

Application of a New Hybrid Method for Day-Ahead Energy Price Forecasting in Iranian Electricity Market

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Abstract: In a typical competitive electricity market, a large number of short-term and long-term contracts are set on the basis of energy price by an Independent System Operator (ISO). Under such circumstances, accurate electricity price forecasting can lead to the more reasonable bidding strategies adopted by the electricity market participants. Using this prediction, the participants raise their profit and manage the relevant market more efficiently. This conspicuous reason has motivated the researchers to develop the most accurate, though sophisticated, forecasting models to predict the short-term electricity price as precisely as possible. In this article, a new method is suggested to forecast the next day's electricity price of Iranian Electricity Market. The authors have used this hybrid model successfully in their previous papers to predict the electric load data of Ontario Electricity Market and of the operating reserve data of Khorasan Electricity Network.

Keywords: Energy Price, Gray Model, Fuzzy Approach, Markov Chain Model, Transition Probability Matrix.

1 Introduction

Accurate short-term forecasting of electricity price can help an Independent System Operator (ISO) to adopt more efficient decisions in managing the electricity market and to significantly raise the profit of the market participants as well [1]. The most important factor in predicting a studied variable is adopting the most appropriate and reasonable model [2]. One can invent a model that can successfully forecast a variable but it may be unable to predict the more fluctuating data. The most conspicuous feature of electricity price is its nonlinear and fluctuating behavior. So, the linear and even exponential models cannot definitely forecast the energy price. Among the proposed methods up to now, the Multilayer Perceptron Neural Networks (MLPNN) [3], Fuzzy Neural Networks (FNN) [4], Adaptive Neuro-Fuzzy Inference Systems (ANFIS) [5], Radial Basis Function Neural Networks (RBFNN) [6] and time series models [7, 8] have been the most popular ones.

Two of novel methods proposed recently to forecast electricity price are presented in [9, 10]. In [9], sensitivity analysis is used to optimize the inputs of Artificial Neural Network (ANN). They have used a

Fuzzy C-Mean (FCM) algorithm to cluster the relevant daily load data. Providing the inputs of their ANN with this strategy, they have simulated their model with a modified Levenberg–Marquardt (LM) algorithm in order to learn the training data. In [10], a Bayesian Neural Network (BNN) method is proposed to forecast locational marginal prices (LMP) in an electricity market. They have utilized correlation coefficient technique to find the most optimum inputs of their forecasting method.

The most noticeable feature of these proposed methods, except for the time series, is their iterative nature. If such a model has been developed professionally, the inventor can claim that the method is as stable as the non-iterative forecasting models but still they may be time-consuming to find the most accurate value. In this paper, a non-iterative model consisting of a Gray model and a Markov Chain model is proposed to predict the next day's electricity price of Iranian Electricity Market. The contributions of this article elucidated in the following sections are:

A. The procedure through which 24 Gray models are assigned to 24 hours of a day in order to improve the prediction accuracy;

B. The procedure through which classic and fuzzy approaches are used to set a link between the Gray model and Markov Chain model;

C. The strategy based on which membership vectors of Markov Chain model are calculated in order to correct the Gray forecasting error.

Iranian Journal of Electrical & Electronic Engineering, 2012.

Paper first received 19 Feb. 2012 and in revised form 22 Oct. 2012.

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2 Gray Model-Definition and Simulation

Grey system theory was proposed by Deng in 1982. He called any random process a Grey process and assumed that all grey variables change with certain amplitudes in specified ranges and in a certain time zone [11]. Basically, "grey" system theory focuses on using a definite amount of available information to build a "grey" model (GM) in order to approximate the dynamic behavior of a system [12]. It is based on GM(n,h), where n is the order of the differential equation, and h is the number of variables. Due to the poor regularity, the accumulated generating operation (AGO) technique is utilized in Grey forecasting to efficiently decrease the uncertainty of raw data. The procedure to build the GM(1,2) was elucidated in the previous article of the authors [13]. One can simulate the proposed model in this article provided that they have studied Ref. [13].

As elaborated in [13], GM(1,1) has an exponential solution. Regarding that the electricity price signal is fluctuating, it is suggested to use GM(1,2) in order to forecast the energy price accurately. Though it will be more accurate to simulate higher orders of Gray model such as GM(1,3), we are willing to consider accuracy and simplicity of the method simultaneously. So, we suffice to make use of the GM(1,2).

