

Modeling and Forecasting Short-term Electricity Load based on Multi Adaptive Neural-Fuzzy Inference System by Using Temperature

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Abstract—In this paper, the use of Adaptive Neural-Fuzzy Inference System (ANFIS) to study the design of Short-Term Load Forecasting (STLF) systems for the east of Iran was explored. While reviewing the probability of chaos and predictability of electricity load curve by Lyapunov exponent, this paper forecasts consumed load by using multi ANFIS. Entries of the presented model are into the multi ANFIS including the date of the day, temperature maximum and minimum, climate condition and the previous days consumed load and its exit is forecasting of power load consumption of every season. The results show that temperature has an important role in load forecast.

Keywords: Load forecasting, Lyapunov exponent, Multi ANFIS

I. INTRODUCTION

Load forecasting had an important role in power system design, planning and development and it is the base of economical studies of energy distribution and power market. The period of load forecasting can be for one year or month (long-term or medium-term) and for one day or hour (short-term) [1, 2, 3, and 4]. Several techniques have been used for load forecasting that among its common methods we can refer to linear-regression model, ARMA, BOX-Jenkins[5] and filter model of Kalman, expert systems [6] and ANN [1-4,7]. According to load-forecasting complex nature, however its studying by linear techniques cannot meet the need of having high accuracy and being resistant. Adaptive neural-fuzzy systems can learn and build any non-linear and complex record through educational input-output data.

Then neural-fuzzy systems have many applications in studying load forecasting and power systems according to the non-linear and complex nature of power nets. Among them we can refer to load-peak forecasting and daily network load-curve forecasting. The east of Iran power plant consumed load information was used for simulation of consumed load forecasting system. The effect of weather forecasting information in consumed load was considered by entering Mashhad climate information gathered from weather forecasting department of the province.

II. A REVIEW OF PREVIOUS WORKS

Certain days load model (formal and informal vacations) is completely different from load model of working days of week (Saturday to Wednesday), but is very similar to its near Fridays. Short-term load forecasting by using fuzzy system cannot have a good function for load forecasting of days by itself since load model of special off-days has a big difference to a usual days. As usual days load model is different regarding the surface and the shape of curve, therefore we need an expert system for adjusting the primary forecasting which apply necessary information for results correction by using an expert person's experience.

On the other hand the power price is a signal with high frequency at competitive market; multi season changes, calendar effect weekends and formal vacation) and the high percentage of unusual prices are mostly during periods of demand increase [8]. The behavior of load curve for different week days is different and in sequential weeks is similar to each other. In this paper, authors use ARMA¹ and ANFIS² models for power signal forecasting. A compound method is also suggested in [9] based on neural network that forecast power price and load simultaneously. In [10, 11], PSO³ has been used for forecasting that in these papers it is in the form of long-term. In [12], the method of neural network learning and SVR⁴ is presented in order to a faster forecasting. A local learning method is introduced here and KNN⁵ is used for model optimizing. In [13], power load model is also mentioned as a non-linear model and a method is suggested that has the capability of non-linear map.

This paper purpose is introducing SVR with a new algorithm for power load forecasting. SVR and ANN are used for error reduction.

III. CONSUMED LOAD MODEL

¹ Autoregressive moving average

² Adaptive Neural- Fuzzy Inference System

³ Particle swarm optimization

⁴ Support vector regression

⁵ K-nearest neighbor

The load forecasting art is in selecting the most appropriate way and model for and the closest ones to the existing reality of the network among different methods and models of load forecasting, by studying and analyzing the last procedure of load and recognizing the effective factors sufficiently and maximizing each of them, and then in this way it forecasts different time periods required for the network with an acceptable approximation. It should be accepted that there is always some error in load forecasting due to the accidental load behavior but never this error should go further than the acceptable and tolerable limit. Relative accuracy has a particular importance in load forecasting in power industry. Especially when load forecasting is the basis of network development planning and power plant capacity. Since, any forecasting with open hand causes extra investment and the installation capacity to be useless and vice versa any forecasting less than real needs, faces the network with shortage in production and damages the instruments due to extra load. Consumed load model is influenced by different parameters such as weather, vacations or holidays, working days of week and etc. in order to build a short-term load forecasting system, we should consider the influence of different parameters in load forecasting, which it can be full field by a correct selection of system entries. Selection of these parameters depends on experimental observations and is influenced by the environment conditions and is determined by trial and error.

IV. REVIEWING THE PREDICTABILITY OF TIME SERIES BY THE HELP OF LYAPUNOV EXPONENT⁶

Chaos is a phenomenon that occurs in many non-linear definable systems which show a high sensitivity to the primary conditions and semi random behavior. These systems will remain stable in the chaotic mode if they provide the Lyapunov exponent equations.

