Forecasting electricity price from the state-of-the-art modeling technology and the price determinants perspectives: A systematic review and recent advances

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Abstract: Accurate electricity price forecasting (EPF) is crucial to both market participants and decision makers in the electricity market environment. The paper reviews the screened 62 literature on EPF during 2012-2022 in terms of model structure and determinants of electricity price, and discusses the evaluation process, model type, research sample, and prediction horizon. Through the above efforts, we find that: (1) data preprocessing and model optimization are often used to improve the forecasting model accuracy, while the performance evaluation is essential, but the extensive benchmark of performance evaluation is still missing; (2) considering determinants of electricity price can significantly improve accuracy of the forecasting model, but there is disagreement over how many and which determinants should be taken into account; (3) most of the existing researches focus on point forecasting, but interval forecasting and density forecasting are more responsive to the range and uncertainty of electricity price changes.

Keywords: Electricity price forecasting; Model structure; Determinants of electricity price; Dual decomposition method; Model optimization

1. Introduction

The energy crisis caused by the Russia-Ukraine conflict since 2022 has caused electricity prices to soar in France, Germany and other European countries, which has led to a considerable impact on the daily life and production of people. Electricity power, as an essential energy for daily life, is an important foundation for economic development and social progress (Wang et al., 2017). The fluctuation of electricity prices not only affects the flows and allocations of various resources in the electricity market, but also brings great risks to the production and operation of market participants. Therefore, accurate electricity price forecasting is crucial to both market participants and decision makers in the electricity market environment (Gabrielli et al., 2022; Meng et al., 2022; Zhang et al., 2022).

Electricity price forecasting refers to predicting future prices on the basis of meeting certain accuracy and speed by collecting historical data, constructing mathematical models and exploring the intrinsic connections and laws between electricity prices and the determinants of electricity prices (Nowotarski and Weron, 2018). Most of the researches on electricity price forecasting in the past are based on the historical electricity price (Zhang et al., 2012; Liu and Shi, 2013; Shrivastava and Panigrahi, 2014), while the fluctuation of electricity prices in reality is influenced by many factors (Maciejowska, 2020; Doering et al., 2021; Wang et al., 2022). For example, with the increasing penetration of renewable energy in the electricity generation industry, the volatile renewable energy generation undoubtedly has a huge impact on the electricity price fluctuation (Gabrielli et al., 2022). In addition, other determinant of electricity prices such as the fossil energy prices (Doering et al., 2021), the carbon price (Bublitz et al., 2017), the electricity demand (Mosquera-López and Nursimulu, 2019), the calendar data (Neupane et al., 2017), and weather (Pena and Rodriguez, 2019) can also have a significant impact on the fluctuation of electricity prices. Therefore, the scientific judgement of determinants of electricity prices and the construction of a forecasting method with high applicability and performance on this basis are essential to the accurate electricity price forecasting (Liu et al., 2022; Tschora et al., 2022; Zhang et al., 2022).

According to the existing literature, the scholars have proposed various effective EPF methods, which can be mainly classified into three categories as follows: the traditional econometric models, the artificial intelligence models, and the hybrid models. With the emergence of various models mentioned above, many scholars have summarized and reviewed EPF from different perspectives in great detail. For example, Weron (2014) provided a detailed classification of mainstream EPF models according to the development stage, explained the complexity of available solutions, their strengths and weaknesses, the opportunities and threats that forecasting tools may encounter, and pointed to the direction of development in the next decade. With the increasing importance of the probabilistic EPF for energy system planning and operation, Nowotarski and Weron (2018) provided an update and a further extension of the otherwise comprehensive EPF review based on Weron's research, and proposed much needed guidelines for the rigorous use of methods, measures, and evaluation. In addition, Lago et al. (2021) provided a detailed review of the state-of-the-art algorithms, the best practices and the open access benchmarks for day-ahead electricity price, and addressed the lack of a unified model evaluation methodology for existing research. Table 1 lists the comparison of the review articles published in recent years and this review article.

The existing literature provided very detailed classification summaries and reviews of the EPF model, which have laid the foundation for further research in this paper. However, there are still possibilities for further refinement in the existing literature. First, most of the existing review articles only categorize and summarize the electricity price forecasting models, and fewer of them summarize the methods of the specific process of electricity price forecasting such as data pre-processing methods, model optimization algorithms and performance evaluation indicators. Second, the analysis of the electricity price determinants is important for the accuracy of electricity price forecasting, but the existing review articles have less generalization of the electricity price determinants. Finally, although the publishing year of the article is important for the evolutionary process of the research topic, the appearance year of the keywords can provide a more detailed picture of the evolution process of the research topic.

On the basis of those, the major contributions of this paper are as follows:

(1) The paper presents a systematic review of the literature related to EPF and provides a comparative analysis of existing EPF models in four modules: data preprocessing module, price forecasting module, model optimization module, and performance evaluation module.

(2) We systematically review the literature on the determinants of the electricity

price and further explore the determinants of the electricity price most used in the existing literature and the impact of adding the determinants of the electricity price as input variables on the performance of the forecasting models.

(3) The paper further discusses the evolution process, the model type, the research sample, and the prediction horizon of EPF through the bibliometric analysis to facilitate the in-depth study of EPF.

The remainder of the paper is organized as follows. Section 2 introduces how to search and screen literature. Section 3 provides a detailed comparative analysis of existing EPF models in terms of data preprocessing module, price forecasting module, model optimization module and performance evaluation module, respectively. Section 4 reviews the literature on the determinants of the electricity price and further explores the determinants of the electricity price most used in the existing literature and the impact of adding the determinants of the electricity price as input variables on the performance of the forecasting models. Section 5 provides a systematic summary of evolution process, model type, research sample, and prediction horizon of EPF. Finally, Section 6 is the main conclusions and future directions.

Table 1

The comparison of the review articles published in recent years and this review article.

Author	Review Objects	Classification(s)	Main contents and discussions
Weron (2014)	Electricity price forecasting	Multi-agent models, Fundamental methods, Reduced-form models, Statistical approaches, Computational intelligence	This review article aims to explain the complexity of available solutions, their strengths and weaknesses, and the opportunities and threats that predictive tools offer or may encounter.
Dutta and Mitra (2017)	Dynamic pricing of electricity	Pricing policies, consumers' willingness to pay and market segmentation	The paper studies literature on various topics related to the dynamic pricing of electricity.
Gürtler and Paulsen (2018)	Forecasting performance of time series models on electricity spot markets	Simulation models, Heuristic methods, Computational or artificial intelligence, Statistical models	This paper gives empirical literature on various statistics to describe the modeling of electricity spot prices and analyzes several model types and their modified forecasting performance.
Nowotarski and Weron (2018)	Probabilistic electricity price forecasting	\	The paper presents guidelines for the rigorous use of methods, measures, and tests in probabilistic electricity price forecasting.
Acaroğlu and García (2021)	Electricity Market Price and Load Forecasting Based on Wind Energy	1.Short-term, middle-term, and long-term price and load forecasting 2. Statistical, artificial intelligence, and hybrid models	The latest electricity price and load forecasting techniques and discusses their strengths and weaknesses.
Lago et al. (2021)	Day-ahead electricity prices forecasting	Statistical methods, Deep learning methods, Hybrid methods	A review of state-of-the-art algorithms, best practices, and an open-access benchmark
Lu et al. (2021)	Energy price prediction using data-driven models (Natural Gas Price, Oil Price, Electricity Price, Carbon Price)	The basic model, the data cleaning method and optimizer	The paper reviews the literature in terms of basic models, data cleaning methods, and optimizers and discusses issues such as literature release time, model structure, prediction accuracy, prediction time domain, and input variables.
The Present Review Paper	Electricity price forecasting, Determinants of electricity price	1.Data preprocessing module, price forecasting module, model optimization module, and performance evaluation module. 2. Model classifications-based determinants of electricity price	Systematic decadal reviews of the literature related to EPF and determinants of electricity price and a summary of the evolutionary process, model structure, study sample, and prediction horizon.

2. Literature query

The electricity price prediction has drawn the attention of numerous academics in recent years, and the quantity of relevant academic work has exploded. In this article, taking "*Web of Science*" (WOS) and Scopus, two of the most widely used databases at the moment in the field of bibliometrics (Nowotarski and Weron, 2018; Weron, 2014), as examples, literature searches were conducted based on the following criteria: (1) Key words: "*Electricity price prediction*" OR "*Electricity price forecasting*" OR "*Electricity price forecast*" OR "*Predict electricity price*" OR "*Forecast electricity price*". (2) Period: 2012-2022[1]. (3) Article type: "*Research Article*". In Fig. 1, the paper plots the number of literatures on electricity price prediction in the WOS and Scopus databases from 2012-2022. The total number of documents searched in the WOS and Scopus databases are 1404 and 1084, including 1331 (94.8%) and 1040 (95.9%) research papers, respectively.

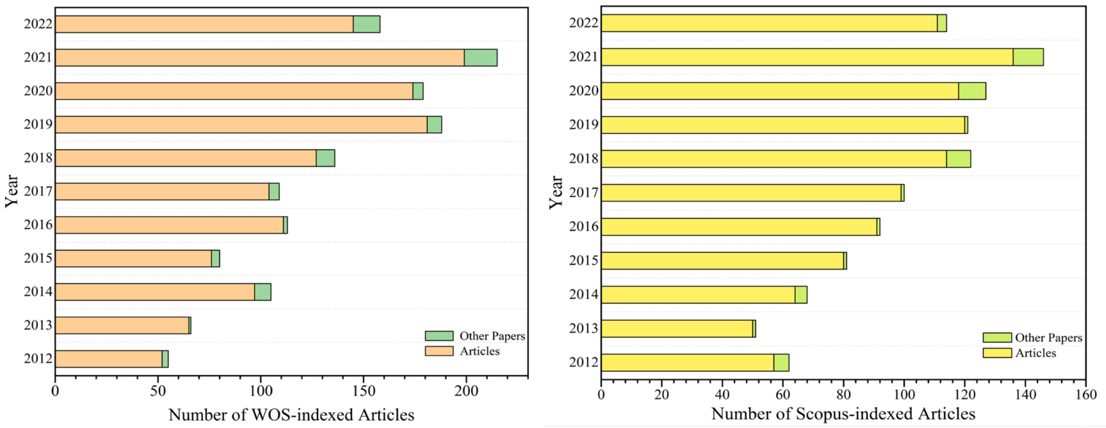

Fig. 1. The numbers of WoS- indexed (left panel) and Scopus-indexed (right panel) EPF articles in the years 2012-2022.

We cannot review every literature because some of them are not representative, and

[1] As of the date of completion, the literature search for this paper was conducted as of October 31, 2022.

we only review valuable and particularly innovative literature. Following Lu et al. (2021), the paper reviews and screens the searched literature in the following steps：

Step 1: Multiple database searches

Although the quality of the literature in the WOS and Scopus databases can be guaranteed, this paper complements the searched literature by combining the search results of several databases, taking into account the delay in literature search. Relevant search information is as follows:

Search Topic: Electricity Price Forecasting (OR Prediction)

Databases: WOS, Scopus, Elsevier, IEEE IEL, Springer and Google Scholar

Key Words: "Electricity price prediction" OR " Electricity price forecasting" OR "Electricity price forecast" OR "Predict electricity price" OR "Forecast electricity price"

Language: English

Period: 2012-2022

Step 2: Review and Screening

We carefully read the literature searched in Step 1 and find that some of the searched literatures are similar to the topic, but the core content is not specific to electricity price prediction. Therefore, we eliminate the literature with low relevance and ensure that the selected literature is directly related to electricity price prediction.