As for the test data, we chose the energy price for two weeks in the summer and winter of 2010 in Iranian Electricity Market. For each test day, the electricity price data of 20 previous days (i.e. 480 samples) are used as the relevant train samples. The energy price data from January 23 to February 11, 2010 are used as the train data of the winter test week and the electricity price samples from July 25 to August 13, 2009 are utilized as the train data of the summer test week. It should be mentioned that the Iranian calendar contains parts of two consecutive years in Christian calendar.

While it is more straightforward to report the prediction result of just the next day in order to forecast the day-ahead electricity price, we prefer to repeat the training process seven times for seven days of a week and, then, report the average error as the forecasting model error. Since the signal of energy price in the next day is likely to have considerably soft fluctuations or on the other hand noticeably volatile variations. So, it is not reasonable to trust the result of just one day. Moreover, this adopted training time is enough for effective extraction of the data trend [4]. In order to evaluate the performance of the proposed method, weekly mean absolute percentage error (WMAPE), is used:

$$\text{WMAPE} = \frac{100}{168} \sum_{i=1}^{168} \frac{|x(i) - y(i)|}{x(i)} \quad (1)$$

where, x and y signify the actual and predicted energy price data, respectively.

As mentioned, the electricity price data from January 23 to February 11, 2010 are used as the training samples for winter and the price data from February 12

to February 18, 2010 are considered as the test samples. For building the Gray model, the adopted contribution is to develop 24 separate Gray models corresponding to 24 hours of a day. Through this strategy, we exclude the behavior related to other hours of a day. In order to simulate the Gray model elaborated in [13], we had to first determine the main and reference sequences. Elucidated in [13], we chose to develop a GM(1,2), we selected a reasonable reference sequence in such a way that it could accurately give feedback to the main sequence. Obviously, the main sequence consists of the training samples of the relevant hour from January 24 to February 11, 2010, i.e., the period when we aim to forecast the electricity price data of February 12. As for reference samples, we suggest to use the energy price data related to the previous hour as it has the greatest correlation with that of the current hour. A comprehensive explanation about finding the more reasonable reference sequences can be found in [13] and [14]. Here, to simulate the first GM(1,2), we consider the price data related to hour 0:00 from January 24 to February 11, 2010 as the main sequence, and the price data related to hour 23:00 from January 23 to February 10, 2010 as the reference sequence. Utilizing this strategy, we predict the energy price of the other 6 days of the test week as well. Fig. 1 shows the forecast results of the winter test week. The WMAPE of GM(1,2) to predict the price data from February 12 to February 18, 2010 is 3.64%.

It can be realized from the figure that the prediction of peak hours, such as the prediction of the first peak on Monday, is not accurate enough. Moreover, the trend of prediction related to some hours is not similar to that of the actual data like the prediction of the second peak on Friday.

As can be obviously observed, the forecasting model has successfully found the trend of the second peak on Friday after some hours, which decreases the accuracy of the prediction.

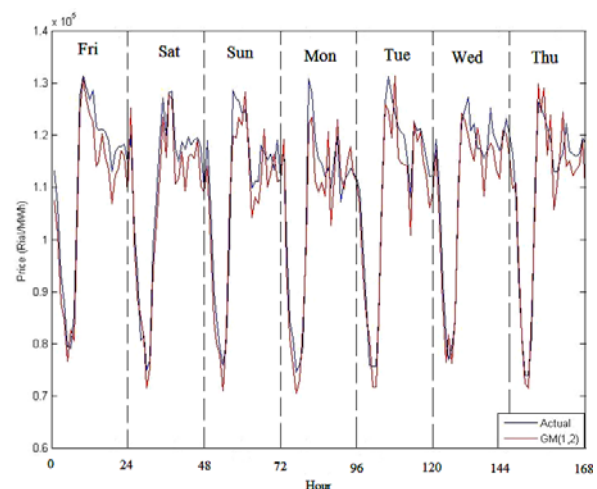


Fig. 1 Forecast result related to the winter test week by GM(1,2).

