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Provision of an Optimal Strategy to Forecast the Prices Set by the Electricity Market in the Competitive Iranian Energy Market in Fall

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ABSTRACT

Given the complexities of the electricity market, various factors, such as uncertainties, the ways upon which the markets are set, how the debts are settled, the market structure and regulations, production prices, constraints governing the units and networks, etc. are influential in determining the optimal pricing strategies. Various methods and models have been presented to resolve the pricing issue in the competitive electricity industry. The most prominent of which include pricing methods are based on the prediction of competitors' behavior; also pricing methods based on the forecasts of market price, methods based on the game theory and lastly, pricing methods based on the intelligent algorithms. Therefore, this study was conducted to provide an optimal strategy in order to forecast the electricity market price set in the competitive Iranian electricity market (based on the data collected). In this paper, the proposed method uses a compound network based on the neural networks. The analyzed data include the amount of the consumed energy as well as temperature (if applicable) and the price set for the past days and weeks. The self-organizing map (SOM) network was used for the input clustering based on the similar days. A number of multilayer perceptron (MLP) neural networks were used to combine the extracted data consisting of the energy levels, the price set, and temperature (if possible). The results showed improvements in the performance of the smart systems based on the neural networks in predicting the electricity prices.

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1. INTRODUCTION

Since the industrial revolution, energy has become a key factor in everyday life. 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]. Most recent research paid attention to renewable resources for their properties of environmental-friendly and sustain-ability. The most competitive renewables include water, wind, photovoltaic energy, and biofuel. Many of them have been proved to be advanced in addressing energy and environmental issues [4, 5]. Today, electrical energy became 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 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 renewable sources 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

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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 scan 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.

Recently, interests regarding algorithms used to control forecasting issues are referred to as artificial neural networks (ANNs). The interesting feature of neural networks is their ability to utilize price properties which in general, either cannot be determined or entail arduous computations for their synthesis. The development of computer technology has enabled vast competencies to combine methods in one place and at one time. A number of papers published in the forecasting field often implement the neural networks method.

In spite of the achievements reported in the field of forecasting, the price forecast issue remains problematic. As an example, there is no general forecaster that can be employed to forecast prices in any geographic region, the reason being that factors that affect prices differ in terms of area and region e.g. if load is considered as one of the influential factors on pricing, it is clear that the system load varies in each geographic region, and the consumption level in one area cannot be considered as the system load for other areas.

The development of statistical methods necessitates significant time and costs to achieve normal operation while the use of a neural network requires a short time period to configure. Herein, the Genetic Algorithm, another section of artificial intelligence, plays an integral role in optimizing game engineering functions. One of the issues of using neural networks is the lack of a solution and specific relationship to determine the number of layers or neurons of the hidden layers, since the determination of the aforementioned parameters depends on experience and cannot be determined definitively. However, the use of the Genetic Algorithm to determine neurons is an efficient, expeditious, and reliable method that may be achieved by integrating it with the neural network to a hybrid network, which significantly enhances forecast accuracy [19].

With the emergence of competitive electricity markets around the world, the issue of optimal pricing strategy has been raised. Electricity vendors in the world's prominent electricity market often have various options for generating revenue at any given time, with various technical and non-technical constraints. Thus, vendors in the electricity market are continuously faced with an optimization issue to make optimal decisions. Since 2003, Iran's electricity market was incepted amidst the reconstruction of Iran's infrastructure. Currently, the market is active only on the production section. Amidst the strengthening of Article 44 of the Iranian Constitution and the transfer of power plants to the private sector, the pricing strategy issue in the electricity market has become more prominent. In Iran, the fear of losing out has always led to pricing being set with high caution. Also, the study of pricing history pertaining to power plants across the country indicates that most vendors have difficulties in selecting the optimal strategies in fuel constraint conditions [20].