Step 3: Extraction of literature information and re-screening

We further read and extract valuable information from the screened literature in Step 2, such as Author, Market, Input Factor, Model, Conclusion and Journal. In addition, the screened literature is further screened to ensure that the selected literature fits the article topic.

Finally, this paper selects 62 electricity price prediction articles for further bibliometric analysis. See Appendix A for the screened literature.

3. The mainstream electricity price forecasting model

The section presents a systematic review of the literature related to EPF and provides a comparative analysis of existing EPF models in four modules: data preprocessing module, price forecasting module, model optimization module, and performance evaluation module. This section is organized as follows：Section 3.1 describes common data preprocessing methods for the current price segment and provides a comparative analysis； Section 3.2 is a summary of the methods commonly used in the mainstream prediction modules at this stage. Section 3.3 is devoted to the introduction of the model optimization module; Section 3.4 presents the commonly used metrics for evaluating model results in the existing literature. In Appendix A, we summarize the important information of the 62 papers screened, including authors, publication year, prediction market, prediction model, methods used in each module, and prediction horizon.

3.1 Data Preprocessing Module

The data preprocessing module is usually the first step of the EPF system and is responsible for the initial processing of the original data in order to make the forecasting model work better. The popular data pre-processing methods used in the existing literature can be categorized into two types: the single decomposition methods and the dual decomposition methods (Yang et al., 2019).

3.1.1 The single decomposition methods

The commonly used data preprocessing methods is the single decomposition method at present, such as wavelet transform (WT) and WT-based expansion methods, empirical mode decomposition (EMD) and EMD-based expansion methods, variational mode decomposition (VMD) and VMD-based expansion methods. In addition, the dual decomposition method is also popular.

The WT method, as one of the most common methods in the data preprocessing module, not only inherits and develops the localization idea of the short-time Fourier transform, but also can carry out multi-scale densification of data signals and convert high-frequency data to low-frequency data, which is a very ideal decomposition tool for signal time-frequency analysis and processing. Singh et al. (2017), Chang et al. (2019), Qiao and Yang (2020) decomposed and processed the "Hourly", "Daily", and "Monthly" datasets using the WT method, respectively, and all obtained satisfactory results. In addition, the WT-based expansion methods are also widely used. Cheng et al. (2019) and Meng et al. (2022) preprocessed the data using the empirical wavelet transform (EWT). Compared with WT, EWT integrates the adaptive decomposition concept of EMD method on the basis of WT theory, which provides a new adaptive time-frequency analysis idea for signal processing. The discrete wavelet transform (DWT) is a discretization of the scales and translations of the fundamental wavelets, and can better process the discrete data than WT (Zhang et al., 2012; Ebrahimian et al., 2018; Memarzadeh and Keynia, 2021).

The EMD method is a new adaptive signal time-frequency processing method creatively proposed by Huang et al. in 1998, which is especially suitable for the analysis and processing of nonlinear non-stationary signals. The EMD method decomposes the signal based on the time-scale characteristics of the data itself, and has strong adaptiveness. In addition, the EMD method has obvious advantages in the decomposition of nonlinear and non-smooth signals due to the unconstrained basis functions (Qiu et al., 2017). However, the EMD method has drawbacks such as the end effect and the mode mixing, which will have negative effects on the accuracy of decomposition methods (Shao et al., 2021; Deng et al., 2022; Zhang et al., 2022). To improve these deficiencies, the variants of EMD have been continuously proposed. For example, the ensemble empirical mode decomposition (EEMD) can effectively solve the end effect and the mode mixing problems by using white noise to separate signals into a uniformly distributed reference scale (Shao et al., 2021). In addition, the bivariate empirical mode decomposition (BEMD) (He et al., 2015), the improved empirical mode decomposition (IEMD) (Zhang et al., 2018), the complete ensemble empirical mode decomposition (CEEMD) (Hu et al., 2022), the complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Wang et al., 2018), and the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN) (Yang et al., 2019) are also widely used.

The VMD method is an adaptive, completely non-recursive approach to modal variation and signal processing. In addition, the VMD method is able to decompose multicomponent signals into multiple single-component signals at one time, which avoids the endpoint effect and the spurious component problem encountered in the iterative process (Dragomiretskiy and Zosso, 2014). The VMD method is widely used to preprocess the original data on electricity prices with good performance (Yang et al., 2020; Zhang et al., 2020; Heydari et al., 2020). For the extended VMD-based approach, Wang et al. (2020) applied the improved variational mode decomposition (IVMD) to electricity price forecasting in Australia and Singapore, and the result showed that the IVMD compared to VMD can adaptively perform optimal decomposition of different electricity price data and achieve high forecasting performance. Moreover, the adaptive parameter-based variational mode decomposition (APVMD) was proposed to address the drawback that VMD requires to manually set parameters, and its advantage is that the decomposition number parameters can be determined automatically without extensive experiments (Yang, 2022).

3.1.2 The dual decomposition methods

Although the forecasting model integrated with single decomposition methods can enhance the predictive ability to some extent in the stage of data preprocessing, there are still some possibilities to improve the predictive ability of the model because the single decomposition methods often cannot completely process the non-smoothness of random and irregular data series (Wang et al., 2017; Yang et al., 2019; Zhang et al., 2022). Therefore, Yang et al. (2019) proposed a dual decomposition strategy to improve the data pre-processing capability, which combines the advantages of ICEEMDAN and VMD. The original data of the electricity price series are firstly decomposed by the ICEEMDAN method into the low-frequency signals and the high-frequency signals, and then the high-frequency signals in the series are processed by the VMD method. The result shows that the strategy can better extract the main features of the electricity price series and fully consider the high frequency signals compared with the single decomposition methods.

Similarly, Deng et al. (2022) also chose the dual decomposition method. The difference is that the original series are first decomposed through the EEMD method into smoothed intrinsic mode functions (IMFs) and non-smoothed IMFs, and the smoothed decomposed IMFs are input into the prediction model while the non-smoothed decomposed IMFs will be further smoothed by the VMD method. The dual decomposition method employs VMD to solve the problem that the non-smoothed IMFs generated during the EEMD decomposition process affect the electricity price prediction performance.

In addition, Zhang et al. (2022) proposed a two-layer decomposition method, which uses the combination of VMD and EEMD methods to preprocess the electricity price series. VMD can decompose the complex signal into several regular IMFs, thus significantly improving the prediction accuracy. However, the residual term containing rich information is paid less attention in VMD, which can reduce the predictive performance of the model. Therefore, the method further decomposes the residual terms generated by VMD with the help of EEMD, which significantly improves the accuracy of the forecasting model.

Table 2
The comparison of main data preprocessing methods.

Data Preprocessing Methods	Advantages	Disadvantages	References
WT	1.WT improves the localization idea of short-time Fourier transform and overcomes the shortcomings such as the window size does not vary with frequency. 2. WT can highlight the characteristics of certain aspects of the problem and has a better decomposition effect on abrupt and non-smooth signals.	1.The selection of wavelet bases is difficult. 2. Compared with other modal decomposition methods, WT lacks strong self-adaptability.	Chang et al. (2019); Qiao and Yang (2020); Singh et al. (2017)
VMD	The method can effectively deal with nonlinear and non-smooth signals, and has the advantages of better accuracy of complex data decomposition and better resistance to noise interference.	1. The method requires artificial selection of decomposition layers and penalty factors. 2. The method has the limitation of boundary effect and sudden signal.	Heydari et al. (2020); Wang et al. (2020); Yang and Schell (2022); Yang et al. (2019, 2020); Zhang et al. (2020)
EMD	1. EMD has obvious advantages in dealing with non-stationary and non-linear data, and is suitable for analyzing non-linear and non-stationary signal sequences with high signal-to-noise ratio. 2. EMD has strong adaptivity because it is based on the local characteristics of the time scale of signal sequences.	The EMD method is subject to the end effect and the mode conflation problem, which makes feature extraction, model training, and pattern recognition difficult.	Huang et al. (1998); He et al. (2020); Qiu et al. (2017); Shao et al. (2021)
The dual decomposition methods	The dual decomposition method can integrate the advantages of different decomposition methods and make up for the shortcomings of each.	The method is more computational and time consuming.	Wang et al. (2017); Yang et al. (2019); Deng et al. (2022); Zhang et al. (2022)

3.1.3 The comparison of main data preprocessing methods

It is crucial to choose the appropriate data preprocessing method in EPF research. Table 2 lists the advantages and disadvantages of the main data preprocessing methods mentioned above to facilitate researchers and practitioners to choose the appropriate method.

3.2 Price Forecasting Module

The selection of forecasting models is the core key of the EPF research and directly affects the performance of the overall forecasting system. According to the existing literature, scholars have proposed many effective forecasting models, which can be mainly classified into the following three categories: the traditional econometric model (Girish, 2016; Gianfreda et al., 2020; Billé et al., 2022), the artificial intelligence model (Keles et al., 2016; Panapakidis and Dagoumas, 2016; Jasiński, 2020) and the hybrid model (Agrawal et al., 2019; Zhang et al., 2019; Zhang et al., 2020). Notably, the different forecasting models have their own strengths and weaknesses.

3.2.1 The Traditional Econometric Model

The traditional econometric model is an early and more developed class of modeling techniques in the study of time series forecasting. The traditional econometric model, with its simplified and fixed model, has good fitting predictive power for electricity price series that meet its assumptions, which is also one of the common tools for electricity price volatility forecasting, risk control, and asset valuation. From the results of literature screened (see Appendix A), the combined ARMA-type model and GARCH-type model are widely used in the study of EPF (Liu and Shi, 2013; Girish, 2016; Loi and Ng, 2018). For example, Bille et al. (2022) used ARFIMAX-GARCH-type models in their study to forecast electricity prices in Italy, and the result shows that the model can introduce exogenous factors to improve the accuracy of the model forecasts. The advantage of the ARMA-GARCH-type model is that the combination of the two models can fully exploit each other's strengths and compensate for each other's weaknesses. Among them, the ARMA-type model is a common method for solving linear time series problems, especially showing good predictive performance for smooth series (Yang et al., 2017). In addition, compared with the ARMA-type model, the GARCH-type model can better characterize the volatility of the electricity price series and can capture the heteroskedasticity phenomenon of electricity prices more effectively (Girish, 2016).

It is clear that the traditional econometric model has good forecasting accuracy for the time series data that meet the assumptions. However, the assumption is contrary to the actual situation in which the vast majority of data are characterized by non-stationarity, non-linearity and high complexity. As a result, the traditional econometric model cannot accurately handle the nonlinear part of the electricity price series and is easily prone to the loss of local transient information, thus failing to obtain satisfactory prediction results.

