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Five-Component Load Forecast in Residential Sector Using Smart Methods

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Abstract
The electrical load is affected by the weather conditions in many countries as well as in Iraq. The weather-sensitive electrical load is, usually, divided into two components, a weather-sensitive component, and a weather-insensitive component. The research provides a method for separating the weather-sensitive electrical load into five components. and aims to prove the efficiency of the five-component load Forecasting model. The artificial neural network was used to predict the weather-sensitive electrical load using the MATLAB R17a software. Weather data and loads were used for one year for Mosul City. The performance of the artificial neural network was evaluated using the mean squared error and the mean absolute percentage error. The results indicate the accuracy of the prediction model used, MAPE equal to 0.0402.

KEYWORDS: Artificial Neural Network, Mean Squared Error, Weather Sensitive Load, Medium Term Load Forecast.

I. INTRODUCTION

Accurate forecasting of electrical loads is essential to the electrical system for various purposes, including load management, plant expansion planning, intelligent operation, and accurate electrical energy pricing [1][2]. The importance of forecasting increases with the increasing use of renewable energy [3][4]. Load prediction (forecast) is to obtain future information based on previous readings that helps in taking appropriate action to achieve a balance between generation and consumption [5][6][7]. In addition to avoiding the disruption of loads at low prediction, and wastage problems in obstetrics at high prediction. Modern technologies such as demand-side management and smart grid have made accurate electrical load prediction more important [8][9]. On the other hand, due to the increasing use of renewable energy sources, accurate forecasting of electrical loads ensures optimum energy savings, battery operation, energy management, and storage [10][11]. Electrical load forecasting is classified according to the forecast horizon into three types: short-term forecasting (a few hours to one week), medium-term forecasting (weeks to a year), and long-term forecasting (more than a year) [12][10]. Prediction of medium-term load forecast has not been studied extensively, compared to the prediction of short-term or long-term loads [15]. Many traditional and smart methods have been used to predict the electrical load such as time series analysis [16][17], artificial neural networks [13][18], wavelet transform [19], vector support machine [20][16], fuzzy logic [8][11], and genetic algorithm [7][21]. Electrical loads in many countries, including Iraq, are affected by weather conditions, especially temperatures. Weather-sensitive loads are studied by dividing them into two components: weather-sensitive and other weather-insensitive. Countries are increasingly suffering from the impact of electrical loads due to weather conditions in winter and summer. Since electrical loads differ in winter and summer, it is best to separate weather-sensitive loads into three components. The first is not affected by weather conditions (base component). The second is affected by high temperatures. The third is affected by low temperatures. Separating electrical loads into three components leads to load management with greater accuracy and efficiency [22][23][24]. The research aims to prove the efficiency of the five-component load prediction model and the main points for its application in predicting the loads as a general case.

II. RESEARCH METHOD

In current forecasting methods that predict weather-sensitive loads, the electrical load divide into two components. A weather-insensitive component and a weather-sensitive component, this component includes the summer and winter electrical load. Electrical loads vary in summer and winter as well as periods. Therefore, separating the weather-sensitive component gives better accuracy, when it is divided into two components, one for summer and the other for winter.

TABLE I
THE MAIN POINTS OF LITERATURE WORKS

	Year	**Forecast Horizon**			**Method**								**Considered issues**		
		S	*M*	*L*	GA	ANN	Logic Fuzzy	Holt Winter	Time series	SVM	SVR	LSTM	*Weather*	*Days and Holidays*	*Load Type*
[17]	2012	x	x					x					x		
[19]	2013		x			x							x		x
[7]	2014			x	x										
[20]	2015			x	x	x	x	x							
[16]	2017	x						x			x		x		x
[14]	2017	x				x							x	x	
[8]	2018	x				x	x								
[12]	2019	x									x	x	x		
[18]	2020	x								x					x
[2]	2020	x							x					x	
[13]	2021		x			x							x		**x**

In this paper, weather-sensitive loads are predicted by five components. Lighting and Domestic (Domestic component refers to electrical appliances used throughout the year, such as television, radio, dishwasher...etc.) These components are not affected by weather conditions. The cooling component is influenced by high temperatures. While Air Heating and Water heating components are influenced by the temperature drop. An artificial neural network was used due to its high efficiency in electrical load prediction.

