Three-Component Weather-Sensitive Load Forecast 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 (baseload). The impact of the weather-sensitive component includes the summer and winter periods, without distinguishing between them.

The characteristics and specifications of this component (weather-sensitive component) differ in summer and winter due to the different loads in the seasons, so it is best to separate these two components into two independent components. The research provides a method for separating the weather-sensitive electrical load into three components, the summer component, the winter component, and the base component. 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 in the research.

Keywords

Weather Sensitive Load Forecast, Artificial Neural Network, Mean Squared Error, IRAQI Loads.

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 mades 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 [12][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].

In this paper, weather-sensitive loads were divided into three components. The first compound is insensitive to weather (the base compound). The second compound is sensitive to temperature rise (summer compound). The third compound is sensitive to temperature drops (winter compound). An artificial neural network has been used to predict weather-sensitive electrical loads. Weather data and electrical loads for the city of Mosul in northern Iraq for one year were used to train and test the network. Then the network performance was tested using mean squared error and mean absolute percentage error. The results demonstrated the accuracy of the artificial neural network in predicting the three components of the load.

Research Method

In current forecasting methods that predict weather-sensitive loads, the electrical load divide into two components. A weather-insensitive component (a primary 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.

In this paper, weather-sensitive loads are predicted by three components. The first component is not affected by weather conditions (base component). The second component, the summer component (influenced by high temperature). The third component, the winter component (influenced by the temperature drop). An artificial neural network was used due to its high efficiency in electrical load prediction.

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][26].

The 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. 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 [27].

Artificial neural network Modeling

The artificial neural network created using MATLAB software. 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 three output layers. refers to the forecast three-component load, and ten hidden layers, with ten neurons in each hidden layer, and eight input layer as show in Fig. 1. Mean Absolute Percentage Error and Mean Squared Error is used to evaluate network performance:

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Y_i - Y'_i}{Y_i} \right|}{n} \quad \ldots\ldots\ldots\ldots\ldots (1)$$

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

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

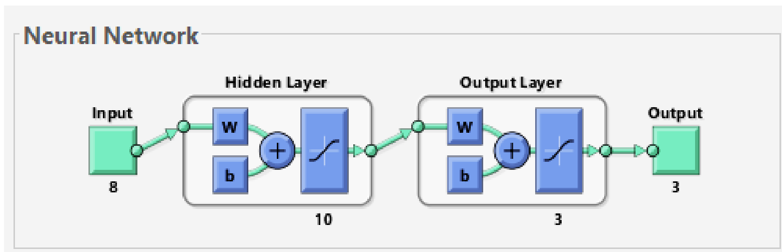

FIGURE 1. feedforward neural network

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 2. 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.

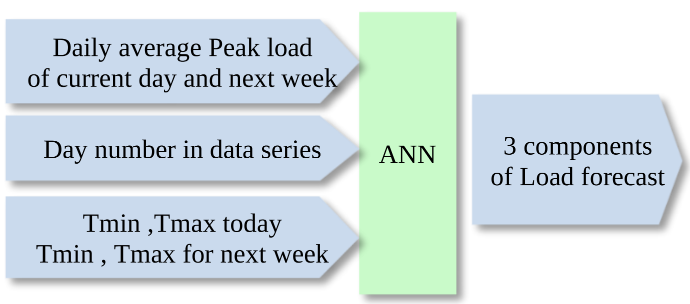

FIGURE 2. Data set of ANN model

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.

Electrical load 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 pregnancy. Figure 3. shows the electrical load of the city of Mosul for a full year, starting on 1/4/2010 and ending on 3/31/2011. These data were recorded and obtained from the General Directorate of North Electricity Distribution /

Northern Control Center / Cultural Group Station. The electrical load in the residential sector can be classified into five main components according to the level of consumption as follows:

- Lighting.
- Home Appliances.
- Cooling.
- Heating.
- Water heater.

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.

