MODELLING ENERGY DEMAND FORECASTING USING NEURAL NETWORKS WITH UNIVARIATE TIME SERIES

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ABSTRACT

The new era of consumption and change in the behavior of people in developing countries that we facing in recent decades has made not only the energy sector but also all resource suppliers in different sectors not to fulfill the demand in the field. The electricity, which is one of the main power resources, has become one of the major issues to be overcome for the governments. Predicting the future energy demand is always the most valuable information to achieve any success in many sectors. In this paper, a daily forecasting of the maximum energy demand in Kurdistan region of Iraq is investigated based on an artificial natural network and sliding window techniques. The standard mean absolute percentage error method is used to evaluate the accuracy of forecasting models.

Keywords: Neural networks, Sliding window technique, Energy demand forecasting.

1. INTRODUCTION

One of the most important factors to improve the quality of life is energy, it also ensures the economic and social development. However, rising energy prices, climate change, and global warming has led to an increase in energy demand throughout the world. On the other side the rapid consumption of fossil fuel and being dependent on it, as well as the insufficiency investment for developing new technologies, to meet the growing demand for commercial energy, makes countries worry about the security of energy supply. the Electricity Control Center located in Erbil is the highest authority for distributing the generated electricity to the cities of the region. The city distribution center directorate manages for the equivalent distribution of the supplied energy according to the hourly schedule for each district in the city. The main energy generation in the region comes from dams and fossil fuel. However, since the late of 2014 due to the economic crises, the gas power plants is not used as one of the main energy sources.

1.1. LITERATURE REVIEW

Using ANN for load forecasting is one of the most popular approaches for predicting the energy demand. In 2006, seasonal autoregressive integrated moving average (SARIMA) has been used for monthly peak-load demand forecasting in Sulaimany in KRG governorate [1]. A similar approach in Bagdad has been handled for short-term load prediction based on hourly consumption adding to weather data combining with electricity consumption in 2010 [2]. since 2008 for predicting the electricity price in a liberal electricity market in Turkey, load forecasting has gain importance for the supporting financial market, many researchers focused on using the different approaches for more accurate results. In 2015, a multivariable approach has been used by supporting the time series data combining with weather historical data for just big cities to predict more accurate electricity consumption in Turkey [3]. In the literature, integration of the neural network approach and sliding window time series technique is employed for the forecasting in several different applications. For example, it has been used by Vornberger and Thiesing for sales forecasting [4], and

by Vafaeipour et al. for prediction of wind velocity [5]. In this study, we have used the neural network approach with sliding window time series technique to forecast the maximum energy demand in the Kurdistan region of Iraq.

2. DEVELOPMENT OF THE ENERGY DEMAND MODELS

2.1. DATASET PREPARATION

In this paper, the data used in the development of the forecasting models is the single time series (univariate) of historical electricity demand data obtained from the Electricity Control Center (ECC) of Kurdistan region in Iraq. The data is accumulated daily and involves the maximum electrical demand load in Mega Watt (MW) from 1st January 2014 to 31st October 2017. by using sliding window technique with the lag size of 14, step size of 1 and horizon size of 1, 3, 7 and 14 we have generated 4 datasets in a tabular format from single time series data. normalization of the dataset could help improve the performance of the network by reducing effects of noisy data and flatting the distribution of the attributes [6]. We have used a transformation technique, which scales the data between the upper and lower limits of -1 and 1. This transformation can be archived by using the following expression:

$$x_{normilized} = \frac{2 \times x - (x_{max} + x_{min})}{x_{max} - x_{min}}$$

being x is original value, $x_{normilized}$ is scaled value between -1 and 1, and x_{max} is the maximum value, x_{min} is the minimum value in the data.

