Load Prediction Using Artificial Neural Network

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Abstract— **The purpose of this project is to study and develop an artificial neural network (ANN) model specifically for short term load prediction. A nonlinear load model is proposed and several structures of ANN for short term load prediction are tested. The outputs obtained were the predicted full day load demand for the next day or week. The ANN model has 4 layers; an input layer, two hidden layers and an output layer. The number of inputs was 6; while the number of hidden layer neurons was varied for different performance of the network. The output layer has 24 neurons. The ANN model was trained for over 5 weeks. A mean absolute percentage errors of 2.52% was achieved when the trained network was tested on random for one week's data.**

Keywords-component; artificial neural network; short term load prediction;

I. INTRODUCTION

Precise models for electrical power load prediction are important to the operation and planning of a utility company. Load prediction helps to make important decisions including decisions on purchasing and generation electric power, load switching and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. Furthermore, the power load is influenced by the weather of the forecasting day [1–3].

Load forecasting in a power system can normally be categorized into the following categories [4], for very short forecasting of up to a few minutes ahead, forecasting with a lead time of up to a few days ahead, forecasting energy requirements over a six month or one year period and long term forecasting of the power system peak load up to 10 years ahead.

In short term load forecasting, the key variables are time, forecasted weather variables, and historical load [5]. Statistical and artificial intelligence method have been widely developed to forecast the load. However the accuracy of the models can be improved. Thus, the objective of this study is to find and improve the algorithm that artificial neural network (ANN) is very effective and reliable in predicting the short-term load prediction. This paper presents load prediction using ANN. The study involved the development of ANN model for prediction purposes.

II. ANN MODEL DEVELOPMENT

In this section description on proposed model, algorithm, data generation and preparation are presented.

A. Proposed ANN Model

The proposed model for the ANN model is shown in Figure 1.

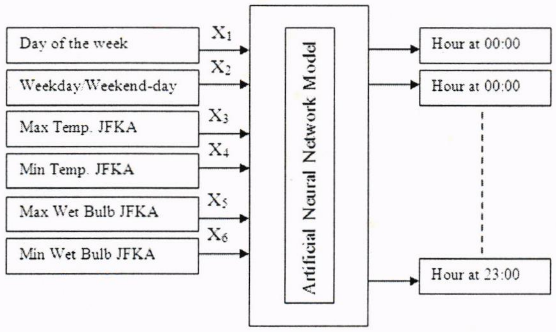

Figure 1. Input-Output Schematic for ANN Model.

B. Algorithm for ANN Implementation

For this project, the overall algorithm can be summarized in the flowchart as shown in Figure 2.

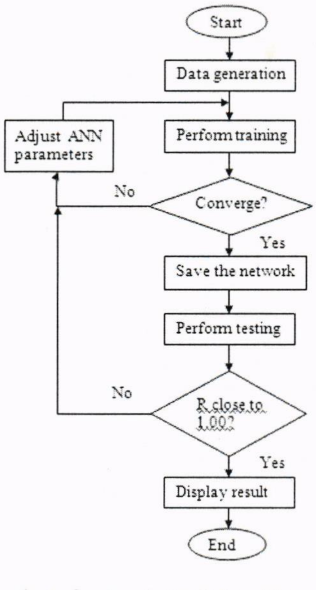

Figure 2. Flowchart for Load Prediction Using Artificial Neural Network.

C. Data Generation

To demonstrate the effectiveness of the proposed approach, historical load demand data which publicly available from the New York Independent System Operator (NYISO) web site have been taken to predict the hourly load for the New York City power system. The historical load data from 1st January 2012 to 31st March 2012 obtained from the NYSIO website were used in this project. Data obtained from NYISO were the hourly load for the full day (24 hours) for New York City and the forecasted weather temperature located at John F. Kennedy International Airport (JFKA) [1].

D. Data preparation

Data preparation is developed by extracting the data from historical load data and temperature available from NYISO.

