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Short Term Load Forecasting Using BPN and RBF Network

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Abstract
Simple neural network based short term load forecaster is designed which predicts load values to be obtained beforehand. The neural network based short term load forecaster has two modules (1). Back Propagation Network (BPN) and (2) Radial Basis Function Network (RBF). The inputs used were the actual hourly load demand for the full day (24 hours) and the outputs obtained were the predicted hourly load demand for the next day. The number of inputs is 25 while the number of hidden layer neurons is varied for different performance of the network and the output layer has 24 neurons. The results obtained from two different approaches are compared and accuracy of neural network is reported better. Also, the network has been trained over one week and an absolute mean error of 2.64% was achieved when the trained network was tested on one week's data. Short-term hourly load forecasting is predicted using Matlab R2010a toolbox.

Keywords: *Back propagation network (BPN), short term load forecasting (STLF).*

INTRODUCTION

Load statement is vitally necessary for the electrical business within the deregulated economy. It's several applications together with energy buying and generation, load switch, contract analysis, and infrastructure development. An outsized sort of mathematical strategies are developed for load statement. Correct models for wattage load statement square measure essential to the operation and designing of a utility company. Load statement helps an electrical utility to create necessary choices on buying and generating wattage, load switch, and infrastructure development. Load forecasts are extraordinarily necessary for energy suppliers, ISOs, national establishments, and different participants in electrical energy generation, transmission, distribution, and markets.

Load forecasting is that the technique for prediction of electrical load. During a deregulated put on the market is far want for a generating company to grasp regarding the market load demand for generating almost about correct power. If the generation isn't comfortable to satisfy the demand, there would be drawback of irregular offer and just in case of excess generation the generating company can have to be compelled to bear the loss. Thus in power systems, there's an excellent want for accurately forecasting the load.

With supply and demand fluctuating and energy prices increasing during peak situations, load forecasting is vitally important for utilities. Accurate load forecast provides the system dispatchers with timely information to operate the system economically and reliably.

The term "short" implies prediction times of the order of minutes or hours. The time boundaries are from ensuing hour, or probably time unit, up to 168 hours. The fundamental amount of interest briefly term load forecasting is, typically, the hourly integrated total system load. In addition to the prediction of the hourly values of the system load, the short term load forecasting (STLF) is also concerned with the forecasting of the daily peak system load, the values of system load at certain times of the day, the hourly of half-hourly values of system energy, the daily and weekly system energy

The load prediction amount is also month or year for the long and also the medium-term forecasts [1], and day or hour for the short-run forecast [2-7]. The short-run forecast is required for management and programing of installation, and additionally as inputs to load flow study or contingency analysis. There are many categories of load forecasting models reported in literature. [8]. Some load models which use no weather information have been represented by time sequences [2-4]. The other load models have included the effects of weather variables on the power system load [5-7].

The approach that doesn't assume specific load model but try to find the rule between the historical load data and dry-bulb temperature from the expert system point of view [9] . The objective of this approach is to use the knowledge, experience and analogical thinking of experienced system operators. Recently authors developed a new method of adaptively identifying the load model which reflects the stochastic behaviour without the aid of weather variables [10].

Forecasting has been mentioned as one of the most promising application areas of artificial neural network (ANN). Several authors have attempted to apply the back propagation learning algorithm [11] to train ANNs for forecasting time series. Application of this idea to the real world problem can be found in Werbos's work [12], applied the back propagation algorithm to the recurrent gas market model. There was additionally a negative opinion [13] that the forecasting ability of the rear propagation algorithm was inferior to easy regression toward the mean. Recently, however, the National Science Foundation organized a workshop to handle the importance of ANNs in installation engineering, and authors states that ANN is with success employed in short-run load forecasting with accepted accuracy [14]. In this paper the rear propagation algorithmic program is projected as a strategy for electrical load forecasting.

EXISTING METHODOLOGY

Back Propagation may be a systematic methodology for coaching multi-layer artificial neural networks. It's a mathematical foundation that's sturdy if not extremely sensible. It's a multi-layer feed forward network victimization extend gradient –descent based mostly delta-learning rule, unremarkably referred to as Back Propagation rule. It provides a computationally economical methodology for dynamic the weights in feed forward network, with differentiable activation operate units, to be told a coaching set of inputs-output examples. Being a gradient descent methodology it minimizes the overall square error of the output computed by the net. The network is trained by supervised learning methodology. The aim of this network is to coach the net to attain a balance between the power to retort properly to the input patterns that are used for coaching and also the ability to produce smart responses to the input that are similar.

