

An accurate analysis of the parameters affecting consumption and price fluctuations of Electricity in the Iranian market during Summer

Seyed Mojtaba Kavooosi Davoodi^a, Seyed Esmail Najafi^{b1}, Farhad Hosseinzadeh Lotfi^c, Hossein Mohammadiyan Bisheh^d

a,b .Department of Industrial Engineering, Science and Research Branch, Islamic Azad university, Tehran, Iran

c. Department of Mathematics, Science and Research Branch, Islamic Azad university, Tehran, Iran

d. Department of Industrial Engineering, Mazandaran University of Science and Technology Branch, Babol, Iran

Abstract

In this paper, a novel method is proposed to predict the cost of short-term hourly electrical energy based on combined neural networks. In this method, the influential parameters that play a key role in the accuracy of these systems are identified and the most prominent ones are selected. In the proposed method, initially, using the SOM network, similar days are placed in close clusters. In the next stage, the temperature parameter and prices pertaining to similar days are trained separately in two MLP neural networks because of their differences concerning the range of changes and their nature. Finally, the two networks are merged with another MLP network. In the proposed hybrid method, an evolutionary search method is used to provide an appropriate initial weight for neural network training. Given the price data changes, the price amidst the previous hour has a significant effect on the prediction of the current state. In this vein, in the proposed method, the predicted data in the previous hour is considered as one of the inputs of the next stage. The proposed method was assessed on the datasets of Iran in the summer. This information pertains to the 2011-2016 period.

Keywords: energy prediction, hybrid network, evolutionary search, data analysis, deep neural network.

1. Introduction

Since the industrial revolution, energy has become a key factor in everyday life [1]. Fossil fuels have become the most primary energy production in the world [1]. However, with the population growth and technological development, the current world is facing two vital problems, environmental pollution, and energy resource shortages [2]. One way to overcome problems is to improve efficiency and reduce emission [3]. The other way is to develop alternate energy resources [2]. People draw their eyes to renewable resources for their properties of environmental-friendly and sustainability. The most competitive renewables include water, wind, photovoltaic energy, and biofuel. Many of them have been proved to be advanced in addressing environmental and energy issues [4,5]. Today, electrical energy has become an essential element of human life as one of the most favorable types of energy. In order to supply this energy, vast and extensive power systems have emerged in various countries. The management and control of such systems was initially the responsibility of governments or quasi-public

¹ corresponding author: Seyed Esmail Najafi

Email: Najafi1515@yahoo.com

institutions, and if assigned to the private sector, would have a vertically integrated management structure. Most of the previous theories presented about power systems were based on the idea that electricity is a public service sector with intrinsic monopolistic properties. Many renewables have been applied to the electricity market. In the last few years, electricity market prices decreased a lot due to the close-to-zero marginal costs from renewable energies [6]. Therefore, the electricity market participants are seeking ways to be more competitive in the market. Many companies have adopted new electricity price plans [7], for example, time-of-use electricity price plans. These plans charge higher rates when demand is high, and lower rates when demand is low. This encourages customers to wisely decide their electricity usages and reduce on-peak energy usages [8]. This situation makes not only the producers but also the customers pursue more precise forecasts of the electricity market prices than ever. However, electricity price usually has complex features, such as highly volatile behavior and non-linearity, which makes it rather difficult to build a precise forecasting model [9–10].

Accurate electricity price forecasting may help electricity market participants to formulate reasonable competition strategies. Specifically, power producer can use the forecasting results to optimize unit output, while power consumers can use the results to optimize purchase portfolio [11]

However, the complex features of electricity prices such as periodicity and high volatility make the forecasting pretty difficult [12]

In recent years, a lot of models have been proposed for electricity price forecasting [13,14]. In general, the commonly used models can be classified into two primary categories: soft computing models [15,16] and time-series models [17,18]

The amount of information available to participants in the market is a fundamental issue in selecting the type of method used to resolve the pricing issue. Since the competitors in the electricity market do not adopt a specific predictable procedure because of the market's competitive nature, thus producers' behavior in pricing strategy regulation is not logical and the assumption of profit maximization is not rational to predict competitors' behavior. Thus, the application of the game theory and smart algorithms is not appropriate due to the restrictive hypothesis in problem modelling, such as predicting competitor power plant costs and the rationality of their behavior in setting pricing strategies.

The factors that influence the prediction of electricity prices are: 1. Weather conditions, seasons, daytime and nighttime, 2. History of electricity price data, 3. Demand and production balance, 4. Market participants' strategies, 5. Fuel prices, 6. Transmission lines congestion, 7. Market design, 8. Time of power cuts from main power plants. The presented solutions can be grouped based on the applied methods or schemes. It is common practice to implement short-term price forecast (STPF), medium-term price forecast (MTPF) and long-term price forecast (LTPF). Based on the method selected for prediction, the input and output of the model can be varied. According to the papers presented, the input of models may be as follows: load history, storage history, heat, production capacity, line constraints, predicted load, predicted storage, weather, oil prices, gas prices, input fuel, price history, bidding strategy, winter index, summer index, possible transmission line information, density index, holidays code and type of day (holiday or non-holiday) [19]. The output of various models can also be of the following type: price profile, quantity profile, load profile, maximum price, average price at peak load time, average error,

average error percentage. The pricing issue is an optimization issue. When the objective is to solve an issue in the real environment, the precise conditions of the issue must be considered.

In the field of market restructuring and privatization, the price factor and its accurate prediction is of increasing significance. Thus, according to the aforementioned issues, the purpose of this research is to answer the following question:

What is the optimal strategy for predicting the price of electricity in a competitive electrical energy market within the framework of the laws and regulations of the Iranian electricity market?

In this regard, in the present research, the following hypotheses will be used to explain the utilized approaches:

Among the types of power plants, only the steam power plant is examined.

In determining the optimal pricing strategy, the prediction of the next day load is considered definitive.

However, to demonstrate load variances in the results, sensitivity analysis is conducted for load variations.

The electricity market, as with all other markets, will be a demand-driven market

As with the real electricity market, the supply suggestion function in this market will be linear and ascending relative to the production level, and the demand function will also be linear but descending relative to the demand level.

To determine the optimal price strategy, the DC load distribution is used in the market pricing model.

For instance, Panapakidis and Dagoumas [20] use the artificial neural networks (ANNs) model for electricity price forecasting in Southern Italy. Sandhu et al. [21] employ the neural networks to forecast Ontario electricity prices. To better capture the characteristics of electricity prices, a combination of ANN models and other models is often presented. For instance, Ortiz et al. [22] propose a combined model based on artificial neural networks. Keles et al. [23] develop a model based on ANNs and optimal parameter model. Singh et al. [24] present a combined model with generalized neuron model and wavelet transform. Itaba and Mori [25] utilize the general radial basis function network and fuzzy clustering. Wang et al. [26] develop a hybrid model combined with ANNs and decomposition technique. It should be noted that although the ANNs model can describe the nonlinear characteristics of electricity price series, it cannot well deal with the linear fitting problem [27]. To describe the linear features of electricity prices, the time series model is often applied, which is considered as one of the most effective techniques [28]. Traditional time series models, such as autoregressive integrated moving average (ARIMA), autoregressive and moving average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH), have been frequently applied to forecast electricity prices. Besides, Diongue et al. [29] and Girish [30] propose some new time series models such as GIGARCH and autoregressive-GARCH. To better capture the features of electricity prices, some other models have been combined with time series models [31,32]. Since electricity price series is composed

by linear and nonlinear components, the integrated models that have linear and nonlinear fitting capabilities can improve the forecasting accuracy [33,34]. For this reason, the empirical mode decomposition (EMD) approach has been used for electricity price decomposition by some researchers [35,36].

