

Review Article:

Monthly Peak-load Demand Forecasting for Sulaimani Governorate Using Different Weather Conditions Based on ANN Model

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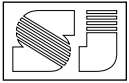
Abstract

Mid-term forecasting of load demand is necessary for the correct operation of electric utilities. There is an on-going attention toward putting new approaches to the task. Recently, Artificial Neural Network has played a successful role in various applications. This paper presents a monthly peak-load demand forecasting for Sulaimani (located in northern Iraq) using the most widely used traditional method based on an artificial neural network, the performance of the model is tested on the actual historical monthly demand of the Governorate for the years 2013 to 2017. The standard mean absolute percentage error method is used to evaluate the accuracy of forecasting models, the results obtained shows a very good estimation of the load. The mean absolute percentage error MAPE is 0.056.

1. Introduction

Power system planning starts with the forecast of load requirements. With the fast growth of power systems networks and increase in their

complexity, many factors have become influential in electric power generation, demand or load management. The forecasting of electricity demand has been one of the major research fields



in electrical engineering. Massive investment decisions for network reinforcement and expansions are made based on the load forecast. Hence it is necessary to have accurate load forecast to carry out proper planning ^[1] ^[2]. Although, Load forecasting is one of the major factors for economic operation of power systems. Future load forecasting is also important for network planning, infrastructure development and so on. Power system load forecasting can be classified into three categories, namely, short term, medium term and long term load forecasting.

The periods for these categories are not defined clearly in literature. Thus different authors use different time periods to define these categories. But roughly, short-term load forecasting covers hourly to weekly forecast. These forecasts are often needed for day to day economic operation of power generating units. Mid-term load forecasting has period time in three months to three years, Maintenance of plants and networks are often roofed in these types of forecast. Long term forecasting on the other hand deals with forecast from few months to one year.

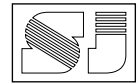
It is primarily intended for capacity expansion plans, capital investments and corporate budgeting. These types of forecasts are often complex in nature due to future uncertainties such as planning and extension of existing power system networks for both the utility and consumers required long- term forecasts. ^[3]

The system load is a random non-stationary process composed of thousands of individual components. The system load behavior is influenced by a number of factors, which can be classified as: economic factors, time, weather and random effects. The economic environment in which the utility operates has a clear effect on the electric demand consumption patterns, such as the service area demographics, level of industrial activity, changes in farming sector etc..^[4]

For the present, there are many algorithms for load forecasting in the computation intelligence like fuzzy logic ^[5], neural network, genetic ^[6]. Many research purposed the article for load forecasting in the power system field : short term load forecasting using autoregressive integrated moving average (ARIMA) and artificial neural network (ANN) method based on non-linear load, a novel method approach to load forecasting using regressive model and artificial neural network (ANN model), the combination of artificial neural network (ANN), Genetic algorithm, and Fuzzy logic (Fs) method are proposed for adjusting short-term load forecasting of electric system. Genetic algorithm is used for selecting better rules and back propagation algorithm is also for this network, papers show that more accuracy results and faster processor than other forecasting methods ^[7].

The aim of this paper is to provide a monthly peak-demand forecast for Sulaimani Governorate (located in northern Iraq). This forecast is of special importance to this region because of the present shortage of generating capacity and the need for extensive load shedding. It is thus important to estimate what the near term demand will be, especially in the peak-demand months, as a key input in determining the availability of enough generating capacity to meet the demand ^[8].

Sulaimani is one of the four Northern Governorates of Iraq (Iraqi Kurdistan Region). It is bounded by Iran; Erbil Governorate and Kirkuk Governorate. The land area of the Governorate is about 18,240 Sq.Km. The city of Sulaimani is located in 335 km northeast to Baghdad. This study is tried to find out the way to forecast the electrical power load in Sulaimani Governorate power distribution network by using artificial neural network with the help of Matlab software. The input is involved 3 feature; precipitation,



temperature and humidity. This parameters effect on power consumption directly.

Mean square error is used as performance measure. The method of learning in ANN which is used in this paper is feed forward back propagation. Finally by comparing different cases is tried to find best solution to estimate the load demand.

