



An intelligent model for predicting the day-ahead deregulated market clearing price: A hybrid NN-PSO-GA approach

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Abstract. Under the restructuring of the electric power industry and transformation of the traditional vertically integrated electric utility structure to the competitive market scheme, Market Clearing Price (MCP) prediction models have become essential for all generation companies (GenCos). In this paper, a hybrid model is presented to predict hourly electricity MCP. The proposed model contains a Neural Network (NN), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The NN is used as a major forecasting module for prediction, PSO is applied to improve the traditional neural network learning capability, and GA is applied to optimize NN architecture. The main contribution of this paper includes: (a) presentation of a new hybrid intelligent model for market clearing price prediction; (b) application of K-means algorithm to clustering NN's test set and seasonality pattern detection; and (c) performance evaluation of the proposed model by improved Mean Absolute Error (MAE) with a penalty factor for positive error. The proposed method has been tested for the real-world electricity market of Iran within one month in each year of 2010-2013; obtained results show that the average weighted MAE designed for prediction purposes is equal to 0.12; the prediction accuracy of MCP by the proposed model can be improved by more than 6.7% and 4% in MAE, compared to a simple NN by a combination of NN and bat algorithm.

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1. Introduction

Over the last decade, under the restructuring of the electric power industry and with the aim of increasing economic productivity and reducing the costs of generation, the electricity markets in many countries have become more decentralized and deregulated. As a consequence, they are no longer monopolistic [1].

The major economies of the world have transformed electricity generation and distribution from vertically integrated operations to deregulated operations of the market. Deregulation in the electricity market has led to competition among market participants to increase efficiency. In the electricity market, GenCos are the best candidates for iteration in competition to improve productivity and efficiency in resource allocation and offer the lowest price with the highest quality [2].

The electricity markets are categorized as: (a) single-settlement markets (or real-time balancing the market), and (b) two-settlement market (day ahead or pre-dispatch market).

In a single-settlement market, competitors buy

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or sell wholesale electricity during the operating day and electricity prices are settled on a daily or hourly basis depending on the demand and available supply. In a two-settlement market, competitors buy or sell wholesale electricity in a day before the operation day in the day-ahead electricity market, and the difference between the proposed and actual demands on the operation day is covered using a real-time market [3].

In the restructuring of the electric power industry around the world, one of the important services in the wholesale competitive deregulated electricity market is a power pool in the day-ahead market [4]. In the day-ahead market, the Independent System Operator (ISO) clears the bids of GenCos for each hour of the next day. For each hour of the next day, every GenCo submits a bidding price offer to the independent system operator. The proposed price must be greater than zero and lower than market limitation level. Bids are analyzed by the ISO so as to determine the hourly MCP and the power to be dispatched by every GenCo based on proposed price and market clearing price [5].

There is a double-auction mechanism: (a) Uniform payment that pays at the accepted level (with price lower than market clearing price) based on hourly MCP and (b) Pay-as-bid auction that pays at the accepted level of every GenCo based on its proposed price [6].

If a GenCo has an accurate estimate of MCP on the next day, it can maximize its benefit, since forecasting both of the electricity demand and MCP is one of the most important parameters for GenCos [7]. Price-forecasting mechanism in any market is related to:

- (a) Market size (refers to the number of potential buyers and sellers);
- (b) Market structure and mechanism such as payment procedures or liquidity;
- (c) Level of access to information of market and participants;
- (d) Risk management choices [8].

However, there is a difference between electricity and other commodities, such that:

- (a) Electricity cannot be stored easily and must be used immediately as generated since the physical delivery system operates much faster than any market [3];
- (b) The electricity transport carries heavy losses and costs and special facility required for distribution;
- (c) Compared to other traded commodities, electricity prices are the most volatile, and all of these reasons make electricity price forecasting challenging [9];
- (d) Electricity supply must be demanded exactly at any given time across the grid since generation and load must be balanced at all times;

- (e) The MCP exhibits strong seasonality at the annual, weekly, and daily levels [10];
- (f) The electricity consumer cannot choose which producer generates load, and the generator cannot direct its production to some consumers [10].

Various methods for forecasting electricity prices have been reported in the literature such as times series models [11], GARCH model [12], a combination of wavelet transform and ARIMA [13], fuzzy auto regression model [14], game theory [15], Bayesian optimization [16], neural network [17], the combination of neural network model and bat [18]. The MCP forecasting algorithm is divided into three groups of game theory, times series models, and simulation models; time series models are classified into three sets of stochastic models, artificial intelligence models, and casual models [19].