2. Research methodology

Since the forecast in this study take place in Iran which has specific climate conditions, thus it was aimed to utilize a new combination of parameters and to categorize data into various classes with higher accuracy. Parameters such as past load price, temperature and humidity in each category are considered with a novel combination of these traits. Data categorization methods and the precise selection of parameters are discussed further.

In this project, information on consumed electricity load price between the years 2014 to 2017 in Mazandaran province was used, as well as considering temperature during this period. Upon the data collection stage, data was analyzed and dynamically identified in order to categorize data into smaller groups based on their common characteristics and to create a separate model for each group. In numerous sources it is emphasized that various pricing activities cannot be presented by one model.

In this vein, initially, without considering the specific data categorization, consumed loads during the defined period was forecasted with no favorable results. Given the substantial changes in electricity consumption amidst season changes, categorization should first be conducted based on seasons. Hence, data are categorized into four groups, i.e. spring, summer, fall and winter. Although, it should be noted that accurate forecasts in all seasons with the exception of summer is conducted accurately by current systems and human expertise.

Various days of the week have their own curves, even though it has been claimed in prior studies that curves of mid-week consumed loads (for Iran, from Sunday to Wednesday) are similar and are different to consumed load curves of the holidays. Moreover, the consumed load curves on days before and after holidays differ to normal days of the week. However, in the real world it is not possible to manually conduct such categorization. Therefore, this paper presents a categorization method to schedule these cases.

One of the other factors impacting the consumption price curve are the holidays. Since there are two types of holidays in Iran, i.e. religious and national holidays, both should be taken into consideration. In this project, forecasts of religious and national holidays are conducted separately. Although, it should be noted that according to consumed load price comparisons of the 2009 to 2012 period, the consumed load in Iran and expert opinions indicate that there is no need for forecasts for some of the holidays since the consumed loads on these days are similar to that of the previous years. For example, the consumed load on 2nd April and Ashura Day are the same as the previous year.

3. Hybrid Neural Network

Artificial neural networks are suitable tools for modeling and forecasting data. Various types of neural networks have been introduced, each with a specific application. One of the main and beneficial capabilities of neural networks is their function on vast quantities of variables as well as on complex systems. Despite the simplicity of utilizing neural networks, there are also drawbacks such as setting network architecture parameters, placing the network in local optimizations and extension of the learning process time period. In this regard, various solutions have been proposed to resolve each issue, one of the most favorable of which is the combination of these networks. The combination of neural networks varies in different applications. One of the most valuable functions of this type of network is the use of a non-monitored neural network to cluster similar data, and in the next stage, to train the supervised networks using similar samples in one cluster. Another use of hybrid networks is that inputs are of different ranges which entails lack of appropriate network training and the negligence of a number of traits. In this regard, the traits that are of different nature are trained with different networks, and ultimately these types of networks are combined.

The reason for utilizing hybrid networks to forecast the price of consumed load is the existence of several effective factors. Due to the lack inaccessibility to all of these factors, two of the most valuable features i.e. temperature and cost of previously consumed loads are used. These two parameters are highly influential on one another but at the same time, are extremely different in nature. The most important reasons for this include:

- 1) Temperature difference of a few degrees may multiply the consumed load price by a few hundred. Therefore, the slightest temperature changes in the network should be accurately modelled.
- 2) The range of temperature changes are within the 5-30 degrees Celsius range if the consumption load in the province under assessment is between 200 to 1500 MW
- 3) The effect of temperature variation in different hours of the day exhibit a different trend. As an example, a temperature change of two degrees between the hours of 13 to 15 shows a significantly greater impact on consumption compared to a two degree change in the early hours of the day.
- 4) Temperature changes in various seasons do not exhibit the same effect. For example, a one degree temperature change in summer exhibits a different change compared to the same change in winter.
- 5) Temperature changes within temperature ranges are also significant. For example, a temperature variation of two degrees within a temperature range of less than 20 degrees may not exhibit much effect on load consumption but a temperature variation of one degree at temperatures over 24 degrees will exhibit significant effect on load consumption.

As previously mentioned, these parameters are of completely different nature in terms of size but are highly influential on one another. For this reason, two different networks have been used in this project for these two parameters.

4. Self-organizing map neural network

The self-organizing map neural network (SOM) is an unsupervised network for clustering data. On each application to an input, this algorithm maps its self-organizing Kohonen feature to neurons from a one or two dimension net type neuron. This net type network of neurons is organized by input samples which ultimately approximates the distribution of network inputs in a discrete environment. This network consists of two layers; the first layer is the input layer where input samples are inserted and through which are applied to the network neurons. The second layer consists of the output neurons. In a normal state, each neuron has only one binary output possessing a value of one or zero. If the neuron in question wins the competition over resources, its output will acquire the value of one and the remaining neurons will have zero outputs. The neuron that's weight has the most resemblance to the input sample is considered the winning neuron for a specific input. In this case, its output will acquire the value of one and the output of the remaining neurons will be zero. The weight vector of the winning neuron is corrected along with its neighboring neurons. This correction causes the progression of the neurons' weights towards the recent input, whilst the weights of the other neurons will remain unchanged.

This is one of the most important parameters for detecting the number of clusters (the number of similar days for this project). For this purpose, the k-mean and Fisher's hybrid algorithm is used for this project.

5. Genetic Algorithm

The Genetic Algorithm is a programming technique that uses genetic evolution as a problem solving model. The input is the problem to be solved and solutions are coded according to a pattern called the fitness function that evaluates each possible solution, most of which are randomly selected.

The Genetic Algorithm is a search technique in computer science to determine the optimal solution and address search issues. These algorithms are a type of evolutionary algorithms inspired by biological science branches such as heredity, mutation, saltation (biology), natural selection and composition.

Evolution starts from a completely random set of entities and is repeated in subsequent generations. In each generation, the most suitable ones are selected instead of the best. Three criteria are typically used as stopping criterion: 1- runtime of algorithm 2-number of generations, 3- convergence error criteria.

The most prominent applications of the Genetic Algorithm include: hydrological routing of runoff in a dry river network, assistance in resolving multi-criteria decision issues, multi-objective optimization in water resources management, optimization and loading of electricity distribution networks etc.

6. Selection of input parameters and variables

Based on prior assessments, the time and temperature variables were selected as two influential factors on price and previously consumed loads. Among the climate variables, only the

temperature variable is used since most other climate factors are included in this variable. Given the fact that temperature has a significant influence on the consumption trend, namely in the northern region of the country, and since forecasts are on an hourly basis, it is apparent that using the temperature parameter on an hourly basis or closer time intervals will entail improved operation. It is important to consider the previous number of days and weeks in terms of the consumed load price and temperature. According to studies and the opinions of electricity distribution experts, the use of load and temperature at various hours of the previous days and weeks is highly effective (although it can be equivalent to the hours of the forecasted day). In this project, data of the preceding two days and two equivalent days of previous weeks were used. In addition, information on hourly temperature of the forecasted day is also used. Other utilized useful information included the load price and temperature of the preceding hour. Since information on the preceding 24 hours of the forecasted day is available, thus in order to forecast the next hours, the data pertaining to the previous hours is used as input.

7. Proposed method

A vital factor in the future planning of power systems and electricity market management is the forecast of short term load price. In recent years, due to the significance of this issue, various methods have been presented to improve the performance of such systems. This paper presents a modern method to forecast short term hourly electrical energy costs based on hybrid neural networks. In this method, influential parameters that play a key role in the accuracy of these types of systems are identified and the most prominent ones are selected. Due to the varying electrical price fluctuations amidst different days and seasons, these parameters do not adhere to a common pattern. In this regard, in order to improve forecasts, data is divided into classes that are close in nature. Since one of the effective forecast parameters is the detection of similar successive days during the week, data pertaining to various seasons are analyzed separately. In the proposed method, initially, by using the SOM network, similar days are placed in close clusters. In the next stage, the price and temperature parameters of similar days are trained separately in two MLP neural networks due to their difference in nature and range of changes. Finally, the two networks are merged with another MLP network. In the proposed hybrid network, the evolutionary search method was used to assign a suitable initial weight to train the neural network. Due to the changes in price data, the price of the previous hour has a significant effect on forecasting the current state. In this regard, in the proposed method, the forecasted data of the preceding hour is used as one of the inputs for the next stage.

