

# Add a New Input to Neural Network with Genetic Learning Algorithm to Improve Short-Term Load Forecasting

Vahideh Miryazdi, Mohammad Ghasemzadeh, Ali Mohammad Latif  
miryazdiva@yahoo.com

**Abstract:** Short-term load forecasting (STLF) plays an essential role in the economic system and save the country's electricity supply. In this paper, are used a neural network with genetic learning algorithm for forecasting the electric power load of Khorasan area in Iran. Because the importance of neural network inputs, select the optimal inputs is deducted errors system. Consumption load is a nonlinear function of various factors such as weather conditions and periodic changes. This paper proposed a new variable together with the data load and temperature parameters for the problem of STLF. The variable obtained from the load curves and effect of periodic changes. The obtained results indicate that the proposed variable is effective for forecasting the short term load in electric power systems

**Keywords—**Short-term load forecast, Neural Network, Genetic algorithm.

## I. Introduction

Load forecasting is an important part of management of electric power systems. Power supply planning is a major objective of short-term load forecasting. High forecast error is concluded large loss in safe economical operation in the power system.

Load forecast methods can be divided into two categories: statistical and artificial intelligence techniques. A group of statistical approaches are regressive integrated moving average (ARIMA) [1], time-series analysis [2], Kalman filter [3], and intelligent algorithms such as artificial neural networks [4-5], fuzzy system [6], neuro-fuzzy systems [7-9], genetic algorithm [10] and support-vector machine (SVM) [11] have been applied for short-term load forecasting.

With the development of power industry, load composition and its regularities has become ever more complex, and it has been recognized that one single method may not be capable of load forecasting under such a diverse and complicated condition.[15]

Recently, hybrid forecasting methods have become a focus of attention by some researchers [12-14].

For example Yang Zhangang et al. [16] proposed a new Gaussian kernel function (RBF) neural network and use genetic algorithm to optimize RBF network parameters.

Polat and Yildirim [17] used genetic algorithm to optimize the spread parameter of the GRNN for pattern recognition, and this optimized GRNN can provide higher recognition ability compared with the un optimized GRNN.

Hamed Kebriaei et al. [18] used a nonsymmetric penalty function with different penalties for over-forecasting and

under-forecasting. Also they used a modified radial basis function (RBF) network, which uses the genetic algorithm to estimate the weights of the network. This network has the ability to handle the new penalty function. Moreover, a fuzzy inference system is combined with the modified RBF network to incorporate the impact of temperature on load.

The rest of this paper is organized as follows. Section II described the impact of relative factors on load pattern.

In section III we are determined the neural network inputs. In Section IV, we are defined a new variable. The case study of Khorasan electric power load forecasting is presented in section V. The paper is concluded in Section VI.

## II. The Impact of Relative Factors on Load Pattern

Electricity demand is nonlinear and many factors such as weather conditions, sophisticated social parameters, economic activities, calendar effect and random factors exist in the assessment of load consumption patterns. Periodic Events in load curves are create the seasonal events. By charting load diagram, seasonal, daily and hourly changes clearly is visibled on the load pattern. Also load behavior for some months is similar. Consumption load is not same in different times of day. Usually the peak load occurs at the exact hours and holidays are effective in load consumption.

All of these factors should be considered for short term load forecasting. These factors determine the total load consumption patterns and when you can identify the effect of each one of them in load curve can be achieve accurate prediction. Therefore to consider the effect of these changes we compared load consumption for a week at the four Seasons. According to the Figure 1, the seasonal changes are observed in this curve clearly. Also load consumption in summer more than winter. because the temperature is increased and thus the use of cryogenic equipment such as air conditioners is increased.

Increasing other climatic conditions such as humidity, wind speed, and cloud cover is increased the load consumption too.

Also, daily changes can be observed in load curves. With observation different days of the week can be concluded consumption load is lower in holidays. Recently some researcher divided days of week in four cluster with using a variety of methods such as K-Means and Self Organized Map(SOM) [11].

In normal mode high consumption respectively is related to Saturday (the day after the holiday), Sunday to Wednesday, Thursday (the day before the holiday) and Friday (holiday).

Can be used a code with amounts of 1,2,3,4 for neural network or using of separate neural networks for effect of daily change.

To evaluate the effect of hourly changes, can be defined low consumption times, normal consumption times and high consumption times for 24 hours a day.

Also changing the time of sunrise and sunset is effective in consumption load. For example, when to near sunset time, the consumers lighting add to system and load consumption is increased.

