Performance of a Hybrid Neural-Based Framework for Alternative Electricity Price Forecasting in the Smart Grid

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Abstract

Electricity forecasting is an essential task for energy management systems of microgrids deployed in smart grids. Accurate price forecasting will eventually enhance the economic operation of microgrids. In this regard, the literature is rich with studies focused on predicting electricity price data using artificial neural networks. However, most of them consider a single model such as multi-layer perceptron (MLP) and radial basis function (RBF) to perform electricity price forecasting. In this paper, a hybrid framework based on simultaneously utilizing MLP-RBF neural networks is presented to predict the Iranian electricity market price. In addition, few works in literature considered Iran's electricity market as their case of analysis and investigation. Forecasting results indicate that MLP neural networks outperform the RBF neural networks. The values for the coefficient of determination (R)

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corresponding to MLP and RBF neural networks are obtained 0.55 and 0.44, respectively. However, the proposed hybrid framework performed better than both MLP and RBF models with R-value equal to 0.71. In addition to this, the MSE and RMSE values show the superiority of the proposed method to the single methods.

Keywords: Electricity price forecasting, artificial neural networks, smart grids, electricity markets.

1 Introduction

The electricity market liberalization has resulted in a shift from a centralized framework i.e., the load consumption was the variable of interest for performing forecasting in a competitive framework, where the forecasting of prices was an inevitable function for consumers and generators [1–3]. High electricity price volatility is the main reason for the risk in the daily market operation. This claim is particularly true for spot price(s), where intermittence could be higher than fifty percent on a day-ahead scale, meaning over ten times greater than for other products of energy (crude oil and natural gas) [1, 4, 5]. Based on research analyzing the financial effect of price prediction inaccuracies on forecasting users in daily market operation, it was revealed that one percent MAPE accuracy amendment led to a 0.1–0.35 percent cost decrease [6].

The paradigm of smart grids is seemed to "redefine the concept of what it means to build and operate the grid" [7, 8]. Notably, while human system operators still make the final decisions, several implementations of intelligent devices would finally operate the power network automatically. The available option for having a bi-directional power flow, a number of micro power plants, and alternative electricity prices would be applied to support more refined control systems than easily turning power plants on-off [7, 9, 10]. Smaller appliances and loads, when put together, can form even smaller grids, pico-grids. These pico-grids can bundle together to form nano-grids and mini-grids. The nano-grid is likely to be smaller in size than a micro-grid with a capacity in the order of 2–20 kW since its niche application is likely to be for remote area power supplies. Furthermore, a nano-grid operates at dc instead of 50/60 Hz and relies on power electronic converters to interface both sources and loads to the system. The management approach of the grid can be made from the bottom-up where the monitoring starts at the pico-grids and move up the level and scale. Figure 1 shows multiple pico-grids

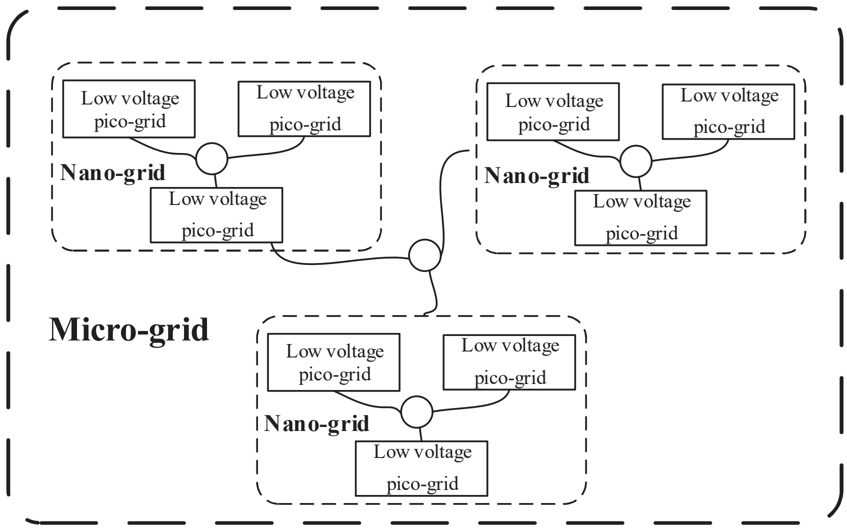


Figure 1 Example of multiple pico-grids forming a micro-grid.

forming into a micro-grid. Generally, nano-grids have many advantages with fewer technical obstacles. They have a low power rating compared with micro-grids. But, their design depends on several numbers of inverters and/or converters sets; standard nano-grids have some barriers. Therefore, they need to separate isolated controllers as well as high cost and loss safety methods. In addition, the interconnection of both inverters and converters leads to more private risks causing noise and interference issues [11, 12].

A microgrid is a system benefiting from at least a renewable source (i.e., photovoltaic power and/or wind power) and a control system that allows the system to operate in grid-connected or off-grid operation modes. Microgrids usually are utilized with energy storage systems like battery storage systems. In this way, they are able to store electricity generated by renewables and perform an economic role in the energy market by optimal charging and discharging of energy storage. A virtual power plant is a cluster of distributed generators, energy storage systems, and controllable loads integrated to operate as an individual plant [13, 14]. The interconnection of microgrids and virtual power plants is depicted in Figure 2. Energy management systems are the core of both microgrids and virtual power plant management centers. Energy management systems take the optimal decisions based on three critical factors: (i), (ii) energy production and consumption, and (iii) load demand. Therefore, it is essential to forecast the future electricity price,

