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Short Term Load Forecasting by Using ESN Neural Network Hamedan Province Case Study

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Abstract

Forecasting electrical energy demand is one of the important decision-making tools in distributing companies for making contracts scheduling and purchasing electrical energy. This paper studies load consumption modeling in Hamedan city province distribution network by applying ESN neural network. Weather forecasting data such as minimum day temperature, average day temperature, maximum day temperature, minimum dew temperature, average dew point temperature, maximum dew temperature, maximum humidity, average humidity and minimum humidity are collected from weather forecasting station in Hamedan province. By studying these parameters and daily electrical energy consumption registered in Distribution Company of Hamedan province and using statistical analysis factors, the parameters which affect daily electricity consumption have been recognized. By applying ESN neural network modeling this load with recognized parameters has been carried out and load forecasting has been assessed. Forecasting result indicates high accuracy of ESN network system for load forecasting short term.

Keywords: short term load forecasting, dynamic neural networks, ESN neural network.

1. Introduction

Load forecasting is one of the most important tools for decision-making of electric systems which keeps electricity production in accordance with required amount of load. By privatization of electric systems and establishment of competitive electric markets load forecasting in modern electric systems has been highly considered. Electricity consumption forecasting has been divided into 3 different category including short time period, average time and long time period. Each of these categories with different has been required periods deal with different decision-making levels. Short term load forecasting (STLF) deals with few hours and few days for making decision about required load which enables decision maker to make accurate load deduction. Understanding required load in short term period requires the plan to set production units. Short term load forecasting plays an important role in economic activities and safety of electric systems.

This issue is important in economical dispatching and transferring systems timing and especially for determining load peak for taking care of electrical unit with safe and constant operation and dedicating suitable rotary reserve. Average period electricity forecasting deals with time limits of months and seasons in which understanding future required load in this time period is essential for coordinating, repairing and maintenance of production units.

Finally long term forecasting deals with ages and decades. Load increasing forecasting in long term period is applicable for constructing new production units, network expansion and long term sales policies There are many methods which help solving load forecasting problem such as the ones based on classic regression, time series neural networks, methods based on neural networks and combination methods.

Neural network is one of the popular methods used in many articles.

Many researches have been carried out for load forecasting by using different methods. Short term load forecasting has been studied by using Bayesian neural network in [1]. This network has been thought by Monte Carlo combination method. In [2], load forecasting was studied by using developed neural network and propagation training method which is popular method for teaching developed neural network. Writers in [3] studied load forecasting by using micro artificial neural networks. Considering that in micro networks, production units and electric energy consumption are close to each other, it is expected that load forecasting in these networks are different from centralized systems. In paper [4] wavelet inverting algorithm and low level analyzed signal used for short term load forecasting. . In paper [5] by using RBF neural network and use of SVR algorithm and two Kalman filters, short term load forecasting has been carried out. In paper [6] short term load forecasting has been carried out by using both neural network and fuzzy logic.

2. ESN Neural Network

Echo mode network introduced by Geager in 2001 as a new method for designing returning networks. Echo mode networks enabled modeling complicated dynamic systems by including the time and on another hand they overcome problems of returning networks such as complicated calculations, low speed convergence and unstable learning algorithms.

So they have been considered during recent years. Echo mode networks successfully used for functions estimations, systems identifying, controlling, and forecasting dependable elements to time.[7] Echo mode network is based on one of the most possible biological structures which describes brain and neurons of creatures called dynamic reserve. Dynamic reserve is a returned layer consists of many neurons which has random and sporadic communications that each one shows different dynamic. In this method, reserve has been stimulated by import-export model and under specific conditions. Then suitable export dynamic obtain only by training of communication weight from reserve to export units while other communication weights are fixed. As a result, this learning process to set up export weights in network has been carried out which means fast learning and convergence. .[8] Echo mode network formed by entrance layer, inner layer (dynamic reserve) and external layer has been shown in Fig. 1. It is assumed that entrance layer with K units, reserve with N units and external layer with L units. As a result, network activator in time called N for internal, inner and external units are as the followings:[9]

$$U(n)=[u_1(n), u_2(n), \ldots, u_L(n)] \tag{1}$$

$$X(n)=[x_1(n), x_2(n), \ldots, x_N(n)] \tag{2}$$

$$Y(n)=[y_1(n), y_2(n),\ldots, y_L(n)] \tag{3}$$

Network communication weights collect for entrance communication in matrix based as follow:
N.K $W_{in} =(wij_{in})$, inner communication
N.N $W =(wij)$, external communication
L.(K+N+L)$W_{out}=(wij_{out})$ outer communication