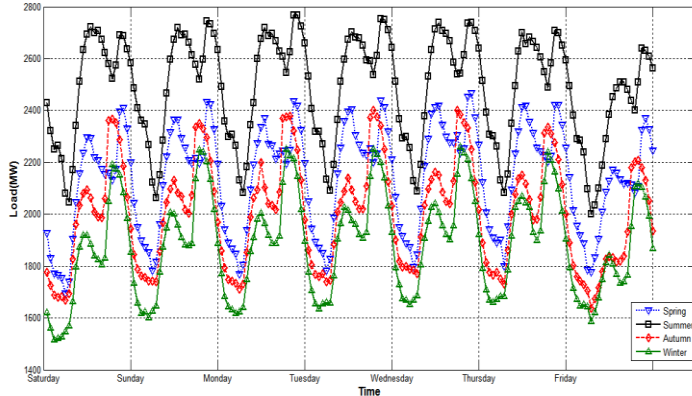


Figure 1: Load Curve for a week in different sessions.

### III. Neural Network Inputs

Select the appropriate inputs is one of the main effective factors in performance the prediction model.

There are many variables in the load forecast which are used for market analysis. Too many variables to predict are extra. Or because of less effect is non essential. In other hands large amount inputs to cause complexity of the training process in the network and it can be increase the forecast error.

Hence to minimize variables should be used the appropriate inputs selection strategies. One of these strategies is the correlation test. The result of analysis with correlation coefficients of the input vector is as follows:

23 past Data load+ peak temperature at day+ lowest temperature at day. Past data load are:

The load of 1, 2, 23, 24, 25, 47, 48, 49, 71, 72, 73, 95, 96, 97, 119, 120, 121, 143, 144, 145, 167, 168, 169 hours ago

### IV. A new variable structure

Now according to section II we can construct a new variable from behavior load curve be suitable with seasonal, daily and hourly changes and for load forecasting problem do like a director. So to construct the new variable do as follow:

- 1) Because in first half-year, consumption load is higher than second half-year, so new input for first half-year must be more from second half-year's code. This increase is dependent on rate of changes surface load.
- 2) The next step according to the load consumption, 24 hours a day is divided into 3 categories (Low consumption times, normal consumption times and high consumption times) and we consider a code for each class.
- 3) In last stage for holiday's effect deduct half a unit of codes, except in low consumption times.

The values obtained are shown in Table 1 and Table 2.

22-24	18-21	10-17	1-9	Hour day
6	5	6	4	Work day
5.5	4.5	5.5	4	holiday

Table 1: New Variable For First Half-Year.

22-24	18-21	9-17	1-8	Hour day
3	4	3	1	Work day
2.5	3.5	2.5	1	holiday

Table 2: New Variable For Second Half-Year.

### V. Implementation

Follow up to evaluate ability of new input on prediction accuracy, we implemented an example for forecasting demand of electricity in khorasan area in iran.

In this paper, multi layered perceptron (MLP) network with three-layer (one layer in hidden unit) is applied. The transformation functions in hidden layer are sigmoid.

Inputs is determined in section III and normalized between [0,1] interval. To select the number of neurons hidden layers still has no fixed analytic or theoretical basis or theorem to determine [16].

With trial and error can be find number of hidden layer neurons. When the number of neurons is too little, it is unable to complete the task, when too many, it will increase computing time [16]. Therefore for determination of the number of neurons hidden layer based on several simulation experience we choose 16 neurons.

We determined one neuron for output layer. Because we want forecast the load for every hour.

To consider effect of new variable in forecast accuracy, training neural network together with this variable to inputs.

Genetic Algorithms because of their extensive global optimization capability are successfully applied on neural network, and so on. [16]

In this section we define genetic algorithm operation to optimize weights of neural network.

The learning process performed with genetic algorithm as follow:

- 1) Generate Initial population (chromosome) of random number in [-0.5, 0.5] interval.
- 2) calculate fitness value for every person with fitness function as follow:  
 $F = \text{MSE}(y - \hat{y})$   
Obviously if cost value is smaller in amount, fitness is bigger. Therefore performance of individual is determined by the fitness.
- 3) Arrange the population with fitness criteria.

Genetic algorithm generate other population with replicate this process. in this paper for 200 generation replicate following process:

- 1) Directly transfer 10 % best of previous generation to new generation.
- 2) 70 % of new generation is generated with crossover operation (crossover from one random place).
- 3) 20% of new generation is generated with mutation operation.

One of properties in this algorithm is fitness value for best person in next generation is bigger than fitness value for best person in previous generations. Therefore finally select best person with biggest fitness and neural network with selected weights will forecast short term load for next times.

The criteria for evaluation efficiency are the Mean Absolute Error (MAE) and mean absolute percentage Error (MAPE) and Mean Square Error (MSE).

Results of the experience is showing in Table 3

	MAPE (%)	MAE	MSE
Genetic	3.84	0.0170	4.9507e-004
Genetic+ new input	2.7582	0.0123	2.5866e-004

**Table 3: Compare Effect of New Variable in Network Accuracy.**

### Conclusion

In this paper we have proposed a new variable for increasing precision of short-term load forecasting problems. This variable obtained from load curve and is function of effective changes in consumption load. The ANN models with genetic algorithm training used load profile and max/min temperature and new variable in input layer and result forecast next hours load. Our case study for the Khorasan load forecasting using MLP neural network with genetic learning algorithm showed that error is minimized and improves the prediction accuracy.

