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A novel system for multi-step electricity price forecasting for electricity market management

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ABSTRACT

Electricity price forecasting is an important and challenging issue for all participants in the power market because of the wide application of electricity in our society and its inherent features. In this context, some current forecasting systems use data preprocessing and optimization for theoretical and practical achievements. However, some limitations to these systems exist which need to be urgently solved. First, future information is overdrawn in the data preprocessing stage of these forecasting systems, which is actually unknown in practical applications. The crucial question, therefore, is how to develop a forecasting system without using any future information. Second, the complex features of original nonlinear and nonstationary electricity price have a negative influence on the generalization ability of these previously developed models. To decrease the negative effects on management, a method to develop a forecasting system to improve the model's generalization ability is required. Therefore, in this study, we developed an adaptive deterministic and probabilistic interval forecasting system for multi-step electricity price forecasting, which can present more valuable information to power market decision makers. Two cases and one comparative study are provided and analyzed to validate the performance of the developed system in multi-step electricity price forecasting. Furthermore, further discussions are presented to illustrate the significance of this study, thus proving that the results of the present study fill the present knowledge gap and provide some new future directions for related studies.

1. Introduction

Data mining, analysis, and forecasting have played a crucial role in the modern economic management field. Accurate forecasting models can help reduce risk and improve the return on management [1]. Specifically, forecasting models are widely used for management and have become a vital part of management science models [2]. Furthermore, price forecasting is one of the most important fields of management forecasting because the most concerning and challenging issue for all participants is the future price change. If future changes of prices are accurately forecasted, the decision makers can propose an optimal decision and devise a reasonable plan to reduce potential market risk and then maximize the economic and social benefits of management [3,4].

As a clean and promising energy source, electric power plays an indispensable role in our daily lives because of its environmental friendliness compared with traditional sources of energy, which is essential in the economic sector [5,6]. Many countries have introduced deregulated and competitive electricity markets in the recent decades, and the electrical power industries are forced to produce electricity at competitive prices [7]. Thus, electricity price, influenced by many factors interconnected in complex ways [8], is an important indicator for the electrical power system. Many electricity price forecasting models have drawn worldwide attention and have become an important management technique for all participants [9]. For example, accurate forecasting results can guide consumers as well as the production schedule of producers, thus helping participants obtain maximized benefits and helping managers devise an optimal power market operation plan. Furthermore, forecasting also plays a vital role in management of investment. However, developing a high quality and effective electricity forecasting model is a concerning and challenging issue for all participants in the power market, including economists and risk managers, because of the wide application of electricity in our society and its inherent features including nonlinearity, high volatility, and high frequency [10,11].

In recent decades, numerous forecasting models have been proposed for solving the aforementioned challenge in the field of management. These models can be grouped into one of the

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following three categories: statistical methods, artificial intelligence methods, and hybrid methods [12]. Statistical methods such as autoregressive moving average (ARMA) [13], autoregressive integrated moving average (ARIMA) [14], generalized autoregressive conditional heteroskedasticity (GARCH) [15], vector auto-regression (VAR) [16], and Kalman filters (KF) [17] perform better in relatively stable power markets [18] but fail to capture the nonlinear features and rapid changes in electricity price because of their inherent weaknesses [11]. In contrast, artificial intelligence methods are superior to statistical methods because of their strength of capturing the abovementioned nonlinear features and rapid changes. Many studies have addressed the electricity price forecasting issue using artificial intelligence methods such as artificial neural network (ANN) [19–21], fuzzy neural network (FNN) [22], recurrent neural network (RNN) [23], support vector machine (SVM) [24], and extreme learning machine (ELM) [25].

However, if we only use the traditional individual models, we cannot effectively extract the complex features of original nonlinear and nonstationary electricity prices and achieve desirable forecasting results, thus leading to many disadvantages. To overcome the abovementioned disadvantages of single models, many hybrid models have been developed for electricity price forecasting, which use data decomposition methods for preprocessing nonlinear and nonstationary electricity price data before forecasting. For instance, Shayeghi and Ghasemi [26] developed a forecasting method using wavelet transform (WT), gravitational search algorithm (GSA), and least squares support vector machine (LSSVM) to predict the electricity price of three power markets. Similarly, Shrivastava and Panigrahi [27] proposed a hybrid wavelet-ELM model for forecasting electricity price. Moreover, Zhang et al. [28] developed a forecasting model using WT, generalized regression neural network (GRNN), and GARCH models for electricity price forecasting, which was validated and performed well in the Spanish electricity market. Zhang et al. [9] proposed a hybrid method based on the ELM model for forecasting day-ahead electricity price, and three real power markets were employed to prove its forecasting effectiveness. To enhance the electricity price forecasting performance, Wang et al. [6] proposed a novel electricity price forecasting model using fast ensemble empirical mode decomposition (FEEMD), variational mode decomposition (VMD), firefly algorithm (FA), and back propagation neural network (BPNN), and the results reveal that the developed model is desirable for electricity price forecasting. In general, data decomposition algorithms are one of the most flourishing fields of data mining and have been widely applied for many forecasting fields, such as air quality forecasting [29,30], wind energy forecasting [31,32], and electrical power load forecasting [33,34]. For example, Ma et al. [35] developed a generalized dynamic FNN model based on singular spectrum analysis (SSA) for wind energy forecasting. Similarly, Jiang et al. [36] developed an innovative hybrid air pollution early-warning system based on data decomposition, BPNN, imperialist competitive algorithm (ICA), and extenics evaluation for pollutant forecasting and evaluation.

In general, several algorithms for time series decomposition have been applied in electricity price forecasting or other time series forecasting. To better understand the characteristics of different algorithms, we review such algorithms and their advantages and disadvantages in this section. Based on a comprehensive review of related studies, the main algorithms for time series decomposition can be assigned into four major categories: (1) Wavelet-based decomposition can decompose the original data into some components with different frequency bands and obtain results with high-resolution. These methods have good positioning performance in the time and frequency domains. However, because the type of method to be used is determined by the structure of a decomposition binary tree, the wavelet function, and the decomposition level to a large extent, enough prior knowledge or experimental data is required to obtain desirable performance in real application. Besides, its application is limited because it is non-adaptive [37]. (2) SSA is an effective technique in time series analysis, which is employed to remove the high frequency components of noisy time series to improve forecasting performance. However, setting and adjusting the parameters is difficult. Once the parameters of the SSA are changed, the accuracy of forecasting would significantly change. (3) For empirical mode decomposition (EMD)-based decomposition, the original EMD algorithm only has few hyperparameters that need to be adjusted, which can better capture the local oscillation of the original data. However, it still has two problems: mode mixing and endpoint effect. Attempts have been made to solve these issues, and after constant improvement and development, the time varying filter based empirical mode decomposition (TVF-EMD) algorithm and improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) algorithm were developed. In general, the improved versions of EMD can reduce the negative influence of mode mixing issues of EMD [38]. (4) VMD has been shown to be better than other algorithms such as EMD, ensemble empirical mode decomposition (EEMD), complete ensemble empirical mode decomposition (CEEMD), and WT for data decomposition [39,40]. As an effective decomposition method, it can reduce the influence of the endpoints effect and mode mixing problems in EMD and has strong robustness for denoising and sampling [41,42]. Besides, the VMD algorithm has several unique properties including finite variance and stationarity of decomposed modes, which make it particularly suitable for the analysis of financial and economic data [41]. Therefore, based on the abovementioned analysis, the VMD method and other existing methods were compared to prove the superiority of the VMD method. As a result, the VMD algorithm was adopted as the basic decomposition algorithm to improve the performance of forecasting of electricity price.

Although the hybrid methods based on data decomposition algorithms can significantly improve the model's forecasting performance, the research and application of data decomposition methods in forecasting areas is not comprehensive and is flawed. Thus, it has many ways and areas for improvement in management practice. More specifically, most previous studies have been based on two schemes, i.e., the decomposition and reconstruction scheme [33] and the divide and conquer scheme [29]. These two schemes have one unique aspect in common: before forecasting, all original time signals are decomposed into some components to decrease the instability of the raw signals and to extract their main features. That is, future information is used in the data preprocessing stage of the proposed hybrid models for time series forecasting, which need that presupposition that using future information or not using it does not affect the decomposition results. However, the future information is actually unknown in management practical applications, and the assumption might be wrong. Thus, forcing the model's users to use the entire original signal to capture the features of raw data might not be reasonable and may lead to poor forecasting performance in management practice irrespective of good performance in research studies.

Therefore, two issues should be solved in the process of modeling. On the one hand, it is difficult to ensure that future information does not affect the decomposition results and the forecasting performance of the developed model. That is, the users cannot be asked to use future information to decompose the original time series in the data preprocessing stage of the proposed hybrid forecasting model; on the other hand, the complex features of original nonlinear and nonstationary electricity price negatively influence the generalization ability of the model. To decrease the negative effects in management practical application, a forecasting model to improve the model's generalization ability for multi-step electricity price forecasting should be developed.

In this study, considering the advantages of the divide and conquer scheme, an adaptive hybrid forecasting system was developed using the VMD algorithm, improved multi-objective sine cosine algorithm (IMOSCA), and regularized extreme learning machine (RELM) for multi-step electricity price forecasting, which can successfully improve the deterministic forecasting performance. In contrast with most previous electricity price forecasting studies, no future information is required in the proposed model. Furthermore, the developed model can self-adjust at the data preprocessing stage and forecasting stage as long as future electricity price information is provided. In this context, the hybrid VMD-IMOSCA-RELM has been system is proposed, in which VMD is the decomposition technique for the preprocessing of original electricity price data. Besides, RELM optimized by IMOSCA is developed as a forecasting model for predicting each component with better accuracy and stability. In the IMOSCA-RELM model, IMOSCA is a newly developed algorithm, which is an improved version of the original multi-objective sine cosine algorithm (MOSCA) and can provide more valuable optimization for the development of the electricity price forecasting system. Moreover, the final electricity price forecasting value can be obtained by aggregating all forecasted components. Because the developed system is adaptively adjusted, it is an adaptive VMD-IMOSCA-RELM model for electricity price forecasting and is denoted as AVMD-IMOSCA-RELM. This model does not require to follow the above-mentioned assumption and will be a novel deterministic forecasting technique with practical value in terms of electricity management.

Moreover, probabilistic interval forecasting could present more valuable information for management of the electricity market when compared with deterministic forecasting. It was significant, thus, to present probabilistic interval forecasting information for uncertainty analysis. In recent decades, a variety of probabilistic interval forecasting algorithms have been proposed in different forecasting fields. These models can be divided into four types: historical simulation [43], distribution-based probabilistic forecasts [44,45], bootstrapped foresting interval [46], and quantile regression averaging [47]. With the increasing importance of probabilistic interval forecasting, proposing an efficient probabilistic interval forecasting model has become highly desirable for the current electricity market.

In this study, a multi-step electricity price probabilistic interval forecasting system was successfully developed based on the framework of the proposed adaptive electricity price forecasting system. Similar to deterministic forecasting, multi-step forecasting is considered in the interval forecasting of electricity price. Specifically, a multi-output version of the RELM model based on lower upper bound estimation (LUBE) theory is devised to perform interval forecasting because the single output version cannot meet the requirements of interval forecasting. Furthermore, the newly proposed optimization algorithm IMOSCA is developed to optimize the RELM model with two widely used interval forecasting evaluation metrics as the objective function: one is to minimize the forecasting interval normalized average width (FINAW) and the other is to maximize the forecasting interval coverage probability (FICP), which can obtain desirable interval forecasting results for electricity price.

The innovation and new contribution of the developed system are as follows: (a) An adaptive deterministic and probabilistic interval forecasting system is developed for multi-step electricity price forecasting, which can present more valuable information for decision makers in the power market and play a vital role in the management of investment. (b) Most previous forecasting models based on the divide and conquer scheme not only use some information from the future but also lack adaptive ability and cannot adapt to the changes in electricity price series. In this study, the developed system is adjusted adaptively and without using any future information. The model does not need to follow the above-mentioned assumption and will be a novel forecasting technique with management practical value. (c) A new algorithm named IMOSCA is developed for system optimization, which incorporates different objective functions for desirable deterministic forecasting and interval forecasting, and the results prove that the IMOSCA outperforms the original MOSCA. (d) A multi-output version of the RELM model based LUBE theory is developed with the aim to perform interval forecasting. This model can avoid distribution assumption, can reduce the model's complexity, and can strengthen the model's robustness. (e) To prove the efficiency of the developed system, several cases are presented in the study. Different benchmarked models are employed, including some typical individual models, RELM based forecasting methods, different optimization algorithm based methods, and the latest studies. (f) The adaptivity of the developed system is discussed by comparing with the previous non-adaptive adjusted model using future information, thus contributing to future divide and conquer-based researches. (g) A comparative study for the probabilistic interval forecasting system is conducted to provide comprehensive analysis based on one-step and multi-step interval forecasting, which not only reveal the relationship between the performance of deterministic forecasting and interval forecasting but also prove that it is a promising alternative for electricity price multi-step probabilistic interval forecasting.

This paper is organized as follows: the algorithms used in the developed system are described in Section 2; Section 3 presents the developed system; a case study is provided in Section 4; a discussion for the developed system is presented in Section 5; a comparative study for the probabilistic interval forecasting is provided in Section 6; further analysis is discussed in Section 7; and Section 8 concludes the paper.