Noted that direct communication between internal and external units and communication between external units have been allowed.[10]

In echo mode network same as return network, current internal network along with previous external feed hidden layer of the network. Due to it, internal unit activator in time N+1 are refreshed based on below equation:[11]

$$x(n+1) = f\begin{pmatrix} W^{in} \times u(n+1) + \\ W \times x(n) + W^{back} \times y(n) \end{pmatrix} \tag{4}$$

In this relationship $f=(f_1, f_2, \ldots, f_N)$are the active functions of internal units which are generally sigmoid functions. Also, considering external-reserve relationship W_{out}, the external echo mode is obtained by the following equation

$$y(n+1) = g\left(W^{out}(u(n+1), x(n+1))\right) \tag{5}$$

Which $g=(g_1, g_2, \ldots, g_L)$ are the active functions of external units. For obtaining relationship between amounts of low consumption with atmospheric parameters in Hamedan city province, we use correlation analysis between these parameters. These atmospheric parameters are as the followings:

- Minimum daily temperature
- Average daily temperature
- Maximum daily temperature
- Minimum dew temperature
- Average dew point temperature
- Maximum dew temperature
- Maximum humidity percent
- Average humidity percent
- Minimum humidity percent

Dew point temperature is temperature in which humid weather must be cool down until it reaches to saturated limit. In this process, humid weather pressure called P and mixing ratio remain constant. We have to consider that in this process, air pressure is constant and no steam is added to weather sample or removed from that. As a result, mixing ratio remains constant. Whereas weather in dew point temperature reach to saturated point and this amount of mixing ratio equals to mixing saturated point in this temperature. Relative cooling of the weather layer near the earth at night may reach the air temperature till the dew point. Then cooling causes steam condensation. Actually, meanwhile the main process is dew formation.

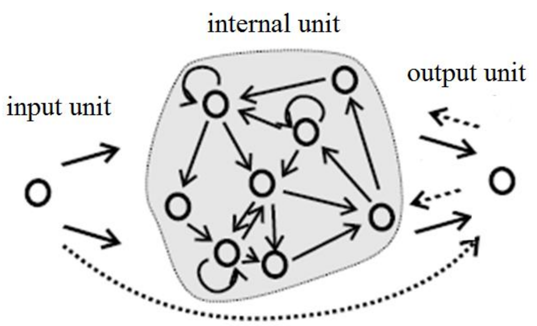

Fig. 1. Echo mode network

In Fig.2 the result of this analysis has been estimated for April in 2013.Generally, we can say in this month the average day temperature and the average dew point temperature have a strong relationship with the electric charge amount. By studying other months of the year which indicating to each of them in this article is out of our tolerance, the average amount of each parameter has been considered as neural network entrance parameters.

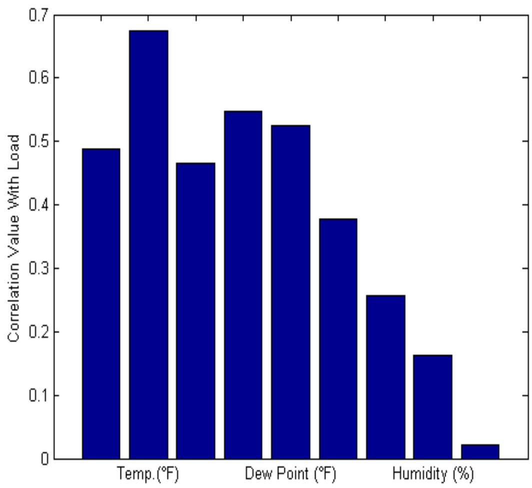

Fig. 2. Result of correlation analysis of daily load and atmospheric parameter 2013 April