3.2.2 The Artificial Intelligence Model

The artificial intelligence model has significant advantages over the traditional econometric model in predicting non-stationary, non-linear and highly complex time series. The artificial intelligence model can capture the hidden nonlinear mapping relationship by training and learning from historical data of electricity price series, and can combine the electricity price characteristics with the complex and variable external environment to minimize the prediction error, which has strong generalization ability and robustness, so it is widely used in EPF research.

The artificial neural network (ANN) model, as the most popular model for EPF, has a powerful ability to portray and model the non-stationary and non-linear characteristics of time series (Panapakidis and Dagoumas, 2016). Keles et al. (2016) predicted the EPEX market electricity price based on the ANN model and the result shows that the ANN model achieves good results and the prediction error is much lower than the ARIMA results. Jasinski (2020) proposed a price forecasting method based on the ANN model to forecast electricity price in Poland, and the method can allow reducing the symmetric mean absolute percentage error (SMAPE) of the forecasting results by up to 15.3%. In addition, the ANN-type models have been widely used in EPF studies, including the convolutional neural network (CNN) (Deng et al., 2021; Deng et al., 2022), the deep neural networks (DNN) (Lago et al., 2018; Shi et al., 2021), the evolutionary neural networks (ENN) (Yang et al., 2019), the bidirectional recurrent neural networks (BRNN) (Ghayekhloo et al., 2019), the general regression neural network (GRNN) (Heydari et al., 2020), etc.

The long short-term memory (LSTM) model, as an excellent variant of the recurrent neural networks (RNN) model, is also widely used in the research of EPF (Qiao and Yang, 2020; Iwabuchi et al., 2022; Meng et al., 2022; Xu et al., 2022). Chang et al. (2019), Memarzadeh and Keynia (2021), and Iwabuchi et al. (2022) applied the

LSTM method to the electricity market in different regions for price forecasting, respectively, which showed better forecasting results. Meng et al. (2022) proposed an attention mechanism (AM) based LSTM hybrid model as a forecasting model in the price forecasting stage. Shao et al. (2021) combined the max-dependency and min-redundancy (MRMR) with the bidirectional long short-term memory (BiLSTM) for the purpose of improving the efficiency of short-term EPF. Yang and Schell (2021) used the gated recurrent unit (GRU) and the transfer learning (TL) to forecast real-time electricity prices for wind farms in New York. In addition, the LSTM-based hybrid model is being further refined as the research progresses (Peng et al., 2018; Qiao and Yang, 2020; Xu et al., 2022).

The support vector machine (SVM) based model and the extreme learning machine (ELM) based model are two other common artificial intelligence models for electricity price prediction (Agrawal et al., 2019; Wang et al., 2020; Yang et al., 2022; Yang et al., 2020; Zhang et al., 2022). Among them, the SVM is a novel small-sample learning method with a solid theoretical foundation. Ifran et al. (2022) used SVM-AO to forecast the week ahead electricity prices in the England. Yan and Chowdhury (2014) proposed a multiple SVM-based medium-term forecasting model for electricity prices. The ELM has more advantages in the aspects of learning rate and generalization ability compared with SVM (Huang et al., 2006). In the study of EPF, Shrivastava and Panigrahi (2014) combined ELM with wavelet techniques to develop a hybrid model WELM to improve forecasting accuracy and reliability. Wang et al. (2020) used the outlier robust extreme learning machine (ORELM) model as a forecasting engine, which retains the advantages of the ELM model while effectively handling the outliers in the electricity price data.

3.2.3 The Hybrid Model

The traditional econometric model and the artificial intelligence model have their own advantages in the EPF researches. Some scholars have fully combined their advantages and proposed corresponding price prediction models in their studies. For example, Zhang et al. (2020) predicted the regular trend of electricity price series with the help of the seasonal autoregressive integrated moving average (SARIMA) model and captured the irregular trend of electricity price series with the help of the self-adaptive particle swarm optimization (SAPSO) optimized the deep belief network (DBM) model. Voronin et al. (2014) used the ARMA-type model to capture the linear relationship between the normal interval electricity price series and the explanatory variables, the GARCH model to reveal the heteroskedasticity characteristics of the residuals, and the neural network to describe the nonlinear effects of the explanatory variables on electricity prices. Similarly, Babu and Reddy (2014) and Zhang et al. (2012) used the traditional econometric model to predict the linear part of the data series, while the nonlinear part was predicted using the artificial intelligence model.

The combination of the artificial intelligence model with other models is also often used in the EPF researches. Agrawal et al. (2019) proposed a new two-stage integrated model for short-term electricity prices. Firstly, the extreme gradient boosting (EGB) takes into account the stochastic fluctuations in electricity costs in the dynamic market, while the relevance vector machine (RVM) provides sparse solutions and probabilistic predictions. Finally, the elastic net regression was used to further stack the results of these models in order to determine the final electricity price prediction. The result shows that the hybrid model has better accuracy and lower computational cost than the commonly used ANN-based models.

In addition, many scholars have made improvements to the feature selection methods, function forms, parameter settings, and running times of existing forecasting methods around the own data characteristics of electricity price samples, such as non-stationarity, seasonality, and volatility, and combined with the influence of external factors on electricity prices, in order to improve the forecasting performance of the models (Kostrzewski and Kostrzewska, 2019; Zhang et al., 2019; He et al., 2020). For example, Zhang et al. (2019) introduced a hybrid feature selection method in the forecasting strategy and combined three methods, the cuckoo search algorithm, support vector machine and singular spectrum, to propose a hybrid forecasting framework for short-term EPF. The results show that the method does outperform existing benchmark models and is a reliable tool for short-term EPF.

3.3 Model Optimization Module

The model optimization module in the forecasting model can optimize the parameters of the original model and solve the problems of over-fitting, parameter sensitivity and local extremes in the forecasting process, so that the price forecasting model can obtain better forecasting performance.

In the screened literature, the particle swarm optimization algorithm (PSO) is the most commonly used optimization algorithm. The PSO algorithm is an evolutionary computational technique proposed by Eberhart and Kennedy (Eberhart and Kennedy, 1995; Kennedy and Eberhart, 1995), which originated from the idea of studying the foraging behavior of bird flocks. The optimization algorithm has the advantages of fast convergence, few parameters, and simple implementation, which is widely used in the research of electricity price prediction (Zhang et al., 2012; Ebrahimian et al., 2018; Zhang et al., 2020). Lei and Feng (2012) and Zhang et al. (2012) used PSO to optimize the model for accurate parameters identification to improve the prediction performance of the model. In addition, Osório et al. (2019) used the hybrid PSO algorithm to optimize the prediction model to make the weight parameters have adaptive properties. Similarly, Yang et al. (2017) adjusted the penalty factor and kernel parameters of the kernel based extreme learning machine (KELM) to achieve stable and more efficient regression performance with the help of the SAPSO algorithm.

In addition to the PSO optimization algorithm, Meng et al. (2022) used the crisscross optimization algorithm (CSO) to retrain the parameters of the fully connected layer to further improve the generalization ability of the forecasting model. Yang et al. (2022) selected the chaotic sine cosine algorithm (CSCA) proposed by Wang et al. (2020) to optimize the price forecasting model. Compared with the traditional sine cosine algorithm, the CSCA has the advantage of faster convergence and less likely to fall into local optimum (Wang et al., 2020). To adapt to the conditions of multi-objective optimization, Yang et al. (2020) used the improved multi-objective sine cosine algorithm (IMOSCA) in the model optimization stage, and Yang et al. (2019) used the multi-objective grey wolf optimizer (MOGWO) to optimize the price prediction model.

The results show that both IMOSCA and MOGWO enable the model to forecast each component with better accuracy and stability. In addition, the Adam algorithm (Kingma and Ba, 2015) is often used in the optimization module of EPF for its efficient computational performance and low memory consumption (Chang et al., 2019; Deng et al., 2021).

3.4 Performance Evaluation Module

The selection of the evaluation indicator is critical to quantifying the performance of the price forecasting model. However, it is unfortunately that the extensive benchmark of performance evaluation has not been identified in the existing literature (Tian et al., 2018). The section presents an econometric analysis of the performance evaluation indicator of the 62 screened literature. Fig. 2 shows the frequency of various performance evaluation indicators in the screened literature, and Table 3 shows the rules of the top 10 evaluation indicators used in the literature.

From Fig. 2, it can be seen that the frequency of the mean absolute percentage error (MAPE), the mean absolute error (MAE) and the root mean square error (RMSE) is much higher than other metrics. As one of the most popular metrics for evaluating predictive performance, MAPE does not have a specific magnitude and allows for parameter comparisons across scenarios. When the value of MAPE is 0%, it means that the model is a perfect model, and when it is greater than 100 %, it means that the model is an inferior model. As shown in Table 3, MAE can be regarded as the numerator of MAPE, and its value indicates how well the predicted value matches the true value. SMAPE is a refined version of MAPE, which makes up for the asymmetry of MAPE.

The value of SMAPE can be taken as a negative number, which makes the evaluation index more intuitive. Compared to MAPE and MAE, RMSE is more intuitive in magnitude and sensitive to extreme values. The RMSE value represents the average difference between the predicted result and the true value.

The above four indicators are mainly used to test the prediction accuracy of the model. In addition, the index of agreement (IA) can be used to measure the prediction ability of the model; Theil's inequality coefficient (TIC) can objectively evaluate the generalization ability of the model; Theil's U1 (U1) measures the prediction accuracy of the model, and Theil's U2 (U2) measures the prediction quality of the model.

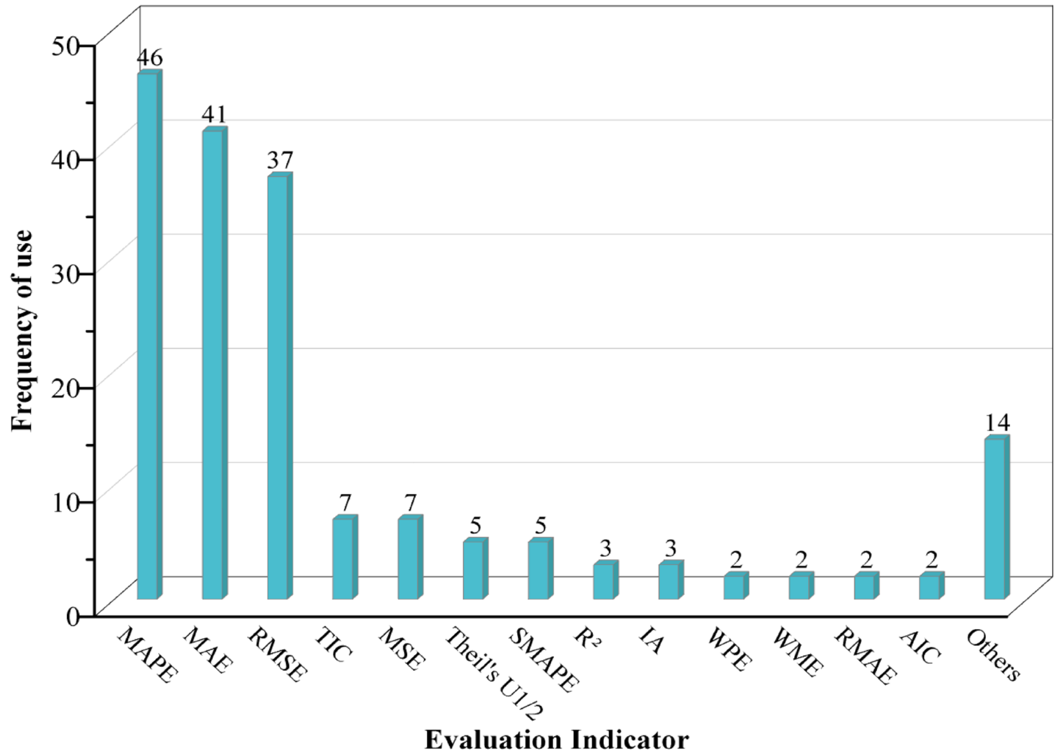

Fig. 2. The frequency of various performance evaluation indicators.