Among the proposed models designed to predict MCP, artificial neural networks are found to be the most suitable tools and have received much attention since they can determine the complex relationship between next-day MCP and historical data of load and other factors such as day type, demand, temperature, settlement point, month, and so on. The neural network models are one of the most widely used techniques for predicting MCP based on historical data [20].

Mandal et al. applied neural network to forecast MCP for several hours ahead of Victorian electricity market. Since the Euclidian norm with weighted factors has been applied to select similar days and the MAPE (Mean Absolute Percentage Error), results display a clear increasing pattern with an increase in the hour-ahead price forecasting from 9.75% for one-hour-ahead price to 20.03% for six-hour-ahead predictions [21].

Abedinia et al. proposed Combinatorial Neural Network (CNN) to forecast MCP in markets of Pennsylvania-New Jersey-Maryland (PJM) and mainland Spain. In this model, Chemical Reaction Optimization (CRO) algorithm is applied to optimize the weights of the NN in CNN, and results show that average WME is equal to 4.04% [5].

Bento et al. developed new hybrid models by combining bat algorithm with neural network to predict MCP in Spanish and Pennsylvania-New Jersey-Maryland electricity markets; numerical results show that average MAPE value is less than 1% [18].

Anbazhagan and Kumarappan proposed a Discrete Cosine Transforms (DCTs) based Neural Network approach (DCT-NN) to predict MCP in Spain and New York electricity markets such that improvements in the average MPCE with respect to the NN approach are 0.7% and 0.9%, respectively [22].

The NN models mentioned above can be categorized into two groups: In the first group, a heuristic

algorithm has been applied to determine seasonality pattern of MCP and, in the second group, heuristic algorithm has been applied to improve NN performance. In this article, both of these characteristics have been considered.

Due to the inherent stochastic and nonlinear trends of MCP, it is very difficult to improve MCP prediction accuracy. Therefore, a new hybrid model composed of a NN, PSO, and GA algorithm is presented. Herein, PSO is applied to improve the learning capability of the traditional neural network and optimize the weights of the NN instead of traditional back propagation method, leading to a local optimum solution [18]. Since networks are sensitive to the number of neurons in their hidden layers (too few neurons can lead to under-fitting and too many neurons can contribute to over-fitting), the GA is applied to optimize the number of hidden layers on NN [18]. Because of seasonality trend in MCP, K-means algorithm has been applied to NN's learning set and to determine seasonality pattern of MCP.

As mentioned above, the contribution of our proposed method can be summarized as follows:

- (a) A new hybrid prediction method composed of neural network, GA, and PSO is proposed in this paper for price forecast;
- (b) In order to select the best records from historical data to learn NN, days of the year have been clustered into three clusters based on daily demands and MCP;
- (c) Finally, the accuracy of the proposed model has been evaluated by improved MAE with a penalty factor for positive error.

The structure of this paper is organized as follows: in the next section, Iran's electricity market and its prominent characteristics including related regulations and mechanism are described. The proposed model is explained in Section 3. In Section 4, proper classification is presented, and the proposed model is applied to a real-world case study and results are shown. Finally, a brief summary and some concluding notes are provided in Section 6.

2. Iran's electricity market

With the restructuring of the electric power industry in the world, the Iranian wholesale electricity market was launched in November 2003 with the aim of clarification of the electricity price and cost reduction, affordable energy supply, and the attraction of private fund [23].

The Iranian electricity market is a pool-based day-ahead market, where competition is on the generation side and settlement is done by a Pay-As-Bid (PAB) mechanism.

In Iran's electricity market, every GenCo submits a bidding price offer by 10:00 a.m. for every hour of the next day in rising steps (with the maximum of ten steps) and a cap price limit to Iran's Independent System Operator (ISO). Bids are analyzed by the ISO so as to determine the hourly MCP and the power to be dispatched by each GenCo at 5 p.m. in one day ahead based on proposed price and market clearing price [23].

