# Short-term and Medium-term Gas Demand Load Forecasting by Neural Networks

**Azari, Ahmad; Shariaty-Niassar, Mojtaba***[+]

*School of Chemical Engineering, College of Engineering, University of Tehran, Tehran, I.R. IRAN*

**Alborzi, Mahmoud**

*Petroleum University of Technology, Ahwaz,, I.R. IRAN*

**ABSTRACT:** The ability of Artificial Neural Network (ANN) for estimating the natural gas demand load for the next day and month of the populated cities has shown to be a real concern. As the most applicable network, the ANN with multi-layer back propagation perceptrons is used to approximate functions. Throughout the current work, the daily effective temperature is determined, and then the weather data with the gas consumption data of the last days are used for network training. It is shown that nearly 93% and 98.9% of the result is in a good agreement with the real data for the daily gas load forecasting and those of the monthly respectively. These results clearly show the capability of the presented networks. The method, however, can further be developed for prediction of other required information in various industries.

**KEY WORDS:** *Gas demand, Gas consumption, Forecasting, Artificial Neural Network (ANN), Back propagation.*

## INTRODUCTION

It is quite obvious that the gas load forecasting can play an important role in the planning and operation of power systems. Since gas resources are usually located in the remote area from end-users, the time taken for gas transport to distributed zones and populated cities can sometimes exceed 48 hours. However, any possible variations in the weather parameters such as sudden temperature changes, etc. can affect the gas consumption rate, which is required to be known. Gas demand load forecasting is not easy because the change in the weather parameters and gas load is not linear, so it is hard to use the statistical methods for such a purpose. Analytical techniques could not deal with the kind of information that the experts had to deal with, which were often incomplete and fuzzy[1]. Because of this, Artificial Neural Network (ANN) is used to easily relate the weather parameters with gas load. In spite of being simple, ANN is considered as an important method that is capable of correlating various parameters.

Load forecasting in a power system can normally be divided into the following four categories [2]:

- very short, up to a few minutes ahead.
- with a lead time, up to a few days ahead.
- energy requirements over a six-month or one-year period.
- long term forecasting of the peak loads up to 10 years ahead.

* To whom correspondence should be addressed.
+ E-mail: mshariat@ut.ac.ir
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Of the above-mentioned types, this paper will only deal with the short and medium-term load forecasting, which were usually performed using statistical time series and regression methods [3, 4]. Of these methods, ARMA and ARIMA (Auto Regressive (Integrated) Moving Average) models have recently been very popular [4, 5].

During the last 10 years, the researchers showed a significant change of the interest in load forecasting from traditional to artificial intelligence based methods. Thus, scientists have proved that an Artificial Neural Network (ANN) produces much better results compared to an ARIMA model [6]. These findings demonstrated that the statistical models could, in fact, be viewed as special cases of ANNs and hence are more powerful and flexible tools to forecast gas load behavior.

There is rich literature providing references about short-term load forecasting with ANN [7-11]. Of many structures of ANNs, two structures are commonly used: the MultiLayer Perceptron (MLP) and the Kohonen network. *Bakirtzis et al.* [7] used a MLP ANN model for the electric power prediction using weather parameters and concluded that the prediction model has better accuracy than the statistical models. *Khotanzad, et al.* [9] also used the ANN model to predict the short term electric load. The availability of historical load data on the utility databases makes this area highly suitable for ANN implementation. ANNs are able to learn the relationship between the past, present, and the future weather variables and loads, combining both time series and regressional approaches. As is the case with time series approach, the ANN traces previous load patterns and predicts (i.e., extrapolates) a load pattern using recent load data. It can also use weather information for modeling. The ANN is able to perform non-linear modeling and adaptation. It does not need assumption of any functional relationships between load and weather variables in advance. We can adapt the ANN by exposing it to new data. Their ability to outperform traditional methods, especially during rapidly changing weather conditions and the short time required to their development, has made ANN based load forecasting models very attractive alternative for on-line implementation in energy control centers [2].

In this research, two models have been presented for daily and monthly gas consumption forecast of Tehran, which are done using MLP with Back-Propagation Algorithm training.

