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Forecasting electricity prices from the state-of-the-art modeling technology and the price determinant perspectives

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A B S T R A C T

Accurate electricity price forecasting (EPF) is crucial to participants and decision-makers within the electricity market. This paper reviews 62 screened literature works 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. From the above efforts, we find that (1) data preprocessing and model optimization are often used to improve forecasting model accuracy; while performance evaluation is essential, extensive performance evaluation benchmarking is still missing; (2) considering electricity price determinants can significantly improve forecasting model accuracy, but there is disagreement over how many and which determinants should be accounted for; (3) while most existing research focuses on point forecasting, interval and density forecasting are more responsive to the range and uncertainty of electricity price changes.

1. Introduction

The energy crisis caused by the Russia–Ukraine conflict since 2022 has led to soaring electricity prices in France, Germany, and other European countries, considerably affecting people's daily lives and productive activities (Lim et al., 2022a). Electricity is essential energy for daily life and an important foundation of economic development and social progress (Wang et al., 2017). Electricity price fluctuations affect resource flows and allocations in the electricity market and result in tremendous production and operating risks for market participants. Therefore, accurate electricity price forecasting (EPF) is crucial to electricity market participants and decision-makers (Gabrielli et al., 2022; Meng et al., 2022; Zhang et al., 2022).

Since the 1990s, electricity market reform has made electricity a special commodity, and EPF has gradually received more scholarly attention (Weron, 2014). EPF research originates from numerous scientific areas, such as statistics and engineering, leading to varied structures and approaches (Ziel and Steinert, 2018). In the past decade, as artificial intelligence has become more popular and technology has advanced, many ideas and approaches have been used in an attempt to improve model forecasting performance, with

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various degrees of success (Weron, 2014). The blossoming of a wide range of models, however, has caused many new scholars to the field to be at a loss. In addition, scholars have been unable to scientifically judge state-of-the-art EPF modeling techniques due to differences in data sources and performance evaluation criteria. Therefore, exploring state-of-the-art modeling techniques in EPF has great significance for further developments in the field and can provide research ideas and methods for scholars in the future.

EPF refers to predicting future prices according to certain accuracy and speed criteria by collecting historical data, constructing mathematical models, and exploring the intrinsic connections and laws between electricity prices and their determinants (Nowotarski and Weron, 2018). Most EPF research has been based on historical electricity prices (Zhang et al., 2012; Liu and Shi, 2013; Shrivastava and Panigrahi, 2014), while fluctuations in electricity prices are, in reality, influenced by many factors (Maciejowska et al., 2021; Doering et al., 2021; Wang et al., 2022). For example, with renewable energy's increasing penetration of the electricity-generation industry, volatile renewable energy generation undoubtedly will tremendously influence electricity price fluctuations (Gabrielli et al., 2022). In addition, other determinants of electricity prices, such as fossil energy prices (Doering et al., 2021), carbon prices (Bublitz et al., 2017), electricity demand (Mosquera-López and Nursimulu, 2019), calendar data (Neupane et al., 2017), and weather (Peña and Rodríguez, 2019), can significantly affect electricity price fluctuations. Therefore, scientific judgments about electricity price determinants and the construction of a forecasting method with high applicability and performance on this basis are essential to accurate EPF (Liu et al., 2022; Tschora et al., 2022; Zhang et al., 2022). Based on this, our study provides scholars with valuable insights and scientific judgments on the impact of electricity price determinants in EPF and the most favored determinants within current research.

The existing literature provided detailed classification summaries and reviews of the EPF model, laying the foundation for the further research in this paper. For example, Weron (2014) provided a detailed classification of mainstream EPF models by development stage, explained the complexity of available solutions, their strengths and weaknesses, the opportunities and threats that forecasting tools may encounter, and noted the direction of development in the following decade. With the increasing importance of probabilistic EPF for energy systems planning and operation, Nowotarski and Weron (2018) provided an update and a further extension of the otherwise comprehensive EPF review from Weron's research and proposed much-needed guidelines for rigorously using methods, measures, and evaluation. In addition, Lago et al. (2021) provided a detailed review of state-of-the-art algorithms, best practices, and open-access benchmarks for day-ahead electricity prices. They addressed the lack of a unified model evaluation methodology in existing research.

Despite the aforementioned comprehensive EPF literature reviews, the scope can be further refined and enhanced. Table 1 compares review articles published in recent years with the present review. First, most existing review articles only categorize and summarize EPF models, with fewer of them summarizing the methods of specific EPF processes, such as data preprocessing, model optimization algorithms, and performance evaluation indicators. Second, an analysis of electricity price determinants is important for accurate EPF, but existing review articles provide less generalization about electricity price determinants. Finally, whereas the publishing year of each article is important for understanding the evolutionary process of the research topic, the appearance year of

Table 1
Comparison of recently published review articles and present review.

\Author	Review Objects	Classification (s)	Contributions
Weron (2014)	Electricity price forecasting	Multiagent models, fundamental methods, reduced-form models, statistical approaches, computational intelligence	Presenting a comprehensive review of EPF literature, explaining EPF modeling techniques, and providing research directions for the next decade
Dutta and Mitra (2017)	Dynamic electricity pricing	Pricing policies, consumers' willingness to pay and market segmentation	Reviewing the literature related to dynamic electricity pricing and summarizing the application of dynamic electricity pricing under various scenarios
Gürtler and Paulsen (2018)	Forecasting performance of time series models on electricity spot markets	Simulation models, heuristic methods, computational or artificial intelligence, statistical models	Reviewing time series modeling techniques for electricity price forecasting and comparing related time series models
Nowotarski and Weron (2018)	Probabilistic electricity price forecasting	Historical simulation, distribution-based probabilistic forecasts, Bootstrapped PIs, quantile regression averaging	Reviewing the literature on and providing valuable guidelines for probabilistic EPF
Acaroğlu and García Márquez (2021)	Electricity market pricing and load forecasting based on wind energy	1. Short-, middle-, and long-term pricing and load forecasting 2. Statistical, artificial intelligence, and hybrid models	Introducing the latest electricity price and load forecasting techniques and discussing their advantages and disadvantages
Lago et al. (2021)	Day-ahead electricity price forecasting	Statistical methods, deep learning methods, hybrid methods	Reviewing 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, oil, electricity, and carbon prices)	Basic model, data cleaning method, and optimizer	Providing a reference for market participants, a prediction error range to make it easier for researchers to understand the accuracy of each model, and a reference for future research directions
Present review	Electricity price forecasting, determinants of electricity prices	1. Data preprocessing module, price forecasting module, model optimization module, and performance evaluation module 2. Model classification-based electricity price determinants	Reviewing state-of-the-art modeling techniques, the role of electricity price determinants, the development process, and directions for future research in the EPF field

keywords can provide a more detailed picture of the evolutionary process. Therefore, our study summarizes gaps in current EPF research, provides an outlook on future research trends, and offers valuable research directions for scholars.

Following the suggestions of Lim et al. (2022b) regarding literature reviews, we summarize the contributions of this paper as follows:

(1) This paper provides a systematic review of EPF literature from the perspectives of state-of-the-art modeling techniques and electricity price determinants. We introduce EPF modeling techniques and then identify those that represent the current state of the art. Second, we present the main determinants of electricity price fluctuations and explore the role of electricity price determinants in EPF.
(2) Most existing review articles mainly categorize and summarize EPF models, with fewer presenting data preprocessing methods, model optimization algorithms, and performance evaluation indicators specifically for EPF. Additionally, although analyzing electricity price determinants is crucial for accurate EPF, existing review articles do not generalize about such determinants. Unlike existing studies, this paper fully demonstrates the specific EPF process and considers the impact of electricity price determinants such as renewable energy on EPF accuracy, which can further chart the EPF research process and fill the gaps in existing studies.
(3) This paper presents a bibliometric analysis of the EPF field, demonstrating its development via figures and charts and providing insight into its evolutionary process, model type, research sample, and prediction horizon. In turn, this analysis provides a foundation for further exploring EPF and identifies potential future research directions.