Generally, the literature on Iran's power market has mainly considered four different factors in the analysis of prices:

- (a) The domestic, industrial, and agricultural sectors have become major energy consumers in Iran by shares of 32%, 33%, and 16%. Because of extreme changes in domestic and agricultural energy demand by the changing climate (a decrease in cold seasons and an increase in hot seasons) and the highest share of consumption (more than 48% of the whole) in Iran's electricity market, extreme changes occur in hourly demand, leading to intense competition in Iran's electricity market most of the time [24];
- (b) By April 2015, the total nominal generating capacity in Iran was around 73.4 GW with private and governmental ownership by shares of 44% and 56%. Due to the presence of governmental GenCos by shares of 56%, some irrational events such as proposed zero price occur in Iran's electricity market;
- (c) In Iran, an electricity price payment mechanism includes two parts: (1) payment for generated amount based on a pay-as-bid mechanism and (2) payment for announced availability based on fixed availability rate (\$/kW) for all GenCos, as legislated by the minister of energy;
- (d) More than 90% of the demands will be supplied by thermal energy, combined cycle, and gas power plants and natural gas, petroleum, and diesel, as the most common fuels used in Iran's electricity market. Because of governmental subsidies, power plant fuels provided by the ministry of energy enjoy lower prices than the real prices.

Considering Iran's electricity market characteristics, this paper presents a new model to predict MCP based on related parameters.

3. A hybrid intelligent model for MCP forecasting

The proposed model containing a NN, PSO, and GA algorithm is shown in Figure 1. The NN is used as a major forecasting module to predict the electricity MCP values, PSO is applied to improve learning capability of the traditional neural network and optimize

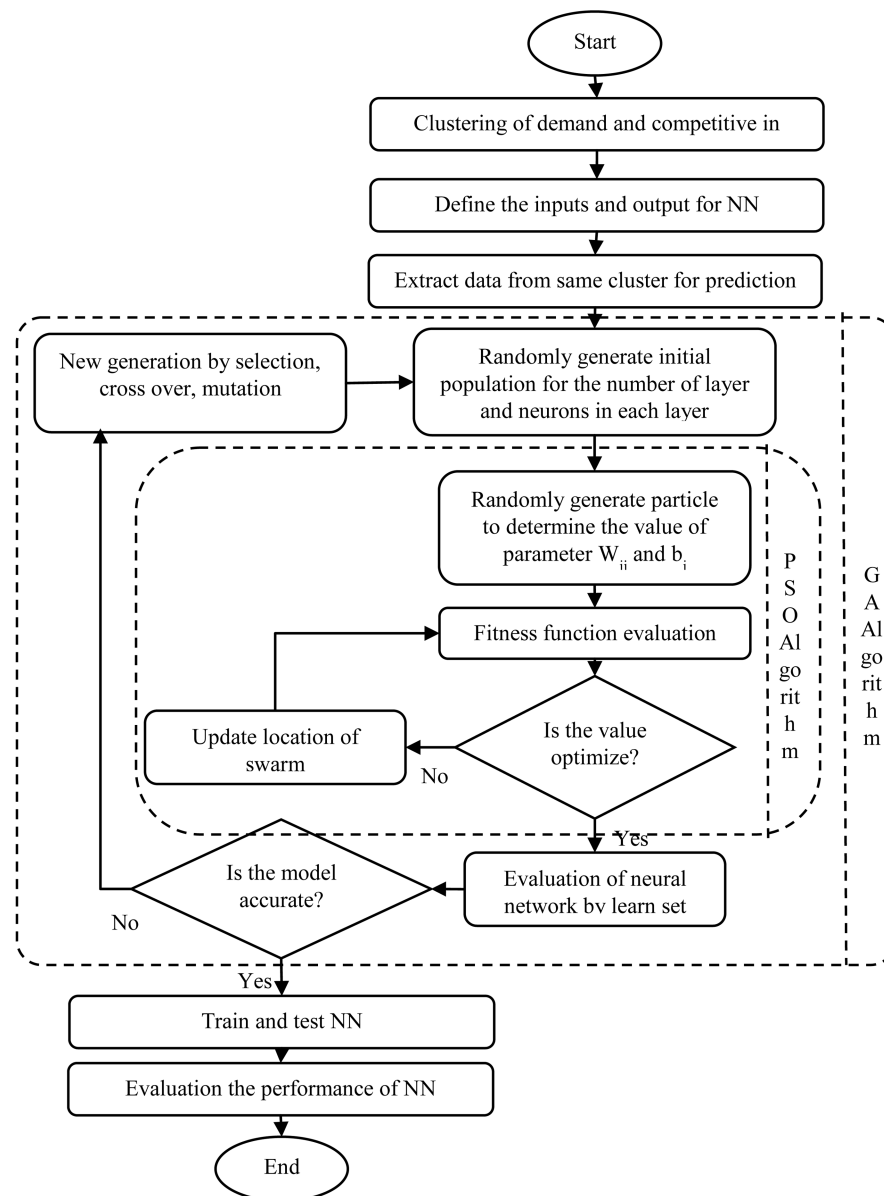


Figure 1. Proposed model for MCP forecasting.

the weights of the NN, and GA is applied to optimize the number of hidden layers on NN.