1) Input and output variables: In this project, the inputs variables to the ANN model are:

- Day of the week indicator.
- Weekday and weekend-day indicator.
- Maximum temperature for JFKA
- Minimum temperature for JFKA.
- Maximum wet bulb temperature for JFKA.
- Minimum wet bulb temperature for JFKA.

The targeted output variable was the predicted hourly load demand for the next day. A set of data comprises of 91 days of hourly load for the full day (24 hours) for New York City and the forecasted weather temperature located at John F. Kennedy International Airport (JFKA) was tabulated in Microsoft Excel for easy viewing. This data will be used for creating data set for training and testing the ANN model.

2) Training data: For the purpose of training the ANN model, 38 days data were selected randomly to build a set of training data. The process of data selection was based on the day of the week. If Monday and Tuesday were selected in the current week, then the next week cannot contain the same day, thus Wednesday and Thursday were selected as the next choice. This data for 38 continues days were selected for the training set.

For input variables, day of the week was presented by the number of 1, 2, 3, 4, 5, 6 and 7 to represent Sunday, Monday, Tuesday, Wednesday, Thursday, Friday and Saturday respectively. Weekday and weekend-day was represented by number of 1 and 0 respectively. Saturday and Sunday was treated as weekend-day. The original data value was used for inputs variable for maximum temperature for John F. Kennedy International Airport (JFKA), minimum temperature for JFKA, maximum wet bulb temperature for JFKA and minimum wet bulb temperature for JFKA. Finally, a 6-by-38 matrix was set as the input variables for the ANN model.

As for the target for training the ANN model, each respective hour's data for the 38 days was set as the target. This set up a matrix of 24-by-38 targeted output variables.

3) Testing data: For the purpose of testing the ANN model, a set of data for 7 days were selected randomly to build a set of testing data. The process of data selection was also based on the description on data selection on the training data. Thus, a 6-by-7 matrix was set.

As for the target for testing the ANN model, respective each hour's data for the 7 days was set as the target. This set up a matrix of 24-by-7 targeted output variables. However, it was not mandatory to set 7 days as the target for testing. The main purpose to set up the target was to compare the actual data and the forecasted data generated from the ANN model.

E. ANN Training Algorithm

A feed-forward back propagation network with two hidden layers was used. The number of neurons in the hidden layers was varied between 5 and 23 before finally being set at 10 and 20 neurons. The activation function used in the first hidden layer neuron was "log-sigmoid" and followed by the second hidden layer which was another "log-sigmoid". The number of output neurons was 24 using "purelin" activation functions. The ANN was implemented using MATLAB. The training algorithm "trainlm" has been used. The number of epochs while training was set at 5000 by which this point the network was sufficiently trained. ". Table I tabulates the properties of the ANN model.

TABLE I: ANN MODEL STRUCTURE

Parameters	Selected
Network	Feed-forward Back Propagation
No. of Input Variables	6
No. of Hidden Layers	2
No. of Hidden Neurons	10, 20
No. of Output Variables	24
Transfer Function	Hidden Layer : Log-sigmoid, Log-sigmoid Output Layer : Purelin
Learning Algorithm	Levenberg-Marquardt back propagation

The training data were pre-processed using "processpca" function which process columns of matrix with principal component analysis and using "mapstd" function, so that they have zero mean and unity variance.

The input variables were post-processed using "reverse" in "mapstd" function which convert these outputs back into the same units by using settings structures "ps1", "ts1" and "ps2".

F. ANN Testing Algorithm

Since "processpca" and "mapstd" have been used to pre-process the training input variables, the testing input variables must be pre-processed with the means and standard deviations that were computed for the training set using "ps1" and with the transformation matrix that was computed for the training set, using "ps2".