A. CALCULATION OF LYAPUNOV EXPONENT FOR TIME SERIES

In order to calculate Lyapunov exponent for those systems which their equation is not determined and their time series is not available, different algorithm is suggested [14-18]. The algorithm proposed by Wolf [17], seeks the time series of close points in the phase space. These points went round the phase space or got divergent rapidly. Close points in the same direction are selected.

The differential coefficient is in the direction of the maximum development and their average logarithm on the route of phase space yields the biggest Lyapunov exponent. Suppose that series of $x_0, x_1, x_2, \dots, x_k$ is available and the interval between them is obtained as $t_n - t_0 = n\tau$ that τ is the interval between two successive measurement. If the system has chaotic behavior, we can explain divergence of the

adjacent routes based on the difference range between them, as following.

$$d_0 = |x_j - x_i| \tag{1}$$

$$d_1 = |x_{j+1} - x_{i+1}| \tag{2}$$

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$$d_n = |x_{j+n} - x_{i+n}| \tag{3}$$

It is supposed that d_n will increase exponential by n increase:

$$d_n = d_0 e^{\lambda n} \tag{4}$$

So by calculating its logarithm we have:

$$\lambda = \frac{1}{n} \ln \frac{d_n}{d_0} \tag{5}$$

There should be at least one Lyapunov exponent bigger than zero to have chaos, the existence of positive value of λ means the chaotic behavior of system. Therefore, in order to Table I we can expect system to forecast.

TABLE I
LYAPUNOV EXPONENT FOR SEASONS OF ONE YEAR

Winter	Fall	Summer	Spring
0.07563	0.05428	0.0444	0.0523

V. PREPARING THE INPUT DATA

First step in the process of electricity load forecasting is to provide last information of the system load being studied. After preparing the input data matrix, it is turn of classification. The reason of this classification is the existence of completely determined models in different days that were referred to in many references. Among different days of weeks, Saturday to Wednesday which are working days in Iran, have the same load model. Consumed load model of Thursdays also defers slightly from working days. Fridays have also their own particular model and have a low level of load. Special days have a completely different model, too. So it seems necessary at the first look that each of these classes should be analyzed separately.

⁶ Lyapunov exponent

VI. ADAPTIVE NEURAL- FUZZY INFERENCE SYSTEM

ANFIS, proposed by Jang [19, 20], is an architecture which functionally integrates the interpretability of a fuzzy inference system with adaptability of a neural network. Loosely speaking ANFIS is a method for tuning an existing rule base of fuzzy system with a learning algorithm based on a collection of training data found in artificial neural network. Due to the less tunable use of parameters of fuzzy system compared with conventional artificial neural network, ANFIS is trained faster and more accurately than the conventional artificial neural network. An ANFIS which corresponds to a Sugeno type fuzzy model of two inputs and single output is shown in Fig. 1. A rule set of first order Sugeno fuzzy system is the following form:

Rule i: If x is A_i and y is B_i then $f_i = p_i x + q_i y + r_i$.

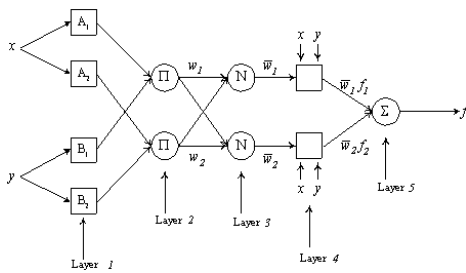


Fig. 1. ANFIS architecture

ANFIS structure as shown in Figure 1 is a weightless multi-layer array of five different elements [20]:

- Layer 1: Input data are fuzzified and neuron values are represented by parameterized membership functions;
- Layer 2: The activation of fuzzy rules is calculated via differentiable T-norms (usually, the soft-min or product);
- Layer 3: A normalization (arithmetic division) operation is realized over the rules matching values;
- Layer 4: The consequent part is obtained via linear regression or multiplication between the normalized activation level and the output of the respective rule;
- Layer 5: The NFN output is produced by an algebraic sum over all rules outputs.

The main objective of the ANFIS design is to optimize the ANFIS parameters. There are two steps in the ANFIS design. First is design of the premise parameters and the other is consequent parameter training. There are several

methods proposed for designing the premise parameter such as grid partition, fuzzy C-means clustering and subtractive clustering. Once the premise parameters are fixed, the consequent parameters are obtained based on the input-output training data. A hybrid learning algorithm is a popular learning algorithm used to train the ANFIS for this purpose.