2. Methodology

In this section, the time series decomposition algorithm, forecasting algorithm, and optimization algorithm are introduced in detail.

2.1. Time series decomposition algorithm

The complex features of electricity price time series, such as non-stationarity, non-linearity, and volatility, makes its forecasting a challenging task. Fortunately, time series decomposition algorithm can solve the forecasting difficulties caused by noise and can extract the inner features of electricity price, which plays an indispensable role in electricity price forecasting fields and other forecasting fields. Therefore, selecting a suitable decomposition algorithm to effectively identify and explore the main characteristics of electricity price and improve the model's performance is extremely important. VMD, developed by Dragomiretskiy and Zosso [48], is a kind of state-of-art decomposition method, which is a better method to non-recursively decompose a multi-component signal into some quasi-orthogonal intrinsic mode functions [49]. More importantly, the VMD algorithm has its own unique advantages compared with local mean decomposition (LMD) and EMD in that it can avoid error caused during the recursive calculating and ending effect. Therefore, VMD is selected to decompose electricity price data.

The detailed procedure of VMD can be summarized as follows:

Step 1: Initialize each mode $\hat{y}_k^1$, center pulsation $\hat{w}_k^1$, and Lagrangian multipliers λ;

Step 2: Update the parameters y_k and w by

$$\hat{y}_k^{n+1} = \frac{\hat{f}(w) - \sum_{i \neq k} \hat{y}_i(w) + \frac{\hat{\lambda}(w)}{2}}{1 + 2\alpha(w - w_k)^2} \tag{1}$$

$$w_k^{n+1} = \frac{\int_0^\infty w \left|\hat{y}_k^{n+1}(w)\right|^2 \mathrm{d}w}{\int_0^\infty \left|\hat{y}_k^{n+1}(w)\right|^2 \mathrm{d}w} \tag{2}$$

where $f(t)$ denotes original data and y_k denotes the kth component of $f(t)$. Besides, n presents the number of iterations; $\hat{f}(w)$, $\hat{y}_i(w)$, $\hat{\lambda}(w)$, and $\hat{y}_k^{n+1}(w)$ are the Fourier transforms of $f(t)$, $y_i(t)$, $\lambda(t)$ and $y_k^{n+1}(t)$, respectively.

Step 3: Update the parameter λ by

$$\hat{\lambda}^{n+1}(w) \leftarrow \hat{\lambda}^n(w) + \pi \left[\hat{f}(w) - \sum_k \hat{u}_k^{n+1}(w)\right] \tag{3}$$

Step 4: The VMD algorithm is stopped if it meets $\sum_k \left\|\hat{y}_k^{n+1} - \hat{y}_k^n\right\|_2^2 / \left\|\hat{y}_k^n\right\|_2^2 < e$; otherwise, return to Step 2.

2.2. Forecasting algorithm

In this section, the flow of the original ELM is introduced. Moreover, the improved version of ELM named RELM, aimed at improving the performance of ELM, is also presented in detail.

2.2.1. Extreme learning machine

ELM, developed by Huang [50], has a simple structure, high accuracy, fast speed, and few training samples and has been frequently employed in many fields, such as training neural networks [51], variable weights combined predictor [52], and renewable energy forecasting [53,54]. Specifically, many studies prove that ELM performs better than other models such as SVM [55], BPNN [56], and Elman neural network (ENN) [57], which becomes one of the most common and promising methods in forecasting fields.

Suppose the training dataset with M samples is (x_t, y_t), the ELM model with L hidden nodes can be presented as

$$\hat{y} = \sum_{i=1}^{L} \beta_i g_i(x_i) = \sum_{i=1}^{L} \beta_i G(w_i \cdot x_t + b_i,) = y_j \tag{4}$$

where β_i denotes the weight connection between the ith hidden node and the output node, G denotes the excitation function, w_i is the input weight vector, and b_i denotes the hidden bias.

Eq. (4) can be presented as

$$H\beta = Y \tag{5}$$

$$\beta = [\beta_1 \cdots \beta_L]^T, Y = [y_1 \cdots y_M]^T \tag{6}$$

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_1) \end{bmatrix} = \begin{bmatrix} G(w_1 \cdot x_1 + b_1) & \dots & G(w_L \cdot x_1 + b_L) \\ \vdots & \dots & \vdots \\ G(w_1 \cdot x_M + b_1) & \dots & G(w_L \cdot x_M + b_L) \end{bmatrix}_{M \times L} \tag{7}$$

where H denotes the hidden layer's output matrix.

The output weight can be obtained by solving the following minimum problem:

$$\min_\beta = \|H\beta - Y\| \tag{8}$$

The optimal solution is

$$\hat{\beta} = H^\dagger Y \tag{9}$$

where $H^\dagger$ denotes the Moore–Penrose generalized inverse matrix of the hidden layer's output matrix, which can be calculated by [58]

$$H^\dagger = \left[H^T H\right]^{-1} H^T \tag{10}$$

2.2.2. Regularized extreme learning machine

One important part of ELM is to minimize the training error; however, this may lead to overfitting and poor forecasting performance. Based on the Bartlett's theory [59], the smaller the output weight norm and training error, the better the generalization performance. In general, the ELM model achieved the best tradeoff between training error and the weight norm will have a good generalization ability. To achieve this aim, an improved version of ELM is developed, in which the regularization parameter C is introduced to regularize the proportion of training error and weight norm. Because of the contribution of regularization terms, the improved version of ELM is named RELM, which has a better generalization performance compared with the ordinary ELM model. In the RELM model, the optimal solution is

$$\hat{\beta} = \begin{cases} \left[H^T H + \frac{I}{C}\right]^{-1} H^T Y & M > L \\ H^T \left[H^T H + \frac{I}{C}\right]^{-1} Y & M < L \end{cases} \tag{11}$$

where I is the identity matrix.

2.3. Model optimization algorithm

The basic sine cosine algorithm (SCA) is introduced first, and then, an improved multi-objective optimizer based on SCA is developed.

2.3.1. Sine cosine algorithm

SCA is a novel optimization algorithm based on sine/cosine functions, which was proposed by Seyedali Mirjalili [60]. In different stages of optimization, some variables are adopted to strengthen the search space's ability of exploration and exploitation.

The position in the exploration and exploitation phases is updated as

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right| \tag{12}$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times \left|r_3 P_i^t - X_i^t\right| \tag{13}$$

where $\boldsymbol{X}$ denotes the current solution's position, i is the dimension of the optimization problem, t is the iteration number, r is a random number, $\boldsymbol{P}$ denotes the destination point, and || means the absolute value.

Eqs. (12) and (13) are redefined as

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times \left|r_3 P_i^t - X_i^t\right|, r_4 < 0.5 \\ X_i^t + r_1 \times \cos(r_2) \times \left|r_3 P_i^t - X_i^t\right|, r_4 \geq 0.5 \end{cases} \tag{14}$$

The range of sine and cosine in Eqs. (12) to (14) is adaptively changed to balance the ability of exploration and exploitation, which can be calculated by

$$r_1 = a - a \times f(x) \tag{15}$$

where a is a constant, $f(x) = x$, $x = t/T$, T represents the maximum iteration number, and t represents the number of current iterations.

2.3.2. Improved multi-objective sine cosine algorithm

Similar to the SCA, the parameter $r_{1,}$ with the strategy of linear decreasing, is also employed in the previously proposed MOSCA. It can ensure that the algorithm has a high exploration ability in the early stages and a high exploitation ability in the later stages. The exploration ability of the algorithm is an important requirement in multi-objective optimization, so we believe that the adjustment strategy of parameter r_1 can be modified to improve the exploration ability of the previously proposed MOSCA.

In Eq. (15), $f(x)$ is a monotonically increasing function in the interval [0, 1], $f(0) = 0$ and $f(1) = 1$. As mentioned above, the

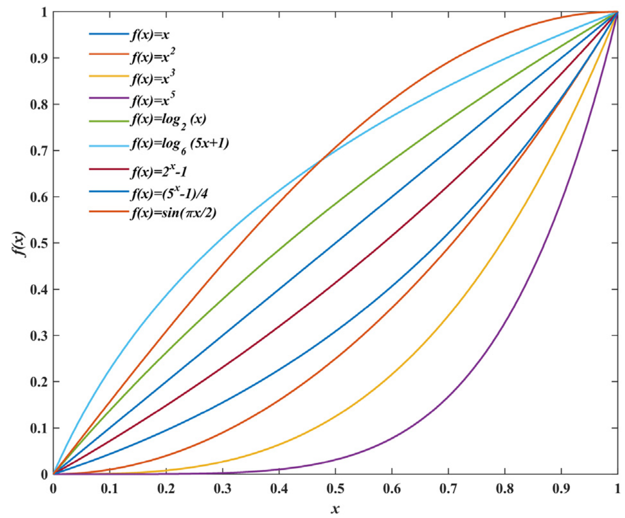

Fig. 1. Characteristics of some commonly used functions.

exploration ability of the original MOSCA should be improved. In general, the higher the value of parameter r_1, the higher the exploration ability of MOSCA. Therefore, the modified version of $f(x)$ should be a concave function in the interval [0, 1]. Fig. 1 shows the characteristics of some commonly used functions. Trigonometric, logarithmic, exponential, and power functions are considered in this study. According to the results shown in Fig. 1, the exponential and power functions are promising candidates. However, considering that the algorithm requires higher exploration ability in the early stages, the power function $f(x) = x^k$ is selected in this study to adjust the value of parameter r_1, where k is a constant greater than 0. The new adjustment strategy of parameter r_1 can be defined as shown in Eq. (16), and then, IMOSCA is successfully developed. Furthermore, the trial and error method is used to determine the appropriate value of k, and finally, 5 is selected as the appropriate value of k in this study.

$$r_1 = a - a \times f(x)^k = a - a \times (t/T)^k \tag{16}$$

2.3.3. Fitness function of IMOSCA in electricity price forecasting

It is important to determine the optimal parameters for the RELM model for forecasting electricity price. Therefore, to provide accurate and stable deterministic forecasting and desirable probabilistic interval forecasting results, IMOSCA is developed in Section 2.3.2. Meanwhile, two fitness functions are designed for deterministic forecasting and probabilistic interval forecasting. For deterministic forecasting, the forecasting accuracy and stability have been proven to be important and can function as the optimization objectives to improve the model's performance in terms of accuracy and stability. Furthermore, the detailed fitness function for deterministic forecasting can be defined as fitness 1 shown in Eq. (17). For probabilistic interval forecasting, another fitness function named fitness 2 is defined in Eq. (18), which also comprises two objectives for providing desirable interval forecasting results. Specifically, these two objectives are to maximize the FICP and minimize the FINAW, which are two commonly used objectives in interval forecasting.

$$fitness_1 = \min \begin{cases} obj_1 = \dfrac{1}{N} \times \displaystyle\sum_{i=1}^{N} (F_i - A_i)^2 \\ obj_2 = std(F_i - A_i) \end{cases} \tag{17}$$

$$fitness_2 = \min \begin{cases} obj_1 = 1 - \alpha - \dfrac{1}{N} \displaystyle\sum_{i=1}^{N} c_i, \begin{cases} c_i = 1, A_i \in [L_i, U_i] \\ c_i = 0, otherwise \end{cases} \\ obj_2 = \dfrac{1}{NR} \displaystyle\sum_{i=1}^{N} (U_i - L_i) \end{cases} \tag{18}$$

where F_i is the forecasting value, A_i is the actual value, and N is the number of corresponding forecasting values. L_i and U_i are the forecasted interval's lower and upper bounds, respectively, R is the range of actual values, and (1- α) is the expectation probability.

2.3.4. Superiority of IMOSCA in solving multi-objective optimization problems

In this section, IMOSCA is developed for the adaptive deterministic and probabilistic interval forecasting system, instead of directly using other advanced recently published multi-objective optimization techniques. The main reason is the superiority of IMOSCA in solving multi-objective optimization problems. More specifically, a classic theory named no free lunch [61] reveals that there is no one method can solve all optimization problems. Therefore, to solve the multi-objective optimization issues existing in the developed forecasting system, a new algorithm with superior performance than other advanced recently published multi-objective optimization techniques needs to be developed. With the aim of developing an effective forecasting system, IMOSCA was developed. To prove the superiority of IMOSCA in solving multi-objective optimization problems and the rationality of using IMOSCA in the developed system, four test functions including ZDT1, ZDT2, ZDT3, and ZDT1 with linear front were selected to compare the IMOSCA with four recently published advanced multi-objective optimizers, i.e., multi-objective dragonfly algorithm (MODA) [33], multi-objective ant lion optimizer (MOALO) [62], multi-objective multi-verse optimization (MOMVO) [63], and multi-objective grey wolf optimizer (MOGWO) [64]. The experiments were repeated 50 times with the same parameters. The optimization performance was measured by inverted generational distance (IGD) [32], and the statistic values of IGD for different optimization techniques are shown in Table 1. From Table 1, the newly developed IMOSCA was found to exhibit the best optimization results among all algorithms considered in almost all cases. The superiority of IMOSCA can be proved based on the testing results. Moreover, the superiority of IMOSCA in solving the multi-objective optimization issues of the proposed electricity price forecasting system also can be proved in the section of comparative analysis of different models. Therefore, IMOSCA was developed and applied in the developed forecasting system, rather than using other advanced recently published multi-objective optimization techniques.

