Electricity Load Forecasting for Urban Area Using Weather Forecast Information

Vasudev Dehalwar[a], Akhtar Kalam[a], Mohan Lal Kolhe[b] Aladin Zayegh[a]
[a]Victoria University, College of Engineering and Science,
PO Box 14428, Melbourne, Victoria 8001, Australia
[b]University of Agder, Faculty of Engineering and Science
PO Box 422, Kristiansand, NO 4604, Norway
e-mail: Vasudev.Dehalwar@live.vu.edu.au; Akhtar.Kalam@vu.edu.au; Mohan.L.Kolhe@uia.no; Aladin.Zayegh@vu.edu.au

***Abstract*—The global demand for energy is increasing daily with the expansion of energy infrastructure and the addition of new appliances. Efficient Energy Management System (EMS) is the need of the day. All residential and commercial buildings can achieve better energy efficiency and consumption with the use of EMS. Load forecasting is one of the methods to enable EMS to work efficiently. The accuracy of load forecast depends on many factors. The load forecast model must consider the weather forecast for the region in developing an accurate forecast. This paper develops Artificial Neural Network (ANN) and Bagged Regression Trees to generate and predicted load forecast in Urban area using Meteorological data. ANN model is compared with Bagged Regression Trees for prediction accuracy. Good agreement was observed by comparing these results with those available in the literature. It has been observed through analysis that Bagged Regression Trees produce better load prediction for the day ahead load in the urban area.**

Keywords-load prediction; electrical load forecasting; urban area electrical load; ann; regression trees; meteorological data

I. Introduction

The global demand for energy is expected to increase by 40% in next 20 years, and two-thirds of this requirement would be supplied by fossil fuels based power plants. There will be 25% increase in carbon emissions by this process which will further influence the climate change [1]. These carbon emissions can be minimised by deploying better environment-friendly Energy Management System (EMS) at residential and commercial buildings. The efficient EMS could achieve continual improvement of energy efficiency and consumption at the customer premise.

A prior knowledge of load through load forecasting at customer premise can benefit the consumer in managing power. The load forecasting will help in understanding the future demand of energy by utilities and consumer alike and assist in planning and generation of power. Our research has focused continuously on load forecasting through various method that has been presented in our paper [2, 3]. Load prediction for an individual house using neural network based on historical power consumption is given in [2], but it has not considered any weather/ meteorological data. Most of these studies have focussed on individual houses or buildings for demand prediction. A model for power prediction based on neural network for load components e.g. electric heater, lightings, cooking, etc. is presented in paper [4]. This information is useful for an individual home energy management system. The method to find aggregated power demand of thermostatically controlled loads is given in paper [5] and it provides information only for a particular load and calculate the energy savings for that particular load. The load prediction of a commercial building is studied in [6] through computational intelligence. It combines regression and clustering methods for power prediction. Regional power usage and its predictions is presented in paper [7]. A review of various energy demand forecasting models and demand side management are presented in paper [8].

The importance of load forecasting in an urban area cannot be underestimated as it has a great impact on energy consumption and utilisation at regional level. Moreover, load forecasting at the regional level will help in incorporating environment-friendly intermittent renewable energy sources at demand and distribution side of the power pyramid. Additionally, energy consumption in the urban area is more prone to changes in weather conditions. Therefore, consideration of meteorological data is essential in accurately predicting the energy demand.

In this paper, short-term load forecasting of an urban area is analysed using an artificial neural network (ANN) and Bagged Regression Trees. These two model have been built and trained by using urban area load data and weather/ meteorological data. Most of the prediction models discussed in the literature use historical power usage data of building or home. Some of them do not consider using meteorological data for load forecasting. Therefore, in this study, we developed ANN and Bagged Regression Trees load forecasting model using weather data. A Bagged regression tree ensemble a predictive model composed of a weighted combination of multiple regression trees. It has been observed that the predictive performance can increase by combining multiple regression trees. Our model will help the customer to develop the load profile of his house/region that can be progressively updated and monitored for any change. This predicted load profile will be very useful for load dispatch center of utilities.

The dataset used in this study is historical data from the Australian Energy Market Operator (AEMO) and Bureau of Meteorology (BOM) of Sydney/NSW region from years

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2006 to 2010 [9]. This paper is organised as follows. Section II provides a background of load forecasting and the process of generating load predictors. It also elaborates building of ANN and Bagged Regression Trees model. Section III provides result and analysis of load prediction developed on the basis of our model for the urban Section IV concludes the paper with highlights.