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 thermal 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 [21] used artificial neural networks (ANNs) model for electricity price forecasting in Southern Italy. Sandhu et al. [22] employed 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. [23] proposed a combined model based on artificial neural networks. Keles et al. [24] develop a model based on ANNs and optimal parameter model. Singh et al. [25] presented a combined model with generalized neuron model and wavelet transform. Itaba and Mori [26] utilized the general radial basis function network and fuzzy clustering. Wang et al. [10] 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] proposed 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 [9, 31]. 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 [32, 33]. For this reason, the empirical mode decomposition (EMD) approach has been used for electricity price decomposition by some researchers [34, 35].

A study conducted entitled "assessing the methods of forecasting the price of electricity in the energy market" where they stated that: today, decision making for market participants to increase profitability is highly complicated [36].

Another study conducted entitled "Simultaneous forecasting of price and demand in a smart electricity distribution network". In this paper, a forecast framework is proposed that provides dynamic forecasts for electricity price and demand [37].

A conducted study titled "Short-term forecast of electricity prices using time-fuzzy neural networks" where it was stated: in the restructured environment, one of the most vital issues in the planning of independent operators and vendors is the forecasting of electricity prices [38].

Other study conducted by Shayeghi and Ghasemi on daily electricity price forecast using an enhanced neural network based on wavelet transform and the chaotic gravitational search algorithm [39].

Meng et al. predicted a model for energy consumption in residential building in rural areas of Chongqing [40]. Recently, a new hybrid artificial neural networks and fuzzy regression model for time series forecasting has been proposed [41]. Artificial neural network (ANN), as the main approach in the field of Artificial Intelligence (AI), has attracted much interest over the past decade for its ability to forecast financial performance [42]. A system dynamics approach is used to capture the long-run behavior of electricity markets and to characterize the evolution of the electricity prices and the demand [43]. Khedmati et al. [44] proposed time series forecasting of bitcoin price based on autoregressive integrated moving average and machine learning approaches.

2. RESEARCH METHODOLOGY

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

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

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

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

The holidays are among the other factors influencing the consumption price curve. 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 the religious and national holidays were conducted separately. Although, it should be noted that according to the comparisons of the consumed load price from 2009 to 2012, the consumed load in Iran and experts̉ opinions indicated no need for the forecasts for some of the holidays since, the consumed loads on these days were similar to that of the previous years. For example, the consumed loads on 2^{nd} April and day of Ashura were the same as the previous year.

2. 1. Hybrid Neural Network Artificial neural networks (ANNs) are suitable tools for modeling and forecasting the data. Various types of neural networks have been introduced, each with a specific application. One of the main and beneficial capabilities of the neural networks is their function on the vast quantities of variables as well as on the complex systems. Despite the simplicity of utilizing the neural networks, there are also drawbacks, such as setting the parameters of the network architecture and 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 the neural networks varies in different applications. The use of a non-monitored neural network to cluster the similar data, and in the next stage, to train the supervised networks using the similar samples in one cluster is one of the most valuable functions of this type of network . Another use of the hybrid networks is that the inputs are of different ranges entailing the 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 hybrid networks are used to forecast the price of the consumed load due to the existence of several effective factors. Due to the lack of access to all of these factors, two of the most valuable features i.e., temperature and cost of the 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 is within 5-30˚Cif the consumption load is between 200-1500 MW in the province under assessment.
3) The effect of temperature variation in different hours of the day exhibits a different trend. As an example, a temperature change of two degrees between 13-15 hours shows a significantly greater effect on the 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 the 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 the load consumption but a temperature variation of one degree at temperatures over 24 degrees will exhibit a significant effect on the consumption load.

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

2. 2. Clustering It should be determined that to which cluster the data belong, and this process is repeated as long as the representatives of the clusters no further change. Clustering is different from the classification. In the classification, the input samples are labeled; however, they are not labeled in the clustering. In fact, clustering methods make the identical data to be identified and implicitly labeled. Actually, prior to the data classification operation, a sample clustering process can be performed and then, the centers of the resulting clusters can be specified. Afterwards, a label can be assigned to the cluster centers, and the classification operation can then be performed for the new input samples.

In the recent years, many methods including k-means, fuzzy k-means, neural network-based clustering, such as self-organizing map (SOM)-based clustering, and othershave been proposed for the clustering.

