Enhancing Electric Load Forecasting of ARIMA and ANN Using Adaptive Fourier Series

Maged M. Eljazzar, IEEE Member
Computer Engineering Dept.
Faculty of Engineering, Cairo University
Giza 12613, Egypt
mmjazzar@ieee.org

Elsayed E. Hemayed, IEEE Senior Member
Computer Engineering Dept.
Faculty of Engineering, Cairo University
Giza 12613, Egypt
hemayed@ieee.org

***Abstract* - Since the early 20th century, Electricity is a necessity and essential to modern life. Producing and delivering electricity to 7.4 billion people is one of the most complex challenges in this decade. It is essential to forecast the energy load at different intervals. Several methods have been developed to carry out those predictions. Examples of such methods are ARIMA, regression and artificial Neural Network (ANN). This work investigates the usage of adaptive Fourier series in enhancing the prediction accuracy of ARIMA and ANN models. Those models along with their enhanced ones are applied to forecasting hourly Peak load data of The Electric Reliability Council of Texas (ERCOT). The experimental results demonstrate that using the adaptive Fourier series enhances the prediction power of the ARIMA and ANN models. The RMSE, MAE and MAPE are enhanced by increasing the number of harmonics required for a specific seasonal component.**

Index Terms—Load Forecasting, ARIMA, ANN, Forecasting, Adaptive Fourier Series.

I. INTRODUCTION

Electrical demand forecasting has an essential impact in the operation and planning of power systems, such as operations management, and maintenance. The electric power industry needs forecasts of supply, demand, price, and user behavior. All these forecasts are required to avoid load imbalance, load switching, and infrastructure development, which become more crucial than before. Through the past decades, load forecasting has been a great topic of research [1].

There are several parameters affecting load forecasting. These parameters differ according to the business needs and the time horizon of forecasting. It is crucial to define the relevant parameters that affect the forecasting and the type of forecasting. Load forecasting using irrelevant parameters adds more operation cost and negatively affects the forecasting accuracy [2].

In some cases, we need to define several parameters to understand the correlation between these parameters to enhance the load forecasting accuracy. The accuracy of load forecasting has a significant effect on the power system. Forecasting errors can cause huge increasing in operation and management costs. Historically, load-forecasting parameters are classified as meteorological, economic, calendar, price and causal parameters, which have the same effect on all the time horizons. Recent approaches conclude that these parameters influence the load forecasting according to the time horizon (long – medium - short) [3]. The more relevant parameters we use the more accurate prediction we can obtain. A forecaster main mission is to study the behaviour of the obtained historical data, and determine the best parameters to use in different patterns of the time series.

In short-term forecasting, the impact of the human behaviour towards electrical load can be realized in several aspects. In the hourly, daily, weekly, or monthly resolution, the impact varies over the seasons, holidays, accidents, or even soccer matches. This is due to the direct influence on significant segments of the end uses [4].

Most existing time series models are developed to handle simple seasonal patterns with a small period (i.e. 12 for monthly data or 4 for quarterly data). In this paper, we apply two techniques ARIMA and ANN for The hourly Peak load data of ERCOT with multiple seasonal time patterns. Then we use Fourier series as a regresor to enhance the proposed model. At last, we compare between the forecasting accuracy of both techniques.

This paper is organized as follows. Section II provides literature review of other works using ARIMA or ANN model in load forecasting. Model evaluation are discussed in Section III. The proposed forecasting models are described in Section IV. The experimental results are presented and discussed in Section V. Finally, Section VI concludes the paper.

II. LITERATURE REVIEW

Different mathematical and statistical techniques have been used for load forecasting. The development and improvements of appropriate tools lead to results that are more accurate. In this paper, we focus on Time series models. Time series models use the past movements of variables in order to predict their future values. Unlike structural models that relate the variable, we want to forecast with a set of other variables, the time series model is not based on economic theory. Box and Jenkins [5] introduced the autoregressive integrated moving

978-1-5090-4228-9/17/$31.00 ©2017 IEEE

average (ARIMA) model, and general exponential smoothing (GES) techniques. Since then these techniques have been applied to several time series forecasting applications. Statistical techniques use historical data about specific events (holidays or special days) to perform hourly or weekly load forecasting [6]. Several works used the ARIMA models with minor modification for different case studies in Thailand [7], Malaysia [8], and Iran [9].