II. Load Forecasting and Data Handling

Predicting load demand is important for capacity planning and future investment in the power system. The urban area load prediction is useful for integrating environment friendly distributed energy sources with district power plant. This information will help in treating district power plant like a virtual power plant for effective coordination with high capacity power plants. Load predictions will help is designing a proper energy management system, which is crucial for sustainable development.

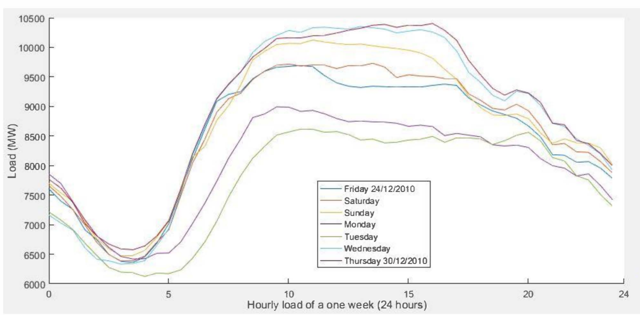

Figure 1. Pattern of electricity load in Sydney region.

It is observed that the power consumption on a given day follows a particular pattern which may be repeated every week. A snapshot of the pattern for the weekly load is depicted in Fig. 1. The diagram illustrates the weekly demand of power (in MW) plotted on an hourly basis for 24 hours in a day during last week of December 2010. The diagram explicitly specifies the spread of load with the timing of peak load and off- peak load.

There is also a close correlation between the weather forecast and load demand in a region. The demand for electricity increases when the temperature falls below 10^0 C due to heating requirements in a household. Similarly, when the temperature increases beyond 23^0 C the electricity demand also increases due to cooling requirements.

The following three steps are used to generate the load forecast model [9]:

(i) Create a matrix of predictor based on historical weather data and electrical loads (chronological data of hourly load and meteorological parameters),

(ii) Design and calibrate a non-linear model using ANN and bagged regression trees, and

(iii) Generate day ahead load forecast on the basis weather data and day of the week (holiday or weekday).

All the three steps is illustrated in Fig. 2 [10]. The historical data used for training and calibration of the prediction model are temperature, humidity, hour of day, day of the week, holiday/weekend or week day indicator, previous 24-hr average load, previous 24-hr lagged load and previous 168-hr (i.e. previous week) lagged load. Apart from weather data, the date information (month, day of week and work day / holiday) is also essential for prediction.

A. *ANN Based Model*

Many load forecasting procedures are given in [11, 12], where ANN is suggested as one of the suitable methods for load forecasting. ANN are good candidate for solving non-linear problems, that is why it is more appropriate for load forecasting [13]. The disadvantage with modeling ANN is that it requires sufficient historical data for accurately developing the model. The implementation of ANN is a little bit complex [14, 15]. However, ANN is better than any other load forecasting method due to its self-learning capabilities.

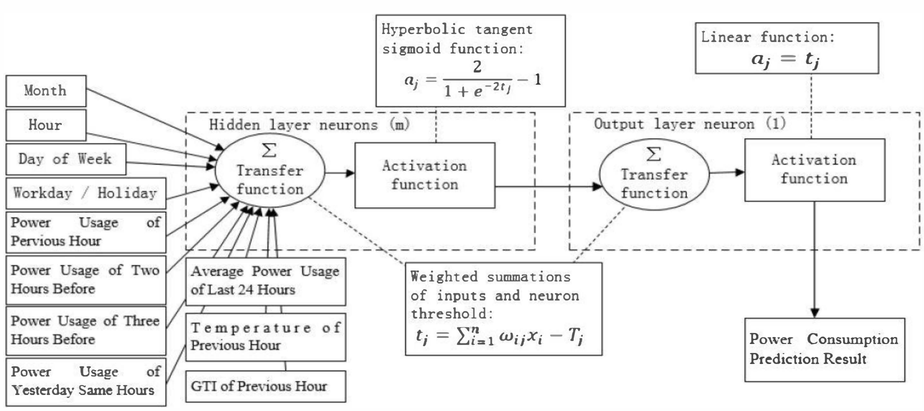

Figure 2. Model for load forecast using ANN [10].

Two-layer feed-forward neural network model with back-propagation is build to trained, validated and test the final result. The two layers are called hidden layer and output layer. Neurons in the hidden layer receive the input data and then each neuron sends its processed output to the outer layer (output) neuron based on activation function.