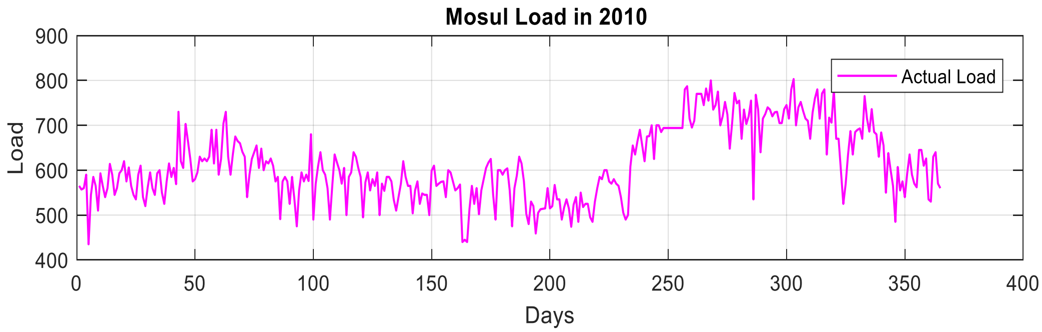

FIGURE 3. The electrical load of Mosul

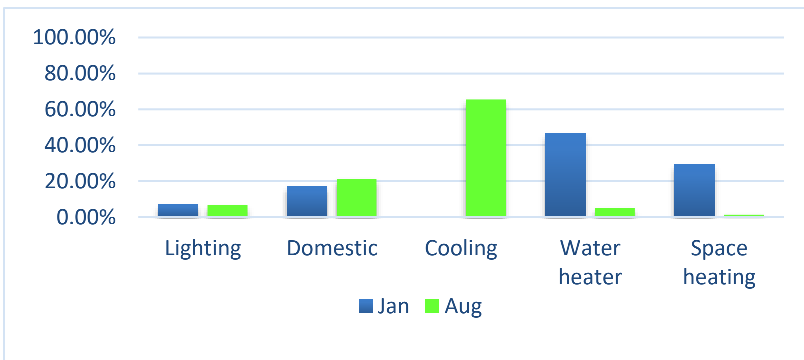

FIGURE 4. Percentages of electrical load components

Weather data

The data of the maximum and minimum temperatures for the city of Mosul were used for a whole year, starting on 1/4/2010 and ending on 3/31/2011. This information was obtained from the General Authority for Meteorology and Seismic Monitoring (Department of Meteorology, Mosul). Figure 5. shows the weather data.

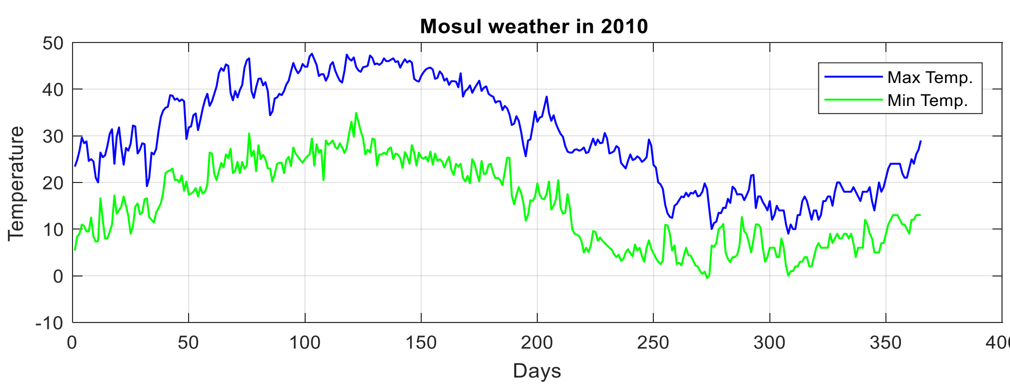

FIGURE 5. Maximum and Minimum Temperatures

Results and discussion

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, 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). Where the results of the model (Output) fit with the original (Target) values very much.