The time series model can mostly produce quite accurate forecasts, especially in case of multidimensional relationships among variables. Influential factors (for example weather conditions and seasonal changes) have been addressed in several works. Huang and Liu [10] presented the accumulative effect of the sunny days according to humidity, temperature and participation. A nonlinear transformation of the temperature was proposed to reflect the nonlinear relationship between the load and temperature [11]. Sahay et. al. [2] added the accumulative human comfort index to analyze short-term load forecasting of Ontario Electricity. They study the effect of human behaviour towards meteorological parameters.

Statistical approaches are offline forecasting techniques and time dependent functions. They are effective in approximating linear fitting curves. Due to the limitations of statistical models, many researchers prefer using artificial intelligence techniques. Researchers have developed input functions that are based on impactful parameters. Since the early 1990s [12], ANN was proposed as an algorithm to combine both time series and regression approaches. The ANN was expected to perform better nonlinear modelling than conventional approach [13].

A review of short-term load forecasting (STLF) using ANN models is discussed in details [14]. It was obvious that the ANN model produced improved accuracy in both peak load forecast and short term forecasting. ANN model for STLF has a similar development path as the regression model. A multilayer ANN was introduced [15] to enhance the forecasting performance when the temperature forecast error increases. Recent research work of the ANN model for STLF included taking advantage of several meteorological forecasts.

In order to adapt complex real-world data, there are two techniques. The first is to develop robust features that detect the required features. However, developing domain-specific features in complex data is time-consuming. The second technique is to use unsupervised learning. Recently, with the raise of deep learning, several works introduce deep learning to perform complex time series forecasting. Deep learning methods offer better representation and classification on a multitude of time-series problems compared to shallow approaches [16]. Deep neural networks are applied to time series data with several kernel configurations [17]. However, the usage of deep neural networks in electric forecasting is still limited due to the inability to access large volume of data and powerful computation machines.

III. How to Evaluate the MODEL

The main statistical methods of measuring errors are commonly used as indicators for forecasting accuracy. Examples of such indicators are Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Below is a brief definition of these indicators.

1- Root Mean Squared Error (RMSE):
It shows the root mean square error for the selected model. It is frequently used to measure the differences between values (sample and population values) predicted by a model and the values actually observed.

2- Mean Absolute Error (MAE):
The mean absolute error is the average absolute of the error value. For a good forecasting, this value should be close to zero. In other words how close predictions are to the results.

3- The mean absolute percentage error (MAPE):
MAPE stands for Mean Absolute Percent Error - Bias refers to persistent forecast error. It is the most commonly used to compare the fits of different forecasting and smoothing methods.

IV. Proposed Models

In this section, we describe the two main forecasting models; ARIMA and ANN. Moreover, we describe the Fourier series and how to use them to enhance the forecasting models.

1. Autoregressive Integrated Moving Average Model

Box–Jenkins approach has three main tasks (a) model identification, (b) parameter estimation and (c) diagnostic checking then forecasting. More details about each task are provided next followed by (d) our implementation specifics.

a) Model identification

In Auto Regression Moving Average (ARMA) model, the current value of the time series $y(t)$ is linearly represented in terms of its values at previous periods $[y(t-1), y(t-2),..]$ and previous values of the white noise $[a(t), a(t-1),\dots]$. Thus, for an ARMA model of order (p, q), the model can be written as:

$$y(t) = \varphi_1 y(t-1)+\dots+\varphi_p y(t-p)+a(t)-\varphi_1 a(t-1)-\dots-\varphi_q(t-q) \quad (1)$$

If the process is dynamic and non-stationary, Box and Jenkins introduced a transformation of the series to the stationary form. This can be done by the differencing process (d) times. For a series that has to be differenced d times, has orders p and q for the AR and MA components, i.e. ARIMA $(p; d; q)$, the first order difference can be expressed as in equation 2.

$$y_t = x_{t+1} - x_t \quad (2)$$

b) Parameter estimation

In this step, we choose the best parameter p and q from equation (1) to get the most accurate x_{t+1} from the last x_t to x_{t-p}. Auto correlated function (ACF) and partial auto correlated function (PACF) are used to estimate these parameters.