Initialization of Weights and Biases

Before training a feed forward network, you must initialize the weights and biases. So some random values between -1 and +1 or between -0.5 to +0.5 are initialized as weights. The newff command automatically initializes the weights, but we might want to reinitialize them. We could do this with the init command. This function takes a network object as input and returns a network object with all weights and biases initialized. There is no specific approach for the initialization

Feed Forward
During this stage each input unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit in the hidden layers then calculates the activation function and sends its signal to the output layer. Finally the output unit calculates the activation function to form the response of the network for the given input pattern.

Back Propagation of Errors
During this stage, each output unit compares its computed activation with its target value to determine the associated error for that pattern with that unit. Based on the error, the factor del (k) is computed and used to distribute the error at output unit back to all units in the previous layer. Similarly the factor del is computed for each hidden layer.

PROPOSED METHODOLOGY
This section is an evidence of the results obtained from the trained ANN model. These embrace the multivariate analysis plots between the output and target vectors, the final network error performance and therefore the coaching state. Once the successful completion of the coaching method 3 plots was created that include:
i. The regression plots
ii. The performance function vs. epochs plot
iii. The training state plot
iv. The Forecast and Actual Data comparison Plot

Basically the input file set was divided into three: 70th was used for as coaching set whereas 15% every was used for testing and validation of the network output results. The coaching knowledge set is important for getting the neural network's weight and bias values throughout network coaching. The validation knowledge set is employed to periodically take a look at the flexibility of the network to generalize. Finally, the take a look at knowledge set is employed within the analysis of generalization error (i.e. MSE).

The regression plot consists of four regression analysis plots; the first is a plot of the computed network output of the training data set vs. the target output, the second is that of validation data output vs. target output. The third is that of the Test data output set against the target output. The final plot is that of the overall network output data set vs. the target data set. All these plots try to show the co relation between the output data and the target data. They give an idea on the accuracy of the trained network will forecast since they show how well the network has learned the complex relationship of the input data. The regression plot is obtained as shown in the Fig 1.

The Performance function (MSE) vs. number of epochs plot describes the plot of the mean squared error against the number of training epochs. It also shows the learning trend and computational error improvement as the number of iterations increases. From the plot it can be concluded that the network was trained to zero. The network can be said to have successfully learned any complex and nonlinear relationship that was presented by the input data. The performance plot is obtained as shown in the Fig 2.

The training state plot will consist of three different plots. The first plot is that of learning function vs. number of epochs. This shows the trend of the gradient values as the number of computational iterations increases. This is necessary in monitoring the manner in which the training progresses. The second plot is that of the learning rate (mu) against increasing number of epochs. This plot is essential in monitoring the rate at which the computed network error reduces during the progress of the training. The final plot here is that of the validation checks carried out mechanically any time a fulminant amendment is determined within the network gradient computation is carried out. Finally, the trained network optimized weights for every of the 2 layers (hidden layer and output layer) and connected biases that gave the simplest network output-target knowledge relationship were documented. The coaching state plot is obtained as shown in the Fig.3.

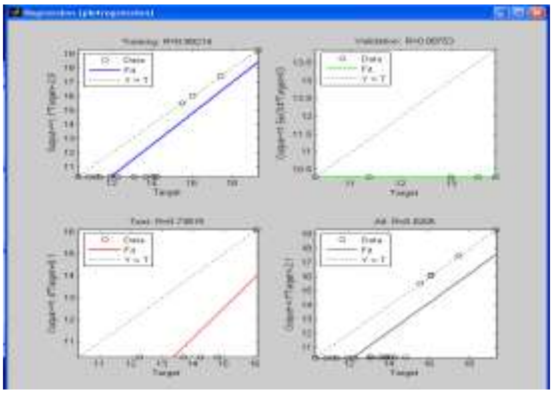

Fig 1.Regression Plot

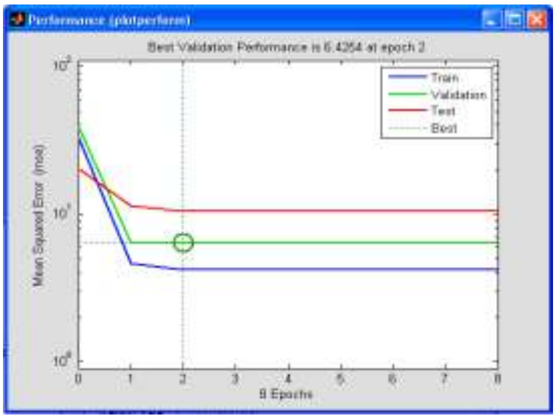

***Fig 2.** Performance Plot*

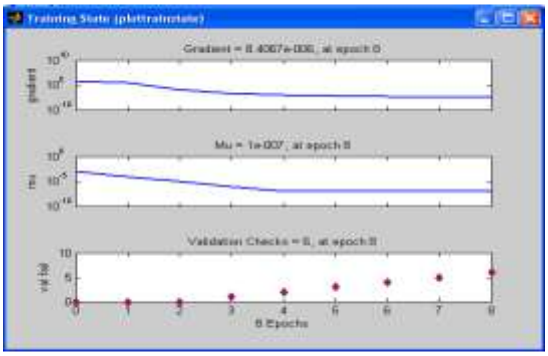

***Fig.3** Performance Plot*

SIMULATION RESULTS AND ANALYSIS

The various design are proposed to compare BPN and RBF Network, to analyse performance characteristics of BPN and RBF Network with varying number of hidden layer neurons using Matlab software.

