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Application of an Improved Neural Network Using Cuckoo Search Algorithm in Short-Term Electricity Price Forecasting under Competitive Power Markets

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ABSTRACT
Accurate and effective electricity price forecasting is critical to market participants in order to make an appropriate risk management in competitive electricity markets. Market participants rely on price forecasts to decide on their bidding strategies, allocate assets and plan facility investments. However, due to its time variant behavior and non-linear and non-stationary nature, electricity price is a complex signal. This paper presents a model for short-term price forecasting according to similar days and historical price data. The main idea of this article is to present an intelligent model to forecast market clearing price using a multilayer perceptron neural network, based on structural and weights optimization. Compared to conventional neural networks, this hybrid model has high accuracy and is capable of converging to optimal minimum. The results of this forecasting method for Market Clearing Price (MCP) of Iranian and Nord Pool Electricity Markets, as well as Locational Marginal Price (LMP) forecasting in PJM electricity market, verify the effectiveness of the proposed approach in short-term price forecasting.

KEYWORDS: Short-term Price Forecasting, Artificial Neural Network, CUCKOO Search Algorithm, Genetic Algorithm, Similar Days.

NOMENCLATURE

Act.-MCP	Actual market clearing price	ICA	Imperialist competitive algorithm
Ave.-MCP	Average market clearing price	LMP	Locational marginal price
ANN	Artificial neural network	MAE	Mean absolute error
ARMA	Auto-regressive and moving average	MAPE	Mean absolute percentage error
ARIMA	Auto-regressive integrated moving average	MCP	Market clearing price
CS	Cuckoo search	MSE	Mean squared error
For.-MCP	Forecasted market clearing price	N	Number of hour
GA	Genetic algorithm	PJM	Pennsylvania–New Jersey–Maryland
h	Hour	PSO	Particle swarm optimization

1. INTRODUCTION

In restructured power systems with complicated market structure, generation companies or customers can sell or buy electricity either from a centralized power pool or directly through bilateral contracts [1]. The structure of the electricity industry is radically changing the manner in which utilities do their business. MCP is the lowest price that would provide enough electricity from accepted sales bids to satisfy all the accepted purchase bids. At MCP, total sales bids in their merit order would be equal to the total purchase bids down to that price in their merit order. LMP is defined as the

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price of supplying the next MW of load at a specific location, considering the generation marginal cost and delivery constraints of the physical network. LMP forecasting, however, is difficult since LMPs are closely affected by complicated market behaviours and depend heavily on transmission congestions. Therefore, accurate MCP and LMP forecasting can help producers and consumers maximize their respective benefits with low risks [2-4].

In modern electricity markets, one objective is to build an accurate predictive model for generating day-ahead price forecasting. This process is important for the transmission company to schedule short-term generator outages and design load response programs as well as bid into the market strategically and manage its assets optimally. If an appropriate price forecasting system is available, large consumers can stem their electricity usage plan strategically to maximize their utility [5]-[8].

Most existing techniques on short term price forecasting try to improve the performance by selecting different prediction models, such as linear regression, exponential smoothing, stochastic process, ARMA models [9], data mining models and the widely used ANN [10,11]. ANNs methods are able to extract an implicit nonlinear relationship among input variables by learning from training data. The back propagation algorithm is one of the most popular techniques used to train neural network parameters (weights and biases) based on gradient descent or conjugate gradient decent method. Moreover, it has been proved that this gradient information technique is slow to train and sensitive to the initial guess, which could possibly be trapped in a local minimum [12].

Determining the number of hidden layers and the number of neurons in the hidden layers in previous researches were based on the experience and trial and error methods, which sometimes, is not able to lead to the global optimum [13-15]. In this paper, in order to improve the learning efficiency of the neural network, GA can be used as an optimization search scheme to determine the optimal or near optimal network architecture design. Therefore, GA is used here to globally optimize the neural network architecture.

The training process has a significant impact on the network. This paper demonstrates the possibility of combining neural networks with optimization algorithms. Four different evolutionary techniques are used as the training algorithm to adjust the weights of the ANN model to predict daily prices. Also, these techniques are compared with each other. The advantage of using evolutionary algorithms over other techniques is their computationally inexpensive nature and easy implementation. Moreover, they do not require the gradient information of the objective function, but only its values. In this article the results were compared with ARIMA model and conventional back-propagation algorithm. Another factor which must be considered in training a network is data selection. Selecting an appropriate set of data for training can improve the accuracy of forecasting process.

The proposed method is implemented on the Iranian, PJM and Nord Pool electricity markets. The results obtained through the simulation show that the proposed model can provide more efficient, more accurate and better results.