VII. THE PROPOSED METHOD FOR POWER CONSUMED LOAD FORECASTING

Since fuzzy methods and systems were presented for using in different applications, researchers noticed that making a fuzzy powerful system is not a simple work. The reason is that finding suitable fuzzy rules and membership functions is not a systematic work and mainly requires many trails and errors to reach to the best possible efficiency. Therefore the idea of using learning algorithms was proposed for fuzzy systems. Meanwhile learning of fuzzy network proposed them as the first goals for being unified in fuzzy methods in order to make the development and usage process of fuzzy systems automatic for different applications. Function estimation by using the learning methods is proposed in neural networks and neural-fuzzy networks.

In the suggested methods we focus on the on the review and the predictability rate of time series load consume that it will be done by Lyapunov exponent through which we can determine the rate and the horizon of forecasting. Then in continue we forecast load consume and its improvement by the help of the offered method. One of the famous neural-fuzzy systems for function estimation is ANFIS model. We used this system for power consumed load forecasting in this paper too, but with this difference that we used one separate adaptive neural-fuzzy system for each season of the year. Although at the time of training these systems data overlapping is considered, because data of each season of the year is not completely independent and there is some similarities between the first days of a season with its previous season regarding the amount of load consumption. Figure 2 shows the diagram of multi adaptive neural-fuzzy system (multi ANFIS).

As it is shown too, in the Figure 2, we us a switch for any subsystem of a season be thought in lieu of that season. Therefore the time of system training and testing will decrease and the entrance of extra data is prevented.

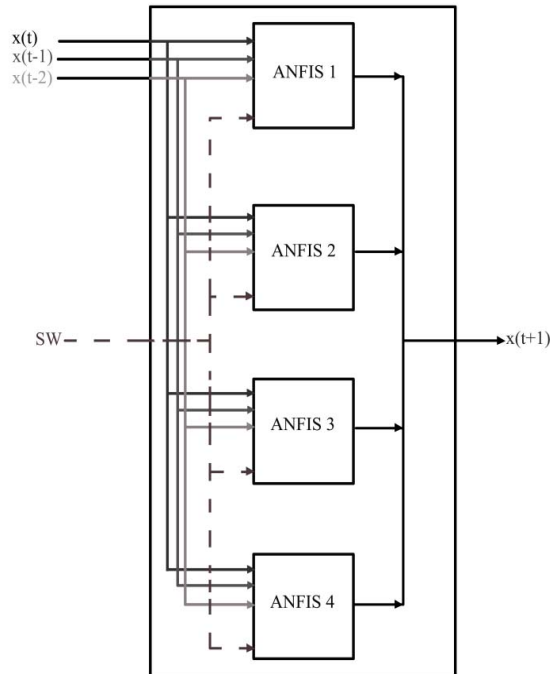


Fig. 2. Implemented Diagram of Multi ANFIS

VIII. RESULT

In the proposed method we classified day into two categories. We divide the season days into two groups of working days (Saturday to Thursday) and holidays that their load consumption is different from other days.

Here we also calculated the output of Multi ANFIS based on the average of load consumption one time with temperature and another time without it. You can see the results in Table II and III.

The amount of the accuracy of the performance of any of calculation methods in load forecasting is determined by measuring the obtained values of system model and comparing it with real data.

Mean Absolute Percentage Error (MAPE) is used for studying the performance of every mentioned method with the data of related test. MAPE is determined by following relation:

$$MAPE = 1/N (\sum_{i=1}^N APE_i)$$

(6)

$$APE = |(V(\text{forecast}) - V(\text{actual})) / V(\text{actual})| * 100\%$$

(7)

TABLE II
POWER LOAD CONSUMPTION FORECASTING FOR THE WORKING DAYS AND HOLIDAYS (Saturday to Thursday) WITHOUT TEMPERATURE

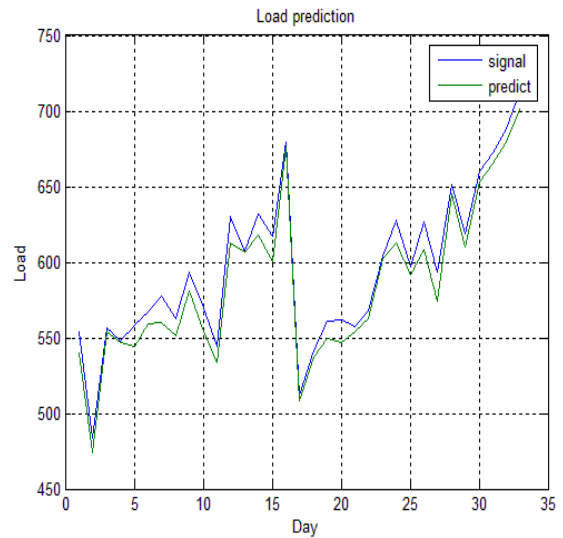
MAPE for holidays	MAPE for working days	load consumption forecasting
0.4924	1.6530	Spring
0.3574	1.8456	Summer
0.6435	2.0920	Fall
0.0936	2.0874	Winter