This dataset consists of 5 years of average monthly load collected 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 2013 to 31st October 2017. The dataset is also accompanied by temperature, humidity and precipitation collected, which can be used to forecast the demand.

2. The Load Profile of Sulaimani Governorate

There is a severe shortage of electricity supply in Sulaimani Governorate. Main sources of electricity supply are Dokan Hydro Power station (5*80MW), Derdandikhan Hydro Power station (3*83MW), Sulaimani Combined Cycle Gas Power Plant (SCCGPP) which is consists of 10 units (8 simple cycle 125 MW per unit and 2 combined cycle 250 MW per unit),

Tasluja Heavy Fuel Power Plant (51 MW), and Bazyan Gas Power Plant (4 * 125 MW), which is also supply Erbil and Dhuk Governorates,. However, the available supply from the above sources dose not meets the power requirements in the Governorate. Consumers are provided for a very short duration, sometimes ten hours per day depending on the generation capacity.

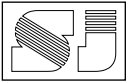
Monthly energy consumption demand (Unit in MWh) data is recorded form (ECC) Kurdistan region from 2013 to 2017. Fig.1 shows the relationship between energy consumption demand and time.

We consider the period from 2013 to 2017 to establish the parameters in forecast model. The original signal (behavior) of energy consumption demand can be seen in Fig.1. It grew the higher demand every year. The maximum demand is occurred on months 11,12,1,2,6,7,8 and Minimum demand is occurred in months 3,4,5,9,10. Kurdistan regions climate is characterized by cool winters and hot summers. This extreme temperature swing affects the demand, and producing a typical summer and winter peak demand periods each year. The monthly peak temperature profile for the years 2013 to 2017 is shown in Fig. 2.

3. Load Forecasting Using ANN

A large variety of artificial intelligence and statistical techniques have been developed for load forecasting. Some of the methods like; Similar day approach, Regression methods, Time series, Neural network, Expert systems, Fuzzy logic are used now a days, among them, artificial neural network is one of a good choice to apply for the load demand forecasting problem because this technique is not requiring explicit models to represent the complex relationship between the load demand and factors.

ANN methods are particularly attractive, as they have the ability to handle the nonlinear relationships between load and the factors affecting it directly from historical data. Artificial neural networks ANN use a dense interconnection of computing nodes to approximate nonlinear functions each node constitutes a neuron and performs the multiplication of the input-signals by constant weight, sums up the results and maps the sum to a nonlinear activation function g , the result is then transferred to its input^[9].



3.1. Basic Theory- feed forward back propagation

In this paper, we use back propagation feed-forward neural network to model the problem. Fig. 1 shows an example of ANN structure; each neural network has at least three layers, input layer, a hidden layer and output layer. In a typical Multilayer network, the input units which are denoted by X_i are connected to all hidden layer units which are defined by Y_j and the hidden layer units are connected to all output layer units which are denoted by Z_k .

The elements W_{ij} or V_{ij} of the weight matrix associate the weight of each connection between the input to hidden and hidden to output layer units. The hidden and output layer units also receive signals from weighted connections (bias) from units whose values are always 1.

In each output and hidden units the incoming signals from the previous layer sums together and apply an activation function to form the response of the net for a given input pattern.

$$X_i = \text{input } [i] \quad (1)$$

$$(Y_j) = f b_j + \sum X_i W_{ij} \quad (2)$$

$$(Z_k) = f b_k + \sum Y_j V_{jk} \quad (3)$$

To determine the error each output will be compare its output (Z_k) with the actual output value which is identified by d_k . Then according to the calculated error, δ_k will be determined. δ_k is a factor which is used to distribute the error at Z_k back to all units in the previous layer.

$$\delta_k = f'(Z_k)(d_k - Z_k). \quad (4)$$

Factor δ_j will be computes for each hidden unit. This factor is a weighted sum of all the back propagated delta terms from units in the previous

layer multiplied by the derivative of the activation function for that unit.

$$\delta_j = f'(Y_j) \sum \delta_k V_{jk}. \quad (5)$$

In the next step the new value of bias and each element of weight matrix will be calculated where η is a learning rate coefficient that is given a value between 0 and 1 at the start of training.