A. Artificial Neural Network

Artificial Neural Networks are a good option for predicting loads, due to their ability to find a complex non-linear relationship between load and factors affecting it. An artificial neural network (ANN) is designed to simulate the way the human brain processes data. They are quite different from statistical methods of analysis. An artificial neural network builds its knowledge by discovering patterns and relationships in data and by learning or training, not by programming. The ANN technique is used to find the relationship between multiple input variables and output variables when it is difficult to find the relationship between them mathematically. It highlights the importance of ANNs in classification, pattern recognition, prediction, modeling, and automated control. Artificial neural networks do not require knowledge of the data source but require large training sets [25]. Network structure consists of nodes (neurons) connected by links and usually organized into many layers. Each node in the layer receives and processes the weighted inputs from a previous layer and transmits its output to nodes in the next layer through links. Each link is assigned a weight, which is a numerical estimate of the conduction force. The weighted aggregation of node inputs is transformed into outputs according to the transfer function (usually a sigmoidal function). Most ANNs have three or more layers as shown in Fig. 1.

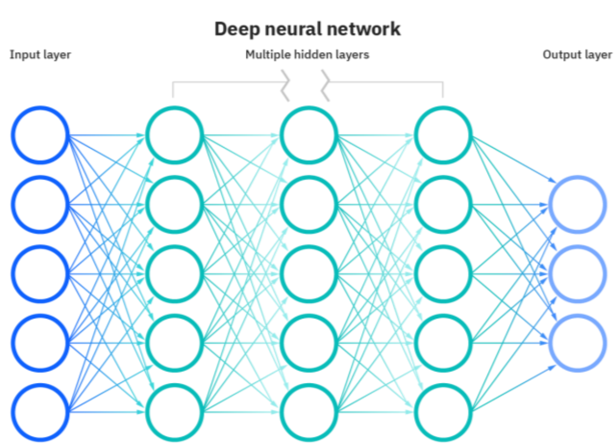

Fig. 1: Deep neural network with 3 hidden layers.

The first layer, the input layer, is used to deliver data to the network (contains nodes equal to the number of input variables). The last layer, the output layer, is used to output the output variables (contains nodes with the same number of output variables). and one or more intermediate layers, which are used to act as a set of isotropic (hidden layers) [26].

B. Artificial neural network Modeling

The artificial neural network created using MATLAB. After defining the training and testing data set, the neural network is created and the advantages of this network are determined, including the type of network, number of hidden layers, number of their neurons, transfer function, training function, and the method of evaluating the performance of the network. A feed-forward backpropagation network created, with thirteen neurons in the input layer and ten hidden layers, has ten neurons in each hidden layer, five neurons in output layers, refers to the forecast five-component load, as show in Fig. 2.

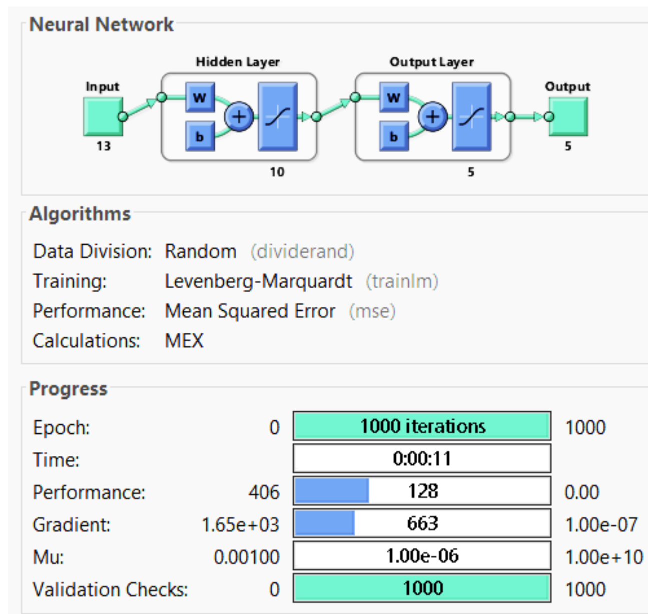

Fig. 2: Feedforward neural network

Mean Absolute Percentage Error and Mean Squared Error is used to evaluate network performance:

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \left| \frac{Y_i - Y'_i}{Y_i} \right|}{n} \tag{1}$$

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} (Y_i - Y'_i)^2}{n} \tag{2}$$

where: Y: the actual load, Y': the forecast load, n: number of samples, i: sequence of the day.

C. Case Study

In this research, Mosul in northern Iraq load data for the city of were used to evaluate the performance of forecasting models. Figure 3. shows the data of peak daily load and weather data for a year. Readings started from April 1 to March 31 2010.

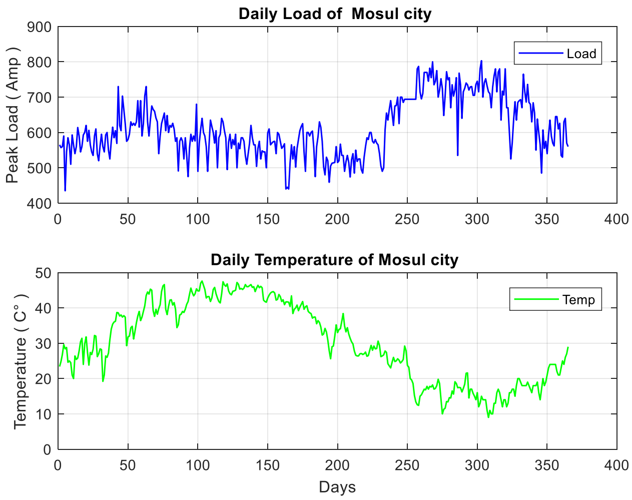

Fig. 3: Mosul Data

Electricity is consumed in the residential sector, the government sector, the industrial sector, the agricultural sector, the commercial sector, and the tourism sector. The residential sector represents the largest electricity consumption sector in Iraq. The residential electrical load consists of many components. They are constantly changing due to many factors affecting these components. Temperature is the most important climatic factor affecting the change of load. The electrical load in the residential sector can be classified into five main components according to the level of consumption as follows:

- Lighting.
- Domestic.
- Cooling.
- Air Heating.
- Water Heating.

Figure 4 shows the consumption rates of electric load components in the residential sector for selected months of summer and winter, August 2010 and January 2011.

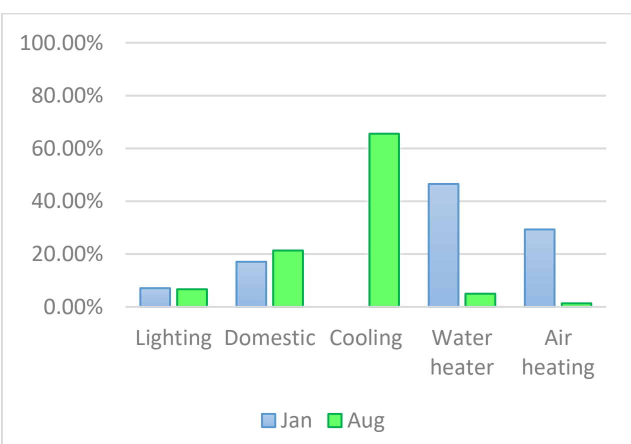

Fig. 4: Percentages of electrical load components

D. Training and Test ANN

The ANN model must go through a training phase, which is the second phase before it can be applied in predicting electrical loads. The goal of the training process is to adjust the network weights and biases and reduce the error between the network output and the desired output [19]. A feed-forward backpropagation neural network was used and trained with the Levenberg- Marquardt back propagation (MLP) algorithm. It adjusts the network's weights and biases very quickly. Training is an iterative process that continues until an acceptable level of error is gained.