2. 3. Self-organizing Map Neural Network The SOM neural network is an unsupervised network used for clustering the data. On each application to an input, this algorithm maps its self-organizing Kohonen feature with respect to the neurons from a one or two -dimensional net type neuron. This net type network of the neurons is organized by the input samples ultimately approximating the distribution of the network inputs in a discrete environment. This network is consisted of two layers; the first layer is the input layer where the input samples are inserted and through which they are applied to the network neurons. The second layer includes 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 the resources, its output will acquire the value of one and the remaining neurons will have zero outputs. The neuron that its 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 were used in this project.

2. 4. Genetic Algorithm The genetic algorithm (GA) is a programming technique that uses the genetic evolution as a problem -solving model. Its input is the problem to be solved and the solutions are coded according to a pattern called the fitness function evaluating each possible solution, most of which are randomly selected [45].

The GA, as a search technique is used in the computer science to determine the optimal solution and address the search issues [46]. These algorithms are a type of evolutionary algorithms inspired by the branches of biological sciences, such as heredity, mutation, saltation (biology), natural selection, and composition.

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

1. Runtime Of The Algorithm
2. Number Of The Generations
3. Convergence Error Criteria

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

2. 5. Selection of the Input Parameters and Variables Based on the prior assessments, the time and temperature variables were selected as two factors influencing on the price and the previously consumed loads. Among the climate variables, only the temperature variable is used since, most of other climate factors are included in this variable. Given the fact that the temperature has a significant influence on the consumption trend, namely in the northern region of the country and since, the forecasts are on an hourly basis apparently, using the temperature parameter on an hourly basis or closer time intervals will entail the 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 the studies and opinions of the experts in the field of electricity distribution, 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 the previous weeks were used. In addition, the information on hourly temperature of the forecasted day was also used. Other utilized useful information included the load price and temperature of the preceding hour. Since, the information on the preceding 24 hours of the forecasted day was available thus, the data pertaining to the previous hours were used as the input in order to forecast those of the next hours [47].

2. 6. Proposed Method forecasting the short-term load price is a vital factor in the future planning of the power systems and electricity market management . In the recent years, various methods have been presented to improve the performance of such systems due to the significance of this issue. In this paper, a modern method is presented to forecast the short term hourly electrical energy costs based on the hybrid neural networks. In this method, influential parameters playing 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, the data are divided into the classes that are close in nature in order to improve the forecasts. Since, detection of the similar successive days during the week is one of the effective forecast parameters , data pertaining to the various seasons are analyzed separately. In the proposed method, initially, similar days are placed in the close clusters using the SOM network. In the next stage, the price and temperature parameters of the similar days are trained separately in two MLP neural networks due to their difference in the 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 in order to train the neural network. Due to the changes in the price data, the price of the previous hour has a significant effect on forecasting the current state. Thus, in the proposed method, the forecasted data of the preceding hour were 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 was initially allocated to the SOM neural network. In this stage, the number of clusters was determined using the k-means and Fisher's criterion hybrid method. This number varied for each hour of the day. Thus, network training for 24 hours was conducted separately and in succession. In the proposed structure, upon specifying the number of clusters, it should be determined that each sample entering to the network from the trained dataset belongs to which cluster and in the next stage, the associated MLP network is setup based on the selected cluster. 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 MLP network associated with the cluster.

In the proposed method, each cluster does not only use one MLP network, but a combination of MLPs is utilized. The input dataset is 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 the 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. In the process of training the perceptron neural network, a GA is used to obtain the initial weights in order to raise the accuracy of the price forecasting.