$$b_j(\text{new}) = b_j(\text{old}) + \eta \delta_j. \quad (6)$$

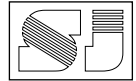
$$W_{ij}(\text{new}) = W_{ij}(\text{old}) + \eta \delta_j X_i \quad (7)$$

In each iteration it will be checked if the stop condition is occurred or not. The stop condition can be reaching error threshold, defined iteration and etc.^[10, 11]

3.2. Problem formulation & methodology

Following steps have been followed by the investigator to formulate the above said problem:

- a- First of all historical weather and load data is scrutinized. All monthly and daily predictions have been read.
- b- Then data base has been created by the investigator for developing load forecasting model.
- c- Accordingly temperature and humidity have been differentiated as average value.
- d- Also the rainy season and predicted rainfall has been considered for making the algorithm for midterm load forecasting.
- e- After this classification some ANN technique has been used to train these input variables for getting the expected outcome. System has been simulated with the help of MATLAB/ SIMULINK.
- f- Then percentage error (PE) has been calculated for the given forecasting model.



3.3. Accuracy of Forecasted

In order to evaluate forecasting accuracy of the whole procedure the following indices have been calculated in equations (8 and 9), Mean Square Error (MSE) for each month of forecasting:

$$MSE = \sum_{i=1}^M \frac{(Actual_i - Forecast_i)^2}{M} \quad (8)$$

Mean Absolute Percentage Error (MAPE) given by:

$$MAPE = \frac{1}{M} \sum_{i=1}^M \frac{(Actual_i - Forecast_i)^2}{Actual_i} * 100 \quad (9)$$

Where *Actual* is the real value of monthly load demand at the each year, *Forecasted* is the forecasted value in the same year, and *M* is month ^[12, 13]

After forecasting the load patterns for each test month, these forecasts were compared with the real load data, and the average error percentages were calculated. In comparing different models, the average percentage forecasting error is used as a measure of the performance.

The reason for using the average percentage error is the fact, that its meaning can be easily understood. It is also the most often used error measure in the load forecasting literature used as reference of this work, and therefore allows for some comparative considerations (although the results are not directly comparable in different situations).

However, when both measures calculated on some test models with relatively small errors, the orders of preference were in practice the same with both measures. Therefore, the average forecasting error will be used throughout this work.

In case of the monthly forecast the training algorithms of Gradient back propagation and Levenberg Marquardt were compared whereas in case of the monthly forecast the simulation was done. Although Levenberg Marquardt is a very fast training algorithm, it often has given fairly inaccurate results due to the large approximations it makes while calculating the Hessian matrix. ^[14, 15]

From years 2013 to 2017 were chosen in different seasons

of the year. The load of each month of the data set was forecast without using the actual load data of that month. Thereby, the monthly forecasting model was applied for each test of monthly peak demand recursively for all months in the year. After forecasting the load patterns for each test month, these forecasts were compared with the real load data, and the average error percentages were calculated.

4. Case Study and Test results

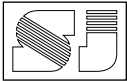
Present study develops midterm electric load forecasting using neural network; based on historical series of power demand the neural network chosen for this network is feed forward network, case study and test results will be present in this section by following:

4.1. Case study

This study used the historical information or data for proposing ANN model to load forecasting as following:

Monthly energy consumption demand (*MWh*), The Humidity (*H*), Precipitation (*P*) and Temperature (*T*). All of data information is recorded from 2013 to 2017.

Fig.4, show the block model for two years ahead demand forecasting which have four inputs: the



historical load demand from -12 months to -48 months, maximum temperature from 0 months to -48 months, humidity from 0 months to -84 months, and precipitation 0 months to -48 months. These are feature inputs to artificial neural network. The output of this model is the load demand of Sulaimani Governorate that is + twenty-four months ahead or two years ahead. Note that, year 2017 (0), 2016 (-12), 2015 (-24), 2014 (-36) and 2013 (-48).