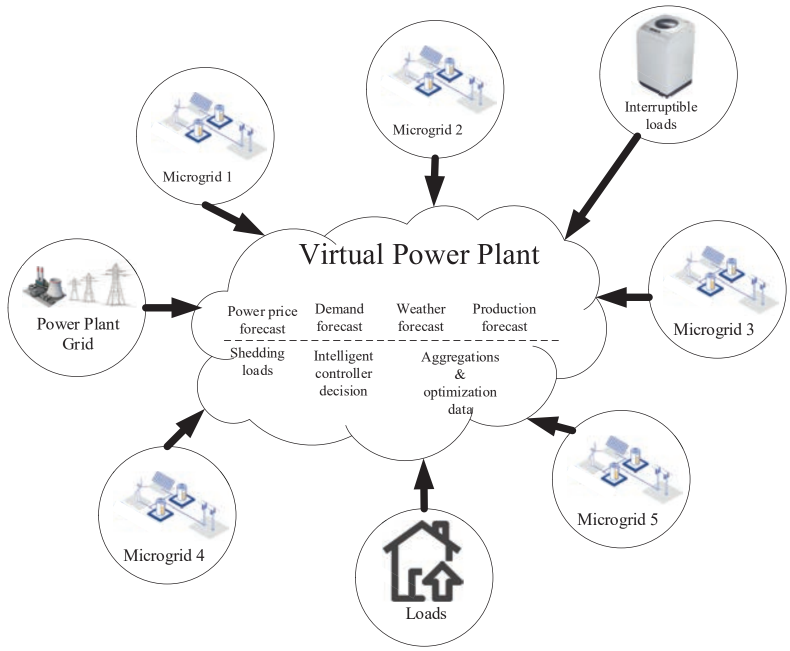


Figure 2 The interconnection of microgrids and virtual power plants.

energy availability accurately, and load demand to take optimal decisions regarding the future time horizon [15]. It is important to mention that these factors have stochastic nature and depend on several features that may not be forecasted with the necessary precision; for example, the weather conditions have impacts on the energy availability (due to renewables like photovoltaic/wind power) [16], load demand (e.g., air conditioning) [17], and importantly the electricity price [18]. Here, we focus on the latest factor, i.e., electricity price forecasting, which is a highly variable factor in the energy management system.

Generally, there are different methods for predicting uncertain variables such as electricity price values [19]. Some methods are computational intelligence (CI) methods, statistical methods, reduced-form methods, fundamental methods, and multi-agent methods. Also, there are three different forecastings based on the prediction time horizons: long-term, mid-term, and short-term electricity price forecasting [20]. The focus of this paper is on short-term load forecasting, which is appropriate for day-ahead smart grid operation. Moreover, the most important electricity price methods are CI and statistical methods in day-ahead electricity markets. Statistical models are typically unable to predict non-linear patterns, which implies the linearity behavior in electricity price [21] and is impractical in forecasting rigid alters in the price signals [22]. This finally leads to inaccurate prediction performance. Nowadays, there is an emerging sub-field of deep learning in neural network methods [23].

In the literature review of electricity price forecasting, considering CI techniques, the sets for training and testing, applying in the point forecast simulation, are generally constant during the designated time series. These ways of setting show that the participants in the electricity market will depend on the non-recalibrated models for the indefinite horizon, for instance, during the whole out of sample testing horizon, once the EPF model is calibrated. Investigation of the training data set size impact on the accuracy of prediction is not entirely analyzed in previous research on neural network-based techniques and conventional methods in [23]. The authors of [24] compared the neural networks, support vector machine, and statistical ARIMA model according to the local electricity data for California. The support vector machine model had the highest accuracy, while both techniques outperformed the ARIMA model. In [23], the Belgium data is used for empirical comparison of traditional algorithms and neural network-based methods. Five years of data is designated for training, and one year of data is used for testing in both models. Neural networks had the highest prediction accuracy. Based on the Spanish and Californian data in [25], the ARIMA model with wavelet transformation and the univariate time-series neural network with wavelet transformation are examined. Four weeks for the different seasons were sued for testing the models. The neural network models were statistically more accurate than the ARIMA model. The daily electricity price prediction is conducted according to the models of neural networks with various structures in combination with supplementary clustering algorithms in [26]. The Italian Southern region data is used for prediction. Training is performed using approximately 3 years of data, and the test is done over four months. Neural networks with a supplementary clustering algorithm performed better than univariate neural networks. Pattern Sequence-based Forecasting method (PSF) is compared and tested with the neural networks with wrapper function for the feature selection of Spanish, New York, and Australian markets [27]. Historical calendar data, weather as well as electricity data were the explanatory variables in the proposed model. The training was performed on three-years data, and testing was conducted on one-year price data. The ANN method was outperformed by the accuracy in comparison with the PSF method. Researchers in [28] conducted spike probability forecasting and electricity price prediction for Finish Nord Pool day-ahead energy market. The neural networks were evaluated with other algorithms, such as the ARIMA time-series model. In addition, two years of data are considered for training the data, and one year of data is designated for testing the data. The neural network-based model had better forecasting results in both cases. In [29], the gradient boosted regression trees examined on the Spanish market was performed better than the linear regression model. The implemented algorithm is an ensemble machine learning method that is related to the random forest algorithm. The training horizon was thirty months period, and the testing horizon was six month period. The proposed method was outperformed the conventional algorithms.

Furthermore, forecasting other intermittent parameters such as load demand and RESs output power has been extensively studied in recent years. In [30], a novel method based on recurrent neural networks (RNN) is proposed to forecast real-world load data from five residential consumers provided by London Hydro. In another paper [31], a classical long short-term memory-based neural network with selected autoregressive features is developed to ameliorate short-term load demand forecasting accuracy by employing three strategies: autoregressive features selection, exogenous features selection, and a "default" state for avoiding overfitting at times of high load variability. The results showed an accuracy improvement of up to 25% in comparison with classical models. In [32], a novel radial basis function (RBF) neural networks-assisted hybrid modeling strategy is suggested to forecast the PV cell temperature. The hybrid model is designed as an explicit mathematical formulation combined with an RBF neural network-assisted correcting factor. The model forecasting performance is evaluated by laboratory and commercial plants. The results indicated that the suggested method accurately performs cell temperature and output power prediction for laboratory and commercial plants. Thus, the hybrid modeling strategy could support a potential solution framework for cell temperature and output power forecasting for different PV cells. In [33], a wind power plant power output is forested by weather and power plant parameters and employing an extended fuzzy wavelet neural network. This method was used for the Manjil wind power plant in Iran, with actual data being recorded every 10 min. The method was also compared with the conventional forecasting methods. The results indicated that the suggested method was more efficient and had higher precision for short-term wind power forecasting than other classical methods.