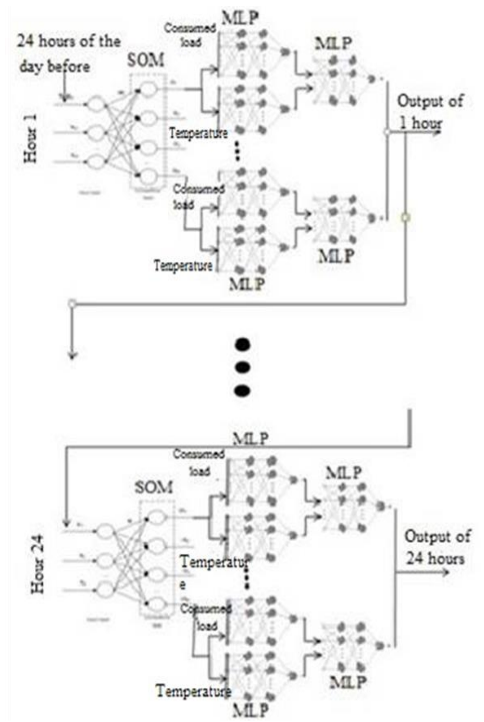


Figure 1. An overview of the hybrid network to forecast the load price of the next 24 hours

Data analysis was done using the MATLAB software. In this paper, evaluation criteria, such as the mean absolute error (MAE), mean absolute percentage error (MAPE), and R^2 were used. The MAE refers to the difference between the predicted value and the real value, which is shown by Equation (1).

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

The MAPE is calculated using the Equation (2):

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

The R^2 criterion statistically measures how close the data are to the fitted regression line. R^2 is also called as the coefficient of determination for detection coefficient. The definition of the coefficient of determination (R^2) is relatively simple:" the coefficient of determination (R^2) indicates the percentage of variations in a dependent variable determined by the independent variable" or in other words, the coefficient of determination indicates "to what extent the variations in 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 coefficient of determination is always between 0.0-100%. Zero percentage indicates that the model does not describe the response data variability around its mean, and 100% indicates that the model describes all the response data variability around its mean [48]. Equation (3) is used to calculate this coefficient.

$$R2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (3)$$

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

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

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

3. RESULTS

Table 1 presents the network structure related to the temperature for different seasons. In this table, forecasts for each year were conducted separately.

It is noteworthy that the values associated with the number of neurons, number of hidden layers, and threshold of the validated set were also calculated. In this regard, Figure 2 shows a sample of the results obtained for the summer for these parameters. As shown in Figure 2(a), the optimal number of neurons is equal to 5. According to Figures 2(b) and 2(c), the number of hidden layers and the threshold are equal to 0.1. All the results for subsequent tests were achieved using the validated data.

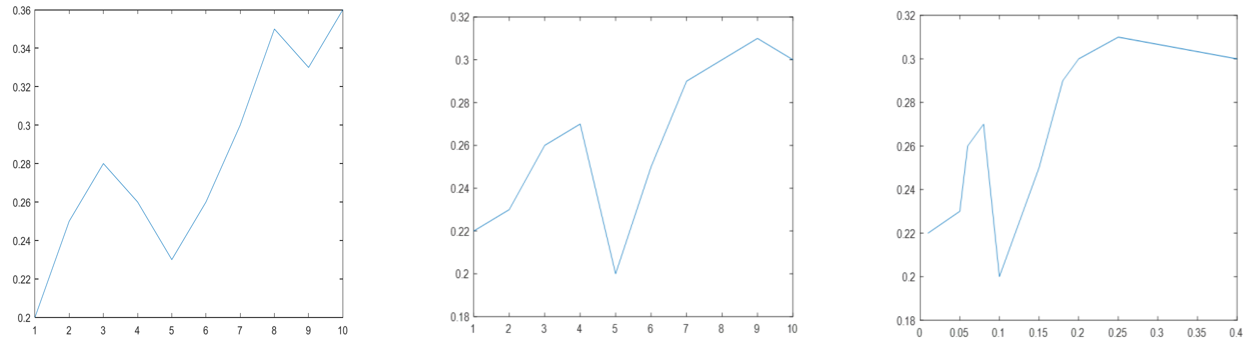
The parameters used for estimation of the neural network based on the validated data, (a) number of the neurons, (b) number of the hidden layers, and (c) threshold. A structure similar to Table 1 was used to design a price-related network. In the proposed structure, the number of price traits is one less than the input structure presented in Table 1, which is related to the forecasted hour. In this network, the forecast of the preceding stage is used for the load of the preceding hour (with the exception of 1 a.m.). Essentially, the forecast for the current hour is the input for the next hour. Table 2 shows the MLP neural network structure used for combination of the previous two MLP networks.