3. Adaptive deterministic and probabilistic interval forecasting system

In this section, the adaptive deterministic and probabilistic interval forecasting system, AVMD-IMOSCA-RELM, is developed considering the advantages of the divide and conquer scheme. The flowchart of the AVMD-IMOSCA-RELM system is shown in Fig. 2, which can be summarized in the following six steps:

Step 1: Divide the original dataset into two periods, i.e., training period denoted as $P_{training}$ and testing period denoted as $P_{testing}$, and set the initial value of data number in the testing period k to 1;

Step 2: VMD is selected as the data decomposition technology to decompose the entire data in $P_{training}$ into n subseries, i.e., S1, S2, $\cdots$, S7, S8;

Table 1
Testing results based on different test functions.

Algorithm	Mean	Std.	Median	Min	Max
ZDT1					
MODA	0.003569	0.001061	0.003303	0.002270	0.006499
MOALO	0.006226	0.003735	0.005683	0.002164	0.019820
MOMVO	0.002412	0.000486	0.002355	0.001638	0.004261
MOGWO	0.001717	0.000482	0.001629	0.000922	0.003824
IMOSCA	0.000996	0.000122	0.000987	0.000754	0.001330
ZDT2					
MODA	0.003605	0.001393	0.003438	0.001387	0.009265
MOALO	0.006125	0.004106	0.004683	0.002502	0.021405
MOMVO	0.002525	0.000612	0.002323	0.001655	0.004836
MOGWO	0.001734	0.000505	0.001595	0.001020	0.004007
IMOSCA	0.000971	0.000089	0.000975	0.000783	0.001159
ZDT3					
MODA	0.024790	0.000370	0.024712	0.024193	0.025776
MOALO	0.024438	0.002628	0.024793	0.006500	0.025752
MOMVO	0.024581	0.000371	0.024475	0.024039	0.025912
MOGWO	0.024452	0.000247	0.024407	0.024045	0.025295
IMOSCA	0.024506	0.000213	0.024492	0.024225	0.025143
ZDT1 with linear front					
MODA	0.003668	0.001188	0.003355	0.001714	0.006999
MOALO	0.007489	0.006293	0.004220	0.002388	0.028795
MOMVO	0.002447	0.000392	0.002387	0.001735	0.003640
MOGWO	0.001440	0.000588	0.001206	0.000894	0.003105
IMOSCA	0.000988	0.000116	0.000974	0.000743	0.001286

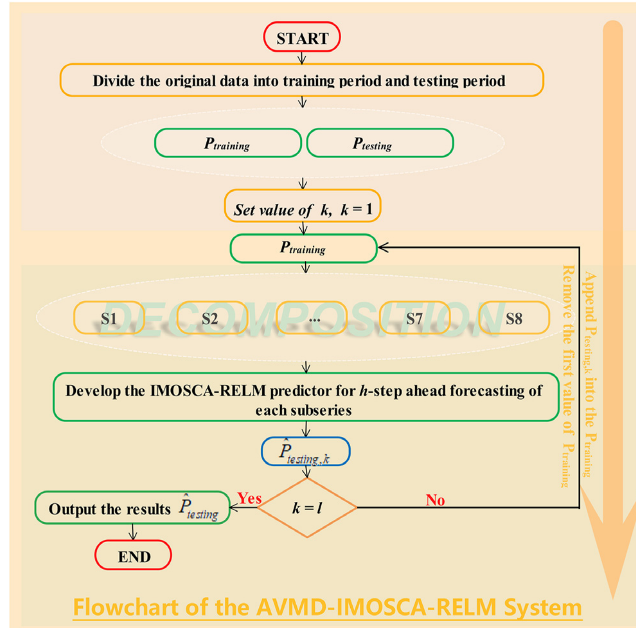

Fig. 2. Flowchart of the AVMD-IMOSCA-RELM system.

Step 3: Develop an improved multi-objective optimization algorithm called IMOSCA to optimize the forecasting system, which can be employed to incorporate different objective functions to develop an accurate and stable deterministic forecasting and desirable probabilistic interval forecasting system.

Step 4: The forecasting model IMOSCA-RELM is developed for each subseries of $P_{training}$, and the IMOSCA-RELM model is employed to predict the h-step ahead forecast of each subseries.

Step 5: Obtain the final h-step prediction result $\hat{P}_{testing,k}$ by aggregating the forecasting results of all developed systems;

Step 6: If $k = l$, where l is the data number in the testing period, the h-step forecasting results $\hat{P}_{testing}$ are output, and the algorithm is stopped. Otherwise, the first data of $P_{training}$ is removed, $P_{testing,k}$ is appended to $P_{training}$, and the algorithm returns to Step 2.

It should be noted that there are two main types of time series decomposition [65]: decomposition based on rates of change and decomposition based on predictability. Moreover, the multi-band components at various frequencies can be obtained by decomposing the original electricity price using the WT, SSA, EMD, and VMD methods, which show the general trend, fluctuations, and different periodicities of the electricity price series separately [66]. As mentioned above, the VMD algorithm is used to decompose the electricity price data into n subseries. Therefore, it can be concluded that the present model belongs to the first type of time series decomposition, i.e., decomposition based on rates of change.

4. Empirical study

4.1. Data description

To verify the effectiveness of the developed forecasting system to handle multi-step electricity price forecasting, two datasets collected from different states of Australia were used in the empirical study. New South Wales (NSW) and Queensland (QLD) are employed as the study area in this study, and the corresponding datasets were denoted as Dataset A and Dataset B, respectively. The dataset can be found from the website of electricity market of Australia (www.aemo.com.au). Specifically, the time resolution of each dataset is 30 min, and the total number of observation values of each dataset is 1440, covering 30 days from June 1, 2016, to June 30, 2016. Moreover, for each dataset, the data from 25 days are used to predict the data for 5 days, which means the number of training data points is 1200 (from June 1, 2016, to June 25, 2016) and the number of testing data points is 240 (from June 26, 2016, to June 30, 2016). The descriptive statistics of each dataset including the maximum, minimum, median, average, and standard deviation are shown in Table 2. According to the information shown in Table 2, these electricity price datasets present a significant difference because of which we selected datasets from different sites rather than only one site. Specifically, these two states have different characteristics in terms of population, geographical features, climatic characteristics, industrial structures, and regional scales. Therefore, the motivation of selecting NSW and QLD as the study areas was to verify the developed system's effectiveness and applicability for remarkably different environments.

Table 2
Descriptive statistics of each dataset used in this study.

Data Set	Number	Statistic values				
		Maximum ($/MWh)	Minimum ($/MWh)	Median ($/MWh)	Mean ($/MWh)	Std. ($/MWh)
Dataset A						
All Samples	1440	301.3400	20.8000	79.1050	97.6900	67.5965
Training set	1200	299.8000	20.8000	77.8950	93.6046	63.7173
Testing set	240	301.3400	28.1100	92.0550	118.1174	81.4927
Dataset B						
All Samples	1440	293.5000	20.7300	73.4050	87.5294	57.3882
Training set	1200	293.5000	20.7300	72.0500	84.5898	54.5103
Testing set	240	282.3900	26.2500	81.7200	102.2276	68.2818

4.2. Performance evaluation metric

To comprehensively and systematically evaluate the proposed system by referring to evaluation metrics used in [6,33,67,68], four performance evaluation metrics including mean absolute

Table 3
Performance evaluation metric.

Metric	Equation
MAE	$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert$
RMSE	$\mathrm{RMSE} = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N}(F_i - A_i)^2}$
MAPE	$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{A_i - F_i}{A_i}\right\rvert \times 100\%$
TIC	$\mathrm{TIC} = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N}(F_i - A_i)^2} \Big/ \left(\sqrt{\frac{1}{N} \times \sum_{i=1}^{N}A_i^2} + \sqrt{\frac{1}{N} \times \sum_{i=1}^{N}F_i^2}\right)$
FICP	$\mathrm{FICP} = \frac{1}{N}\sum_{i=1}^{N}c_i \times 100\%, \quad \begin{cases} c_i = 1, A_i \in [L_i, U_i] \\ c_i = 0, otherwise \end{cases}$
FINAW	$\mathrm{FINAW} = \frac{1}{NR}\sum_{i=1}^{N}(U_i - L_i)$
AWD	$\mathrm{AWD} = \frac{1}{NR}\sum_{i=1}^{N}\mathrm{AWD}_i, \quad \mathrm{AWD}_i = \begin{cases} (L_i - A_i)/((U_i - L_i)), & A_i < L_i \\ 0, & A_i \in [L_i, U_i] \\ (L_i - A_i)/((U_i - L_i)), & A_i > U_i \end{cases}$

error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and theil inequality coefficient (TIC) were used to evaluate the performance of deterministic forecasting (Table 3). Specifically, MAE, RMSE and MAPE can be used to evaluate the forecasting accuracy of one model, and smaller values present better forecasting accuracy. Meanwhile, TIC can be used to evaluate the forecasting ability of one model, and the smaller TIC has better forecasting ability. These metrics are employed to evaluate the forecasting method from two perspectives, i.e., forecasting accuracy and forecasting ability. Meanwhile, by referring to metrics used previously [45,47], FICP, FINAW, and accumulated width deviation (AWD) are implemented in the evaluation of the probabilistic interval forecasting results (Table 3). In summary, seven metrics are used in this study, which can be used for scientific and comprehensive evaluation.

4.3. Analysis of the subseries decomposed by VMD

As mentioned above, the data decomposition technique is widely used for forecasting complex time series and has shown desirable performance in previous studies. However, in most previous studies, the entire original data are decomposed into some subseries, and the future information is used in the modeling process. Therefore, in this study, the developed system is adjusted adaptively and without using any future information. The system is not required to follow the above-mentioned assumption and will be a novel forecasting technique with practical value in management. In this section, the different decomposition strategies from most previous studies and our developed system are compared and analyzed. As mentioned above, in this study, the VMD algorithm is used in the decomposition of original electricity price. For simplicity, the decomposition results used in previous studies are denoted as Result A, while the results from this study are denoted as Result B. The decomposition results of Dataset A and Dataset B are presented in Figs. 3 and 4, respectively. The results indicate that Result A and Result B obviously differ, which will lead to different forecasting performances. Besides, the comparison study also reveals the research gap of previous studies and provide some new contributions for related future studies.

As shown in Figs. 3 and 4, in the testing period, the original data are decomposed into 8 subseries, which reveals the difference between result A and result B. Moreover, the difference is also why these two methods show different forecasting performances and different practical values in management practice. Furthermore, the predictor for each subseries can be established using the newly proposed improved multi-objective optimizer and RELM, which can be combined with different fitness functions for different forecasting targets. Specifically, the forecasting accuracy and forecasting stability are adopted in deterministic forecasting, while FICP and FINAW are analyzed simultaneously and employed in probabilistic interval forecasting. The desirable forecasting performance can be obtained using the developed predictor of each subseries.

4.4. Comparative analysis of different models

The different models are comparatively analyzed to verify the proposed system's forecasting performance in this section. The two cases are analyzed from different perspectives: Case 1, for transverse comparison; and Case 2, for longitudinal comparison.

4.4.1. Case 1: transverse comparison experiment

Case 1 conducts a transverse comparison experiment, which includes a comparative study between the developed system and the system's component models. In this case, RELM, AVMD-RELM, MOSCA-RELM, and IMOSCA-RELM models are employed to prove the superiority of the presented AVMD-IMOSCA-RELM system. Thus, three comparisons are performed in this case, and the forecasting results are shown in Tables 4–5 and Figs. 5–6.

The details of the alalyses are as follows:

(1) In comparison I, the developed AVMD-IMOSCA-RELM system is compared with the other four benchmark models, which can give us a basic understanding of the proposed system's superiority. More importantly, the simulation results validate the rationality and validity of modeling theories and methods. For example, the MAPE values presented by Dataset A in NSW of the proposed system are 6.2210%, 5.9536%, 12.9430%, and 21.4721% for one-step, two-step, four-step, and six-step forecasting, respectively; meanwhile, the TIC values are 0.0231, 0.0249, 0.0500, and 0.0796 for one-step, two-step, four-step, and six-step forecasting, respectively. Experimental results reveal that the proposed system can successfully predict the future electricity price changes, thus exhibiting desirable forecasting performance when compared with other models.

(2) Comparison II further validates the effectiveness of the adaptive ability of the presented work. Specifically, the superiority of the adaptive data preprocessing technique AVMD can be quantified by comparing the RELM model and AVMD-RELM model or the developed AVMD-IMOSCA-RELM system and IMOSCA-RELM model. For instance, for one-step forecasting at NSW, the data preprocessing technique provides reductions of 31.7615 in MAE, 46.0555 in RMSE, 25.4478% in MAPE, and 0.1700 in TIC and leads to reductions of 43.9654 in MAE, 61.1048 in RMSE, 39.6614% in MAPE, and 0.2571 in TIC for six-step forecasting. Based on the abovementioned analysis, we found that data preprocessing contributes well to the final forecasting performance. More importantly, the developed system achieves self-adjustment at the data preprocessing stage and forecasting stage as long as future information is coming, which can be widely used in many forecasting fields and easily implemented in application.