2.2 ARTIFICIAL NEURAL NETWORKS

In this paper, we have used the multilayer ANN models to forecast the maximum energy demand. The multilayer perceptron is one of the widely used Multilayer ANN models, which is an advancement of single layer perceptron. A single perceptron [7] and a typical multilayer perceptron network are depicted in Figure 1 and 2 respectively. Multilayer network design of perceptron makes able the ANN models to solve the non-convex classification and non-linear regression problems. MLP models are boosted after the introduction of the backpropagation (BP) algorithm, which is one

of the widely employed training algorithms in ANN models and initially formulated in 1986 by Rumelhart, Hinton, and Williams and it is developed more later [7].
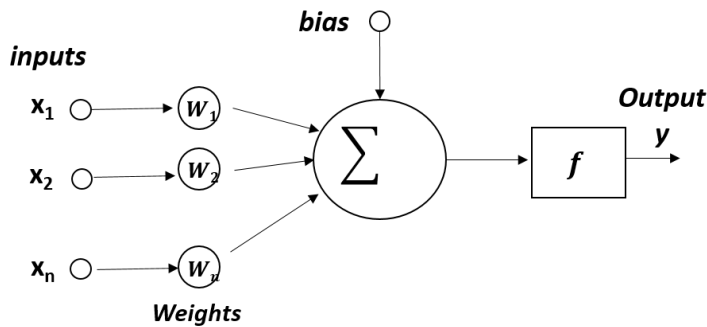

FIGURE 1. A single neuron

Backpropagation method overcomes the adjustment shortcoming of the intermediate weights to justify the strength of the connections in the hidden layers that is the training process of the neural network. BP uses the gradient descent training algorithm, which aims to minimize the total squared error (E), defined as follows [7]:

$$E = \frac{1}{2}\sum_{s}^{S} E_s = \frac{1}{2}\sum_{s}^{S}\sum_{i}^{N}(t_{si} - p_{si})^2$$

where E_s is the error presented after input s, t is the real output and p is the predicted output. This calculation iterated thorough the nested loop for each input set indexed as *s* and each processing unit indexed as *i* [7].

2.3 DEVELOPMENT OF THE ANN FORECASTING MODEL

In this study, we have used the Time Series Analysis and Forecasting package [8] and WEKA workbench [9] to develop time series models based on the multilayer ANN models to forecast the maximum electrical energy demand. Various network models based on multi-layer feedforward architecture are tested with different designs and different configurations of hyper-parameters. After several trials, the near-optimal values for the parameters of the multilayer neural network are observed as the learning rate of 0.05, momentum value of 0.1, and one hidden layer with neurons of 14. The architecture of the network is illustrated in Figure 2. It has 14 sigmoid type of neurons

in the hidden layer and one linear type of output neuron and trained by using the backpropagation algorithm. Also, it has 14 inputs labeled by P_{t-1} to P_{t-14}, which denote the maximum power demands of the day before, two days before and so forth.
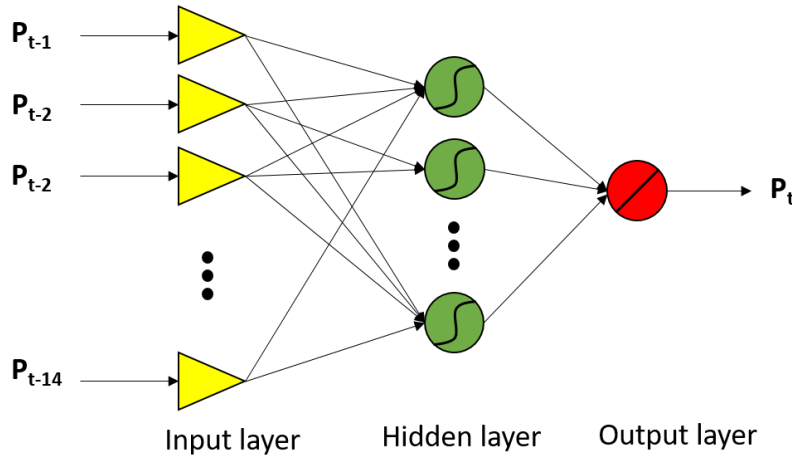

