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Forecasting Power Demand Using Neural Networks Model

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Abstract— In recent years, by entering the competition arena, not only providing the needed electricity demand, but also reducing the cost of purchased electricity has been one of the biggest challenges of power distribution companies. Solving this challenge has lots of profits and high efficiency for these companies, this research deals with forecasting power demand using neural networks model. To test the power demand , two consecutive years in the West Azarbaijan Province have been selected as a case study.Daily consumption of electricity demand follows time series models. In this study, the daily demand for two years, temperature and humidity of each day and type of days (weekdays or weekends) have been considered. In order to fit the neural network model, the architecture of multi-layer perceptron (MLP) with back propagation learning algorithm has been used. The results indicate that data related to humidity, temperature and also weekends or off-days have an effect on prediction of electricity demand.

Index Terms— Forecast, Neural network, Time series, Power demand.

I. INTRODUCTION

Nowadays, due to population growth, industry development and rising living standards, electricity consumption has increased and paying not enough attention to accurate electricity distribution management, socio-economic development have encountered countries with a serious threat. Electricity distribution is associated with the set of variables supplying and producing electricity. The distribution model deals with the relationship between production and consumption in the network. Forecasting the consumed power determines the power of the network. As low prediction causes outage, high forecast of power can impose unnecessary excessive costs, Therefore power consumption must be accurately forecasted. Power consumption distribution is different in days of week and hours of a day. Accordingly, in this study consumed power is forecasted using time series. Power receivers with maximizing utility and firms with minimizing costs determine their demands.

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II. STATEMENT OF THE PROBLEM

The first duty of a power grid is supplying electrical energy economically possible for consumers. Today's society expects to have online access to electrical energy on-demand. This level of exception needs a power grid with high reliability and since increasing the reliability of a power grid is too costly, electrical networks designers attempt to design a power grid with maximum reliability and minimum costs. Thus, power plants production plan is adjusted based on forecasted changes of power consumption at different periods of time. As a result, prediction of consumed power is the basis of determining optimum forecast and optimal allocation of the capacity in power plants in order to supply demanded power for consumers in the most economical possible way in the network. Energy consumption varies during day, month and year. However, consumption method or in other words, the consumption trend in a society remains constantly. Hence, with studying and analyzing past consumption, the closest model to actual consumption can be estimated because of random behavior of consumption. There is always some error in the prediction of consumption but this error should be greater than an accepted level because accepted level in the prediction of consumption is very important and exceeding this, power distribution companies are obliged to pay a fine for their false prediction as any predictions more than the consumption cause loss of capital and the prediction less than required causes network outage. Owing to the complexity and non-linearity neural networks can be used to forecast the electricity demand and according to the results, the optimal allocation of power demand between power plants can be managed.

III. RESEARCH BACKGROUND AND LITERATURE REVIEW

Balkin at al (2000) with presenting a new method for designing neural networks as an automatic neural network, determined the number of input and hidden neurons lawfully. In this study, two series of 36 and 37 chapters were used. The results showed that the proposed methods are not applicable for the case of both series and automatic modeling of neural network does not provide reliable results. The researchers believe that neural networks act well on non-linear relations and simple methods for prediction such as exponential smoothing particularly when the data are limited in terms of quantity, will produce good results[1].
Darbly and Slama (2000) proceeded short-term electricity demand forecasting in Czech country.

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In this paper, first, a non-linear model i.e. artificial neural network is used to forecast power demand and then the demand is forecasted using a linear model and therefore, artificial neural network cannot be used as a better model in electricity demand prediction[2].

Khaloozadeh et al. (2001) applied the ability of different models including time series models, auto regressive conditionally heteroskedastic (ARCH) and artificial neural networks in predicting the long term stock price index of Tehran. For this purpose, a three- layer feed forward network with a mixture of neurons (S input layers,15 hidden layers and 1 output layer), hyperbolic trans for function and error back propagation algorithm was designed and the results were compared with other models in order to predict stock prices for the next 30 days. The results revealed that linear classic models with respect to the dynamics of stock prices in Tehran are not efficient enough to forecast and neural network models have a better and more reliable capability in long term prediction of these variables[3]. Tkacz ,G. (2001) studied the ability of linear model, Time series and artificial neural networks in forecasting Canada's gross domestic product growth. However, unlike previous studies, in addition to using multi variate neural networks, GDP growth for short-term (one season) and long-term (four seasons) horizons was predicted. The data included were seasonal and contained the periods 1968 and 1999. The results suggest that neural networks significantly have less error than linear and univariate linear models in prediction of annual growth rate of GDP[4]. Andrews et al. (2002) predicted exchange rate of Greece dirham against the U.S dollar, British Pound, French franc and German Mark using neural networks[5]. Rech , G (2002), using various techniques such as early stop and adjustment, for artificial neural networks models, Compared the prediction performance of some neural network models with linear models. In comparison to these models, some measurements as root-mean Square and mean error were used. The results showed that artificial neural networks had the best performance in prediction of one period[6].