Table 3
The performance indicator rules.

Indicator	Definition	Equation
MAPE	Mean Absolute Percentage Error	$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left\lvert\frac{y_i - \hat{y}_i}{y_i}\right\rvert$
MAE	Mean Absolute Error	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$
RMSE	Root Mean Square Error	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
MSE	Mean Square Error	$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
TIC	Theil's Inequality Coefficient	$TIC = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i^2}}$
U1	Theil's U1	$U1 = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i^2}}$
U2	Theil's U2	$U2 = \frac{\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2}}$
SMAPE	Symmetric Mean Absolute Percentage Error	$SMAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\lvert y_i - \hat{y}_i\rvert}{\frac{1}{2}\left(\lvert y_i\rvert + \lvert\hat{y}_i\rvert\right)}$
R^2	R-squared	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2}$
IA	Index of Agreement	$IA = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sqrt{\sum_{i=1}^{n}(\lvert y_i - \overline{y}\rvert + \lvert\hat{y}_i - \overline{y}\rvert)^2}}$

Notes: n, y_i, $\hat{y}_i$, $\overline{y}$ denote the number of samples, the i-th sample real value, the i-th sample predicted value and the sample mean value, respectively.

4. Electricity price forecasting with determinants of electricity price

The accurate electricity price forecasting is a widespread concern for the market participant. However, with the increasing penetration of renewable energy in the electricity generation industry, the volatile renewable energy generation undoubtedly has a huge impact on the electricity price fluctuation, which also brings new challenges to EPF. To address this challenge, many scholars would like to improve the forecasting performance of the model by including factors affecting electricity prices as input variables in the EPF model, rather than relying simply on the historical electricity price data for forecasting (Gabrielli et al., 2022; Meng et al., 2022; Tschora et al., 2022). Therefore, the section aims to review the literature on the determinants of electricity price (Section 4.1) and further explore the impact of the determinants of electricity price on the performance of forecasting models (Section 4.2).

4.1 Determinants of electricity price

This section summarizes and analyzes the literature on the topic of "*Determinants of Electricity Price*" using the literature searching and screening method mentioned in Section 2. And then, we classify the determinants of the electricity price in the screened literature, as shown in Table 4. From Table 4, it can be found that the determinants of electricity price fluctuations in the screened literature fall into three main categories, which are the supply and demand of electricity, the fossil energy prices and other factors such as climate, import and export, carbon price, etc.

The electricity supply and demand affect the electricity price mainly based on the relationship between supply and demand, and especially the volatile renewable energy generation has a huge impact on electricity price fluctuations. Peura and Bunn (2021) conducted a detailed empirical analysis of the relationship between renewable energy generation and electricity prices using a game-theoretic market model, and the result shows that the instability of renewable generation can not only affect the spot market price of electricity through the merit-order effect, but also have an impact on the forward market price. Maciejowska (2021) analyzed the impact of two renewable energy sources (wind and solar) on the spot price of electricity in Germany. The result shows that the specifical effect of wind power generation and solar power generation on the electricity price fluctuations depends on the electricity demand of customers. Similarly, Da Silva and Cerqueira (2017), Mosquera-López et al. (2017), Mosquera-López and Nursimulu (2019) and Wang et al. (2022) also highlight the influence of electricity demand on electricity price fluctuations in their studies.

The most stable form of power generation is the fossil energy generation at this stage, so the fossil energy price fluctuation will also affect the electricity price fluctuation accordingly (Boersen and Scholtens, 2014; Moreno et al., 2014; Bublitz et al., 2017; Peña and Rodríguez, 2019). However, there are different viewpoints on the impact of fossil energy on the electricity price. For example, Bublitz et al. (2017) found that the impact of carbon and coal prices on German electricity prices has been twice as high as the renewable expansion between 2011 and 2015. Peña and Rodríguez (2019) considered the impact of renewable energy and other fundamental determinants on electricity prices in ten EU countries from 2008 to 2016. The result shows that the increase in renewable energy production reduces wholesale electricity prices in all countries, but the explanatory power of other factors such as fuel prices, meteorological conditions and the net balance of imports and exports varies between countries.

Notably, the carbon price is gradually paid more and more attention by scholars as a special factor influencing electricity prices with the focus on climate issues and carbon emissions (Boersen and Scholtens, 2014; Bublitz et al., 2017; Mosquera-López et al., 2017; Mosquera-López and Nursimulu, 2019; Wang et al., 2022). In addition, the weather factor is also the focus of scholars' attention (Mosquera-López et al., 2017; Peña and Rodríguez, 2019). For instance, Mosquera-López et al. (2017) used quantile regressions to assess the impact of weather factors on electricity prices and found that wind speed and temperature are the main drivers, especially in the tails of the price distribution. In summary, the existing research has well demonstrated that the electricity price fluctuation is not only influenced by one factor, but is the combined result of multiple factors. Based on this, how to select the external factors to improve the forecasting model accuracy will become a critical step in EPF research (Gabrielli et al., 2022), which also brings a great challenge to future EPF research.

Table 4

The determinants of the electricity price.

Reference	Renewable Energy Generation	Other Generation	Electricity Demand	Electricity Load	Weather	Electricity Import/Export	Fossil Fuels Price	Carbon Price	Other Factor(s)
Wang et al. (2022)	√	√	√			√	√	√	√
Peura and Bunn (2021)	√								
Doering et al. (2021)	√	√		√			√		√
Maciejowska et al. (2021)	√								
Pereira et al. (2019)									√
Peña and Rodríguez (2019)	√				√	√	√		
Mosquera-López and Nursimulu (2019)	√		√				√	√	
Li et al. (2019)									√
Mosquera-López et al. (2017)	√		√		√		√	√	√
Bublitz et al. (2017)	√			√			√	√	
Da Silva and Cerqueira (2017)	√		√				√		√
Paschen (2016)	√								
Sapio and Spagnolo (2016)		√							√
Moreno et al. (2014)							√		
Boersen and Scholtens (2014)							√	√	
Papler and Bojnec (2012)									√
Moreno et al. (2012)	√								√

4.2 Electricity price forecasting model with determinants of electricity price

From the existing literature, there is a common agreement that the electricity price fluctuations are determined by many factors. Some scholars believe that adding the determinants of electricity price as input variables in the EPF model can improve the predictive performance of the model (Gabrielli et al., 2022; Meng et al., 2022; Tschora et al., 2022). Based on this, we divide the screened literature into two categories, which are the EPF without determinants of electricity price and the EPF with determinants of electricity price. As shown in Table 5, the EPF with determinants of electricity price take into account the data of electricity price determinants besides the historical electricity price data, such as the renewable energy generation, the electricity demand, the fossil energy prices, weather, etc.

The electricity price forecasting model with determinants of electricity price showed better accuracy in price forecasting and this opinion is strongly supported by the present literature (Wang et al., 2022; Meng et al., 2022; Tschora et al., 2022). Gianfreda et al. (2020) compared the accuracy of forecasting models with and without determinants of electricity price with the help of the historical data for four countries: Germany, Denmark, Italy and Spain. The result shows that the prediction accuracy of the model with determinants of electricity price (electricity demand, renewable energy generation and fossil energy prices) is significantly superior for both point and interval forecasts. Meng et al. (2022) considered the influence of renewable energy on EPF in their study and introduced wind power generation, solar power generation and historical electricity price series as input features into the forecasting model. The result shows that the proposed model with determinants of electricity price has a greater advantage in electricity markets with high penetration of renewable energy. Billé et al. (2022) considered the fundamental drivers such as electricity demand, renewable energy generation, fossil energy prices, and electricity imports, and included these exogenous regressors in the conditional mean and variance equations. The result shows that the proposed model with determinants of electricity price can obtain a higher forecasting performance in terms of the point forecasting and the interval forecasting.

The reasonable choice of variables is the key to ensure the accuracy of the forecasting model. However, the interdependence of variables may appear if all the electricity price determinants are considered because there are many determinants of electricity prices. To address this issue, Gabrielli et al. (2022) conducted a sensitivity study on a total of 13 electricity price determinants in five categories, including electricity demand, electricity generation, electricity imports, energy price, and carbon price. The empirical result shows that using 2-4 determinants of electricity price as input variables will allow the model to achieve the best predictive performance rather than more electricity price determinants.

As shown in Figure 3, the frequency ranking of the input factor is approximately the identical to that of the determinants of electricity price fluctuations. The renewable energy generation, the electricity demand, and the fossil energy prices are used most frequently among all the input factors, except for the historical electricity price data. In addition, the weather factor is also widely used as an important input variable that cannot be ignored. It is interesting to find that carbon price, an important factor influencing electricity price fluctuations, is rarely mentioned in studies on electricity price forecasting.