FIGURE 2. ANN model with 14-lag and one-day-ahead horizon

3. RESULTS AND DISCUSSION

Neural network models are evaluated on the out-of-sample dataset, which is obtained by holding out of 20-percent of the whole dataset linearly. We have used the performance metrics of mean absolute percentage error (MAPE) and R^2 to report the results presented by the neural network on the test datasets. with the implementation of the sliding window technique on the time series and neural network, we have developed a forecasting model using the energy demand time series. The addition scaling data transformation is done to adjust the demand time series for the better forecast accuracy. neural network demonstrated R^2 0.9741 and MAPE of 2.98% accuracy results for one-day-ahead forecasting and demonstrated R^2 of 0.72 and MAPE of 9.4557 % accuracy results for 14-day-ahead forecasting for the test dataset as seen in Table 1. from the simulation results shown in tables 1 and 2, and in figures 2 and 3, the proposed model has achieved a reasonable accuracy in one-day-ahead maximum demand load forecasting. However, the model performance by means of accuracy is not as good as one-day-ahead forecasting when the forecasting horizon increases as demonstrated in table 1.
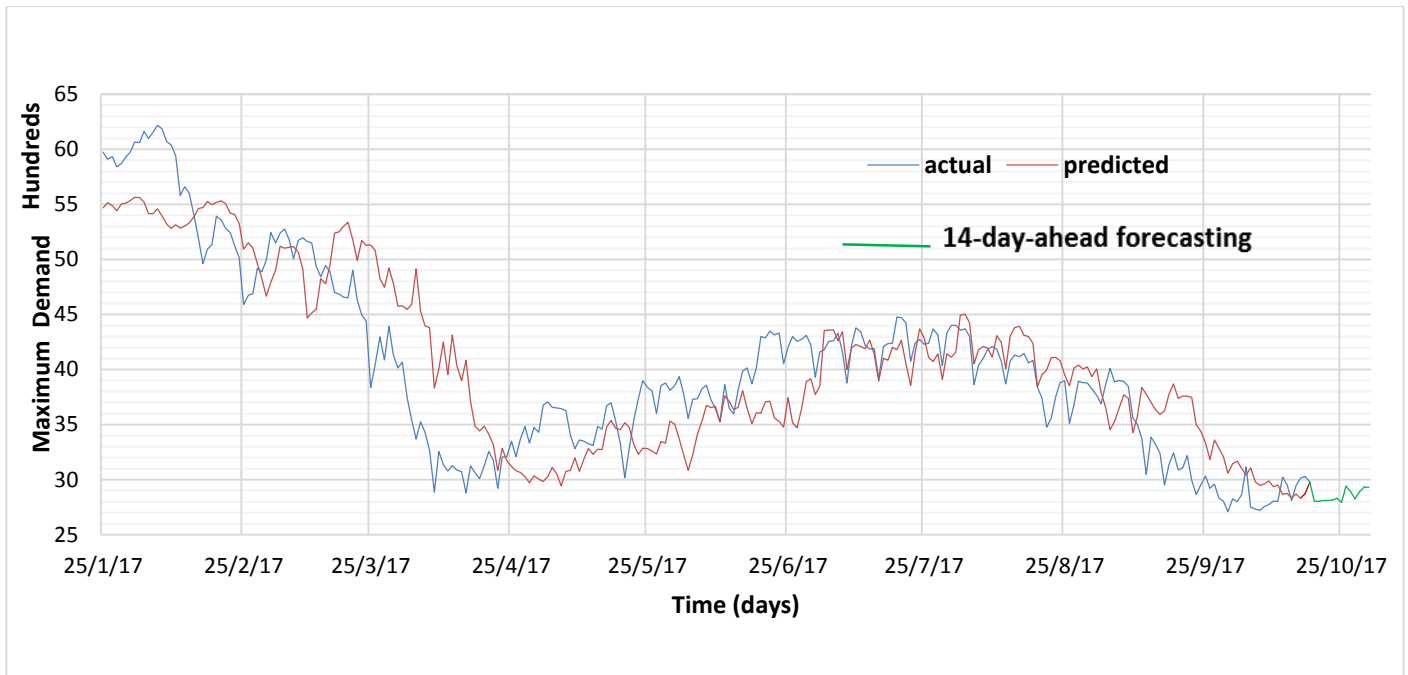
FIGURE 3. Forecasted versus actual maximum demand load for the test dataset and 14 days ahead forecasting

TABLE 1.

