected data from BUET power plant. From this data we have created a dataset for 20 years.

We have created a mat file from the data we have collected. Precisely our dataset contains information about 20 years. Also this includes information about each month, each day & each hour. However the dataset mainly includes 5 parameters. They are:

- Hour.
- Dry Bulb Temperature(Fahrenheit)
- Dew Point Temperature(Fahrenheit)
- System Load(Kilowatt)
- Date of the year.

Besides these the dataset contains information about the "Holiday". For this purpose we have created an excel file. And we have imported it in the MATLAB code using command lines from MATLAB built in library function.

For forecasting one day load ahead, we have used a dataset from https://www.iso-ne.com/ .From this link we have used dataset of (2018 -19) hourly load information. For our purpose we have extracted the date & System-load information in an excel file.

Model Design

The forecast model processes the exogenous relation of the provided data and consequently anticipates the future load demand. Figure 1 illustrates the block diagram of processes on how to design a load forecast model that predicts the future load demand.

There are three steps in designing a model.
Step 1: Access Historical Data
Step 2: Select and Calibrate Model
Step 3: Run Model Live

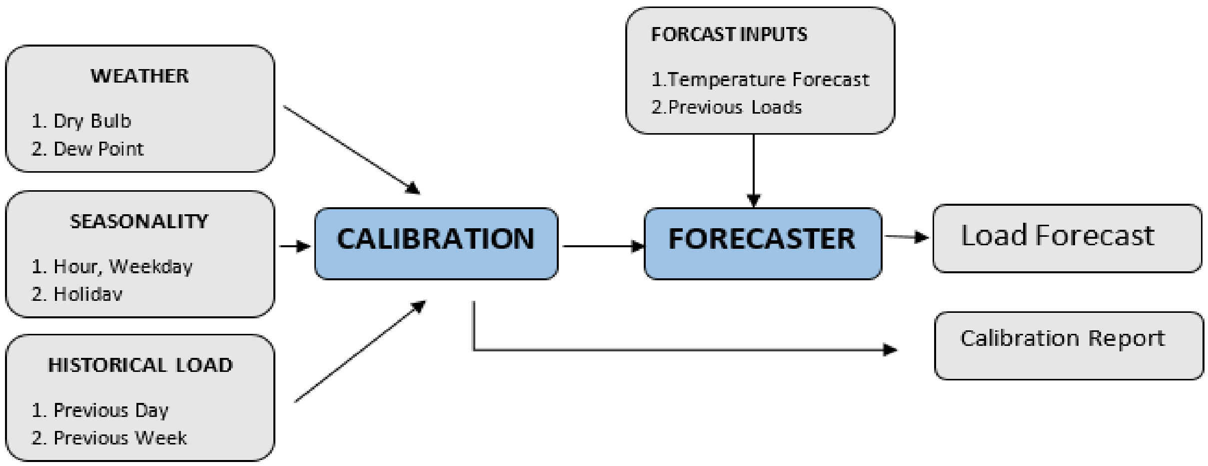


Figure 1: Block Diagram of Model Design Procedure

Neural Network

Using NN which is part of artificial intelligence (AI) to forecast is very good due to the flexibility provided by NN and their ability to do nonlinear relationships. The whole model is a matrix of weights that will be trained by the historical loads and then using these weights, we can predict any output for any given input. A neural network is a computing model whose layered structure resembles the networked structure of neurons in the brain, with layers of connected nodes. A neural network can learn from data—so it can be trained to recognize patterns, classify data, and forecast future events.
A neural network breaks down your input into layers of abstraction. It can be trained over many examples to recognize patterns in speech or images, for example, just as the human brain does. Its behavior is defined by the way its individual elements are connected and by the strength, or weights, of those connections. These weights are automatically adjusted during training according to a specific learning rule until the neural network performs the desired task correctly.