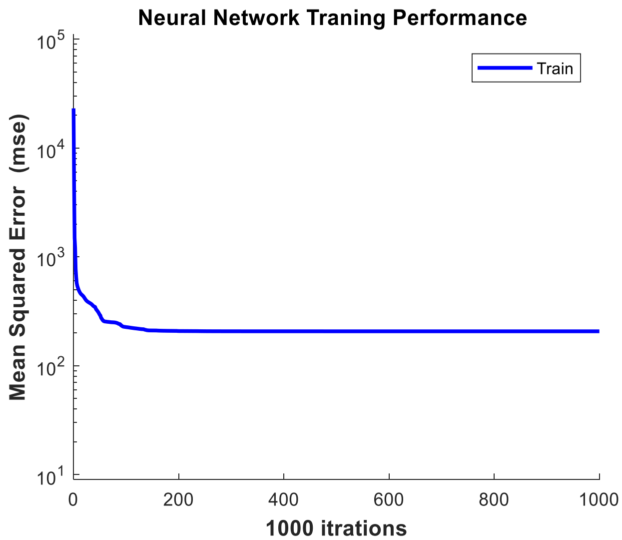

FIGURE 6. Artificial neural network training performance

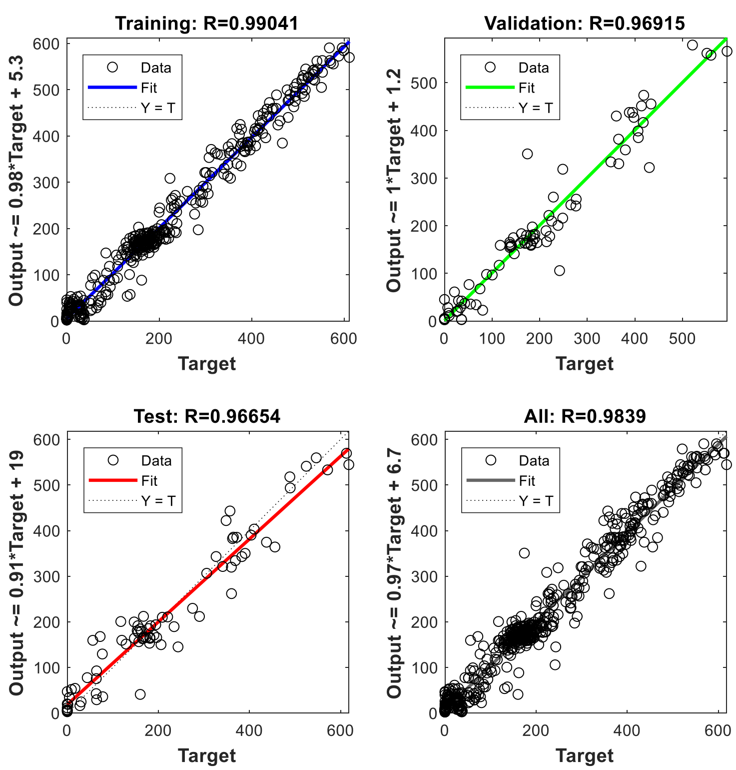

FIGURE 7. Regression of the neural network in training and testing

The trained neural network was tested with a set of data to predict the three load compounds. Table 1. shows the mean absolute percentage error (MAPE) for the prediction of the three load components. We note that the summer component has the lowest prediction error, then the base component, and then the winter component. Figure 8. shows the test results for the artificial neural network. The base component always appears because unaffected by the weather, while the summer component appears as the temperature rises and disappears when the temperature drops, while the winter component appears when the temperature drops and disappears as the temperature rises. Table 2. shows the results of the prediction model in the training and testing. The results indicate the efficiency of the artificial neural network in predicting weather-sensitive load components.