In this research, separate tests were designed for each season to analyze the consumed loads in each season separately. Although, it should be noted that the fundamental issue for this type of data concerns the summer season, which should be considered despite the favorable results achieved for all the seasons. The training results and test data for the consumed load in fall were presented. Moreover, a comparison was made between the proposed hybrid method and the MLP method.

Initially, the number of clusters was determined through the k-means clustering method and Fisher's criterion. Figure 3 shows the results of a specific hour in fall. Evidently, the number of clusters for this specific hour was equal to 4. Essentially, a network was considered for the temperature and price for each cluster.

TABLE 1. MLP network configuration parameters for load and temperature inputs

Number of input neurons	11	2 temperature trait of previous weeks 2 temperature trait of the previous days 2 load trait of the previous weeks 2 load trait of the previous days 1 temperature trait of the preceding hour 1 load trait of the preceding hour 1 temperature trait of the forecasted hour
Number of trained samples		46 samples for each hour
Number of validated samples		10 samples for each hour
Number of test samples		23 samples for each hour
Number of hidden layers		1
Number of neurons in the hidden layers		5
Error back propagation algorithm	Learning rate	0.05
	Maximum number of repetitions	100
	Error threshold to stop learning	0.1
	Slope of activation function value of β in $f(x) = \tanh(\beta x)$	1
Genetic Algorithm	Initial population	200
	Number of generations	10
	Size of each chromosome	30
	Selection function	@selectiontournament
	Termination function	@crossoversinglepoint
	Mutation function	@mutationgaussian



(a): horizontal: number of neurons, errors (b): horizontal: number of hidden layers, (c): horizontal: threshold vertical: error

Figure 2. Errors vs number of neurons, number of hidden layers and threshold

TABLE 2. Multi-layer perceptron neural network configuration parameters to combine networks

Number of input neurons	2	1 output trait related to the MLP network with load price input 1 output trait related to the MLP network with temperature input
Number of trained samples		46 samples for each hour
Number of validated samples		10 samples for each hour
Number of test samples		23 samples for each hour
Number of hidden layers		1
Number of neurons in the hidden layer		3
Error back propagation algorithm	Learning rate	0.05
	Maximum number of repetitions	100
	Error threshold to stop learning	0.1
	Slope of activation function value of β in $f(x) = \tanh(\beta x)$	1
Genetic Algorithm	Size of initial population	200
	Number of generations	10
	Size of each chromosome	9
	Selection function	@selectiontournament
	Termination function	@crossoversinglepoint
	Mutation function	@mutationgaussian

In the next step, the GA was used to calculate the initial weights, the results of which are shown in 10 iterations in Figure 4.

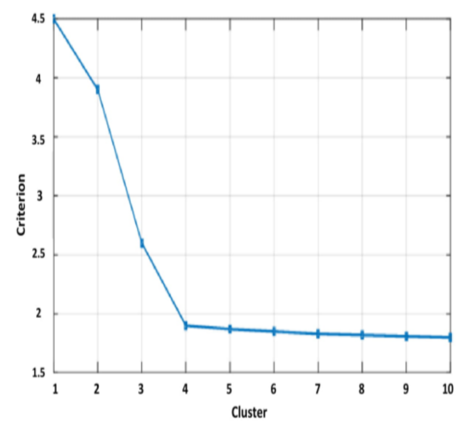


Figure (3). The rate of change in Fisher's criterion in regard to the number of clusters in the load set pertaining to fall