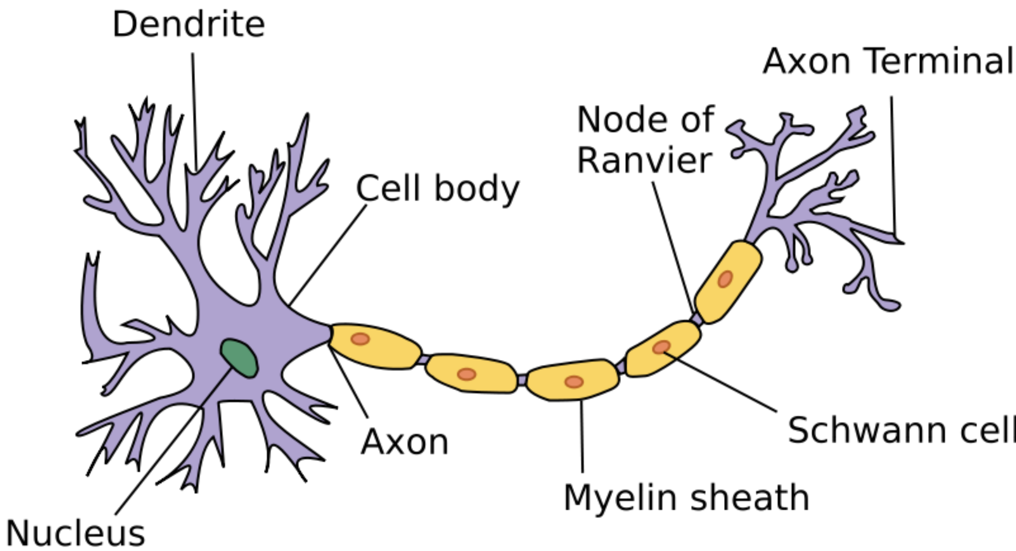


Figure 2: A Neuron Cell.

How Do Neural Networks Work?

A neural network combines several processing layers, using simple elements operating in parallel and inspired by biological nervous systems. It consists of an input layer, one or more hidden layers, and an output layer. The layers are interconnected via nodes, or neurons, with each layer using the output of the previous layer as its input.

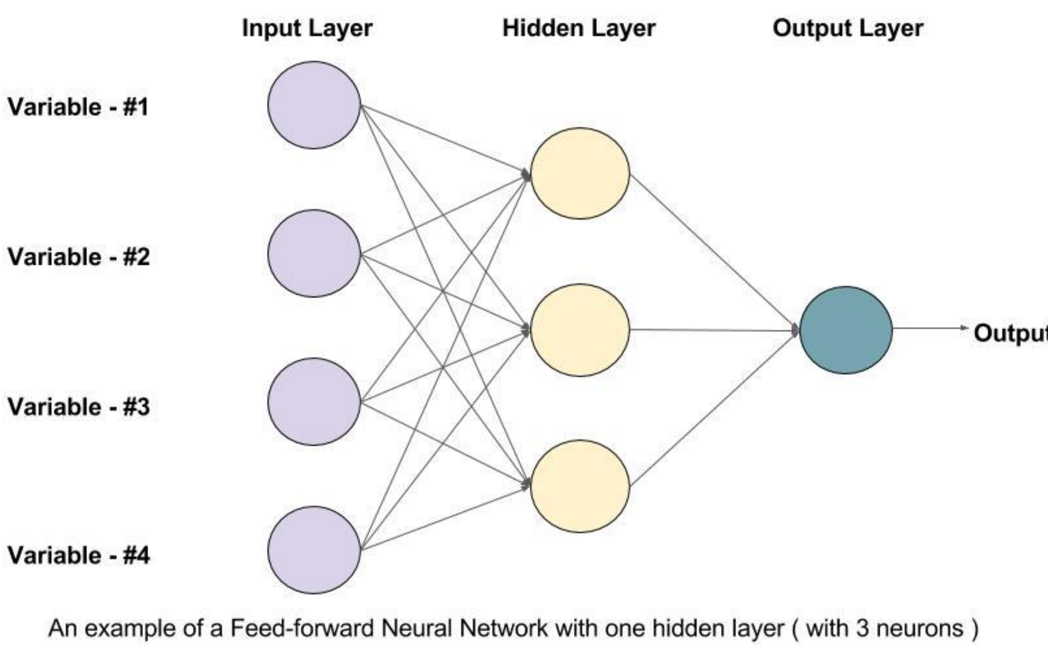


Figure 3: Processing Layers of Neural Network.

Regression Tree Model

Classification and Regression Trees or CART for short is a term introduced by Leo Breiman to refer to Decision Tree algorithms that can be used for classification or regression predictive modeling problems. Classically, this algorithm is referred to as “decision trees”, but on some platforms like R they are referred to by the more modern term CART.
The CART algorithm provides a foundation for important algorithms like bagged decision trees, random forest and boosted decision tree.

