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143. Prediction of grid parameters by applying only set of dates externally to the trained Neural Network

Abdul Rauf Bhatti[a,*], Abdul Ghafoor Bhatti[a], Sajid Hussain Qazi[b], Irfan Ahmed[b], Raja Masood Larik[c]

[a]*Department of Electrical Engineering, Government College University Faisalabad (GCUF), 38000 Faisalabad, Pakistan*
[b]*Department of Electrical Engineering, Mehran UET SZAB Campus, Khairpur Mir's, Pakistan*
[c]*Department of Electrical Engineering NED University of Engineering and Technology, Karachi, Pakistan*
*Corresponding Author: *E-mail address:* bhatti.abdulrauf@gmail.com

Abstract

In this work a new technique of using the trained neural network (NN) for prediction of any parameter related to the electrical grid is introduced. Previously the user has to apply multiple inputs to already trained NN like load, demand or price but in the proposed solution only a set of dates is needed to apply externally at the time of prediction. For this purpose, a real-time historical data is used for prediction of required grid parameter for the given period. The results have been validated by comparing with real-time data of New England's electricity market. The comparison of simulation results with real load data confirms the validity of the proposed work. It is envisaged that this model will serve as a useful tool in the system energy management.

Keywords: *Grid parameters; artificial intelligence; prediction model; load forecasting; neural network (NN)*

1. Introduction

The forecasting of electrical parameters play a key role in the operation of electrical power systems [1]. The most famous parameters that needed to be forecasted to manage the available power properly and to maximize the total profit are electrical load, power demand and electricity price. The forecasting of loads enables the grid system to manipulate an optimized loading and unloading control by measuring the electrical supply each hour for achieving the best economical and power efficiency [2]. And the demand prediction is also vital for maintaining stability and controlling risks of electricity market. Moreover it is expected that in future smart grids, consumers of electricity will be enabled to react to electricity prices [3]. And with a good electricity price forecasting, a market participant would be able to delineate better financial decisions [4]. So the forecasting of all these load, demand and price parameters enables the producer to develop appropriate strategies to maximize its payoff and a consumer can minimize its utilization cost as well [4]. An extensive work on forecasting of these parameters in previous literature is available continuously which shows the importance of this area. Majority of researchers in this field are applying Artificial Intelligence (AI) based techniques, especially Neural Network (NN) for the prediction of grid related parameters. The NNs are useful tools to understand the complex and non-linear relationships among data, without any previous assumption concerning the nature of these correlations. They are extensively employed in modelling, identification, optimization, prediction and control of complex systems [5]. The previous studies show that the NN provides better results than the alternative classical regression, time-series and state-space methods [6]. For example, prediction error obtained by the NN is half the errors obtained by the other classical methods [7]. In [8] authors proposed long term load forecaster and considered three different networks for this purpose. The networks used are Functional Iink net, Multi-layer perceptron neural network and Wavelet network. Authors in [1] developed a load forecasting model. For this purpose, they used a Self-Recurrent Wavelet Neural Network (SRWNN) as the forecast engine. Moreover, the Levenberg-Marquardt (LM) learning algorithm is implemented and adapted to train the SRWNN. In [9] Kohonen neural networks are trained using past hourly load data, hourly spot price data and extreme weather data (temperatures and relative humidity) to make them suitable for load forecasting.

The above work shows the efforts of researchers for developing forecasting models to predict various grid related parameters like, load, price and demand. But the availability of many inputs required by the already trained NN for prediction of parameters is sometimes not possible. This unavailability of large number of parameters makes the trained NN invaluable. To overcome this shortcoming while predicting the grid related parameters a simple solution is proposed in this work where by just using a set of dates as an external inputs the NN can predict the required parameter. This solution enables the user of prediction model to apply only the set of dates to the already trained NN to get the predicted value of that grid parameter for which NN has been trained. User has no need of current real-time data for prediction purpose at all to apply externally to the trained neural network. The historical data used for training purpose is used for prediction automatically. The model trained in this work for prediction of load uses ten years of data. Forecasting can be done using small data but data of long period helps the model to predict more accurately. The accuracy of proposed model has been validated by comparing the results with real-time data of New England's electricity market. This model is very useful for electricity market which can be used by non-trained persons as well due to its simplicity.

The remaining paper is organized as: Section II explains the methodology of proposed work. Section III presents results and discussion. And finally, in Section IV, conclusion and future work is given.