Forecasting errors 1 to 14 days ahead for the test dataset

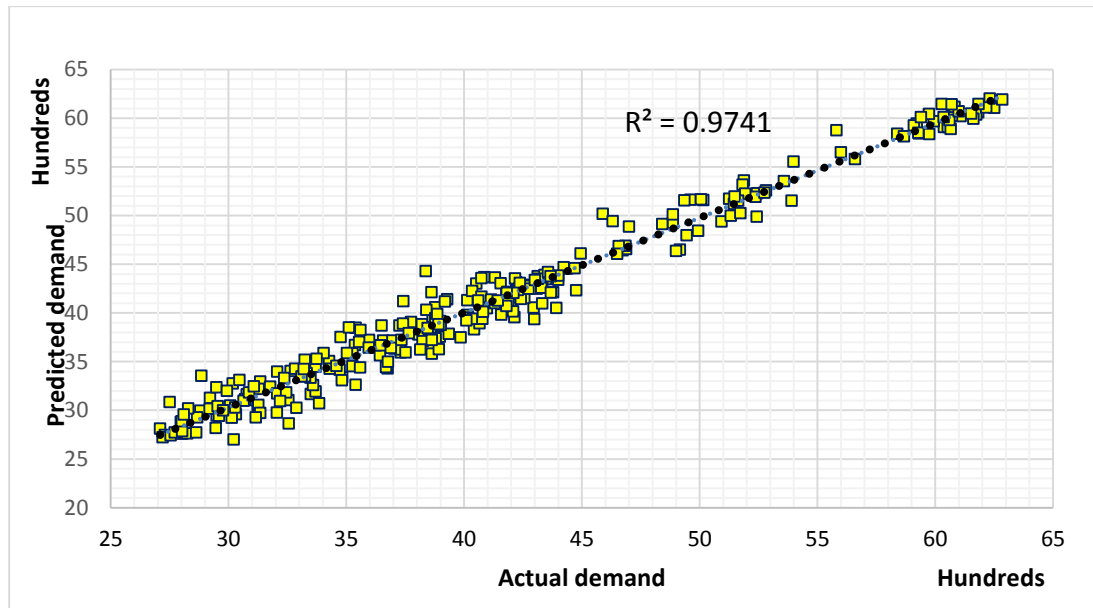| Target	1 day ahead	3 days ahead	7 days ahead	9 days ahead	14 days ahead
Mean absolute percentage error (%)	2.9797	4.7363	6.2725	7.5372	9.4557
R^2	0.9741	0.9326	0.8695	0.8263	0.719

FIGURE 4. Correlation of actual and predicted maximum demand load in MW (1-step ahead)

TABLE 2.

Forecasted versus actual maximum demand

load for the last 10 data points in the test dataset

using 1-step ahead forecasting model

instance #	actual (MW)	predicted (MW)
1391	2772	2771.29
1392	2804	2783.36
1393	2803	2887.68
1394	3023	2700.35
1395	2954	3041.65
1396	2811	2956.41
1397	2947	2818.57
1398	3014	2922.05
1399	3029	3029.05
1400	2978	2999.72

4. CONCLUSION

In this paper, we have developed a neural network model based on a multilayer feedforward neural network to forecast the maximum electrical energy demand by employing the single time series data (univariate) for the case of Kurdistan region in Iraq. This study treats the single time series data as multivariable by employing the moving window data pre-processing method which is a way to apply the machine learning and data mining forecasting techniques in the case of having the single time series. Like many other previous successful attempts for the demand forecasting and function approximation in the literature, in this case, multilayer neural network is also demonstrated satisfactory estimation with an accuracy of MAPE 2.98%. Neural networks are able to successfully approximate the continuous functions including the non-linear functions and can also efficiently deals with noisy data. These properties make the neural network a strong forecasting tool [6]. Yet another side, it requires a systematic development methodology starting from data pre-processing, designing of the network architecture, configuration of the parameters to the evaluation of the network. Especially implementation and configuration stages of the neural networks are more of an art than science, which requires many trials and fails.

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