Pruning The Tree

The stopping criterion is important as it strongly influences the performance of your tree. You can use pruning after learning your tree to further lift performance. The complexity of a decision tree is defined as the number of splits in the tree. Simpler trees are preferred. They are easy to understand (you can print them out and show them to subject matter experts), and they are less likely to over fit your data.

Multiple Linear Regression Model

Linear regression is a **linear model**, e.g. a model that assumes a linear relationship between the input variables (x) and the single output variable (y). More specifically, that y can be calculated from a linear combination of the input variables (x).
When there is a single input variable (x), the method is referred to as **simple linear regression**. When there are **multiple input variables**, literature from statistics often refers to the method as multiple linear regression.

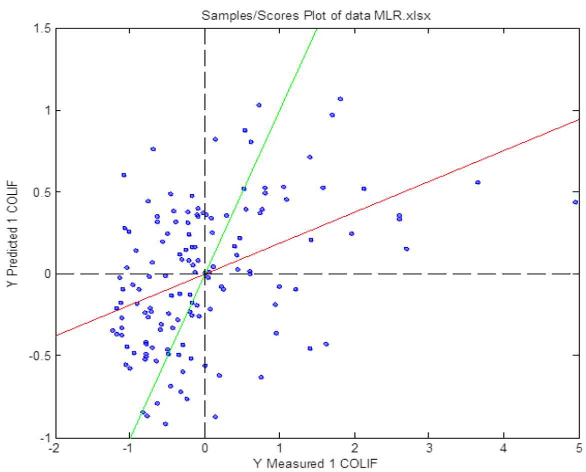


Figure 4: Multiple Linear Regression Model

Different techniques can be used to prepare or train the linear regression equation from data, the most common of which is called **Ordinary Least Squares**. It is common to therefore refer to a model prepared this way as Ordinary Least Squares Linear Regression or just Least Squares Regression.

Linear Regression Model Representation

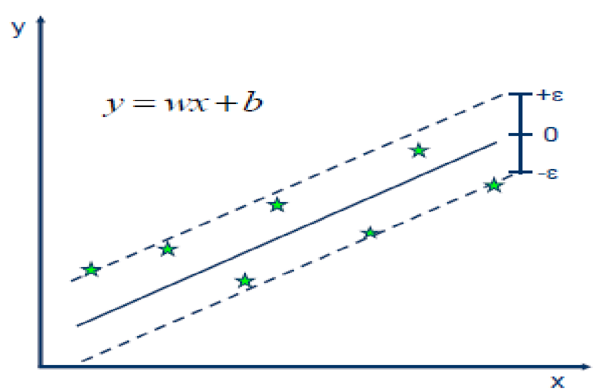
For example, in a simple regression problem (a single x and a single y), the form of the model would be:

$$y = B0 + B1*x$$

In higher dimensions when we have more than one input (x), the line is called a plane or a hyper-plane. The representation therefore is the form of the equation and the specific values used for the coefficients.

Support Vector Machine (Regression):

Support Vector Machine can also be used as a regression method, maintaining all the main features that characterize the algorithm (maximal margin). The Support Vector Regression (SVR) uses the same principles as the SVM for classification, with only a few minor differences. First of all, because the output is a real number it becomes very difficult to predict the information at hand, which has infinite possibilities. In the case of regression, a margin of tolerance (epsilon) is set in approximation to the SVM which would have already requested from the problem. But besides this fact, there is also a more complicated reason, the algorithm is more complicated therefore to be taken in consideration. However, the main idea is always the same: to minimize error, individualizing the hyper plane that maximizes the margin, keeping in mind that part of the error is tolerated.



- Solution:

$$\min \frac{1}{2}\|w\|^2$$

- Constraints:

$$y_i - wx_i - b \le \varepsilon$$
$$wx_i + b - y_i \le \varepsilon$$

Figure 5: Support Vector Machine(Regression)

Linear SVR:

$$y = \sum_{i=1}^{N} \left(\alpha_i - \alpha_i^*\right) \cdot \langle x_i, x \rangle + b$$

Curve Fitting Model

Curve fitting is the process of constructing a curve, or function, which has the best fit to a series of data points, possibly subject to constraints. Curve fitting can involve either interpolation, where an exact fit to the data is required, or smoothing, in which a "smooth" function is constructed that approximately fits the data. A related topic is regression analysis which focuses more on questions of statistical inference such as how much uncertainty is present in a curve that is fit to data observed with random errors. Fitted curves can be used as an aid for data visualization, to infer values of a function where no data are available, and to summarize the relationships among two or more variables] Extrapolation refers to the use of a fitted curve beyond the range of the observed data,] and is subject to a degree of uncertainty since it may reflect the method used to construct the curve as much as it reflects the observed data.