3.1. Neural network

Neural network is a type of the nonlinear regression model that maps an input parameter to output (outputs) value by using connected neurons in three layers, i.e., input layer, hidden layer, and output layer, as shown in Figure 2. The input layer is marked by vectors $X_n = [x_1, x_2, \dots, x_n]$, and the output layer is represented by y , where n is the number of inputs.

The NN input parameters in this research include historical MCP, day type, forecast load, forecast temperature, generation capacity, and accessible fuel type as multiplied by the corresponding weights' values;

then, they are summed up and added to a scalar parameter called bias; results are forwarded to the next layer. The output value is the result of the last layer, which is dependent on NN architecture (the number of layers and neurons in each layer) and NN parameters (weights and biases in each step).

The NN architecture and NN parameters should be set before analysis. In order to adjust network architecture and train the network, PSO and GA have been used.

3.2. PSO algorithm

PSO is a heuristic algorithm for finding a global optimum by iterative searching to increase the quality of candidate solutions. This algorithm foundation is

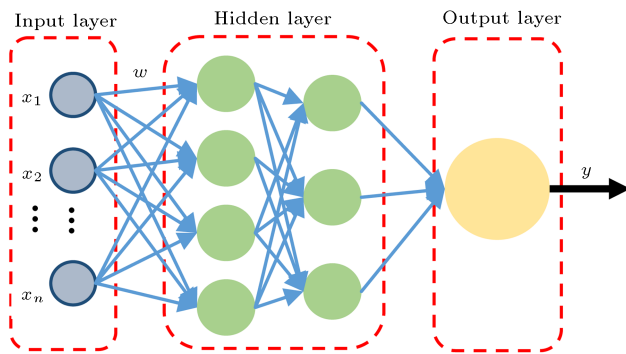


Figure 2. Neural network model for MCP forecasting.

created based on a group of birds that search for food in the solution space randomly. Each bird represents a single solution that moves in the solution space to look for better solutions.

In each iteration of PSO, there are two parameters: p_{best} (different for each particle) and g_{best} . p_{best} is the best position for each particle, and g_{best} is the best solution among all the particles. In each iteration, the particles move towards p_{best} and g_{best} with a specific velocity.

In this paper, PSO is applied to train the network with a certain architecture specified in the following steps:

- (a) The process starts with randomly generated particles. Each particle represents weights' matrix and biases. The i^{th} particles for NN by one hidden layer will be denoted by P_i^0 in Eq. (1):

$$P_i^0 = \{W_{1i}^0, W_{2i}^0, a_{1i}^0\}, \quad (1)$$

where W_{1i}^0 is a $a \times b$ weight matrix for the i^{th} particle from the input layer to the hidden layer, W_{2i}^0 is a $b \times 1$ weight matrix for the i^{th} particle from the hidden layer to the output layer, and a_{1i} is a bias for the i^{th} particle:

- (b) Update particle location by Eq. (2) for each particle.

$$P_i^{j+1} = P_i^j + V_i^{j+1}, \quad (2)$$

where V_i^{j+1} is the velocity for the i^{th} particles in the $j + 1$ th iteration that is applied to update weight matrix, and it is computed according to the formula given in Eq. (3):

$$V_i^{j+1} = V_i^j + r\alpha[P_{\text{best},i}^j - P_i^j] + s\beta[g_{\text{best}}^j - P_i^j], \quad (3)$$

where $P_{\text{best},i}^j$ is the best position for the i^{th} particle in the j^{th} iteration, P_{best}^j is the best position for all particles in the j^{th} iteration, α and β are random parameters between 0 and 1, and r and s are constants in Eq. (8):

$$P_i^j = \{W_{1i}^j, W_{2i}^j, a_{1i}^j\}, \quad (4)$$

$$g_{\text{best}}^j = \{W_{g_{\text{best},1}}^j, W_{g_{\text{best},2}}^j, a_{g_{\text{best},1}}^j\}, \quad (5)$$

$$P_{\text{best},i}^j = \{W_{p_{\text{best},i,1}}^j, W_{p_{\text{best},i,2}}^j, a_{p_{\text{best},i,1}}^j\}, \quad (6)$$

$$V_i^j = \{V_{1i}^j, V_{2i}^j, V_{1i}^{j'}\}, \quad (7)$$

$$P_i^{j+1} = \{W_{1i}^j + V_{1i}^{j+1}, W_{2i}^j + V_{2i}^{j+1}, a_{1i}^j + V_{1i}^{j+1}\}. \quad (8)$$