(3) Similarly, the newly proposed multi-objective optimization algorithm IMOSCA also plays a vital part in the development of the AVMD-IMOSCA-RELM forecasting system, which makes a great contribution for the success

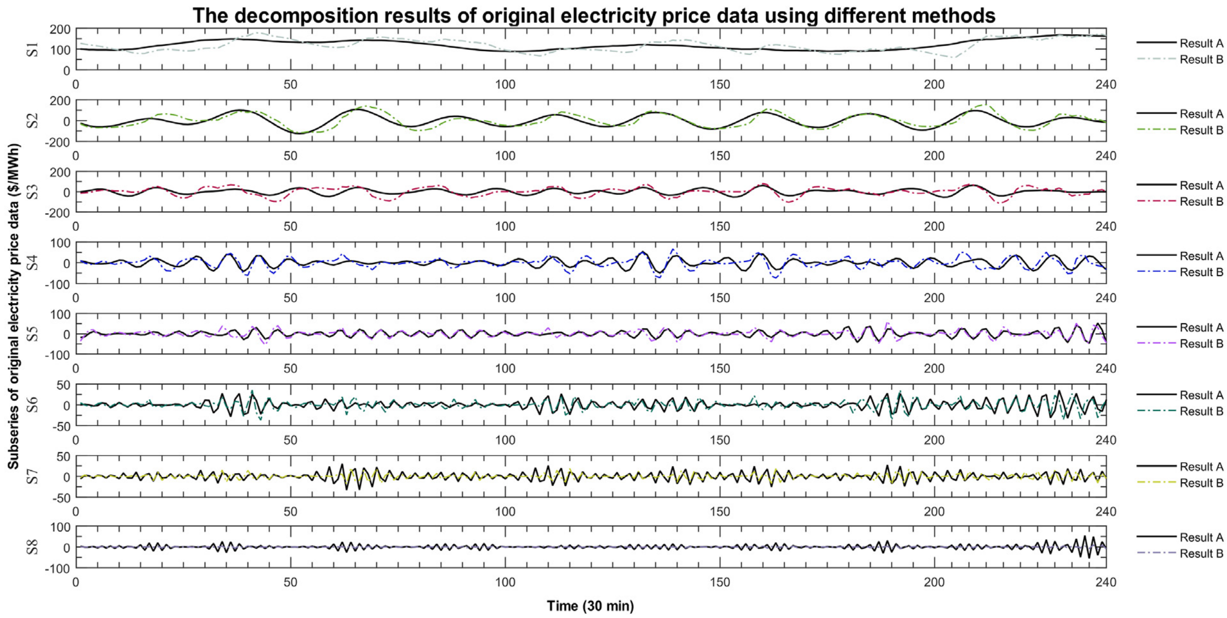

Fig. 3. Decomposition results of Dataset A.

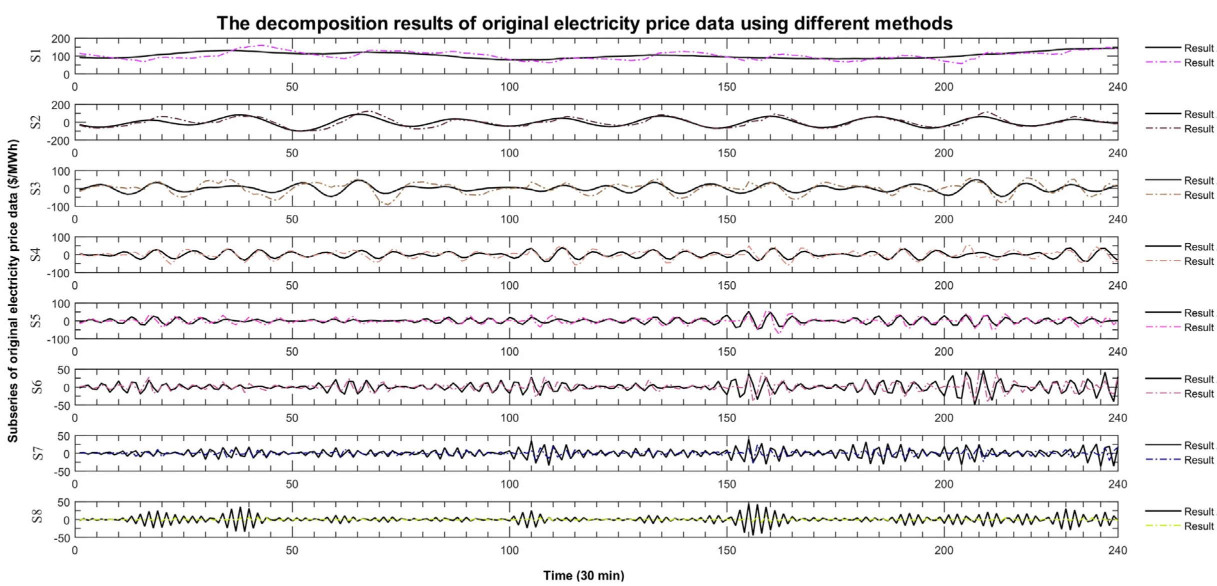

Fig. 4. Decomposition results of Dataset B.

of the developed system. Furthermore, the superiority of the newly proposed IMOSCA can be proved by comparing the RELM model and IMOSCA-RELM model or the AVMD-RELM model and the developed AVMD-IMOSCA-RELM system. For example, the newly proposed IMOSCA contributes to performance improvements of 0.5325 in MAE, 0.7213 in RMSE, 0.2900% in MAPE, and 0.0025 in TIC for one-step forecasting in NSW. Results prove the contribution of the newly proposed IMOSCA to final forecasting effectiveness of the presented system and the significance of the improved multi-objective optimization algorithm.

(4) Except the abovementioned analysis focusing on proving the contribution and effectiveness of the developed system's main components, the newly proposed IMOSCA as an improved version of original MOSCA should be compared and analyzed in more detail. Therefore, the IMOSCA-RELM model and the MOSCA-RELM model must be compared to prove the superiority of the newly proposed algorithm over the original algorithm. Furthermore, the value of improving the original optimization algorithm can be presented in a clear way. For example, the newly developed IMOSCA resulted in reductions of 0.9800 in MAE, 1.2224 in RMSE, 0.2467% in MAPE, and 0.0045 in TIC for one-step forecasting in NSW; meanwhile, the reductions for six-step forecasting in NSW were 1.3600 in MAE, 0.5038 in RMSE, 2.1263% in MAPE, and 0.0014 in TIC. The comparison study shows that the significance of improvement studies of multi-objective optimization in electricity price forecasting. Furthermore, the corresponding improvement focusing on multi-objective optimization can be studied in the future.

4.4.2. Case 2: longitudinal comparison experiment

Different from the transverse comparison experiment conducted in Case 1, the longitudinal comparison experiment is

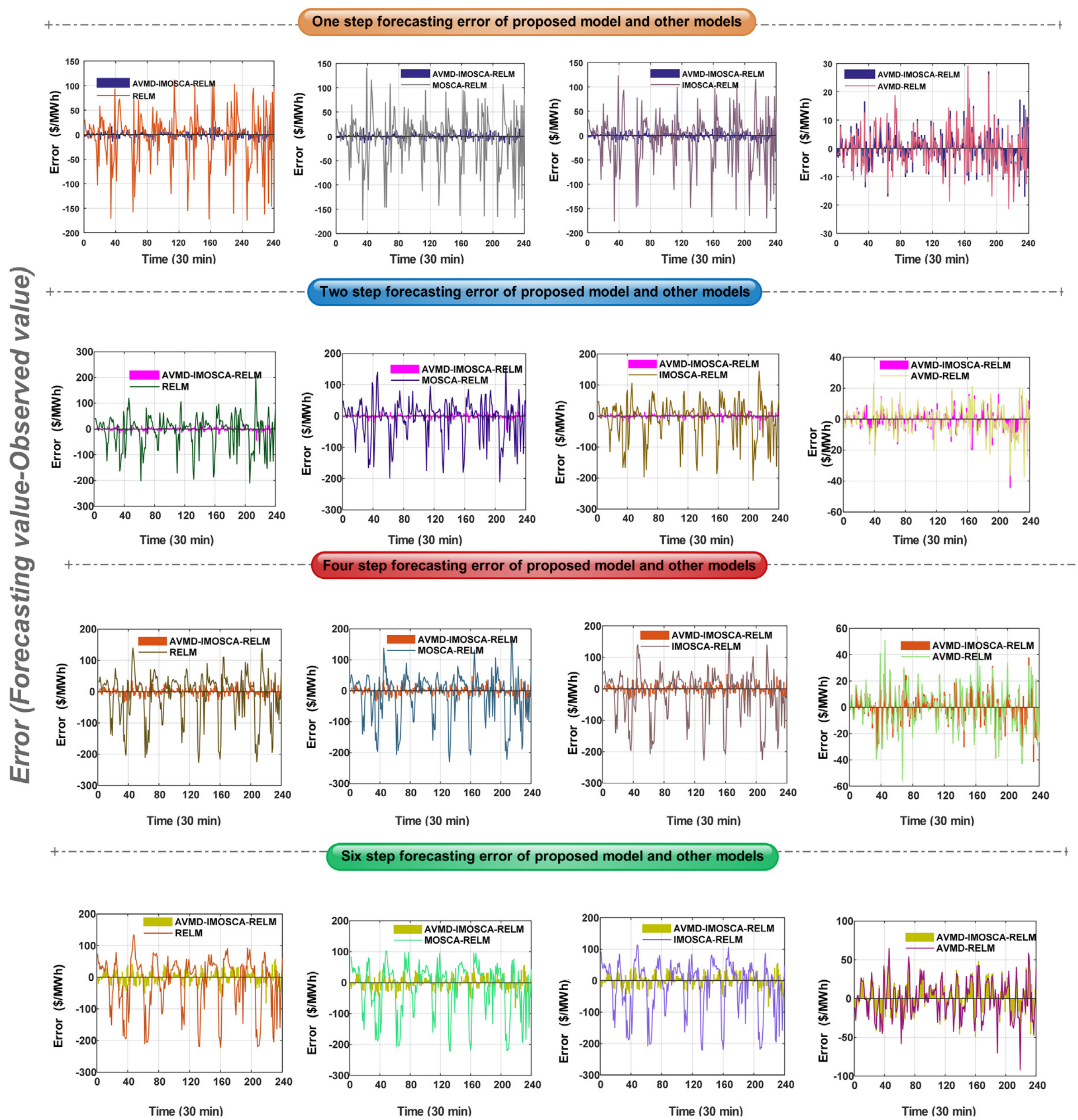

Fig. 5. Results of the proposed system and other models for Dataset A.

Table 4
Results of the developed system and other compared models for Dataset A.

Forecasting horizon	Metric	RELM	MOSCA-RELM	IMOSCA-RELM	AVMD-RELM	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	37.0144	37.1298	36.1498	5.2529	5.0526
	RMSE ($/MWh)	53.1597	53.4240	52.2016	7.1042	6.6198
	MAPE (%)	31.8856	31.7691	31.5224	6.4378	6.2210
	TIC (–)	0.1949	0.1960	0.1915	0.0248	0.0231
Two step forecasting	MAE ($/MWh)	46.3195	45.5155	44.5901	6.4591	5.0436
	RMSE ($/MWh)	64.7371	64.1599	63.6450	8.7287	7.1178
	MAPE (%)	42.0131	40.6590	38.5641	7.5208	5.9536
	TIC (–)	0.2428	0.2430	0.2405	0.0306	0.0249
Four step forecasting	MAE ($/MWh)	56.6309	55.6897	55.1677	12.2761	10.9829
	RMSE ($/MWh)	78.4857	78.2481	78.3339	16.1884	14.2507
	MAPE (%)	52.3604	50.9731	50.5068	14.2160	12.9430
	TIC (–)	0.3060	0.3072	0.3099	0.0570	0.0500
Six step forecasting	MAE ($/MWh)	63.3496	62.6764	61.3164	19.3842	18.0260
	RMSE ($/MWh)	85.2268	83.9949	83.4910	24.1220	22.5203
	MAPE (%)	62.7961	60.7990	58.6727	23.1347	21.4721
	TIC (–)	0.3426	0.3385	0.3370	0.0855	0.0796

