One day ahead load forecasting for electricity market of Iran by ANN

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***Abstract*— one of the basic requirements for power systems is accurate short-term load forecasting (STLF). In this study, the application of artificial neural networks is explored for designing of short-term load forecasting systems for electricity market of Iran. In this paper, two seasonal artificial neural networks (ANNs) are designed and compared; so that model 2 (hourly load forecasting model) is partitioning of model 1 (daily load forecasting model). Our study based on feed-forward back propagation is trained and tested using three years (2003-2005) data. At the end, extensive data sets test the results; and good agreement is founded between actual data and NN results. Results show that daily forecasting model is better than the hourly one.**

***Index Terms*— STLF, ANN, feed-forward back propagation.**

I. INTRODUCTION

One of the basic requirements for power systems is accurate short-term load forecasting (STLF). STLF is a very essential task for power system operation because it can help the electric utility to make important decisions including unit commitment, load switching, etc [1]. Furthermore, accurate load forecasting improves the security of the power system [2]. Also, load forecasting is one of important requirements for price forecasting in bidding strategy. In other words, in a restructured electricity market, a generation company (GENCO) would have to forecast the system demand and its related price with the purpose of make an appropriate market decision [3]. Usually, historical load data are used to prediction. These data show a short-term correlation between the total demand and climatic information. This information may include temperature, cloudiness and wind, and other factors such as the day of the week. Relationships specification is difficult between the load and these factors [4].

The research methods of short-term load forecasting can be categorized into two main groups: statistical methods and artificial intelligence methods. In statistical methods, an equation show the relationship between load and its corresponding factors after training the historical data. While in the artificial intelligence methods, human being's way of thinking and reasoning in forecasting would be copied.

To correspond the input and output variables; the majority of the STLF methods consider a regression function or a network structure. Therefore, selection of the regression form or the network structure is important because if it is inappropriately selected the forecast result would be unacceptable. Furthermore, choose the input variables always face to a difficulty. Accuracy of prediction would be reduced if too many or too few input variables are selected [2]. ANN has some good characters such as its clear model, easy implementation and good performance. These characters cause ANN receive more attention among other forecasting algorithms.

For load forecasting, the network was divided into the following groups based on day of week in Ref. [5]: The Monday, Tuesday and Wednesday through Friday, Saturday and Sunday. In some studies, One week was divided into three groups [5-6]: Saturday, Sundays, and weekdays. Some researchers applied a network divided into seven ANN shows 24 outputs [8]. However, Bacha (1992) indicated that forecasting by one ANN for every day of each week was better than the forecasting by partitioning method [9].

Division the inputs based on hours or seasons is another way to partition the network. In Ref. [10], two models were applied, one was used for summer data and the other was used for winter data. In Ref. [11], three modules to represent weekly, daily and hourly modules were used for short-term load forecasting; and an adaptive linear element merged the modular outputs. Division the year into four seasons is another way for partitioning the network. In Ref. [12], each season was divided into three groups (Monday, weekday and weekend), and each day was divided into five periods (1am, 6 am, 11 am, 1 pm, 9pm)

In this paper, two ANN models are designed. In the first model, daily loads are forecasted using a daily seasonal ANN. While in second model, hourly loads are forecasted using hourly-seasonal ANNs. In fact, model 2 partitions model 1 to 24 sub networks. For developing the designed models, the actual hourly electrical load data for three years (2003-2005) from electricity market of Iran are used season by season. It is identified that temperature and day of the week affect the forecasting accuracy. Therefore, identified factors are taken into the two proposed models considered. To ascertain the forecasting accuracy, the developed models are tested for one forth of input data.

This article is organized as follow: Section II gives an introduction to ANN. Section III shows ANN architecture for

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STLF including the proposed ANN models. Section IV presents ANN procedure for this study. Test results are shown by Section V. Conclusions are drawn in Section VI.