TABLE 1. Artificial neural network test results

Error	Base	Summer	Winter	Total
MAPE	0.0915	0.9103	0.387	0.0275

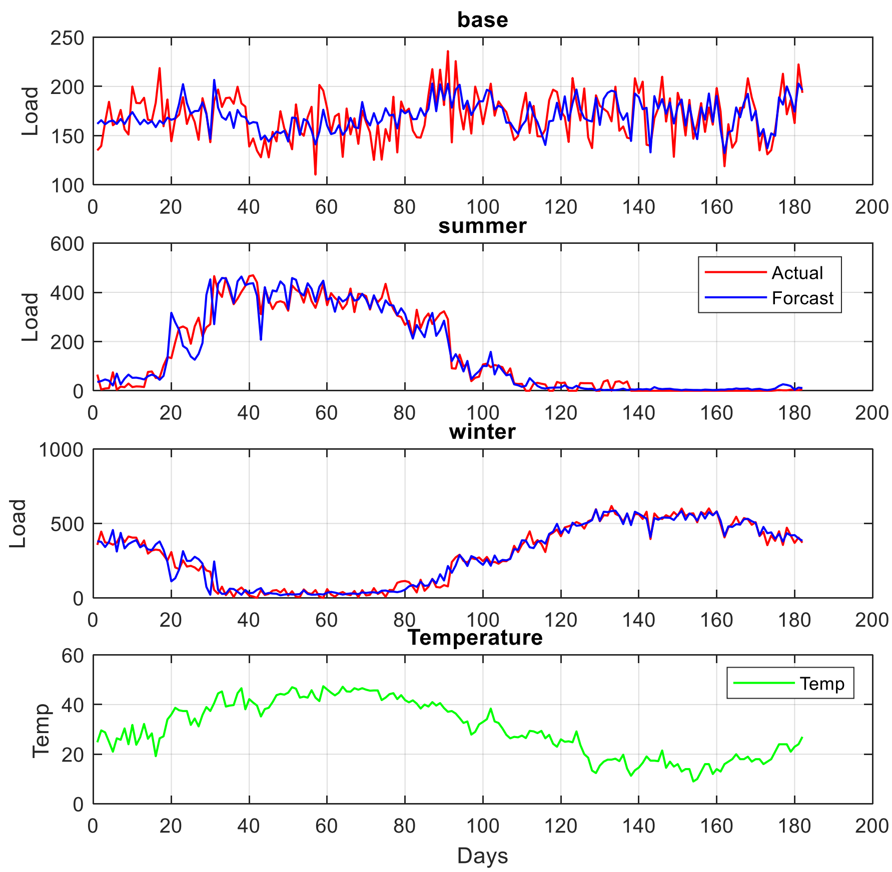

FIGURE 8. Artificial neural network test results

TABLE 2. Prediction Model Results

Type and structure of ANN	3 layers FF BP with structure (8-10-3)
Transfer functions	Tan-sig
No. of epochs	1000
MAPE% for training	2.61%
MAPE% for testing	2.75%
Correlation coefficient (R) for training	0.99
Correlation coefficient (R) for testing	0.966

Validation of the prediction model

The prediction results were compared with the results of the reference [19]. The research proposes, in the reference, to predict medium-term load using an artificial neural network to predict load in the city of Mosul, northern Iraq. The same data was used in both studies. Table 3. shows the prediction results for the published research. When comparing the results of the current research shown in Table 2. with the prediction results of the published research shown in Table 3. we conclude that the new model is a more accurate and efficient prediction.

TABLE 3. Prediction results for a published research

Type and structure of ANN	3 layers FF BP with structure (12-5-1)
Transfer functions	Tan-sig
No. of epochs	1000
MAPE% for training	3.39 %
MAPE% for testing	4.58 %
Correlation coefficient (R) for training	0.938
Correlation coefficient (R) for testing	0.891

CONCLUSION

The electrical load in Iraq and many countries are affected by weather conditions. When predicting a weather-sensitive pregnancy, the pregnancy is divided into two components, a weather-sensitive component, and a weather-insensitive component. The effect of a weather-sensitive component extends to the summer and winter periods, without distinguishing between them.

Because of the different characteristics and specifications of loads in summer and winter, it is preferable to separate these two components into two independent components. The research uses a new method to predict the weather-sensitive electrical load with three components, the summer component, the winter component, and the base component. Using an artificial neural network Mosul city loads have been forecast for a year.

The results indicate the accuracy of the prediction model when predicting three load components. By comparing the results of the model with previous research, it was found that the proposed model is much more accurate than the previous research. We conclude from the research that separating the weather-sensitive load into three components increases the prediction accuracy significantly.

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