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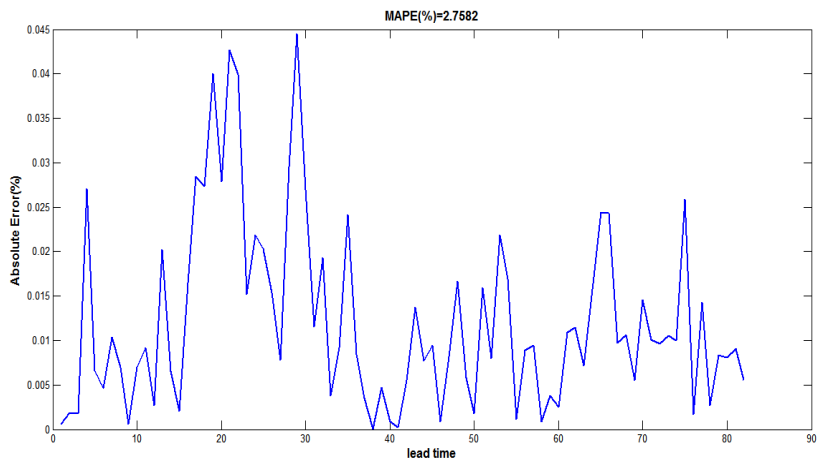
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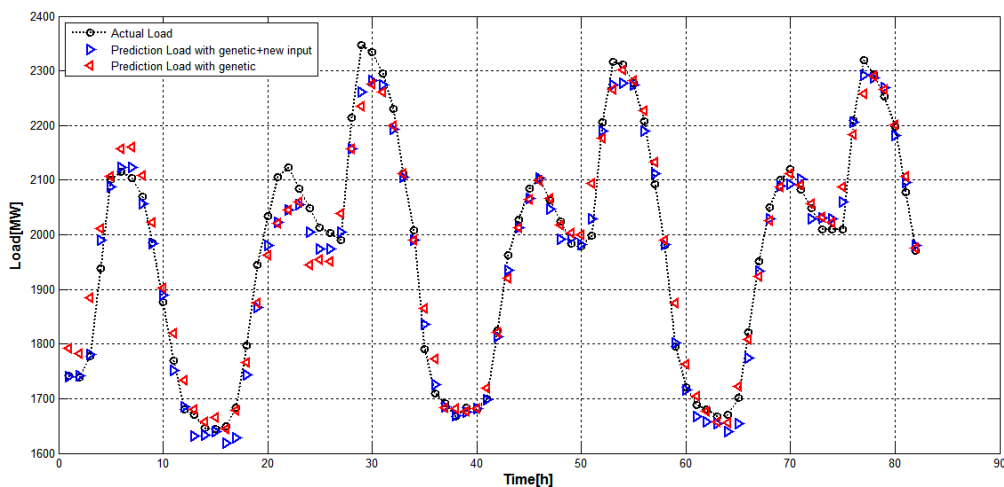
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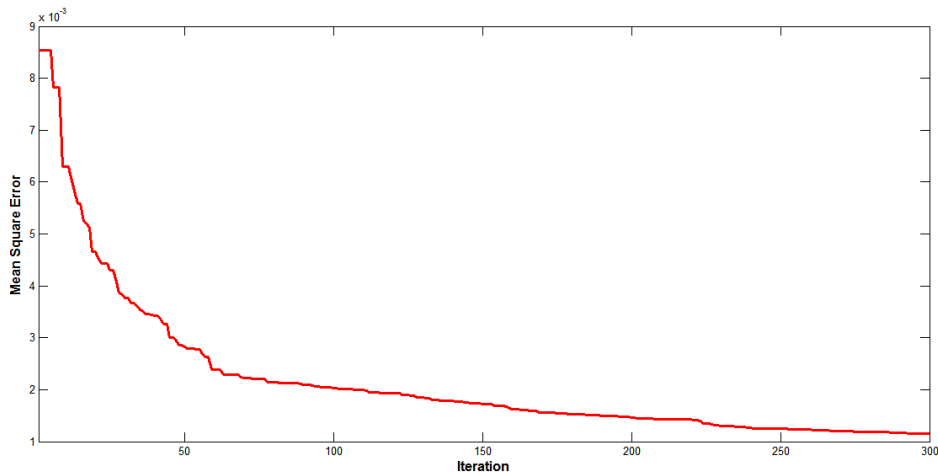
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**Figure 2: Mean absolute percentage Error (MAPE) for Training Data.**



**Figure 3: Effect of New Variable in Load Forecasting Accuracy.**



**Figure 4: process of Learning Genetic Algorithm .**