Figure 1 shows an overview of the proposed method.

In the proposed method, the trained dataset is initially allocated to the SOM neural network. In this stage, the number of clusters is determined using the k-means and Fisher criterion hybrid method. This number varies for each hour of the day. Thus, network training for 24 hours is conducted separately and in succession. In the proposed structure, upon specifying the number of clusters, each sample that is entered to the network from the trained dataset should be determined

to which cluster it belongs to and in the next stage, based on the selected cluster, the associated MLP network is setup. Essentially, each MLP network is trained with the dataset pertaining to its relevant cluster. Finally, for the test dataset, the sample distance from the clusters is initially determined along with its relevant cluster. Then, the test sample is evaluated using the associated MLP network to the cluster.

In the proposed method, each cluster does not only use one MLP network, but a combination of MLPs are utilized. The input dataset are divided into two categories i.e. load price and temperature which are of extremely different nature and their effects vary significantly according to the range of changes. In the proposed method, two separate networks are used for temperature and load. Finally, the outputs from these networks are merged with other MLPs and the forecast is achieved. In the proposed method, the output for each hour is used as the input for the next hour.

The data pertains to the years 2010-2016. In addition to extracting price information, the consumed load and temperature are also extracted in terms of hours. Data analysis is done using MATLAB. In this paper, evaluation criteria such as the mean absolute error (MAE), mean absolute percentage error (MAPE) and R^2 are used.

The mean absolute error refers to the difference between the predicted value and the real value which is shown by equation (1).

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (1)$$

The mean absolute percentage error or MAPE is calculated using equation (2):

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\hat{y}_i - y_i}{\hat{y}_i} \right| \times 100 \quad (2)$$

The R^2 criteria is the statistical measurement of how close the data are to the fitted regression line. R^2 is also called the determination coefficient of the detection coefficient. The definition of the determination coefficient (R^2) is relatively simple:” the determination coefficient (R^2) indicates the percentage of variations of a dependent variable determined by the independent variable” or in other words, the determination coefficient indicates “how much of the variations of the dependent variable are influenced by the independent variable and the rest of the changes of the dependent variable are related to other factors”. The determination coefficient is always between 0 and 100%. 0% indicates that the model does not describe the response data variability around its mean, and 100% indicates that the model describes all response data variability around its mean.

Equation (3) is used to calculate this coefficient

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (3)$$

In equation (4), SS_{res} and SS_{tot} are derived as:

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \quad (4)$$

In the equations above, \bar{y} is the mean of the main data which is derived by $\bar{y} = \sum_i y_i$.

The most important innovations of this paper are as follows:

- 1- A detailed analysis of parameters affecting the consumption and price fluctuations in the Iran market.
- 2- The proposed system is completely automated and many assumptions, which were empirically calculated and considered by experts, are eliminated. The obtained results of the next season indicate that the proposed system has a very good performance and works better and more accurately than the human experts who usually make mistakes due to the large bulk of data.
- 3- K-means clustering method is used in the proposed method for calculating the number of similar methods. The proposed method uses a new method based on Fisher's algorithm to automatically calculate the number of clusters of this method.
- 4- A hybrid network is used to analyze data that is different in nature. In fact, a distinct network is trained for inputs with near nature. Finally, the output of networks is combined together.
- 5- The initial weighing of network is a fundamental challenge in learning neural networks. In this regard, an initial evolutionary genetic algorithm is used to improve the initial weighing, so that initial weights are well selected. It should be noted that it could be also used for another evolutionary algorithm such as genetics or bee colony algorithms. Each of these methods can have proper function in the proposed method. This method is used for its simplicity of implementation and also application in many studies in recent years.
- 6- The lack of precise information is the main challenge in the price forecast. In this regard, the experiments indicated that if there was no information on a region, the proposed method still would have good performance.
- 7- The proposed method has a better performance than other introduced methods in recent years.

8. Results

Table (1) shows the structure of the temperature network for separate seasons. In this table, each year is predicted separately.

It is noteworthy that for values related to the number of neurons, the number of hidden layers and thresholds are derived from the validation set. In this vein, a sample of the results obtained for the summer season is shown in Figure (2) for these parameters. As shown in Fig 2 (a), the best number of neurons is 5. The number of hidden layers according to Fig 2 (b) and the threshold according to Fig 2 (c) was considered 0.1. All results for subsequent experiments are obtained by validated data.

A structure similar to Table (1) is used to design a network related to price. In the presented structure, the number of price attributes is one less than the inputs of Table (1) which is related to the prediction hour. In this network, for the load consumed in the previous hour (except for 1am) the prediction from the previous stage is used. Essentially, the prediction for the current hour is used as the input for the next hour.

The MLP neural network structure in order to combine two MLP networks is shown as Table (2).

In this research, in order to analyze each season separately, separate tests are designed for each season. However, it should be noted that the main issue with this type of data concerns the summer season, thus it should be focused on even though the proposed method exhibited appropriate results for all seasons. The results of the training and testing of load data for the summer season and autumn season which represent the other two seasons (due to the similarity of consumption in these seasons), are shown. Also, a comparison between the proposed hybrid method and the MLP method is presented. This chart shows the error rate for the autumn season of year 2016 in Iran.

8.1 Summer season

Based on Fig.3, the slope of Fisher's criterion changes in the k-means algorithm is not evident from six clusters to seven clusters, thus six clusters are automatically considered for the outputs of this particular hour. In the next step, a neural network for temperature and price are considered for each cluster, which are finally combined by another perceptron network. In the training of these networks the backward propagation of errors algorithm is used but in the first step, in order to select appropriate initial weights, the Genetic Algorithm is used instead of random selection. Fig.4 shows the steps involved in implementing the training stage of a network using the Genetic Algorithm. As previously mentioned, the training number is kept low to increase computing speed. The weights obtained from this method are considered as the initial weights in the network. It should be noted that a Genetic Algorithm should be implemented for each MLP neural network. Lastly, the network is trained and tested according to the previous steps. This chart shows the error rate for summer days of the year 2016 in Iran.

The results for the training data for the summer season are shown in Fig.5. Fig 5(a) presents the results of the network training using MLP and Fig. 5(b) presents the results from combining the MLP and SOM network. As depicted in this figure, the proposed method exhibited superior performance compared to typical methods in the training stage.

The results for the experiment series for the summer season are shown in Fig. 6. Fig. 6(a) shows the results using MLP and Fig. 6(b) shows the results of the combined MLP and SOM networks,

which, similar to the training stage in the proposed method, exhibited superior performance in the experiments stage.

9. Conclusion

In this paper, a dynamic method was proposed to predict electricity prices. In the proposed method, artificial-intelligence based algorithms were used. Data variances and analysis were the main focus to achieve more accurate predictions. As stated, numerous factors influence price prediction but acquiring all the required information in the current world state is an arduous task. In this regard, it was aimed to utilize a system that is compatible with existing data. A hybrid approach based on neural networks was used in the proposed method. Related data of different days at different hours may show similar performance, hence, similar data at the training and experiment stage are used as the input. Thus, the unsupervised SOM neural network was used to cluster samples.