## THEORITICALL SECTION

### *Artificial neural network input variables*

The most important work in building an ANN load forecasting model is the selection of input variables. Determination of appropriate selection of input variables is the most important factor in extracting suitable relation for forecasting [12]. There is no general rule that can be followed in this process. It depends on engineering judgement and experience and is carried out almost entirely by a process of trial and error. However, some statistical analyses can be very helpful in determining which variables have significant influence on the system load. In this work, two types of variables are used as inputs to the neural network: weather-related inputs and historical loads.

The main advantage of using ANNs to forecast gas load lies in their ability to learn the relationship between the weather parameters and the demand load. The ANN input is the first layer in the network through which the information is supplied. The number of neurons in the input layer depends on the network input parameters. Hidden layers connect the input and output layers. Hidden layers strengthen the network for globalizing many various data. In theory, ANN with only one hidden layer and enough neurons in the hidden layer has the capability of approximation of any continuous functions [13]. Transfer function is the mathematic function that determines the relation between neuron output and the network. In other words, transfer function indicates the degree of nonlinearity in the network. Practically, we use some limited functions as transfer functions [13]. Normally, the transfer functions of all neurons in the hidden layers are similar. Also, for all neurons in the output layer, the same transfer function is used. To forecast, the most conventional transfer function for neurons, in the hidden layers, is the logistic transfer function [14-16].

$$O_{Pj} = f(\text{net}) = \text{Sig}(\text{net}) = \frac{1}{1+e^{-\text{net}}} \quad (1)$$

One of the main reasons for using sigmoid transfer function is its simple differential for this function that it is simple for using in BP algorithm. To complete this section we illustrate the learning algorithm.

### *Algorithm*

The Back-Propagation Algorithm is one of Least Mean Square methods, which is normally used in engineering.

In a multilayer perceptron, each neuron of a layer is linked to all neurons of the previous layer. Fig. 1 shows a perceptron with a hidden layer. Each layer output acts as the input to the next neurons. In order to train Multilayer Feed Forward Neural Network, Back-Propagation Law is used. In the first stage, all weights and biases are selected according to small random numbers. In the second stage, input vector $X_p= x_o, x_1,\ldots, x_{n-1}$ and the target exit $T_p= t_o, t_1,\ldots, t_{m-1}$ are given to the network, where the subscripts n and m are the numbers of input and output vector respectively. In the third stage, the following quantitative values are calculated and transferred to the subsequent layer until it eventually reaches the exit layer [17].

$$y_{Pj} = f\left[\sum_{i=0}^{n-1} w_i x_i\right] \tag{2}$$

The forth stage begins from the exit layer, during which the weight coefficients are corrected.

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_{Pj}O_{Pj} \tag{3}$$

Where $w_{ij}(t)$ stands for the weight coefficients from node i to node j in time t, $\eta$ is the rate coefficient and $\delta_{Pj}$ refers to the corresponding error of input pattern P to the node j. $\delta_{Pj}$ is calculated from below equations for exit layer and hidden layer respectively:

$$\delta_{Pj} = O_{Pj}(1-O_{Pj})(t_{Pj}-O_{Pj}) \tag{4}$$

$$\delta_{Pj} = O_{Pj}(1-O_{Pj})\sum_k \delta_{Pk} w_{jk} \tag{5}$$

Here, the $\sum$ acts for k nodes on the subsequent layer after the node j [17].

*Data Normalization*

The importance of data pre-processing in network training, for preparing the algorithm necessities and preventing the calculation complexity, is of a great concern [18]. Therefore, in order to predict gas consumption, the MinMax pre-processing function is used and the network inputs and outputs are normalized within the range of 0-1, as below [19]:

$$P_n = \frac{P - P_{min}}{P_{max} - P_{min}} \tag{6}$$

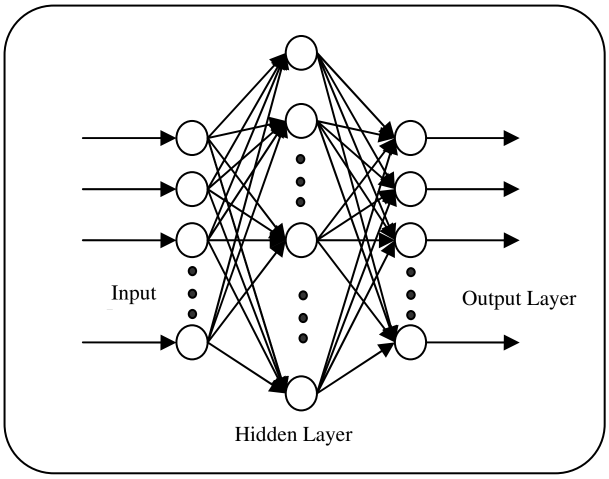


***Fig. 1: Perceptron structure with a hidden layer.***

Where $P_{min}$ , $P_{max}$ , P and $P_n$ are the minimum, maximum, real and normalized values for meteorology as well as gas consumption parameters. After network training and using the following equation, simulation data are transferred to the real values:

$$P = P_n(P_{max} - P_{min}) + P_{min} \tag{7}$$

After network training process, the mean percent of relative error of the simulation data is calculated from [20-22]:

$$MRE(\%) = \frac{1}{N}\sum_{i=1}^{N}\frac{|Forecast_i - Actual_i|}{Actual_i}\times 100 \tag{8}$$

And the corresponding mean square values are determined for the equation below:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Actual_i - Forecast_i)^2 \tag{9}$$

***Data collection***

As the ANN depends on the corresponding data, the preparation of the data is an important step in using Neural Network. In this research, however, the daily gas consumption data as well as the meteorological data from 21 March, 2001 to 8 August, 2005, overall 1611 pieces of data, is used to train the network and test the accuracy of the performance of the network. Such data are taken from the recording office of the Tehran Weather Office and National Iranian Gas Company (NIGC) respectively. After training the network for 90% of the data, the rest, considered as validation set data, are used for checking the accuracy of the network performance.

## RESULTS AND DISCUSSION

### *Daily Prediction Model*

Almost all short-term forecasting techniques use as independent variables certain weather condition information such as temperature, humidity or wind speed. After many processes of trial and error for daily gas consumption prediction, since some variables like day type (i.e. working day and holiday), wet bulb temperature and gas price haven't any effect on the network performance thus they are deleted from the model input for the simplicity of the network and 29 desired network inputs are considered. At the input, meteorological parameters (i.e. daily effective temperature, cloudiness, rain rate and wind velocity) and also the gas consumption for the previous five days are fixed. The meteorological parameters for the prediction day are also considered as the network input. However, at the output, the gas consumption rate for the prediction date is estimated [23,24].

The daily gas consumption rate depends on the meteorological background and the gas consumption of the previous five days. Since meteorological parameters for the sequential six days in this model are used, therefore the kind of day, month and season is omitted from the network input. As the gas consumption value, compared to the other input network parameters, is fairly large, a ratio of daily consumption to the previous day consumption is defined. With this, the network prediction error is considerably decreased. After the required calculation and applying different temperatures on the network and determining the output error, the daily effective temperature, which has a higher linear relationship with gas consumption, is calculated from the following relation [25]:

$$T_{eff_i} = 0.8\times T_{eff_{i-1}} + 0.05\times T_{min_i} + 0.15\times T_{max_i} \quad (10)$$

where $T_{maxi}$ , $T_{mini}$ , $T_{effi}$ and $T_{eff\ i-1}$ are the maximum, minimum, the effective temperature of the prediction day and the effective temperature of the previous day respectively.

Fig. 2 shows the gas load consumption versus the daily average temperature for all available data and Fig. 3 shows the gas load consumption versus the daily effective temperature according to Eq. (10). It is obvious from such figures that variation of the gas load consumption versus effective temperature is more linear than the average temperature and it causes the network to learn the corresponding relation easily [24]. The network output indicates the gas load consumption for the prediction day. After many processes of trial and error in each layer, the perceptron with two hidden layers, each of which has fifteen nodes, was achieved for the daily gas load consumption. Thus, in order to predict the daily gas load consumption, we use the network with the topology of {29-15-15-1} with sigmoid transfer function in two hidden layers and a linear transfer function at the output layer.

ANN model for daily gas demand load was consistent after 850 training cycles with a MSE error of about 0.0047. The minimum, maximum and average amount of the network weights are 0.0015, 1.7532 and 0.8976, respectively. After the network training with 90% of data, the validation data covering the remaining data are given to the network to confirm the performance accuracy. In Fig. 4 where the predicted load versus the actual consumption load is indicated, it is clear that the consistency Pearson coefficient of about 0.9877 for validation data was achieved. Also, the gas consumption prediction for the whole data (training and validation), together with the actual gas consumption value, is displayed in Fig. 5.