In describing the performance of the ANN model, the mean absolute percentage errors (MAPE), were calculated from 24 forecasts over the day is used. MAPE is given as;

$$MAPE = \frac{1}{n}\sum_{i=1}^{n=24} \frac{|(\hat{x}_i - x_i)|}{x_i} \times 100\% \quad (1)$$

Where x_i is the hourly data and $\hat{x}_i$ is the predicted value.

III. RESULTS

The developed ANN model has been validated using real historical load data from NYISO. The results are presented in the following section.

A. ANN Model Training Result

As shown in the Figure 3 below, the developed ANN model manage to produce correlation coefficient, R of 0.99988 which mean the ANN model was successfully trained.

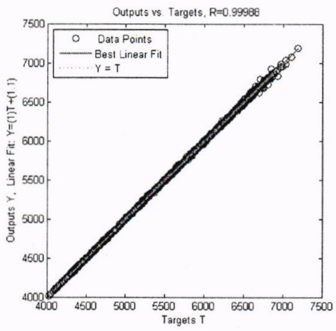

Figure 3. Correlation Result from Training the ANN Model

B. ANN Model Testing Result

A set of data for 7 days were selected randomly to build a set of testing data. As for the target for testing the ANN model, respective each hour's data for the 7 days were set as the target. As shown in the Figure 4 below, the developed ANN model manage to produce correlation coefficient, R of 0.97239 which mean the ANN model was successfully learnt.

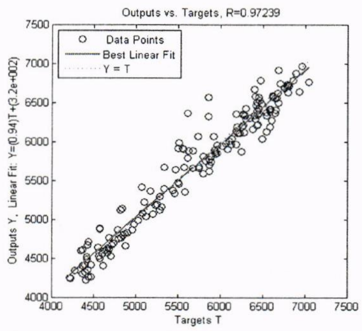

Figure 4. Correlation Result from Testing the ANN Model

The response matching between the actual load demand on 15th January 2012 which was fall on Sunday and the predicted load demand is shown in Figure 5. The MAPE for that day was 1.4268%.

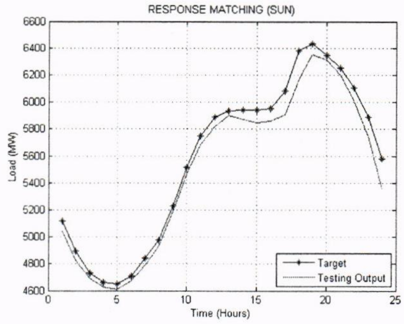

Figure 5. Response Matching for Sunday

The response matching between the actual load demand on 23rd January 2012 which was fall on Monday and the predicted load demand is shown in Figure 6. The MAPE for that day was 1.3846%.

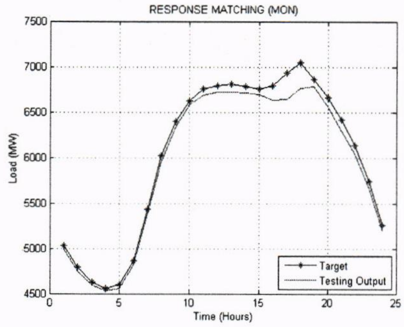

Figure 6. Response Matching for Monday

The response matching between the actual load demand on 31st January 2012 which was fall on Tuesday and the predicted load demand is shown in Figure 7. The MAPE for that day was 2.567%.

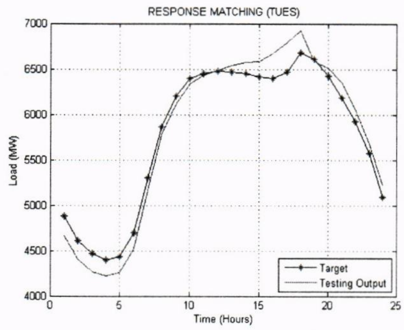

Figure 7. Response Matching for Tuesday

The response matching between the actual load demand on 8th February 2012 which was fall on Wednesday and the predicted load demand is shown in Figure 8. The MAPE for that day was 2.5743%.