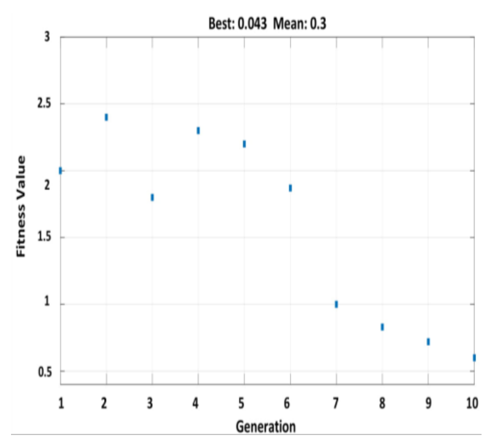
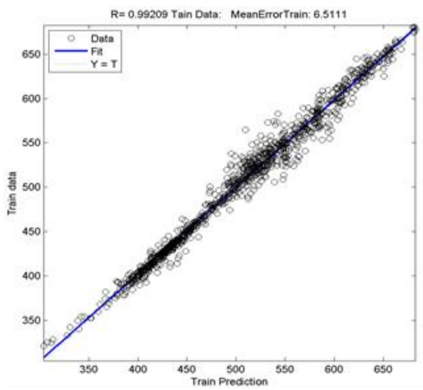
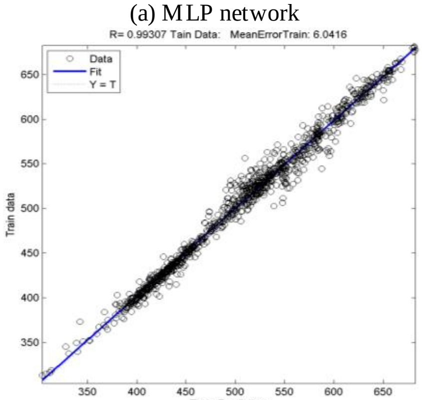


Figure 4. The achieved fitness value using the Genetic Algorithm in 10 repetitions

Figures 5 and 6 show the results obtained for the training and test datasets in fall. Clearly, the results achieved for summer and fall using the proposed method were superior to those obtained using the MLP -based method. Overall, the hybrid MLP and SOM method exhibited the superior results. Table 3 shows a comparison between the results obtained from the MLP network in various seasons and those obtained using the proposed method.

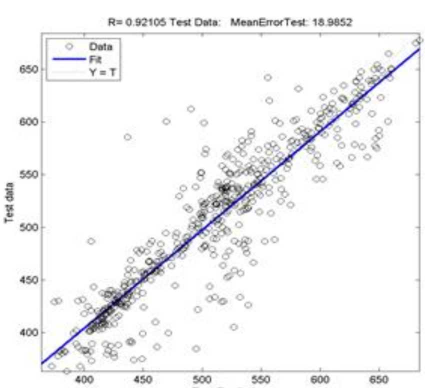


(a) MLP network

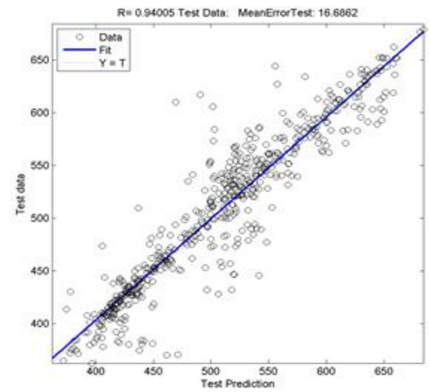


(b) MLP-SOM hybrid network

Figure 5. Results achieved in the training stage for fall



(a) MLP network



(b) MLP-SOM hybrid network

Figure 6. Results from the test stage for fall

TABLE 3. Comparison between the load forecasts achieved using the simple MLP method and those obtained from the MLP-SOM hybrid method

Year	Season	Method	R
2016	Spring	MLP	90.57%
		Proposed method	93.4%
	Summer	MLP	85.2%
		Proposed method	91.28%
	Fall	MLP	92.10%
		Proposed method	94%
	Winter	MLP	94.49%
		Proposed method	95.72%
2017	Spring	MLP	91.32%
		Proposed method	94.02%
	Summer	MLP	87.70%
		Proposed method	92.89%
	Fall	MLP	90.17%
		Proposed method	93.45%
	Winter	MLP	93.65%
		Proposed method	94.36%

Figures 7, 8 and 9 show samples of the achieved results. Figure 7 shows proposed system output in month 8 of 2017. Figure 8 shows the proposed system output in month 10 of 2016. Figure 9 shows the proposed system output in month 4 of 2015. Figure 10 shows the chart of real and forecasted price changes of 365 days in 2015. Figure 11 shows the results achieved by the proposed method for various seasons of 2016.