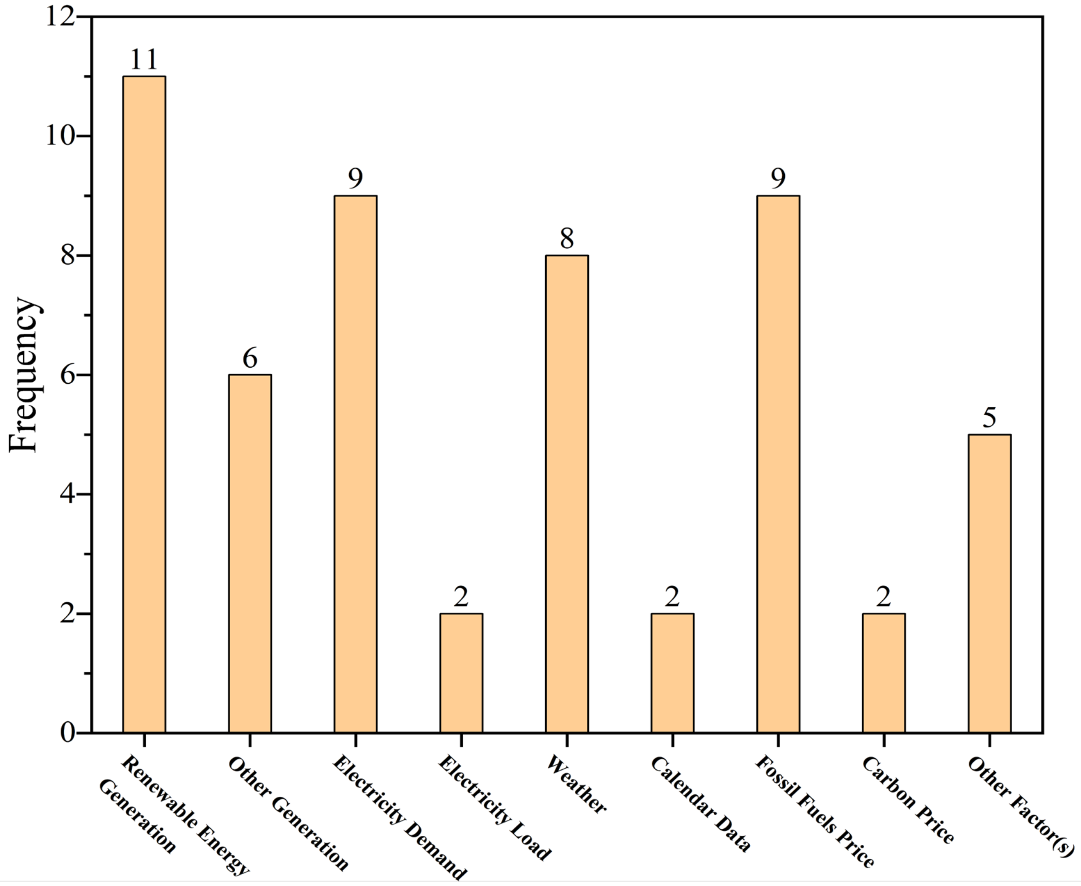

Fig. 3. The frequency of determinants of electricity price used.

Table 5

The input factors of the electricity price forecasting model.

Reference	Renewable Energy Generation	Other Generation	Electricity Demand	Electricity Load	Weather	Calendar Data	Fossil Fuels Price	Carbon Price	Other Factor(s)
Meng et al. (2022)	√								
Tschora et al. (2022)									√
Gabrielli et al. (2022)	√	√	√				√	√	√
Bille et al. (2022)	√	√	√				√		
Wang et al. (2022)	√	√	√				√	√	√
Jasinski (2020)	√				√				
Gianfreda et al. (2020)	√		√				√		
Zhang et al. (2019)					√				
Vu et al. (2019)	√	√	√						
Loi and Ng (2018)							√		
Lago et al. (2018a)	√	√		√	√		√		
Lago et al. (2018b)	√	√			√		√		
Neupane et al. (2017)					√	√			
Keles et al. (2016)	√		√	√	√	√	√		
Cerjan et al. (2014)	√		√						
Yan and Chowdhury (2014)			√				√		√
Voronin et al. (2014)			√		√				√

5. Discussion

5.1 The Evolution Process of EPF

To further explore the evolution process of EPF, we used VOSviewer Version 1.6.11 to conduct a bibliometric analysis and visualization of the keywords for the screened 62 articles, as shown in Fig. 4 and Fig. 5.

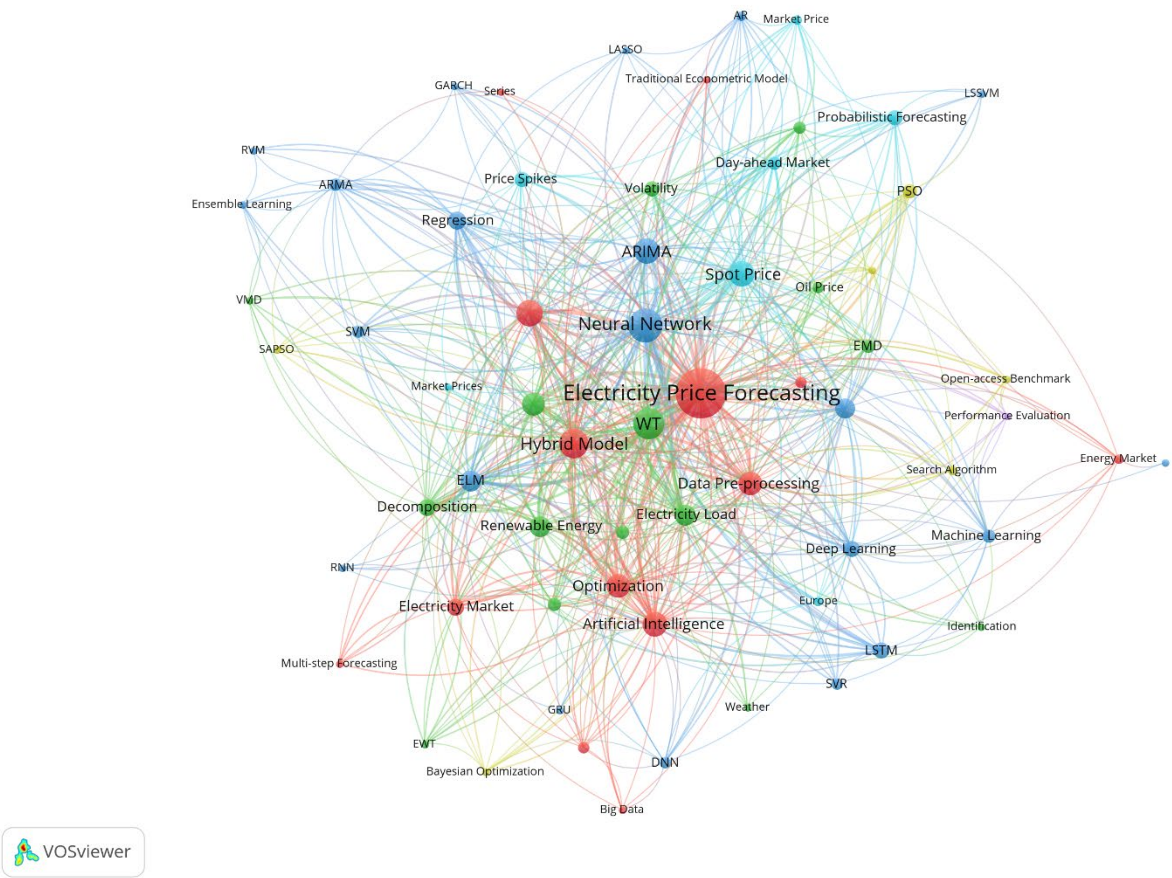

Fig. 4. The network visualization of the keyword co-occurrence.

The network visualization of the keyword co-occurrence is drawn by the clustering method, as shown in Fig. 4. The same color represents the same category[2], and the sizes of the nodes represent the frequency of the keyword (i.e., the Degree Centrality). The

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[2] In this paper, we preprocess the data by removing keywords with few occurrences, combining synonyms and removing outliers, and divide the keywords into 5 categories for cluster analysis: the forecasting methods and modules (Red), the specific forecasting models (Purple), the data preprocessing (Green), the forecasting objects (Blue), and the optimization algorithms (Yellow).

overlay visualization of the keyword co-occurrence is plotted based on the average year taking the score value, as shown in Fig. 5. The darker the color means the older the average year of the keyword mentioned.

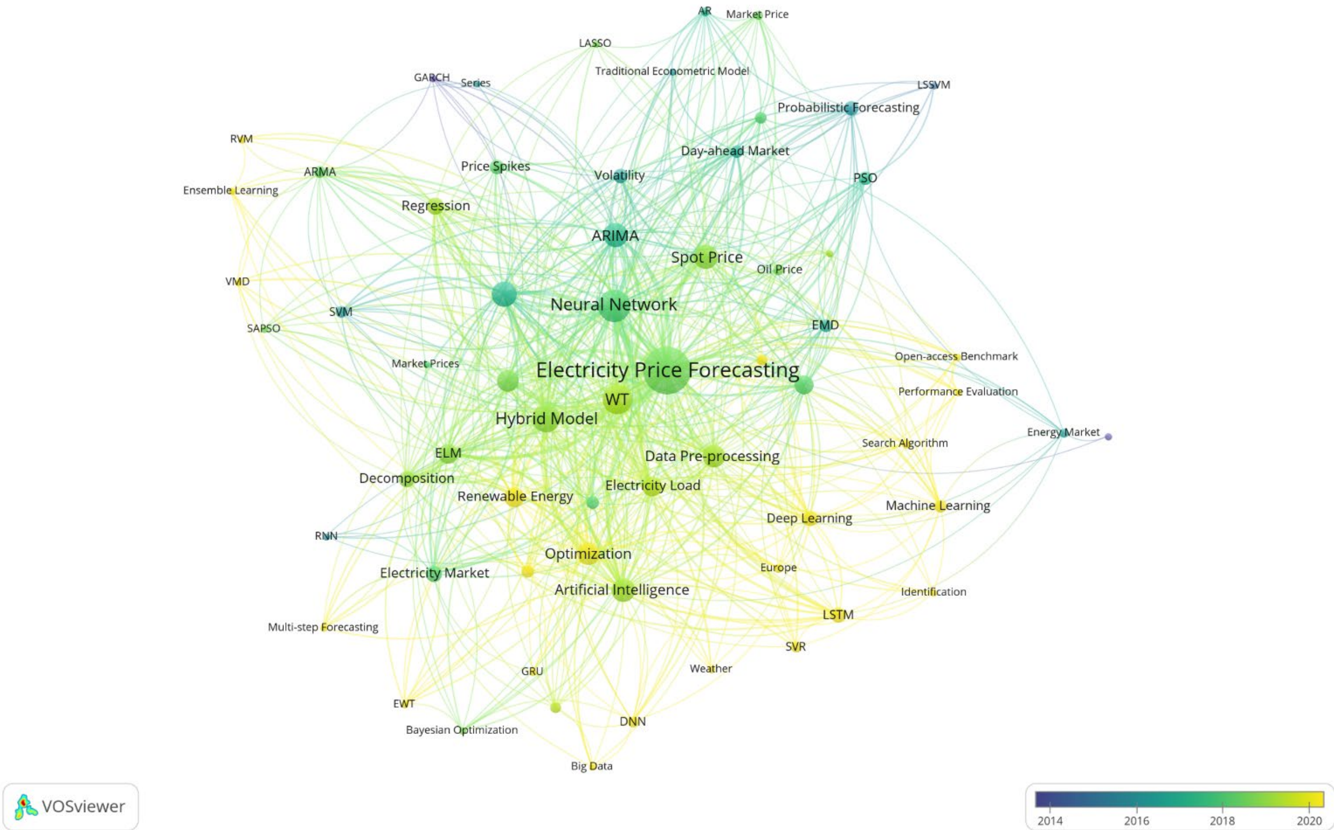

Fig. 5. The overlay visualization of the keyword co-occurrence.