There is only one neuron in the output layer. The outer layer neuron synthesis the outcome of the hidden layer and provide the load forecast. The transfer function is a Levenburg-Marquardt fitness function that use weighted sum of input and the bias [16].

The load prediction of next hour (next step) is obtained using Eq. (1), where v_j (j=1, 2, m) and T_{out} expresses the weight and bias value of the output layer neuron respectively.

$$\text{Output} = \sum_{j=1}^{m} \frac{2v_j}{1+e^{-2(\sum_{i=1}^{n}\omega_{ij}x_i)-T_j}} - T_{out}. \quad (1)$$

The weights and bias of each neuron are adjusted through recursive training of input data with an objective to obtain lower prediction error. The model initializes with two layers having 20 neurons in hidden layer. Levenburg-Marquardt fitness function makes the training period shorter [11]. The entire dataset is divided into three sets, a training set of 70%, validation set of 15% and test set of remaining 15%.

B. *Bagged Regression Trees Model*

Another prediction method called bagging or bagged regression tree is a statistical classification and regression technique designed to improve the stability and accuracy of machine learning algorithms [17]. It is a machine learning ensemble technique used to improve the predictive performance of a base procedure such as decision trees or methods that do variable selection and fitting in a linear model. It constructs a linear combination of model fitting by generating and combining multiple predictors instead of using a single fit of the method.

Another bagged regression trees are used to generate the output function. The regression tree is used to build the model, that are set of regression trees each with a different set of rules for performing the non-linear regression. The process starts with building an aggregate of 20 such trees, with a minimum leaf size of 40. The larger the leaf sizes the smaller the tree. This provides a control for overfitting and performance. The model also determines the relative feature (input) of importance which provides the most predictive power for the predictors. Fig 3 gives the relative importance of the features. After analysing the given parameters, final model is built with an aggregate of 20 trees and leaf size of 20 with all the features.

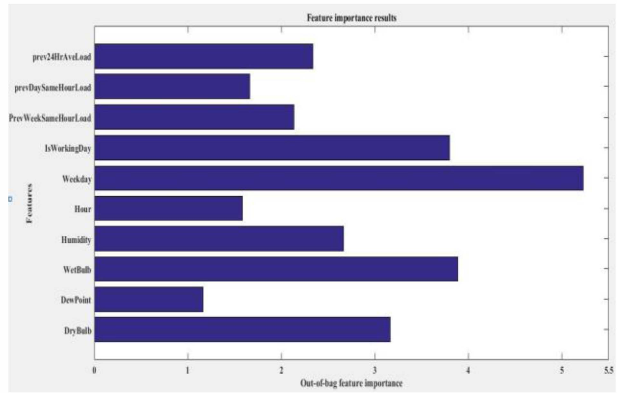

Figure 3. Bagged regression tree relative importance of features.

III. Result and Discussion

The model once calibrated can be used to forecast load of any given day by providing input of weather forecast and day of week (holiday or weekday) information. The model after processing gives day ahead (24- hours) load prediction. Comparison of the actual load with forecasted load is plotted with forecast error. The plot using ANN for actual and predicted load for one year duration is given in Fig. 4. The prediction error is given in lower part of the plot. Similarly, the plot using Bagged Regression Trees is given in Fig. 5. A brief weekly snapshot of the actual and predicted load is also given in Fig. 6 and 7 for ANN and Bagged Regression Trees respectively with prediction error in lower part of the plot.