Thus, particles' locations will be calculated through Eq. (9):

$$\begin{aligned} P_i^{j+1} = & \{W_{1i}^j + V_{1i}^j + r\alpha[W_{p_{\text{best},i,1}}^j - W_{1i}^j] \\ & + s\beta[W_{g_{\text{best},1}}^j - W_{1i}^j], W_{2i}^j + V_{2i}^j \\ & + r\alpha[W_{p_{\text{best},i,2}}^j - W_{2i}^j] + s\beta[W_{g_{\text{best},2}}^j - W_{2i}^j], a_{1i}^j \\ & + V_{1i}^{j+1} + r\alpha[a_{p_{\text{best},i,1}}^j - a_{1i}^j] + s\beta[a_{g_{\text{best},1}}^j - a_{1i}^j]\}. \end{aligned} \quad (9)$$

3.3. Genetic algorithm

The genetic algorithm is a heuristic algorithm for random search referred to as the biology evolution. These algorithms have been successful in solving hard optimization problems, such as training NNs, i.e., problems in which the steepest descent techniques fall into local minima or fail because of complexity. The GA includes operations of initial population generation, fitness evaluation, selection, crossover, and mutation [25].

In this paper, GA will be applied to adjust NN architecture in the following steps:

Step I: Randomly generate an initial population of chromosomes. The i^{th} chromosomes in the initial population will be shown by P_i^0 as $m \times n$ matrix (n is the maximum number of layers for the proposed NN, and m is the maximum number of neurons in layers) in the form of zero value or one in Eq. (10):

$$P_i^0 = \begin{bmatrix} 1 & \dots & 1 \\ \dots & \dots & \dots \\ 0 & \dots & 1 \end{bmatrix}_{m \times n}, \quad (10)$$

Step II: Learn and test the neural network by the proposed architecture and, then, evaluate the fitness of each chromosome in the population;

Step III: If the stop condition is satisfied, stop and resume elsewhere;

Step IV: Create a new population through selection, crossover, and mutation operations:

- (a) Selection: Select two parent chromosomes from a population according to their fitness;

- (b) Crossover: Randomly generate I (integer value between 1 to m) and change the i th rows of parents by each other;
- (c) Mutation: Randomly change the value of selected chromosome from 1 to 0 or vice versa.

Step V: Go to Step II.

4. Numerical result

In this research, the dataset includes the proposed historical price of a real power plant, historical MCP, day type, forecast load, forecast temperature, generation capacity, and accessible fuel-type hourly MCP, and hourly electricity power consumption of Iran’s electricity market in years 2010 to 2013.

At first, years are clustered by K-means algorithm; then, the proposed model is applied to each cluster to predict MCP.

The proposed hybrid model was applied to predict hourly MCP from each cluster. Historical data from each cluster were divided into training and testing sets. The testing set in each cluster includes 720 records of data, and learning set includes all data of clusters except learning set.

To measure the model performance, the result of predictions is evaluated by simple MAE and improved MAE through Eq. (11):

$$MAE_{\text{simple}} = \sum_{i=1}^n \frac{|p_i - \hat{p}_i|}{n} \tag{11}$$

In simple MAE, there is no difference between overestimation and underestimation, while the risk of overestimation is more than that of underestimation; therefore, in improved MAE, we applied penalty for overestimation in Eq. (12):

$$MAE_{\text{Improved}} = \sum_{i=1}^n \frac{|R_i|}{n}, \tag{12}$$

where R is calculated through Eq. (3):

$$R_i = \begin{cases} m(p_i - \hat{p}_i) & p_i \geq \hat{p}_i \\ m'(p_i - \hat{p}_i) & p_i < \hat{p}_i \end{cases}, \tag{13}$$

where $m < m'$.