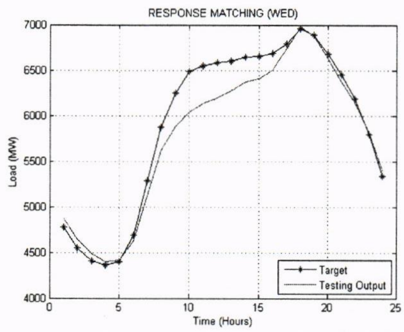

Figure 8. Response Matching for Wednesday

Response matching between the actual load demand on 23rd February 2012 which was fall on Thursday and the predicted load demand is shown in Figure 9. The MAPE for that day was 1.4853%.

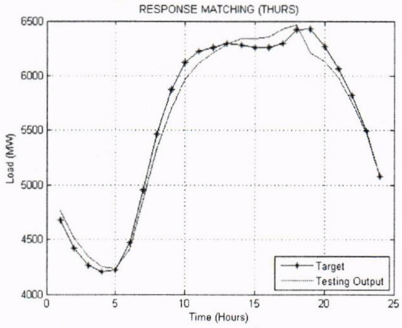

Figure 9. Response Matching for Thursday

The response matching between the actual load demand on 2nd January 2012 which is fall on Friday and the predicted load demand is shown in Figure 10. The MAPE for that day was 1.7287%.

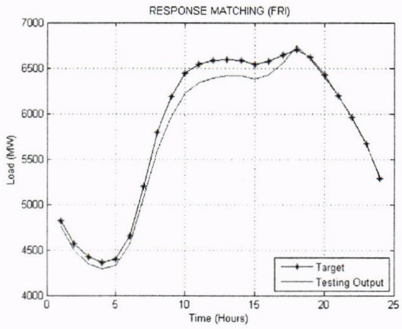

Figure 10. Response Matching for Friday

Lastly, the response matching between the actual load demand on 10th February 2012 which was fall on Saturday and the predicted load demand is shown in Figure 11. The MAPE for that day was 6.4474%.

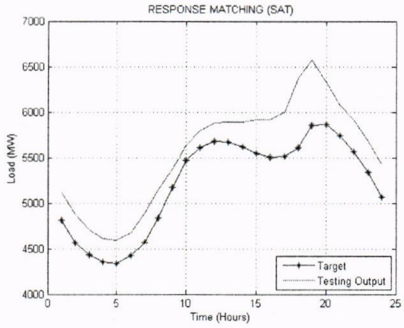

Figure 11. Response Matching for Saturday

TABLE II: MAPE RESULTS FOR THE CHOSEN DAY

Day	MAPE
Sunday	1.4268%
Monday	1.3846%
Tuesday	2.567%
Wednesday	2.5743%
Thursday	1.4853%
Friday	1.7287%
Saturday	6.4474%
AVERAGE	2.5163%

Table II tabulates the MAPE results for the chosen day. It was shown that the ANN model is able to predict the load demand with an average MAPE of 2.5163%.

IV. CONCLUSION

It was expected that from this project, the load prediction using artificial neural network (ANN) have improve and enhance the algorithm that ANN was very effective and reliable in predicting the short-term load prediction. ANN provides a system with safety environment and is an economical method of addressing load prediction.

Consideration in developing a good load prediction require vast amount of data such as temperature, relative humidity and historical loads that can only be achieved by cooperation between government, power supply authority and manufacturers.

From the results, it is observed that the predicted load by ANN model is very much similar to the actual load. The performance evaluation parameter, MAPE was used for testing this proposed prediction model. The proposed ANN model can be used to predict the load accurately.

V. RECOMMENDATIONS FOR FUTURE WORK

The simulation to obtain the short term load prediction in this study has lead toward several future works which are:

- To investigate and compare other factors and variables that affecting the load prediction accuracy, specifically short term load prediction.
- To develop an artificial neural network model using other training algorithm method that could predict load based on historical data.

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