From Fig. 4 and Fig. 5, it can be found that: (1) Most of scholars have conducted more researches on data preprocessing module, price forecasting module, and model optimization module. Furthermore, scholars tend to innovate more in the price forecasting module over time, but less in the evaluation of model performance. It may be due to the fact that the existing model evaluation metrics are fixed and authoritative, and it is difficult to make a breakthrough in this area. Most of the existing researches on the innovation of evaluation indicators are weighted summation of evaluation indicators, and less of them propose new model evaluation indicators. (2) Compared to the traditional econometric models, the artificial intelligence models and the hybrid models are more widely used in electricity price forecasting in the last decade, and most of the studies focus on the period 2017-2022. The neural network is the most widely used Among price prediction models. In addition, the deep learning, the machine learning, and the ensemble learning are getting more and more attention from the researchers as time goes by. (3) The determinants of electricity price such as the renewable energy, the electricity demand and the electricity load are increasingly mentioned as research progresses, which indicates that the determinants of electricity price will play an more important role in electricity price forecasting.

5.2 Model Structure

Following Lu et al. (2021), we also divide the forecasting models into four categories according to the structure: (1) Data Pro-processing + Price Forecasting + Model Optimization + Performance evaluation (P-F-O-E); (2) Data Pro-processing + Price Forecasting + Performance evaluation (P-F-E); (3) Price Forecasting +Model Optimization + Performance evaluation (F-O-E); (4) Price Forecasting + Performance evaluation (F-E). It is interesting to find that all structures of the model include the performance evaluation, which also indicates that the performance evaluation is a necessary module to check the accuracy of the model, as well as plays an important role in EPF.

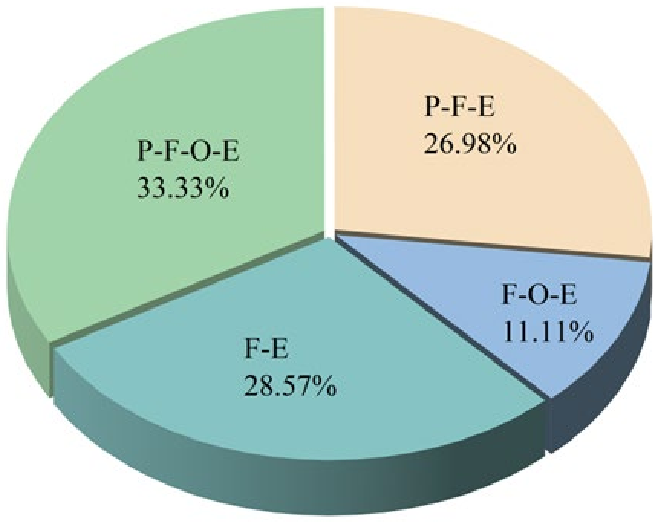

Fig. 6. The percentage of models with various architectures.

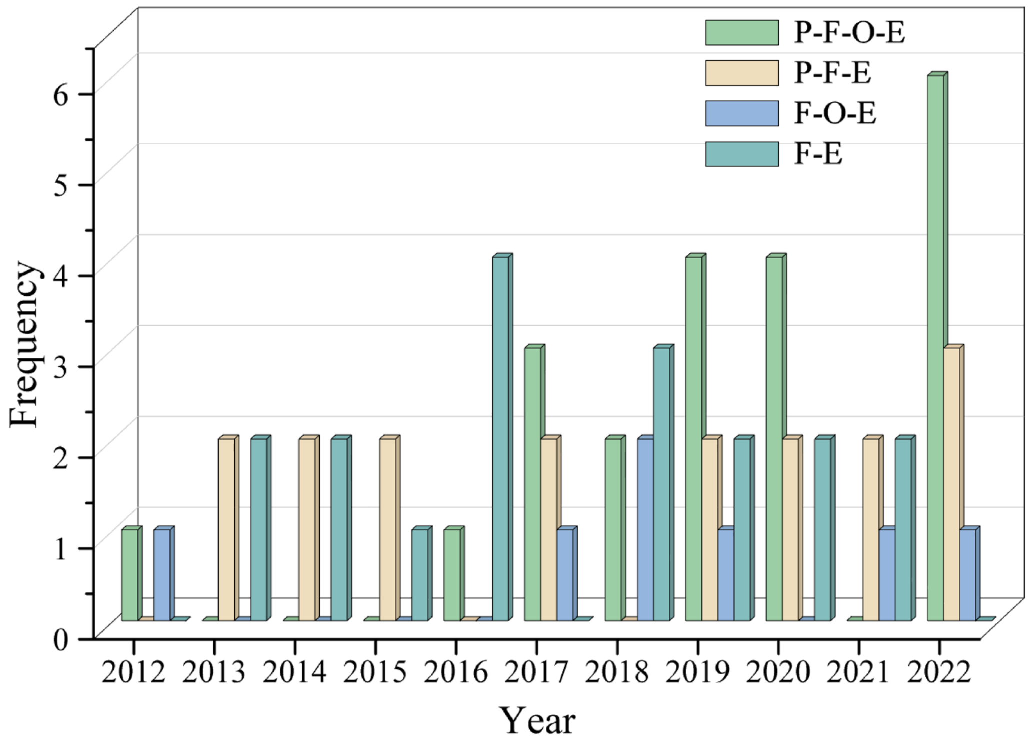

Fig. 7. The use trend of models with various architectures.

As shown in Fig. 6, the P-F-O-E-type models are the most used among all models for EPF, while the F-O-E-type models account for the smallest share. This indicates that data preprocessing and model optimization play increasingly important roles in EPF. As can be shown in Fig. 7, the use of the P-F-O-E-type model shows a rising trend and develops rapidly after 2017. The advantage of this model is that it cannot only make the model input variables more suitable for the prediction with the help of data preprocessing methods, but also optimize the parameters of the model using optimization algorithms, thus making the forecasting results more accurate. In addition, it can be observed from the figures that scholars prefer to use data preprocessing alone rather than using model optimization algorithms alone. Notably, the F-E type models are also widely used, but the proportion of the model is decreasing as the research progresses. The F-E type models do not use data preprocessing or model optimization methods, and rely only on their own proposed new forecasting models to forecast electricity prices, which requires the forecasting models to have strong adaptability and data processing capabilities.

5.3 Research Sample and Prediction Horizon

The selection of research sample plays a significant role in EPF. From Fig. 8, it can be seen that the sample data selected for the existing researches are mainly from Europe, Australia, and America, where the electricity markets have developed earlier and the data are easily accessible. As shown in Fig. 9, the Spanish electricity market is the most studied among European countries, which is closely related to the advantages of the Spanish electricity market itself. The renewable energy generation in Spain is well developed and the country has the most flexible grid in the world, which can provide a superior source of data for EPF and a solid basis for testing the accuracy of the model. The Australian electricity market is one of the most liberal electricity markets in the world, and the Australian regions most commonly used in the EPF studies are New South Wales and Queensland. PJM is the first electricity market established in America, and its real-time electricity prices are updated every 5 minutes. Therefore, it is widely used as a research sample for EPF.

The prediction horizon is often made based on policy or management needs. In this paper, we define "5-Min," "30-Min," and "Hourly" as ultra-short-term, "Daily" as short-term, and "Monthly" and "Annual" as medium- and long-term (Lu et al., 2021). In particular, the ultra-short-term and short-term electricity price predictions are more focused on providing a basis for management, while the medium- and long-term electricity price predictions are used for the guidance of policy. As seen in Fig. 10, "Hourly" has the highest percentage, followed by "30-Min" and "Daily". It shows that most of the existing researches focus on ultra-short-term and short-term real-time EPF, and fewer researches are conducted for medium- and long-term EPF.

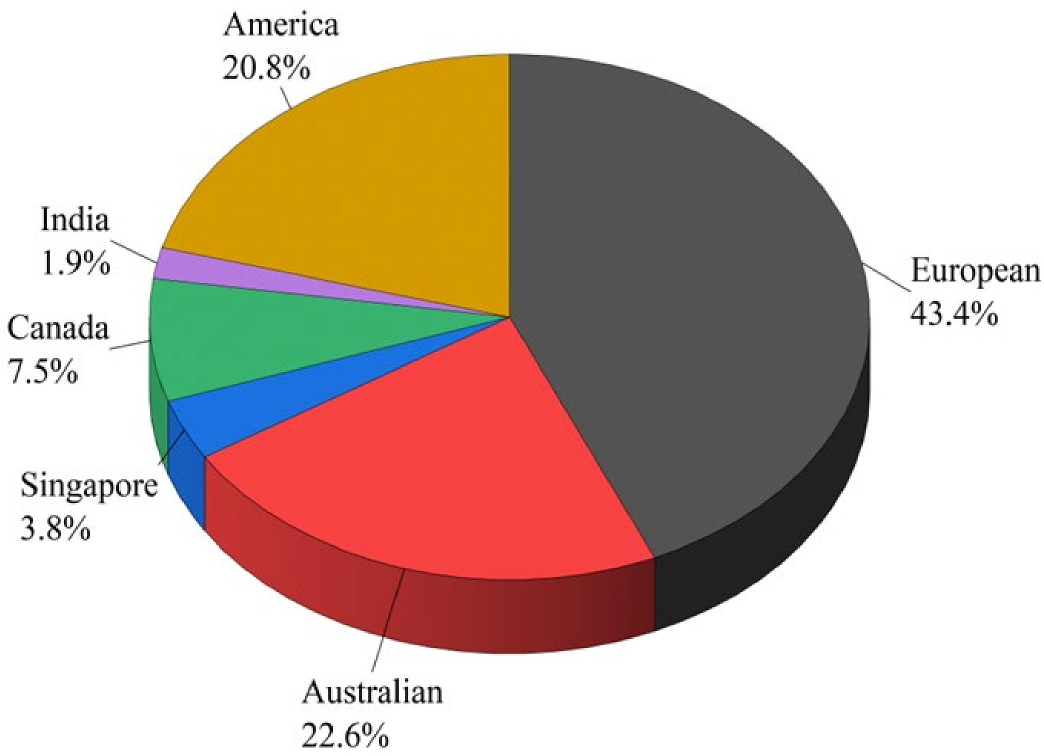

Fig. 8. The regional distribution of the research sample.