The rest of this paper is organized as follows: selecting input details presented in Section 2. In Section 3, the proposed framework is explained. In Section 4, simulation results and discussions are presented. Finally, concluding remarks are presented in Section 5.

2. DATA SELECTION

Previous research results show that the behaviour of similar days is close to each other in many cases. The application of this information has a positive impact on the training process of neural network. Similar days selection can be simplified by choosing days with the same day types [16, 17].

As a first step, the days similar to the forecasted day are extracted by using day type, then, the cluster center of the similar days is obtained by calculating the average value of the similar days. After that, the distance from every extracted similar day to the cluster centre is calculated. The similarity between a similar day and the cluster center is measured by Euclidean distance [18] shown as (1).

$$d(X,Y)=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2} \tag{1}$$

where $X=\{x_1, x_2,\ldots,x_n\}$ and $Y=\{y_1, y_2, \ldots, y_n\}$ are two nodes in N-dimensional Euclidean space. Finally, the abnormal days, *i.e.* the days having long distances from the cluster center, are filtered out.

In this paper, the forecasting results show that similar days have a positive effect on the training process. In addition, the other parameter which affects the price curve is the historical price data, *i.e.* the last day price data. So, these two parameters have been used at the same time to achieve a better accuracy.

3. THE PROPOSED FARAMEWORK

Multilayer feed-forward neural network is one of the most commonly used networks in various applications. Here, a multi-layer feed-forward network is applied to the short-term price forecasting modelling. The calculation of weight adjustment for a given neuron is denoted as:

$$\Delta W(t+1)=\mu\times\Delta W(t)+(1-\mu)\times\delta\times u(t) \tag{2}$$

where μ is the momentum, $\Delta W(t)$ is the previous weight change, δ is an associated error term, and *u(t)* is the input to the neuron [19].

In this section, first, the structural optimization of the neural network is discussed and the weights optimization of the neural network is considered afterwards. Also, the last part of this section is devoted to the introduction of cuckoo search algorithm.

3.1. ANN structure optimization

The number of hidden layers and the number of neurons in each hidden layer in previous research was based on the experience and trial and error methods, which sometimes, is not able to lead to the global optimum. Thus, genetic algorithm is applied to optimize the neural network structure which can lead to the optimal solution due to its discrete nature. The optimization problem in this approach is to determine the number of hidden layers and the number of neurons in each hidden layer using genetic algorithm. More specifically, two issues will be considered. One pertains to searching for the optimized network architecture and the other defines the fitness evaluation function. In this approach, the chromosome for an individual is chosen from real numbers. The first bit of the chromosome represents the number of hidden layers while the remaining bits represent the number of neurons in the hidden layer [19, 20]. The fitness evaluation function is defined as:

$$Fitness=\frac{1}{1+e} \tag{3}$$

$$e=\sum_{i=1}^{q}\frac{\left(\hat{U}_i-U_i\right)^2}{q} \tag{4}$$

where q is the number of samples used during the training process, $\hat{U}_i$ and U_i are the predicted output and the actual output during the learning process, respectively, and e is the MSE after 5 epochs of training.

3.2. ANN weights optimization

A neural network uses a learning function to modify the variable connection weights at the inputs of each processing element according to some neural based algorithm. Multiple layers of neurons with nonlinear activation functions allow the network to learn linear and nonlinear relationships between the input and the output of the network. The training process in our network requires a set of examples to make proper network behaviour. Hence, the network can be trained for function approximation. Through the training process, the weights and biases are taken to be a dimension in space and updated iteratively to minimize the error function to find the lowest point in this multi-dimensional surface [21].

The perceptron training algorithm is a form of supervised learning algorithm where the weights and biases are updated to reduce errors whenever the network output does not match the desired values. Based on the principle mentioned above, real number coding is used in this paper. Each weight is represented by a real number. All the weights in a network are represented by a group of real numbers. The weights connected with the same hidden node are put together. In order to optimize the neural network weights, four different evolutionary algorithms, namely GA, PSO, ICA and CS, are implemented and also compared. Finally, the proposed model is optimized with CS algorithm, which is described as follows.

3.3 CUCKOO search algorithm

Cuckoo search algorithm, developed by Yang and Deb in 2009 [22], is one of the latest optimization algorithms which imitates some cuckoo species' breeding behaviour. Recent studies have revealed that CS is potentially far more efficient than GA and PSO [23, 24].