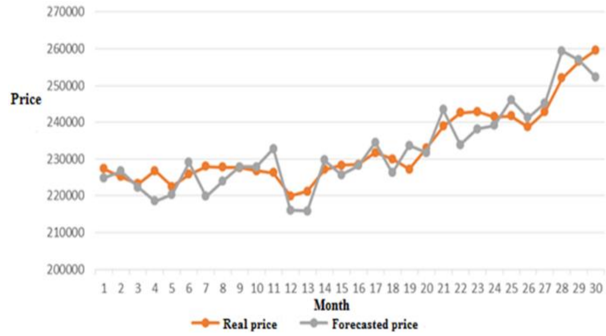


Figure 7. Chart of price changes in Iran October 2017

Figure 8. Chart of price changes in Iran December 2016

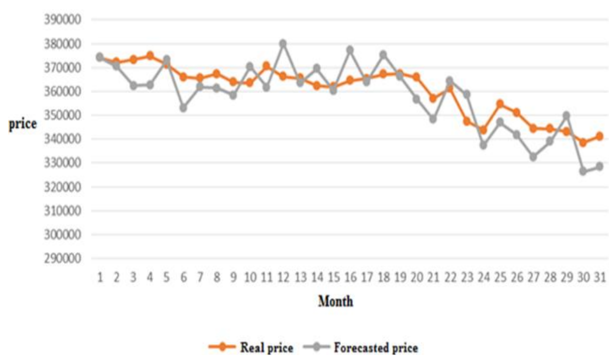


Figure 9. Chart of price changes in Iran June 2015

Figure 10. Chart of price changes for 365 days in 2016

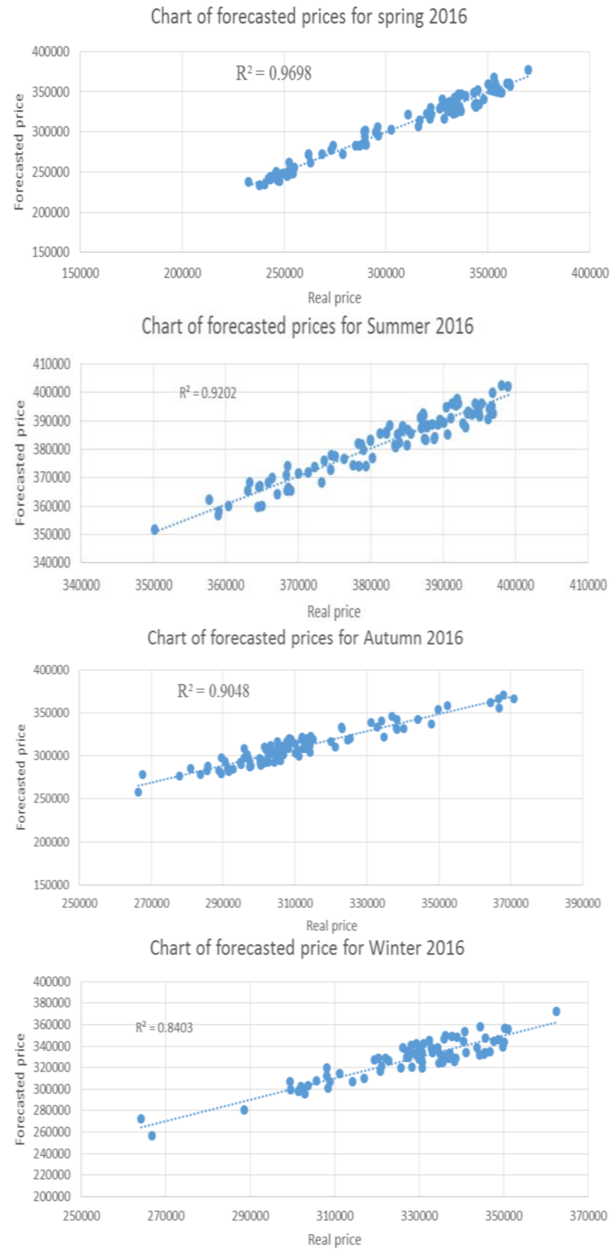


Figure 11. Results achieved by the proposed method in 2016

4. CONCLUSION

The provision of a smart system to forecast the price of electricity can entail an integral contribution to the competitive market in the dependent industry and country. In this regard, herein, a solution was presented based on the neural networks. Results showed an improved performance of such systems. Nevertheless, efforts can be made for further improving these systems. In this section, the suggestions are presented that may aid the researchers and enthusiasts in this field based on the experiences attained in this study.

1) Data should be extracted in addition to the energy and temperature data
2) A fuzzy system should be applied to extract the rules governing the market of such energy. Essentially, there are rules and regulations for the complex forecast systems, such as energy, which are typically extracted based on the experiences, e.g., the effect of stock changes in the stock market or political changes in a country severely influencing the precision of forecasting. To this end, it is possible to acquire and analyze these changes using a fuzzy system.

In the proposed method, as well as in the implementation phases of the project, there were some limitations which upon elimination will appease many of the issues pertaining to the price forecasting systems. Some of the limitations of this paper and relevant applications are as follows.

Since, the load and temperature-related information is not available in many regions on an hourly basis, the design of a comprehensive system to gather hourly temperature and load information may be significantly effective in improving such applications. For example, herein, the temperature information was used for Iran.