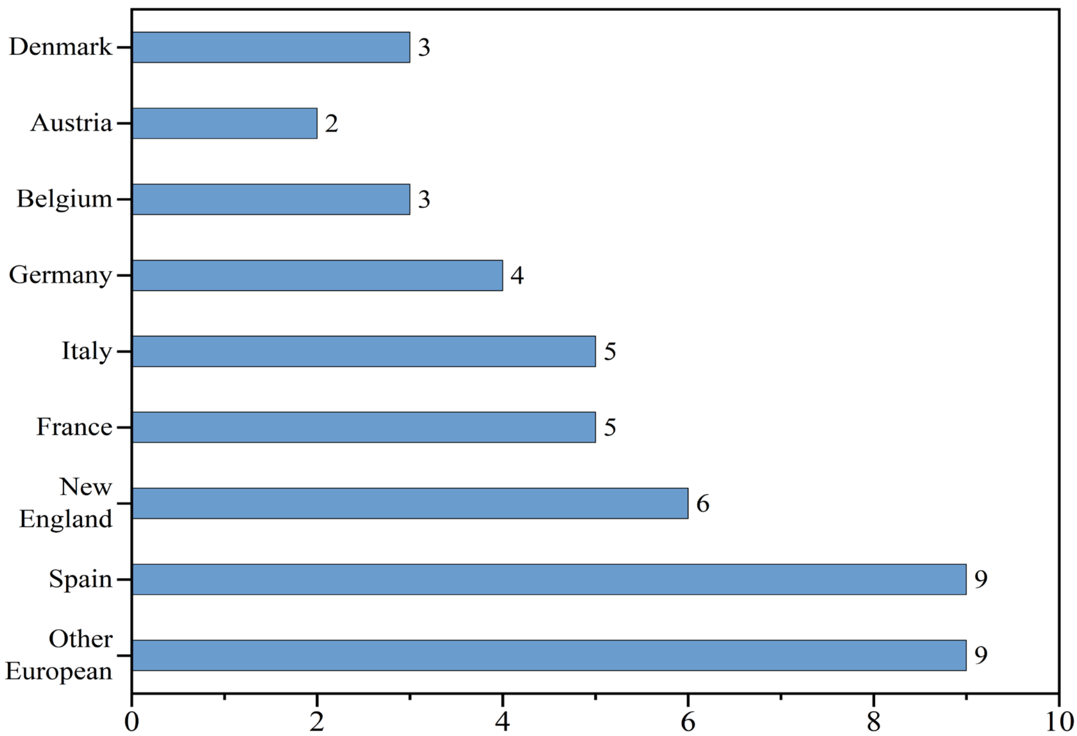

Fig. 9. The distribution of the research sample in European.

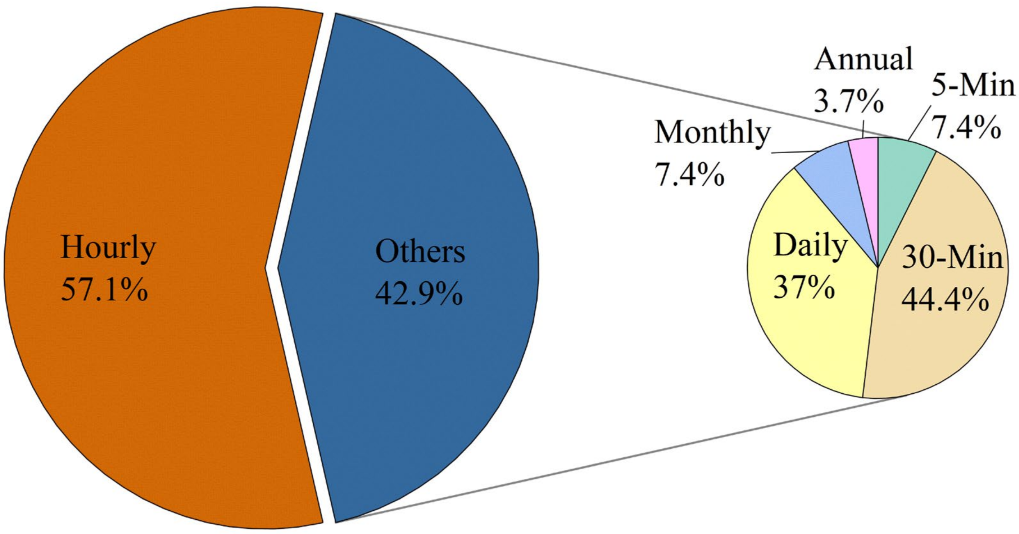

Fig. 10. The percentage of the prediction horizons.

6. Conclusions and future directions

6.1 Conclusions

This study systematically reviews and compares the screened 62 literature of EPF during the period 2012-2022. The contributions of this paper to the existing literature are as follows. First, this paper provides a detailed classification and comparison of the data preprocessing methods, price forecasting methods, model optimization methods, and performance evaluation indicators from the perspective of model structure. Second, this paper reviews the literature on the determinants of the electricity price and further explores the extent to which external variables affect the performance of the EPF model. Finally, this paper presents an econometric analysis of the evolution process, model structure, research sample, and prediction horizon of EPF with the help of bibliometric methods. Based on the above efforts, this paper summarizes the following:

(1) The number of researches on EPF shows an upward trend in general. The P-F-O-E-type model is the most popular among the four structural models and has

a significant growth in the number of applications after 2017. In addition, scholars prefer to use data preprocessing methods alone compared to using model optimization algorithms alone. However, both data preprocessing methods and model optimization algorithms can be useful to improve the price forecasting model performance.

(2) In the data preprocessing module, the single decomposition methods are still widely used, such as WT, VMD, and EMD. Moreover, the dual decomposition methods have been proven to have good data preprocessing capabilities, but less research has been done on this. In the price forecasting module, the artificial intelligence is widely used and are mainly based on neural networks. As research advances, deep learning, integrated learning and machine learning are also attracting more attention. In the model optimization module, most of the existing studies are based on the heuristic algorithms to optimize the model parameters and thus improve the performance of the prediction models. In the result evaluation module, scholars prefer to use MAPE, MAE and RMSE to evaluate the prediction accuracy of models, but there is still no standardized evaluation system.

(3) Considering determinants of electricity price in EPF can significantly improve the accuracy of the price forecasting model. As the penetration of renewable energy in the power generation industry increases, scholars have become more concerned about the impact of renewable energy on the electricity price volatility. Besides, electricity generation, electricity demand and weather are

also determinants of the electricity price fluctuations. However, how many and which determinants of electricity price should be considered in EPF are still worth discussing.

(4) In terms of the research sample, the electricity markets in Europe, Australia and America are more frequently used. In terms of the prediction horizon, scholars prefer to forecast the short-term electricity price, and the "Hourly" type data are most widely used. However, the medium- and long-term EPF are more beneficial for policy decisions and risk aversion than short-term EPF.

6.2 Future research directions

Based on the above conclusions, this paper summarizes the future development direction of EPF as follows:

(1) In the data preprocessing module, the dual decomposition method has a strong data processing capability and can make up for the shortcomings of the single decomposition method. Therefore, the dual decomposition method should be explored more to improve the model prediction performance in the future. In the price forecasting module, the existing research focuses on neural networks, however, deep learning, integrated learning and machine learning also have powerful forecasting capabilities and should be developed more in the future. In the model optimization module, besides focusing on the improvement of model prediction accuracy, multi-objective optimization and the setting of objective function should be considered more. In the performance evaluation module, the extensive benchmark of performance evaluation should be further

explored in the future.

(2) Scholars have realized the importance of determinants of electricity price for EPF and have added some determinants of electricity price as input variables in EPF modeling. There are many determinants of electricity price fluctuations. Considering all determinants would not only make data collection difficult, but also lead to a redundancy of effects. In addition, considering fewer external factors may miss key variables. Therefore, how many and which external factors should be discussed further in future EPF research.

(3) In terms of the research target, most of the existing researches focus on the electricity price point forecasting. However, compared with point forecasts, the interval forecasts and the density forecasts are more responsive to the range and uncertainty of electricity price changes and provide more complete and rich information, which can provide more systematic decision support to government departments and market participants for asset allocation and risk management, etc. Therefore, the interval forecasts and the density forecasts should be paid more attention in the future.

Appendix A. The important information of the 62 papers screened

Author (Year)	Market	Model	Data Preprocessing	Price Forecasting	Model Optimization	Performance Evaluation	Prediction Horizon(s)
Meng et al. (2022)	Danish	EWT-AM-LSTM-CSO	EWT	AM-LSTM	CSO	MAE, RMSE	Hourly
Tschora et al. (2022)	France, Germany, Belgium	ML	\	ML	\	RMAE, SMAPE,	Daily
Gabrielli et al. (2022)	United Kingdom, Germany, Sweden, Denmark	GPR	\	GPR	\	MAPE	Annual, Monthly, Hourly
Yang et al. (2022)	Australian, Singapore	APVMD-CSCA-KELM	APVMD	KELM	CSCA	MAE, RMSE, MAPE, TIC, IA	Hourly
Deng et al. (2022)	Ontario	EEMD-VMD-TCMS-CNN	EEMD+VMD	CNN	TCMS	MSE, MAE, RMSE, R^2	Hourly
Ifran et al. (2022)	New England	SVM-AO, DenseNet-AO	RFE, XGboost, RF	SVM, DenseNet	AO	MAPE, RMSE, MSE, MAE	Daily
Bille et al. (2022)	Italy	ARFIMA-GARCH	\	ARFIMA-GARCH	\	RMSE, CRPS	Hourly
Zhang et al. (2022)	Australian, Spanish	VMD-EEMD-DE-ELM	VMD+EEMD	ELM	DE	RMSE, MAPE, MAE	30-Min
Iwabuchi et al. (2022)	Australian	WT-LSTM	WT	LSTM	\	MAPE	Hourly
Xu et al. (2022)	Australian	LSTM-LUBE-MGWA	\	LSTM-LUBE	MGWA	PICP, PIAW	Hourly
Deng et al. (2021)	Ontario	Multi-Scale Dilated Deep CNN	\	Multi-Scale Dilated Deep CNN	Adam	\	5-Min
Memarzadeh and Keynia (2021)	PJM, Spanish, Iran	DWT-LSTM	DWT	LSTM	\	MAPE, RMSE, MAE, VAR	\
Yang and Schell (2021)	NYISO	GRU-TL	\	GRU-TL	\	MAPE, MAE	5-Min
Shi et al. (2021)	France	TSEP	\	ANN, DNN	\	MAE, MAPE	Daily
Shao et al. (2021)	Australian, PJM	EEMD-BiLSTM-MRMR	EEMD	BiLSTM-MRMR	\	RMSE, MAPE	Daily
Jasinski (2020)	Poland	ANNs	\	ANN	\	DM	Hourly
Qiao and Yang (2020)	US	WT-SAE-LSTM	WT	SAE-LSTM	\	RMSPE, MAE, MAPE, RMSE, Theil's U1, Theil's U2, R2	Monthly
Yang et al. (2020)	Australian	AVMD-IMOSCA-RELM	VMD	RELM	IMOSCA	MAE, RMSE, MAPE, TIC, PICP, FIAW, AWD	30-Min
Zhang et al. (2020)	Australian, PJM, Spanish	VMD-SAPSO-DBM-SARIMA	VMD	Regular: SARIMA Inregular: DBN	SAPSO	RMSE, MAPE, MAE	30-Min
He et al. (2020)	Singapore	DCNN–LDLFs	DNDT	DCNN–LDLFs	\	MAPE, MAE, RMSE	30-Min
Gianfreda et al. (2020)	Germany, Denmark, Italy, Spain	AR(X), VAR(X)	\	AR(X), VAR(X)	\	RMSE, CRPS	Hourly
Heydari et al. (2020)	PJM, Spanish, Italy	VMD-GRNN-GSA	VMD	GRNN	GSA	RMSE, MAE, MAPE, R, TIC	Hourly