A. Cuckoo breeding manner

Some cuckoo species lay their eggs in communal nests, although quite a number of species engage in the obligate brood parasitism by laying their eggs in the host birds' nests (often other species). The brood parasitism basically falls into three categories, namely intra specific brood parasitism, cooperative breeding and the nest take over. After laying the eggs, if the host birds can discover that the eggs are not their owns, they will either destroy the alien eggs or abandon their nests and build new nests elsewhere; while some female cuckoo species can lay their eggs very specialized in mimicry in pattern of the host bird's eggs. This reduces the probability of their eggs being discovered [25].

Moreover, parasitic cuckoos usually choose a nest where the host bird just laid its eggs. This increases the chance of hatching alien chicks sooner than the host bird's chicks. Once the first cuckoo chick is hatched, it will propel the other eggs out of the nest instinctively; therefore, the cuckoo chicks will access more feeding opportunity.

B. Lévy flights

Many researches have shown that the flight behaviour of many insects and animals may follow some typical characteristics of lévy flights. A general issue of lévy flights and random walk in order to obtain new solution is presented in (5) and (6):

$$\mathrm{L}_i^{(t+1)} = \mathrm{L}_i^{(t)} + \alpha \oplus \mathrm{Levy}(\lambda) \tag{5}$$

$$\mathrm{Levy} \sim \omega = t^{-\lambda} \qquad 1 < \lambda \le 3 \tag{6}$$

where, $\mathrm{L}_i^{(t+1)}$ represents new solutions, and α >0 is the step size related to the problem scale. Some of the new solutions should be generated by random levy walk around the best solution. However, a considerable fraction of new solutions should be produced by far field randomization. This will guarantee the algorithm not to be trapped in local optimums.

C. Cuckoo search

In order to model the standard cuckoo search algorithm, the following three idealized rules are developed:

- Each cuckoo lays just one egg at a time, and dumps it in a randomly chosen nest.
- The best nests with high quality of eggs (solutions) will carry over to the next generation (algorithm iteration).
- The number of available host nests is constant, and each cuckoo egg can be discovered by the host bird with the probability of $P_a \in [0,1]$.

According to these three rules, the basic steps of CS can be summarized as the pseudo code represented in Fig. 1.

Regardless of what type of algorithm to be used, firstly the related cost function of weights optimization should be extracted. So, to find the solution, a row vector of real numbers (called in this article as: A variable) is defined. Actually, this variable is one of the population matrix rows which contain neural network weights. Hence, a function is formed according to its number of layers and neurons in each layer which its main task is to create the network. After the network creation, the assessment phase based on different values of variables is started. Finally, assuming a weight function, by adding input values, the output is simulated; subsequently, the MSE is obtained by subtracting the network output and the actual output and is stored as a cost function. The MSE is defined as follows:

$$MSE = \frac{1}{N}\sum_{h=1}^{N}(Act.-MCP(h)-For.-MCP(h))^2 \quad (7)$$

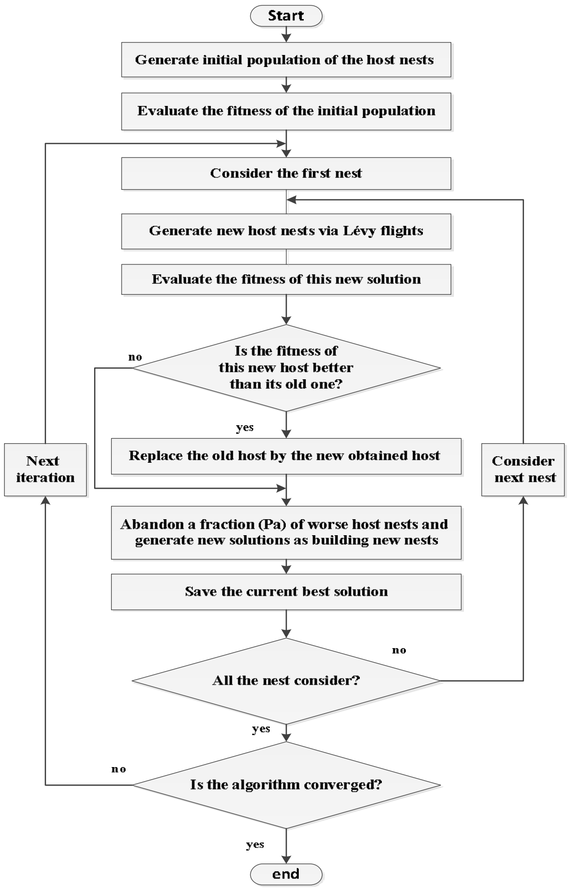

Fig. 1. General steps of the standard cuckoo search algorithm

4. CASE STUDIES AND SIMULATION RESULTS

To evaluate the performance of the proposed model MAE and MAPE indices, which are widely used, are adopted in this paper. They are defined as follows:

$$MAE = \frac{1}{N}\sum_{h=1}^{N}\left|Act.-MCP(h)-For.-MCP(h)\right| \quad (8)$$

$$MAPE = \frac{1}{N}\sum_{h=1}^{N}\frac{\left|Act.\_MCP(h)-For.\_MCP(h)\right|}{Ave.\_MCP}\times 100 \quad (9)$$