In Fig. 6 the validation data are demonstrated together with the real value of the gas consumption. MRE for the validation set of data varies within the range of 2-58% and an average MRE of about 7% is achieved. It is obvious that we can use this model to predict the gas consumption of some sequential days. This is subject to the availability of previous day's gas consumption rates as the network input. Therefore, with an increase in estimation days in a fixed time, the model accuracy is decreased. Model accuracy for the first prediction day is about 93%. Some of the prediction data and their relative errors are shown in Table (1).

### *Monthly Prediction Model*

After many processes of trial and error in each layer, a perceptron with one hidden layer, which has seven nodes, was achieved for the monthly gas load consumption. Thus, in order to predict the monthly gas load consumption, we use the network with the topology of {3-7-1} with sigmoid transfer function in the hidden layer and a linear transfer function at the output layer. The input vector contains the monthly effective temperature for the previous and prediction months and the gas consumption for the previous month. And the network output is the monthly gas consumption prediction. Monthly effective temperature according to the Eq. (11) is calculated.

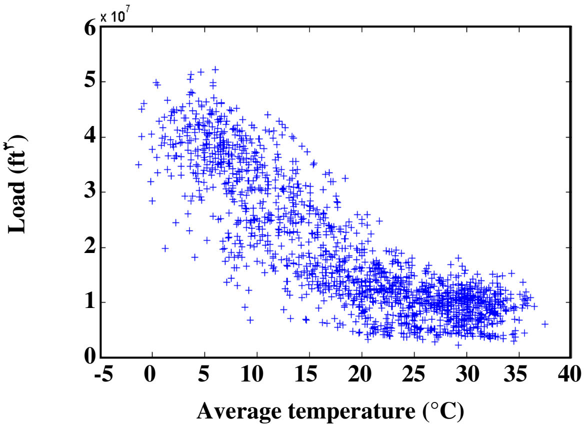


***Fig. 2: Gas load consumption vs. the average daily temperature.***

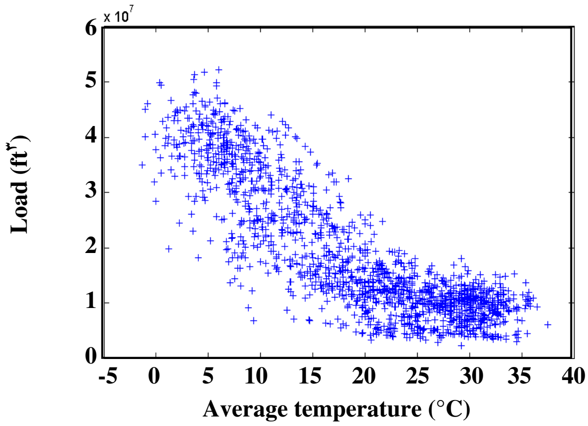


***Fig. 4: Predicted load vs. actual load for validation set data (daily model).***

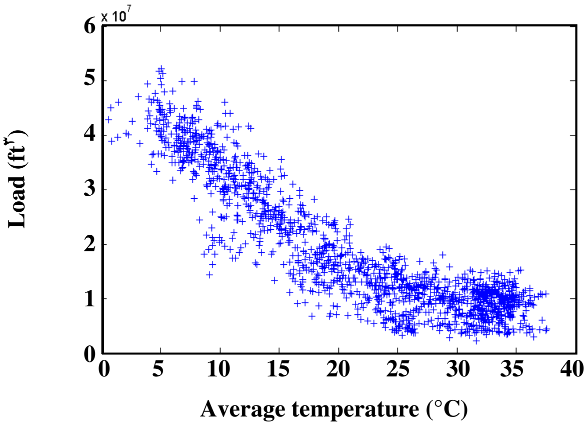


***Fig. 3: Gas load consumption vs. effective daily temperature.***

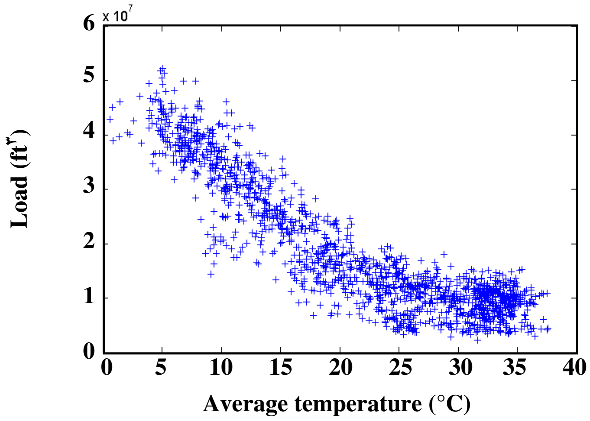


***Fig. 5: Predicted and actual load for all present data (daily model).***

$$\text{Monthly } T_{eff} = \frac{1}{30}\sum_{i=1}^{30} T_{eff_i} \qquad (11)$$

Where $T_{eff_i}$ is the daily effective temperature for $i^{th}$ day of the month according to Eq. (10). It is obvious that network inputs should be normalized before network simulation and the network output should be un-normalized after network simulation to achieve the prediction of the monthly gas consumption.