c) Diagnostic checking followed by forecasting

In traditional regression, drawing a plot of residuals versus fits is a useful diagnostic tool, which is very common in statistics. The ideal for this plot is a horizontal band of points. For the model to be valid, residuals checking must satisfy the hypothesis that the residuals are zero-mean normal distribution.

d) Our Implementation Specifics

The Standard ARIMA model only look at proximal entries in the time series to forecast subsequent entries using forecast package, TBATS. The idea of these methods is almost the same. They conduct a search over possible model within the order constraints provided. After using this function, the best ARIMA model is selected according to both Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) value. The idea is to choose a model with minimum AIC and BIC values. Another popular technique is Exponential smoothing in which previous time series entries contribute as a weighted moving average to forecast the next term which known as Holt-Winters.

Although Holt-Winter is a simple technique and easy to implement, but it produce less reliable results than ARIMA. As ARIMA searches over a restricted parameter space to ensure the resulting model is forecastable, while Holt-Winters ignores this issue [18]. We use it to make a first overview. While TBATS model is designed for use when there are multiple cyclic patterns. This model will be very helpful if we have multiple years of load data.

Our implementation of the ARIMA model has the following steps. Firstly, we fitted a model for the trend and seasonal data and hence creating model 1. After this step, we use the residuals and check if we need to fit ARIMA model and hence creating model 2. In addition, we apply shapiro test to check the normal distribution of the samples. The last step is fitting model 1 and model 2 together to prepare for forecasting, according to a specific time horizon.

2. Artificial Neural Network Model

ANN mimics human brains to learn the relationship between certain inputs and outputs from experience. The computational units in each layer are called neurons. The inputs value to the input neuron i: x_i, $i = (1, 2, 3, ..I)$. each connection to a neuron has an adjustable weight factor w_{ij} associated with it. These weights are adjusted during the training phase to achieve the desired output of the network. The hidden and output neurons usually calculate their outputs of their inputs:

$$v_i = \sum w_{ij}\, x_{ij} - w_{i0} \quad (3)$$

Where w_{ij} is the weight of the connection from input j to neuron i, and x_{ij} is input j to neuron i, and w_{i0} is the threshold associated with neuron i. Fig. 1 shows a schematic diagram of a neural network.

There are several ways to set the weights. A well-known way is using a priori knowledge. Another way is to train the neural network by using teaching patterns. In this work, we applied the most common way to STLF by setting a supervised learning rule. The network is trained using (e.g., weather variables) and the observation (load) is specified, and the ANN is trained to minimize the error between the ANN actual output and the desired output. The training process should result in an optimal solution (assuming the global minimum is reached).

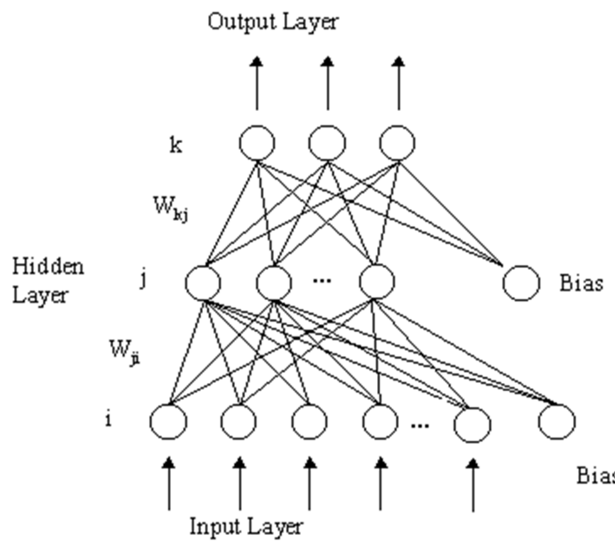

Figure 1: A schematic diagram of neural network with three layers

In this study, several feed-forward back propagation ANN are developed using R programming language. Each network design has different number of neurons and transfer functions, which are determined during the learning phase. The best network design is determined by using cross validation method. Based on the average of 20 networks, three layers NN (input-hidden-output layer) is used. The architecture of network used is a 43-22-1 with 991 weights.