4.1. Applying the proposed framework to Nord pool market

Nord Pool spot runs the leading power market in Europe and offers both day-ahead and intraday markets to its customers. 370 companies from 20 countries trade on this market. The Nord Pool electricity market is highly volatile with a large number of unexpected abnormalities and outliers.

This proposed model is applied to forecasting price in the deregulated electricity market of Nord Pool 2012 (zone SE1) [26]. The set of 17 lagged prices (the prices of 1, 2, 3, 24, 25, 48, 49, 72, 73, 96, 97, 120, 121, 144, 145, 168 and 169 hours ago) are proposed as the set of input features for the MCP prediction in this study. The proposed feature selection method correctly detects the short-run trend (such as the selection of 1, 2 and 3 hours ago prices), daily periodicity (such as strong dependencies on the 24 hours prices, that is, the price of hour *h* or price forecast for 24 hours ago, 48 hours ago, etc.) and weekly periodicity (such as selection of 168 h features) hours characteristics of the price signal. The output feature of these input variables is P_h, which is obtained ahead via recursion, that is, by feeding input variables with the previous outputs. In other words, when P_h is forecasted, it is used as P_{h-1} for the MCP prediction of the next hour and this cycle is repeated until the MCP of the next 24 hours are forecasted by 24 iterative predictions. Besides, the training period of the proposed method has been selected as recommended in [1] and [7], which consists of 48 days ago. Thus, the training data includes 1152 learning patterns. After training, 24 hourly MCP values of the next day can be forecasted.

Figure 2 shows the fitness function of the architectural optimization of GA in which the best solution was a three layer feed forward neural network with 29 neurons in the hidden layer. Figure 3 indicates the convergence of the best solutions among 50 independent runs for each algorithm. Notice that the fitness used in Fig. 3 is the cost of the MSE which is obtained by subtracting the network output and the actual output and is stored as a cost function for the case May 14th. Table 1 represents comparison results for the applied algorithms in these 50 runs. It is worth mentioning that the fifth column in Table 1 shows the average iteration at which each algorithm has converged through the mentioned 50 runs. In these simulations, each of the used algorithms has been implemented by the same number of initial population, i.e. equal to 40. Moreover, the used cuckoo search algorithm in the proposed method has been employed by the discovery rate of alien eggs (P_a) equal to 0.3 and λ equal to 2.5. The flowchart of the proposed model is shown in Fig. 4.

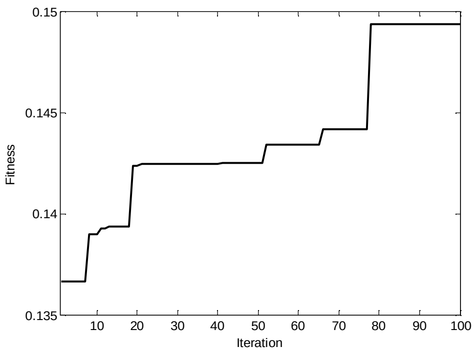

Fig. 2. The fitness function of the architectural optimization

In order to show the efficiency of this model, four different days which cover all seasons in the year 2012 have been chosen as sample days. The accuracy of the model is shown in Figs. 5 to 8.

Table 2 compares MAPE values of ARIMA, ANN and the proposed model for electricity market of Nord Pool 2012 (zone SE1).