ANN model for monthly gas demand load was consistent after 275 training cycles with a MSE error of about 0.02. The minimum, maximum and average amount of the network weights are 0.2052, 1.9532 and 0.9211, respectively After the network training with 50% of data, the validation data covering the remaining data are given to the network to confirm the performance accuracy. In Fig. 7 where the predicted load versus the actual consumption load is indicated, it is clear that the consistency Pearson coefficient of about 0.9998 for validation data was achieved. In addition, the gas consumption prediction for the whole data (training and validation), together with the actual gas consumption value, is indicated in Fig. 8.

In Fig. 9 the validation data are demonstrated together with the real value of the gas consumption. MRE for the validation set of data varies within the range of 0.45-4.5% and an average MRE of about 1.06% is achieved. Model accuracy for the prediction month is about 98.9%. Some of the prediction data and their relative errors are shown in Table (2).

## CONCLUSIONS

Due to the importance of the Gas as a source of energy and the fuel in the domestic and industrial consumption, any possible disruptions in distribution,

***Table 1: Some prediction and their relative errors for the validation data (daily model).***

| Actual Load (MMCFD) | Predicted Load (MMCFD) | Relative Error (%) |
|---|---|---|
| 19.58 | 20.91 | 6.8 |
| 24.76 | 24.10 | 2.7 |
| 36.92 | 35.11 | 4.9 |
| 32.01 | 33.25 | 3.9 |
| 36.48 | 38.98 | 6.8 |
| 34.02 | 34.38 | 1.5 |
| 27.44 | 28.95 | 5.5 |

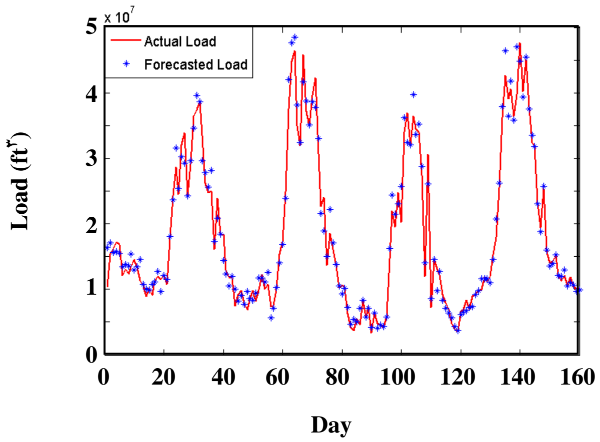


***Fig. 6: Predicted and actual load for the validation set data (daily model).***

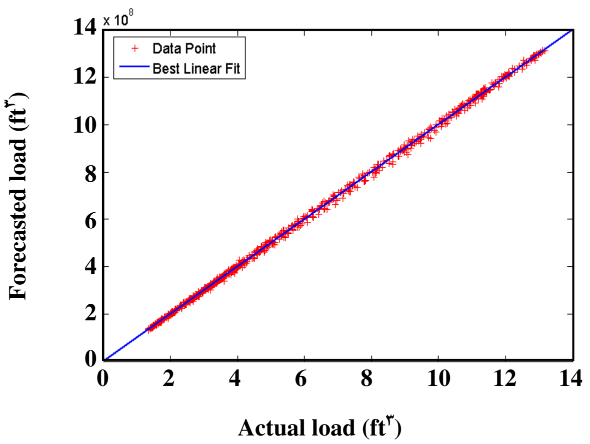


***Fig. 7: Predicted load vs. actual load for validation set data (monthly model).***

especially at peak periods can have a severe effect on people's daily lives. Continuation of such circumstances can violate the current community affairs.