2. Methodology

Load forecasts also have significant roles in energy transactions, market shares and profits in competitive electricity markets [1]. Though this work is mainly for prediction of grid parameters using already trained neural network but as a case study the NN is trained only for grid load variable. For this purpose, a database is maintained on first stage keeping in view the basic data rule that it should be of value and it must be in the right form in the right place at the right time [10]. The database contains all variables shown in Table 1. The weather and grid related parameters are taken from Independent System Operator (ISO)'s official website [11]. The maintained database consists of ten years data from 01/07/2003 to 30/06/2013 and contains the value of each variable for every hour of the day.

2.1. Training of neural network

In the presence of ten years the neural network is trained for load forecasting. This kind of large database provides a long range to NN for its better training and ultimately for accurate prediction of desired variable. The specifications of trained neural network in this work are as under:

- **Algorithm: Bayesian regulation backpropagation**

Bayesian regularization (trainbr) network is used as a training function in our work because few variables especially demand and price are quite fluctuating and trainbr is good choice when problem is more challenging because it produces better generalization capability [12]. It updates the weight and bias values according to Levenberg-Marquardt optimization and then determines the correct combination so as to produce a network that generalizes well.

- Layers**:** Nine hidden layers with sizes of 11 11 11 10 10 10 5 5 5 respectively and one output layer.

The weather parameters used for training the NN are quite fluctuating, so to get more accurate training of NN and to have more generalized prediction capabilities hidden layers are increased. To get the finalized structure as shown in Fig. 1 with less amount of training error the number of hidden layers and their sizes are kept on changing many times during training phase.

- **Transfer function:** Tan-sigmoid for each hidden and linear transfer function for output layer.

Tan-sigmoid is selected since it covers both positive and negative values of variables.

Table 1. Inputs applied for neural network training

Time	Day of year	Dew point temp
Day of week	Working day	Demand
Day of month	Dry bulb temp	Past Load

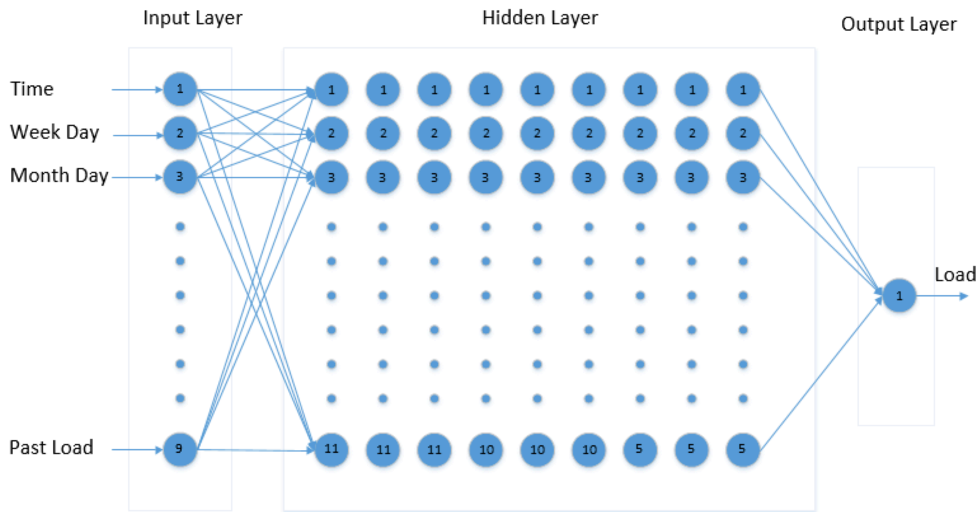

Fig. 1. Structure of Neural Network for load forecasting

2.2. Prediction of load through the external application of dates only

The trained neural network is used in a quite different way to predict the load for not only a day ahead but week, month and years ahead. The operator needs to apply only single date for day ahead prediction and two dates (set of dates) for week, month or year ahead load forecasting. This is the main contribution of this work. For this purpose, another algorithm is developed which makes use of already trained NN. This algorithm, at the time of execution, asks the user for dates to apply only for required period of prediction. Then the algorithm extracts all weather and power parameters needed by trained NN from ten years' database against the period with the given dates. Moreover, the day of year, day of week and day of month are extracted from given date using Matlab built-in functions. As the database contains the value of each parameter for ten years, so it takes the mean of each variable to convert into single input for individual variable. Because every input applied to the trained NN is the mean of ten years, it gives a very close value to the real one. The actual values of day's related parameters extracted from given dates and mean values of power and weather parameters extracted from database are applied to the trained NN by the proposed algorithm for prediction of desired parameter for the given period. So, this prediction approach makes the prediction process completely independent of any kind of external data except a set of dates once the model has been developed

3. Results and Discussion

The results are validated by comparing predicted load with the real value of load data taken from ISO as shown in Fig. 2. This comparison is done for day, week and month ahead forecasted as shown in Fig. 1 (a), (b) and (c). The close relation of predicted power with actual power both in shapes and magnitudes provides a good validation of proposed prediction model. Moreover, the mean absolute percentage error (MAPE) is calculated to check the performance of the model like [13, 14] using Eq. (1).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{A_i - P_i}{A_i}\right]\times 100\% \quad i = 1, 2, \ldots N \qquad (1)$$

Where A_i and P_i are the actual and predicted, respectively and N is the number of hours.