Table 2. MAPE results for electricity market of Nord Pool 2012 (zone SE1)

Date	ARIMA	ANN	Proposed model
Jan. 15th	5.2433	5.0114	3.2944
Feb. 14th	3.4222	3.3825	1.6211
Mar. 14th	2.6768	2.8725	1.064
Apr. 15th	3.7447	3.2074	1.9146
May. 14th	5.0953	4.5669	3.136
Jun. 15th	3.7195	4.0704	2.6877
Jul. 15th	5.5863	5.2884	4.6197
Aug. 14th	7.1047	6.2921	4.3949
Sep. 15th	9.4071	8.5551	7.3978
Oct. 15	4.1982	4.4243	2.9017
Nov. 15th	3.3097	3.2215	1.4813
Des. 14th	6.6342	5.3774	3.6983
Mean	5.0110	4.7788	3.18429

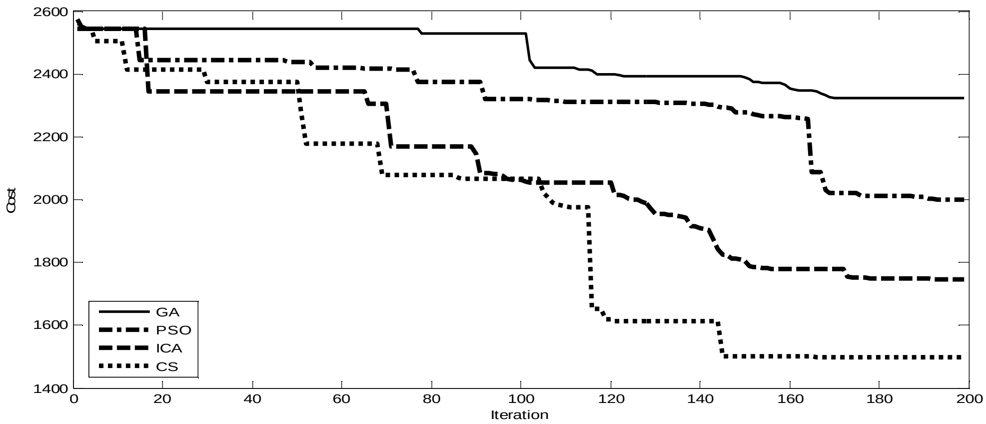

Fig. 3. Trajectories of the best solution for GA, PSO, ICA and CS

Table 1. The results of 50 independent runs for each iteration

Solution approach	Best (fitness)	Ave. (fitness)	Worst (fitness)	Ave. convergence iteration
GA	2324.84	2603.032	2902.885	159
PSO	2000.71	2485.54	2962.05	184
ICA	1747.08	2312.68	2665.59	171
CS	**1503.57**	**1802.11**	**2256.65**	**139**