Input data include daily peak load, daily maximum and minimum temperatures, and day sequence. The output is three compounds load predicting as shown in Fig 5. The load and weather data for the period (April 1, 2010, to March 31, 2011) were used to train and test the network. The data set was divided into two groups:

- 50% of the data set is used for training.
- The other 50% is used to test the model.

After training the network and obtaining the lowest error value, the accuracy of the model is tested with a set of data. After the network is trained and tested, it can be given new input information to predict the desired output.

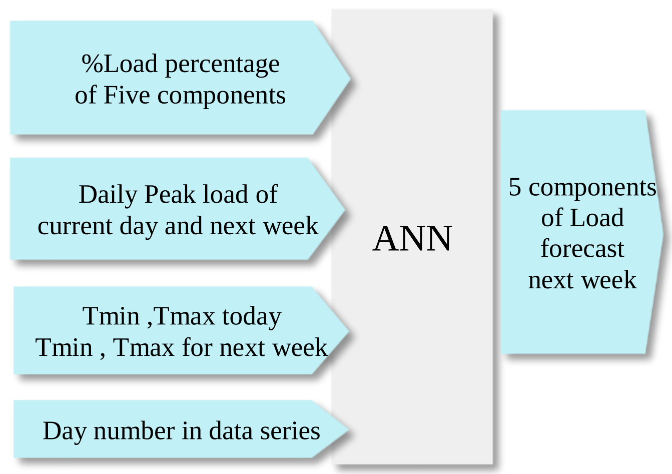

Fig. 5: Data set of ANN model

III. ANN Prediction Results

The artificial neural network model was applied to the weather and load data for the city of Mosul for the period (1 April 2010 - 31 March 2011). The input data includes the maximum and minimum temperatures, the daily peak load, load percentage of Five components and the day sequence. Network training performance was evaluated using mean square error (MSE).

Figure 6. shows the training performance of the neural network. Network training continues to reach maximum convergence of the output values and the target. The training stops at (1000 iterations). Figure 7. shows the regression of the neural network in the training and testing, and the value of the Correlation coefficient (R) is (0.98) for training and testing respectively, Where the results of the model (Output) fit with the original (Target) values very much.

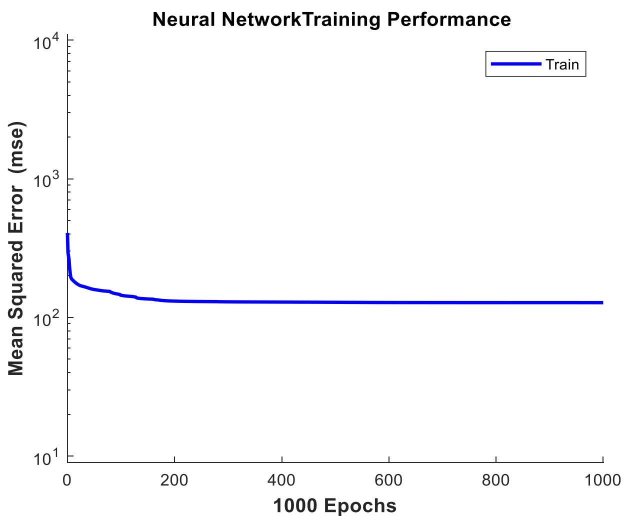

Fig. 6: Artificial neural network training performance.