Wilson et al. (2002) used artificial neural networks for prediction of residential property prices in the U.K. The researchers used different variables including nominal and real rates, general level of prices and incomes as input to the networks. Root-mean square error indicator was considered as a measure of performance for different methods of prediction; one of the main points of this study was the use of gamma test which is one of the algorithms for data analysis. This test is used to determine the optimal mean Square error to stop the training process and to prevent excessive compliance[7].

Olsen and Mossman (2003) used artificial neural networks in classification of financial markets. In this study back propagation neural networks and ordinary least squares were compared. The results indicate that neural networks are more robust in identifying non-linear relationship between dependent variables and also in producing more accurate predictions and classifying the companies more accurate than other methods[8].

Heravi et al. (2004) according to the studies in the field of economic variables prediction in Europe compared the ability of neural networks with a self-regression process in prediction of industrial production in three European countries of Germany, France and Britain. To do so, root-mean square error criterion was used.These researchers believe that neural networks are better than other methods in prediction of variables path[9].

Darabelly and Slama (2005) who aimed to answer the question of whether neural networks have better ability in short-term prediction, predicted electricity demand in Czechoslovakia. In this study, using various criteria such as mean square error, absolute percentage of error and normalized mean square error, short-term prediction of power demand was compared by using neural network models, time-series processes and ARIMAX process for horizons of 1, 12, 24 and 36 hours later.

In this study, a three-layer feed forward neural network with one hidden layer and 6 to 10 neurons were used. The results showed that while the neural network has the same results as mentioned time-series process in the next 24 and 36 hours, the prediction of the above process are more accurate than other models in these horizons[10].

Sozen et al (2005) forecasted the consumption of net energy in Turkey using artificial neural networks. In this study, two models of neural networks were used to predict energy. The first model was designed with the input variables of population, nominal capacity and GPD and the second model was designed with the input variables of energy sources.

Also, net energy intake was used as the dependent variable in the output layer. The results revealed that determination coefficient R^2 of the first and second model for training and testing data was obtained and the researcher concluded that neural networks could be a useful tool for energy planners[11].

Hippert et al (2005) predicated daily power consumption in Brazil using artificial neural networks. In this study, using different methods power consumption was predicted and appropriated functionality of neural networks was assessed in comparison to other competing models[12].

Murat and Ceylan (2006), using feed forward neural networks, predicted energy demand in the transport sector. Input variables included Socio-economic variables such as population, GDP, distance traveled, and the rate and energy consumption in the transport sector.

The data used in this study were a 30- year period. Comparison of neural networks prediction and real data related to training data showed that artificial neural networks could be an appropriate method for prediction of energy consumption in the transport sector[13].

Azadeh et al (2008) in an article entitled "an algorithm based an neural networks for prediction of electricity consumption "provided an integrated algorithm for forecasting electricity consumption using neural networks and computer simulations based on stochastic processes. First of all, the approach of neural networks based on MLP for power consumption prediction was purposed. The selected model could be compared with time series. Computer simulation was used to generate random variables of power consumption. With variance analysis, it can be reacted in four ways: real data, time series, neural networks and simulated neural networks. Analysis of variance can be used for null hypothesis based on the statistically equality of four options. If the null hypothesis is accepted, the value of MLP will determine which Model ought to be chosen as the best model.

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In this case, comparison of pairs is used to choose the best model. That can be time series, artificial neural networks and simulated neural networks . Here, MAPE is selected as a selection criterion. This integrated algorithm has several unique features. It is flexible and gives the best model according to the results obtained from variance and MAPE. Even though former studies suggest that the best model can be obtained from neural networks based on the least MAPE or any other error criterion- the proposed algorithm can select time series model because of its dynamic structure as the best model[14].

Kutluk KaganSumer et al (2009) in an article entitled" the influence of hidden seasonal variations in electricity demand prediction " compared ARIMA and SARIMA methods with the proposed regression model with the latent seasonal variable to predict electricity demand. This research showed that ARIMA and SARIMA models have been more unsuccessful than regression model in power demand prediction[15].