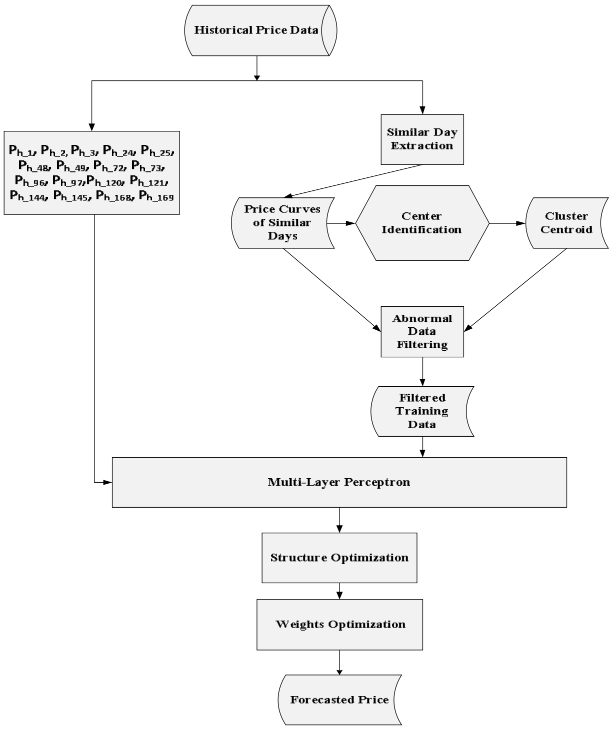

Fig. 4. The proposed model

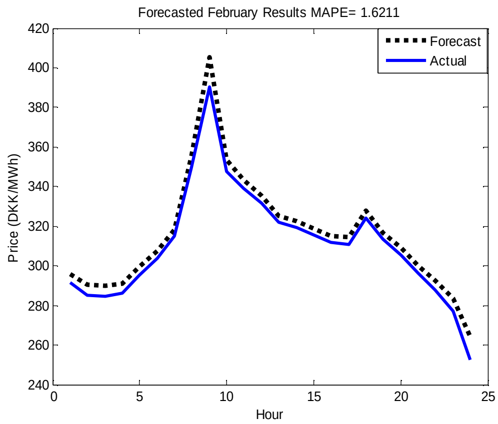

Fig. 5. Price forecasting applying the proposed model for February 14th

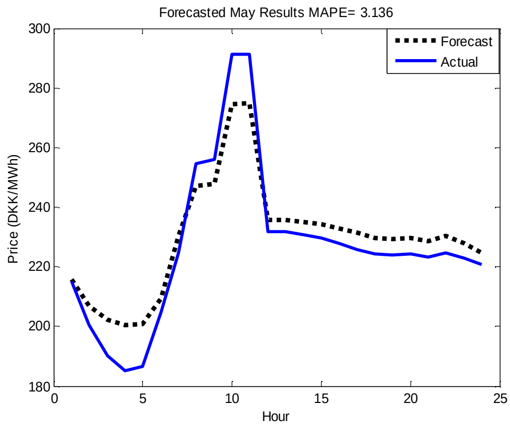

Fig. 6. Price forecasting applying the proposed model for May 14th

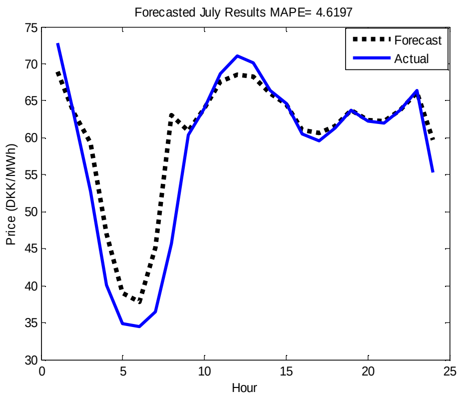

Fig. 7. Price forecasting applying the proposed model for July 15th

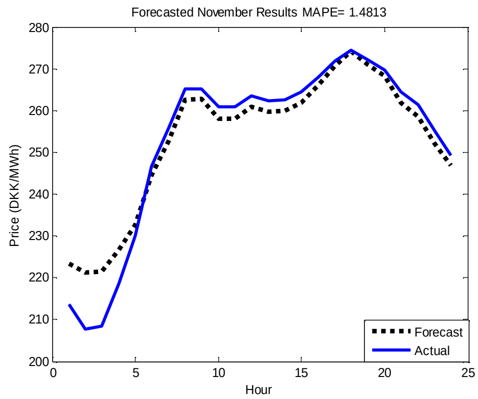

Fig. 8. Price forecasting applying the proposed model for November 15th

4.2. Applying to PJM market

PJM operates the world's largest competitive wholesale electricity market and one of North America's largest power grids which includes more than 51 million people. The proposed model is compared with Ref. [27] for a winter week from 18th to 24th February and a spring week from 20th to 26th May in year 2002 of PJM electricity market [28] which shows the efficiency of this model. The historical hourly LMPs data used for the proposed model and employed to forecast the LMPs of the test week for PJM market are shown in Table 3.

Table 3. Hourly LMPs data for forecasting model construction and testing

Seasons	Historical hourly LMPs data	Test weeks
Winter	Jan. 1 – Feb. 17	Feb. 18 – Feb. 24
Spring	Apr. 2 – May. 19	May. 20 – May. 26

Figures 9 and 10 show the forecasting for winter and spring weeks, respectively. In order to evaluate the performance of the proposed model MAE and MAPE indices, are presented and compared. Table 4 proves the efficiency of the proposed model.

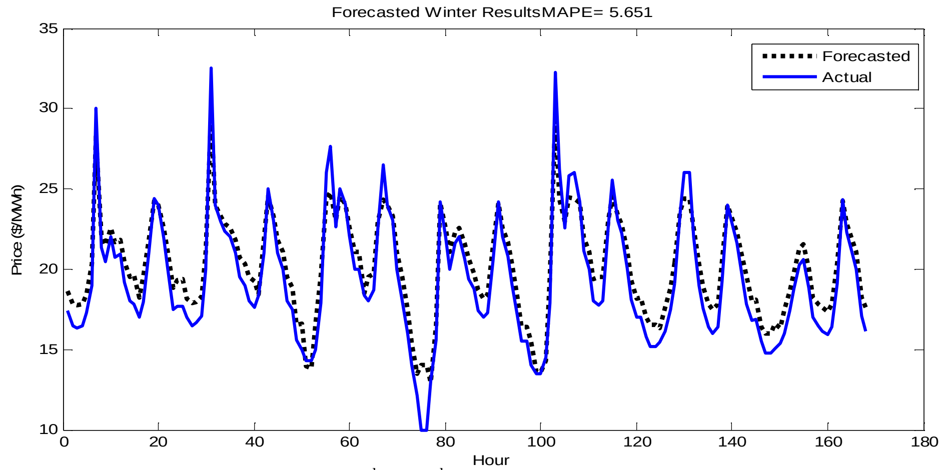

Fig. 9. The winter week from 18th to 24th February in year 2002 of PJM electricity market