Various network models based on multi-layer back propagation feed-forward architecture are tested with different designs and different configurations of hyper-parameters (one and two) hidden layer with neurons of (10, 12, 15 and different transfer functions.). After several trials, the near-optimal values have been taken. The information about different cases (for one month January -2013 for example) is described in Table 1. A back-propagation network with momentary and with adaptive learning rate was trained and the neural network can forecast future load one day peak load per month ahead given in various inputs to the network.

A sigmoid transfer function was used in the hidden layer while a linear transfer function was used in. It has been observed that using 12 neurons and transfer function of logsig gave less percentage error for nearly all months. And depending on this result, the forecasted values (by using model in Fig.4 can be observed. Fig. 5 represent the results of two years forecasting.

By using the model developed, load, error and % error of all the months have been calculated.

Then error and % error is found out using the below given formula.

Error = Output by NN - Actual Output

% Error = (Error / Actual Output) x 100

Actual Output, Output by NN, Error and % Error in 2016 and 2017 has been given in Table 2.

5. Conclusions

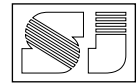
Artificial Neural Network models provide a very useful tool for midterm load forecasting. Radically different from statistical methods, these models have shown promising results in load forecasting. The aim of this paper is to develop a practical model for the peak load demand of Sulaimani Governorate which gives a best expectation values with minimum errors so that Directorate of Central Control planners can estimate what the near term demand will be. The monthly peak-demand estimation is a key input in determining if there is enough generating capacity available to meet the demand.

The result of this research shows the high efficiency of the neural network in estimating the electrical power load and this is because ANN can define the nonlinear relation between the weather data and the load with high Accuracy.

Midterm monthly load forecasting using ANN can lead to very good results if the ANN structure is well designed and training data selection is appropriate.

As it can be seen on the table above, the electricity demand is increasing to the peak in January, February and December every year. From this point, Sulaimani city needs extra investment on electricity energy load to satisfy the demand of consumption. In 2014 and 2015 years electricity demand is above 2000 MW in January.

In this work, Sulaimani maximum electrical energy demand has been forecasted by considering different ANN models with high accuracy, in order to model the effects of weather, proper ANN models have been implemented. Because any prediction model does not give the best results, nine different ANN models for prediction were performed with the same period data and the superior ANN model was detected for forecasting electricity demand.



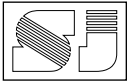
Forecasts model can be varied number of neuron in hidden layer 10, 12 and 15 neurons. The results show two years ahead mid-term load forecasting model of twelve neurons in hidden layer can be reduced error. Mean Absolute Percentage Error (MAPE) in this model is 5.6%.

This research and generally every research about load forecasting can be helpful for scheduling on requirement on developing electrical distribution network, switching, selling energy, maintenance and repairmen.

In order to have even better results, we may need to have more sophisticated topology for the neural network which can discriminate start-up months from other months. Here, we utilized only temperature, humidity, and precipitation among other weather information. Nevertheless, ANN may enable us to model such weather information for midterm procedure. Use of additional weather variables such as cloud coverage and wind speed should yield even better result.

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تنبؤات شهرية بالطلب لحمل الذروة لمحافظة السليمانية باستخدام ظروف الطقس المختلفة بناءً على نموذج شبكة اعصاب صناعية (ANN)

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المستخلص

إن التنبؤ بالطلب على المدى المتوسط لحمل الذروة ضروري من أجل التشغيل الصحيح للمعدات الكهربائية. هناك اهتمام مستمر نحو وضع أساليب جديدة لهذه المهمة. في الآونة الأخيرة، لعبت الشبكة العصبية الاصطناعية (ANN) دوراً ناجحاً في العديد من التطبيقات. يقدم هذا البحث توقعات شهرية لحمل الذروة لمحافظة السليمانية (شمال العراق) باستخدام الطريقة التقليدية الأكثر استخداماً على أساس الشبكة العصبية الاصطناعية، ويتم اختبار أداء النموذج بناءً على الطلب الشهري الفعلي للمحافظة خلال السنوات من عام 2013 إلى عام 2017. يتم استخدام طريقة النسبة المئوية للخطأ المطلق التياسي لتقييم دقة نماذج التنبؤ، وتُظهر النتائج التي تم الحصول عليها تقديراً جيداً جداً للحمل. متوسط النسبة المئوية للخطأ المطلق (MAPE) هو 0.056.