4.1. Clustering

The K-means algorithm has been used to divide samples into k clusters based on the closeness of observations according to Eq. (14) [26].

$$\min f := \sum_{j=1}^k \sum_{i=1}^n Dis(X_i, C_j). \tag{14}$$

The algorithms give K (the number of cluster) and dataset as inputs and apply the iterative procedure to produce clusters. The K-means algorithm starts

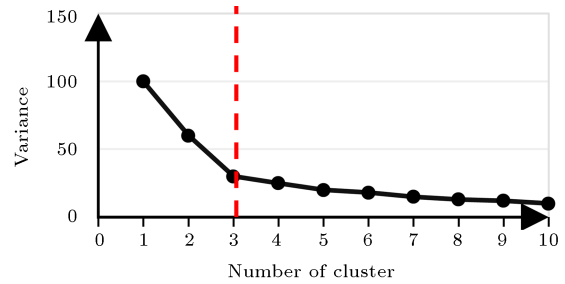


Figure 3. Evolution of the optimum number of clusters.

with K clusters by randomly generated centroids or randomly selected dataset and is improved by the iteration of the two following steps:

- (a) Assigning each data to the nearest cluster;
- (b) Updating the centroids of clusters by means of all data points assigned to that cluster.

In this study, the dataset includes hourly MCP and hourly electricity power consumption of Iran electricity market in years 2010 to 2013. The MCP and electricity consumption will be denoted as X_{it} and Y_{it} , where i is the number of days and t is the number of hours in the i th days. Therefore, parameters of the i th days will be denoted in Eq. (15):

$$A_i = \begin{bmatrix} X_{i1} & \dots & X_{i24} \\ Y_{i1} & \dots & Y_{i24} \end{bmatrix}. \tag{15}$$

The centroid of the k th cluster, randomly generated, will be given in Eq. (16):

$$C_k = \begin{bmatrix} X_{k1} & \dots & X_{k24} \\ Y_{k1} & \dots & Y_{k24} \end{bmatrix}. \tag{16}$$

By iterating the allocation of each data to the nearest cluster and updating the centroids of clusters by means of all data points assigned to that cluster, the centroid of clusters for $k = 2$ to $k = 10$ is determined. To determine the right number of clusters, within-cluster variance is used as an evaluation metric, and the evaluation graph of the number of clusters versus within-cluster variance is plotted, as shown in Figure 3, and the right cluster number is 3.

A summary of the results of K-means algorithm by $k = 3$ is shown in Table 1.

The next section evaluates the performance of the proposed model in predicting the hourly MCP in comparison to simple NN for each cluster.

4.1.1. Cluster 1

This cluster includes days of the year at the lowest temperature. The temperature decrease in these days results in a decrease in domestic and agricultural demand for electricity. Because of an extreme reduction in domestic and agricultural energy demand due to

Table 1. Clusters of days for Iran’s electricity market.

| Days | Cluster |
|-----------|--|
| Cluster 1 | From 12th October to 15th April |
| Cluster 2 | From 23th September to 11th October and 16th April to 31th May |
| Cluster 3 | From 1st June to 22th September |

the degrees of temperature and the highest share of consumption (more than 48% of the whole) in Iran’s electricity market, the overall demand has reduced, leading to intense competition in this cluster.

The application of PSO as the training process and GA as the architecture of NN adds a new dimension called ‘high calculation time’ to this model; however, this calculation time is not that serious since the learning process is implemented in an offline fashion. The convergence curve for GA and PSO for the learning set in the hybrid model in the Cluster 1 is shown in Figures 4 and 5, respectively.

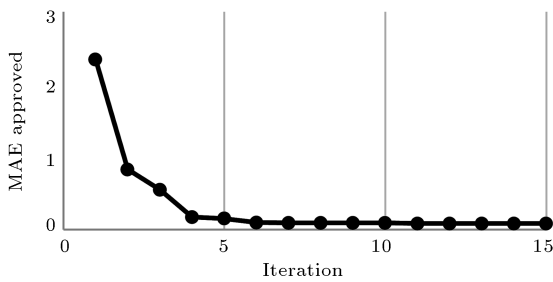


Figure 4. Convergence trend of the GA for Cluster 1.

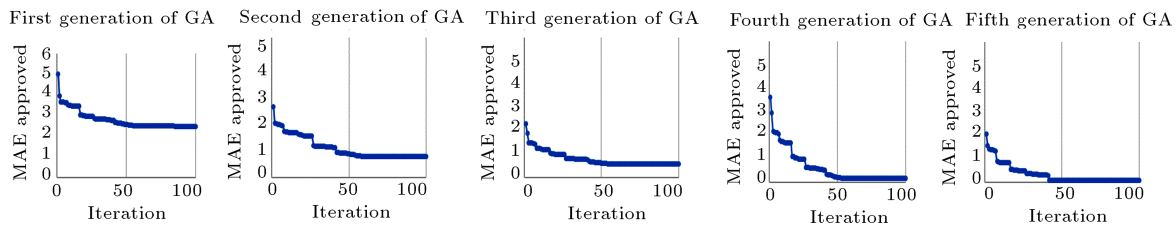


Figure 5. Convergence trend of the PSO for the fifth generation of GA in Cluster 1.