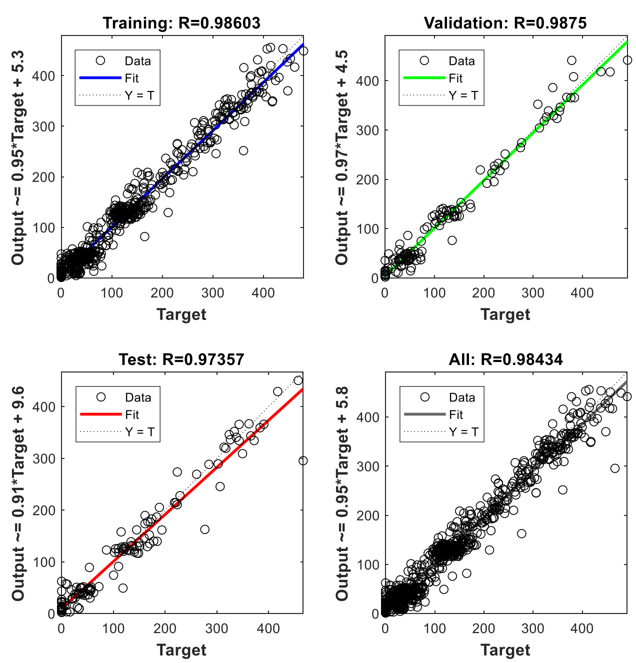

Fig. 7: Regression of the neural network

The trained neural network in Fig. 8. was tested with a set of data to predict the five load compounds. The base component (Lighting and Domestic) always appears because unaffected by the weather, while the summer component (Cooling) appears as the temperature rises and disappears when the temperature drops, while the winter component (Air Heating and Water Heating) appears when the temperature drops and disappears as the temperature rises.

The results indicate the efficiency of the artificial neural network in predicting weather-sensitive load components. Table II shows the mean absolute percentage error (MAPE) for load prediction. The mean absolute percentage error (MAPE) for two weeks load forecasting is equal to (4.02%). Figure 9 shows the two weeks load forecasting results.

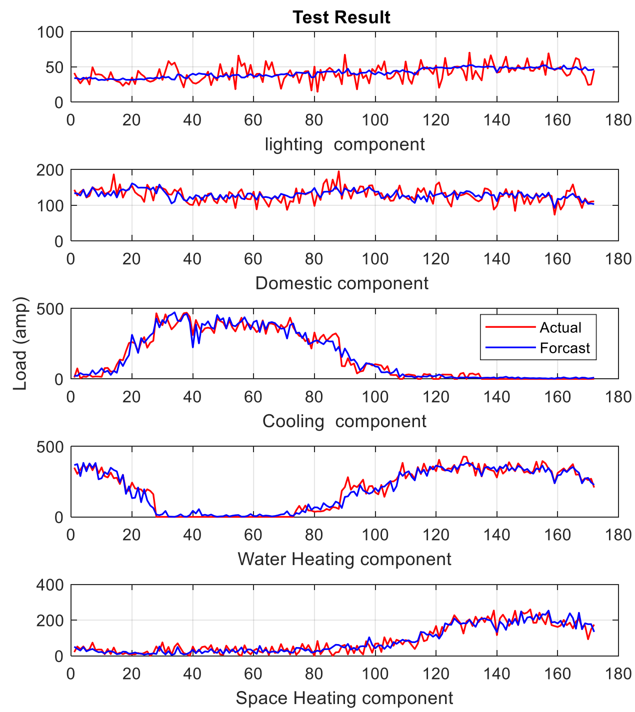

Fig. 8: Neural network testing result.

By comparing the current research with previous research that used the same data [17], but the previous research predicted the total load only, while the current research obtains the five load components each separately, to know the properties of each component and its relationship to the weather and the ratio of capacity in the daily load's.

The error (MAPE) for the previous search model was 4.58%. While the proposed prediction model equals 4.02%. This means that the separation of components improves the prediction model by 0.56%, this percentage is considered good because the new model gives us accurate information about each component as well as its relationship to the weather during the year.