II. INTRODUCTION TO ANN

ANN is a system that can process computer information and simulate the function of human brain. Architecture, processing and training are the factors that ANNs can be classified based of them. The neural connections can be described by its architecture. Produced output for every input and weight can be described based on processing. The weight for every training vector is adapted due to the training algorithm. This algorithm mainly determines the network parameters such as weights. Also, other issues that affect on achieving good results based on the existing training sets are determined by network training [3].

In general, input layer, hidden layer and output layer are three important parts that compose the ANN architecture. There are four types of ANN architecture that are usually used that is a single layer network, a multi layer perceptron, a Hopfield network and a Kohonen network [3].

III. ANN ARCHITECTURE FOR STLF

A. Seasonal ANN

Figure 1 depicts the daily loads for some days of each season in Iran. As observed, the highest loads occur in summer. The loads have slight fluctuations in spring. The temperature would also vary in every season, that is, winter would have the lowest temperature and summer have the highest temperature.

Therefore, it would be better to use different ANN modules for discriminating between the seasons. For this reason, the data can be easily trained and there is more chance to achieve more appropriate results [3]. Therefore, ANN modules can be considered for each season. In this paper, summer ANN is constructed.

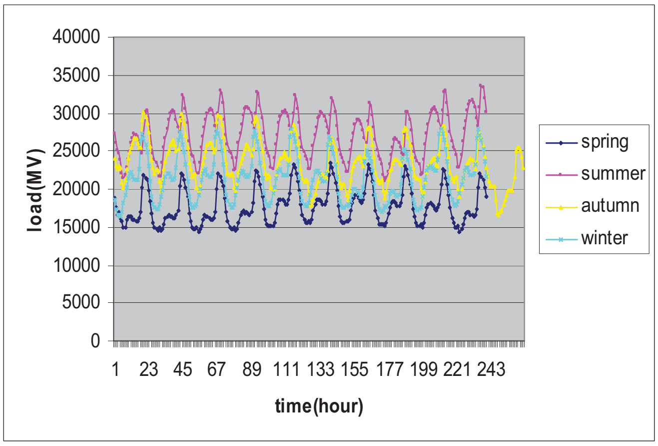

Fig.1. Daily load curves for several days of each Season

B. Proposed ANN Architecture

Choosing proper input variables and data is one of the keys for designing a good ANN architecture. Time, electrical load and weather information can be considered for the short-term load forecasting. The type of season, days of a week and hours of a day are some time information. Previous loads may be included in the load information. Also, previous and future temperatures, cloud cover, thunderstorm, humidity and rain may be included in the weather information [3]. In the follow, two proposed seasonal models are constructed:

<u>Case 1:</u> In the first proposed architecture, network is designed based on the follow inputs:

- Year
- Type of day
- Previous day loads
- Pervious day's average temperature
- Pervious day's maximum temperature
- Pervious day's minimum temperature
- Average temperature forecast
- Maximum temperature forecast
- Minimum temperature forecast

A block diagram for the first proposed model is shown by Figure 2.

There are a total of 32 neurons in the input layer of designed network. The first neuron is used to define the year. The second neuron is used to define the day type of the forecast. A day of the week would be assigned to a number ranging from 1 to 7 (Sunday as 1, Monday as 2, Tuesday as 3 and so on). The next 24 input neurons represent the previous day's hourly loads. The last 6 neurons are used to take the effect of temperature into consideration. The first three of them show previous day's temperature consist of average- maximum and minimum temperature and another neurons show the next day's temperature (average-maximum-minimum) forecast. In the hidden layer, a seasonal network is used. The output layer of network consists of 24 neurons. These neurons correspond to 24 hours in a forecasting day.

<u>Case 2:</u> second proposed architecture is partitioning of the first model to 24 sub networks. In other word, in the second proposed architecture, 24 seasonal hourly ANN are designed for hourly load forecasting. A block diagram for the second proposed model is shown by Figure 3.