The availability of price and load-related information pertaining to the numerous years may be vital in designing a comprehensive system and statistical analysis of the information, but regrettably for Iran, only the information related to 5 years i.e., from 2011 to 2016 was available.

Upon considerable inquiries, the information was extracted for the Mazandaran province in Iran. Unfortunately, such information is not archived in many of Iran's provinces and thus, it cannot be studied comprehensively.

Numerous factors, such as political and economic events have a significant effect on the energy prices. Unfortunately, there was no comprehensive information on the important events in Iran to be used in this investigation. If such information is available, it could result in improvements in the proposed method.

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Persian Abstract

چکیده

بـا توجه به پیچیدگی‌های موجود در بازار برق عوامـل بسـیاری از جمله عدم قطعیت‌های موجود، نحوه بسته شدن بـازار، نحـوه تسویه حساب، ساختار و قوانین بازار، هزینه تولید، قیود حاکم بر واحدها و شبکه و ... در تعیین استراتژی بهینه قیمـت‌دهـی موثر است. تاکنون روش‌ها و مـدل‌هـای مختلفـی بـرای حـل مسـأله قیمت‌دهـی در فضـای رقـابتی صـنعت بـرق ارائـه شـده کـه مهمترین آنها شامل روش‌های قیمت‌دهی مبتنی بـر پـیش‌بینـی رفتار رقبا، روش‌های قیمت‌دهی مبتنی بر پیش‌بینی قیمت بازار، روش‌های مبتنی بر تئوری بازی و بـالاخره روش‌هـای قیمت‌دهی بر مبنای الگوریتم‌های هوشمند می‌باشد. هدف این پژوهش ارائه استراتژی بهینه جهت پیش‌بینی قیمت تسویه بازار انرژی الکتریکی در بازار رقابتی برق ایران (بر اساس داده‌ها در فصل پاییز) است. در روش پیشنهادی مقاله حاضر از شبکه ترکیبی بر پایه شبکه‌های عصبی استفاده شده است. در داده‌های مورد تحلیل میزان انرژی مصرفی و همچنین دما (در صورت امکان) و قیمت در روزهای گذشته و هفته گذشته استفاده شده است. در روش پیشنهادی از شبکه ترکیبی از SOM برای خوشه‌بندی ورودی بر اساس روزهای مشابه استفاده شده است. از چند شبکه عصبی MLP برای ترکیب داده‌های استخراجی از میزان انرژی، قیمت گذشته و دما (در صورت امکان) استفاده شده است. نتایج نشان‌دهنده بهبود عملکرد سیستم‌های هوشمند متنی بر شبکه‌های عصبی در پیش‌بینی قیمت برق بود.