TABLE II

LOAD FORECASTING RESULTS

No.	Actual Load	Forecast Load	MAPE
1	635	628.68	0.00071
2	590	582.59	0.00089
3	570	538.23	0.00398
4	562	546.34	0.00198
5	645	633.24	0.0013
6	645	688.79	0.00484
7	610	607.89	0.00024
8	626	617.76	0.00094
9	535	454.67	0.01072
10	530	566.01	0.00485
11	630	634.24	0.00048
12	640	649.25	0.00103
13	570	593.47	0.00294
14	560	601.51	0.00529
		Total	0.0402

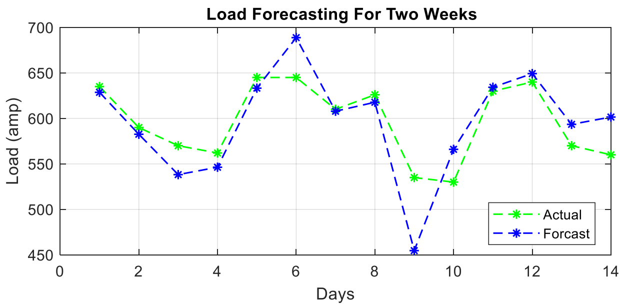

Fig. 9: Load Forecasting Results

IV. Conclusions

The research used a new method to predict the weather-sensitive electrical load by five components. Because of the different characteristics and specifications of loads in summer and winter. Mosul city loads have been forecast for a year using Artificial neural network. The results indicate the accuracy of the prediction model when predicting five load components, the mean absolute percentage error (MAPE) load forecast is equal to (4.02%). We conclude from the research that separating the weather-sensitive load into Five components increases the prediction accuracy significantly.

Conflict of Interest

The authors have no conflict of relevant interest to this article.

References

[1] M. A. Hammad, B. Jereb, B. Rosi, and D. Dragan, “Methods and Models for Electric Load Forecasting: A Comprehensive Review,” Logist. Sustain. Transp., vol. 11, no. 1, pp. 51–76, 2020.

[2] T. Sun, T. Zhang, Y. Teng, Z. Chen, and J. Fang, “Monthly Electricity Consumption Forecasting Method Based on X12 and STL Decomposition Model in an Integrated Energy System,” Math. Probl. Eng., vol. 2019, no. 3, 2019.

[3] M. Selim, R. Zhou, W. Feng, and P. Quinsey, “Estimating Energy Forecasting Uncertainty for Reliable AI Autonomous Smart Grid Design,” Energies, vol. 14, no. 1, p. 247, 2021.

[4] M. Q. Raza, N. Mithulananthan, J. Li, and K. Y. Lee, “Multivariate Ensemble Forecast Framework for Demand Prediction of Anomalous Days,” IEEE Trans. Sustain. Energy, vol. 11, no. 1, pp. 27–36, 2020.

[5] A. Gupta and P. K. Sarangi, “Electrical load forecasting using genetic algorithm based back- propagation method,” ARPN J. Eng. Appl. Sci., vol. 7, no. 8, pp. 1017–1020, 2012.

[6] M. Lekshmi and K. N. Adithya Subramanya, “Short-term load forecasting of 400kV grid substation using R-tool and study of influence of ambient temperature on the forecasted load,” 2019 2nd Int. Conf. Adv. Comput. Commun. Paradig. ICACCP 2019, pp. 1–5, 2019.

[7] R. Behera, B. B. Pati, and B. P. Panigrahi, “A Long Term Load Forecasting of an Indian Grid for Power System Planning,” J. Inst. Eng. Ser. B, vol. 95, no. 4, pp. 279–285, 2014.

[8] E. Akarslan and F. O. Hocaoglu, “A novel short-term load forecasting approach using Adaptive Neuro-Fuzzy Inference System,” Proc. - 2018 6th Int. Istanbul Smart Grids Cities Congr. Fair, ICSG 2018, pp. 160–163, 2018.

[9] N. Shabbir, R. Amadiahangar, H. A. Raja, L. Kutt, and A. Rosin, “Residential Load Forecasting Using Recurrent Neural Networks,” Proc. - 2020 IEEE 14th Int. Conf. Compat. Power Electron. Power Eng. CPE-POWERENG 2020, pp. 478–481, 2020.

[10] G. Weng, C. Pei, J. Ren, H. Jiang, and J. Xu, “Modeling and Forecasting of Wind Power Output of Urban Regional Energy Internet Based on Deep Learning,” Journal of Physics: Conference Series, vol. 1732, 2021.