The remainder of the paper is organized as follows. Section 2 introduces searching and screening of literature. Section 3 compares the data preprocessing, price forecasting, model optimization, and performance evaluation modules of existing EPF models. Section 4 reviews the literature on electricity price determinants and explores those most used in the existing literature. It also addresses the impact on forecasting model performance from adding electricity price determinants as input variables. Section 5 systematically summarizes the EPF evolutionary process, model type, research sample, and prediction horizon. Finally, Section 6 provides the main conclusions and future directions.

2. Literature query

EPF has received attention from numerous academics in recent years, and the volume of relevant academic work has exploded. We cannot review every published work because some are not representative; we only review valuable and particularly innovative literature. To do so, our paper adopts and implements the Scientific Procedures and Rationale for Systematic Literature Reviews (SPAR-4-SLR) protocol (Paul et al., 2021), which consists of three main stages: assembling, arranging, and assessing (Paul et al., 2021; Kraus et al., 2022; Kumar et al., 2022b). A summary of the review process is shown in Fig. 1.

2.1. Assembling

Assembling includes identifying and acquiring literature that has not been synthesized (Paul et al., 2021). First, we identify the search topic, search fields, source type, and source quality. Academic publications are particularly valued because they advance scholarly research and are subject to stringent peer review (Kumar et al., 2022b). For quality assurance, we only review articles at the SCI Q1, Q2, and Q3 and SSCI Q1 and Q2 levels (Paul et al., 2021). For acquisition, we take WOS and Scopus, two of the most widely used databases now in the field of bibliometrics (Weron, 2014; Nowotarski and Weron, 2018), as the search mechanism and for material acquisition. Research on EPF can be traced back to the electricity market reform in the 1990 and abundant academic publications on EPF in recent decades (Weron, 2014). It is clear that the EPF research area is quite mature, with abundant literature (Loi and Ng, 2018). Therefore, referring to the search period selection rules mentioned by Paul et al. (2021), we chose 2012–2022 as the search period. Notably, many scholars who have published excellent articles in the past have also used a decade as a search period to review their papers (Faff et al., 2019; Gupta et al., 2020; Lu et al., 2021). Furthermore, our paper aims to explore the state-of-the-art modeling techniques in the last decade, which have clear requirements on the timeliness of the data. For the literature outside the sample period (before 2012), Weron (2014) has provided a highly detailed review of academic publications on EPF and the papers outside the sample period are not very significant for the topic and purpose of our research. Therefore, our paper chooses data from the last decade for the econometric analysis, which helps our study to accurately grasp the research dynamics in the emerging field and indicates the direction for future research. To assemble academic articles on EPF, this paper identifies relevant search keywords through a process of brainstorming among research team members and a review of the relevant literature (Acaroğlu and García Márquez, 2021; Lago et al., 2021; Lu et al., 2021). Moreover, we consult with appropriate professionals to ensure the accuracy and relevance of the keywords used to represent EPF. Based on this, our paper finally identifies the following search keywords: "Electricity price prediction" OR "EPF" OR "electricity price forecast" OR "predict electricity price" OR "forecast electricity price". Following the above procedures, our study conducts a preliminary acquisition of EPF literature. In Fig. 2, the numbers of published works on electricity price predictions from the WOS and Scopus databases are plotted for 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.

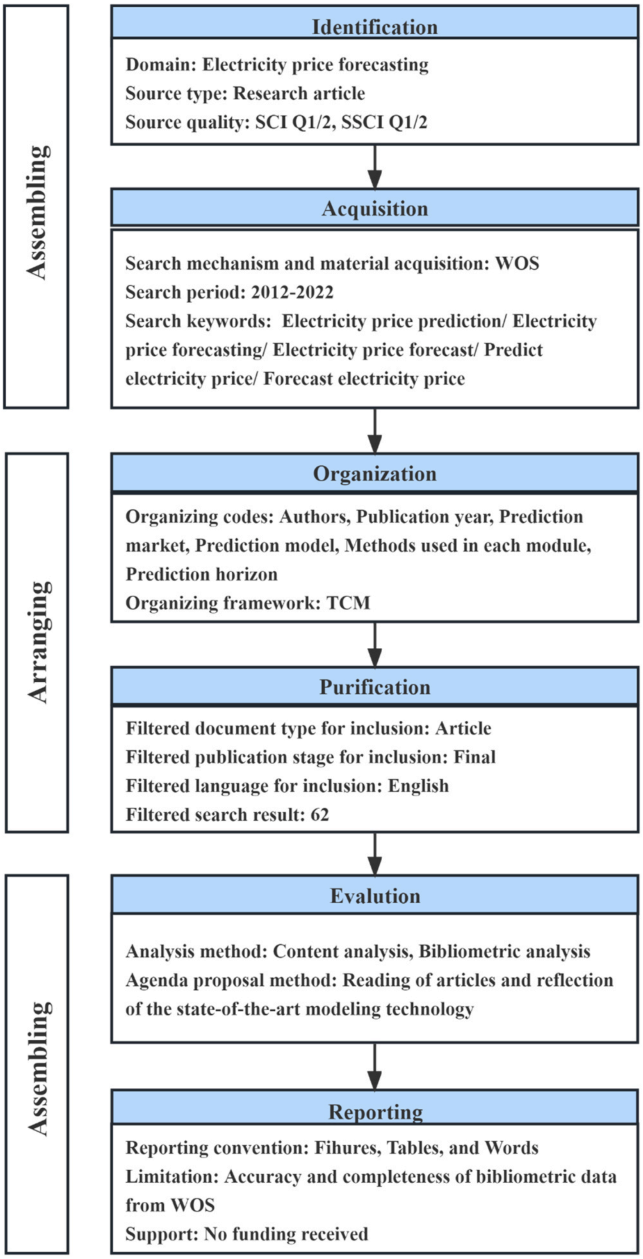

Fig. 1. Systematic review procedure using the Scientific Procedures and Rationale for Systematic Literature Reviews (SPAR-4-SLR) protocol.

2.2. Arranging

Arranging involves organization and purification of the literature being synthesized (Paul et al., 2021). To further organize and classify the assembled literature, our study uses the organizing codes according to journal title, article type, database, publication year, research area, language, keywords, journal partition, and impact factor to review the search results from the acquisition stage (Kumar et al., 2022b). Although the quality of the literature in the WOS databases can be guaranteed, this paper complements the searched literature by combining the search results of several databases such as Scopus, Springer, and Google Scholar, taking into account the delay in literature search (Lu et al., 2021). In addition, our search results are filtered and limited to “article”, “final”, “WOS core collection”, and “English” in the purification stage. These filters are implemented in line with the recommendations of Paul et al. (2021). Academic articles in particular are valued because they advance scholarly research and are subject to stringent peer review (Kraus et al., 2022). Only the final articles are taken into account, as they are already finalized. Other sources, such as books, book chapters, and conference proceedings are excluded because they may not have undergone rigorous peer review (Kumar et al., 2022b).

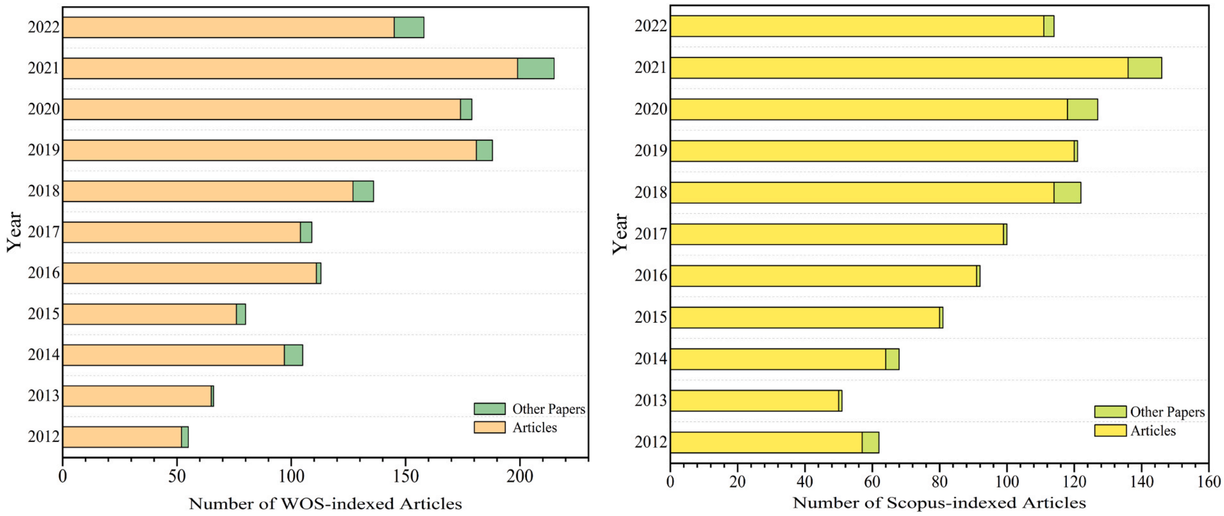

Fig. 2. The number of WOS-indexed (left panel) and Scopus-indexed (right panel) EPF articles, 2012–2022.