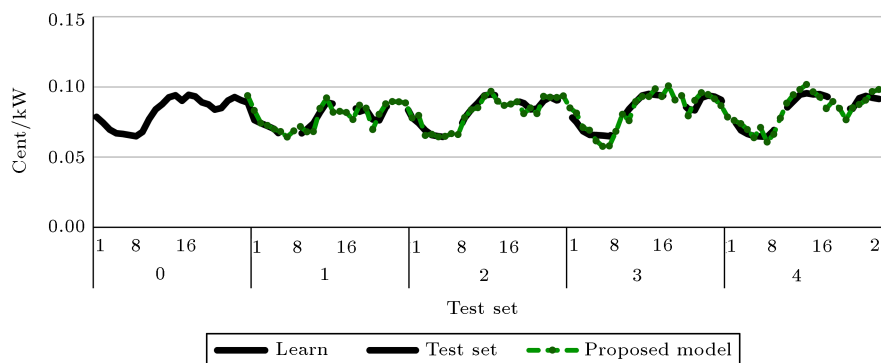


Figure 6. Predicted and actual prices for Cluster 1.

The corresponding performance curves, which show the comparison of the predicted results obtained by the proposed model and simple NN and the actual results, for the test set of the first cluster are shown in Figure 6.

4.1.2. Cluster 2

This cluster includes transition days from Cluster 1 to Cluster 3, and vice versa. The most important characteristic of this cluster is a high variance of changes of MCP in a long day.

The convergence curve in the case of GA for the learning set in the hybrid model in the second cluster is shown in Figure 7.

The corresponding performance curves, which show the comparison of the predicted results obtained by the proposed model and simple NN and the actual results, for test set of the second cluster are shown in Figure 8.

4.1.3. Cluster 3

This cluster includes days of the year at the highest temperature. An increase in the temperature of these days leads to an increase in domestic and agricultural

Table 2. MAE and approved MAE for Iran’s electricity market.

| | Simple MAE | | | Improved MAE | | |
|--------------------|------------|-----------|-----------|--------------|-----------|-----------|
| | Cluster 1 | Cluster 2 | Cluster 3 | Cluster 1 | Cluster 2 | Cluster 3 |
| Proposed models | 0.09 | 0.13 | 0.04 | 0.11 | 0.17 | 0.08 |
| Simple NN | 0.14 | 0.18 | 0.15 | 0.21 | 0.21 | 0.19 |
| NN & bat algorithm | 0.11 | 0.13 | 0.09 | 0.18 | 0.17 | 0.14 |

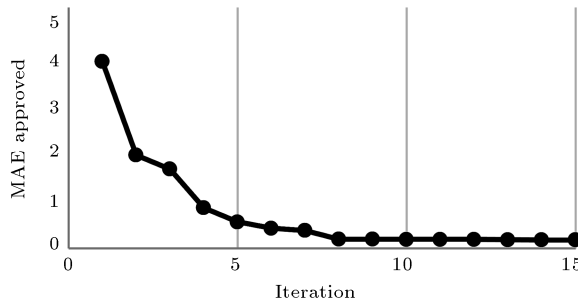


Figure 7. Convergence trend of the GA for Cluster 2.

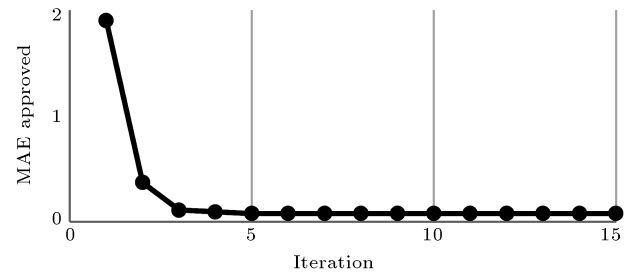


Figure 9. Convergence trend of the GA for Cluster 3.

demand for electricity, leading to MCP’s moving up to the top with the lowest variance in a long day.

