

Introduction of Neural Network Model and Fuzzy Regression Method for Short Term Load Forecasting in The Center Regional of IRAN

Mohammad ghomi¹⁺, Mohammad Taghi Moeti² Mohammad.Azimi³

¹ Department of Electrical Engineering, Touyserkan Branch, Islamic Azad University, Touyserkan, Iran

² Bakhtar Regional Electric Company, Load Estimate Office

³ Hamadan University of Technology

Abstract. Short term load forecasting plays an important role in power system studies. For reduction of costs and enhancing reliability as well as operational efficiency, load forecasting is used. Awareness of this issue provides the ability of load scheduling for generation; transmission and distribution of electrical energy. The most applicable technique for load forecasting is intelligence algorithm with statistical and fuzzy regression models. In this study, effective factors on load forecasting were evaluated as well as the using Fuzzy Regression Method (FRM) and Artificial Neural Network (ANN) for load forecasting in the center regional of Iran. The results show that the ANN is better in comparison with fuzzy regression technique while at peak load times while the fuzzy regression technique has more accuracy. It's possible to use the up and down limits of fuzzy regression in order to load forecast in specific days.

Keywords: Load Forecasting, Artificial Neural Network, Peak Load, Possibility Regression.

1. Introduction

By increasing the consumption of electrical energy an industrial growth, the electrical energy is converted into the essential motivation character of development. Disability of new technology for storing the high level of energy results in the use novel methods which play an essential role on optimal and economic consumption of electrical energy [1, 2]. Load forecasting is vital in design and implementation of industrial plans. The load oscillation, source variation and the change of weather condition as well as the cost of energy at the time of peak load. The presented method is able to estimate load variation which is suitable in the reduction of over load. Applying this technique in strategic time's results in improving of accruing errors, also it can reduce load shedding. Load forecasting is effective tool for evaluating the price of contrast and cost exchanging in electrical power market. Load management is implemented to enhance the quality of services by transferring the load from high price hours to the lowest level of cost.

2. Load forecasting types

Generally load forecasting is divided into three parts:

Short term, mean term and long term load forecasting. The most common methods for short term or mean term load forecasting named economical load forecasting based on statistics.

2.1. Load forecasting methods

For this aim lots of techniques were introduced surely, each one of them has strength and windrow points, for example the comparison of similar days with different regression models, time series, intelligent

⁺ Corresponding author. Tel.: + (989166652494); fax: +(986624225151).
E-mail address: (ghomi_ee@yahoo.com).

techniques and statistical algorithms [3]. It generally accepted that this factor is more effective in comparison with others. Unit network factors, economical factors, forecasting time and Weather conditions.

3. Fuzzy regression models

It is possible that related observations of one or a group of variables and relation among them are difficult. In this case, classical regression technique has not enough ability to simulate information or data. One of the alternative classical regression methods in this condition is fuzzy and it can be divided into four categories. In the following models, capital letters show the fuzzy number and small letters introduces exact numbers [4, 5].

In addition to this mentioned classification it is better off classifying these regression fuzzy techniques into these parts. The type of pattern, The type of fuzzy number, The type of fuzzy method.

3.1. Possibility regression

After the inception of the notion of fuzzy sets in [6], there are efforts by many authors to apply this notion in statistics. Fuzzy regression techniques are considered to be useful when it is known that a causal relation exists, but only few data points are available in [7]. The correlated equations for a fuzzy regression program can be written in the usual forms ($y = a + bx$). It should be pointed out that four parameters of the above equation can generally be fuzzy. When it is so, \sim symbol over the parameter will hereafter represent the fuzzy number. In the context of modelling, it is expected that neither the model and its parameters nor the data are certain. Because the oversimplification of a modelling system has always been considered as a great risk in the evaluation process so that the uncertainties will be increased at the sequence these or imprecise information will be reflected in some appropriate results. The uncertainties in the model parameters, model inputs, etc., can then be taken into account by fuzzy numbers with their shape which derived from experimental data or expert knowledge [8]. The text continues on considering Possibility regression model, where a, b, and y are taken as fuzzy numbers [9]. In this section, those models with fuzzy coefficients of the regression are considered. The mathematical details and background are well documented [4, 10]. Let the model be of the form:

$$\tilde{Y} = \tilde{A}_0 + \tilde{A}_1 X_1 + \tilde{A}_2 X_2 + \tilde{A}_3 X_3 \quad (1)$$

where $\tilde{A}_0, \tilde{A}_1, \tilde{A}_2$ and \tilde{A}_3 correspond to the fuzzy numbers of the following form:

$$\tilde{A} = \begin{cases} 1 - \frac{x-a}{S^L} & a - S^L \leq x \leq a \\ 1 - \frac{a-x}{S^R} & a < x \leq a + S^R \end{cases} \quad (2)$$