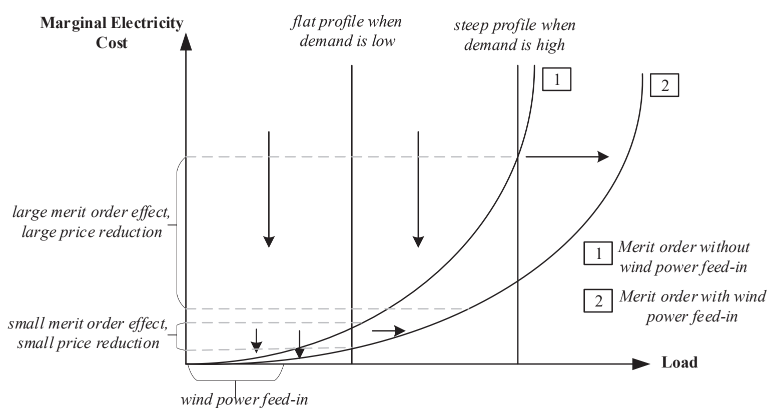
In this paper, a hybrid method based on multi-layer perceptron (MLP) neural networks and RBF neural networks is proposed to accurately forecast the electricity price data of the Iranian electricity market. While some articles, such as in [34] and [15], predicted uncertain parameters in micro-grids' energy management system, there proposed method of this paper is based on hybrid utilization of these methods, which enhances the performance of prediction, and ultimately improves the operation of the micro-grids. Each of the forecasting models is compared with the proposed hybrid method to validate the results. More importantly, Iran's electricity market has not been carefully analyzed for electricity price prediction in recent years. Therefore, this paper aims to investigate the accuracy of the forecasting methods on the price patterns extracted from reliable sources. Consequently, we implemented the proposed forecasting methodology on the actual data and comprehensively compared it with the results of the suggested method and conventional CI models of RBF and MLP neural networks. The essential contributions of the paper are as follows:

(1) Proposing a novel forecasting method based on neural networks for energy management of micro/nano grids.
(2) Validating the proposed method on Iran's electricity market prices, which has not been addressed in previous studies.
(3) Comparing the proposed method with other conventional neural networks such as the methods presented in [34] and [15]. Also, the merits of the proposed method, including the accuracy and precision, are discussed.

The structure of the paper is as follows. In Section 2, an introduction to the Iranian day-ahead electricity market is provided. In Section 3, the MLP and RBF ANN methodologies as well as the proposed method for electricity price forecasting, are presented. In Section 4, test results of the electricity price prediction are explained. And in the last section, the conclusion of the paper is given.

2 The Iranian Day-ahead Electricity Market

While changes in the electricity industry were occurring in the world around thirty years ago, the first steps for restructuring the Iranian electricity industry were taken in the 1990s. It was in November 2003 that the Iranian wholesale electricity market officially launched and resulted in the electricity price clarification, the attraction of the private sector's investment, and obtaining long term security of supply, as the significant restruction goals in the Iranian electricity industry. In the year 2000, the termination of the government monopoly and privatization officially initiated with starting the third development plan. Consequently, it has resulted in the 48.05 percent contribution of the private sectors in the yearly electricity production in 2015 [35]. Currently, the share of private sectors is about 60 percent [36]. The daily market in Iran is a generally wholesale market where the standard hourly contracts are exchanged for the daily physical delivery. The competitive price is designated by the intersection of the market demand and supply curves in this market, as depicted in Figure 3(a). The supply curve profile is indicated by the ranking of the generation units by their short-run marginal cost in rising order, together with the dispatched energies, in merit order [1, 35]. Regional electricity companies (RECs) and electricity distribution companies (EDCs) are the primary buyers (retailers) in the wholesale electricity market. These companies



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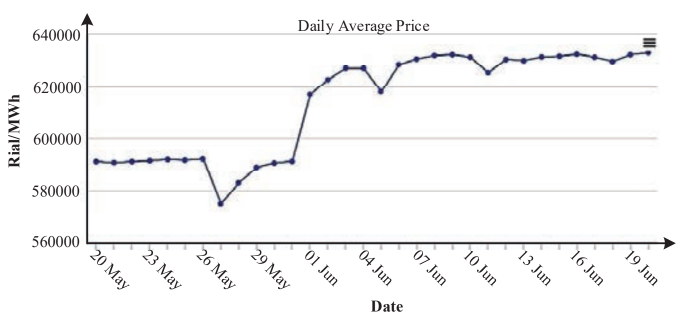


(b)

Figure 3 (a) Iran's electricity market supply and demand curve [1]; (b) Iranian wholesale market over three months of 2021 (May–June) [36].

are able to supply their demand through the wholesale day-ahead market, power exchange, and bilateral contracts. Generally, industrial end-users are supported by RECs. At the same time, large industrial end-users (demand exceeding 5 MW) can buy their required power bilaterally. Retailers buy the power needed from power exchange and supply their customers. Therefore, RECs and EDCs are considered as the retailers in Iran's energy market. They are responsible for delivering the electricity to the end-users based on the market price. Each DEC is responsible for supplying electricity to a specific district. Microgrids are connected to DECs and trade energy according to the regulations. Figure 3(b) shows a typical price electricity pattern in the Iranian wholesale market over three months of 2021 (May–June) [36].

3 Electricity Price Forecasting Methodology

In this section, the proposed method for predicting electricity prices is described. First, the MLP neural networks mathematical formulation is explained. Then, the basis for RBF neural networks is provided. Finally, the suggested formulation for the hybrid forecasting of neural networks is described.