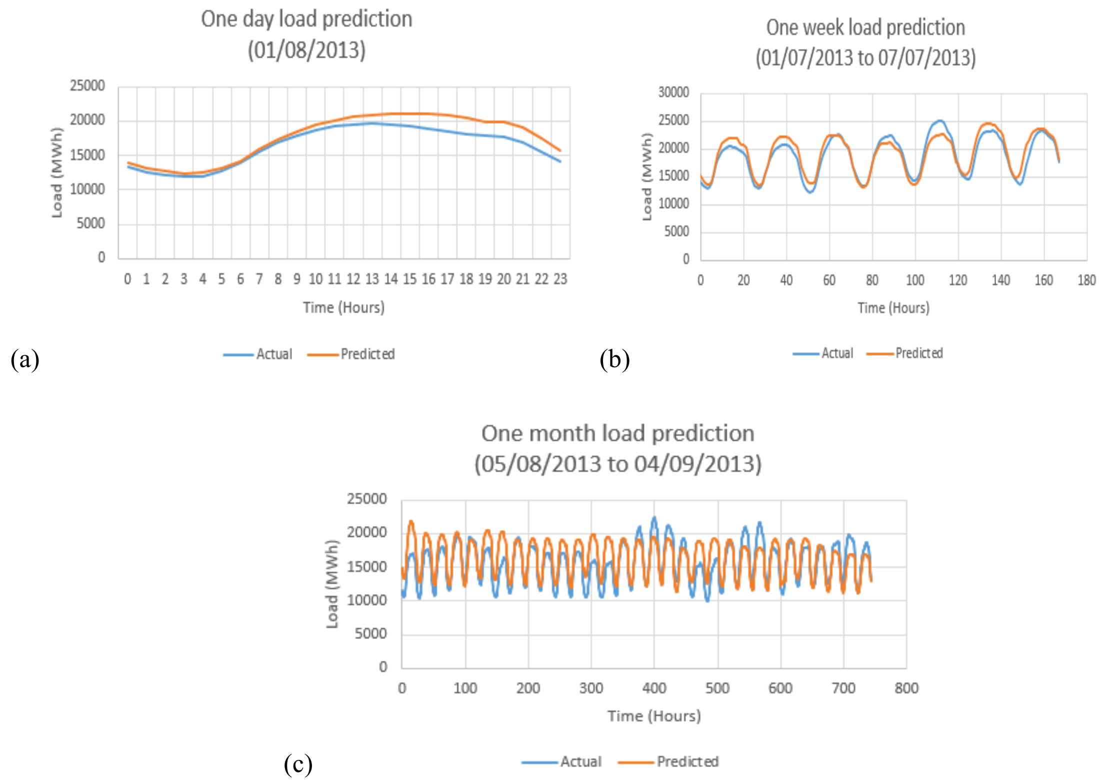

Fig. 2. Comparison of actual and predicted load for (a) one day (b) one week and (c) one month.

Table 2 shows MAPE calculated for different periods. The small amount of error even for long period of forecasting like one month ahead without having current real-time data shows the effectiveness of the proposed approach.

Table 2. Mean absolute percentage errors for different periods

Prediction Period	MAPE (%)
Day ahead	7.25
Week ahead	6.07
Month ahead	11.12

4. Conclusion and future work

Load prediction through NN is a real-life application of artificial intelligence but it requires the same number of inputs at the time of prediction as are applied during the time of training. However, in certain cases it is not possible to have the data related to the inputs in real-time. This work solved this problem by using historical data, where user needs to apply only set of dates externally. The developed algorithm extracts remaining inputs from historical data automatically and applies to the trained NN for prediction purpose. Though the approach adopted in this work is simple but quite novel and is very useful for prediction of not only load but other grid related parameters when current real-time data for input of trained NN is not available. The mean absolute percentage error calculate is quite low than the approaches adopted in previous literature. The accuracy of proposed work can further be enhanced by training the NN for the data of long periods.

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