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Forecasting day-ahead electricity prices using a new integrated model

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ABSTRACT

Electricity price forecasting proves useful for power producers and consumers to make proper decisions in a market-oriented environment. However, due to the complex drivers and sharp fluctuation of electricity prices, accurate electricity price forecasting turns to be very difficult. To better capture the characteristics of day-ahead electricity prices, a new integrated model based on the improved empirical mode decomposition (IEMD), autoregressive moving average with exogenous terms (ARMAX), exponential generalized autoregressive conditional heteroscedasticity (EGARCH) and adaptive network-based fuzzy inference system (ANFIS) is proposed in this paper. Then it is validated by using the data from Spanish and Australian electricity markets. The results indicate that the forecasting accuracy of the new integrated model proves higher than that of some well-recognized models in the literature.

1. Introduction

Accurate electricity price forecasting may help electricity market participants to formulate reasonable competition strategies. Specifically, power producers can use the forecasting results to optimize unit output, while power consumers can use the results to optimize purchase portfolio [1]. However, the complex features of electricity prices such as periodicity and high volatility make the forecasting pretty difficult [2].

In recent years, a lot of models have been proposed for electricity price forecasting [3–5]. In general, the commonly used models can be classified into two primary categories: soft computing models[1] [6–8] and time-series models [9,10]. For instance, Panapakidis and Dagoumas [11] use the artificial neural networks (ANNs) model for electricity price forecasting in Southern Italy. Sandhu et al. [12] employ the neural networks to forecast Ontario electricity prices. To better capture the characteristics of electricity prices, a combination of ANN models and other models is often presented. For instance, Ortiz et al. [13] propose a combined model based on artificial neural networks. Keles et al. [14] develop a model based on ANNs and optimal parameter model. Singh et al. [15] present a combined model with generalized neuron model and wavelet transform. Itaba and Mori [16] utilize the general radial basis function network and fuzzy clustering. Wang et al. [17] develop a hybrid model combined with ANNs and decomposition technique. It should be noted that although the ANNs model can describe the nonlinear characteristics of electricity price series, it cannot well deal with the linear fitting problem [18].

To describe the linear features of electricity prices, the time series model is often applied, which is considered as one of the most effective techniques [19]. Traditional time series models, such as autoregressive integrated moving average (ARIMA), autoregressive and moving average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH), have been frequently applied to forecast electricity prices. Besides, Diongue et al. [20] and Girish [21] propose some new time series models such as GIGARCH and autoregressive-GARCH. To better capture the features of electricity prices, some other models have been combined with time series models [22–26]. Since electricity price series is composed by linear and nonlinear components, the integrated models that have linear and nonlinear fitting capabilities can improve the forecasting accuracy [27,28]. For this reason, the empirical mode decomposition (EMD) approach has been used for electricity price decomposition by some researchers [29–31].

Through the above-mentioned analysis, we can find that existing relevant models have two main problems. The first problem is that the

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[1] In general, soft computing models often include evolutionary computation, fuzzy logic, artificial neural networks (ANNs), rough sets, and probabilistic reasoning.

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hybrid model combined with EMD has an end effect, which becomes the main factor affecting the accuracy of EMD. To address this problem, the improved EMD (IEMD) approach is brought into use. In this way, the linear and nonlinear components can be extracted more accurately and effectively. Second, the hybrid model combined with linear and nonlinear models cannot well describe the characteristics of electricity prices. Therefore, the ARMA with exogenous terms (ARMAX) model combined with the exponential GARCH model (ARMAX-EGARCH) is used to describe the linear component, while the adaptive network-based fuzzy inference system (ANFIS) model is used to capture the nonlinear component. Hence, an integrated model based on IEMD combined with ARMAX-EGARCH and ANFIS is proposed in this paper for the day-ahead electricity price forecasting. Meanwhile, the data from Spanish and Australian electricity markets are used for testing. The reason is that Spanish electricity market is the most commonly used market for electricity price forecasting in the literature, while Australian electricity market is one of the most volatile electricity markets in the world. Thus, different markets adopted in this paper can comprehensively estimate the effectiveness and practicability of the newly proposed forecasting model.

The main contribution of this paper can be summarized as four aspects: (1) Unlike most hybrid models which simply combine some existing models, the new model in this paper is developed so as to capture the different characteristics of electricity prices (such as linearity, heteroscedasticity, and nonlinearity). (2) The improved EMD approach is used for reducing the loss of information, which is rarely discussed in the literature related to electricity price decomposition, so as to better extract the characteristics of electricity prices. (3) Each component decomposed from the original electricity prices is forecasted by an appropriate model according to its specific characteristics. Thus, different characteristics associated with original electricity prices can be effectively captured. (4) An integrated model combined with IEMD, ARMAX, EGARCH, and ANFIS is firstly proposed for the day-ahead electricity price forecasting and displays significant superiority in forecasting accuracy based on the results of multiple robustness checks.