There are a total of 9 neurons in the input layer. The first neuron is used to define the year. The second neuron is used to define the day of the forecast like as pervious model. The next input neuron represents the previous day's hourly load for considered hour. The last 6 neurons are used to take the effect of temperature into consideration like as pervious model. In the hidden layer, an hourly seasonal network is used. The output layer of network consists of one neuron. This neuron corresponds to one hourly load for forecasting hour.

The number of neurons in the input or output layer is set due to type of the selected input and output data. The number of hidden layer neurons is resulted as follows. We test the network with a small number of neurons and then increase the number of neurons step by step until the training process is qualified [3].

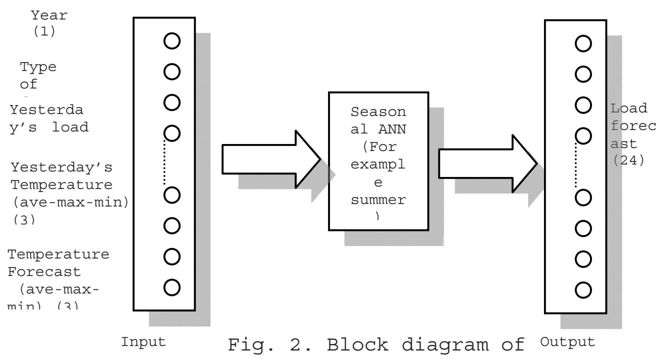

Fig. 2. Block diagram of model 1

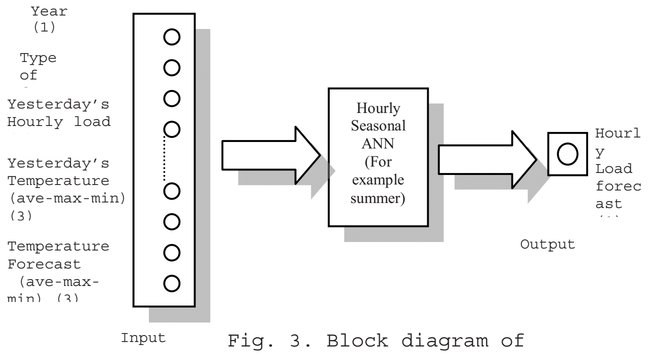

Fig. 3. Block diagram of model 2

IV. ANN PROCEDURE FOR STLF

The STLF procedure for the proposed ANN models is shown by Figure 4.

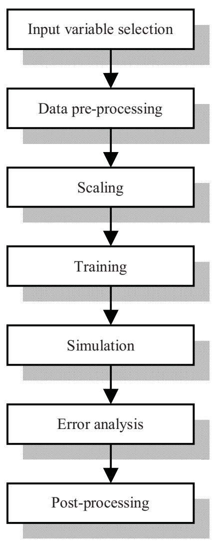

Fig. 4. ANN-based load forecasting procedure

Input Variable Selection: as mentioned before, identification factors affected load patterns is the first important step for making an acceptable load forecasting. Input variables were defined in section 2.3.

Data Pre-processing: unacceptably recorded data and observation errors are unavoidable. Hence, usually a statistical method is used to identify bad and irregular data and discard or adjust these data.

Scaling: since there are very different ranges for variables; convergence problems may be caused by direct use of input data. Follow scaling method is used in this study.

$$x(k)_i = \frac{x(k)}{\max(x(k))} \quad (1)$$

x(k) is an element in the input or output vector/pattern. All x_i (input or output) would be scaled to the [0, 1] range.

Training: when the neural network is started; system initializes weights and biases of each layer. The connection power among the interior nodes can be adjusted by network. Finally, network learns the appropriate transformation between past inputs and outputs from the training cases. In this paper, Feed-forward back propagation with three layers is used. TRAINLM is used as training function. TANSIG is used as transfer function from input layer to hidden layer and PURELIN is used from hidden layer to output layer.

Simulation: The forecasting output is simulated using the trained neural network.