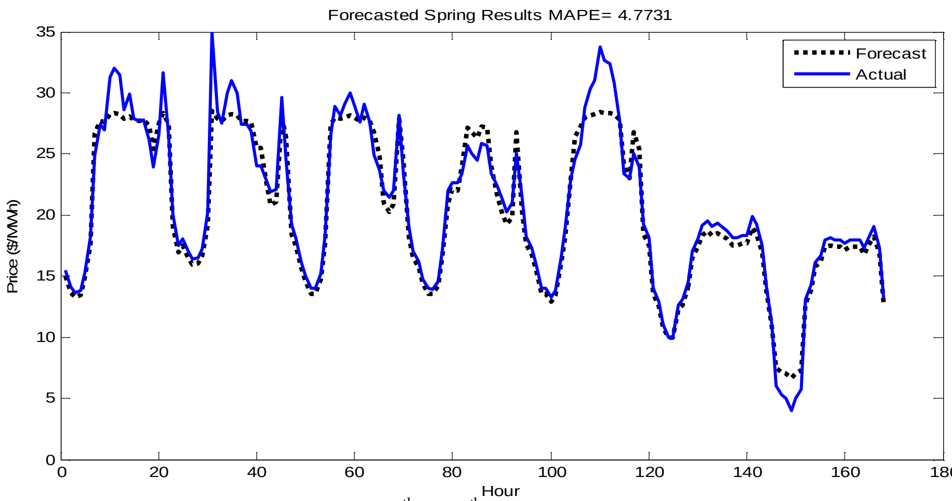

Fig. 10. The spring week from 20th to 26th May in year 2002 of PJM electricity market

4.3. Applying to the Iranian market

Price forecasting in a power market with Pay-As-Bid (PAB) auction, especially in Iran, is very important, because in markets with PAB auction, each participant will receive a payment based on the amount of its bid. Participant having more accurate forecasting and applying better strategies, will gain the maximum profit.

In order to show the efficiency of the proposed model, four different weeks in the

Iranian electricity market in year 2012-2013 are chosen. Also, each week contains seven days to cover all day types (i.e. weekdays, weekends and holidays) [29]. Thus, four sample days are chosen and the forecast results are shown in Figs. 11 to 14. Also, Table 5 shows the forecasting results of ARIMA, the conventional ANN and the proposed methods.

Table 4. Comparing the error results of reference [27] and the proposed model

Model \ Case		Winter week	Spring week
Ref. [27]	MAPE	6.160	5.603
	MAE	1.216	1.204
Proposed	MAPE	5.651	4.7731
	MAE	1.0947	0.9905

Table 5. Comparing MAPE resultes for the Iranian market

a- 23th to 29th April of year 2012

Day	ARIMA	ANN	Proposed
Monday	4.0978	3.7693	1.6089
Tuesday	4.3663	3.1952	2.4129
Wednesday	7.9725	8.0812	5.6146
Thursday	4.8768	2.3013	1.9067
Friday	4.4963	2.443	2.0976
Saturday	3.1524	3.6784	1.3413
Sunday	3.2506	2.9872	1.6208
Mean	**4.60181**	**3.77937**	**2.37183**

b- 23th to 29th July of year 2012

Day	ARIMA	ANN	Proposed
Monday	1.7709	2.3265	0.91588
Tuesday	1.0921	1.0209	0.75681
Wednesday	2.0575	1.7988	1.1148
Thursday	2.3412	1.9221	1.3061
Friday	2.0302	2.3443	1.0717
Saturday	3.4416	2.6654	1.9907
Sunday	5.7781	4.443	1.7508
Mean	**2.65463**	**2.36014**	**1.27179**

c- 5th to 11th November of year 2012

Day	ARIMA	ANN	Proposed
Monday	2.6666	2.4736	1.023
Tuesday	3.2987	3.7508	2.0978
Wednesday	5.0792	4.8872	1.9381
Thursday	1.7791	2.0292	1.0426
Friday	3.6378	3.2518	2.2889
Saturday	2.2901	2.1213	1.2634

d- 14th to 20th January of year 2013

Day	ARIMA	ANN	Proposed
Monday	2.2534	1.8749	1.1414
Tuesday	2.0838	2.4012	1.1662
Wednesday	1.9902	2.151	1.1536
Thursday	2.9126	2.1669	1.548
Friday	2.2066	2.0037	1.0825
Saturday	2.4279	2.0363	0.94869