Note that the subscripts 0,1,2 and 3 were ignored for the sake of simplicity and the triangular fuzzy number can then be denoted by $\tilde{A} = T(a - S^L, a, a + S^R)$. S^L and S^R are called the left and right spreads of the fuzzy number, respectively. $\tilde{A}_0, \tilde{A}_1, \tilde{A}_2$ and \tilde{A}_3 must be determined in such a way that the fuzziness in the output of fuzzy \tilde{y} of all the observed responds becomes minimum. In other words, it is desired that we could find the regression parameters that have the smallest spreads around their central value. Mathematically, it corresponds to the minimization action of the following target function:

$$Z = m(S_0^L + S_0^R) + \sum_{j=1}^3 \left[(S_j^L + S_j^R) \sum_{i=1}^m |x_{ij}| \right] \quad (3)$$

This is subjected to the following constraints:

$$(1-H)S_o^L + (1-H) \sum_{j=1}^3 S_j^L |x_{ij}| - a_o^c - \sum_{j=1}^3 a_j^c |x_{ij}| \geq -Y_i \quad \forall i = 1, 2, \dots, m \quad (4)$$

$$(1-H)S_o^R + (1-H) \sum_{j=1}^3 S_j^R |x_{ij}| + a_o^c + \sum_{j=1}^3 a_j^c |x_{ij}| \geq Y_i \quad \forall i = 1, 2, \dots, m \quad (5)$$

It is supposed that the regression parameters are symmetric fuzzy numbers, that is, $S_j^R = S_j^L = S_j$. Also, note that there

exists only one input of $X = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{m1} & x_{m2} & x_{m3} \end{bmatrix}$ in the model. Thus using (3) the problem is:

$$\min Z = 2(mS_o + \sum_{j=1}^3 S_j \sum_{i=1}^m |x_{ij}|) \quad (6)$$

which is subjected to the following refined constrains using (4, 5):

$$a_o + a_1x_{i1} + a_2x_{i2} + a_3x_{i3} + (1-H)(S_o + S_1x_{i1} + S_2x_{i2} + S_3x_{i3}) \geq Y_i, \quad \forall i = 1, 2, \dots, m \quad (7)$$

$$-a_o - a_1x_{i1} - a_2x_{i2} - a_3x_{i3} + (1-H)(S_o + S_1x_{i1} + S_2x_{i2} + S_3x_{i3}) \geq -Y_i, \quad \forall i = 1, 2, \dots, m \quad (8)$$

Where x_{ij} ($j=0,1,2,3$) represent i th observation for j th variable. Notice that, there are two constrains for data observation. In this paper we used QSB software for minimizing Z target function with $2m$ constrains.

4. The selected case for study

4.1. Fuzzy regression method Short term load forecasting

In this study the short term load forecasting with fuzzy regression method has been done on center regional of Iran. Is assumed as a vector of independent variables $X = (x_1, x_2, x_3)$ which are x_1 minimum temperature, x_2 maximum temperature, x_3 sorted set of load operations (for example the number one indicates that the minimum value of variables has occurred at output).

Regarding (1) we want to compute the fuzzy parameters $\tilde{A}_0, \tilde{A}_1, \tilde{A}_2$ and \tilde{A}_3 , also the primary assumption of symmetrical and triangular shape for these variables results in considering two separated factors, once as the amplitude and the other as the length of a variable. Therefore by using the relation of (6) the goal function can be written, after that for each input value two restriction will be obtained (7, 8). In this paper 14 samples of hours on Saturday 31 July, 11 samples of hours on Sunday 1 August, and 11 samples of hours on Monday 2 August 2010 with classification sampling constrains were selected randomly. All in all it is obvious that we are confronted with a linear programming problem with 72 constrains. Surely the use of present software in linear programming such as QSB software will resolve this obstacle. With attention to calculated values in Table III the average error of represented technique (9, 10) in comparison to actual load on Thus day 3 August 2010. Is less than 2 percent over a 24 hours period, finally the differences between predicted and real estimated numbers have been compared in output. The criterion for measuring the error is the difference between suitable and real values. The absolute percentage error (APE%) and the mean absolute average of error (MAPE) are used in order to separate errors and N_h is number of hours in load forecasting period, these are defines as follow:

$$APE = \frac{|Load_{forecast} - Load_{actual}|}{Load_{actual}} \times 100\% \quad MAPE = \frac{1}{N_h} \sum_{N_h} APE \quad (9), (10)$$

5. Artificial neural network short term load forecasting

By considering the weather condition the short term load forecasting in the central regional of Iran was investigated. The most important discussion in designing process of an intelligent system related to the collection of effective combination of input which should have the linear independence as well as having suitable information of the past. The figure(1-a) shows the relation of inputs and outputs. Effective factors which were assumed are electrical load, minimum and maximum temperature in three days ago. Stability is an important case in ANN design and the optimum result because the suite designs. Thus in each test, data of learning and examining selected randomly and 10 time intervals were achieved [3]. All of data divided two classifications for training system that 70% of them were learning and 30% for examining was used. the most reason for this data selection, downsized in testing of ANN power in load forecasting and predicting.

Then the mean absolute average was computed with regards to error (MAPE%) finally, selected the optimal structure was suggested for ANN.

5.1. Design of optimal neural network

For, finding the best ANN plan with the minimum error, ANN with neurons, layers and various learning was designed which were compared via their errors together. So that, number of neurons, optimal learning rate and optimal recursive learning, obtained as can be observed through figure (1-b).

- Step1. At first recursive learning method fixed and changes the neurons of hidden layer. This step consists of two sequential steps. After that ANN with one hidden layer was assumed which results in finding number of optimal layers, following that the error and number of optimal neurons found.
- Step2. In the second step by using the optimal number of layer and neurons foregoing step ,evaluated ANN performance for different rate of network training then in each test increase the rate of learning in proportion to before test and record these effects on error produced. Then compute the optimal learning rate. This rate in this case study obtained 4%.
- Step3. Step 1 and 2 continues with different recursive learning to get the best learning plan of ANN.

All parts of learning and examining the structure of neural network in order to compute weights and biases have been down with Matlab, the results of this simulation is shown in table(1-a). The selected (AAN2) has lowest amount of error with respect to presence data. It should be mentioned that the type of selected network regarding nature of load in each region is not unit and can be changed.

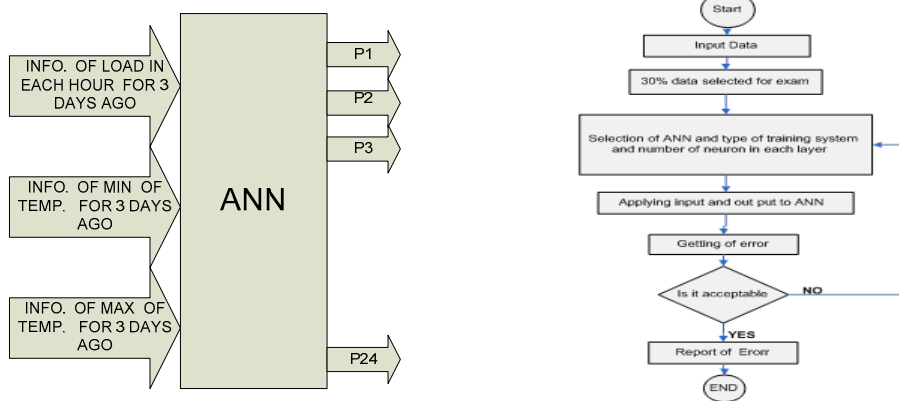


Fig.1: (a): Schematic of input and output neural network. (b): Learning method in artificial neural network

Table1: (a)Mean absolute avrage of error for different learning and examining data.(b):Optimal strcure and spesifications of selected ANN

Artificial Neural Networ	Structure	MAPE%	
		Learning	Examining
ANN1	9-3-24	1.54	1.64
ANN2	9-2-24	0.7	1.42
ANN3	3-3-24	1.78	2.18
ANN4	6-3-24	1.85	2.26
ANN5	6-24	2.31	2.71