A. Comparison between BPN and RBF

B. Performance of the network with varying Hidden Layer Neurons

C. Performance of the network with different activation functions

D. Comparison of actual and predicted load curves on one week data

Comparison between BPN and RBF

The error value in Table 1 shows satisfactory approximation between the target values and the results of the forecast. It can be seen that the MAPE value is better while using RBF network. The MAPE obtained using BPN and RBF were found to be 0.3862572 % and $6.6872*10^{-5}$% respectively.

***TABLE 1** COMPARATIVE MODEL FOR LOAD PREDICTION*

	BPN NETWORK	**RBF NETWORK**
1/11/2016	0.098247	3.75947E^-12
2/11/2016	0.193425	4.5468E^-10
3/11/2016	0.266656	1.46394E^-11
4/11/2016	0.167992	9.47728E^-13
5/11/2016	0.630086	1.26631E^-12
6/11/2016	0.67985	9.74415E^-12
7/11/2016	0.667546	7.48803E^-11

Performance of the network with varying Hidden Layer Neurons

The performance of the network is determined for BPN by varying the number of neurons in the hidden layer by choosing 6, 12 and 24 neurons with "log-sig" activation function. The MAPE obtained using 6, 12, 24 Hidden Neurons were found to be 0.386257429%, 0.581092% and 0.599165% respectively.

TABLE 2: *EFFECT OF NUMBER OF NEURONS*

MAPE	6 NEURONS	12 NEURONS	24 NEURONS
1/11/2016	0.098247	0.361594	0.518348
2/11/2016	0.193425	0.653397	0.454127
3/11/2016	0.266656	0.944428	0.514398
4/11/2016	0.167992	0.424987	0.673503
5/11/2016	0.630086	0.668249	0.774189
6/11/2016	0.67985	0.406865	0.58201
7/11/2016	0.667546	0.608124	0.67758

Performance of the network with different activation functions

The Transfer function used in the hidden layer is varied for BPN and RBF Network and is compared between two different activation functions like log sigmoidal activation function and tan sigmoidal activation function and the corresponding MAPE is obtained. The one week data is given as input and the results are tabulated as shown in the Table 3.

TABLE 3 *EFFECT OF ACTIVATION FUNCTION*

	LOGSIGMOIDAL (6 NEURONS)	TANSIGMOIDAL (6NEURONS)
1.11.2016	0.098247	0.647731
2.11.2016	0.193425	0.499669
3.11.2016	0.266656	0.26656
4.11.2016	0.167992	0.25832
5.11.2016	0.074189	0.293153
6.11.2016	0.67985	0.190578
7.11.2016	0.406865	0.056743

Comparison of actual and predicted load curves on one week data

The load curves for different days are compared between the actual and the predicted load curves as shown in Fig 4.

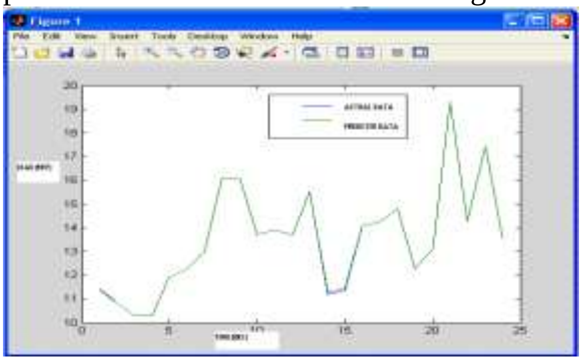

Fig.4 *Load Curve*

CONCLUSION

Neural Network prediction methods like Back Propagation and Radial Basis Function methods have been used for the prediction of future load values. On analysis and working of the above two methods, the Radial Basis Function Network gives very good performance with minimum error compared to Back Propagation Network. The hidden layer with minimum number of neurons gives minimal error. The log-sig activation function gives greater accuracy. The proposed methodologies were fully data-driven and provided more or less accurate forecasts with very little information from the user. Hence this project serves as a short term load forecaster based completely on the neural networks and devoid of manual prediction measures.

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