In this section, two initial solutions can be suggested in order to improve the accuracy of the Gray forecasting model. The first one is the use of electric load data as the other reference sample and utilization of GM(1,3) with two reference sequences rather than GM(1,2) with just one reference sequence. As mentioned in [14], unlike Neural Networks, when we simulate Gray model, we are not allowed to normalize the input because of the exponential feature of its function. So, we cannot enter load and price data as the input of the Gray model since their units are different. The second suggestion is the utilization of other price samples, as the second reference sequence, which normally has the considerable correlation with the current price data like price data related to 24 previous hours. This suggestion may improve the accuracy of the GM(1,2) since it builds up a GM(1,3) with two reference sequences. But the authors suggest thinking of a more fundamental solution and making use of a hybrid method rather than a single one to predict the electricity price as accurately as possible. So, in the next section we try to integrate a Markov Chain model with the simulated Gray model through two different approaches - i.e., the Classic and the Fuzzy.

3 Markov Chain Model, Definition and Simulation

As it was shown in the previous section, the prediction of the Gray model was accompanied with some conspicuous errors in some hours. The most significant reason for such a shortcoming is related to the anomalies originating from the uncertain nature of electricity price signal and even to its dependency on the fluctuations of electric load data. In this section, we simulate a Markov Chain model and integrate it with the simulated Gray model to improve the prediction accuracy.

A Markov chain is a special case of a Markov process, which, in turn, is a special case of a stochastic process. A random process X_n is called a Markov chain if:

$$P(X_{n+k} = q_{n+k} | X_n = q_n, \dots, X_1 = q_1) = P(X_{n+k} = q_{n+k} | X_n = q_n) \quad (2)$$

where, $q_1, q_2, \dots, q_n, \dots, q_{n+k}$ take discrete values.

To simulate a Markov Chain model, we should first determine the variable building up different states of the Markov Chain and then find out how to calculate the membership vectors of the Markov Chain. In this article, we propose to use the relative errors between the actual training energy price data and the GM's fitted data as the variable of the proposed Markov Chain. So, the classified relative errors set up the different states of membership vectors. In this section, we compare the results of Classic and Fuzzy approaches in integrating the Gray and Markov models.

Table 1 presents the actual training electricity price data related to the first simulated GM(1,2) together with the fitted data forecast by the relevant Gray model. As can be perceived, these errors are the foundation of

determining the classic and fuzzy membership vectors. While the more the number of classes, the more the accuracy of the proposed hybrid model, we suggest using just 3 classes in order to prevent the more complexity of the forecasting model. As can be noticed from the table, the relative errors of days 3, 4 and 5 are considerably greater than those of the rest. The reason for such noticeable difference originates from the fact that the Gray model requires some time to gradually update itself with the training data. Noteworthy here is that the relative error related to day 2 equals 0 owing to the basic assumption of simulating Gray model elaborated in [13].

For developing the Markov Chain model, we should first set up the mentioned link between Gray and Markov models. So, the membership vectors are calculated through two different approaches - i.e., Classic and Fuzzy ones. As for the Classic approach, we preferred to ignore the considerably large relative errors related to days 3, 4 and 5. Then, we should just divide

Table 1 Classic and Fuzzy States of the Relative Errors of Train Energy Price Data Related to Hour 0:00.

Day	Actual Value (Rial/MWh)	GM(1,2) Forecast (Rial/MWh)	Relative Error (%)	Classic Membership Vector	Fuzzy Membership Vector
2	116600	116600	0	(0,1,0)	(0.32,0.68,0)
3	113200	128041	-13.11	(1,0,0)	(1,0,0)
4	110180	99085	10.07	(0,0,1)	(0,0,1)
5	104080	111253	-6.89	(1,0,0)	(1,0,0)
6	112180	111005	1.05	(0,1,0)	(0.62,0.38)
7	108270	109174	-0.83	(1,0,0)	(0.87,0.13,0)
8	107930	108160	-0.21	(0,1,0)	(0.46,0.54,0)
9	110400	109791	0.55	(0,1,0)	(0.95,0.05)
10	116390	116246	0.12	(0,1,0)	(0.24,0.76,0)
11	116390	116380	0.008	(0,1,0)	(0.31,0.69,0)
12	114630	114727	-0.08	(0,1,0)	(0.37,0.63,0)
13	109570	111514	-1.77	(1,0,0)	(1,0,0)
14	116580	115523	0.90	(0,1,0)	(0.72,0.28)
15	111390	111482	-0.08	(0,1,0)	(0.37,0.63,0)
16	114960	113344	1.40	(0,0,1)	(0.38,0.62)
17	120220	116941	2.73	(0,0,1)	(0,0,1)
18	117180	117390	-0.18	(0,1,0)	(0.44,0.56,0)
19	118330	118245	0.07	(0,1,0)	(0.27,0.73,0)
20	114300	114773	-0.41	(1,0,0)	(0.59,0.41,0)