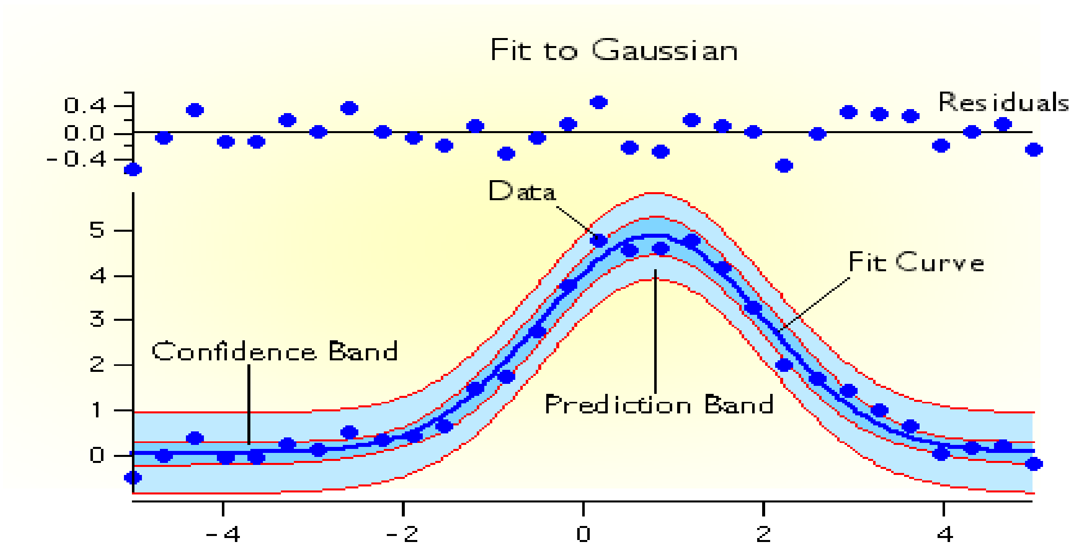


Figure 6: Curve Fitting Model

Result Analysis Of Prediction Over A Month

Neural Network Model

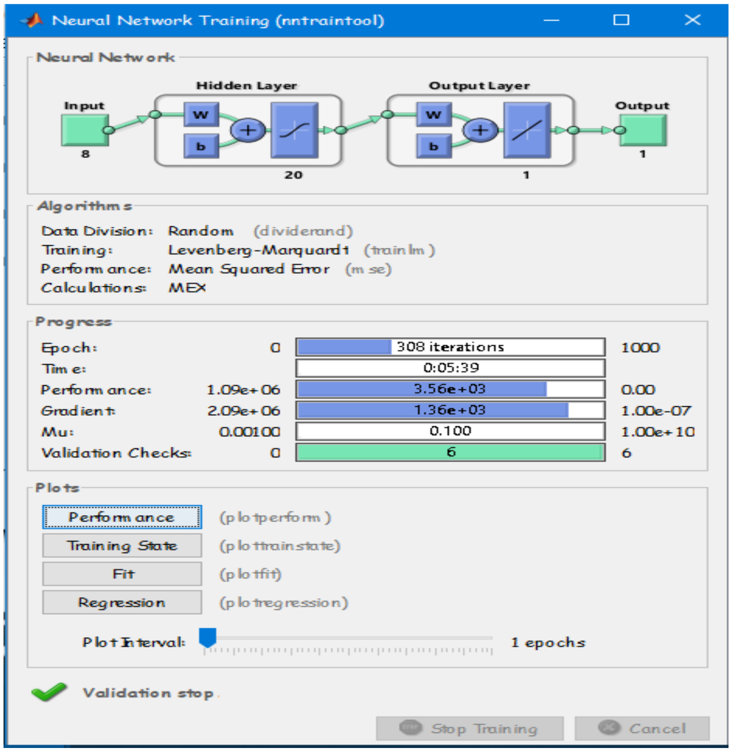


Figure 7: Neural Network Training Tool

Required Train Time: 0.2655sec

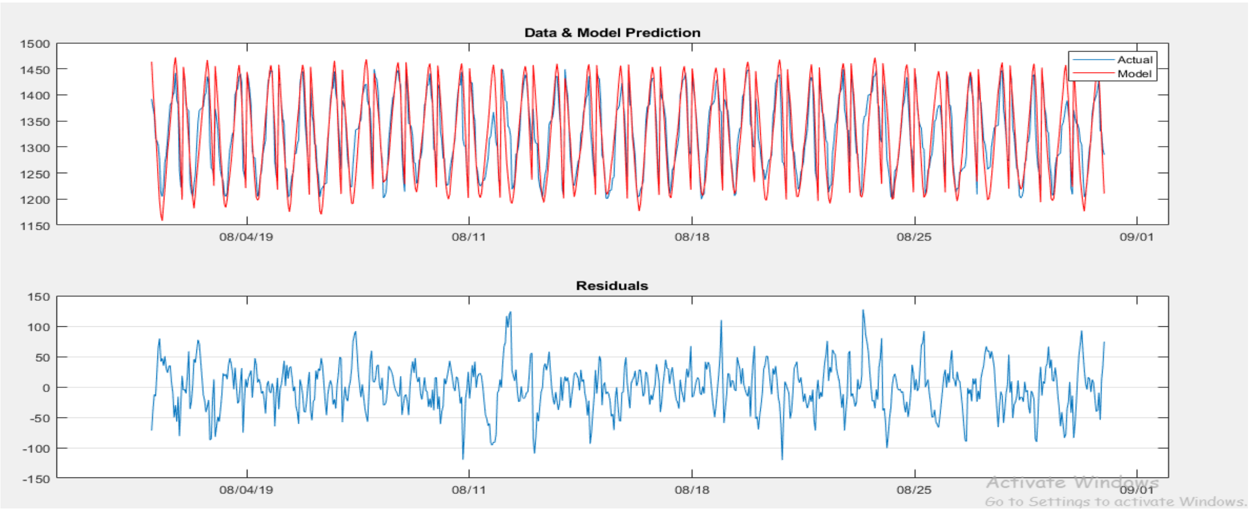


Figure 8: Data and Model Prediction for (neural Network)

```
************************************************************
 (1) Neural Network Model
 (2) Regression Trees Model
 (3) Multiple linear regression Model
 (4) Curve Fitting Model(fourier)
 (5) Support Vector Machine
 (6) Curve Fitting + Regression Trees + Neural Network averaging Model(Run 1,2,4 models first)
************************************************************
Choose the desired model from the menu above:  1
Elapsed time is 0.265509 seconds.
Mean Absolute Percent Error (MAPE): 2.21%
Mean Absolute Error (MAE): 29.12 MWh
Daily Peak MAPE: 1.21%
    'DryBulb'
```

Figure 9: MAPE values of NN.

Acquired Mape Score: 2.21%

Regression Tree Model

```
Elapsed time is 245.576134 seconds.
    "Prasun"

Mean Absolute Percent Error (MAPE): 2.51%
Mean Absolute Error (MAE): 33.24 MWh
Daily Peak MAPE: 1.06%
```