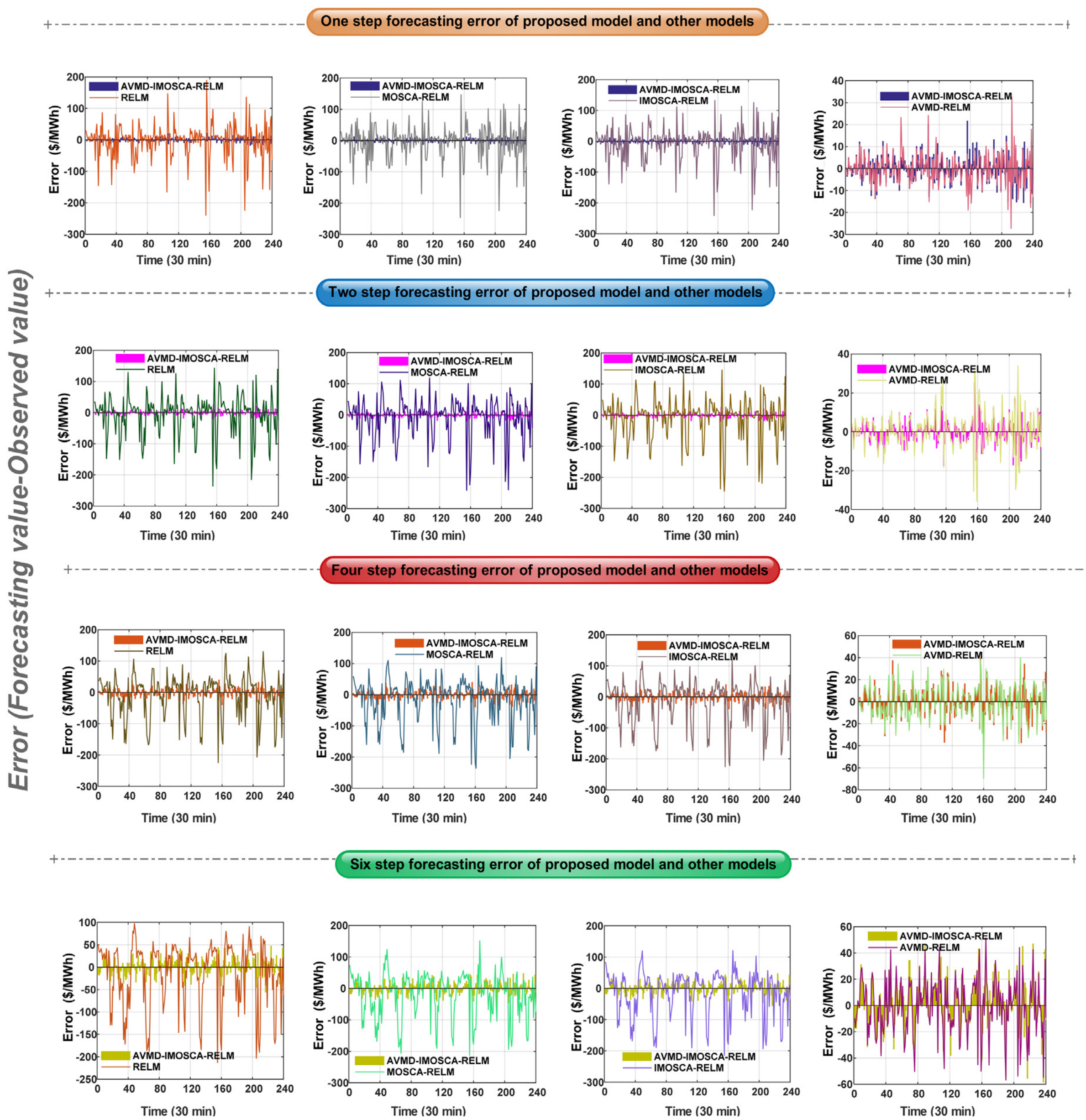

Fig. 6. Results of the proposed system and other models for Dataset B.

Table 5
Results of the developed system and other compared models for Dataset B.

Forecasting horizon	Metric	RELM	MOSCA-RELM	IMOSCA-RELM	AVMD-RELM	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	35.6170	36.0121	37.0248	5.2942	4.9065
	RMSE ($/MWh)	54.3252	53.2991	55.4741	7.1881	6.4098
	MAPE (%)	38.6256	38.1870	37.6175	7.2829	6.8934
	TIC (–)	0.2308	0.2270	0.2406	0.0294	0.0261
Two step forecasting	MAE ($/MWh)	41.3169	42.7565	42.1722	6.3022	4.9240
	RMSE ($/MWh)	61.0999	63.0315	64.3035	9.1355	6.5223
	MAPE (%)	44.1722	43.6300	42.2353	8.3865	6.5717
	TIC (–)	0.2660	0.2783	0.2843	0.0373	0.0267
Four step forecasting	MAE ($/MWh)	48.7931	50.3204	48.8927	12.2735	11.5707
	RMSE ($/MWh)	67.4779	70.6512	69.3549	15.2767	14.3208
	MAPE (%)	54.0121	52.9873	51.2272	17.2810	16.0150
	TIC (–)	0.3052	0.3280	0.3196	0.0628	0.0588
Six step forecasting	MAE ($/MWh)	52.9197	53.8629	52.1431	16.2881	15.8338
	RMSE ($/MWh)	70.7142	73.4345	71.3251	20.6190	19.9962
	MAPE (%)	60.5524	59.2155	58.0909	22.4856	22.3033
	TIC (–)	0.3292	0.3473	0.3326	0.0856	0.0826

designed in this case which can be combined with Case 1 to constitute a systematic and comprehensive case study for the evaluation of the developed system. In this case, the comparison studies are designed from three perspectives, i.e., perspective I: compared with the individual artificial intelligence model, perspective II: compared with the traditional forecasting model; and perspective III: compared with the models published in previous literature. These comparative studies adopt five models as benchmark models, that is, the ELM model, RELM model, ARIMA model, persistence model, and FEEMD-VMD-FA-BP method [6].

The forecasting results of each model are shown in Tables 6–7 and Figs. 7–8. According to the results, the same conclusion with Case 1 can be obtained. The proposed system is superior to other considered benchmark methods. However, the role of Case 2 is different from Case 1, which can obtain some new findings by conducting some different comparisons.

And the detailed analysis are as follows:

(1) The ELM model is compared with the RELM model and the developed system, as per perspective I (compared with the individual artificial intelligence model). The RELM model is the improved version of the well-known ELM model; thus, its superiority over the original ELM model should be verified and analyzed. Besides, the system's superiority needs to be proved by comparing with the original ELM model. According to the results shown in Tables 6–7 and Figs. 7–8, it can be concluded that the RELM model can significantly outperform the original ELM model. Furthermore, the conclusion can be supported by the improvement values of MAPE in NSW, which are 3.3102%, 2.4845%, 3.4369%, and 1.3474% for one-step, two-step, four step and six-step, respectively.

(2) In the perspective II, the traditional forecasting models including ARIMA model and persistence model are considered as benchmark models for further proving the developed system's effectiveness of electricity price forecasting. For instance, for one-step forecasting in NSW, the MAPE (TIC) values of the presented system and the comparison models (i.e., ARIMA model, persistence model) are 6.2210% (0.0231), 34.3438% (0.2010), and 30.0115 (0.1980), respectively. Therefore, the newly proposed system performs better than other traditional forecasting methods.

(3) To further prove the proposed system's novelty and contribution, the previous studies must be considered in the case study. Therefore, in this case, perspective III is designed to compare the models published in previous literature. Specifically, the advancement of this study compared with the FEEMD-VMD-FA-BP model [6] is evaluated and proved in NSW and QLD. It is obvious that the forecasting performance of the newly proposed system is superior to that of the FEEMD-VMD-FA-BP model from previous literature. Therefore, it can be concluded that the newly developed forecasting technique is more effective than previous models for improving the electricity price forecasting performance, which can be widely used in management practice.

4.5. Statistical significance based on nonparametric testing method

Based on the above-mentioned analysis in Case 1 and Case 2, four evaluation metrics are used to evaluate the model's performance from two perspectives, i.e., forecasting accuracy measured by MAE, RMSE, and MAPE and forecasting ability measured by TIC. Performance metric based evaluations are necessary but not sufficient to prove the superiority of one forecasting model. More specifically, the statistical performance must be proved from a statistical perspective. Therefore, in this study, three nonparametric testing methods, i.e., Friedman, Friedman Aligned Ranks, and Quade tests [69], are used to prove the statistical significance of the newly proposed system. The testing results for Case 1 and Case 2 are presented in Tables 8–9, which is calculated based on MAPE and TIC to prove the forecasting accuracy and ability from statistical perspectives. Specifically, the developed system obtains the minimum rank in all cases, and the corresponding p-value is less than 0.05, which proves that the developed system obtains the best forecasting accuracy and ability in the statistical sense. Taking MAPE values of Case 1 as an example, the ranks of the developed system by Friedman, Friedman aligned ranks, and Quade tests are 1.0000, 3.7500 and 1.0000, respectively, and the corresponding p-value are 0.0030, 0.0116, and 0.0001, respectively. Furthermore, the same conclusion can be supported by the testing results obtained by Case 2. Thus, based on the above-mentioned statistical testing and previous evaluation based on four metrics, we can believe that the proposed system has the best forecasting performance compared with others, which can be an effective technique in management practice.

4.6. Hypothesis testing

To further prove the superiority and robustness of the newly developed model, the model should be compared against other forecasting methods using hypothesis tests. Diebold–Mariano (DM) test is a commonly used hypothesis testing method, proposed by Diebold and Mariano [70], and has been widely used for model comparison in many forecasting fields [71,72]. Therefore, the DM test is selected as a hypothesis testing method for testing the proposed system's superiority against other models. The results of the DM test are presented in Table 10, which reveals that the proposed system significantly performs better than other benchmark models because the values of the DM test are greater than the critical value at different significance levels, and most of which are at a 1% significance level. In summary, the model's superiority compared with other models is not only supported by some accuracy metrics but also by the hypothesis testing methods. Therefore, the developed model exhibits excellent forecasting performance than other methods in electricity price forecasting.

5. Discussion

5.1. Problem to be discussed

As mentioned above, data preprocessing is widely used in complex time series forecasting fields and has yielded definite results recently. In most previous studies, the data decomposition technology is used to decompose the entire time series. However, a limitation with this technique is that future information is used in the data preprocessing stage of the hybrid forecasting model for time series forecasting, which needs the presupposition that using future information will not affect the decomposition results. Thus, the developed system may perform well in research studies but cannot obtain the desirable forecasting performance in management practice. In other words, the forecasting performance of the developed system in management practice cannot achieve the same performance as the performance reported in published papers. From the analysis on present phenomenon, we know that there are problems with the present models, i.e., the assumption might be wrong, so the previous studies lack management practical value, and the models cannot be applied in management practice because the future information is actually unknown in management practical applications. It is not reasonable to expect the user to obtain the unknown future information

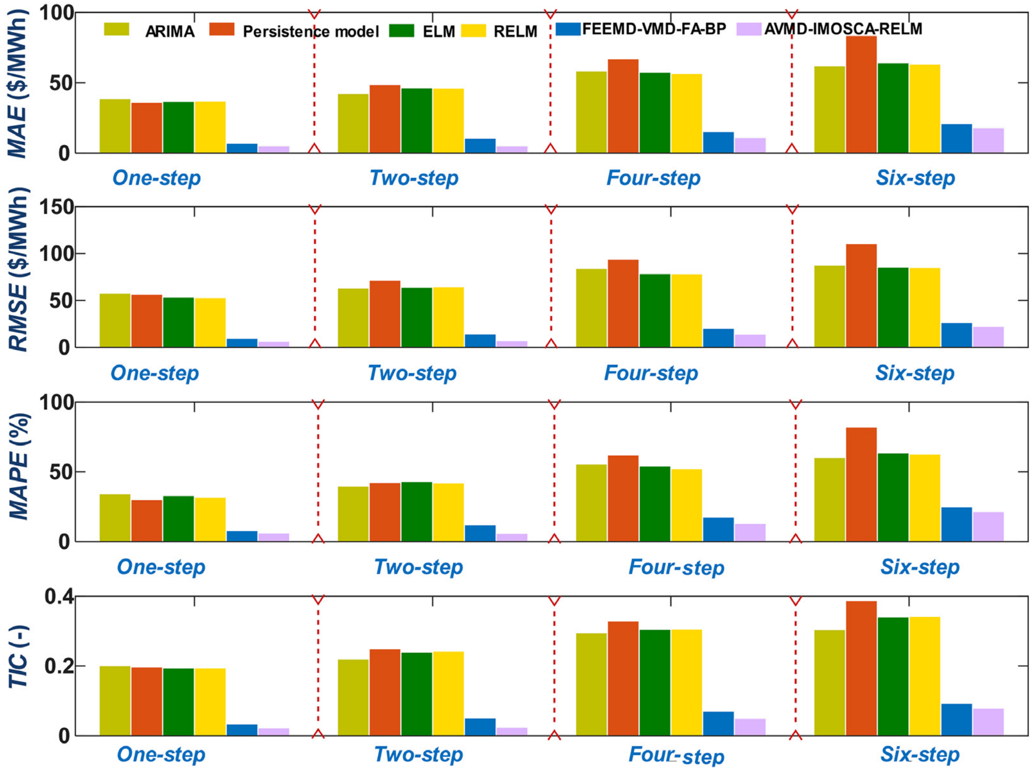

Fig. 7. Results of the developed system and other models for Dataset A.

Table 6
Results of the developed system and other compared models for Dataset A.

Forecasting horizon	Metric	ARIMA	Persistence model	ELM	RELM	FEEMD-VMD-FA-BP	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	38.6569	36.0653	36.7739	37.0144	7.1700	5.0526
	RMSE ($/MWh)	57.6842	56.7951	53.5548	53.1597	9.7700	6.6198
	MAPE (%)	34.3438	30.0115	32.9772	31.8856	7.8800	6.2210
	TIC (–)	0.2010	0.1980	0.1948	0.1949	0.0342	0.0231
Two step forecasting	MAE ($/MWh)	42.3888	48.7729	46.4954	46.3195	10.5400	5.0436
	RMSE ($/MWh)	63.2344	71.6023	64.1495	64.7371	14.5000	7.1178
	MAPE (%)	39.8166	42.2555	43.0835	42.0131	12.1700	5.9536
	TIC (–)	0.2204	0.2498	0.2400	0.2428	0.0509	0.0249
Four step forecasting	MAE ($/MWh)	58.5089	67.0062	57.6035	56.6309	15.4300	10.9829
	RMSE ($/MWh)	84.2328	94.0418	78.6492	78.4857	20.2500	14.2507
	MAPE (%)	55.5595	62.0614	54.2241	52.3604	17.6400	12.9430
	TIC (–)	0.2956	0.3293	0.3053	0.3060	0.0710	0.0500
Six step forecasting	MAE ($/MWh)	62.0675	83.6430	64.1661	63.3496	21.1000	18.0260
	RMSE ($/MWh)	87.5942	110.6989	85.6308	85.2268	26.6100	22.5203
	MAPE (%)	60.3076	82.0720	63.6538	62.7961	24.8900	21.4721
	TIC (–)	0.3045	0.3878	0.3410	0.3426	0.0936	0.0796

and decompose the entire original data to capture the main features from past data and future data, which may lead to poor forecasting performance in management practice while providing good performance in research studies.