The WOS core collection is normally considered to be of high quality. Since English is the dominant language in writing, nonEnglish articles are not included. Finally, this study selects 62 articles on EPF for further bibliometric analysis. See Appendix A for the screened literature.

2.3. Assessing

In the assessing stage, this study evaluates and reports on the final corpus. A bibliometric analysis approach is adopted for this review. Bibliometric analysis is the measurement and processing of literature, using algorithms, arithmetic, and statistics to analyze, explore, organize and investigate large amounts of data (Paul et al., 2021; Kraus et al., 2022; Lim et al., 2022c). Following previous studies (Kumar et al., 2022a; Lim et al., 2022c), our study uses VOSviewer to conduct bibliometric analysis and visualization of the keywords co-occurrence for the screened 62 articles. Finally, we further read and extract valuable information from the screened literature, such as Author, Market, Input Factor, Model, Conclusion, and Journal. In addition, to advance insights in the field, this study proposes a future research agenda based on a comprehensive review of the existing relevant literature and an assessment of current gaps within each of the major themes (Kumar et al., 2022b). The findings from the review are presented in the subsequent sections in the form of narrative and visualized content.

3. Mainstream electricity price forecasting model

This 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. The 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; and 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 to make the forecasting model work better. The popular data preprocessing 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. 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 multiscale densification of data signals and convert high-frequency data to low-frequency data, which is an 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. (1998), which is especially suitable for the analysis and processing of nonlinear nonstationary 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 nonsmooth 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, variants of EMD have been continuously proposed. For example, the ensemble EMD (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 EMD (BEMD) (He et al., 2015), the improved EMD (IEMD) (Zhang et al., 2019a), the complete ensemble EMD (CEEMD) (Hu et al., 2022), the complete ensemble EMD with adaptive noise (CEEMDAN) (Jun et al., 2018), and the improved complete ensemble EMD with adaptive noise (ICEEMDAN) (Yang et al., 2019) are also widely used.

The VMD method is an adaptive, completely nonrecursive 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 (Heydari et al., 2020; Yang et al., 2020; Zhang et al., 2020). For the extended VMD-based approach, Wang et al. (2020) applied the improved VMD (IVMD) to EPF in Australia and Singapore, and the result showed that the IVMD compared with VMD can adaptively perform optimal decomposition of different electricity price data and achieve high forecasting performance. Moreover, the adaptive parameter-based VMD (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. *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 nonsmoothness 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 preprocessing 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 low- and 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 nonsmoothed IMFs, and the smoothed decomposed IMFs are input into the prediction model while the nonsmoothed decomposed IMFs will be further smoothed by the VMD method. The dual decomposition method employs VMD to solve the problem that the nonsmoothed 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.

3.1.3. *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., 2023), the artificial intelligence model (Keles et al., 2016; Panapakidis and Dagoumas, 2016; Jasinski, 2020) and the hybrid model (Agrawal et al., 2019; Zhang et al., 2019b; Zhang et al., 2020). Notably, the different forecasting models have their own strengths and weaknesses.

Table 2
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 nonsmooth 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 nonsmooth 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 nonstationary and nonlinear data and is suitable for analyzing nonlinear and nonstationary 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)

3.2.1. 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, Billé et al. (2023) 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 nonstationarity, nonlinearity, 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. Artificial intelligence model

The artificial intelligence model has significant advantages over the traditional econometric model in predicting nonstationary, nonlinear, 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 nonstationary and nonlinear 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., 2018a; 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 LSTM (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., 2020; Zhang et al., 2022; Yang and Schell, 2022). Among them, the SVM is a novel small-sample learning method with a solid theoretical foundation. Irfan et al. (2022) used SVM-AO to forecast the week ahead electricity prices in 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 ELM (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. Hybrid model

The traditional econometric model and the artificial intelligence model have their own advantages in EPF research. 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 EPF research. Agrawal et al. (2019) proposed a new two-stage integrated model for short-term electricity prices. First, 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 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 nonstationarity, seasonality, and volatility, and combined with the influence of external factors on electricity prices, to improve the forecasting performance of the models (Kostrzewski and Kostrzewska, 2019; Zhang et al., 2019b; He et al., 2020). For example, Zhang et al. (2019a) introduced a hybrid feature selection method in the forecasting strategy and combined three methods, the cuckoo search algorithm, SVM, 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 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 ELM (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 multiobjective optimization, Yang et al. (2020) used the improved multiobjective sine cosine algorithm (IMOSCA) in the model optimization stage, and Yang et al. (2019) used the multiobjective gray 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 unfortunate 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. 3 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. 3, 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.

4. EPF with determinants of electricity price

Accurate EPF is a widespread concern for the market participant. However, with the increasing penetration of renewable energy in the electricity generation industry, volatile renewable energy generation undoubtedly has a tremendous 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, this 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).

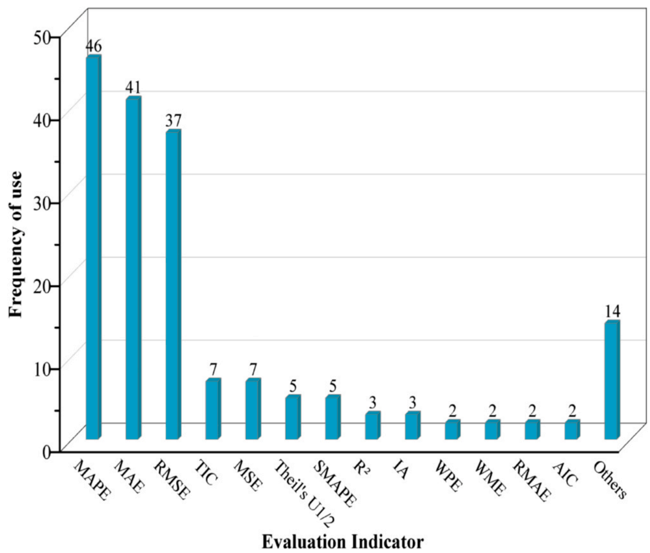

Fig. 3. The frequency of various performance evaluation indicators.

Table 3
The performance indicator rules.

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

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

4.1. Determinants of electricity prices

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 tremendous 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 instability in renewable generation not only affects the spot market price of electricity through the merit-order effect but also has an impact on the forward market price. Maciejowska et al. (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 demonstrated that the electricity price fluctuation is influenced

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)	√								√

not just 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.

4.2. EPF model with determinants of electricity price

From the existing literature, there is a common agreement that 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 EPF model with determinants of electricity price showed better accuracy in price forecasting and this opinion is strongly supported by the present literature (Meng et al., 2022; Tschora et al., 2022; Wang 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 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. (2023) 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.

A 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.

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)	√	√	√				√	√	√
Billé et al. (2023)	√	√	√				√		
Wang et al. (2022)	√	√	√				√	√	√
Jasinski (2020)	√				√				
Gianfreda et al. (2020)	√		√				√		
Zhang et al. (2019a)					√				
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)			√		√				√

As shown in Fig. 4, 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 onEPF.