It should be noted that upon analysis, extracted data of different seasons exhibited different performances. In the same vein, analyzes related to different seasons were conducted separately. For the next stage, similar data were used based on day, prior to the analysis of the neural network's input data. Upon this analysis, it was evident that data related to the consumed load and temperature were different in nature compared to price related data.

In this regard, this research uses two multilayer perceptron neural networks for prediction. Essentially, in the proposed method, a network is used for training data related to temperature and another network is used for training data related to price. According to the obtained results, data analysis using different networks is influential on the accuracy of the proposed method. In the training phase, the appropriate selection of initial weights is vital in training neural networks. Thus, for improved training of the proposed network, an evolutionary search method is used to derive initial weights. Finally, the proposed networks were combined with another MLP neural network and the results indicate improved performance of the proposed method compared to other methods.

Some of the most significant innovations presented in this study are listed below:

1. An accurate analysis of the parameters affecting consumption and price fluctuations in the Iranian market is presented. In Iran, Mazandaran province was selected due to its atmospheric volatility, which, according to experts, is one of the most challenging regions in the country.
2. The proposed method is completely automated and many of the empirically derived preconditions set by experts have been eliminated. The obtained results indicate that the proposed method exhibits favorable performance and is more accurate than the results acquired by a human expert that entails several mistakes due to the high volume of data.
3. In the proposed method, the k-means clustering method was used to calculate the number of similar methods. In this method, a novel method based on Fisher's Algorithm is used to automatically calculate the number of utilized clusters.

4. A hybrid network is used to analyze data that are different in nature. A separate network is trained for each input of data close in nature to the network. Finally, outputs of the networks are combined.
5. One of the fundamental challenges of training neural networks is the allocation of initial weights. In this regard, an evolutionary Genetic Algorithm is used to improve initial weighting so the initial weights are selected appropriately.
6. One of the main challenges in the prediction of prices is the lack of accurate information. In this regard, the conducted experiments showed that if there is no information for a particular region, the proposed method still exhibits favorable performance.
7. The proposed method exhibits superior performance compared to other methods presented in recent years.

References

- [1] Lin Lin, Cunshan Zhou, Vittayapadung Saritporn, Xiangqian Shen, Mingdong Dong. "Opportunities and challenges for biodiesel fuel". *Appl Energy*; 88(4), pp. 1020–31 (2011).
- [2] Dhinesh B, Raj Y Maria Ambrose, Kalaiselvan C, KrishnaMoorthy R. "A numerical and experimental assessment of a coated diesel engine powered by high-performance nano biofuel". *Energy Convers Manage*;171, pp. 815–24 (2018).
- [3] Vigneswaran R, Annamalai K, Dhinesh B, Krishnamoorthy R. "Experimental investigation of unmodified diesel engine performance, combustion and emission with multipurpose additive along with water-in diesel emulsion fuel". *Energy Convers Manage X*;172, pp. 370–80(2018).
- [4] Dhinesh B, Annamalai M. "A study on performance, combustion and emission behaviour of diesel engine powered by novel nano nerium oleander biofuel". *J Clean Prodction* (2018).
- [5] Nomura Noboru, Inaba Atsushi, Tonooka Yutaka, Akai Makoto. "Life-cycle emission of oxidic gases from power-generation systems". *Appl Energy*; 68(2), pp. 215–27 (2001).
- [6] Sánchez de la Nieta AA, González V, Contreras J. "Portfolio decision of short-term electricity forecasted prices through stochastic programming". *Energies*; 9(12), pp. 1069 (2016).
- [7] Najafi A, Falaghi H, Contreras J, Ramezani M. "Medium-term energy hub management subject to electricity price and wind uncertainty". *Appl Energy*; 168, pp. 418–33 (2016).
- [8] Yang P, Tang G, Nehorai A. "A game-theoretic approach for optimal time-of-use electricity pricing". *IEEE Trans Power Syst*; 28(2), pp. 884–92 (2013).
- [9] Wang D, Luo H, Grunder O, Lin Y, Guo H. "Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and bp neural network optimized by firefly algorithm". *Appl Energy*; 190, pp. 390–407 (2017).
- [10] Yang Z, Ce L, Lian L. "Electricity price forecasting by a hybrid model, combining wavelet transform, arma and kernel-based extreme learning machine methods". *Appl Energy*; 190, pp. 291–305 (2017).

- [11] Abedinia O, Amjady N, Shafie-khah M, Catalão JPS. "Electricity price forecast using Combinatorial Neural Network trained by a new stochastic search method". *Energy Convers Manage*; 105, pp. 642–54 (2015).
- [12] Lago J, Ridder FD, Vrancx P, Schutter BD. "Forecasting day-ahead electricity prices in Europe: the importance of considering market integration". *Appl Energy*; 211, pp. 890–903 (2018).
- [13] Weron R. "Electricity price forecasting: a review of the state-of-the-art with a look into the future". *Int J Forecast*; 30(4), pp. 1030–81 (2014).
- [14] Lago J, Ridder FD, Schutter BD. "Forecasting spot electricity prices: deep learning approaches and empirical comparison of traditional algorithms". *Appl Energy*; 221, pp. 386–405 (2018).
- [15] Wang JZ, Liu F, Song YL, Zhao J. "A novel model: dynamic choice artificial neural network (DCANN) for an electricity price forecasting system". *Appl Soft Comput*; 48, pp. 281–97 (2016).
- [16] Bento PMR, Pombo JAN, Calado MRA, Mariano SJPS. "A bat optimized neural network and wavelet transform approach for short-term price forecasting". *Appl Energy*; 210, pp. 88–97 (2018).
- [17] Ghasemi A, Shayeghi H, Moradzadeh M, Nooshyar M. "A novel hybrid algorithm for electricity price and load forecasting in smart grids with demand-side management". *Appl Energy*; 177, pp. 40–59 (2016).
- [18] Mirakyan A, Meyer-Renschhausen M, Koch A. "Composite forecasting approach, application for next-day electricity price forecasting". *Energy Econ*; 66, pp. 228–37 (2017).
- [19] Sanjeev Kumar Aggarwal, Lalit Mohan Saini, Ashwani Kumar, "Electricity price forecasting in deregulated markets: A review and evaluation," *Electrical Power and Energy Systems* 31, pp. 13–22(2009).
- [20] Panapakidis IP, Dagoumas AS. "Day-ahead electricity price forecasting via the application of artificial neural network based models". *Appl Energy*;172, pp. 132–51 (2016).
- [21] Sandhu HS, Fang LP, Guan L. "Forecasting day-ahead price spikes for the Ontario electricity market". *Electr Pow Syst Res*;141, pp. 450–9 (2016).
- [22] Ortiz M, Ukar O, Azevedo F, Múgica A. "Price forecasting and validation in the Spanish electricity market using forecasts as input data". *Electr Pow Energy Syst*;77, pp. 123–7 (2016).
- [23] Keles D, Scelle J, Paraschiv F, Fichtner W. "Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks". *Appl Energy*;162, pp. 218–30 (2016).
- [24] Singh N, Mohanty SR, Shukla RD. "Short term electricity price forecast based on environmentally adapted generalized neuron". *Energy*;125, pp. 127–39 (2017).
- [25] Itaba S, Mori H. "A fuzzy-preconditioned GRBFN model for electricity price forecasting". *Proc Comput Sci*;114, pp. 441–8 (2017).
- [26] Wang DY, Luo HY, Grunder O, et al. "Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm". *Appl Energy*;190, pp. 390–407 (2017).