the range of the remaining errors into three classes. Through this approach, each relative error absolutely belongs to only one class. Table 1 indicates the determined membership vectors through the Classic approach. One can think of ignoring the relative error related to day 17 as well because it is considerably higher compared with the relative error of the other days. It should be emphasized that this measure is absolutely wrong and may result in conspicuous prediction error. The reason based on which we ignored the relative errors of days 3, 4 and 5 was related to the initial process of Gray model training. The large relative error related to day 17 originates from the noticeable fluctuation in electricity price signal between days 16 and 17. It is not related to bad training of the Gray model since the GM(1,2) has accurately forecast the price data related to days before and after day 17. So, if we ignore this relative error, we deprive the Markov Chain to learn the fluctuations of training samples.

In order to apply the Fuzzy approach, the authors select the triangle membership method, elaborated in [13], to define the membership vectors. While there are a variety of Fuzzy classifying methods, the triangle method was selected for its simplicity in simulation. Once the range of relative errors are divided into three states, we apply the triangle membership functions in such a way that these three functions cover the mentioned range of errors instead of assigning only one class to each error. A comprehensive explanation about triangle membership functions can be found in [13]. Eq. (3) indicates the three triangle membership functions corresponding to hour 0:00 or the first simulated GM(1,2).

$$\begin{aligned}
 u(k,1) &= \begin{cases} 1 & \varepsilon(k) \leq -1.02 \\ -\frac{1}{1.5}(\varepsilon(k) - 0.48) & -1.02 \leq \varepsilon(k) \leq 0.48 \\ 0 & \text{otherwise} \end{cases} \\
 u(k,2) &= \begin{cases} \frac{1}{1.5}(\varepsilon(k) + 1.02) & -1.02 \leq \varepsilon(k) \leq 0.48 \\ -\frac{1}{1.5}(\varepsilon(k) - 1.98) & 0.48 \leq \varepsilon(k) \leq 1.98 \\ 0 & \text{otherwise} \end{cases} \\
 u(k,3) &= \begin{cases} \frac{1}{1.5}(\varepsilon(k) - 0.48) & 0.48 \leq \varepsilon(k) \leq 1.98 \\ 1 & \varepsilon(k) \geq 1.98 \\ 0 & \text{otherwise} \end{cases}
 \end{aligned} \tag{3}$$

where, $u(k, m)$ signifies the membership degree of k^{th} relative error for each of the three classes and $\varepsilon(k)$ is the relative error corresponding to each train data. Applying the membership functions of Eq. (3) to the relative errors of first GM(1,2), shown in Table 1, we can calculate the fuzzy membership vectors. These vectors are presented in the last column of Table 1. Needless to say, this procedure should be done for other 23 hours of

a day which are related to 2nd simulated GM(1,2) to 24th relevant model.

Now, we have the required tool (i.e. membership vectors) to develop the Markov Chain model. First, we should determine the transition probability matrix. This matrix indicates the probability of transmission of studied variable; here, the relative error between GM(1,2) prediction and actual price data, from one state to another during one step. Eq. (4) shows a typical transition probability matrix.

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdot & \cdot & \cdot & P_{1m} \\ P_{21} & P_{22} & \cdot & \cdot & \cdot & P_{2m} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ P_{m1} & P_{m2} & \cdot & \cdot & \cdot & P_{mm} \end{bmatrix} \tag{4}$$

where, P_{ij} stands for the probability based on which state i can be transferred to state j in one step. It is so clear that such a probability is the proportion of the number of variables transferred between two classes to the total number of variables existing in the previous class during each step:

$$P_{ij} = \frac{m_{ij}}{M_i} \tag{5}$$

The vital point here is that for calculating p_{ij} we should know which class each relative error absolutely belongs to. This is so clear for the adopted classic approach. But for the fuzzy approach a reasonable strategy should be regarded for this purpose. We found it more justifiable to consider the class to which each relative error belongs more than the others. So, for calculating Eq. (5), we only need to regard the maximum probability of each fuzzy membership vector. For instance, the state assigned to the relative error of day 20 is class 1 (see Table 1). The transition matrix calculated for hour 0:00 by the Classic and the Fuzzy approaches through this strategy are presented in Eq (6).