5.2. Solution of the problem and conclusion

Therefore, in this study, an adaptive forecasting system was developed which successfully improved the deterministic forecasting performance in management practice. Different from most previous electricity price forecasting studies, there is no future information required in the modeling process. In addition, the developed system achieves self-adjustment at the data preprocessing stage and forecasting stage as long as future electricity price information is provided. Thus, the presumption that using the future data will not affect the results of the model is not required, thus making the model a novel deterministic forecasting technique with management practical value. To verify the management practical value and analyze the difference between the developed system and previous studies, the comparative study between the developed system AVMD-IMOSCA-RELM and the VMD-IMOSCA-RLM model is discussed in this section. The comparison results of these two models are shown in Table 11. From the information presented in Table 11, it can be observed that the proposed system performs better than the VMD-IMOSCA-RLM model in some cases, while it performs worse than the VMD-IMOSCA-RLM model in other cases. Moreover, there are differences between these two models' performances, and taking MAPE as a measurement standard, the proposed system is superior to the benchmark model in almost all cases. Therefore, we can tentatively conclude that the presented system may not only obtain a better performance but also have a promising future in applications and a good practical value in terms of management.

Table 7
Results of the developed system and other compared models for Dataset B.

Forecasting horizon	Metric	ARIMA	Persistence model	ELM	RELM	FEEMD-VMD-FA-BP	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	38.7566	36.5113	36.1961	35.6170	8.6000	4.9065
	RMSE ($/MWh)	59.2428	58.3602	54.1360	54.3252	12.0400	6.4098
	MAPE (%)	43.6008	38.1938	39.2060	38.6256	10.2500	6.8934
	TIC (−)	0.2398	0.2379	0.2310	0.2308	0.0491	0.0261
Two step forecasting	MAE ($/MWh)	38.6882	44.3420	42.3827	41.3169	9.2100	4.9240
	RMSE ($/MWh)	58.3634	69.1275	61.3902	61.0999	12.6500	6.5223
	MAPE (%)	40.0503	45.5398	44.7835	44.1722	11.2100	6.5717
	TIC (−)	0.2395	0.2816	0.2685	0.2660	0.0516	0.0267
Four step forecasting	MAE ($/MWh)	46.1681	58.9435	49.6327	48.7931	14.3300	11.5707
	RMSE ($/MWh)	67.9453	82.6337	68.7087	67.4779	19.2200	14.3208
	MAPE (%)	48.5901	62.7094	54.8294	54.0121	17.8500	16.0150
	TIC (−)	0.2806	0.3382	0.3118	0.3052	0.0789	0.0588
Six step forecasting	MAE ($/MWh)	52.9860	69.1331	53.7929	52.9197	18.5700	15.8338
	RMSE ($/MWh)	73.1410	92.6139	71.8278	70.7142	24.2800	19.9962
	MAPE (%)	57.1438	76.6586	61.0365	60.5524	24.9200	22.3033
	TIC (−)	0.3007	0.3791	0.3331	0.3292	0.0998	0.0826

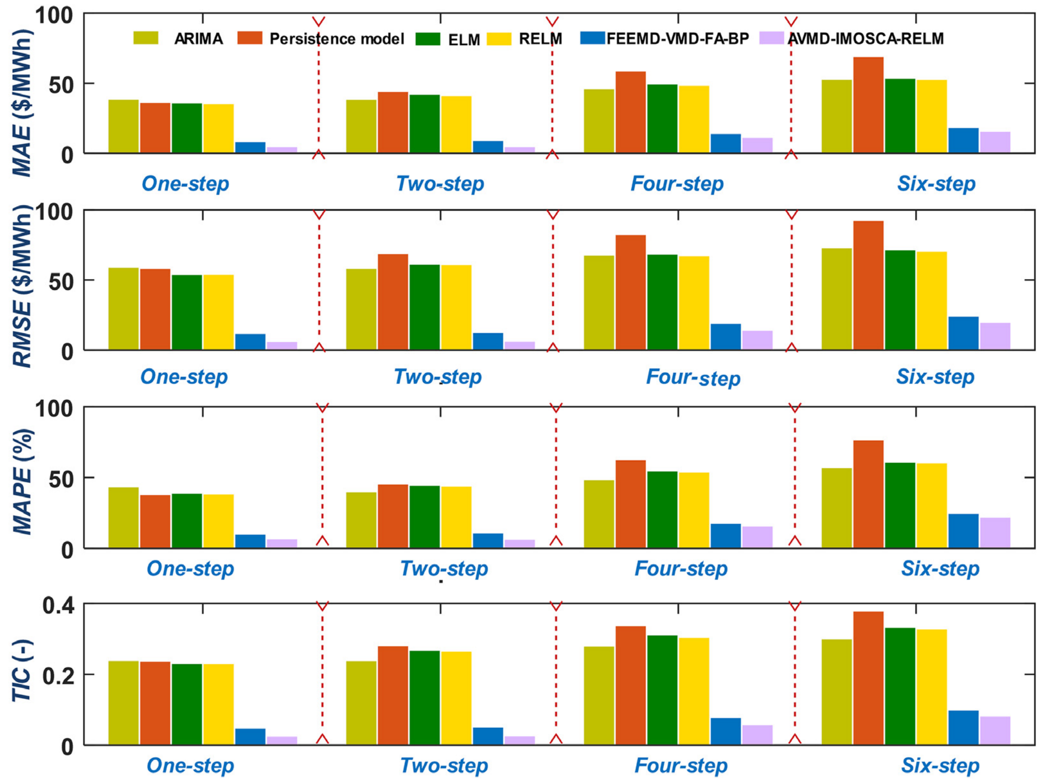

Fig. 8. Results of the developed system and other models for Dataset B.

Table 8
Testing results of the developed forecasting system and other compared models in case 1.

	Models	MAPE			TIC		
		Friedman	Friedman aligned	Quade	Friedman	Friedman aligned	Quade
Dataset A	RELM	5.0000	16.7500	5.0000	4.0000	14.5000	4.1000
	MOSCA-RELM	4.0000	14.5000	4.0000	4.5000	15.0000	4.3000
	IMOSCA-RELM	3.0000	12.2500	3.0000	3.5000	14.0000	3.6000
	AVMD-RELM	2.0000	5.2500	2.0000	2.0000	5.2500	2.0000
	AVMD-IMOSCA-RELM	1.0000	3.7500	1.0000	1.0000	3.7500	1.0000
	p-value	0.0030	0.0116	0.0001	0.0087	0.0165	0.0047
Dataset B	RELM	5.0000	17.0000	5.0000	3.2500	14.5000	4.1000
	MOSCA-RELM	4.0000	14.5000	4.0000	4.2500	15.0000	4.3000
	IMOSCA-RELM	3.0000	12.0000	3.0000	4.5000	14.0000	3.6000
	AVMD-RELM	2.0000	5.7500	2.0000	2.0000	5.2500	2.0000
	AVMD-IMOSCA-RELM	1.0000	3.2500	1.0000	1.0000	3.7500	1.0000
	p-value	0.0030	0.0094	0.0001	0.0067	0.0165	0.0047

Table 9
Testing results of the developed forecasting system and other compared models in Case 2.

	Models	MAPE			TIC		
		Friedman	Friedman aligned	Quade	Friedman	Friedman aligned	Quade
Dataset A	ARIMA	4.2500	15.0000	3.9000	3.7500	12.2500	3.3000
	Persistence model	5.0000	18.7500	5.5000	5.7500	19.5000	5.9000
	ELM	5.0000	17.7500	4.9000	3.7500	16.5000	3.9000
	RELM	3.7500	14.5000	3.7000	4.7500	17.7500	4.9000
	FEEMD-VMD-FA-BP	2.0000	5.5000	2.0000	2.0000	5.2500	2.0000
	AVMD-IMOSCA-RELM	1.0000	3.5000	1.0000	1.0000	3.7500	1.0000
	p-value	0.0082	0.0103	0.0015	0.0038	0.0070	0.0002
Dataset B	ARIMA	3.7500	13.0000	3.3000	3.7500	11.2500	3.3000
	Persistence model	5.2500	20.0000	5.7000	5.7500	20.7500	5.9000
	ELM	5.0000	17.2500	5.0000	4.7500	18.2500	4.9000
	RELM	4.0000	15.7500	4.0000	3.7500	15.7500	3.9000
	FEEMD-VMD-FA-BP	2.0000	5.7500	2.0000	2.0000	6.0000	2.0000
	AVMD-IMOSCA-RELM	1.0000	3.2500	1.0000	1.0000	3.0000	1.0000
	p-value	0.0064	0.0084	0.0003	0.0038	0.0039	0.0002

Table 10
Testing results of the DM test for different models.

Dataset	Model	Forecasting horizon				
		One step	Two step	Four step	Six step	Average
Dataset A	Persistence model	7.4750*	8.3945*	9.3551*	10.5293*	8.9385*
	ARIMA	7.6618*	7.1951*	8.5980*	8.9595*	8.1036*
	ELM	7.4928*	8.4994*	8.7380*	8.8569*	8.3968*
	RELM	7.8820*	8.3427*	8.4835*	8.7000*	8.3521*
	AVMD-RELM	1.5473****	3.3209*	2.9603*	2.4695**	2.5745**
	MOSCA-RELM	8.0954*	8.4015*	8.5147*	8.6815*	8.4233*
	IMOSCA-RELM	7.8750*	8.2777*	8.4581*	8.5597*	8.2926*
	AVMD-IMOSCA-RELM					
Dataset B	Persistence model	6.1650*	7.5244*	9.2395*	9.9087*	8.2094*
	ARIMA	6.2286*	6.7559*	7.6557*	8.5417*	7.2955*
	ELM	6.4084*	7.7396*	8.2563*	8.4448*	7.7122*
	RELM	6.3505*	7.6058*	8.3821*	8.1867*	7.6313*
	AVMD-RELM	1.7724***	4.4178*	1.4297*****	1.0163	2.1590**
	MOSCA-RELM	6.5753*	7.1020*	7.9587*	8.5389*	7.5437*
	IMOSCA-RELM	6.8164*	7.1443*	7.9731*	8.2386*	7.5431*
	AVMD-IMOSCA-RELM					
Average	Persistence model	6.8200*	7.9594*	9.2973*	10.2190*	8.5739*
	ARIMA	6.9452*	6.9755*	8.1269*	8.7506*	7.6995*
	ELM	6.9506*	8.1195*	8.4972*	8.6508*	8.0545*
	RELM	7.1163*	7.9742*	8.4328*	8.4433*	7.9917*
	AVMD-RELM	1.6599***	3.8693*	2.1950**	1.7429***	2.3668**
	MOSCA-RELM	7.3354*	7.7518*	8.2367*	8.6102*	7.9835*
	IMOSCA-RELM	7.3457*	7.7110*	8.2156*	8.3992*	7.9179*
	AVMD-IMOSCA-RELM					

*1% significance level.
**5% significance level.
***10% significance level.
****15% significance level.
*****20% significance level.

Table 11
Comparison results for Dataset A and Dataset B.

Dataset A	MAE ($/MWh)	RMSE ($/MWh)	MAPE (%)	TIC (–)	Dataset B	MAE ($/MWh)	RMSE ($/MWh)	MAPE (%)	TIC (–)
One step forecasting					One step forecasting				
VMD-IMOSCA-RELM	5.5149	6.6906	6.7652	0.0233	VMD-IMOSCA-RELM	5.2487	6.5964	7.5765	0.0268
AVMD-IMOSCA-RELM	5.0526	6.6198	6.2210	0.0231	AVMD-IMOSCA-RELM	4.9065	6.4098	6.8934	0.0261
Two step forecasting					Two step forecasting				
VMD-IMOSCA-RELM	5.5491	7.2723	6.6214	0.0254	VMD-IMOSCA-RELM	5.5501	7.0996	8.2733	0.0290
AVMD-IMOSCA-RELM	5.0436	7.1178	5.9536	0.0249	AVMD-IMOSCA-RELM	4.9240	6.5223	6.5717	0.0267
Four step forecasting					Four step forecasting				
VMD-IMOSCA-RELM	11.8297	15.2171	14.4697	0.0535	VMD-IMOSCA-RELM	11.8011	14.5836	16.4251	0.0600
AVMD-IMOSCA-RELM	10.9829	14.2507	12.9430	0.0500	AVMD-IMOSCA-RELM	11.5707	14.3208	16.0150	0.0588
Six step forecasting					Six step forecasting				
VMD-IMOSCA-RELM	18.5801	23.2700	20.5991	0.0828	VMD-IMOSCA-RELM	17.7140	22.4880	23.7736	0.0935
AVMD-IMOSCA-RELM	18.0260	22.5203	21.4721	0.0796	AVMD-IMOSCA-RELM	15.8338	19.9962	22.3033	0.0826

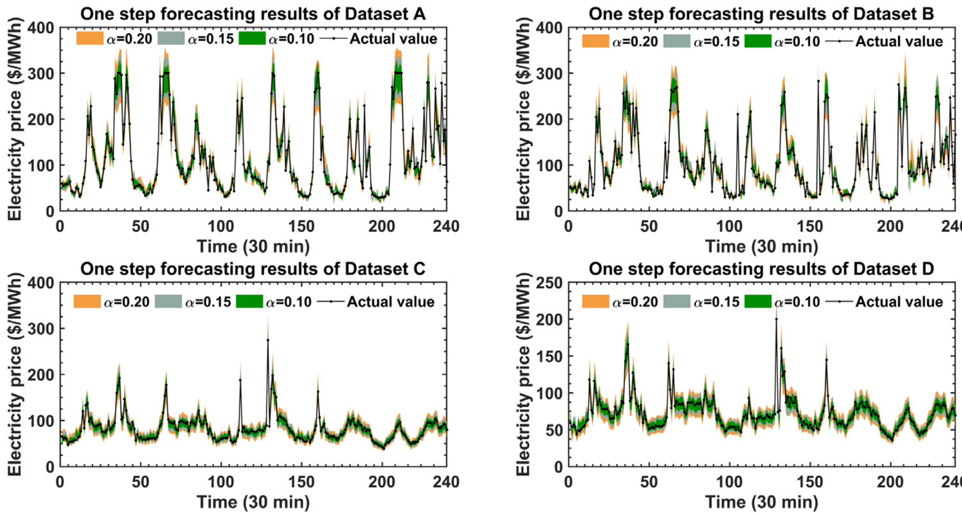

Fig. 9. Interval forecasting results for one step electricity price forecasting.