Kavaklioglu et al (2009) modeled the electrical energy consumption in Turkey and predicted using artificial neural networks. In this study a multi-layer prediction neural network was used. The tangent sigmoid function in the hidden layer and a linear function in the output layer were applied. The results showed that using neural networks, power consumption can be modeled and predicted[16].

Mun˜oz et al (2010) in an article entitled" short – term prediction of electric power system "evaluated and predicted the three major electric power systems including load, wind power and electricity price and since each of these time series has its own characteristics, they are predicted in different states and modes[17].

Hongzhan NIE et al (2012) in an article entitled "short-term load prediction using Hybrid ARIMA and SVM method"express that as the short- term load prediction is influenced by many factors, accurate prediction with a model is really difficult and therefore, ARIMA method is used for linear prediction of load and SVM is used for nonlinear section of load[18].

Khashei et al (2012) in an article entitled" combination of seasonal ARIMA model with computational intelligent techniques to predict time series" express that since ARIMA seasonal models are used in time series for prediction of linear, behaviors, these methods lose accuracy in nonlinear series and are not appropriate for those series and totally.SARIMA models require a lot of data for prediction. Nowadays, a combination of several models is used as a prediction model to remove the limitations of a model and to increase the accuracy of prediction. In this paper a hybrid model of SARIMA, artificial neural networks and fuzzy models is proposed for seasonal time series which leads to more accurate results[19].

Gam and Ben Rejeb (2012) in his research entitled "power demand in Tunisia" expressed the power demand as a function of price, population and temperature. This demand probed during a period of thirty one year from 1976 to 2006 and it was concluded that electricity price had a reverse effect on its consumption and expressed that his findings in this research helped greatly in determining a proper strategy to specify the amount of power demand[20].

IV. POWER DEMAND PREDICTION USING NEURAL NETWORKS MODEL

A. *Data collection*

One of the points that helps the researcher achieve realistic results is using suitable tools in gathering research data .This is discussed below.

B. *Data collection tools*

The aim of this study is to forecast the power demand using neural networks. For this purpose , power demand was studied on a daily basis between 07/22/2009 and 04/09/2010. Figure 1 shows the power demand of the data shown above .

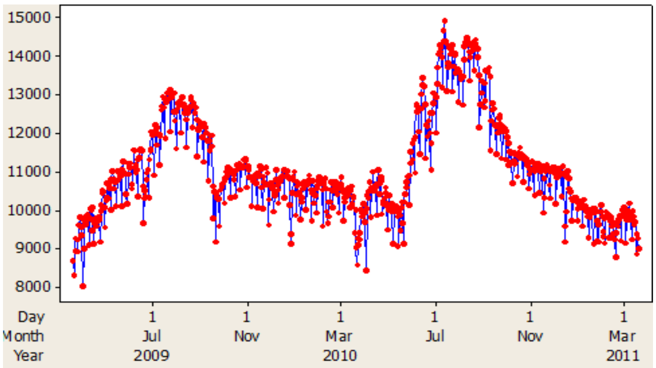

Figure 1

As can be seen , electricity demand pattern is the same on different days of a week but the demand for electricity varies during different days of a week. Therefore , to obtain a suitable model prediction of different days of week was evaluated according to weekends, weekdays, tempreture and humidity: In this study for analysis of data, input and output and architecture of the neural network, MATLAB software(MATLAB R2011) has been used.

Furthermore, in order to select the most appropriate architecture of artificial neural networks, in addition to authoritative review of papers and articles in this field, trial and error method has been used.

C. *Statistical population*

In this study, daily electricity consumption during 2009 and 2010 has been used for prediction .This information includes 730 data, from which 80% of data have been used for training and 20% for testing and validation of the model.

D. *Data preparation*

It is highly recommended that inputs be standardized in order to prevent from excessive shrinkage of weights in neural networks. Data standardization ,which is commonly done by training the networks, aims at performing conversions on network inputs and outputs in order to extract features from inputs and to convert outputs more understandable to the network. In this study, the following equation is used to standardized data which makes inputs between 0 and 1.

$$N_i = 0.5 * \left[\frac{x_i - x_{average}}{x_{max} - x_{min}}\right] + 0.5 \qquad (1)$$

In the equation above N_i is the standardized value, X_i is real value, X_{max} is maximum real value, X_{min} is the minimum real value and $X_{average}$ is the average real value of power consumption.

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For the variable of power consumption , the rate of humidity of the data is given by mega watt while for a variable like temperature ,the Celsius temperature can not be applied to the equation and it must be converted to the Kelvin temperature also, nominal variable in the problem are encoded.