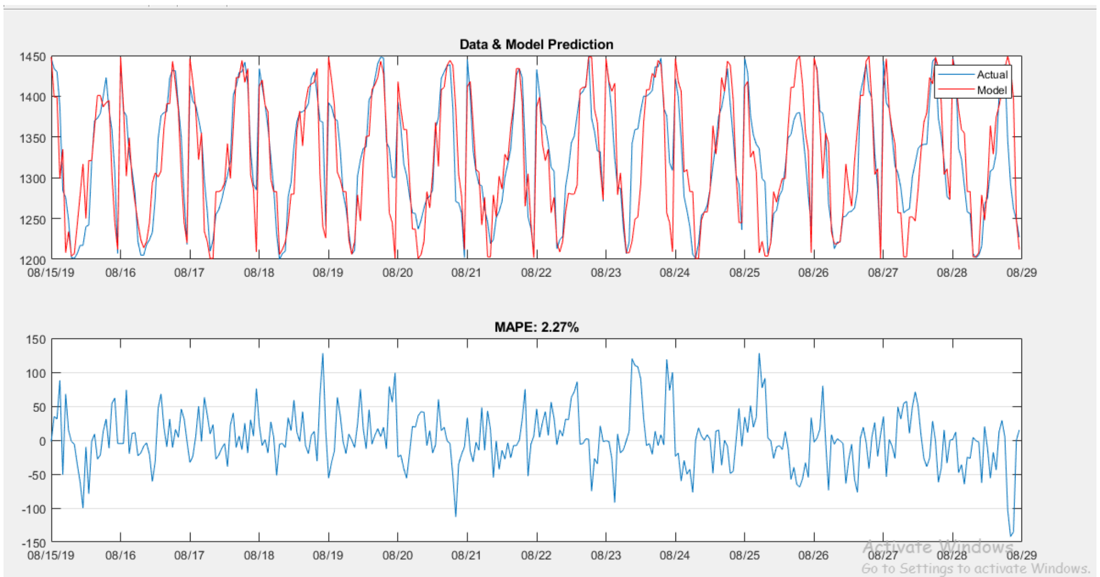
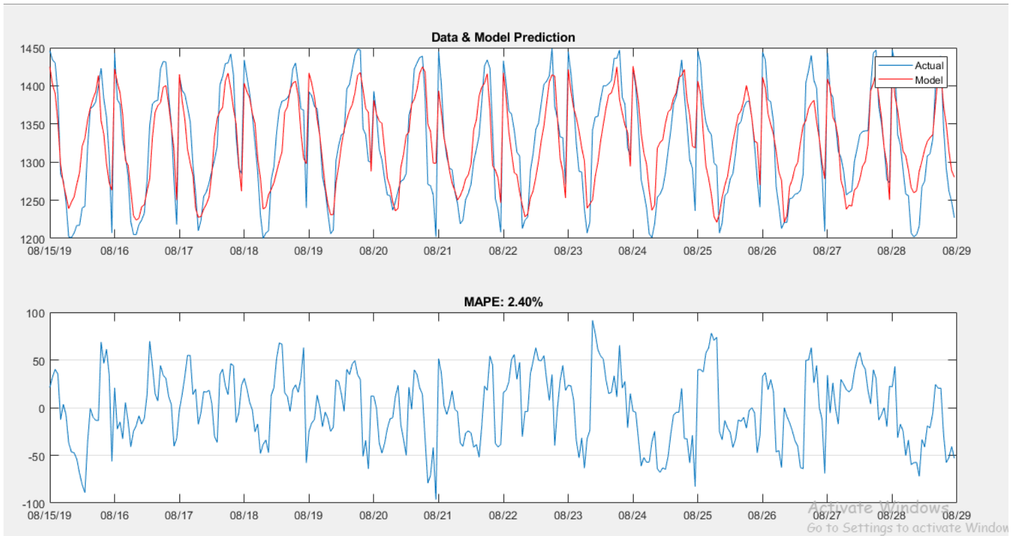


Figure 10: MAPE and Prediction of Regression Tree Model

Required Time For Training : 245.576sec.
Acquired Mape Score: 2.51%

Multiple Linear Regression Model

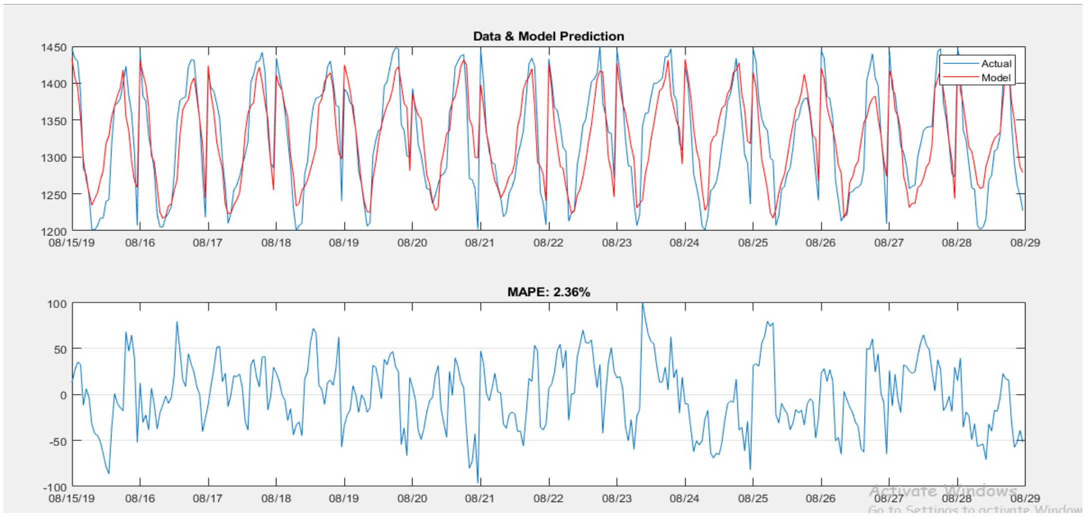



```
**********************************************************
 (1) Neural Network Model
 (2) Regression Trees Model
 (3) Multiple linear regression Model
 (4) Curve Fitting Model(fourier)
 (5) Support Vector Machine
 (6) Curve Fitting + Regression Trees + Neural Network averaging Model(Run 1,2,4 models first)
**********************************************************
Choose the desired model from the menu above:  3
in progress.........done
Elapsed time is 0.150556 seconds.
Mean Absolute Percent Error (MAPE): 2.40%
Mean Absolute Error (MAE): 31.68 MWh
Daily Peak MAPE: 1.59%
    'DryBulb'
```