3. Fourier Series

Fourier analysis is based on the concept that any arbitrary signal can be represented as linear combination of sinusoids over finite range of time [19]. To represent any arbitrary signal, it is the summation of constant, sines, and cosines multiples of the fundamental frequency with right amplitudes in that finite time interval. In this work, the time interval is represented by the seasonal period of the time series. The Fourier series can be expressed as in equation 4.

$$y(t) = a_0 + \sum_{n=1}^{M} a_n \cos(nwt) + \sum_{n=1}^{M} b_n \sin(nwt) \quad (4)$$

where M is the length of the Fourier polynomial, and a_0, a_n and b_n are the adjustable Fourier coefficients. a_0 is any offset of the time-series data, n is the order of harmonic, and w is the frequency of the signal. Usually the number of harmonics required for a specific seasonal component equal half of the period. In this work, Fourier series is introduced as a regressor to ARIMA and ANN to enhance the forecasting performance. Fourier series simulate the three seasonal periods (daily, weekly, and yearly).

V. EXPERIMENTAL RESULTS

In this work, we used (statistical and artificial intelligence) time-series approaches for forecasting using R language. For electric load forecasting, we used hourly Peak load data of Texas states [20] (see Fig. 2).

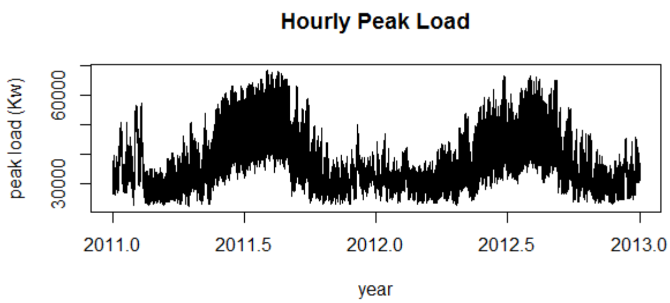

Figure 2: Hourly peak load of Texas State

This work considered the effect of the special days, such as holidays as it has different load consumption rather than ordinary day. Three seasonal periods are defined as 24, 168 and 8766 for daily, weekly, and annually effect respectively. Moreover, Several Fourier series with varying number of coefficients are applied to enhance results. Using Fourier series enhanced the model prediction of the same season. This work aims to measure the variation between ARIMA and ANN load forecasting. In addition, the effect of adding the Fourier series as input parameter on load forecasting.

In this work, we developed multiple models to test multi-seasonality in the time series. Three models are tested for both ARIMA and ANN, on two years of data. The seasonal periods of the data are represented by the number of hours in the period of 2011 to 2012. Firstly, we use ARIMA model without Fourier series. We did not obtain a good fit for the data in this case. Then we use ARIMA with few Fourier series coefficients $K = (1, 1, 1)$ to represent the seasonality, where K is the number of harmonics. We call this model ARIMA M1. Then we use more Fourier series coefficients, $K = (5, 5, 5)$. We call this model ARIMA M2. At last we use more coefficients, $K = (10, 10, 10)$ and we call this model ARIMA M3. It is noticed that, it is difficult to increase the number of K when using ARIMA due to ARIMA limitation with high frequencies. Secondly, we applied ANN M0 that uses the ANN model without Fourier series. Then we use different Fourier series coefficients in ANN model M1, M2, and M3. The K values were equal to (1, 1, 1), (5, 5, 5), and (12, 24, 72) respectively. We can notice that ANN had overcome the ARIMA model limitation with the number of K values.

Figure 3, 4, and 5 shows the ARIMA model using different Fourier time series coefficients. The black line represent the real data, the blue line represents the ARIMA model predicting the same seasonal period. It is clear that increasing the number of coefficients enhance the accuracy of the model. However, ARIMA model has some limitation when increasing the number of coefficients as it becomes difficult to find an ARIMA model.