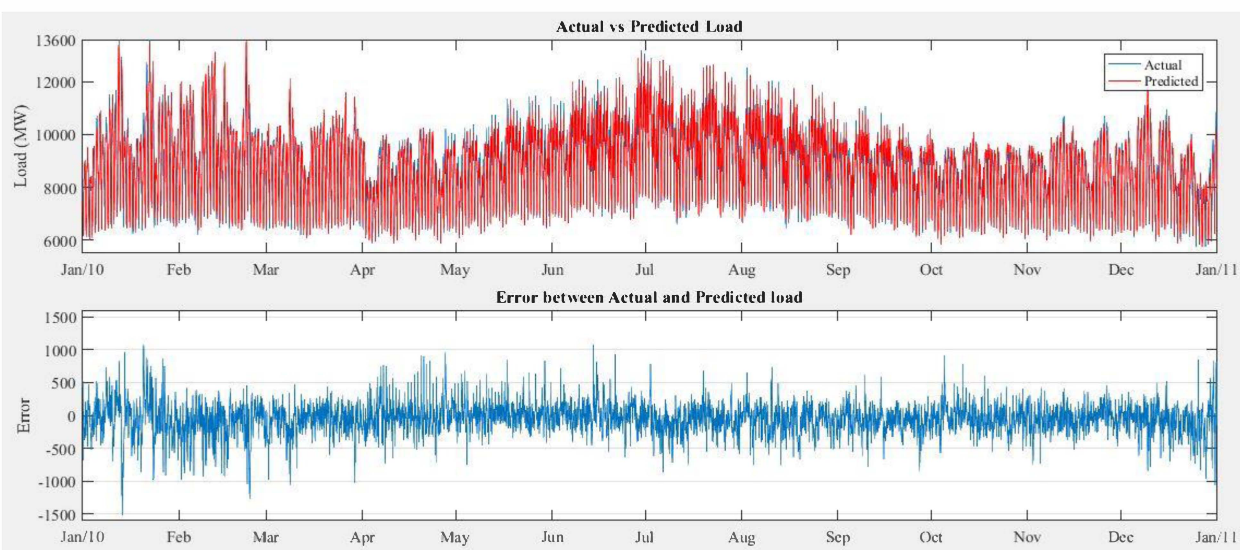

Figure 4. ANN model predicting (i) Actual and Predicted Load (ii) Prediction Error.

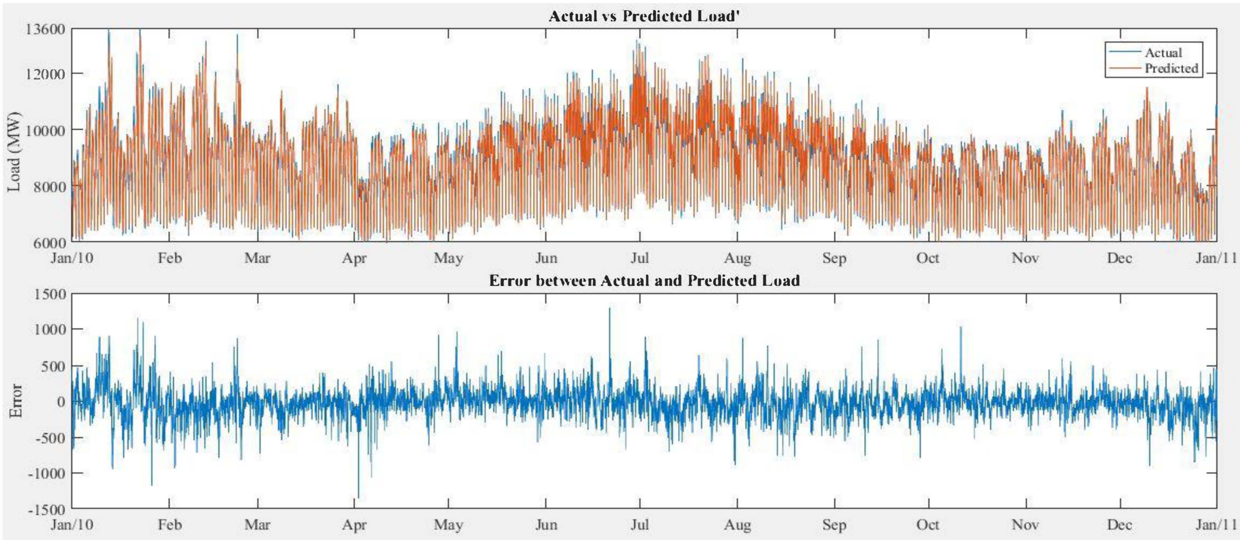

Figure 5. Bagged Regression Tree model predicting (i) Actual and Predicted Load (ii) Prediction Error.

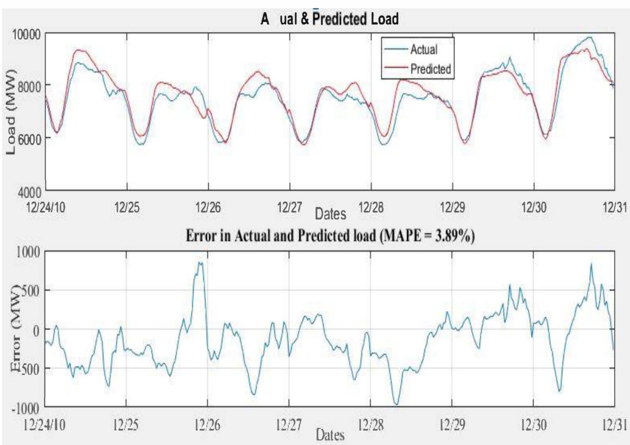

Figure 6. Weekly load using ANN.