3.1 MLP Neural Networks

Artificial neural networks have received significant attention in recent years and are considered an alternative for electricity price prediction [37–39]. Neural methods are beneficial for approximating any degree of complexity and with no prior knowledge of the problem. The MLP neural networks is a type of feed forward (FF) neural network based on the different perceptron layers. MLP is structured on three individual layers as the input layer, hidden layer, and output layer. Input data are imported to the input layer, and the output layer exports the systems' output (forecasting output). Figure 4 shows the fundamental structure of the MLP neural networks. From the mathematical point of view, the following formulation can be used for describing neuron *k*, as follows [40]:

$$y_k = \Phi(u_k - \theta_k) \quad \text{Where } u_k = \sum_{1}^{p} w_{kj} x_j \tag{1}$$

In (1), y_k is the neuron's output signal, $\Phi()$ is the activation function, u_k is the linear combiner output, θ_k is the threshold, w_{kj} is the weight between the *k*th input neuron and the *j*th hidden layer, x_j is the value of the jth input

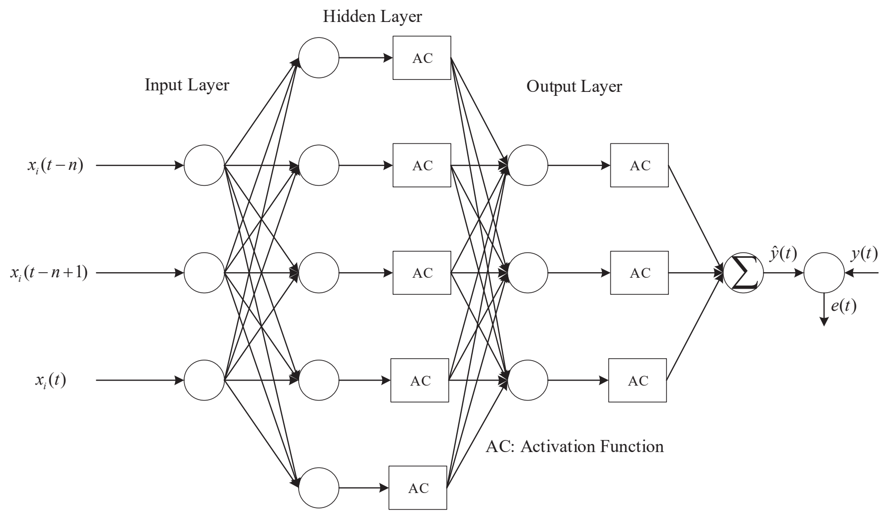


Figure 4 Simplified framework of MLP neural network [40].

neuron. Also, in the model, the activation function for each neuron is selected as a sigmoid function, which is available in the Matlab library. The following Equation (2) represents the activation function:

$$\Phi(j) = \frac{1}{1+e^{-a}} \quad a > 0 \quad \text{and} \quad a = \sum_{1}^{p} w_{li} + b_s \tag{2}$$

In the above equation, b_s is the network bias unit, w_{li} updates over the training process. An error term is also defined for testing the accuracy of learning of the MLP neural networks, as below:

$$Ec = 0.5 \times \sum_{1}^{M} (y_n - \hat{y}_n)^2 \tag{3}$$

In (3), N is the number of the sample, $\hat{y}_n$ and y_n are *i*th forecasted and real data. The algorithm that is responsible for this method is called the learning rule. The most commonly used one is the backpropagation algorithm which is responsible for this method. The backpropagation algorithm uses the steepest descent algorithm for minimizing the mean square error (MSE). The backpropagation algorithm is formulated as below:

$$w_{kj}(n+1) = \lambda \Delta w_{kj} + \eta \left(\frac{\partial Ec}{\partial w_{kj}} \right) + w_{kj}(n) \tag{4}$$

In (4), λ is the momentum rate, Δw_{kj} is the change of weight during the last iteration, η is the learning rate.

3.2 RBF Neural Networks

Like MLP neural networks, the RBF neural network is a type of FF artificial neural network that works using a single hidden layer. RBF neural networks are supervised neural networks that are identical to MLP networks. The fundamental framework of an RBF network with *n* inputs and output is illustrated in Figure 5 [10]. The RBF networks' input and output layers can be formulated as follows [40]:

$$u_i = G\left(\frac{|x - c_i|}{\kappa_i}\right) \quad i = 1, \ldots, n \tag{5}$$

$$y = Cu \tag{6}$$

In (4) and (5), parameters c_i, κ_i, C, y, u, and x respectively present the center of the *i*th neuron, the variance of the *i*th neuron, weight matrix, the network output, the output of the hidden layer, and the input of the hidden layer. In addition to this, Gaussian and the distance is Euclidean described in (6):

$$\Phi(h) = e^{\frac{-r^2}{\kappa_h^2}} \tag{7}$$

The RBF neural networks merely depend on the distance between the center of the RBF and the input, presenting by *r*. The parameter κ_i shows

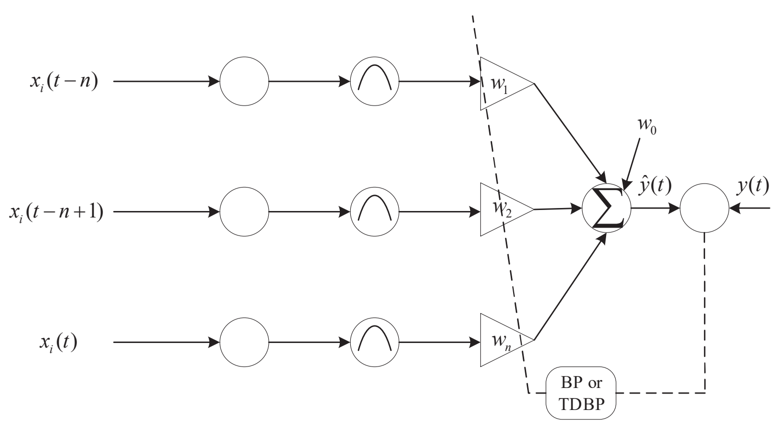


Figure 5 Simplified framework of RBF neural network [40].

the width of the Gaussian function and updates during training. Hence, the algorithm is continued until the least mean square (LMS) condition is achieved. The weight could be updated by the mentioned backpropagation algorithm.