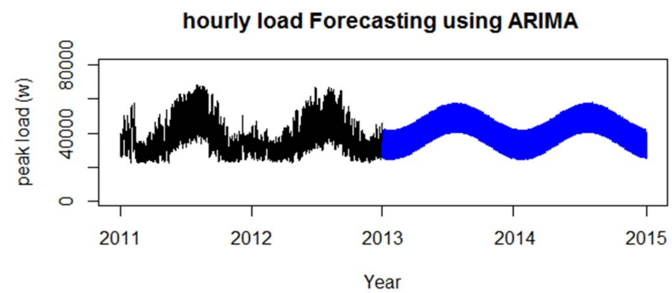

Figure 3: ARIMA model 1

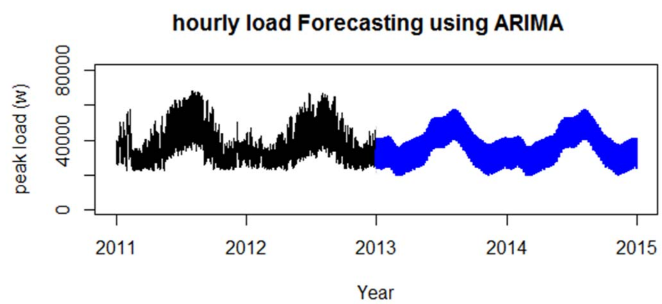

Figure 4: ARIMA model 2

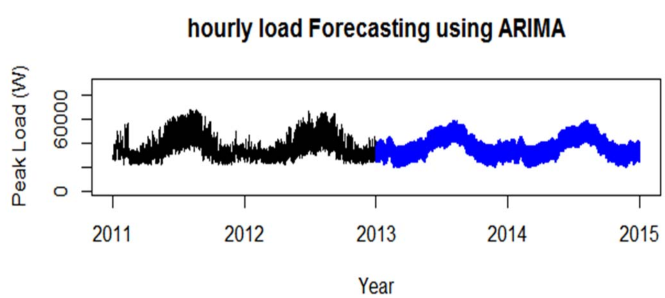

Figure 5: ARIMA model 3

Figure 6 and 7 show ANN model M2 and ANN model M3. It is clear that the prediction accuracy of the ANN model is improved when increasing number of Fourier series coefficients, K values.

Figure 8 and 9 show the residuals of ARIMA and ANN models with different numbers of coefficients. As shown in the figures, the residuals are less when increasing number of Fourier series coefficients in both ARIMA and ANN models. Figure 10 shows the residuals of ARIMA model M3 vs ANN model M3. The residual of ANN model is much less than the ARIMA model indicating that ANN model is better than the ARIMA model.

Table 1 summarizes the effect of Fourier series coefficients values in terms of RMSE, MAE, and MAPE. It is obvious that ANN model performs better than ARIMA model in terms of RMSE, MAE, and MAPE. Moreover, increasing the number of harmonics enhance the results as shown in ANN model M3.