TABLE III
POWER LOAD CONSUMPTION FORECASTING FOR THE WORKING DAYS AND HOLIDAYS (Saturday to Thursday) WITH TEMPERATURE

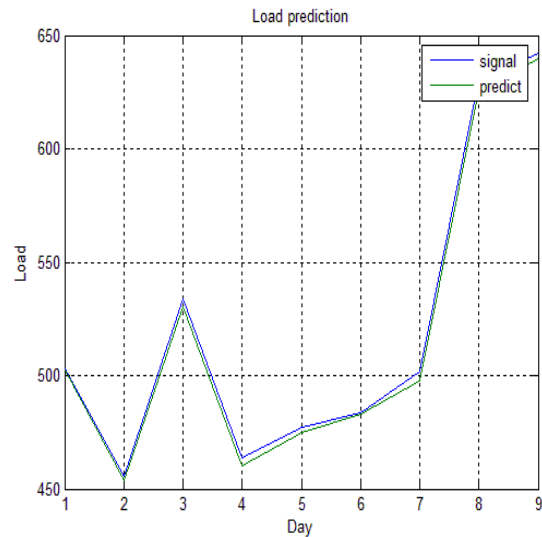
MAPE For holidays	MAPE For working days	Load consumption forecasting
0.1055	0.9602	Spring
0.6661	0.8568	Summer
0.4590	1.1392	Fall
0.2553	1.3015	Winter

As it is obvious of the above Tables, making working days separate from holidays with using a temperature yields a better result, in load consumption forecasting.

Also in order to compare, the diagram of daily load forecasting curves for spring through both groups is shown in Figures 3 and 4. It should be mentioned that MATLAB software is used for load forecasting and simulation.



(A)



(B)

Fig. 3. Power load forecasting for two groups of spring days without temperature. A) Working days (Saturday to Thursday); b) holidays

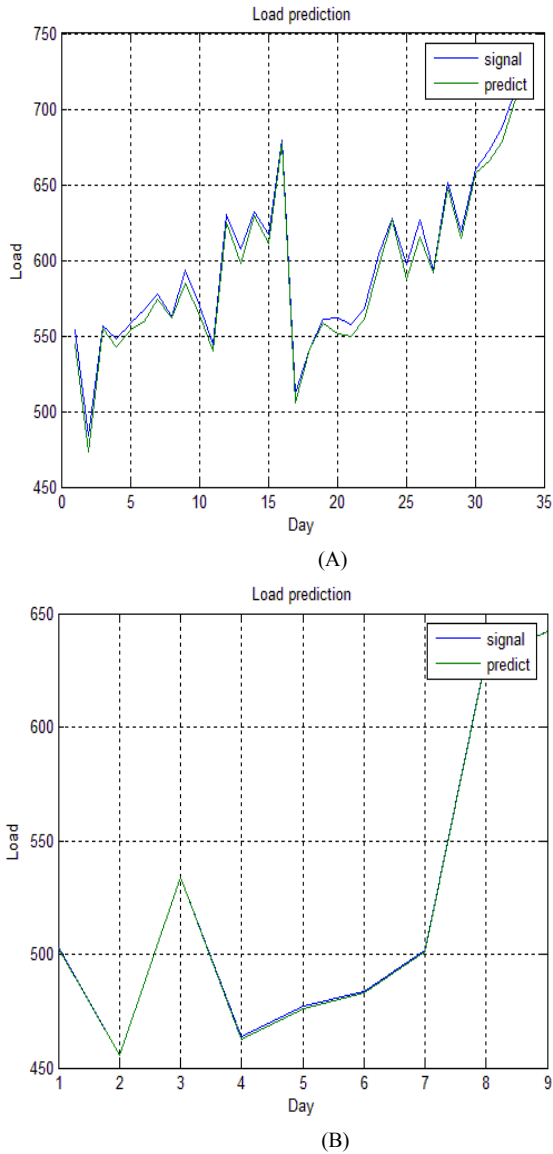


Fig. 4. power load forecasting for two groups of spring days with temperature. A) Working days (Saturday to Thursday); b) holidays

IX. CONCLUSION AND SUGGESTION

Comparing mentioned methods above shows that separation of working days from holidays by adding a temperature time series has a better result in load consumption forecasting.

According to this that in most proposed methods load consumption time series data is used, it seems that we can obtain better results by using time series data of one or more parameters effective in load consumption (like climate) also with load consumption time series.

By using the estimation of the biggest Lyapunov exponent and calculation of Lyapunov spectrum we can also determine the range of the system forecasting.

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