$$P_{\text{Classic}} = P_{\text{Fuzzy}} = \begin{bmatrix} 0 & 1 & 0 \\ 4 & 6 & 1 \\ 11 & 11 & 11 \\ 1 & 1 & 1 \\ 3 & 3 & 3 \end{bmatrix} \tag{6}$$

As can be observed, the matrix obtained through the Fuzzy approach equals to the one calculated by the classic theory. It should be emphasized that this coincidence does not happen again for the other GM(1,2)s except for the Gray model related to hour 19.

This procedure should be followed for the other 23 GM(1,2)s as well. So, the membership vectors and the transition matrices have been calculated successfully. The last stage for developing the Markov Chain model

is predicting the next class of each relative error through multiplying the relevant membership vector in the transition matrix:

$$F(\varepsilon(n+1)) = F(\varepsilon(n)) P = [u_{A1}(\varepsilon(n+1)), \dots, u_{Am}(\varepsilon(n+1))] \quad (7)$$

Each component of $F(\varepsilon(n+1))$ indicates the membership degree of each relative error to each fuzzy state at the time step $n+1$. As can be noticed from the last row of Table 1, the membership vectors for the Classic and Fuzzy approaches are (1,0,0) and (0.59,0.41,0) respectively. Utilizing the transition probability matrix, we can forecast the membership vectors related to day 21 as follows:

$$F_{Classic}(\varepsilon(21)) = F_{Classic}(\varepsilon(20)) P = (1,0,0) \begin{bmatrix} 0 & 1 & 0 \\ 4 & 6 & 1 \\ 11 & 11 & 11 \\ 1 & 1 & 1 \\ 3 & 3 & 3 \end{bmatrix} = (0,1,0)$$

$$F_{Fuzzy}(\varepsilon(21)) = F_{Fuzzy}(\varepsilon(20)) P = (0.59,0.41,0) \begin{bmatrix} 0 & 1 & 0 \\ 4 & 6 & 1 \\ 11 & 11 & 11 \\ 1 & 1 & 1 \\ 3 & 3 & 3 \end{bmatrix} = (0.15,0.81,0.04) \quad (8)$$

Noteworthy here is that as for the Gray model related to hour 19, not only the transition matrices of the Classic and the Fuzzy approaches but also the membership vectors of these two approaches related to the last day of training (i.e. day 20) are the same. It means that the application of Classic and Fuzzy approaches results in a similar prediction for the price data related to hour 19.

In this section we should assign a reasonable relative error to the forecast membership vector related to day 21. We used the weight sum method for this purpose because of its simplicity in simulation as well as its clear concept:

$$\varepsilon(n+1) = \frac{1}{2} \sum_{i=1}^m f_i(\varepsilon(n+1))(\varepsilon_{i-1} + \varepsilon_i) \quad (9)$$

where, ε_{i-1} and ε_i are respectively the minimum and maximum relative errors of training sample in class i . $f_i(\varepsilon(n+1))$ refers to the i^{th} component of the predicted $F(\varepsilon(n+1))$ by Markov Chain model. The $\varepsilon(n+1)$ is the forecast error between the predicted electricity price by GM(1,2) and the actual relevant energy price.

Now, in the final step, we need to apply the predicted relative error by the Markov Chain model to

the forecast electricity price by the GM(1,2) in order to result in a more accurate prediction of energy price:

$$\hat{y}(n+k) = \frac{\hat{x}(n+k)}{1 - \varepsilon(n+k)} \quad (10)$$

where $\hat{x}(n+k)$ and $\hat{y}(n+k)$ are the forecast values by GM(1,2) and GM(1,2)-Classic or Fuzzy-Markov models, respectively.