Figure 11: MAPE and Prediction of Multiple Linear Regression Model

Required Training Time: 0.15055sec
Acquired Mape Score: 2.40%

Support Vector Regression Model

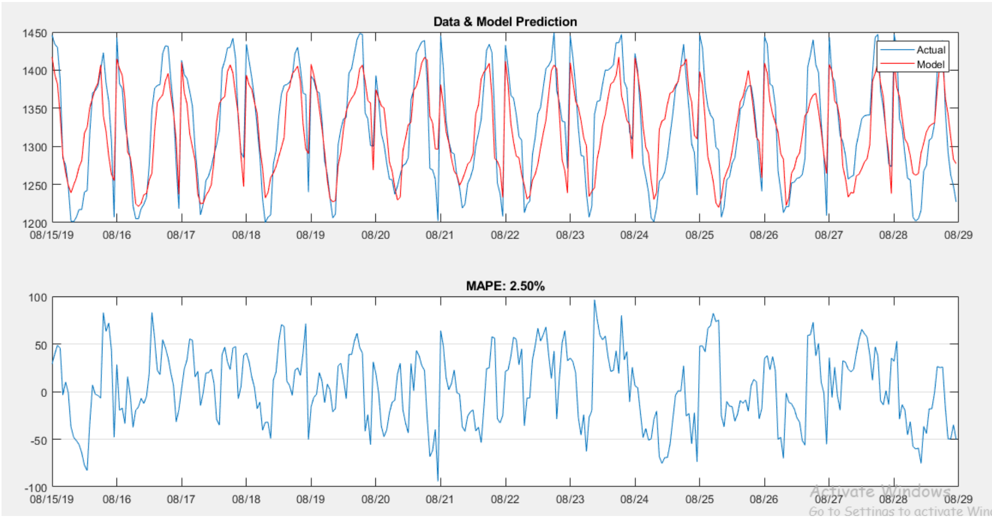



```
RegressionSVM
           ResponseName: 'Y'
  CategoricalPredictors: []
      ResponseTransform: 'none'
                  Alpha: [96119×1 double]
                   Bias: 1.0947e+03
       KernelParameters: [1×1 struct]
                     Mu: [1×8 double]
                  Sigma: [1×8 double]
        NumObservations: 166272
         BoxConstraints: [166272×1 double]
        ConvergenceInfo: [1×1 struct]
        IsSupportVector: [166272×1 logical]
                 Solver: 'SMO'


  Properties, Methods

    "Prasun"

Mean Absolute Percent Error (MAPE): 2.38%
Mean Absolute Error (MAE): 31.44 MWh
Daily Peak MAPE: 1.16%
```

Figure 12: MAPE and Prediction of Support Vector Regression Model

Required Training Time: 300sec.
Acquired Mape Score: 2.38%

Curve Fitting Model




```
**********************************************************
  (1) Neural Network Model
  (2) Regression Trees Model
  (3) Multiple linear regression Model
  (4) Curve Fitting Model(fourier)
  (5) Support Vector Machine
  (6) Curve Fitting + Regression Trees + Neural Network averaging Model(Run 1,2,4 models first)
**********************************************************
Choose the desired model from the menu above:  4
Elapsed time is 11.898366 seconds.
Mean Absolute Percent Error (MAPE): 2.50%
Mean Absolute Error (MAE): 33.16 MWh
Daily Peak MAPE: 2.07%
```