3.3 The Proposed Hybrid Framework

Both MLP and RBF neural networks are advanced CI methods for forecasting different non-linear patterns, which have been used in previous years. However, there are some differences between them. One of the major differences could be in the hidden layer of RBF neural networks, which is different from MLP. To put it differently, it requires additional computations. Each hidden unit acts as a point in input space and activation/output for any instance, depending on the distance between that particular point and instance. Therefore, RBF is accompanied by learning two types of parameters: (1) Weights from the linear combination of outputs achieved from hidden layer; (2) width and centers of RBF neural networks. To benefit from both methods, a hybrid utilization of the methods can be considered for any forecasting. Figure 6 shows the overview of the introduced hybrid method. According to this figure, both MLP and RBF are initialized simultaneously and perform price forecasting for the same data. Using the control system, the system operator observes hourly forecasted values and chooses the combination of the predicted values according to the mean values of the outputs. Considering this approach, we will advantage features of both models and improve the forecasting accuracy. The formulation for considering both models is as

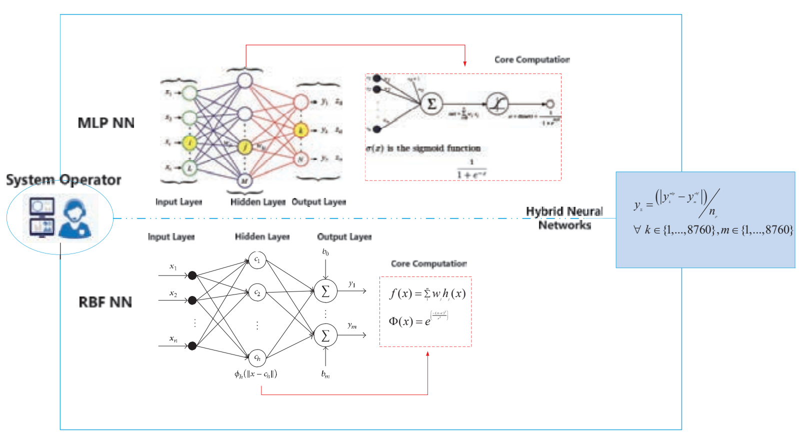


Figure 6 The proposed hybrid framework based on MLP-RBF neural networks.

follows:

$$y_o = \left(\frac{\Phi\left(\sum_1^p w_{kj} x_j - \theta_k\right) - C \times G\left(\frac{|x - c_i|}{\kappa_i}\right)}{n_\rho} \right)$$

$$\forall\, o, i, k \in \{1, \ldots, 8760\},\ \forall\, n_\rho = \{2\} \tag{8}$$

$$y_o = \frac{(|y_k^{mlp} - y_i^{rbf}|)}{n_\rho} \tag{9}$$

In literature, there are various error indices for displaying the system states' accuracy prediction to evaluate the algorithms. According to the indicated main features of the criteria and their similarity, in this paper, MSE, Root MSE (RMSE), and coefficient of determination (R^2) are used for comparing the forecasting performance of the models as formulated below [41]:

$$MSE = \frac{1}{N} \sum_1^N (\hat{y}_i - y_i)^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_1^N (\hat{y}_i - y_i)^2} \tag{11}$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \mu)^2} \tag{12}$$

$$STD = \sqrt{\sum_1^N \frac{(\hat{y}_i - y_i)^2}{N - 1}} \tag{13}$$

4 Test Results

In this section, we will test different forecasting methods, including the proposed hybrid framework. In order to have a better evaluation of the methods, three case studies are introduced as follows:

Case 1: Forecasting Iranian electricity market price using MLP neural networks like the method of [42].

Case 2: Forecasting Iranian electricity market price using RBF neural networks like the method of [43].

Case 3: Forecasting Iranian electricity market price using the proposed hybrid MLP-RBF framework.

Before performing price forecasting, it is important to analyze the input data, which is hourly electricity price over 168 days in Iran's electricity market. The real data is obtained from Tehran Power Distribution Company and is set as times-series input data [44]. Different factors affect day-ahead pricing in Iran. The first factor is the weather conditions. Extreme temperatures can increase demand for heating and cooling, and the resulting increases in electricity demand can push up fuel and electricity prices. Rain and snow provide water for low-cost hydropower generation, and wind can provide low-cost electricity generation when wind speeds are favorable. However, when there are droughts or competing demand for water resources, or when wind speeds drop, the loss of electricity generation from those sources can put upward pressure on other energy/fuel sources and prices. The second factor is fuel prices, especially for natural gas and petroleum fuels, may increase during periods of high electricity demand and when there are fuel supply constraints or disruptions because of extreme weather events and accidental damage to transportation and delivery infrastructure. Higher fuel prices, in turn, may result in higher costs to generate electricity. In addition, power plant costs should not be neglected. Each power plant has financing, construction, maintenance, and operating costs which may impact the electricity pricing. Figure 7 shows the electricity price values over 168 days (1 Jan 2020 – 18 Jun 2020). It is clear that the load data is accompanied by uncertainties and non-linear patterns are visible. Therefore, utilizing classical methods would not certainly result in desirable accuracies. Knowing that, we focused on analyzing CI methods, especially the mentioned models in Section 3.

MATLAB 2020b is utilized for coding the forecasting algorithm, also the proposed hybrid MLP-RBF framework. A delay of 24 hrs (t–24) is applied to predict the next-day electricity price. In addition, In addition, 70 percent of

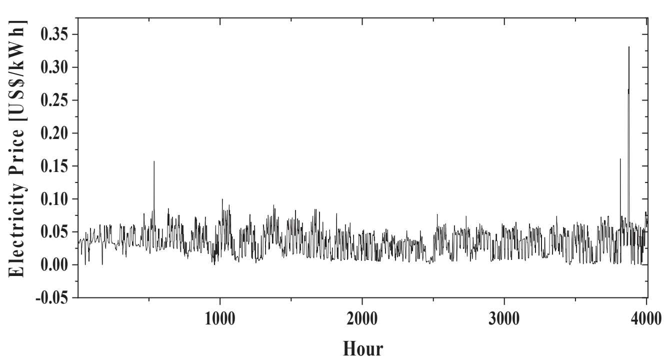
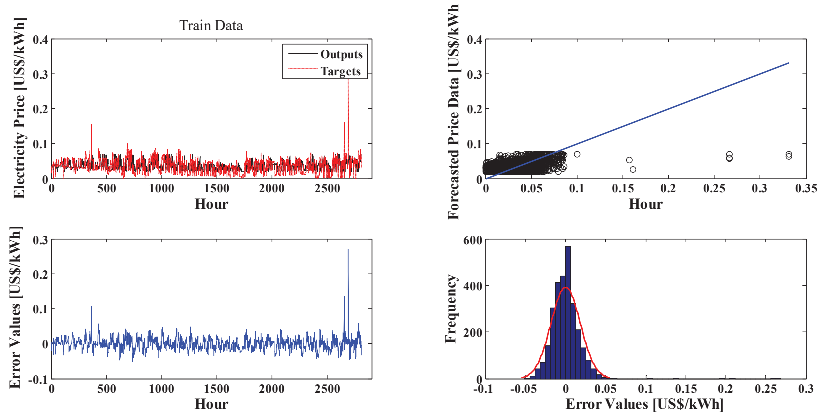


Figure 7 Historical electricity price data using for time-series forecasting [44].

the values are designated for training the model, and the other 30 percent of price values are considered for testing the algorithms [42].