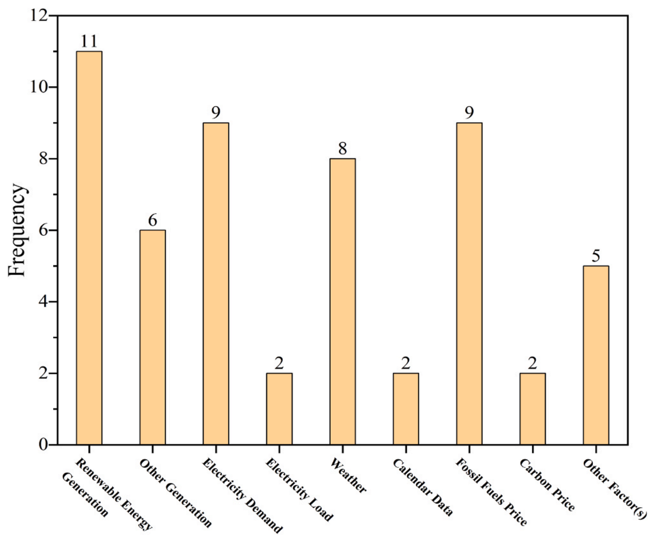

Fig. 4. The frequency of determinants of electricity price used.

5. Discussion

5.1. Evolutionary process of EPF

Bibliometric analysis is a very common and rigorous method to explore and analyze large amounts of scientific data (Donthu et al., 2021a). Leading journals and scholars from different fields have published a large number of highly influential articles that use bibliometric techniques to explore the evolution of different fields while pointing to emerging directions in the field (Mukherjee et al., 2022). There are two main types of bibliometric analysis: performance analysis and science mapping (Donthu et al., 2021a; Lim et al., 2022c; Mukherjee et al., 2022). Performance analysis can be used to review the performance of authors, journals, and countries, based on the number of publications and citations (Donthu et al., 2021a; Lim et al., 2022c). In comparison, science mapping can be used to construct a network of article attributes based on the article features, in which the co-citation analysis and keyword co-occurrence analysis are most widely used (Donthu et al., 2021a; Lim et al., 2022c).

Keywords are the core elements of the research-based article (Kumar et al., 2022a). They can reflect the main content and essence of the paper, as well as convey the conceptual structure of a particular field (Donthu et al., 2021b; Kumar et al., 2022a). Given that keywords represent the key features of a particular study, the paper uses VOSviewer Version 1.6.11 to conduct a keyword co-occurrence analysis of the keywords in the screened articles. Keyword co-occurrence analysis, as a science mapping technique, allows unraveling the interrelationships between keywords among articles in the review corpus to understand the knowledge clusters in EPF studies (Kumar et al., 2022a). Following Kumar et al. (2022a), the paper uses keywords that appear at least twice in the review corpus and generates a network visualization of the keywords with the help of VOSviewer, which are shown in Fig. 5 and Fig. 6.

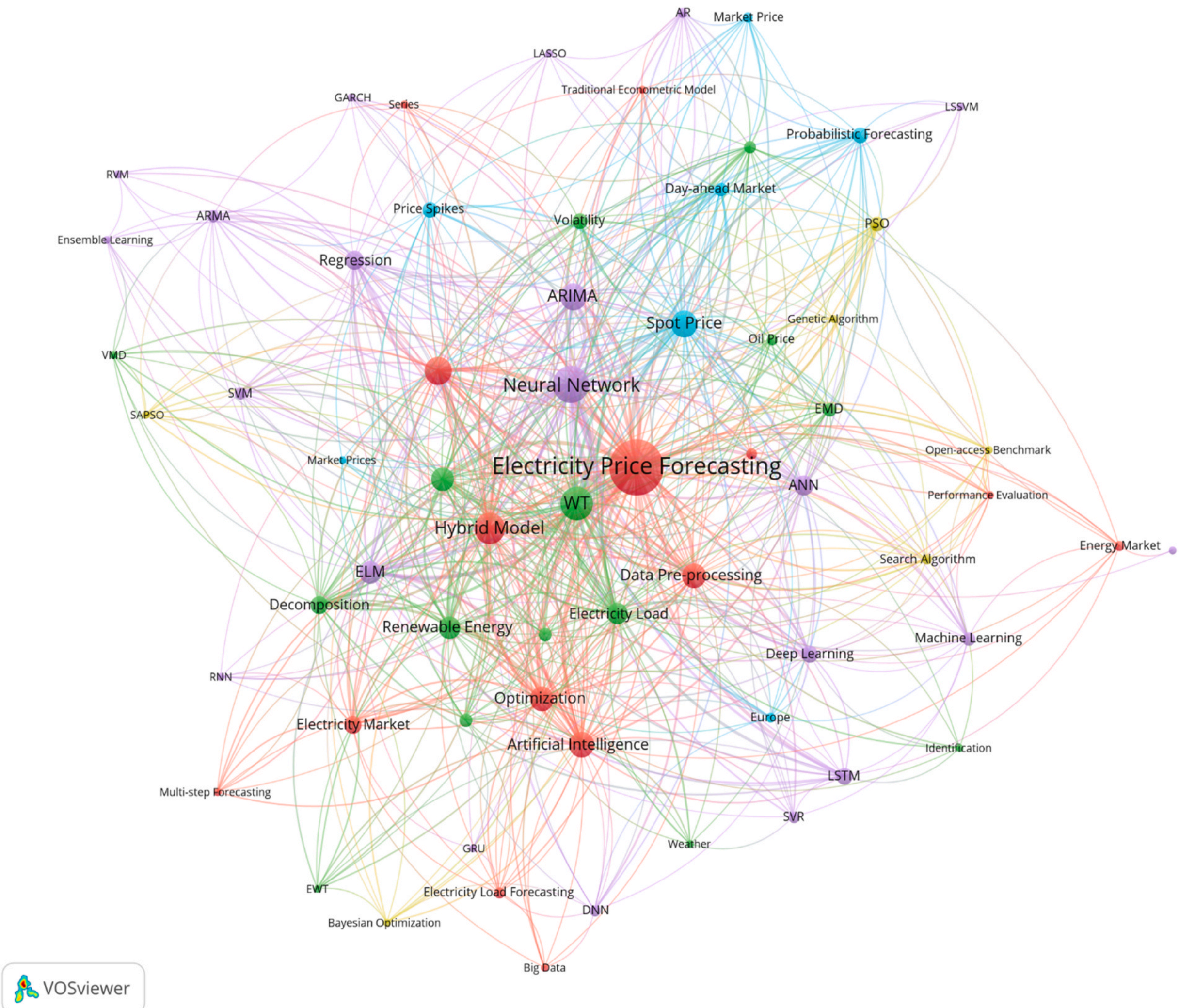

Fig. 5. The network visualization of the keyword co-occurrence.