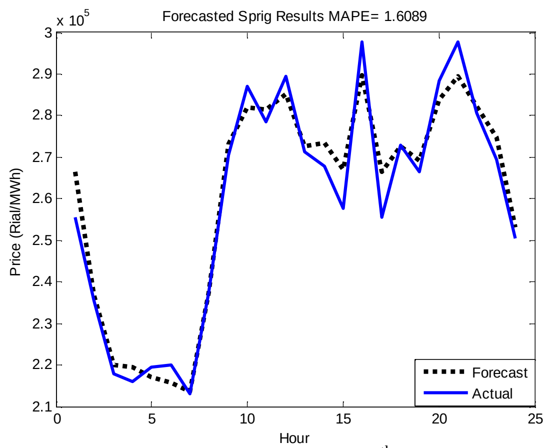

Fig. 11. Forecasting results of April 23th in year 2012 on Iranian market

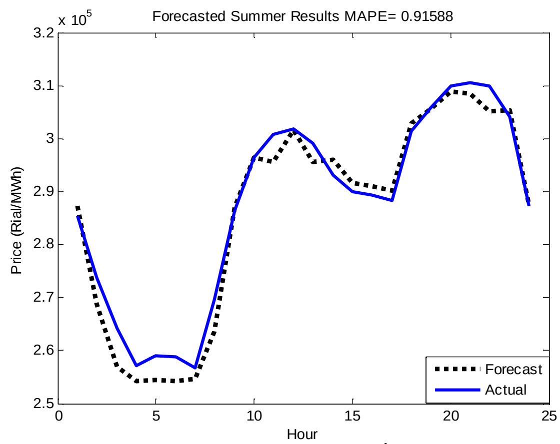

Fig. 12. Forecasting results of July 23th in year 2012 on Iranian market

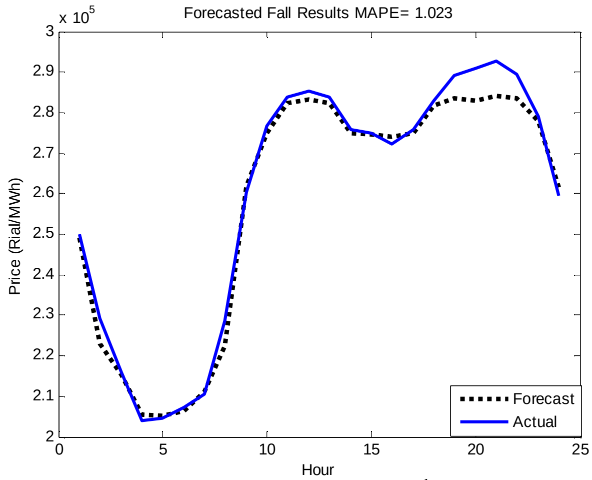

Fig. 13. Forecasting results of November 5th in year 2012 on Iranian market

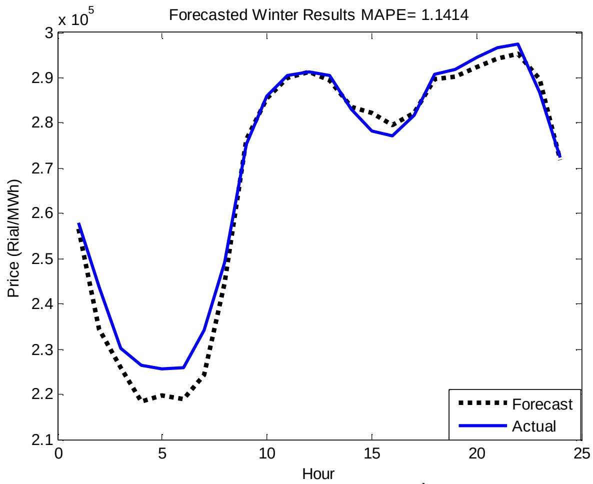

Fig. 14. Forecasting results of January 14th in year 2013 on Iranian market

5. CONCLUSIONS

Electricity price forecasting in irregular electricity market is essential to facilitate the decision-making process and many research projects are carried out in this field. Based on the simulation results presented in the current paper, it can be stated that the application of evolutionary algorithm in multi-layer perceptron neural network's weights and structural optimization is a very effective method. Also, applying similar day data for price forecasting is an efficient idea in order to improve the forecasting results. In this paper, the Iranian, the PJM and the Nord Pool electricity markets were subjected to short-term price forecasting. Simulation results was proved the higher efficiency of the proposed model over the conventional methods.

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