[11] T. Fujiwara and Y. Ueda, “Load forecasting method for Commercial facilities by determination of working time and considering weather information,” 7th Int. IEEE Conf. Renew. Energy Res. Appl. ICRERA 2018, vol. 5, pp. 336–341, 2018.

[12] H. L. Imam, M. S. Gaya, and G. S. M. Galadanci, “Short term load forecast of Kano zone using artificial intelligent techniques,” Indones. J. Electr. Eng. Comput. Sci., vol. 16, no. 2, pp. 562–567, 2019.

[13] Yamama A. I. Al-Nasiri and Majid S. M. Al-Hafidh, “Three Component Weather-Sensitive load Forecast using Artificial Neural Network,” Al-Rafidain Eng. J., vol. 26, no. 2, pp. 143–149, 2021.

[14] K. B. Sahay, S. Sahu, and P. Singh, “Short-term load forecasting of Toronto Canada by using different ANN algorithms,” 2016 IEEE 6th Int. Conf. Power Syst. ICPS 2016, 2016.

[15] S. Nuchprayoon, “Forecasting of daily load curve on monthly peak day using load research data and harmonics model,” Proc. - 6th IEEE Int. Conf. Control Syst. Comput. Eng. ICCSCE 2016, no. November, pp. 338–342, 2017.

[16] W. Yang, L. Qiuyu, C. Qiuna, L. Sijie, Y. Yun, and Y. Binjie, “Short-term Load Forecasting Based on Load Decomposition and Numerical Weather Forecast,” IEEETrans. Power Syst., 2017.

[17] Majid S. M. Al-Hafidh and G. H. Al-maamary, “Short term electrical load forecasting using holt-winters method,” Al-Rafidain Engineering, vol. 3, no. 3. pp. 2697–2705, 2011.

[18] A. O. Hoori, A. Al Kazzaz, R. Khimani, Y. Motai, and A. J. Aved, “Electric Load Forecasting Model Using a Multicolumn Deep Neural Networks,” IEEE Trans. Ind. Electron., vol. 67, no. 8, pp. 6473–6482, 2020.

[19] Majid S. M. Al-Hafidh and M. A. Gasim, “Application of Artificial Neural Networks in Mid-Term Load Forecasting for Residential Sector in Mosul City (Iraq),” in The Second Engineering Conference Golden Jubilee - University of Mosul, vol. 1, pp. 1–10, 2013.

[20] D. Sonika, S. D. S, and K. Daljeet, “Long Term Load Forecasting Using Soft Computing Techniques”, vol. 6, no. 6, pp. 450–457, 2015.

[21] F. Li and X. Zhao, “The Application of Genetic Algorithm in Power Short-term Load Forecasting,” IPCSIT, vol. 50, 2012.

[22] Majid S. M. Al-Hafidh, M. Al-Nama, and A. Al-Fahadi, “Determination of Residential Electrical Load Components In Iraqi North Region,” Iraqi J. Electr. Electron. Eng., vol. 13, no. 2, 2017.
[23] Majid S. M. Al-Hafidh, M. Al-Nama, and A. Al-Fahadi, “Utilization of Solar Water Heaters to Reduce Residential Electrical Load,” UHD J. Sci. Technol., vol. 1, no. 1, pp. 23–26, 2017.
[24] Majid S. M. Al-Hafidh, A. S. Al-Fahadi, and Y. A. Mahmoud, “Separating the components of the electrical load in the Iraqi distribution system,” in The Fifth International Arab Libyan Conference on Electrical and Electronic Engineering, 2010.
[25] J. P. Teixeira and P. O. Fernandes, “Tourism Time Series Forecast -Different ANN Architectures with Time Index Input,” Procedia Technol., vol. 5, pp. 445–454, 2012.
[26] A. R. Senthil Kumar, K. P. Sudheer, S. K. Jain, and P. K. Agarwal, “Rainfall-runoff modelling using artificial neural networks: Comparison of network types,” Hydrol. Process., vol. 19, no. 6, pp. 1277–1291, 2005.