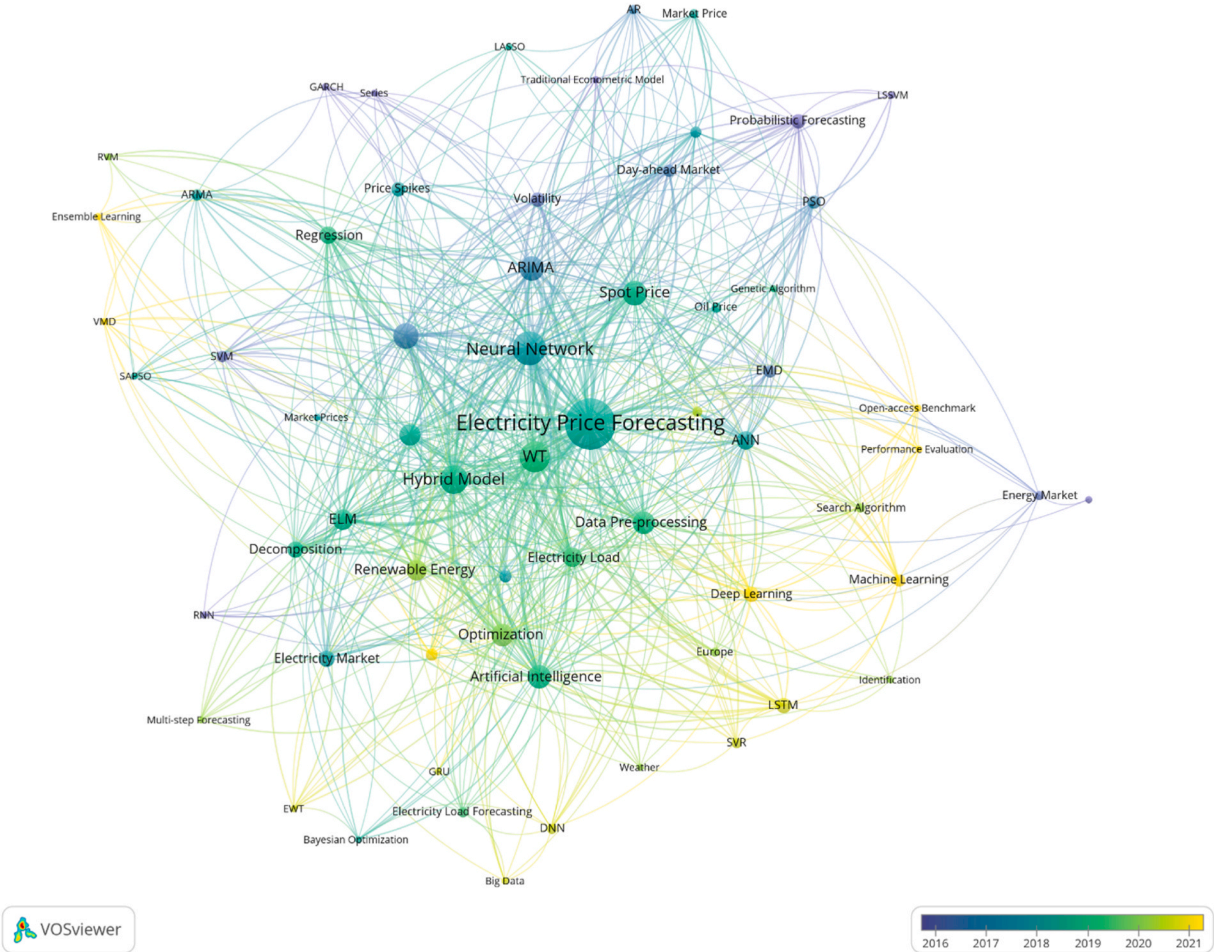

Fig. 6. The overlay visualization of the keyword co-occurrence.

Summary statistics are also provided in Table 6, detailing the number of occurrences of each keyword and the total link strength of each keyword to other keywords.

5.1.1. knowledge clusters through keyword co-occurrence analysis

Keywords are organized in a logical manner to convey the essence of the research for each knowledge cluster. The same color represents the same category, and the sizes of the nodes represent the frequency of the keyword (i.e., degree centrality). The keyword co-occurrence analysis reveals five knowledge clusters that underlie the knowledge structure of the EPF study, and we will discuss these clusters next using semantic analysis.

5.1.1.1. Cluster 1: Forecasting methods and modules. The first knowledge cluster contains 15 keywords, mainly around the forecasting methods and modules. From Fig. 5 and Table 6, it can be found that the most frequently mentioned forecasting methods in the study of "EPF" are "hybrid model", "time series forecasting" and "artificial intelligence", and the most frequently mentioned forecasting modules are "data preprocessing" and "optimization". Compared to the traditional econometric models, artificial intelligence models and hybrid models are more widely used in EPF in the last decade. Most of scholars have conducted more research on data pre-processing module, price forecasting module, and model optimization module. Furthermore, scholars tend to innovate more in data preprocessing module, price forecasting module, and model optimization module over time, but less in the evaluation of model performance.

5.1.1.2. Cluster 2: Data and data preprocessing. There are 15 keywords about data and data preprocessing in knowledge cluster 2. Besides the electricity price history data, "electricity demand", "electricity load" and "renewable energy" are often used as primary data for EPF. For data preprocessing methods, the most commonly used decomposition methods are "WT" and "EMD".

Table 6
Keyword co-occurrence for knowledge clusters in EPF.

Key words	OC	TLS
Cluster 1: Forecasting methods and modules (Number: 15; Color: Red)		
Artificial Intelligence	20	115
Big Data	2	10
Data Preprocessing	19	98
Electricity Load Forecasting	4	17
Electricity Market	10	42
Electricity Price Forecasting	93	412
Energy Market	3	12
Energy Price	4	19
Hybrid Model	30	175
Multistep Forecasting	2	15
Optimization	19	85
Performance Evaluation	2	16
Series	2	12
Time Series Forecasting	24	119
Traditional Econometric Model	2	14
Cluster 2: Data and data preprocessing (Number: 15; Color: Green)		
Classification	6	25
Decomposition	10	76
Electricity Demand	17	91
Electricity Generation	6	29
Electricity Load	14	82
EMD	6	28
EWT	2	17
Identification	2	10
Oil Price	4	21
Renewable Energy	15	80
Seasonal Factors	5	40
VMD	2	15
Volatility	8	32
WT	34	204
Weather	2	11
Cluster 3: Specific forecasting models (Number: 21; Color: Purple)		
ANN	13	70
AR	3	22
ARIMA	22	104
ARMA	5	30
Deep Learning	9	51
DNN	4	19
ELM	15	104
Ensemble Learning	2	11
GARCH	2	11
GRU	2	6
LASSO	2	11
LLWNN	2	2
LSSVM	2	9
LSTM	9	49
Machine Learning	6	24
Neural Network	42	210
Regression	11	61
RNN	2	9
RVM	2	8
SVM	5	28
SVR	4	16
Cluster 4: Optimization algorithms (Number: 6; Color: Yellow)		
Bayesian Optimization	2	15
Genetic Algorithm	2	14
Open-access Benchmark	2	16
PSO	7	30
SAPSO	2	17
Search Algorithm	3	22
Cluster 5: Forecasting objects (Number: 7; Color: Blue)		
Day-ahead Market	6	48
Europe	3	16
Market Price	3	18
Market Prices	2	10
Price Spikes	8	30
Probabilistic Forecasting	8	41
Spot Price	23	126

Notes: We preprocess the data by removing keywords with few occurrences, combining synonyms, and removing outliers. “OC” means the number of occurrences of each keyword and “TLS” means the total link strength of each keyword to other keywords.

5.1.1.3. Cluster 3: Specific forecasting models. Knowledge cluster 3 contains 21 keywords about specific forecasting models. As shown in Fig. 5 and Table 6, “neural network” has become the most popular forecasting model for EPF. In addition, “ARIMA”, “ELM”, “ANN”, “deep learning”, and “LSTM” have been used more frequently in the last decade. It is interesting to note that the above models are often not used alone in studies on EPF, but are often combined with other models to form hybrid models for EPF.

5.1.1.4. Cluster 4: Optimization algorithms. The fourth knowledge cluster contains six keywords, mainly about the optimization algorithm of the model. In the group of knowledge cluster 4, the keywords show that there are relatively few innovations in model optimization algorithms in the study of EPF, with the most used being “PSO” and its variants.

5.1.1.5. Cluster 5: Forecasting objects. The fifth group of knowledge cluster contains seven keywords, which mainly focus on the selection of forecasting objects. As shown in the figure and table, it is not difficult to find that the main research center of EPF focuses on “spot price” at this stage, and “probabilistic forecasting” is also more frequently mentioned.

5.1.2. Topic evolution through keyword co-occurrence analysis

Keywords not only summarize the essence of the article but also represent the theme of the article (Kumar et al., 2022a). The overlay visualization of the keyword co-occurrence is plotted based on the average year taking the score value, as shown in Fig. 6. The darker the color means the older the average year of the keyword mentioned. The overlay visualization of the keyword co-occurrence can visualize the evolution of the research topic and research center of gravity (Donthu et al., 2021a). As can be seen in Fig. 6, in terms of the EPF methods and models, the traditional econometric models (i.e., “ARIMA”, “GARCH”, “AR”, etc.) not only have a smaller share but also have been around for a longer time. In contrast, keywords such as “neural networks”, “hybrid models”, and “artificial intelligence” occur more frequently and more recently. In addition, deep learning, the machine learning, and the ensemble learning are getting more and more attention from the researchers as time goes by. Following Weron (2014), it is easy to find that the methods used for EPF have started to shift from the traditional econometric models to the artificial intelligence and hybrid models that combine both. Moreover, for the EPF module, data preprocessing and model optimization have gradually received increasing attention from scholars over time. It is further evident that the study of EPF has started to shift from only caring about forecasting model performance to the "Data preprocessing + Forecasting + Optimization" paradigm.