The rest of the paper is organized as follows: Section 2 introduces the proposed methods. Section 3 describes the data and results, and Section 4 concludes the paper.

2. Methods

2.1. The framework of the new model

As mentioned above, electricity prices contain linear and nonlinear components. To better describe the different characteristics of electricity prices, the IEMD approach is used here because it can decompose the original electricity prices into some linear and nonlinear components. Then, the proper models can be built to forecast the linear and nonlinear components, separately. By using the IEMD approach, the electricity prices can be decomposed into some intrinsic mode functions (IMFs) and one residual term as shown in Eq. (1):

$$P_t = \sum_{i=1}^{n} N_i(t) + R_n(t) \tag{1}$$

where P_t is the original electricity price series, while $N_i(t)$ and $R_n(t)$ represent the intrinsic mode functions and residual term, respectively.

Because $R_n(t)$ follows a linear trend, an ARMAX model is built to forecast it. The reason is that ARMAX model can well describe the linear characteristics. The next task is to select proper exogenous variables for this model. Although electricity prices are affected by many factors, taking all the factors into account for forecasting is impossible. Fortunately, there is high correlation between electricity price and electricity demand [32]. The correlation between hourly electricity price and electricity demand can be seen in Fig. 1, which is an example for the period of November 1, 2017 to November 30, 2017 in the Spanish electricity market, with 720 hourly observations. Their correlation coefficient is 0.74, which provides an appropriate reason for us to select demand as an exogenous variable for electricity price forecasting. As a result, electricity demand is selected as the only influencing factor for electricity price forecasting in Spanish and Australian electricity markets in this paper.

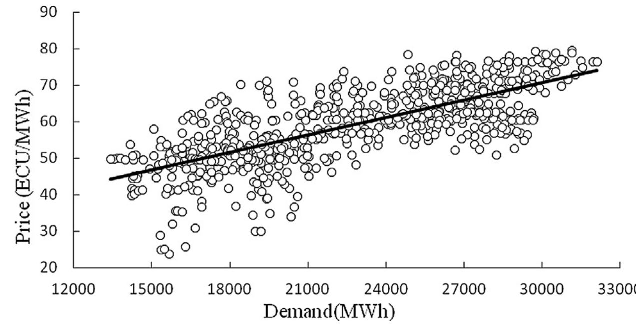

Fig. 1. Relationship between hourly prices and demand in Spanish electricity market (November 1, 2017-Novermber 30, 2017).

However, the direct application of electricity demand to build the ARMAX model for forecasting $R_n(t)$ cannot improve the forecasting accuracy. The reason can be attributed to the difference between electricity price curve and demand curve [33]. To select a more suitable variable, electricity demand is also decomposed into some IMFs and one residual term, defined as $D_n(t)$. Then we find that the shape of $R_n(t)$ is more similar to the shape of $D_n(t)$ than that of $R_n(t)$ and demand. The results show that the correlation between $R_n(t)$ and $D_n(t)$ for the period of November 1, 2017 to November 30, 2017 (0.86) is higher than that between $R_n(t)$ and demand (0.78), which indicates that $D_n(t)$ is more appropriate than demand for the forecast of $R_n(t)$. Thus, $D_n(t)$ is used as the exogenous variable. Besides, Hickey et al. [34] find the heteroscedasticity in the error term when the ARMAX model is used for electricity price forecasting. Therefore, the ARMAX-EGARCH model is singled out to forecast $R_n(t)$.

For the IMFs, the nonlinear model such as ANNs will be a good choice, due to its superior capability for nonlinear modeling. However, the ANNs model is merely a black box, which cannot well express the reasoning function. To overcome this problem, the ANFIS model is used to forecast IMFs, which can integrates the advantages of fuzzy systems and neural networks. In the neuro-fuzzy system, neural networks automatically extract fuzzy rules through the learning process, and the membership functions are adaptively adjusted [35].

Hence, a new integrated model based on IEMD, ARMAX-EGARCH and ANFIS is proposed to forecast the day-ahead electricity prices. Besides the suitable model, the selection of explanatory variables will also affect forecasting accuracy [36,37]. Due to the periodicity of electricity price and demand, the set of $\{R_n(t-1), R_n(t-2), \cdots, R_n(t-200), D_n(t-1), D_n(t-2), \cdots, D_n(t-200)\}$ is selected as the initial explanatory variables for $R_n(t)$. The initial explanatory variables for IMFs are dependent on their own lagged values. All the final explanatory variables for each component are determined by the significance testing. The framework of the proposed model is shown in Fig. 2.

2.2. The components of the new model

(1) The IEMD approach for electricity price and demand

Although the EMD approach proposed by Huang et al. [38] has many advantages, the end effect will be produced in the decomposition process, which may increase the bias of the final results. To obtain more accurate decomposition results, the mirror method is used to eliminate the end effect [39].