- [27] Tang L, Yu L, He K. "A novel data-characteristic-driven modeling methodology for nuclear energy consumption forecasting". *Appl Energy*;128, pp. 1–14 (2014).
- [28] Chai J, Zhang ZY, Wang SY, Lai KK, Liu J. "Aviation fuel demand develop in China". *Energy Econ*;46, pp. 224–35 (2014).
- [29] Diongue AK, Guegan D, Vignal B. "Forecasting electricity spot market prices with a k-factor GIGARCH process". *Appl Energy*; 86, pp. 505–10 (2009).
- [30] Girish GP. "Spot electricity price forecasting in Indian electricity market using autoregressive-GARCH models". *Energy Strateg Rev*; 11, pp. 52–7 (2016).
- [31] Zhang JL, Tan ZF. "Day-ahead electricity price forecasting using WT, CLSSVM and EGARCH model". *Electr Pow Energy Syst*; 45, pp. 362–8 (2013).
- [32] Zhang Y, Li C, Li L. "Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods". *Appl Energy*; 190, pp. 291–305(2017).
- [33] Yan X, Chowdhury NA. "Mid-term electricity market clearing price forecasting: a hybrid LSSVM and ARMAX approach". *Electr Pow Energy Syst*; 53, pp. 20–6 (2013).
- [34] Zhu BZ, Wei YM. "Carbon price prediction with a hybrid ARIMA and least squares support vector machines methodology". *Omega*; 41, pp. 517–24 (2013).
- [35] He KJ, Yu L, Tang L. "Electricity price forecasting with a BED (Bivariate EMD Denoising) methodology". *Energy*; 91, pp. 601–9 (2015).
- [36] Qiu XH, Suganthan PN, Amaratunga GAJ. "Short-term electricity price forecasting with empirical mode decomposition based ensemble kernel machines". *Proc Comput Sci*; 108, pp. 1308–17 (2018).

Biography

Seyed Mojtaba Kavooosi Davoodi is a Candidate Ph.D. of Industrial Engineering Department at the Islamic Azad University, science and Research Branch in Tehran, Iran. He received the B.A. degree from the Mazandaran University of Science and Technology (MUST), the M.S. degree from the Industrial Engineering Department, Islamic Azad University, Science and Research Branch, Tehran, Iran. His research interests include engineering management, and strategic management, decision making, Fuzzy Systems, computational modeling, data envelopment analysis, neural network and optimization techniques.

Seyed Esmaeil Najafi is an Assistant Professor Of industrial Engineering Department at the Islamic Azad University, science and Research Branch in Tehran, Iran. He received the B.A. degree from the Power and Water University of Technology (PWUT), the M.S. degree from the Islamic Azad University, and the Ph.D. degree in industrial engineering from the Science and Research Branch, Tehran, Iran. He is currently an Assistant Professor with the Industrial Engineering Department, Islamic Azad University, Science and Research Branch, Tehran, Iran. His research interests include computational modeling, decision making, data envelopment analysis, engineering management, and strategic management. His published research articles appear in the Journal of Intelligent and Fuzzy System, the Mathematical Problems in Engineering, and the International Journal of Data Envelopment Analysis.

Farhad Hosseinzadeh Lotfi is currently a full professor in Mathematics at the Science and Research Branch, Islamic Azad University (IAU), Tehran, Iran. In 1991, he received his undergraduate degree in Mathematics at Yazd University, Yazd, Iran. He received his MSc in Operation research at IAU, Lahijan, Iran in 1995 and PhD in Applied Mathematics (O.R.) at IAU, Science and Research Branch, Tehran, Iran.in 1999. His major research interests are operation research and data envelopment analysis. He has been Advisor and Co-advisor of 46 and 31 Ph.D. Dissertations, respectively. He has published more than 300 scientific and technical paper in leading scientific journals, including European Journal of Operational Research, Computers and Industrial Engineering, Journal of the Operational Research Society, Applied Mathematics and Computation, Applied Matematical Modelling, Mathematical and Computer modelling, and Journal of the Operational Research Society of Japan, among others. He is Editor-in-chief and member of editorial board of Journal of Data Envelopment Analysis and Decision Science. He is Also manager and member of Editorial board of International Journal of Industrial mathematics.

Hossein Mohammadian Bishe received the B.Sc. degree in Electrical Engineering from Sharif University of Technology,Tehran,Iran in 1971,and the Msc and PhD degree both in Industrial engineering from Mazandaran University of Science and Technology, Babol, Iran in1996 and 2009 . He is an assistant professor of Mazandaran University of Science and Technology, Babol, Iran . His research interests are power system planning and control, energy management systems, and optimization techniques.

figures and tables

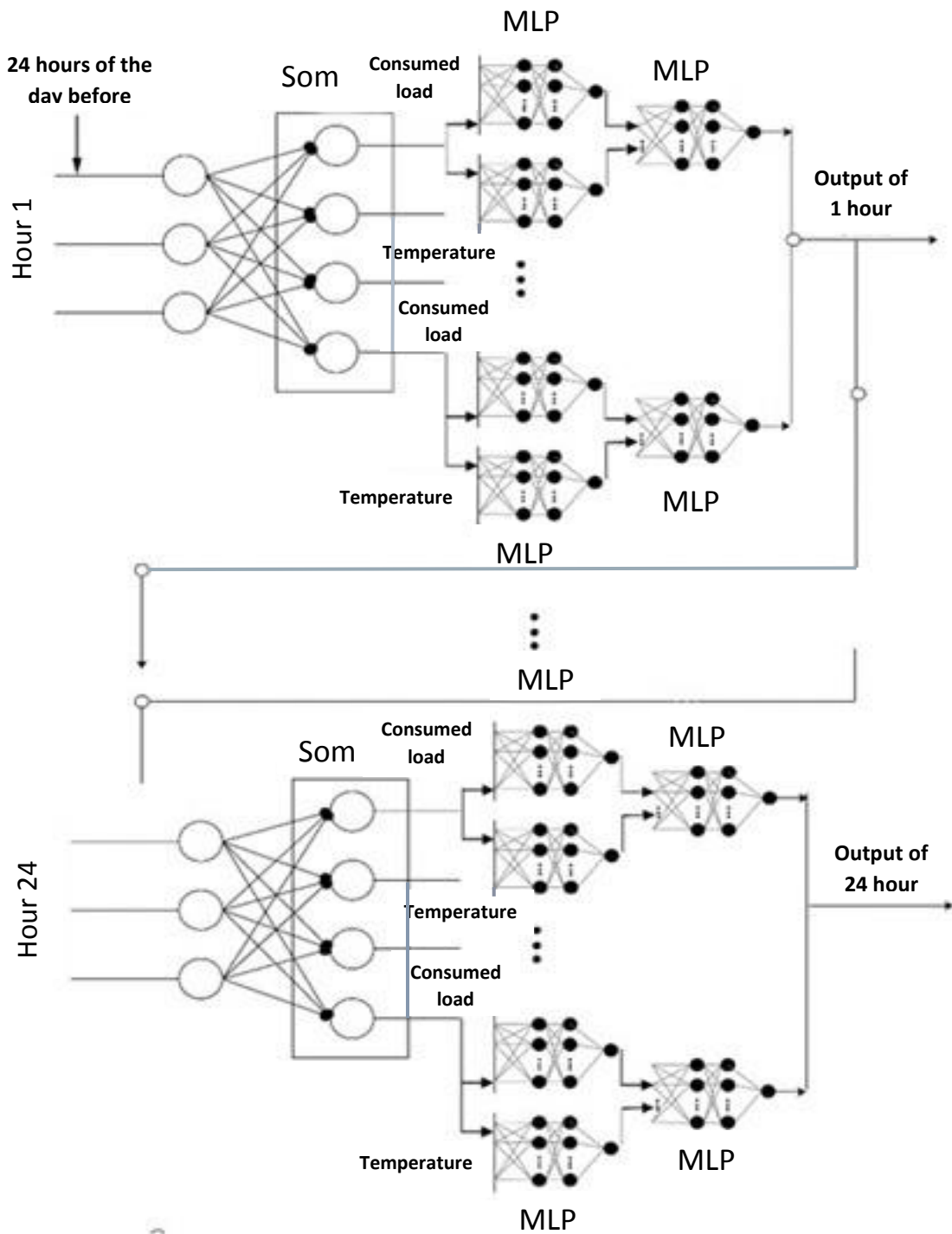
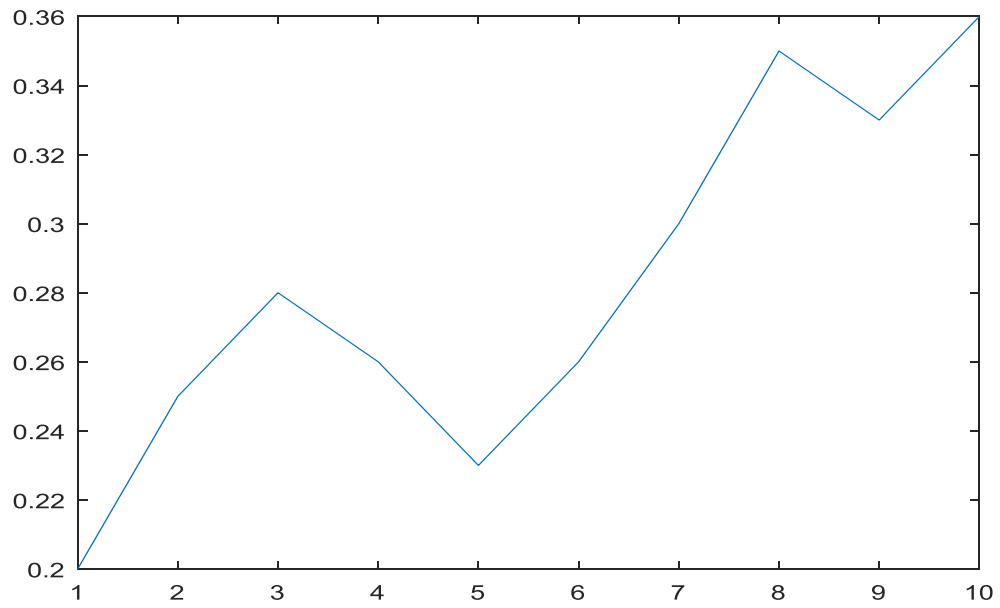