Error Analysis: since load characteristics differ, error analysis is important for the forecasting process. Hence, the following Mean Absolute Percentage Error (MAPE) ε is used here for error analysis after simulation:

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N}\frac{|X_t - X_f|}{X_t}\times 100 \quad (2)$$

Where X_t shows the actual load and X_f shows the forecasted load.

Post-Processing: The neural network output need to be de-scaled for generating the preferred forecasted loads.

V. NUMERICAL RESULTS

The constructed networks are implemented by MATLAB 7.0 Neural Networks Toolbox. The minimum MAPE is a key to identify optimal number of neurons in the hidden layer. Also, training time and training results are important to determine the appropriate number of neurons in the hidden layer of each model. Simulation results are shown by Table I and Table II. For example, four neurons are chosen as the most appropriate number of neurons in the hidden layer of model 1 because the minimum MAPE has been resulted.

TABLE I
RESULTS OF MODEL 1

Model 1		
Type of network	number of neuron in hidden layer	MAPE
Seasonal ANN	4	1.1%

TABLE II
RESULTS OF MODEL 2

Model 2		
Type of network	number of neuron in hidden layer	MAPE
Hourly seasonal ANN[2]	1	1.9%
Hourly seasonal ANN[3]	1	2.5%
Hourly seasonal ANN(3)	3	1.7%
Hourly seasonal ANN(4)	1	1.9%
Hourly seasonal ANN(5)	3	1.4%
Hourly seasonal ANN(6)	1	1.5%
Hourly seasonal ANN(7)	1	2.6%
Hourly seasonal ANN(8)	5	3.9%
Hourly seasonal ANN(9)	10	6.1%
Hourly seasonal ANN(10)	4	5.1%

Model 2		
Type of network	number of neuron in hidden layer	MAPE
Hourly seasonal ANN(11)	3	5.2%
Hourly seasonal ANN(12)	2	4.9%
Hourly seasonal ANN(13)	3	4.8%
Hourly seasonal ANN(14)	3	4.4%
Hourly seasonal ANN(15)	3	4.1%
Hourly seasonal ANN(16)	10	6.4%
Hourly seasonal ANN(17)	2	5.9%
Hourly seasonal ANN(18)	3	4.8%
Hourly seasonal ANN(19)	1	4.5%
Hourly seasonal ANN(20)	1	5.3%
Hourly seasonal ANN(21)	4	3.7%
Hourly seasonal ANN(22)	3	3.5%
Hourly seasonal ANN(23)	5	2%
Hourly seasonal ANN(24)	5	2.8%

In this study, average of hourly seasonal ANNs MAPE of model 2 is considered as MAPE of model 2 for comparison between two proposed models. Considered average MAPE equals to 3.7%. Results show that forecasted loads with model 1 are more reliable and accuracy than model 2 for our forecasting.

Summer Results: Figure 5 and Figure 6 shows the summer forecasting results of the first and second proposed model. Figure 7 and Figure 8 represent differences between forecasted loads between proposed models. Table III shows comparison of MAPE between two proposed models for forecasted days.

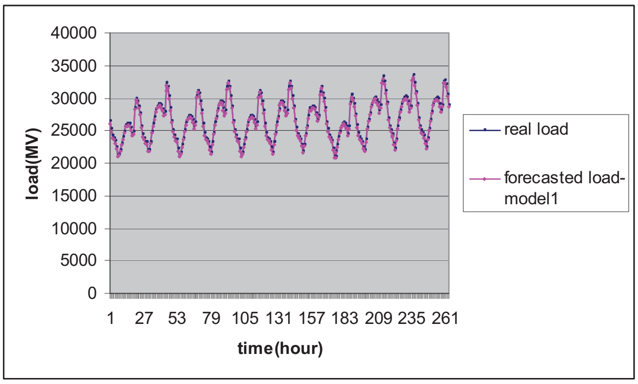

Fig. 5. Summer forecasted loads and actual loads for the first proposed architecture