The convergence curve in the case of GA for the learning set in the hybrid model in the Cluster 3 is shown in Figure 9.

The corresponding performance curves, which show the comparison of the predicted results obtained by the proposed model and simple NN and the actual results, for test set of the third cluster are shown in Figure 10.

Table 2 shows the result of the proposed model in comparison to the results of simple NN and a combination of NN and bat algorithm of [18] for each cluster by simple and improved MAE s.

According to Table 2, all simple and improved MAE values of the proposed model are much lower than those of the simple neural network and the combination of NN and bat algorithm models. This examination

and the previous one reveal the price forecast capability of the proposed strategy.

5. Discussion and conclusion

In this paper, a new hybrid intelligent prediction model composed of neural network, GA, and PSO was proposed to predict the market clearing price. Therefore, in order to select the best records based on historical data to learn NN, days of the year were clustered into three clusters based on daily demands and MCP. The NN module was utilized to predict the electricity MCP; the PSO and the GA were utilized to improve NN learning algorithm and NN architecture. In order to select the best records from historical data to learn NN, days of the year were clustered into three clusters based on daily demands and MCP. Thus, the NN’s learning set is classified into three clusters as follows:

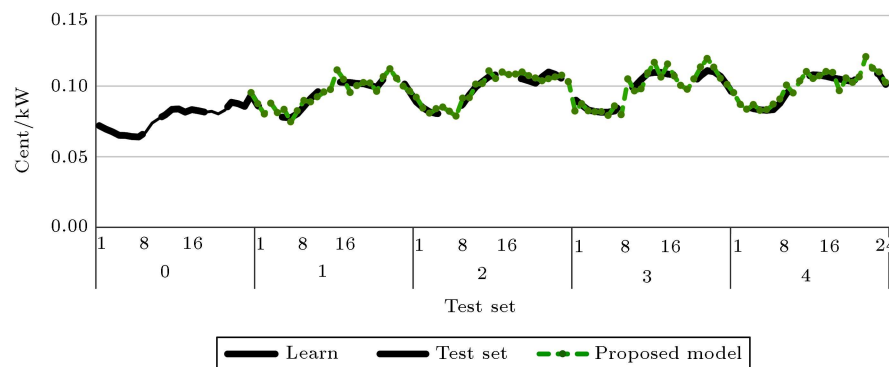


Figure 8. Predicted and actual prices for Cluster 2.

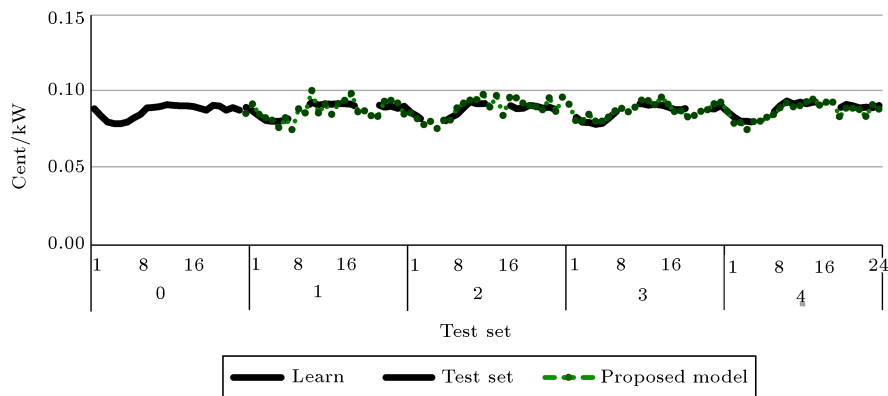


Figure 10. Predicted and actual prices for Cluster 3.

- Cluster 1: This cluster includes days of the year by the lowest MCP;
- Cluster 2: This cluster includes transition days from Cluster 1 to Cluster 3, and vice versa;
- Cluster 3: This cluster includes days of the year by the highest MCP.

Finally, the proposed hybrid model was applied to predict hourly MCP from each cluster, and the numerical results exhibit sharp improvements in the prediction accuracy as measured by simple MAE and improved MAE. The accuracy of the proposed model was evaluated by improved MAE with a penalty factor for positive error. In particular, the average simple MAE and improved MAE of the tested proposed model in the real-world electricity market of Iran for one month of years 2010 and 2013 in three clusters decreased from 15.3% and 20.3% to 8.6% and 12%, as compared to simple NN. The performance of the proposed models outperforms the combination of NN and bat algorithm by as much as 4%.

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