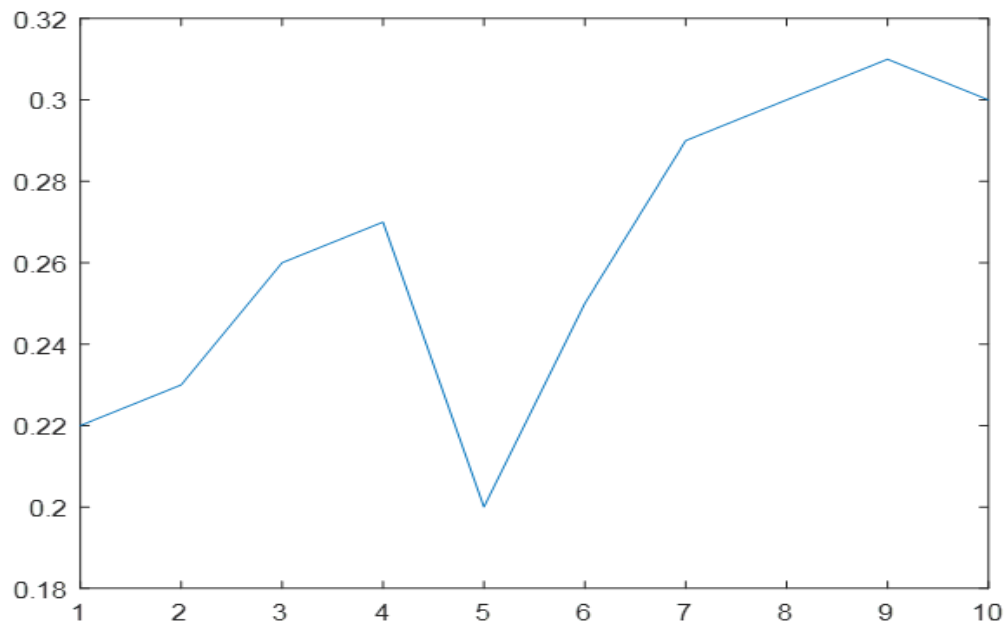
Fig.1 An overview of the hybrid network to forecast the load price of the next 24 hours

Table (1): MLP network configuration parameters for input temperature and load consumption

Number of input neurons	11	2 temperature attributes related to previous weeks
		2 temperature attributes related to previous days
		2 load attributes related to previous weeks
		2 load attributes related to previous days
		1 temperature attributes from the previous hour
		1 load attributes from the previous hour
		1 temperature attributes related to the predicted hour
Number of training samples		46 samples for each hour
Number of validation samples		10 samples for each hour
Number of test samples		23 samples for each hour
Number of hidden layers		1
Number of neurons in hidden layers		5
Backward propagation of errors Algorithm	Learning rate	0.005
	Maximum number of repetitions	100
	Error threshold to stop learning	0.1
	Activation function slope Value of β in $(f(x) = \tanh(\beta x))$	1
Genetic Algorithm	Primary population	200
	Number of generations	10
	Size of each chromosome	30
	Selection function	@selectiontournament
	Termination function	@crossoversinglepoint
	Mutation function	@mutationgaussian



(a) number of neurons



(b) number of hidden layers

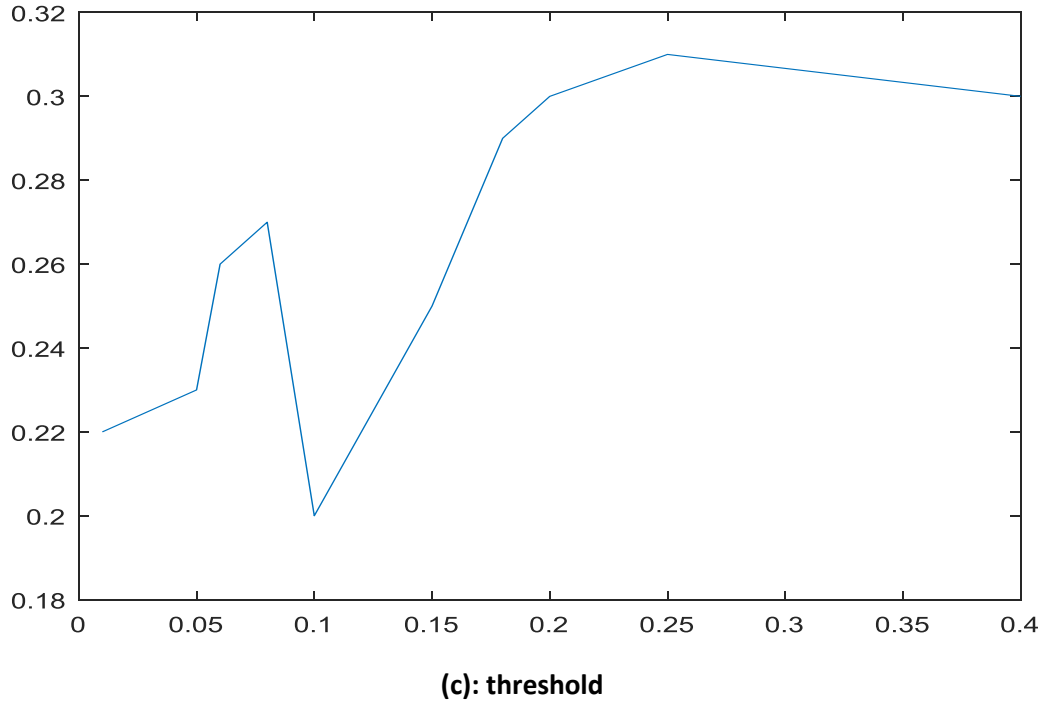


Figure (2): Estimation of parameters used for the neural network based on the validation data set.