V. MODEL DESIGN

After data collection and preparation , in order to find the best neural network in identifying the required power demand six views were evaluated to determine the required power .Thus ,after the data were prepared , six models of feed forward artificial neural networks were created .

All five networks are MLP with error correction learning rule(back propagation) and supervised training paradigms. The difference between created neural networks is in the selection of input variables.

First approach : The information of the former seventh day is given as an input to the model and the information of the consumption of the day after is given as output to the model.

Second approach : The data of consumption of three days as inputs and data of the fourth day are given as output to the model.

Third approach : The data of consumption of seven days as input and the data of the eighth day as

out put are given to the model

Fourth approach: in the third scenario, maximum and minimum temperatures of the eighth day are applied to the problem.(12 inputs)

Fifth approach: in the fourth scenario, maximum and minimum temperature and humidity of the seventh and eighth days and weekend or non weekend status of the eighth day are also applied to the problem.(16 inputs)

Sixth approach :in the fifth scenario ,maximum and minimum temperature and humidity of the fifth, sixth ,seventh and eighth days(the last three days and prediction day) and weekend or non weekend status of the eighth day are also applied.(24 inputs)

The following steps have been taken to design a neural network model.

1.Data preparation

2.Input,output and hidden layers

3.Training and testing data with prepared training data

VI. TESTING AND VALIDATION OF NETWORK

First of all, the input , output and hidden layers of neural network are determined and then some data as inputs for training and some data for testing the network are randomly selected.

Generalization is one of the significant characteristics of artificial neural networks. Indeed, a network that has the ability to generalize, in the case of being trained by training samples, can act accurately for the test specimen which has not been given to the network in the training process because the training data are kind of selection from the data sets. But in some cases ,the network remembers the training set but can not generalize it. This problem is theoretically called over fitting in neural networks. In over fitting not only does the network learn useful information from the data, but also detects unwanted information from the data. The result is weak performance of the network in generalization. To avoid this problem, several solutions are proposed such as early stopping. From 100% of the data provided in the data set for modeling, 80% of the data as training and test data, to avoid the problem of over fitting , and the remaining 20% of data are used to validate designed network. Both groups should be representative of different types of outcomes.

For selection of training data, testing and validation random function in MATLAB is used.

VII. EVALUATION OF FITTED MODELS OF ARTIFICIAL NEURAL NETWORKS

Using neural network models, different variables can be defined as input layer nodes and with an accurate neural network architecture, a suitable model can be obtained for power demand prediction.

Neural networks have different models. As mentioned before ,in this study in order to forecast electricity demand ,Multi layer perceptron (MLP) and error back propagation learning algorithm are used.To apply neural network model , first the original data are normalized in a range between [0,1] and then they are used to build and test the model.

Power demand prediction model is evaluated by MATLAB software.

First approach : the data of the former seventh day as input and the data of the next day as output are applied.

Table 1. architectural details of the best selected model(first scenario)

The number of hidden layers	1
The number of input layer neurons	1
The number of hidden layer neurons	2
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt

Table 2. Error values of the best architecture of the network(first scenario)

	MSE[0,1]	MAD	BIAS	TS	R^2
1-2-1-1	0.00841	0. 139	0.00045	0.0032	0.7019

Second approach: The consumption data of three days as input and the consumption data of the fourth day as output are given to the model.

In this case,to begin learning step of neural network, the data of the first three days as input and the data of power demand of the fourth day as output are applied to the neural network and this process is repeated until the data related to 80% of two years enters . As a result , the neural network is trained by using the information of 578 days i.e. the data of training sample group and with successive iterations the weights of optimal model are obtained. Then using demand data of 145 days later i.e. the data out of the sample, the proposed model is tested. Architectural details of the best selected model and evaluation parameters of these models are shown in tables 3 and 4.

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Table 3. architectural details of the best selected model the second scenario

The number of hidden layers	1
The number of input layer neurons	3
The number of hidden layer neurons	4
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt

Table 4. the result of evaluation parameters of the second scenario

MSE	MAD	BIAS	TS
0.00073	0.0161	0.0004	0.0025

Third approach : consumption data of seven days as input and consumption data of the eighth day as output are applied to the model.
In this case, first the power demand data of seven days as input and the data of the eighth day as output are applied to the neural network and this process is repeated for the sample data. With changing different modes, neural network architecture during training is obtained as table 5.

Table 5: the features of the best selected network

The number of hidden layers	1
The number of input layer neurons	7
The number of hidden layer neurons	4
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt
Validity algorithms	Random

The results of obtained evaluation is given in table 6.