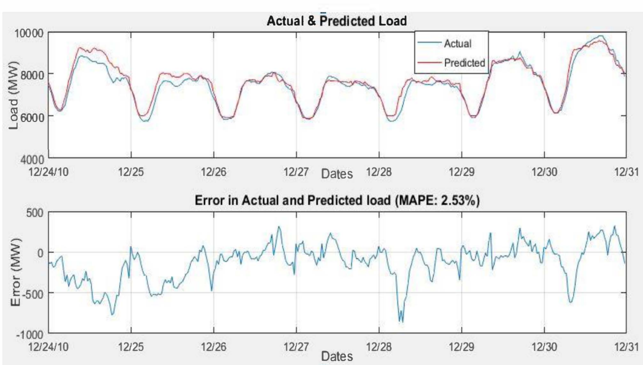

Figure 7. Weekly load using Bagged Regression Tree.

The three performance parameters are used to check the accuracy of prediction. The performance parameters are mean average error (MAE), mean average percent error (MAPE) and Daily Peak MAPE. Mean Absolutely Percentage Error (MAPE) measures the accuracy of prediction by comparing percentage error in actual and predicted values. The result of errors is compiled in Table 1.

The comparison of the prediction error is also shown in Fig 8 and 9 for ANN and Bagged Regression Trees respectively. Based on our evaluation it can be deduce that Bagged Regression Trees provide better prediction compared to ANN. However, the Bagged Regression Trees took long time to converge compared to ANN may be due to statistical nature of algorithm.

The load forecasts have many advantages in power grid. The prediction can help in reducing the periodicity of communication of IEDs with control center if it is installed at the customer premises and substation. The reduction in periodicity of communication with control center can help in reducing the congestion in the network, which is going to become big challenge with Big Data. The deviation in power consumption pattern at customer premises can provide an alert to the utilities to take corrective actions.

TABLE I. PREDICTION ERROR

Models	MAPE	MAE	Daily Peak MAPE E
ANN	1.90%	167.91 MW	2.08%
Regression Trees	1.54%	136.39 MW	1.67%

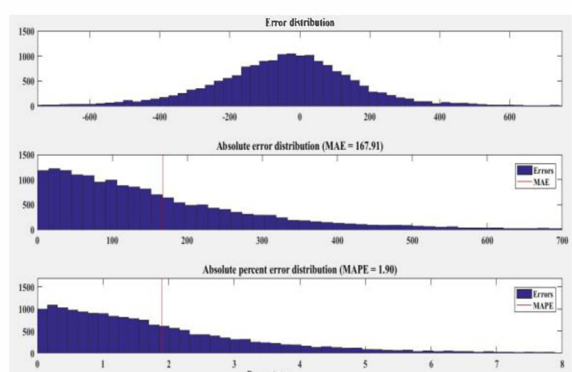

Figure 8. Error plot of ANN.

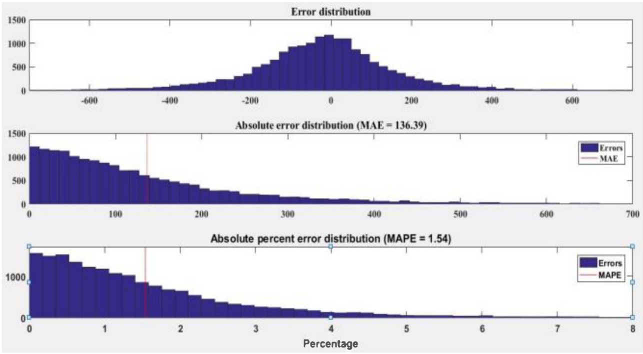

Figure 9. Error plot of Bagged Regression Tree.

IV. Conclusion

The development of Smart Grid with the use of information and communication technology facilitate growth in the power industry. The energy infrastructure is increasing daily with the addition of new appliance in the network. Energy Management System (EMS) at the customer premises can help in better management and control of energy. Energy forecasting is one of the potential areas of interest in demand management at the consumer side. This paper explores the use of ANN and Bagged Regression Trees to forecast the energy demand in the urban area using meteorological data. The accuracy of prediction depends on reliable historical, and meteorological data. The ANN model is compared with and Bagged Regression Trees and found latter to provide better prediction accuracy for day-ahead load in the urban area.

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