This procedure should be followed for the other 23 GM(1,2)s related in hour 1:00-23:00. Then we should continue such a prediction for the other 6 days of the test week. Fig. 2 depicts the prediction of GM(1,2)-Classic-Markov model along with that of GM(1,2)-Fuzzy-Markov model for the winter test week. The WMAPEs of GM(1,2)-Classic-Markov model and of GM(1,2)-Fuzzy-Markov model are respectively 3.15% and 1.03%.

Regarding that the WMAPE of the GM(1,2) was 3.64%, the utilization of the Classic approach for the integration of Gray and Markov models seems not so productive. On the other hand, the conspicuous difference between the WMAPEs of GM(1,2) and GM(1,2)-Fuzzy-Markov model confirms the influential role of the adopted triangle fuzzy functions in correcting the prediction of Gray model through the application of the Markov Chain model. It cannot be forgotten that the more complicated fuzzy approaches can bring about less prediction error but it can also make the simulation of the proposed method more sophisticated than the one already simulated. It should be mentioned here that the training process of the proposed method for electricity price prediction in Iranian Electricity Market takes 0.45 seconds on a PC with Intel(R) core2 Due CPU E7500, 2.93 GHz, and 2 GB RAM which is the consequence of the non-iterative nature of this hybrid model. It means that once the model is simulated, it will result in exactly same result if we run it in different times.

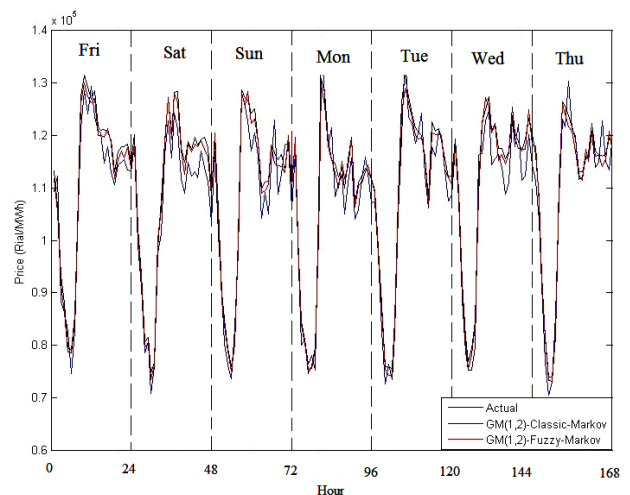


Fig. 2 Forecast results related to the winter test week by GM(1,2)-Classic and Fuzzy-Markov Chain.

Table 2 WMAPE for the two test weeks of study

Electricity Market	Test Weeks	GM(1,2)	GM(1,3)	GM(1,2)-Classic-Markov	GM(1,2)-Fuzzy-Markov	MLP
Iran	Winter	3.64	2.97	3.15	1.03	3.59
	summer	3.81	3.17	3.43	1.29	3.73

Table 2 compares the forecast results of GM(1,2), GM(1,2)-Classic-Markov and GM(1,2)-Fuzzy-Markov for the winter and summer test weeks. As mentioned earlier, the prediction of GM(1,3) with two reference sequences will have less accuracy than the proposed hybrid model even with only one reference sequence (i.e. GM(1,2)-Fuzzy-Markov). The forecast result of GM(1,3) can be found in Table 2 as well. The reference sequences of the GM(1,3) are the energy price data related to the previous hour and the 24 previous hours. A comprehensive explanation about the simulation of GM(1,3) can be found in [14]. In order to compare the forecasting result with an artificial neural network, we utilized the 3-layer MLP Neural Network presented in [13] that has 3 inputs in the input layer, and also has 8 and 2 neurons in the first and second hidden layers. It should be emphasized here that we did not use any fuzzy model or any Markov Chain model as an energy price forecaster persuading us to compare their result with that of the proposed hybrid model. The Markov Chain model was used to forecast the next fuzzy state of the relative errors and the fuzzy approach was used to set a link between the Gray model and the Markov Chain model.

4 Reasons for the Differential Performance of Classic and Fuzzy Approaches

The most important question arising here is: why is it that the utilization of the Fuzzy approach to integrate the Gray and Markov models resulted in a more accurate forecasting prediction, while the application of the Classic approach for this purpose did not bring about any noticeable correction of the Gray forecasting result?

The most significant reason leading to this considerable difference between the outcomes of these two approaches arises from the difference between transition probability matrices of the classic and the fuzzy approaches. As it was mentioned, only the models related to hours 0:00 and 19:00 have a same matrix for the Classic and Fuzzy approaches.