3. Simulation

In this sub-section, we deal with teaching a neural network for modelling the consumption load behaviour against the changes of week day weather. Using the resulting model, we will be able to gain the amount of load consumption with an excellent approximation by weather simulation given the calendar terms such as holidays and weekdays and by coding holidays with number 0.25.The selected entrances for gaining meteorology models are average daily temperature, average daily humidity and average dew point temperature. One of the main reasons for choosing this collection of entrance data for meteorology modelling is that measuring and forecasting these amounts is simpler and has been carried out with high attention because they are average. Using the minimum and maximum amount instead of using average amount can lead to more errors in forecasting because estimating the amount of average meteorology parameters is applicable with higher attention and for more timescales.

In this modelling each of the meteorology parameters in each day are located in a separated column and in the next column the amount of holidays and week day's index has been estimated. As mentioned, for holiday's index 0.25 and for weekday's index 0.75 have been used.

A) Developing 2011 model

In the following, this neural network is applied for load modelling by using the ESN teaching method. By using this neural network and separating teaching validity measuring and trial with the ratio 60% 20% and 20%, the Fig. 3 has been obtained for forecasting trial data. The trial data has been selected randomly with the ratio 20% to the total 2011 data. The amount of MPA obtained error which consists of the mean absolute percent error is for 4.34% modelling.

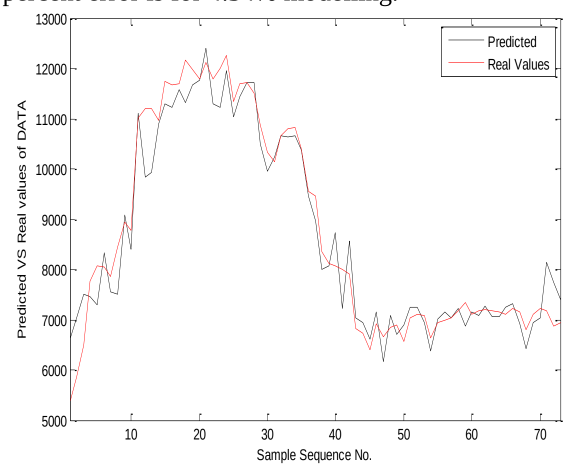

Fig. 3. Forecasting and actual amounts in trial data for neural network with 22 neurons in 2011

In the following, we have increased the quantity of neurons from 22 neurons to 35 neurons. By using of the obtained neural network in this chapter, trial chapter data of the neural network are of 20% of the total current data in 2011. The Fig. 4 is obtained for forecasting these amounts. The amount of MAPE error in this neural network is obtained equal to 4.27%.

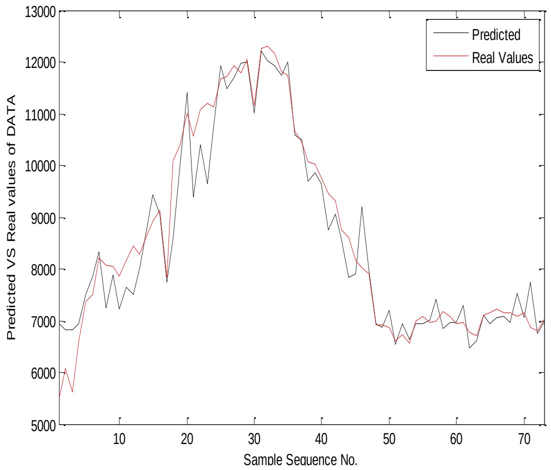

Fig. 4. Forecasting and actual amounts in trial data for neural network with 35 neurons in 2011.

B) Developing model 2012

The trial phase operation of neural network in 2012 has been shown in Fig.5. In this figure the actual load data which have been selected randomly during the whole year based on 20% of the total load data in 2012 has been shown with red colour. The forecasting amounts by thought neural network are brought in black colour in this figure. The neural network with a good approximation has been succeeding in 2012 load modelling. The amount of MPA is equals 3.25%.