SPECIFICATIONS OF OPTIMAL SELECTED ANN	
TYPE OF ANN	MLP
NO. OF NEURONS IN HIDDEN LAYERS	2
NO. OF NEURONS FRIST HIDDEN LAYER	2
NO. OF NEURONS SECOUND HIDDEN LAYER	3
NO. OF NEURONS IN OUTPUT LAYER	24
NO. OF LEARNING	200
LEARNING FUNCTION	Trainlm
LEARNING ERROR	0.00001

The graph introduced a comparison between real and predicted values for learning data (MAPE%=0.7) in one side and a comparison between real and predicted values for learning data (MAPE%=1.42) on the other side as shown in figure3.4.

The structural characters of optimal neural network in order to get minimal predictive error are mentioned on Table (1-b).

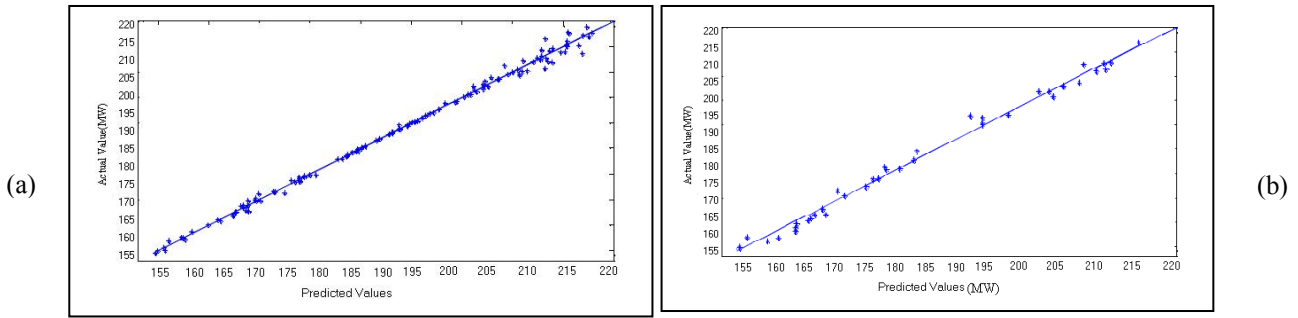


Fig. 2:(a) Real and forecasted data for learning data(MAPE%=0.7), (b): Real and forecasted data for examining data(MAPE%=1.42)

6. Conclusion

Based on load forecasting it's possible to calculate entering and exiting time for different power plants as well as their contribution on generation cycle, also this technique can forecast the effects of load variations on reliability of the power system and all of these findings can be applied to the load shedding of power system. Finally, these two methods implemented for 24 period of time in the consumption of the central regional of Iran.

By referring to the results of simulations on Table(2), it was cleared that the amount of error in fuzzy regression was 1.85 while this factor 1.45 in neural networks.

Considering the selected network and load pattern of the central regional of Iran all of two presented methods were useful, so that they can be introduced as basic methods in other power systems with similar behaviours, on other hands, By evaluating the curves of figure5, 6 it can be concluded that the overall average error of neural network is lower than fuzzy regression. But at the peak load times (June) the fuzzy regression has better accuracy. Also it is possible to use the up and down limits of fuzzy regression for load forecasting in specific days.

Table2: Percentage error forecasted peak load in the central region of Iran

Hours	Real load	Forecasted load			APE%		
		FRM	ANN	ANN	FRM		
1	179.8	177.4	186.6	195.8	180.5	3.79	0.39
2	168.8	166.9	176.1	185.2	174.1	4.3	3.14
3	164.4	159.2	168.4	177.6	162.8	2.44	0.98
4	159.4	148.2	157.4	166.5	161.2	1.3	1.13
5	157.2	143.1	152.3	161.5	153.3	3.2	2.54
6	152.1	138.9	148.1	157.3	147.5	2.72	3.12
7	156.4	141.4	150.6	159.8	151.2	3.84	3.44
8	165	154.5	163.7	172.9	162.5	0.81	1.54
9	181.3	171	180.1	189.3	178.2	0.64	1.74
10	194.5	182.4	191.6	200.7	193.4	1.53	0.57
11	206	190.8	200	209.2	204.1	2.99	0.93
12	210.6	191.8	200.9	210.1	208.2	4.81	1.15