The second significant reason causing such difference between the forecasting results of GM-Classic-Markov and GM-Fuzzy-Markov originates from the difference between the last classic membership vector and the last fuzzy one. Noteworthy here is that such a difference of membership vectors between the classic and fuzzy approaches results in future similar differences for the other 6 days of the test week.

5 Conclusion

In this article, a hybrid model consisting of a Gray model and a Markov Chain model is proposed to predict the next day's energy price of the Iranian Electricity Market. For integrating the Gray and Markov models two approaches– Classic and Fuzzy– are suggested. It was shown that the application of the Fuzzy approach could dramatically improve the prediction accuracy of the Gray model. A comparison confirmed that the application of the GM(1,2)-Fuzzy-Markov brought about a more prediction accuracy in comparison with that of the GM(1,3).

Acknowledgment

The authors would like to thank Khorasan Regional Electricity Company (KREC) for providing the electricity price data of the Iranian Electricity Market.

References

- [1] Gorgizadeh S, Akbari Foroud A and Amirahmadi M., "Strategic Bidding in a Pool-Based Electricity Market under Load Forecast Uncertainty", *Iranian Journal of Electrical & Electronic Engineering*, Vol. 8, No. 2, pp. 164-176, June 2012.
- [2] Barforoushi T., Moghaddam M. P., Javidi M. H. and Sheik-El-Eslami M. K., "A New Model Considering Uncertainties for Power Market Simulation in Medium-Term Generation Planning", *Iranian Journal of Electrical & Electronic Engineering*, Vol. 2, No. 2, pp. 71-81, Apr. 2006.
- [3] Ghodsi R. and Zakerinia M., "Forecasting short term electricity price using artificial neural network and fuzzy regression", *International Journal of Academic Research in Business and Social Sciences*, Vol. 2, pp. 286-293, 2012.
- [4] Amjady N., "Day-ahead price forecasting of electricity markets by a new fuzzy neural network", *IEEE Transactions on Power Systems*, Vol. 21, pp. 887-896, 2006.
- [5] Rodriguez C. P. and G. J. Anders, "Energy price forecasting in the Ontario competitive power system market", *IEEE Transactions on Power Systems*, Vol. 19, pp. 366-374, 2004.
- [6] Ghods L. and Kalantar M., "Long-term peak demand forecasting by using radial basis function neural networks", *Iranian Journal of Electrical & Electronic Engineering*, Vol. 6, No. 3, pp 175-182, Sep. 2010.

- [7] Contreras J. and Santos J. R., "Short-term demand and energy price forecasting", *IEEE Mediterranean Electrotechnical Conference in Melecon*, pp. 924-927, 2006.
- [8] Papalexopoulos A. D. and Hesterberg T. C., "A regression-based approach to short-term system load forecasting", *IEEE Transactions on Power Systems*, Vol. 4, No. 4, pp. 1535-1547, 1990.
- [9] Vahidinasab V., Jadid S. and Kazemi K., "Day-ahead price forecasting in restructured power systems using artificial neural networks," *Electric Power Systems Research*, Vol. 78, No. 8, pp. 1332-1342, 2008.
- [10] Vahidinasab V. and Jadid S., "Bayesian neural network model to predict day-ahead electricity prices", *European Transactions on Electrical Power*, Vol. 20, No. 2, pp. 231-246, 2008.
- [11] Deng J. L., "Introduction to gray system theory", *Journal of Gray System*, Vol. 1, No.1, pp. 1-24, 1989.
- [12] Deng J. L., "Control problems of gray systems", *Systems & Control Letters*, Vol. 5, No.1, pp. 228-294, 1982.
- [13] Asrari A, Javan D. S., Javidi M. H. and Monfared M. "Application of Gray-Fuzzy-Markov Chain Method for day-ahead electric load forecasting", *Przegląd Elektrotechniczny (Electrical Review)*, Vol. 2012, No. 3b, pp. 228-237, 2012.
- [14] Asrari A., Kargarian A., Javidi M. H. and Monfared M., "A stochastic hybrid method to forecast operating reserve: Comparison of Fuzzy and Classical set theory", *Electric Power Components and Systems*, Under Review.



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