5.2. Model type

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 Proprocessing + Price Fore-casting + 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 and plays an important role in EPF.

As shown in Fig. 7, 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. 8, 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 not only makes the model input variables more suitable for prediction with the help of data preprocessing methods but also optimizes the model parameters 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. 9, it can be seen that the sample data selected for existing research are mainly from Europe, Australia, and America, where the electricity markets have developed earlier, and the data are easily accessible. As shown in Fig. 10, 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 min. 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. 11, "Hourly" has the highest percentage, followed by "30-Min" and "Daily". It shows that most existing research focuses on ultra-short-term and short-term real-time EPF, and little research is conducted on medium- and long-term EPF.

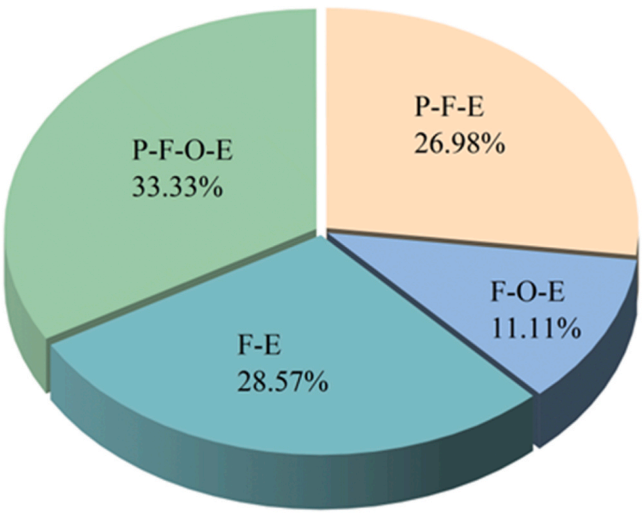

Fig. 7. The percentage of models with various architectures.

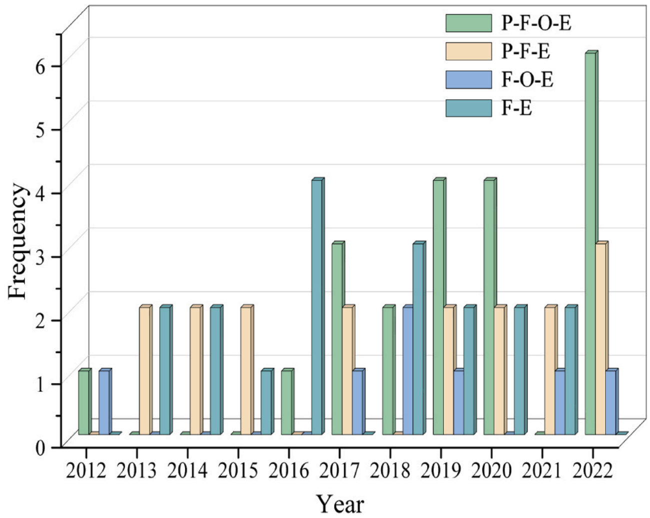

Fig. 8. The use trend of models with various architectures.

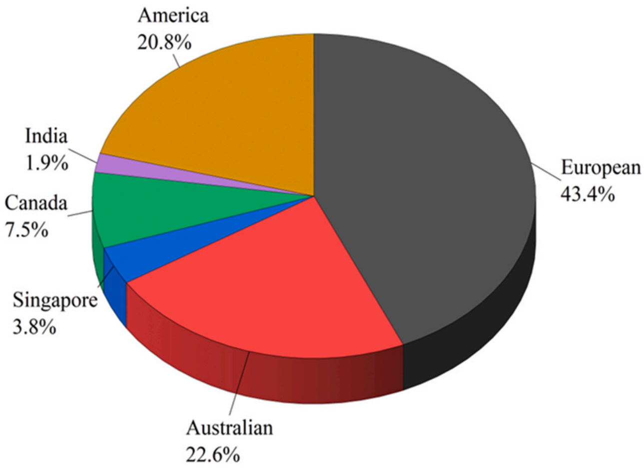

Fig. 9. The regional distribution of the research sample.

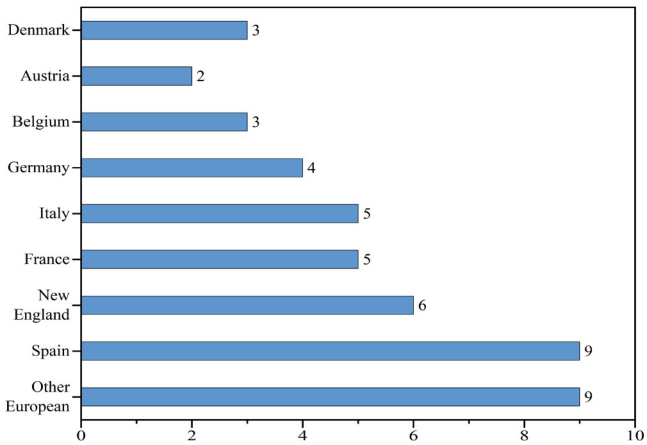

Fig. 10. The distribution of the research sample in European.

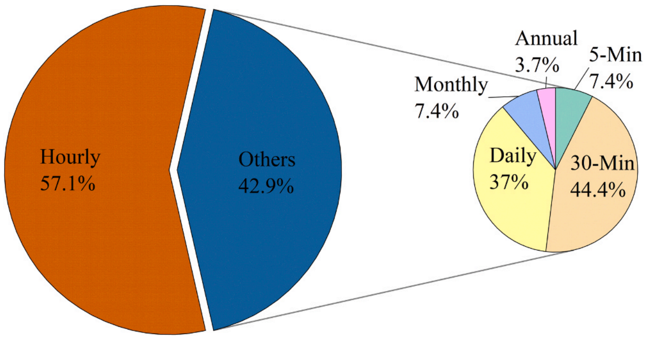

Fig. 11. The percentage of the prediction horizons.

6. Conclusions and future directions

6.1. Conclusions

This paper presents a systematic review of the current hot topic “EPF”. In this study, we use the SPAR-4-SLR method (Paul et al., 2021) to screen the relevant literature on EPF during 2012–2022 and provide a systematic overview of the screened articles. Through the above overview, this paper aims to further explore the state-of-the-art EPF modeling techniques and the role played by electricity price determinants in the EPF process, to expect to provide a valuable reference for future research. Furthermore, we perform a bibliometric analysis, specifically a keyword co-occurrence analysis, on the selected literature to offer insights into potential research trends and novel research directions for scholars in the field. Finally, summarizing the entire text, we present the following conclusions:

(1) This paper classifies the EPF modeling process into four modules. In the data preprocessing module, a variety of single decomposition techniques such as WT, VMD, and EMD are commonly employed. Moreover, dual decomposition methods have also demonstrated promising data processing capabilities, but the research in this area remains limited. Regarding price forecasting, artificial intelligence is widely used and is mainly based on neural networks, with increasing interest in deep learning, integrated learning, and machine learning. In the context of model optimization, heuristic algorithms constitute the primary approach for optimizing model parameters to enhance predictive performance. Evaluation of results typically employs metrics such as MAPE, MAE, and RMSE, although no standardized evaluation system has yet been established.
(2) Through this review, it is easy to find that considering the electricity price determinants in the EPF can significantly improve the accuracy of the price prediction model. In particular, as the penetration of renewable energy in the power generation industry increases, scholars have become more concerned about the impact of renewable energy on electricity price volatility. Besides, electricity generation, electricity demand and weather are also determinants of the electricity price fluctuations. However, the number and selection of determinants to incorporate in EPF models still require further discussion and investigation. Understanding the determinants of electricity prices is critical for researchers in accounting and finance to analyze the influence of electricity prices on various aspects of business operations, such as profitability and stock prices. However, there exists a dearth of research on the determinants of electricity prices.
(3) This paper provides noteworthy discussions regarding the model structure, the study sample, and the prediction horizon. Specifically, the P-F-O-E-type model is widely regarded as the most popular and has experienced significant growth in its applications since 2017. Concerning the study sample, electricity markets in Europe, Australia, and the United States are frequently utilized. With respect to the prediction horizon, scholars commonly apply EPF to short-term electricity prices, with “hourly” data being the prevailing option. Nevertheless, medium- and long-term EPFs may be more advantageous for policy-making and risk management purposes compared with short-term EPFs.
(4) EPF and its determinants have important implications for relevant research in the accounting and finance fields. They provide valuable insights into how electricity prices are determined and how to forecast them, which are valuable reference for investment decisions and financing behaviors in the business world. For instance, with accurate electricity price predictions and identification of determinants, market participants can plan their investments, production schedules, and trading strategies more effectively, thereby improving the efficiency of market participation. In addition to improving market decisions, the study of EPF and its determinants has great implications for risk management, energy policy, and market liquidity in the accounting and finance fields. Moreover, understanding EPF and determinants provides valuable insights that can be used to extend research in accounting and finance. For example, the electricity price fluctuation reflects the supply and demand in the electricity market, and its forecasting can help improve the accuracy of pricing in the electricity financial market.