الكلمات المفتاحية: توقعات الحمل الشهرية لمنتصف المدة، الشبكة العصبية الاصطناعية (ANN)، المستقبلات متعددة الطبقات (MLP)، التحميل الفعلي، التحميل المتوقع. سنوياً في المستقبل.

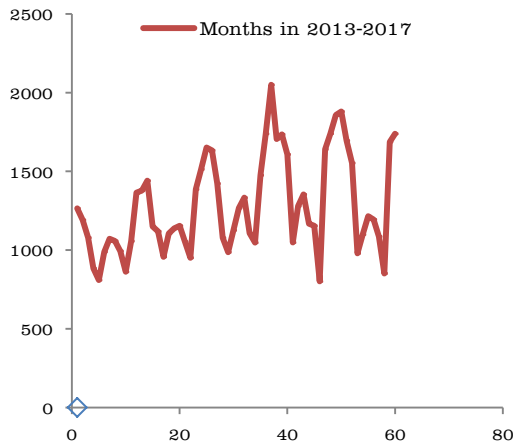
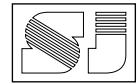


Fig.1: Monthly Energy consumption demand of Sulaimani city from January 2013 to December 2017. (Source: Researcher)

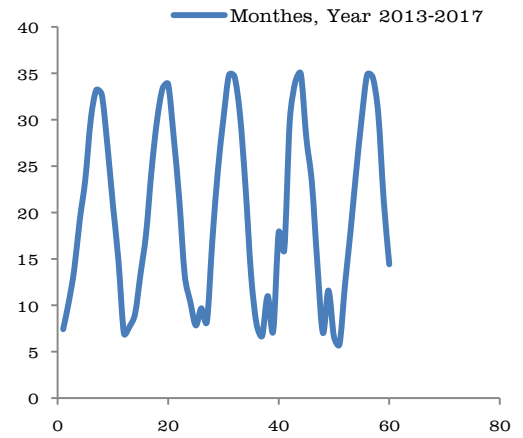


Fig.2: Average temperature of Sulaimai Governorate from 2013 to 2017. (Source: Researcher)

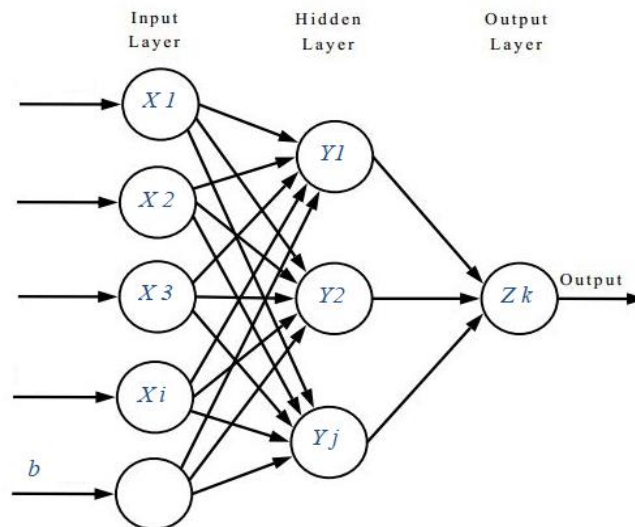


Fig.3: ANN structure used in mid-term load forecasting. (Source: Researcher)

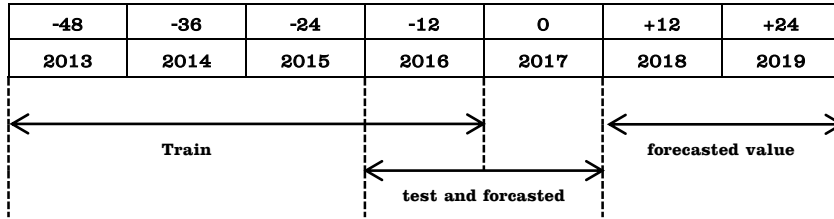
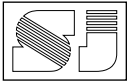
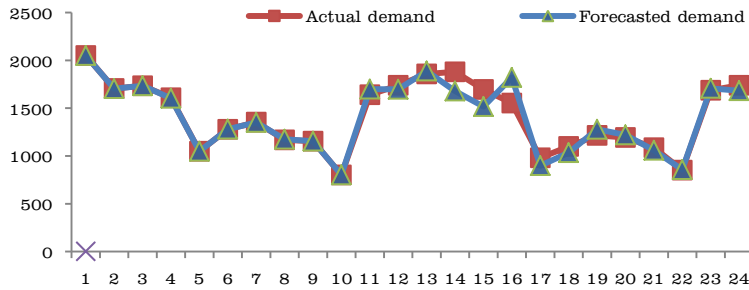