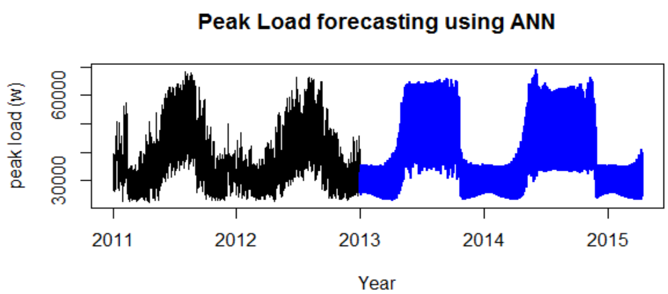

Figure 6: ANN model 2

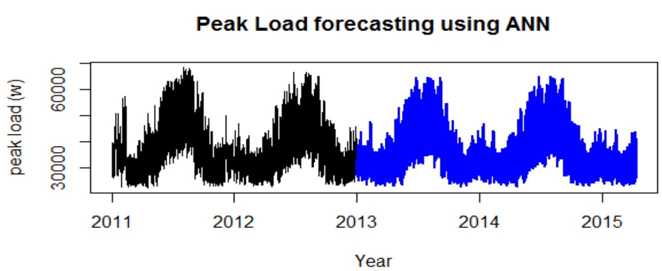

Figure 7: ANN model 3

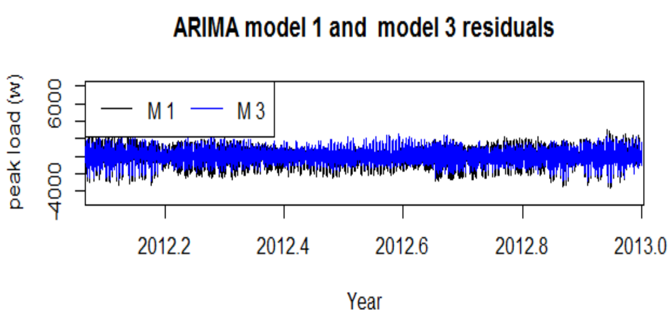

Figure 8: ARIMA models residuals

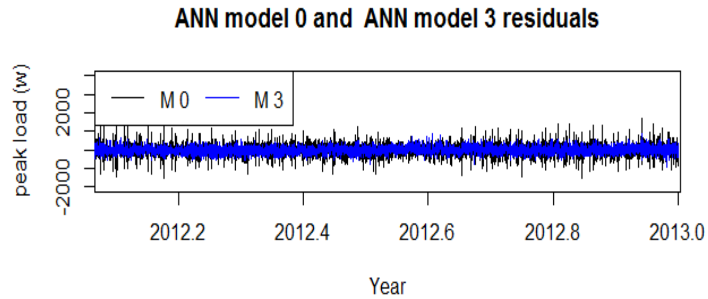

Figure 9: ANN models residuals

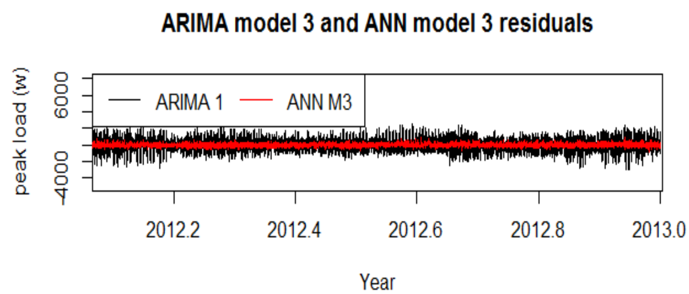

Figure 10: ARIMA and ANN models residuals

Table 1: Evaluation of the models

Parameter	RMSE(W/H)	MAE (W/H)	MAPE (%)
ARIMA (M1)	747.5604	514.4708	1.412851
ARIMA (M2)	652.1144	465.0188	1.270171
ARIMA (M3)	637.2679	456.7208	1.24839
ANN (M1)	289.7702	210.1409	0.5919032
ANN (M2)	273.8649	199.6178	0.5614839
ANN (M3)	222.546	164.8827	0.4533329

CONCLUSION AND FUTURE WORK

In this paper, we presented two main modelling techniques for electric load forecasting; statistical time series models (ARIMA) and ANN models. The proposed techniques were applied to multiple seasonal data. Through the comparison between the ARIMA and ANN model we showed that the ANN model produced better results in terms of RMSE, MAE, and MAPE. The developed ANN model is much better than the ARIMA model in case of hourly peak load from The Electric Reliability Council of Texas (ERCOT). Moreover, we introduced three ANN models representing varying Fourier series coefficients. With increasing the number of harmonics required for a specific seasonal period, better results were obtained. Thus, the forecasting accuracy of the ANN model is enhanced by adding more Fourier series coefficients that overcome the ARIMA model limitation.

ACKNOWLEDGMENTS

This research is supported by grant's number ARP2015.R17.11 under ITAC program, ITIDA Egypt.

REFERENCES

[1] P. Mandal, A. U. Haque, J. Meng, A. K. Srivastava and R. Martinez, "A novel hybrid approach using wavelet, firefly algorithm, and fuzzy ARTMAP for day-ahead electricity price forecasting," in IEEE Transactions on Power Systems, vol. 28, no. 2, pp. 1041-1051, May 2013.

[2] K. B. Sahay, N. Kumar and M. M. Tripathi, "Short-term load forecasting of Ontario Electricity Market by considering the effect of temperature," 2014 6th IEEE Power India International Conference (PIICON), Delhi, 2014, pp. 1-6.