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 compensate for the shortcomings of the single decomposition method. Therefore, the dual decomposition method should be explored further 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, apart from focusing on the improvement of model prediction accuracy, multiobjective optimization and the setting of objective function should be considered in more depth. 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 redundant effects. In addition, considering fewer external factors may miss key variables. Therefore, how many and which external factors should be further discussed in future EPF research.

(3) In terms of the research target, most existing research focuses on 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 lead to 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 afforded more attention in the future.

Data Availability

Data will be made available on request.

Acknowledgments

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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
Irfan et al. (2022)	New England	SVM-AO, DenseNet-AO	RFE, XGboost, RF	SVM, DenseNet	AO	MAPE, RMSE, MSE, MAE	Daily
Billé et al. (2023)	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	Multiscale Dilated Deep CNN	\	Multiscale Dilated Deep CNN	Adam	\	5-Min

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Author (Year)	Market	Model	Data Preprocessing	Price Forecasting	Model Optimization	Performance Evaluation	Prediction Horizon (s)
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. (2019a)	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. (2020)	PJM, Ontario, Australian	MKELM-WCA	\	MKELM	WCA	RMSE, MAE, MAPE	Hourly
Osório et al. (2019)	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 Nonlinear: 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

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Author (Year)	Market	Model	Data Preprocessing	Price Forecasting	Model Optimization	Performance Evaluation	Prediction Horizon (s)
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. (2014)	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

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Abbreviations	
CSCA	chaotic sine cosine algorithm
CSS	combination of 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 multiobjective 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 gray wolf algorithm
MKELM	multikernel extreme learning machine
MLE	maximum likelihood estimator
MLFFANN	multilayer feed-forward ANN model
MOGWO	multiobjective gray 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 squares 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

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Abbreviations	
SD	similar days methodology
SDE	standard deviation 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 honeybee 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

References

Acaroğlu, H., García Márquez, F.P., 2021. Comprehensive review on electricity market price and load forecasting based on wind energy. Energies 14 (22), 7473. https://doi.org/10.3390/en14227473.

Agrawal, R.K., Muchahary, F., Tripathi, M.M., 2019. Ensemble of relevance vector machines and boosted trees for electricity price forecasting. Appl. Energ. 250, 540–548. https://doi.org/10.1016/j.apenergy.2019.05.062.

Anbazhagan, S., Kumarappan, N., 2013. Day-ahead deregulated electricity market price forecasting using recurrent neural network. IEEE Syst. J. 7 (4), 866–872. https://doi.org/10.1109/JSYST.2012.2225733.

Babu, C.N., Reddy, B.E., 2014. A moving-average filter based hybrid ARIMA–ANN model for forecasting time series data. Appl. Soft Comput. 23, 27–38. https://doi.org/10.1016/j.asoc.2014.05.028.

Billé, A.G., Gianfreda, A., Del Grosso, F., Ravazzolo, F., 2023. Forecasting electricity prices with expert, linear, and nonlinear models. Int J. Forecast. https://doi.org/10.1016/j.ijforecast.2022.01.003.

Bisoi, R., Dash, P.K., Das, P.P., 2020. Short-term electricity price forecasting and classification in smart grids using optimized multi-kernel extreme learning machine. Neural Comput. Appl. 32 (5), 1457–1480. https://doi.org/10.1007/s00521-018-3652-5.

Boersen, A., Scholtens, B., 2014. The relationship between European electricity markets and emission allowance futures prices in phase II of the EU (European Union) emission trading scheme. Energy 74, 585–594. https://doi.org/10.1016/j.energy.2014.07.024.

Bublitz, A., Keles, D., Fichtner, W., 2017. An analysis of the decline of electricity spot prices in Europe: who is to blame? Energy Policy 107, 323–336. https://doi.org/10.1016/j.enpol.2017.04.034.

Cerjan, M., Matijaš, M., Delimar, M., 2014. Dynamic hybrid model for short-term electricity price forecasting. Energies 7 (5), 3304–3318. https://doi.org/10.3390/en7053304.

Chang, Z.H., Zhang, Y., Chen, W.B., 2019. Electricity price prediction based on hybrid model of Adam optimized LSTM neural network and wavelet transform. Energy 187. https://doi.org/10.1016/j.energy.2019.07.134.

Cheng, H., Ding, X., Zhou, W., Ding, R., 2019. A hybrid electricity price forecasting model with Bayesian optimization for German energy exchange. Int. J. Electr. Power 110, 653–666. https://doi.org/10.1016/j.ijepes.2019.03.056.

Cifter, A., 2013. Forecasting electricity price volatility with the Markov-switching GARCH model: Evidence from the Nordic electric power market. Electr. Pow. Syst. Res 102, 61–67. https://doi.org/10.1016/j.epsr.2013.04.007.

Da Silva, P.P., Cerqueira, P.A., 2017. Assessing the determinants of household electricity prices in the EU: a system-GMM panel data approach. Renew. Sustain Energy Rev. 73, 1131–1137. https://doi.org/10.1016/j.rser.2017.02.016.

Deng, Z., Liu, C., Zhu, Z., 2021. Inter-hours rolling scheduling of behind-the-meter storage operating systems using electricity price forecasting based on deep convolutional neural network. Int J. Electr. Power 125, 106499. https://doi.org/10.1016/j.ijepes.2020.106499.

Deng, Z., Qi, X., Xu, T., Zeng, Y., 2022. Operational scheduling of behind-the-meter storage systems based on multiple nonstationary decomposition and deep convolutional neural network for price forecasting. Comput. Intel. Neurosci. 2022, 1–18. https://doi.org/10.1155/2022/9326856.

Doering, K., Sendelbach, L., Steinschneider, S., Lindsay, Anderson, C., 2021. The effects of wind generation and other market determinants on price spikes. Appl. Energ. 300, 117316 https://doi.org/10.1016/j.apenergy.2021.117316.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., Lim, W.M., 2021a. How to conduct a bibliometric analysis: an overview and guidelines. J. Bus. Res 133, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070.

Donthu, N., Kumar, S., Pattnaik, D., Lim, W.M., 2021b. A bibliometric retrospection of marketing from the lens of psychology: Insights from Psychology & Marketing. Psychol. Mark. 38 (5), 834–865. https://doi.org/10.1002/mar.21472.

Dragomiretskiy, K., Zosso, D., 2014. Variational mode decomposition. IEEE Trans. Signal Process 62 (3), 531–544. https://doi.org/10.1109/TSP.2013.2288675.

Dutta, G., Mitra, K., 2017. A literature review on dynamic pricing of electricity. J. Op. Res Soc. 68 (10), 1131–1145. https://doi.org/10.1057/s41274-016-0149-4.

Ebrahimian, H., Barmayoon, S., Mohammadi, M., Ghadimi, N., 2018. The price prediction for the energy market based on a new method. Econ. Res. Istraživanja 31 (1), 313–337. https://doi.org/10.1080/1331677X.2018.1429291.

Faff, R., Prasadh, S., Shams, S., 2019. Merger and acquisition research in the Asia-Pacific region: a review of the evidence and future directions. Res Int Bus. Financ 50, 267–278. https://doi.org/10.1016/j.ribaf.2019.06.002.

Gabrielli, P., Wüthrich, M., Blume, S., Sansavini, G., 2022. Data-driven modeling for long-term electricity price forecasting. Energy 244, 123107. https://doi.org/10.1016/j.energy.2022.123107.