Fig.4: The model for two years ahead forecasting. (Source: Researcher)

Fig. 5 (a) and (b) show the value of actual load demand in 2016 to 2017 on dash line. Solid line shows the forecasted values. The mean absolute percentage error (MAPE) is 5.6%.



Fig, 5(a): Actual and Forecasted load demand for 24 months. (Source: Researcher)

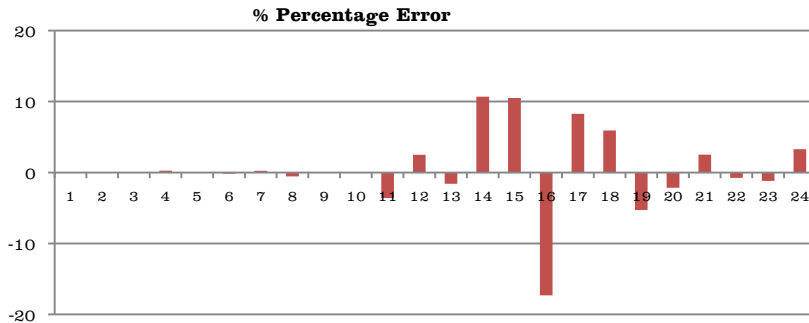
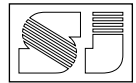


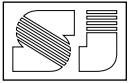
Fig. 5(b): Percentage Error for 24 months. (Source: Researcher)

**Table 1: Percentage Error of different cases for January - 2013.** (Source: Researcher)

No. of Hidden Layer	Neurons	Transfer Function	PE
1	10	LOGSIG	-53.5031
	12		-25.4602
	15		-25.4602
1	10	TANSIG	0
	12		-119.092
	15		0
2	10	LOGSIG	-0.33203
	12		-40.0727
	15		-56.5244

Table 2: Actual, Forecasted Load Demand and Percentage Error. (Source: Researcher)

Month	Actual demand	Forecasted demand	%Error
1	2050	2050	0
2	1705	1704.797	0.011883
3	1735	1734.866	0.00774
4	1608	1603.985	0.249687
5	1049	1049	0
6	1279	1281.096	-0.16384
7	1354	1350.822	0.234717
8	1168	1174.335	-0.54235
9	1154	1154	0
10	802	801.9246	0.009407
11	1640	1699	-3.59756
12	1740	1696.65	2.491406
13	1858	1887.73	-1.60011
14	1880	1679.241	10.67865
15	1695	1516.967	10.5034
16	1553	1821.83	-17.3104
17	980	898.92	8.273469
18	1099	1034	5.914468
19	1215	1279.29	-5.29136
20	1194	1219.61	-2.14489
21	1086	1058.76	2.508287
22	851	857.36	-0.74736
23	1687	1707	-1.18554
24	1739	1682.05	3.274871



In Table 3, Forecasted output demand for 2018 has been given using ANN.

Table 3: Forecasted Load demand for 2018. (Source: Researcher)

Month	Actual demand	Forecasted demand	%Error
1	2050	2097	0
2	1705	1809.797	0.011883
3	1735	1745.866	0.00774
4	1608	1611.985	0.249687
5	1049	1052	0
6	1279	1291.096	-0.16384
7	1354	1379.822	0.234717
8	1168	1174.335	-0.54235
9	1154	1161	0
10	802	811.9246	0.009407
11	1640	1699	-3.59756
12	1740	1796.65	2.491406