(a)

Hours	Real load	Forecasted load			APE%		
		FRM	ANN	ANN	FRM		
13	202.7	191.7	200.8	210	200.4	0.93	1.15
14	202.4	189.8	199	208.2	200.1	1.72	1.15
15	197.3	189.4	198.6	207.8	195.2	0.67	1.08
16	198.4	189.8	199	208.1	199.2	0.28	0.4
17	199.6	188.6	197.7	206.9	202.2	0.94	1.3
18	197.2	185.6	194.8	203.9	200.1	1.25	1.47
19	192.1	182.6	191.8	201	189.7	0.17	1.27
20	198.8	187.7	196.9	206.1	200.2	0.97	0.7
21	223.4	216.2	225.3	234.5	226.1	0.87	1.21
22	219.1	212	221.1	230.3	221.6	0.93	1.14
23	208.6	202.2	211.4	220.6	210.8	1.34	1.05
24	194.3	188.8	198	207.2	198.4	1.91	2.11
MAPE						1.85	1.45

(b)

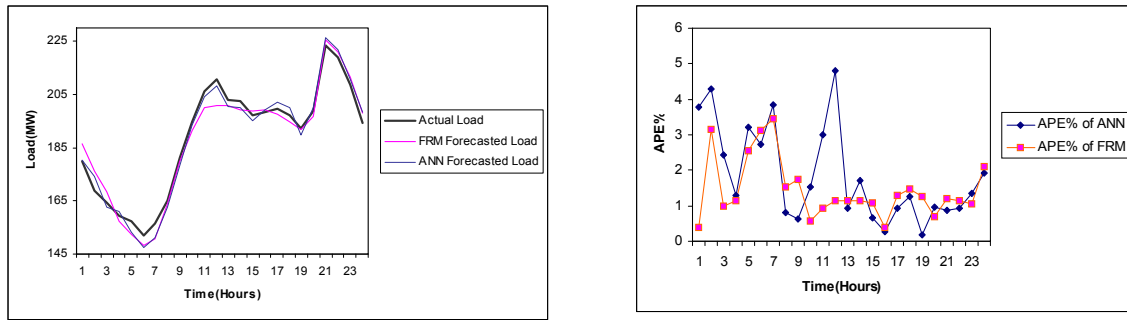


Fig. 2:(a) Real and forecasted load load using both method(FRM,ANN), (b): Comparison beetwin error percentage forecasted load.

7. References

- [1] K. Sinha, "Short Term Load Forecasting Using Artificial Neural Networks", IEEE Trans. On Power Systems, pp.548-553, 2000.
- [2] I. Drezga, S. Rahman, "Short Term Load Forecasting with Local ANN Predictors", IEEE Trans. On Power Systems, Volume 14, Aug. 1999.
- [3] A. Onsilvai, M.E. El-Hawary, "Wavelet neural network based short term load forecasting of electric power system commercial load" in: Proceedings of IEEE Canadian Conf. Elect. Comput. Eng., vol. 3, Edmonton, Canada, May 1999, pp. 1223–1228.
- [4] H.Tanka, S.Uejima, K.Asia, "Linear Regression Analysis with Fuzzy Model" IEEE Trans, System Man cybernetic 12, pp 903-907, 1982.
- [5] H.Tanka, "Fuzzy Data Analysis by Possibility Linear Model" Fuzzy sets and sytem 24,pp. 363-375•1987.
- [6] L. A. Zadeh, "Fuzzy Sets, Information and Control "(1965), 338-35.
- [7] Bardossy, A., Bogardi, I., and Duckstein, L.,. *Fuzzy Regression in Hydrology*. Water Resources Research 25(7), 1497–1508, 1990.
- [8] K.J.Kim, H.R.Cheng, "A Comparsion of Fuzzy and non Parametric Linear regression" computer, opr,res,24,pp 505-519, 1997.
- [9] K.J. Kim, H.Moskowitz, M.Kokslan, "Fuzzy Versus Statically Linear Regression", Euro .j.oper.res, 92, pp 417-437, 1996.
- [10] Yen, K.K., Gheoshary, G., Roig, G.,. A Linear Regression Model Using Triangular Fuzzy Number Coefficients. Fuzzy Sets and Systems 106: 167-177, 1999.