4.1 Case 1

In this case study, prediction results based on the implementation of MLP neural networks are presented. The algorithm is implemented in MATLAB software. Forecasting results for the electricity price data using the RBF neural network are indicated in Figure 8. In Figure 8(a), training data (70



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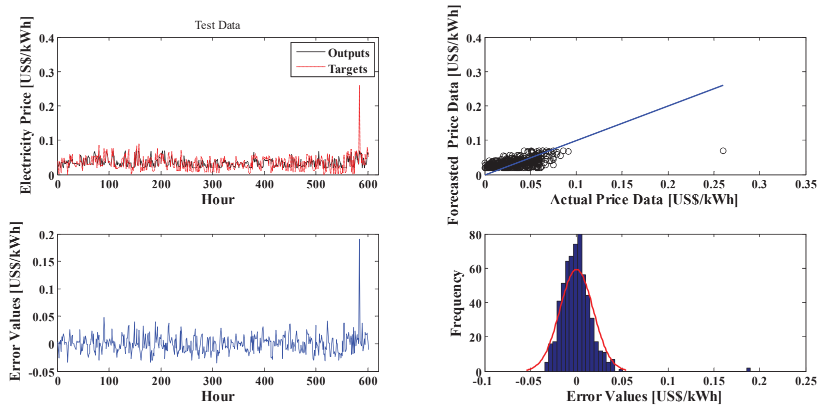
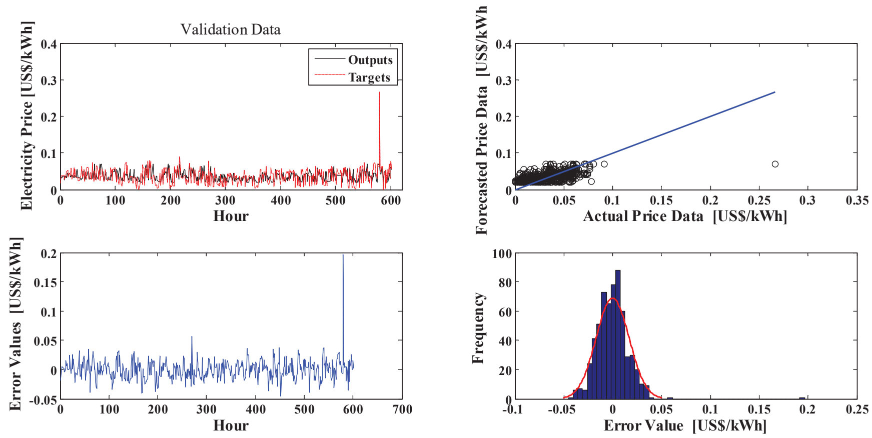


(b)

Figure 8 Forecasting results of electricity price using MLP neural networks: (a) training data; (b) testing data; (c) validation data; (d) all data.



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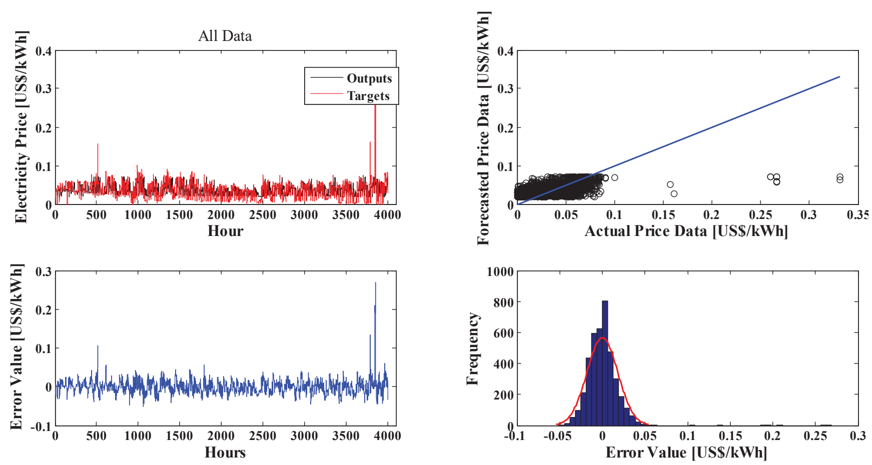


(d)

Figure 8 Continued

percent of the actual data) is shown in four parts. Hourly training values show that the model could learn the non-linear patterns using the backpropagation algorithm. Therefore satisfying results are achieved considering the fact that the variation of the data is high on an hourly scale. As shown in Figures 8(a) and 8(b), MSE and RMSE values are in an acceptable range. Validation results in Figure 8(c) also prove the training and testing results, and similar outcomes are achieved. Figure 8(d) shows the forecasting results

Table 1 MLP-ANN statical results for predicting electricity price data

Type	R	MSE	RMSE	STD	Mean
Train	0.5468	0.0003347	0.01829	9.3711×10^{-5}	0.01829
Test	0.5899	0.0003295	0.01815	0.0002625	0.01816
Validation	0.5614	0.0002830	0.01682	-8.7435×10^{-5}	0.01683
All Data	0.5554	0.0003262	0.01806	9.1863×10^{-5}	0.01806

Table 2 Effect of different number of neurons on the forecasting criteria

No. Neurons	RMSE	STD
1	0.01988	0.01911
2	0.01201	0.02110
3	0.01806	0.01806
4	0.01463	0.03632
5	0.01233	0.03101
6	0.02000	0.03988
7	0.01578	0.01154
8	0.01835	0.01856
9	0.01922	0.01902
10	0.01709	0.01805

for all data. MLP-ANN statical results for predicting electricity price data are shown in Table 1. According to this table, MSE and RMSE values are obtained 0.0002830 and 0.01682, respectively. Also, mean and standard deviation values are achieved 0.0002625 and 0.01816, respectively. The R-value is obtained at 0.5558, which can be improved by considering some enhancements in the forecasting framework.