5.3. The most reasonable explanation and conclusion

However, the new findings may appear different from our previous guesses. The reason for the phenomenon shown in this comparative study is that the forecasting performance of the previous models may be influenced by data characteristics. Therefore, it is necessary to conduct a further comparative study and analysis to verify the rationality of the above-mentioned reason and then obtain more reasonable and credible conclusions. For this aim, two new datasets collected from NSW and QLD are employed in this comparative study, denoted as Dataset C and Dataset D, respectively. Similarly to Dataset A and Dataset B, the time resolution is 30 min. The total number of observation values of each dataset is 1440, covering 30 days from June 1, 2018, to June 30, 2018. The number of training data points is 1200 (from June 1, 2018, to June 25, 2018) and the number of testing data points is 240 (from June 26, 2018, to June 30, 2018). The comparative study between the developed system AVMD-IMOSCA-RELM and the VMD-IMOSCA-RLM model is conducted and analyzed based on Dataset C and D, and the corresponding results are shown in Table 12. Different from results obtained from previous comparative studies based on Dataset A and Dataset B, a completely opposite result was obtained. Taking MAPE as a measurement standard, the proposed system performs worse than the benchmark model in almost all cases. Based on this, we can safely and reasonably believe that the previous obtained tentative conclusions are not reasonable. In general, because of the influence of data characteristics, the proposed forecasting system may be better or worse than the benchmark methods.

5.4. Summary based on the above-mentioned analysis

In summary, the forecasting model will obtain different forecasting performances based on different datasets. Furthermore, the above-mentioned difference always exists but may be different in each case. Specifically, sometimes the developed system performs worse than the compared model, sometimes not. However, it does not mean the developed system is unstable. This perfectly illustrates the fact that using future information or not using it in a modeling process will affect the final forecasting performance. Besides, the future information is actually unknown in management practical application, and the above-mentioned assumption is wrong. Furthermore, it is not reasonable to develop a forecasting model by overdraft future information. More importantly, modeling using future information leads to low management practical value because the future information is unknown. Therefore, developing an adaptive forecasting system to improve the model's generalization ability and to decrease the previous researches' negative effects in management practical application is highly desirable. In this study, the developed system achieves self-adjustment at the data preprocessing stage and forecasting stage as long as future electricity price information is available, and the above-mentioned assumption does not need to be followed. This model is a novel deterministic forecasting technique with high management practical value. This provides persuasive evidence for proving that our study fills the research gap and provides some new suggestions for related future studies.

6. Comparative study for the probabilistic interval forecasting

As mentioned before, performing effective probabilistic interval forecasting for electricity price has become highly desirable for the whole society. Therefore, in this paper, a probabilistic interval forecasting system for electricity price was successfully developed based on the framework of the proposed adaptive electricity price deterministic forecasting system. Furthermore, a comparative study for the probabilistic interval forecasting is conducted as follows:

6.1. Analysis based on one-step electricity price interval forecasting

To validate the effectiveness of the proposed probabilistic interval forecasting system, a detailed comparison is conducted between those two sets of data, i.e., (1) Dataset A and Dataset B, and (2) Dataset C and Dataset D. The main aim of conducting this comparative study was to analyze the difference of the model's forecasting performance on different datasets and further to explore the relationship between the system's performance for deterministic forecasting and probabilistic interval forecasting.

Therefore, in this section, one-step electricity price probabilistic interval forecasting results are presented in Table 13, which includes comparative results based on Dataset A, Dataset B, Dataset C, and Dataset D for three expectation probability (i.e., $(1-a)\times 100\%$, 90%, 85% and 80%). Besides, the forecasting results are shown in Fig. 9. According to the results shown in Table 13 and Fig. 9, it can be found that the forecasting performance of the proposed system on Dataset C and Dataset D is superior to Dataset A and Dataset B. Through the comparison and analysis, we found a similarity in both deterministic forecasting results shown in Tables 11–12 and the probabilistic interval

Table 12
Comparison results for Dataset C and Dataset D.

Dataset C	MAE ($/MWh)	RMSE ($/MWh)	MAPE (%)	TIC (–)	Dataset D	MAE ($/MWh)	RMSE ($/MWh)	MAPE (%)	TIC (–)
One step forecasting					One step forecasting				
VMD-IMOSCA-RELM	2.8106	3.6267	3.5577	0.0207	VMD-IMOSCA-RELM	2.0712	2.9979	2.8919	0.0198
AVMD-IMOSCA-RELM	3.3231	4.4097	4.3047	0.0251	AVMD-IMOSCA-RELM	2.3136	3.3701	3.3834	0.0222
Two step forecasting					Two step forecasting				
VMD-IMOSCA-RELM	2.6933	3.6921	3.4620	0.0210	VMD-IMOSCA-RELM	1.9604	2.7208	2.7439	0.0179
AVMD-IMOSCA-RELM	2.8614	3.9362	3.6306	0.0224	AVMD-IMOSCA-RELM	2.4001	3.2023	3.5518	0.0212
Four step forecasting					Four step forecasting				
VMD-IMOSCA-RELM	5.1497	6.7807	6.4631	0.0388	VMD-IMOSCA-RELM	3.1399	4.0820	4.4290	0.0271
AVMD-IMOSCA-RELM	5.5547	8.1245	6.9021	0.0466	AVMD-IMOSCA-RELM	3.4908	4.5502	5.1706	0.0302
Six step forecasting					Six step forecasting				
VMD-IMOSCA-RELM	7.6383	10.0088	9.6223	0.0577	VMD-IMOSCA-RELM	5.2402	7.1287	7.4042	0.0472
AVMD-IMOSCA-RELM	6.1212	8.4333	7.3928	0.0488	AVMD-IMOSCA-RELM	4.7830	6.5553	6.9157	0.0436

forecasting results presented in Table 13. Thus, whether for deterministic forecasting and probabilistic interval forecasting, the developed system performs better on the latter two datasets than the previous two. This may be due to the different characteristics of different datasets. More importantly, according to the presented similar results, it can be found that the probabilistic interval forecasting performance based on multi-input multi-output scheme have certain correlations with the deterministic forecasting performance. More specifically, if one model performs better in deterministic forecasting, it will be a good predictor in probabilistic interval forecasting.

6.2. Analysis based on multi-step electricity price interval forecasting

Analysis based on one-step electricity price interval forecasting was conducted in Section 6.1while they are insufficient in management of the electricity market. It was necessary, thus, to develop a multi-step interval forecasting system for all participants. Therefore, the second aim was to analyze a multi-step electricity price interval forecasting method. The forecasting results are shown in Table 14 and Figs. 10–11, which comprise of the experiments based on three expectation probability ((1- a) $\times$ 100%, 90%, 85% and 80%). The similar conclusions obtained in Section 6.1 can be supported by the results shown in Table 14 and Figs. 10–11. Besides, we can also see that the developed system gets worse with the increase of the forecasting horizon. For expectation probability of 90%, taking dataset C as an example, the FICP values are 99.166667% and 94.166667% for two-step and three-step ahead forecasting, respectively.

Moreover, the multi-step interval forecasting effectiveness of the proposed system based on Dataset A and B became worse compared with the one-step forecasting method, thus leading to a lower forecasting value. As previously analyzed, it is probably because the developed system for multi-step deterministic forecasting performs worse than one-step forecasting. In fact, this case was unavoidable because of the challenge of improving the performance of the multi-step ahead forecasting in the forecasting fields. Furthermore, for Dataset C and Dataset D, the developed system performs better than the previous two datasets. For instance, as for 90% expectation probability, the FICP values of two-step forecasting are 68.333333%, 66.250000%, 87.500000% and 93.333333% for Dataset A, Dataset B, Dataset C and Dataset D, respectively, while the values are 59.166667%, 55.833333%, 75.833333%, and 88.750000% for three-step forecasting, respectively. In summary, although the developed system has a worse interval forecasting performance in some cases, for example in multi-step interval forecasting for Dataset A and Dataset B, it still performs better than the other benchmark models. In view of the forecasting performance of the proposed system, it can be concluded that it is a promising alternative for electricity price multi-step probabilistic interval forecasting.

7. Further analysis

In this section, robustness analyses, superiority analyses, analyses of system nature, and analysis on the novelty, opportunities, and limitations are provided.

7.1. Robustness analyses of the developed system

For an effective forecasting system, the forecasting system's robustness in different time and locations needs to be proved. The above-mentioned analysis only focuses on drawing the conclusion that the proposed forecasting system is superior to other benchmark models, without considering the robustness. Fortunately, based on above-mentioned experimental results, further analyses can be done to prove its robustness at different times and locations. Firstly, the two datasets in 2016, i.e., Dataset A and Dataset B, and another two datasets in 2018, i.e., Dataset C and Dataset D, are employed in the case study, which can be considered as the validation studies from the perspective of different times. From the forecasting results shown in the comparative studies, it can be found that the proposed system performs well in both Dataset A and Dataset B. Therefore, we can reasonably prove the robustness in electricity price forecasting of different times. Secondly, in this paper, four datasets collected from different locations, i.e., two datasets are collected from NSW while another two are collected from QLD, are used as experimental datasets. Comparative results reveal that the developed model performs better in NSW and QLD. Due to the significantly different environments of these two locations, these four datasets collected from different locations can be employed to measure the system's robustness at different locations. Therefore, based on the system's superiority in NSW and QLD, we can safely believe that the system is robust for electricity price forecasting at different locations. In summary, according to the superior performance of the developed system in electricity price forecasting of different times and different locations, the forecasting system's robustness in different times and locations can be proved.

7.2. Superiority analyses of the developed system

To further validate the system's superiority for forecasting electricity price, it is necessary to provide a comprehensive comparison between the proposed method and current existing methods. Therefore, in this section, four existing methods in [6] including FEEMD-FA-BP, VMD-FA-BP, EEMD-Genetic algorithm (GA)-BP, and WT-GA-SVM are considered as compared models to conduct the superiority analyses of the proposed system. The values of four evaluation metrics including MAE, RMSE, MAPE and TIC of

Table 13
One-step electricity price probabilistic interval forecasting results.

One step forecasting				
Dataset A	Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
	0.10	77.083333	0.086321	0.000427
	0.15	89.166667	0.128913	0.000142
	0.20	92.916667	0.173009	0.000061
Dataset B	Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
	0.10	77.500000	0.079227	0.000503
	0.15	89.583333	0.119833	0.000181
	0.20	93.333333	0.160391	0.000099
Dataset C	Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
	0.10	96.250000	0.070133	0.000035
	0.15	99.583333	0.105341	0.000005
	0.20	100.000000	0.140517	0.000145
Dataset D	Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
	0.10	96.250000	0.088025	0.000049
	0.15	98.750000	0.131662	0.000008
	0.20	99.166667	0.175209	0.000007

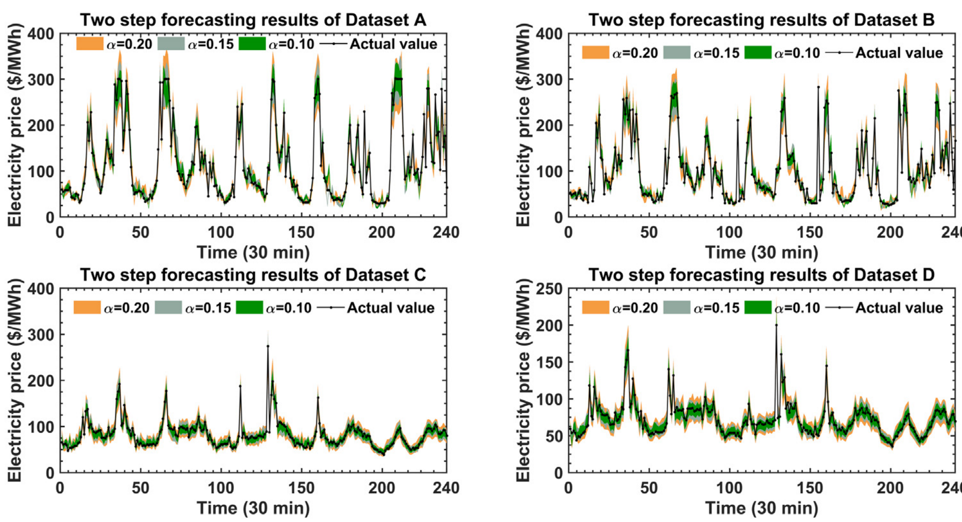

Fig. 10. Interval forecasting results for two step electricity price forecasting.