a) Number of neurons, b) number of hidden layers, c) threshold

Table (2) network configuration parameters for multi-layer perceptron network in order to combine networks

Number of input neurons	2	1 output attribute related to the MLP network with price input
		1 output attribute related to the MLP network with temperature input
Number of training samples	46 samples for each hour	
Number of validation samples	10 samples for each hour	
Number of test samples	23 samples for each hour	
Number of hidden layers	1	
Number of neurons in hidden layer	3	
Backward	Learning rate	0.005

propagation of errors Algorithm	Maximum number of repetitions	100
	Error threshold to stop learning	0.1
	Activation function slope Value of β in ($f(x) = \tanh(\beta x)$)	1
Genetic Algorithm	Primary population	200
	Number of generations	10
	Size of each chromosome	9
	Selection function	@selectiontournament
	Termination function	@crossoversinglepoint
	Mutation function	@mutationgaussian

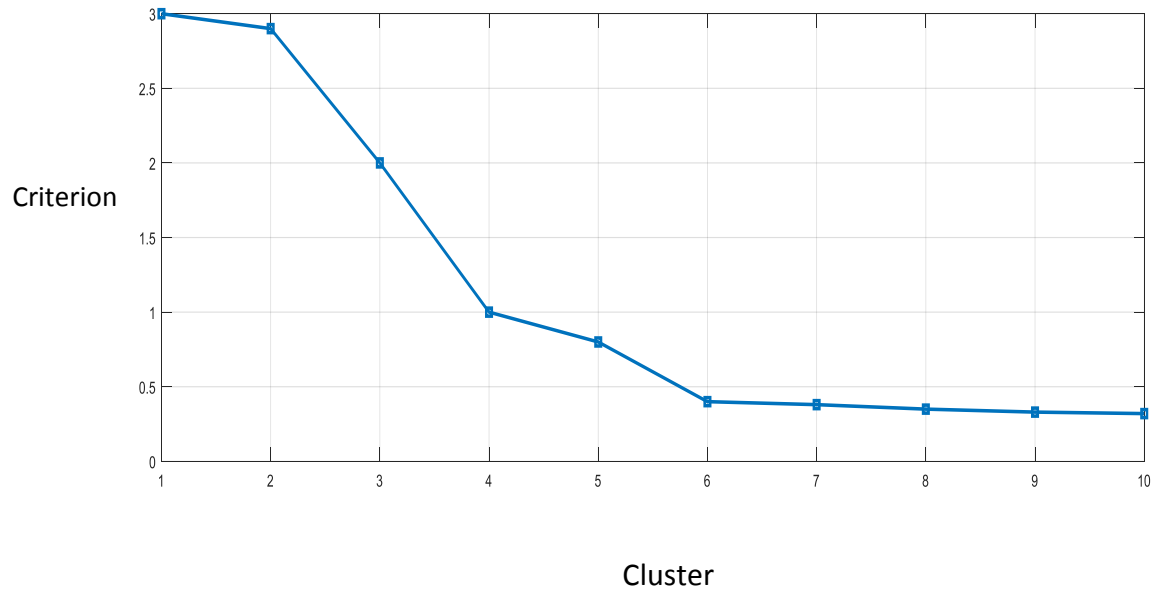


Fig 3: The rate of change in Fisher's criterion based on the number of clusters

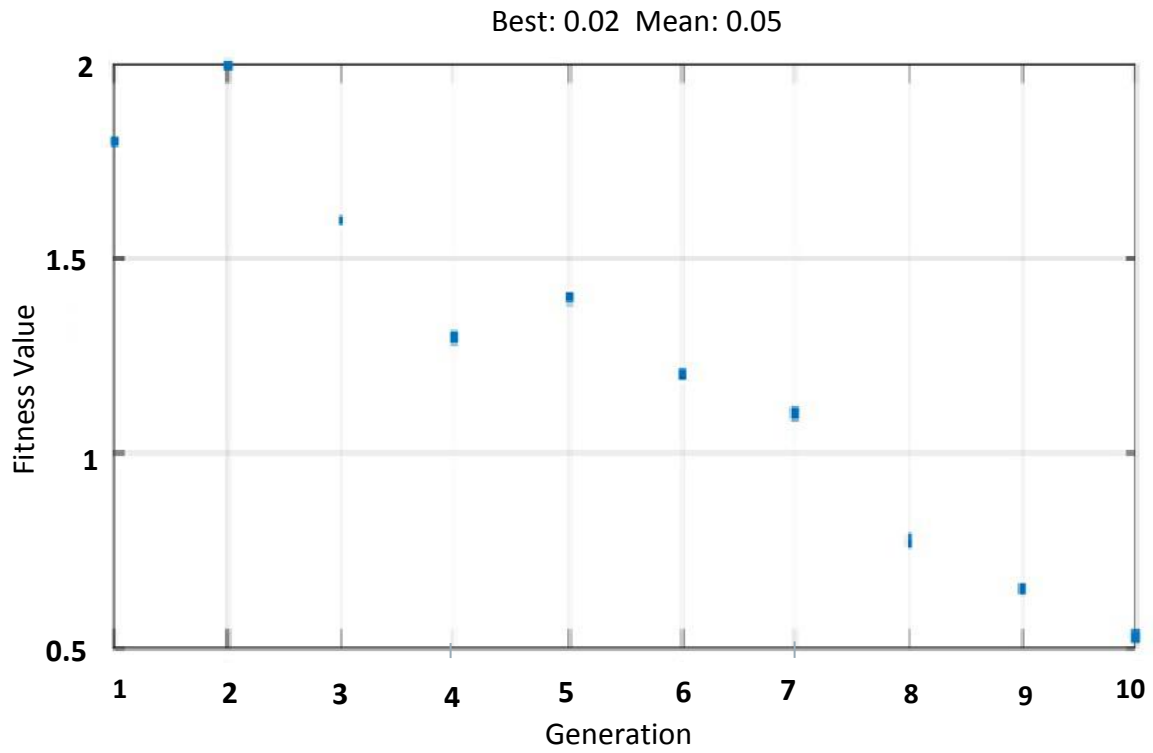
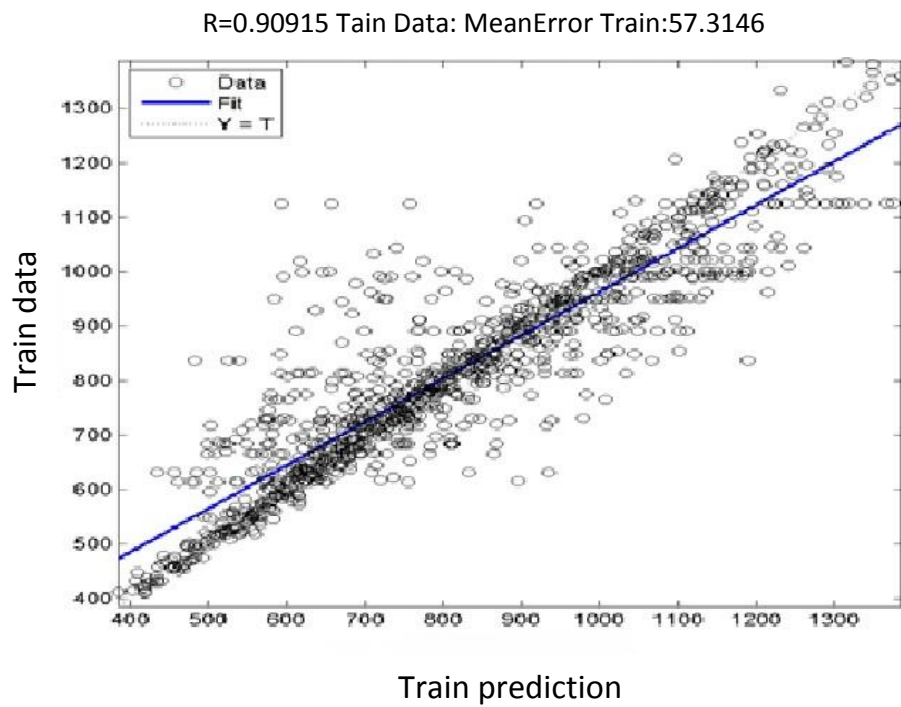
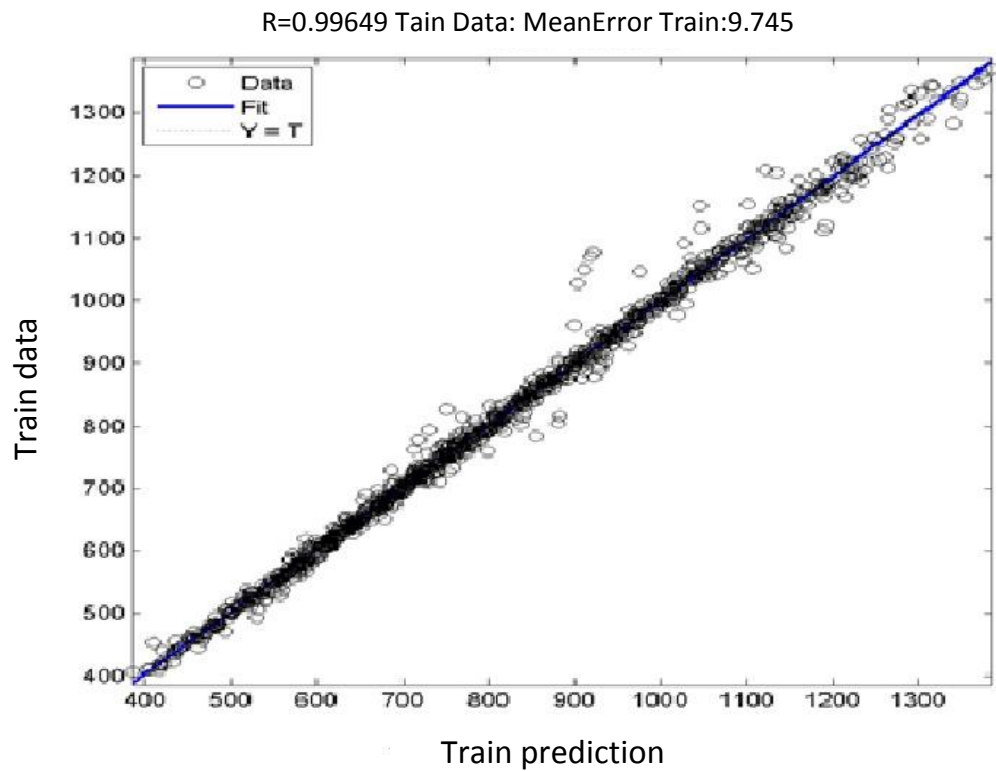