In this paper, the number of hidden layers is considered as three neurons. However, the impact of a different number of neurons on the forecasting criteria of the paper is analyzed in Table 2. It was shown that increasing the number of a neuron does not improve forecasting results. Therefore, with a low number of neurons, it is possible to reach a satisfying accuracy criterion. However, the error values and R show that some improvements are necessary for having a more accurate prediction. Therefore, for price patterns with such rigid variations, it would be more reasonable to implement other CI models to evaluate as well as validate the forecasting results.

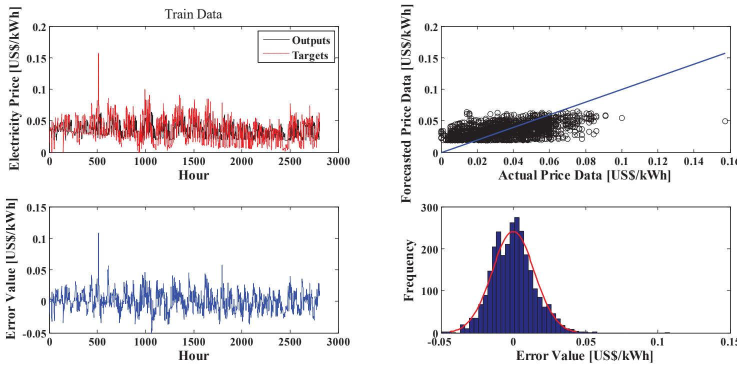
4.2 Case 2

In Case 2, electricity price forecasting is performed using RBF neural networks. In the following MATLAB implementation for training, the RBF network is provided. In addition, specifications of the network including, the goal, spread, and the maximum number of neurons in the network, are indicated.

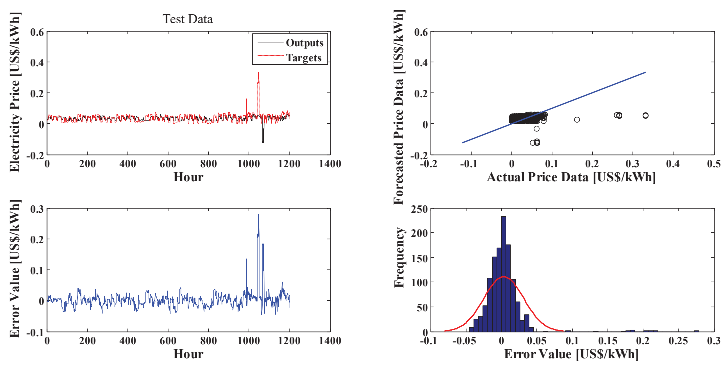
Forecasting results based on RBF networks are illustrated in Figure 9. According to the results, the accuracy of the prediction is satisfying compared to the actual price values. In comparison with the MLP network, RBF also has satisfying outcomes. However, the need for improvement is necessary for this algorithm. Figure 9(a) shows forecasting results for the training phase. According to this figure, the R-value is obtained 0.5741, and the MSE value is achieved 0.0021. Figure 9(b) indicates testing results. It can be seen that while testing the data, inaccuracies are increased using the RBF algorithm. Apart from this, the value of R is lowered, which shows the inability to predict non-linear patterns of hourly electricity prices. Figure 9(c) illustrates forecasting results for all the data. According to this figure, we found that RBF neural networks with all their characteristics are unable to have accurate forecasting of price values solely; hence, we have to enhance the network structure using other models to get the maximum precision in the forecasting. RBF-ANN statical results for predicting electricity price data are shown in Table 3. The value of R is achieved 0.44001, MSE and RMSE values are also obtained 0.0038 and 0.0197, respectively. Also, it was found that the number of neurons has a limited effect on achieving the desired accuracy goal. To put it differently, increasing the number of neurons (epochs) does not necessarily enhance the accuracy level. In this study, the best performance is achieved at 0.002143 after 15 epochs (Figure 10). It can be observed that the accuracy level has not been changed from epochs 3. Therefore, the optimum number of neurons to perform forecasting on this particular type of data is three neurons.

4.3 Case 3

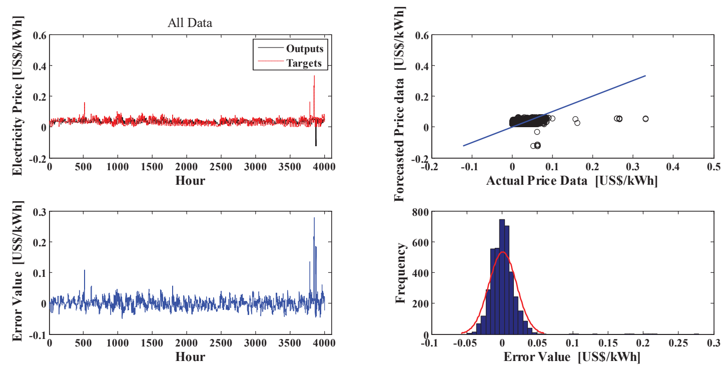
In this case, which is the proposed method of this study, a hybrid framework based on MLP and RBF is used for predicting hourly values of electricity prices. Figure 11 shows forecasting results using the proposed hybrid method. In Figure 11(a), the prediction results of the hybrid method and the actual electricity price data are illustrated. It can be seen that in most hours, we have an accurate prediction of the non-linear patterns. Figure 11(b) compares the proposed method with other neural networks such as MLP and RBF models. The adequacy of the proposed model in comparison to the other ones is visible from this figure. Figure 11(c) also shows the error values of the predicted values. Comparing the error values of this case study with those



(a)



(b)



(c)

Figure 9 Forecasting results of electricity price using RBF neural networks: (a) training data; (b) testing data; (c) all data.