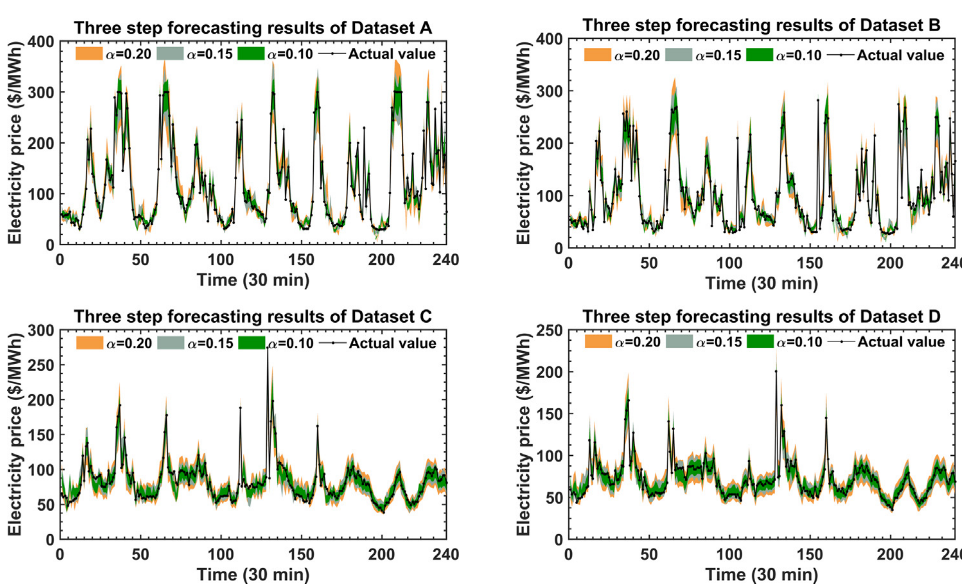

Fig. 11. Interval forecasting results for three step electricity price forecasting.

Table 14
Multi-step electricity price probabilistic interval forecasting results.

	Two step forecasting			Three step forecasting		
	Dataset A					
Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
0.10	68.333333	0.086478	0.000654	59.166667	0.085977	0.001178
0.15	76.250000	0.129748	0.000291	72.916667	0.129088	0.000287
0.20	87.500000	0.172462	0.000118	77.916667	0.172539	0.000526
	Dataset B					
Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
0.10	66.250000	0.080452	0.000666	55.833333	0.080045	0.001199
0.15	80.833333	0.118886	0.000243	71.666667	0.118591	0.000611
0.20	87.083333	0.160193	0.000192	76.666667	0.159093	0.000422
	Dataset C					
Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
0.10	87.500000	0.070057	0.000096	75.833333	0.070088	0.000329
0.15	95.416667	0.105364	0.000026	87.083333	0.104929	0.000145
0.20	99.166667	0.141206	0.000004	94.166667	0.140208	0.000034
	Dataset D					
Alpha	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})	FICP (%)	FINAW (–)	AWD ($/MWh^{-1})
0.10	93.333333	0.087666	0.000103	88.750000	0.087925	0.000113
0.15	98.750000	0.131470	0.000011	97.083333	0.132128	0.000022
0.20	99.583333	0.175962	0.000007	98.750000	0.176170	0.000005

these considered benchmark models and the developed models for Dataset A and Dataset B are shown in Tables 15–16. From Tables 15–16, it can be observed that the metric values of the proposed system are all smaller than those of all considered benchmark models in both one step and multi-step forecasting, which further proves the developed system's superiority. All experiments and discussions are conducted based on electricity price data collected from two regions with different characteristics, time, and locations, leading to different forecasting performances in the above cases but the best forecasting results when compared with all benchmark models. In summary, all the above-mentioned analyses can reasonably prove the developed system's superiority in electricity price forecasting.

Specifically, a comprehensive comparison between the proposed method and current methods can be conducted and provided with more details. Firstly, by comparing the VMD-FA-BP and FEEMD-FA-BP model, it can be observed that the VMD algorithm is superior to the FEEMD method, which indicates that the VMD approach is helpful to achieve more accurate forecasting than other methods. Secondly, the comparison between the proposed method and other methods can also verify the superiority of the developed system's components. Finally, except the comparison between the proposed system and current existing models listed in Tables 15 and 16, the developed system shows a significant difference when compared with the current models, that is, the nature of no future information and adaptive self-adjustment model.

7.3. Analyses of the nature of the developed system

As it is clear, there are many studies that have used decomposition and optimization techniques and advanced forecasting tools. However, most previous studies decompose all original time series into some components before forecasting, which is unsuitable for real application and is the most important issue that needs to be solved in engineering applications. Therefore, the main aim of this study is developing an electricity forecasting system without using any future information for real application in the management of electrical power systems and electricity market, which will make up for the deficiencies in the existing research. In this system, the decomposition and forecast models are highly self-adaptive and can be updated as long as new electricity price information is added rather than being fixed.

Specifically, when we expect to predict the price of electricity at the current moment, the future information can be defined as the electricity price information at the current moment and after the current moment. For example, at a given time t, the future electricity price value of time $t+1$ needs to be forecasted, and then, all the actual values after time t are defined as future information. According to whether or not future electricity price information are employed in the modeling process, the forecasting model can be divided into hindcast forecasting model and adaptive forecasting model. Specifically, because the future information is considered in the modeling of hindcast forecast, the hindcast model cannot be applied in real practical applications, which may lead to an illusion of desirable effectiveness and cannot draw the conclusion that the VMD technique is helpful to achieve more accurate forecasting. This means we cannot draw the conclusion based on the hindcast model. On the contrary, different from the hindcast model, the adaptive forecast model developed in this study is suitable for electricity price forecasting in real application, which does not use any future electricity price information. Besides, different from the conventional forecasting model, the model of decomposition and forecasting is adaptively adjusted as long as new electricity price information is added rather than being fixed. Therefore, compared with the hindcast model and conventional forecasting model, the developed adaptive model is more flexible regarding the optimal integration of the new information that is revealed in each step. Moreover, the decomposition results are provided in Figs. 3 and 4, which indicate that these two methods have an obvious difference and will lead to different forecasting performance. Based on the obvious difference and excellent forecasting performance of the developed model, it can be concluded that the VMD technique is helpful to achieve more accurate forecasting. In summary, the present work is different from previous works based on not using future information and adaptive self-adjustment, which is not only the most important novelty of our study but also the main reason why this approach is significantly better and different than similar approaches.

7.4. Analysis on novelty, opportunities, and limitations

The novelty of the present study is summarized and provided in the introduction. Specifically, the main novelty including not using future information and adaptive self-adjustment feature is

Table 15
Results of the developed system and four existing methods for Dataset A.

Forecasting horizon	Metric	FEEMD-FA-BP	VMD-FA-BP	EEMD-GA-BP	WT-GA-SVM	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	15.3300	13.8200	20.6700	15.9600	5.0526
	RMSE ($/MWh)	22.3900	17.4000	27.7200	23.9900	6.6198
	MAPE (%)	13.8900	16.3100	18.8900	17.0100	6.2210
	TIC (–)	0.0791	0.0617	0.0986	0.0849	0.0231
Two step forecasting	MAE ($/MWh)	21.8700	14.8100	28.9900	30.5400	5.0436
	RMSE ($/MWh)	31.6600	18.7000	39.8500	41.5600	7.1178
	MAPE (%)	20.3100	17.0000	27.9000	30.4300	5.9536
	TIC (–)	0.1117	0.0665	0.1437	0.1498	0.0249
Four step forecasting	MAE ($/MWh)	25.1100	18.2800	36.2700	39.8000	10.9829
	RMSE ($/MWh)	34.6800	22.7700	49.4900	56.1500	14.2507
	MAPE (%)	25.0800	20.9300	35.5600	38.7600	12.9430
	TIC (–)	0.1220	0.0811	16.8400	0.2087	0.0500
Six step forecasting	MAE ($/MWh)	28.7900	24.0300	42.8300	45.8800	18.0260
	RMSE ($/MWh)	38.4300	30.1100	53.4100	59.8100	22.5203
	MAPE (%)	30.4000	27.4900	42.6100	44.5100	21.4721
	TIC (–)	0.1360	0.1080	0.1855	0.2221	0.0796

Table 16
Results of the developed system and four existing methods for Dataset B.

Forecasting horizon	Metric	FEEMD-FA-BP	VMD-FA-BP	EEMD-GA-BP	WT-GA-SVM	AVMD-IMOSCA-RELM
One step forecasting	MAE ($/MWh)	19.9600	11.8600	17.6800	15.4900	4.9065
	RMSE ($/MWh)	27.0000	14.9900	24.7100	21.6300	6.4098
	MAPE (%)	22.2900	15.2100	21.6200	18.7600	6.8934
	TIC (–)	0.1116	0.0620	0.1011	0.0894	0.0261
Two step forecasting	MAE ($/MWh)	20.7000	12.1400	23.3700	19.7900	4.9240
	RMSE ($/MWh)	27.3800	15.4900	33.1500	27.1400	6.5223
	MAPE (%)	23.5800	15.6800	27.3100	23.5200	6.5717
	TIC (–)	0.1128	0.0642	0.1436	0.1129	0.0267
Four step forecasting	MAE ($/MWh)	23.5400	15.3600	31.7900	27.9100	11.5707
	RMSE ($/MWh)	30.4700	19.2900	44.8300	40.6600	14.3208
	MAPE (%)	28.7200	19.6100	36.5400	33.9100	16.0150
	TIC (–)	0.1254	0.0802	0.1857	0.1673	0.0588
Six step forecasting	MAE ($/MWh)	25.3700	20.5500	38.1100	34.5300	15.8338
	RMSE ($/MWh)	35.4100	26.0700	54.2800	49.8100	19.9962
	MAPE (%)	30.4200	26.1000	43.7700	39.1600	22.3033
	TIC (–)	0.1469	0.1090	0.2517	0.2264	0.0826

further discussed based on analyses of the developed system. Furthermore, other innovations and new contributions of the developed system are presented in the introduction. The discussions on opportunities and limitations are presented in this section. To analyze the opportunities in electricity price forecasting, this study discusses the difference of hindcast forecasting model and adaptive forecasting model, the superiority of the newly proposed IMOSCA, and the superiority of the developed system compared with other benchmark models. The developed adaptive forecasting model is validated well for electricity price multi-step deterministic and probabilistic interval forecasting in NSW and QLD. The study will benefit the field of power system engineering and management as energy use continues to face major challenges. For example, QLD accounted for a large proportion of the country's average energy demand in 2012–2013 [73].

Although this study developed an adaptive electricity price forecasting system and successfully solved some major problems from most previous studies, some limitations need to be solved in future research. In this study, only electricity price data is considered in the modeling process of electricity price. However, modeling of electricity price can also take electricity demand, temperature, and other climatic data into consideration for improving the forecasting performance. Therefore, in future research, the climatic factors and electricity demand can be employed as candidate features to design the optimal input feature for better modeling of electricity price. Besides, day-ahead electricity price forecasting can provide more valuable information for the management of the power market and electrical power system, which can be investigated in future studies. Moreover, while the study provides NSW and QLD with an effective and superior forecasting model, different states and different regions of the state may present different scenarios. Finally, inspired by Zhou et al. [74], data preprocessing focused on outlier detection and processing may retain the main tendencies of electricity price data, which will further improve the forecasting performance and can be considered as another research direction.

8. Conclusion

In this study, an adaptive deterministic and probabilistic interval forecasting system is proposed for electricity price multi-step forecasting in this study, which is not required to follow the assumption that future values in preprocessing will not affect the results of the model and will be a novel forecasting technique with high management practical value. Furthermore, the developed system can self-adjust at the data preprocessing stage and forecasting stage as long as future electricity price information is available, which successfully improves the forecasting performance in management practice. To prove its performance in electricity price forecasting, some experiments are also presented in this paper. The results reveal that the presented system has the best forecasting performance among all benchmark models. Moreover, to illustrate the significance of this study and provide some new contributions for related studies, we conducted discussions on the above-mentioned issues by following three problems and one summary, which provides persuasive evidence for proving that our work fills the research gap and provides some new suggestions for related studies.

Furthermore, a multi-step probabilistic interval forecasting system for electricity price is successfully developed based on the framework of the proposed adaptive electricity price deterministic forecasting system. The comparative study for the probabilistic interval forecasting system is conducted to comprehensively analyze the model based on one-step and multi-step interval forecasting, which not only reveal the relationship between the performance of deterministic forecasting and interval forecasting but also prove that it is a promising alternative for electricity price multi-step probabilistic interval forecasting. In the future, further research will be required to study the detailed relationship and focus on improving the framework of the probabilistic interval forecasting system based on deterministic forecasting.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2019.106029.

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