Wang et al. (2020)	Australian, Singapore	IVMD-CSCA-PSR-ORELM	IVMD	ORELM	CSCA	MAE, RMSE, MAPE, IA, TIC	30-Min
Yang et al. (2019)	Australian	ICEEMDAN-VMD-MOGWO-ENN	ICEEMDAN+VMD	ENN	MOGWO	AE, MAE, MAPE, RMSE, Theil's U1, Theil's U2	30-Min
Zhang et al. (2019)	Australian	HFS-CSS-r, HFS-CSS-ρ, HFS-CSS–τ	SSA	SVM	CSA	IMAPE, SMAPE	30-Min
Agrawal et al. (2019)	New England	RVM-EGB	\	RVM	EGB	MAE, MAPE, RMSE	Hourly
Ghayekhloo et al. (2019)	NYISO	EGT-Cluster-BRNN	EGT-Cluster	BRNN	\	MSE, MAPE, RMSE	Hourly
Cheng et al. (2019)	EU	EWT-BiLSTM-SVR-BO	EWT	Low freq.: SVR High freq.: BiLSTM	BO	MAE, MAPE, RMSE	Hourly
Chang et al. (2019)	Australian, France	WT-Adam-LSTM	WT	LSTM	Adam	MSE, RMSE, MAE, MAPE, Theil's U1, Theil's U2	Daily
Vu et al. (2019)	Australian	ARTV, SVM, KR	WT	ARTV, SVM, KR	\	MAE, MAPE, RMSE	30-Min
Windler et al. (2019)	Germany, Austria	WNN, TBATS, DFNN	\	WNN, TBATS, DFNN	\	SMAPE, RMSE	Hourly
Kostrzewski and Kostrzewska (2019)	PJM	Bayesian SVDEJX	\	Bayesian SVDEJX	\	\	Hourly
Peng et al. (2018)	Australian, Germany, Austria, France	DE-LSTM	\	LSTM	DE	RMSE, MAE, MAPE	Hourly
Loi and Ng (2018)	Singapore	ARIMA-GARCH	\	ARIMA-GARCH	\	AIC, RMSE, MAE, MAPE, TIC	30-Min
Lago et al. (2018a)	Belgium	LSTM–DNN, GRUNN–DNN	\	LSTM–DNN, GRUNN–DNN	\	SMAPE	Hourly
Ebrahimian et al. (2018)	PJM, New England	WT-NN-MPSO	DWT	Three Stage Cascade NN	MPSO	MAE, MAPE, WME, WPE	Hourly
Lago et al. (2018b)	Belgium, France	DNN	\	DNN	\	SMAPE	Hourly
Bisoi et al. (2018)	PJM, Ontario, Australian	MKELM-WCA	\	MKELM	WCA	RMSE, MAE, MAPE	Hourly
Osório et al. (2018)	Spanish, PJM	WT-DEEPSO-ANFIS-MCS	WT	ANFIS-MCS	DEEPSO	MAPE	Hourly
Yang et al. (2017)	PJM, Spanish, Australian	WT-ARMA-SAPSO-KELM	WT	Linear: ARMA Non-linear: SAPSO-KELM	SAPSO	MAPE, MAE, DMAE, WMAE, RMSE, Theil's U1, Theil's U2,	Daily
Singh et al. (2017)	Australian	WT-GNM-IEMA	WT	GNM	IEMA	MAPE, MAE, VAF, RMSE	Hourly
Qiu et al. (2017)	Australian	EMD-KRR-SVR	EMD	KRR-SVR	\	RMSE	30-Min
Shao et al. (2017)	Ontario, New York	TSS-RFE-MRMR-SVM	TSS-RFE-MRMR	SVM	\	MPCE	Hourly
Neupane et al. (2017)	New York, Australian, Spanish	FWM, VWM	\	ANN, SVR, RF	FWM, VWM	MER, MAE, MAPE	30-Min
Gollou and Ghadimi (2017)	PJM	WT-NN-VEHBMO	DWT	Three Stage Cascade NN	VEHBMO	WME, WPE	Hourly

Keles et al. (2016)	EU	MLFFANN	\	FFANN	\	MAD, RMSE	Daily
Panapakidis and Dagoumas (2016)	Italy	ANN	\	ANN	\	MAPE, APE, MAE, Theil's U1, Theil's U2	Hourly
Sandhu et al. (2016)	Ontario	ANN	\	ANN	\	MAPE, RMSE, MAE	Hourly
Girish (2016)	India	AR-GARCH	\	AR-GARCH	\	RMAE. MAPE, MAE, TIC	Hourly
Rafiei et al. (2016)	Ontario, Australian	WT-ISCA-LSE	WT	TNN-ICSA, ELM	LSE	PINC, PICP, ACE, SC	Hourly
Kou et al. (2015)	Australian, PJM, New England	VHGP	\	VHGP	\	RE, SE, NLPD, MAPE	30-Min
He et al. (2015)	Australian	BED	BEMD	VAR	\	MSE, MAE	Hourly
Pany and Ghoshal (2015)	Ontario, Indian	LLWNN	WT	LLWNN	\	DMAE, DMAPE, WMAE, WMAPE	Hourly
Babu and Reddy (2014)	Australian	ARIMA-ANN	MA	Low freq.: ARIMA High freq.: ANN	\	MAE, MSE	Hourly
Shrivastava and Panigrahi (2014)	Ontario, PJM, New York, Italian	WELM	WT	ELM	\	MeDE, MAE, MAPE, MDE, (W/D)RMSE	Hourly
Cerjan et al. (2014)	EU	SD-NN-PS	\	SD, NN, PS	\	MAE, MAPE, RMSE	Daily
Yan and Chowdhury (2014)	PJM	Multiple SVM	\	SVM	\	MAE, MAPE	Hourly
Liu and Shi (2013)	New England	ARMA-GARCH-M	\	ARMA-GARCH-M	\	RMSE, MAPE, MAE, TIC	Hourly
Anbazhagan and Kumarappan (2013)	New York, Spanish	RNN	\	RNN	\	MAPE, SSE, SDE	Hourly
Cifter (2013)	EU	MS-GARCH	MS	GARCH	\	RMSE	Daily
Voronin et al. (2013)	Finnish	(S)AR(I)MAX-GARCH-ANN	MTSD	(S)AR(I)MAX-GARCH-ANN	\	MSE, MAE, MAPE, AMAPE	Daily
Lei and Feng (2012)	Nordpool, California, Ontario	PGM	\	PGM	PSO	MAPE	Hourly
Zhang et al. (2012)	Australian	WT-ARIMA-PLSSVM	DWT	ARIMA, PLSSVM	PSO	MAPE, MAE, RMSE	Hourly

Appendix B. List of Abbreviations

Abbreviations	
ACE	Average Coverage Error
AE	Average Error
AMAPE	Adapted MAPE
AM-LSTM	Attention Mechanism-based LSTM
ANFIS	adaptive neuro-fuzzy inference system
AO	Aquila Optimizer
AWD	Accumulated Width Deviation
AIC	Akaike's Information Criterion
APE	Absolute Percentage Error
APVMD	Adaptive Parameter-based VMD
ARTV	Autoregressive Time Varying
BED	Bivariate EMD Denoising
BEMD	Bivariate EMD
BO	Bayesian Optimization
CEEMD	Complete Ensemble EMD
CNN	Convolutional Neural Networks
CRPS	Continuous Ranked Probability Score
CSCA	Chaotic Sine Cosine Algorithm
CSS	The Combination of the Cuckoo Search Algorithm, Support Vector Machine and Singular Spectrum Analysis
DAE	Daily Average Error
DBN	Deep Belief Network
DEEPSO	hybrid particle swarm optimization
DFNN	Deep Feedforward Neural Network
DM	Diebold-Mariano
DMAE	Daily Weighted MAE
DRMSE	Daily Weighted RMSE
DMAPE	Daily Weighted MAPE
DNDT	Data Normalization and Dimension Transformation
EEMD	Ensemble EMD
EGB	Extreme Gradient Boosting
EMD	Empirical Mode Decomposition
ENN	Elman Neural Network
EWT	Empirical Wavelet Transform
GME	General Maximum Entropy
GNM	Generalized Neuron Model
GRU-TL	Gated Recurrent Unit-Transfer Learning
HFS	Hybrid Feature Selection
IA	Index of Agreement
ICEEMD	Improved CEEMD
ICEEMDAN	ICEEMD with Adaptive Noise
ICSA	Improved Clonal Selection Algorithm
IEAM	Improved Environment Adaptation Method
IMF	Intrinsic Mode Function
IMOSCA	Improved Multi-Objective Sine Cosine Algorithm
KELM	Kernel-based Extreme Learning Machine
KR	Kernel Regression
LLWNN	Local Linear Wavelet Neural Network
LMP	Locational Marginal Price
LSE	Least-Squared Error
LSTM	Long Short-term Memory
LUBE	Lower–Upper Bound Estimation
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MCS	Monte Carlo Simulation
MDE	Mean Daily Error

MER	Mean Error Relative
MeDE	Median Daily Error
MGWA	Modified Grey Wolf Algorithm
MKELM	Multi-kernel Extreme Learning Machine
MLE	Maximum Likelihood Estimator
MLFFANN	Multi-Layer Feed-Forward ANN model
MOGWO	Multi-objective Grey Wolf Optimizer
MPSO	Modified Particle Swarm Optimization
MTSD	Multiplicative Time Series Decomposition
NARDL	Nonlinear Autoregressive Distributed Lags
NLPD	average Negative Log Predictive Density
OLS	Ordinary Least Square Regression
ORELM	Outlier-Robust Extreme Learning Machine
PCA	Principal Component Analysis
PIAW	Prediction Interval Average Width
PICP	Prediction Interval Coverage Probability
PINC	Prediction Interval Nominal Confidence
PMLR	Panel Multivariate Linear Regression
PS	Price Spikes Detection
RE	Reliability Evaluation
RELM	Regularized Extreme Learning Machine
RF	Random Forest
RFE	Recursive Feature Eliminator
RMAE	Relative Mean Absolute Error
RMM	Regression-based Mixture Model
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RVM	Relevance Vector Machine
SAE	Stacked Autoencoder
SAPSO	Self-adaptive Particle Swarm Optimization
SC	Sharpness Criterion
SD	Similar Days Methodology
SDE	Standard Deviations of Error
SE	Sharpness Evaluation
SMAPE	Symmetric Mean Absolute Percentage Error
SSA	Singular Spectral Analysis
SSE	Sum Squared Error
SVAR	Structural Vector Autoregressive
SVDEJX	Stochastic Volatility Model with Double Exponential Distribution of Jumps and Exogenous Variables
TBATS	Exponential Smoothing State Space Model with BoxCox Transformation, ARMA errors, Trend and Seasonal Components
TSS	Time Series Segmentation
TCMS-CNN	Multiscale CNN using Time-cognition
T-GARCH	Threshold-GARCH
TIC	Theil's Inequality Coefficient
TNN	Training Neural Networks
VAR	Variance
VEHBMO	Chaotic Vector Evaluated Honey Bee Mating Optimization
VHGP	Variational Heteroscedastic Gaussian Process
VMD	Variational Mode Decomposition
WCA	Water Cycle Algorithm
WMAE	Weekly Weighted Mean Absolute Errors
WME	Weekly Mean Error
WNN	Weighted Nearest Neighbor
WPE	Weekly Peak Error
XGboost	Extreme Gradient Boosting

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