Fig 4: Obtained fitted values using the Genetic Algorithm in 10 repetitions



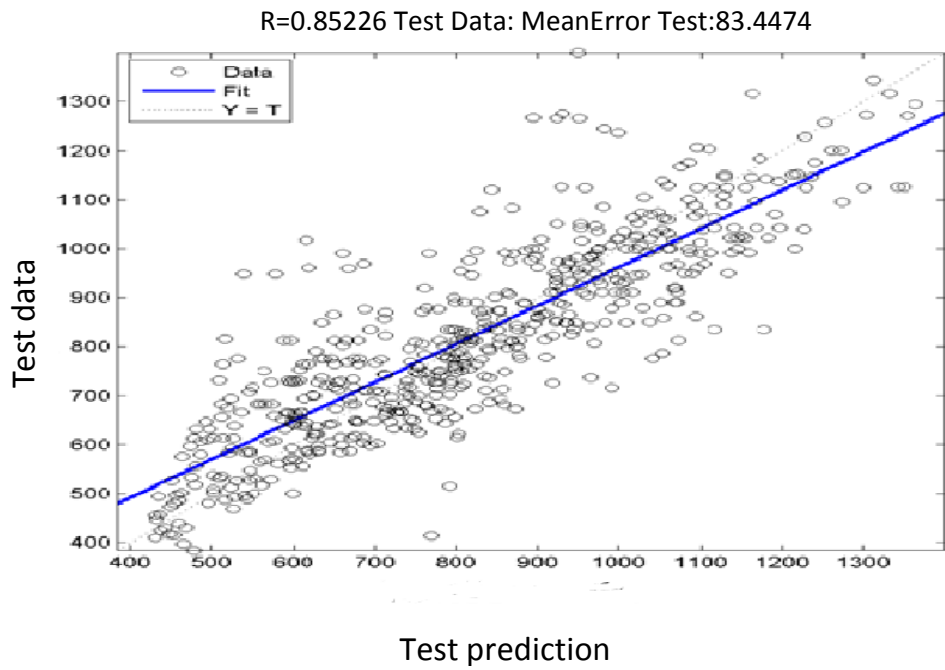
(a)



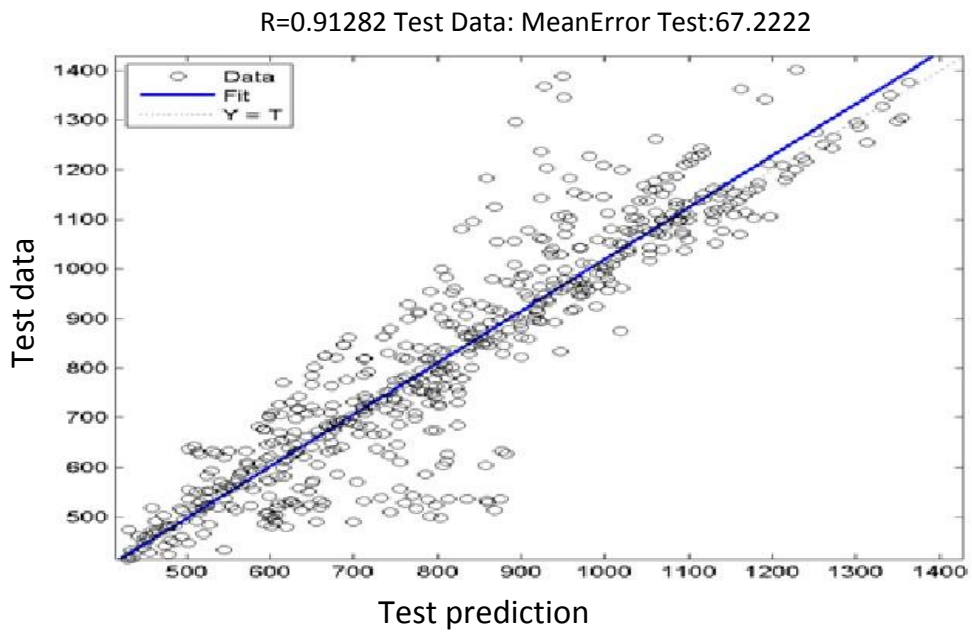
(b)

Fig 5: Results of the training stage for the summer season

(a) MLP network (b) MLP and SOM hybrid network



(a)



(b)

Fig 6: Results of the experiment stage for the summer season

(a) MLP network (b) MLP and SOM hybrid network