Table 3 RBF-ANN statical results for predicting electricity price data

Type	R	MSE	RMSE	STD	Mean
Train	0.5741	0.0002143	0.01464	-9.2036×10^{-7}	0.01464
Test	0.3131	0.0007953	0.02130	0.003316	0.02801
All Data	0.4400	0.0003886	0.01971	0.0009941	0.01969

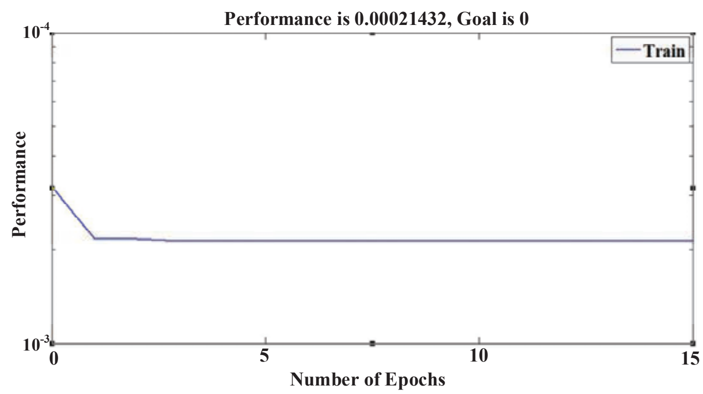


Figure 10 Best performance of the network under 15 epochs.

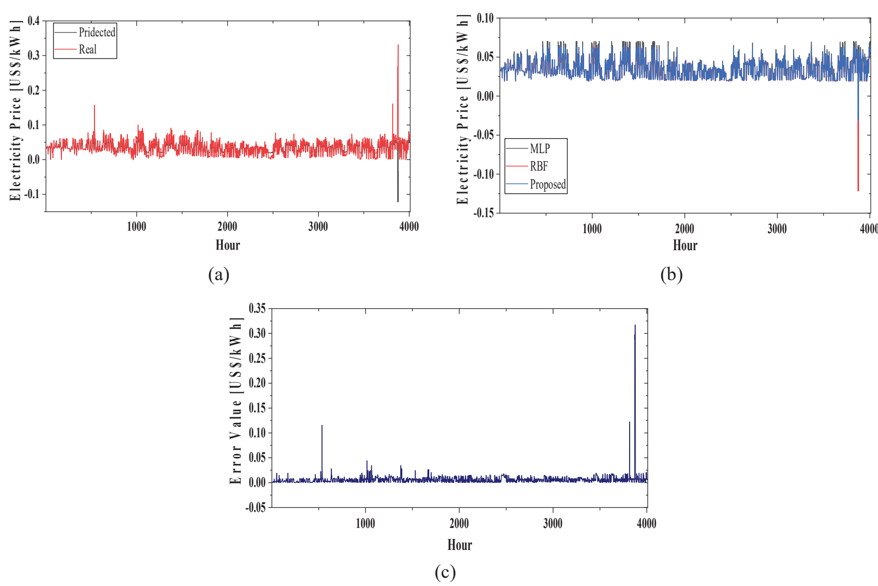


Figure 11 (a) Forecasting results of the hybrid model and real electricity price data; (b) Comparison of the proposed model with MLP and RBF models; (c) Error values of the predicted values.

Table 4 Comparison results of the proposed method and the conventional methods for predicting electricity price data

Type	R	MSE	RMSE	STD	Mean
MLP-ANN	0.5554	0.0003262	0.01806	9.1863×10^{-5}	0.01806
RBF-ANN	0.4400	0.0003886	0.01971	0.0009941	0.01969
Hybrid Method	0.7145	0.0003157	0.01770	0.0009342	0.01753

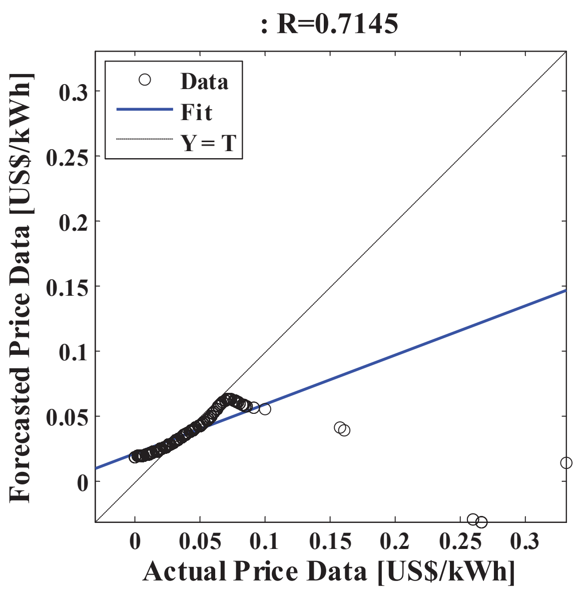


Figure 12 R diagram of input and output values according to the hybrid model.

of others, we clearly see that the error values are decreased significantly. Another result that claims attention is the value of R in this case study. Comparison results of the proposed method and the conventional methods for predicting electricity price data are indicated in Table 4. While the value of R in previous cases achieved 0.55 and 0.44 for cases 1 and 2, in the current case study, the value of this criterion is improved significantly to 0.7145. Figure 12 shows the R diagram of input and output values. Comparing this diagram with similar ones in other case studies, it can be seen that the proposed model enhanced the prediction accuracy. In addition to this, MSE and RMSE values are achieved 0.00031573 and 0.0177, which show improvement in the prediction results. Therefore, the prediction results of the proposed indicate the successful performance comparing to RBF and MLP neural networks.

5 Conclusion

In this paper, a hybrid framework on the basis of MLP and RBF neural networks is presented. The proposed forecasting model is tested for real electricity price data of Iran's electricity market. In the proposed method, both MLP and RBF neural networks are initialized simultaneously and perform prediction for the same data. Then, the algorithm selects the combination of the predicted values according to the mean values of the outputs. The forecasting models are tested on 168 days of data (in hourly time scale). Forecasting results for MLP and RBF show the reasonable accuracy of the MLP neural networks over RBF networks. The value of R for the MLP neural networks achieved 0.55, while this value is obtained 0.44 for the RBF neural networks. In addition, the values of MSE and RMSE for MLP reached 0.0002830 and 0.01682, respectively. However, the proposed algorithm performed better than both RBF and MLP considering MSE, RMSE, and R. Results showed that the value of R obtained 0.71, and for MSE, RMSE achieved 0.00031573 and 0.0177, respectively. In future works, the authors will enhance the forecasting accuracy by combining reinforcement learning and corrective actions with the presented method.

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