Table6. the results of evaluation parameters of the third scenario .

MSE	MAD	BIAS	TS
0.00022	0.014	-0.0044	-0.3143

Fourth approach : In the third scenario model maximum and minimum temperature and humidity of the eighth day and weekend or non weekend status of the eighth day are also applied. (12 inputs)
In the fourth approach, in addition to power demand of seven days, the data related to maximum and minimum temperature ,humidity and weekend or non weekend status of the eighth day as input for prediction of power demand in the eighth day are considered.
Neurons in the input layer in this scenario in addition to the data of seven days , maximum and minimum temperature ,humidity and closure of the eighth day are added and totally these are 12 neurons.

Table 7: the features of the best selected network (fourth approach)

The number of hidden layers	1
The number of input layer neurons	12
The number of hidden layer neurons	5
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt
Validity algorithms	Random

The main purpose of this problem is to determine the predicted demand on the next day,so there will be only one neuron for the output layer.

Table 8.evaluation index of neural networks (fourth approach)

MSE	MAD	BIAS	TS
0.00019	0.014	-0.004	-0. 319

Fifth approach :Under this scenario , the data of the former seven days , the data of maximum and minimum temperature and humidity of the day before and the data of maximum and minimum temperature and humidity of prediction day and weekend or non weekend status of that day as input and demand as output are considered.
In this scenario there will be 16 neurons the main purpose is to determine the predicted demand for the next day, thus there will be only one neuron of or the output layer.

Table 9. the features of the best selected network(fifth approach)

The number of hidden layers	1
The number of input layer neurons	16
The number of hidden layer neurons	4
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt

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Table 10. the results of performance measurement(fifth approach)

MSE	MAD	BIAS	TS
0.00017	0.0094	-0.0003	-0.032

Sixth approach : Based on this scenario , the data of the former seven –day demand and the data of maximum and minimum temperature and humidity of the previous three days and the data of maximum and minimum temperature and humidity of the prediction day and weekend or non weekend status of that day as input and demand as output were considered.
In this scenario ,there were be 24 neurons the main purpose is to determine predicted demand for the next day ,hence there will be only one neuron for the output layer.

Table 10.the features of the best selected network(Sixth approach)

The number of hidden layers	1
The number of input layer neurons	24
The number of hidden layer neurons	10
The number of output layer neurons	1
Transfer function between input and hidden layers	TanSig
Transfer function between hidden and output layers	Linear
Training algorithm	Levenberg-Marquardt

Table 11.the results of performance measurement(Sixth approach)

MSE	MAD	BIAS	TS
0.00014	0.0089	-0.0031	-0.34

Comparing the results obtained from different neural networks models for electricity demand prediction,it can be revealed that the sixth scenario that has the least error , is selected as the optimal neural network model.
Figure 2 shows the predicted value using the optimal model for out-of-sample data compared with actual data values.

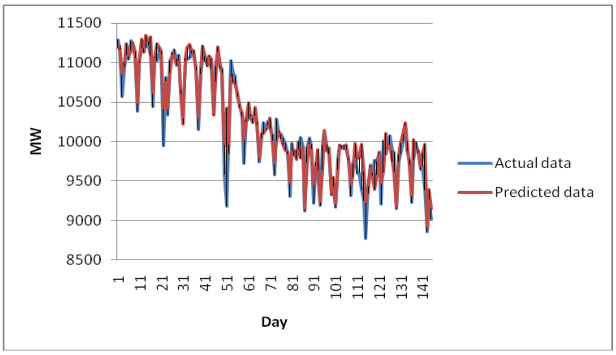

Figure 2

VIII. CONCLUSION

Using artificial neural networks, modeling power demand prediction in different states were studied and comparison results are given in table 12.

Table12.

	MSE[0,1]	MAD	BIAS	TS	R^2
First approach	0.00841	0. 139	0.00045	0.0032	0.7019
second approach	0.00073	0.0161	0.0004	0.0025	0.7744
Third approach	0.00022	0.014	-0.0044	-0.3143	0.7921
Fourth approach	0.00019	0.014	0.004	-0. 319	0.8649
Fifth approach	0.00017	0.0094	-0.0003	-0.032	0.9216
Sixth approach	0.00014	0.0089	-0.0031	-0.34	0.9198

Considering the table above , the following results are obtained.
1.The sixth model has greater accuracy than previous models and error prediction i.e. , the difference between the model output and desired output, is lower.
2.The power demand is depending upon weekend or non weekend status , temperature and humidity.

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