[3] S. R. Khuntia, B. W. Tuinema, J. L. Rueda, and M. A. M. M. van der Meijden, "Time-horizons in the planning and operation of transmission networks: an overview," IET Generation, Transmission & Distribution, vol. 10, no. 4, pp. 841-848, 2016.

[4] M. Dai, Z. Yu, R. Zeng, C. Zhuang, J. Hu, T. Li, W. Zhu, "A neural network short-term load forecasting considering human comfort index and its accumulative effect," 2013 Ninth International Conference on Natural Computation (ICNC), Shenyang, 2013, pp. 262-266.

[5] George E. P. Box, Gwilym M. Jenkins, Gregory C. Reinsel, Greta M. Ljung. "Time series analysis: forecasting and control", fifth edition, Wiley, August 2015.

[6] K. Kalaitzakis, G. S. Stavrakakis and E. M. Anagnostaki, "Short-term load forecasting based on artificial neural networks parallel implementation," Electrical Power Systems Research, vol. 63, pp. 196-281, 2002

[7] P. Bunnoon, K. Chalermyanont and C. Limsakul, "Mid Term Load Forecasting of the Country Using Statistical Methodology: Case Study in Thailand," 2009 International Conference on Signal Processing Systems, Singapore, 2009, pp. 924-928.

[8] F. A. Razak, A. H. Hashim, I. Z. Abidin and M. Shitan, "Moving holidays' effects on the Malaysian peak daily load," Power and Energy (PECon), 2010 IEEE International Conference on, Kuala Lumpur, 2010, pp. 906-910.

[9] A. Esmaeili K., M. Eghlimi, M. Oloomi B., H. Shakouri G. and A. Sadeghi, "Forecasting the electrical energy price in Iran power market: A comparison between single and multi-hour models," IPEC, 2010 Conference Proceedings, Singapore, 2010, pp. 824-829.

[10] J. Huang, Y. Li and Y. Liu, "Summer daily peak load forecasting considering accumulation effect and abrupt change of temperature," 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, pp. 1-4.

[11] Nahid-Al-Masood, M. Z. Sadi, S. R. Deeba and R. H. Siddique, "Temperature sensitivity forecasting of electrical load," 2010 4th International Power Engineering and Optimization Conference (PEOCO), Shah Alam, 2010, pp. 244-248.

[12] D. C. Park, M. A. El-Sharkawi, R. J. Marks, II, L. E. Atlas, and M. J. Damborg, "Electric load forecasting using an artificial neural network," IEEE Transactions on Power Systems, vol. 6, pp. 442-449, 1991.

[13] B. Suresh Kumar, "Short Term Load Forecasting Using Artificial Neural Networks", International Journal of Research in Computer and Communication Technology, Vol 3, Issue 2, February 2014, pp. 247-255.

[14] A. Baliyan, K. Gaurav, and S. K. Mishra, "A review of short term load forecasting using artificial neural network models," Procedia Computer Science, vol. 48, pp. 121-125, 2015

[15] K. Methaprayoon, W.-J. Lee, S. Rasmiddatta, J. R. Liao, and R. J. Ross, "Multistage Artificial Neural Network Short-Term Load Forecasting Engine With Front-End Weather Forecast," IEEE Transactions on Industry Applications, vol. 43, pp. 1410-1416, 2007.

[16] Martin Längkvist, Lars Karlsson, Amy Loutfi, A review of unsupervised feature learning and deep learning for time-series modeling, Pattern Recognition Letters, Volume 42, 1 June 2014, Pages 11-24

[17] E. Busseti, I. Osband, and S. Wong, "Deep learning for time series modeling," Technical report, Stanford University, Tech. Rep., 2012.

[18] R. J. Hyndman, M. Akram, B. C. Archibald, "The admissible parameter space for exponential smoothing models", Annals of the Institute of Statistical Mathematics, June 2008, Volume 60, Issue 2, pp 407–426.

[19] M. J. Roberts, "Signal and Systems: Analysis Using Transform Methods and MATLAB", International Ed., Boston: McGraw-Hill, 2004, pp. 208 – 209.

[20] The Electric Reliability Council of Texas (ERCOT), USA, http://www.ercot.com/