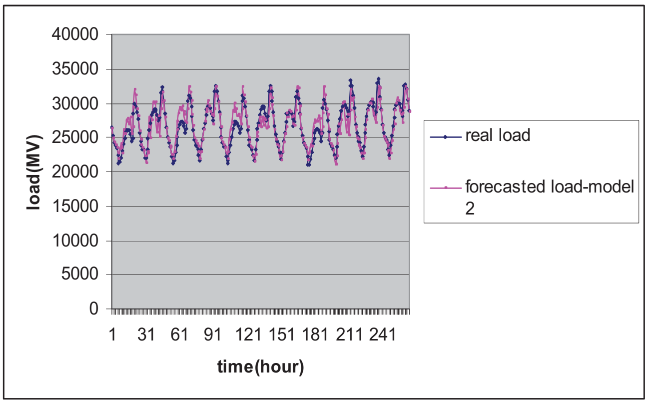

Fig. 6. Summer forecasted loads and actual loads for the second proposed architecture

As observed above, error depends on several factors such as the homogeneity in data, the choice of model, the network parameters and finally the type of solution [8].

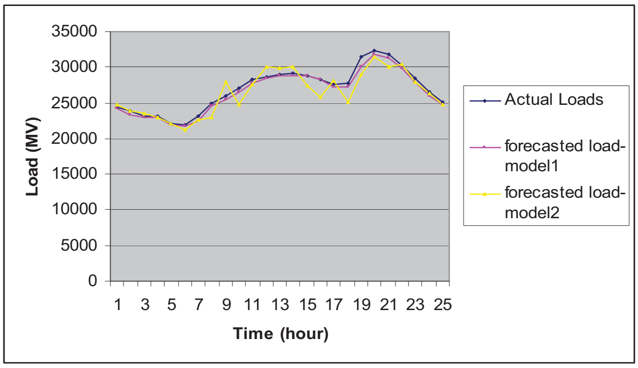

Fig. 7. Comparison between two proposed models for summer- 12 Aug, 2005

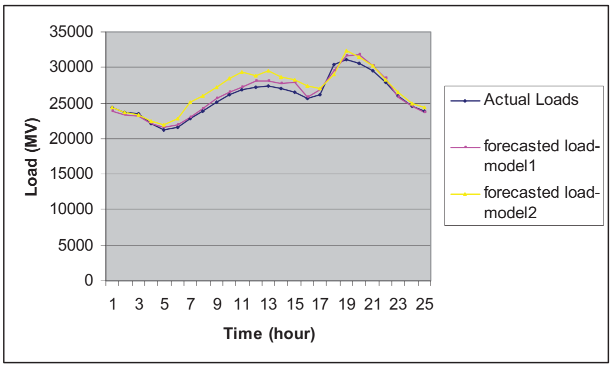

Fig. 8. Comparison between two proposed models for Summer- 13 Aug, 2005

TABLE III
COMPARISON OF MAPE BETWEEN TWO PROPOSED MODELS FOR FORECASTED DAYS

Day	MAPE1 (%)	MAPE 2 (%)
12 Jul, 2005	1.4	3.6
13 Jul, 2005	1.9	4.5

VI. CONCLUSION

One of the basic requirements for power systems is accurate short-term load forecasting (STLF). In this study, the application of two different neural networks was explored to study the design of short-term load forecasting (STLF) Systems for electricity market of Iran. In this paper, two seasonal ANNs were designed and compared. The results obtained in this work confirm the efficient applicability of neural network in short term load forecasting for electricity market of Iran. First designed model (model 1) was used for daily load forecasting. Second designed model (model 2) was used for hourly forecasting. Since, the weather parameters temperature and day of the week affect the forecasting accuracy; therefore they were included in the two proposed model. To ascertain the forecasting accuracy, the developed models were tested for one forth of input data. At the end, results showed MAPE of model 1 is 1.1% and average MAPE of model 2 is 3.7%. Therefore, first model is more reliable and accuracy than second model in STLF via ANN in our studied region.

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