Figure 13: MAPE and Prediction of Curve Fitting Model

Required Training Time: 11.898sec.
Acquired MapeScore: 2.50%

Result Analysis Of One Day Ahead Load Forecast

Neural Network Model

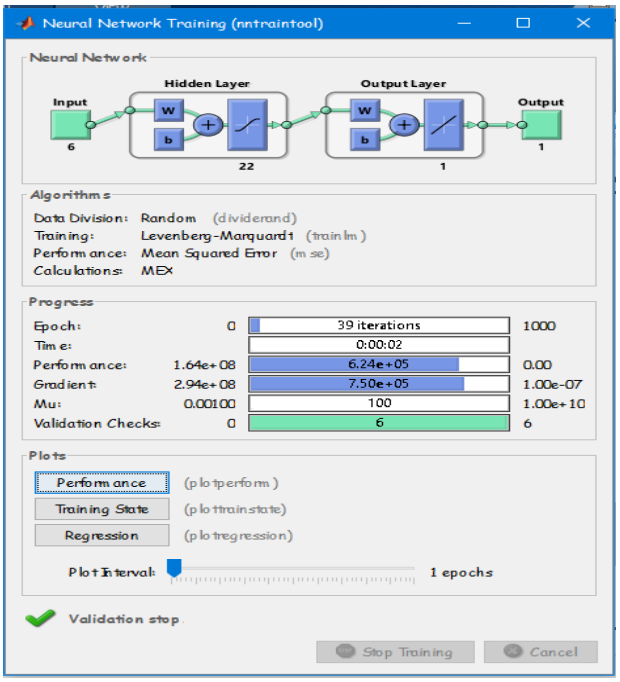


Figure 14: Neural Network Training Tool (One day ahead)

Required Time For Training: 19.06 sec
Acquired Mape Score: 4.637%

Comparison Among The Models

Here is the MAPE value and the training time for prediction over one month of all the methods used.

Model Name	MAPE Value	Time
Regression Tree Model	2.51%	245.576sec.
Multiple Linear Regression Model	2.40%	0.15055sec
Curve Fitting Model	2.50%	11.898sec.
Neural Network	2.21%	0.2655sec

Averaging Model

Averaging Model takes the best three of the four models used and average them to get a better model and therefore better results. Here we can see the neural network gives the best result of all the other methods. Hence this last method combines the best of all the methods and gives the best result.

Conclusion

It is a goal for every power system manager to have their power system operate efficiently, securely, and economically. To meet this goal, the behaviour of their power system must be understood. Analysis of the system's normal operating bounds, response to customer demands, and reaction to weather events will provide insight on system loading. Short-term electric load forecasting can provide that insight for the following day to assist in making power system operational decisions. The demand charges and associated system loading can be reduced by energy demand management techniques such as conservation, on-site generation, or implementing demand-response agreements with the serving utility. Energy demand management is a process where the energy use for a facility is planned and coordinated with the system's various load centres.

According to the results obtained by using different methods it can be concluded that Neural Network gives better result than the other methods. It has a Mape value of 2.21%. Which is slightly lower than the other methods. The close values of MAPE of all the models shows that other methods are also suitable for load forecasting. Here we can see a noticeable difference in the time. Neural Network technique gives the fastest result which is several times lower than some other methods.

Scope For Improvement

The structure and size of the NN should only be as complex as required to produce acceptable forecast on out-of-sample data. Overly complex NNs can over fit their training data producing very low error on in-sample input data, but high error on out-of-sample input data. Overfitting reduces the NN's ability to generalize on data it has not been trained on. In addition, a complex NN will have a high training runtime as there are more weights and biases to be estimated during the learning process.This is time series data.Hence if we can implement LSTM model the MAPE Score can be reduced further.Also the dataset is responsible for this MAPE Score.Uniform Dataset and good preprocessing ensures more convergence and therefore good result.Hence in this way we can improve this project in a more creative way.

Appendix

Dry Bulb Temperature: The Dry Bulb Temperature refers to the ambient air temperature. It is called "Dry Bulb" because the air temperature is indicated by a thermometer not affected by the moisture of the air.

Dew Point Temperature: The dew point is the temperature to which air must be cooled to become saturated with water vapor. When further cooled, the airborne water vapor will condense to form liquid water.

MAPE: The Mean Absolute Percentage Error, also known as mean absolute percentage deviation, is a measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation, also used as a loss function for regression problems in machine learning.

Artificial Intelligence (AI): Artificial intelligence (AI), sometimes called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans.

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