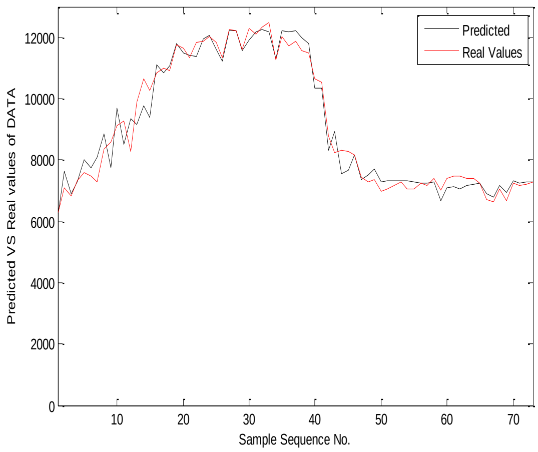

Fig. 5. Comparing the actual and predicted loads by neural network for trial phase data in 2012

C) Developing 2013 model

By using 2013 similar method for current data in 2013, a separated neural network has been shown for load modelling in this year. Here, a neural network with the quantity of neurons 40 has been selected for modeling.2013 neural network operation has been shown in. Fig. 6 for correct load modelling in trial phase. The MAPE error amount for this phase is obtained 3.9%.

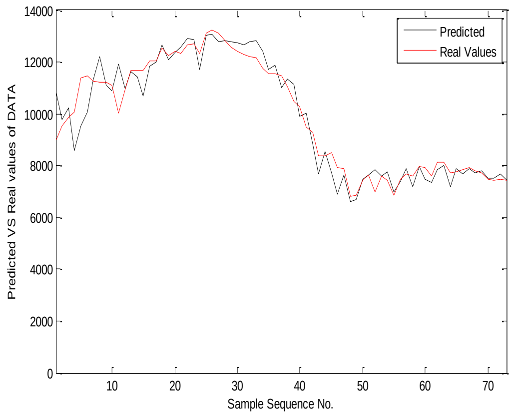

Fig. 6. Comparing the actual load and predicted loads by neural network for trial phase data in 2013

D) Developing 2014 model

In Fig. 7 comparison between actual data and forecasting ones by neural network for trial section data which forms 20% of the total data has been shown.

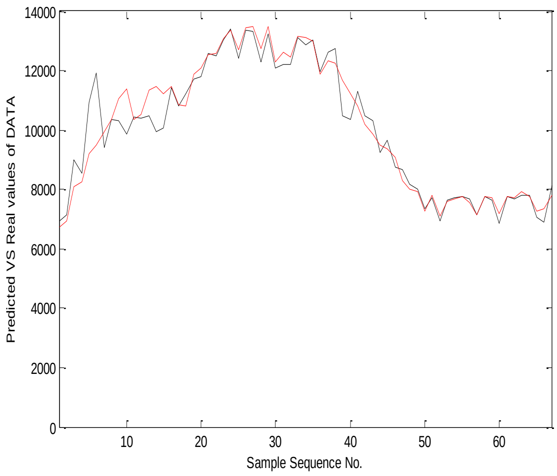

Fig. 7. Comparing neural network and forecasting results with actual amounts

4. Conclusion

In this paper we deal with modelling and short term load forecasting in Hamedan city province distribution network by using ESN neural network. By using meteorology actual data of Hamedan province meteorology and the amount of distribution network consumption load ,which is obtained of Hamedan province distribution company market office, consumption load modelling has been carried out separately in the province in 2011-2013.For this reason from among 9 meteorology parameters including minimum daily temperature, average daily temperature, maximum daily temperature, average daily temperature, maximum daily temperature, minimum dew point temperature, average dew temperature, maximum dew temperature, maximum humidity percent, average humidity percent, minimum humidity percent after studies carried out by regression analysis, parameters average amount have been selected for developing this model. By using ESN neural network, a model has been developed separately for each year and forecasting on the trial data of each year, which had been 20% of each year load data, result in above accuracy.

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