Multilayer perceptron with enough nodes in each hidden layer are able to predict each complex relation between a lot of parameters. Finally, in order to predict the daily gas load consumption, an artificial neural network with two hidden layers and fifteen nodes in each hidden layer was used. And the input layer contains a vector with 29 elements, including meteorological parameters, gas consumption data for the previous five days, the meteorological parameters forecasting for prediction day and one output, which is the daily gas demand. The final topology of {29-15-15-1} is, however, achieved for this model. This model uses the sigmoid transfer function in hidden layers and linear transfer function in the output layer. Model accuracy for the prediction day is about 93%.

In order to predict the monthly gas load consumption, an artificial neural network with one hidden layer and seven nodes in a hidden layer was used. And the input layer contains a vector with 3 elements, including the monthly effective temperature for the previous and prediction months and the gas load consumption for the previous month and one output, which is a monthly gas demand. The final topology of {3-7-1} is achieved for this model. Monthly model uses the sigmoid transfer function in the hidden layer and linear transfer function in the output layer. Model accuracy for the prediction month is about 98.9%.

**Nomenclatures**

| | |
|---|---|
| $Actual_i$ | Actual gas load for $i^{th}$ day |
| $Forecast_i$ | Forecasted gas load for $i^{th}$ day |
| MRE% | Mean percent relative error |
| MSE | Mean square error |
| N | Total number of training or test data |
| Net | Sum of inputs to the node |
| $O_{Pj}$ | Node output of input pattern P to the node j |
| P | Meteorology parameters and gas consumption amount |
| Sig(x) | Sigmoid transfer function |
| T | Temperature |
| Teff | Daily effective temperature |
| wij(t) | Weight coefficients from node i to node j in time t |

***Table 2: Some prediction and their relative errors for the validation data (monthly model).***

| Actual Load (MMCFM) | Predicted Load (MMCFM) | Relative Error (%) |
|---|---|---|
| 502.10 | 500.42 | 0.33 |
| 344.79 | 340.99 | 1.10 |
| 384.07 | 389.12 | 1.32 |
| 863.00 | 834.71 | 3.28 |
| 1127.40 | 1122.50 | 0.44 |
| 550.49 | 545.58 | 0.89 |
| 510.89 | 501.38 | 1.86 |

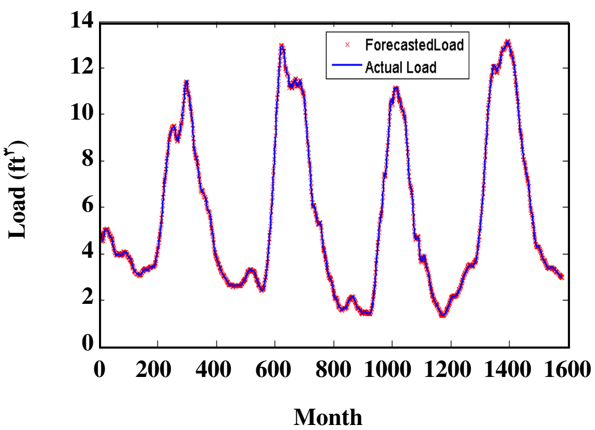


***Fig. 8: Predicted and actual load for all present data (monthly model).***

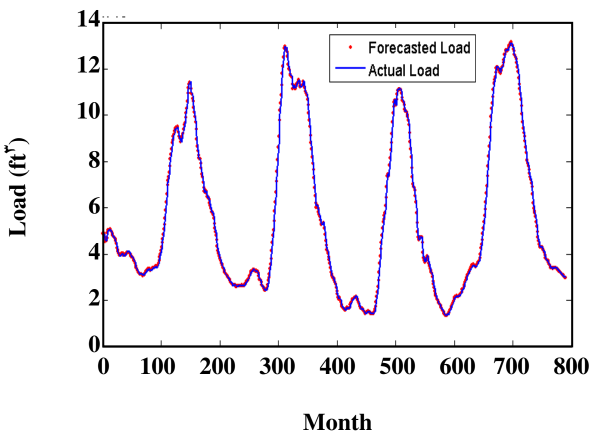


***Fig. 9: Predicted and actual load for the validation set data (monthly model).***

$\eta$ Rate coefficient

$\delta_{Pj}$ Corresponding error of input pattern P to the node j

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