Ghayekhloo, M., Azimi, R., Ghofrani, M., Menhaj, M.B., Shekari, E., 2019. A combination approach based on a novel data clustering method and Bayesian recurrent neural network for day-ahead price forecasting of electricity markets. Electr. Pow. Syst. Res 168, 184–199. https://doi.org/10.1016/j.epsr.2018.11.021.

Gianfreda, A., Ravazzolo, F., Rossini, L., 2020. Comparing the forecasting performances of linear models for electricity prices with high-RES penetration. Int J. Forecast. 36 (3), 974–986. https://doi.org/10.1016/j.ijforecast.2019.11.002.

Girish, G.P., 2016. Spot electricity price forecasting in Indian electricity market using autoregressive-GARCH models. Energy Strateg Rev. 11–12, 52–57. https://doi.org/10.1016/j.esr.2016.06.005.

Gollou, A.R., Ghadimi, N., 2017. A new feature selection and hybrid forecast engine for day-ahead price forecasting of electricity markets. J. Intell. Fuzzy Syst. 32 (6), 4031–4045. https://doi.org/10.3233/JIFS-152073.

Gupta, P., Chauhan, S., Paul, J., et al., 2020. Social entrepreneurship research: a review and future research agenda. J. Bus. Res 113, 209–229. https://doi.org/10.1016/j.jbusres.2020.03.032.

Gürtler, M., Paulsen, T., 2018. Forecasting performance of time series models on electricity spot markets: a quasi-meta-analysis. Int J. Energy Sect. Ma 12 (1), 103–129. https://doi.org/10.1108/IJESM-06-2017-0004.

He, H., Lu, N., Jiang, Y., Chen, B., Jiao, R., 2020. End-to-end probabilistic forecasting of electricity price via convolutional neural network and label distribution learning. Energy Rep. 6, 1176–1183. https://doi.org/10.1016/j.egyr.2020.11.057.

He, K., Yu, L., Tang, L., 2015. Electricity price forecasting with a BED (bivariate EMD denoising) methodology. Energy 91, 601–609. https://doi.org/10.1016/j.energy.2015.08.021.

Heydari, A., Majidi Nezhad, M., Pirshayan, E., Garcia, D.A., Keynia, F., De Santoli, L., 2020. Short-term electricity price and load forecasting in isolated power grids based on composite neural network and gravitational search optimization algorithm. Appl. Energ. 277, 115503 https://doi.org/10.1016/j.apenergy.2020.115503.

Hu, B., Xu, J., Xing, Z.X., Zhang, P., Cui, J., Liu, J., 2022. Short-Term combined forecasting method of park load based on CEEMD-MLR-LSSVR-SBO. Energies 15 (8). https://doi.org/10.3390/en15082767.

Huang, G., Zhu, Q., Siew, C., 2006. Extreme learning machine: theory and applications. Neurocomputing 70 (1–3), 489–501. https://doi.org/10.1016/j.neucom.2005.12.126.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C., Liu, H.H., 1998. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc. R. Soc. Lond. Ser. A: Math., Phys. Eng. Sci. 454 (1971), 903–995. https://doi.org/10.1098/rspa.1998.0193.

Irfan, M., Raza, A., Althobiani, F., Ayub, N., Idrees, M., Ali, Z., Rizwan, K., Alwadie, A.S., Ghonaim, S.M., Abdushkour, H., Rahman, S., 2022. Week ahead electricity power and price forecasting using improved DenseNet-121 method. Comput., Mater. Contin. 72 (3), 4249–4265. https://doi.org/10.32604/cmc.2022.025863.

Iwabuchi, K., Kato, K., Watari, D., Taniguchi, I., Catthoor, F., Shirazi, E., Onoye, T., 2022. Flexible electricity price forecasting by switching mother wavelets based on wavelet transform and long short-term memory. Energy AI 10, 100192. https://doi.org/10.1016/j.egyai.2022.100192.

Jasinski, T., 2020. Use of new variables based on air temperature for forecasting day-ahead spot electricity prices using deep neural networks: a new approach. Energy 213, 118784. https://doi.org/10.1016/j.energy.2020.118784.

Jun, W., Yuyan, L., Lingyu, T., Peng, G., 2018. A new weighted CEEMDAN-based prediction model: An experimental investigation of decomposition and non-decomposition approaches. Knowl. Based Syst. 160, 188–199. https://doi.org/10.1016/j.knosys.2018.06.033.

Keles, D., Scelle, J., Paraschiv, F., Fichtner, W., 2016. Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. Appl. Energ. 162, 218–230. https://doi.org/10.1016/j.apenergy.2015.09.087.

Kennedy, J., Eberhart, R., 1995. Particle swarm optimization, 4, 1942–1948. https://doi.org/10.1109/ICNN.1995.488968.

Kingma, D.P., Ba, J., 2015. Adam: A method for stochastic optimization. CoRR. abs/1412.6980.

Kostrzewski, M., Kostrzewska, J., 2019. Probabilistic electricity price forecasting with Bayesian stochastic volatility models. Energ. Econ. 80, 610–620. https://doi.org/10.1016/j.eneco.2019.02.004.

Kou, P., Liang, D., Gao, L., Lou, J., 2015. Probabilistic electricity price forecasting with variational heteroscedastic Gaussian process and active learning. Energ. Convers. Manag 89, 298–308. https://doi.org/10.1016/j.enconman.2014.10.003.

Kraus, S., Breier, M., Lim, W.M., et al., 2022. Literature reviews as independent studies: guidelines for academic practice. Rev. Manag Sci. 16 (8), 2577–2595. https://doi.org/10.1007/s11846-022-00588-8.

Kumar, S., Sahoo, S., Lim, W.M., Dana, L., 2022a. Religion as a social shaping force in entrepreneurship and business: insights from a technology-empowered systematic literature review. Technol. Forecast Soc. 175, 121393 https://doi.org/10.1016/j.techfore.2021.121393.

Kumar, S., Sharma, D., Rao, S., Lim, W.M., Mangla, S.K., 2022b. Past, present, and future of sustainable finance: insights from big data analytics through machine learning of scholarly research. Ann. Oper. Res. https://doi.org/10.1007/s10479-021-04410-8.

Lago, J., De Ridder, F., De Schutter, B., 2018a. Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms. Appl. Energ. 221, 386–405. https://doi.org/10.1016/j.apenergy.2018.02.069.

Lago, J., De Ridder, F., Vrancx, P., De Schutter, B., 2018b. Forecasting day-ahead electricity prices in Europe: the importance of considering market integration. Appl. Energ. 211, 890–903. https://doi.org/10.1016/j.apenergy.2017.11.098.

Lago, J., Marcjasz, G., De Schutter, B., Weron, R., 2021. Forecasting day-ahead electricity prices: a review of state-of-the-art algorithms, best practices and an open-access benchmark. Appl. Energ. 293, 116983 https://doi.org/10.1016/j.apenergy.2021.116983.

Lei, M., Feng, Z., 2012. A proposed grey model for short-term electricity price forecasting in competitive power markets. Int J. Elec Power 43 (1), 531–538. https://doi.org/10.1016/j.ijepes.2012.06.001.

Li, K., Cursio, J.D., Sun, Y., Zhu, Z., 2019. Determinants of price fluctuations in the electricity market: a study with PCA and NARDL models. Econ. Res. istraživanja 32 (1), 2404–2421. https://doi.org/10.1080/1331677X.2019.1645712.

Lim, W.M., Chin, M.W.C., Ee, Y.S., Fung, C.Y., Giang, C.S., Heng, K.S., Kong, M.L.F., Lim, A.S.S., Lim, B.C.Y., Lim, R.T.H., Lim, T.Y., 2022a. What is at stake in a war? A prospective evaluation of the Ukraine and Russia conflict for business and society. Glob. Bus. Organ Excell 41 (6), 23–36. https://doi.org/10.1002/joe.22162.

Lim, W.M., Kumar, S., Ali, F., 2022b. Advancing knowledge through literature reviews: "what", "why", and "how to contribute". Serv. Ind. J. 42 (7–8), 481–513. https://doi.org/10.1080/02642069.2022.2047941.

Lim, W.M., Rasul, T., Kumar, S., Ala, M., 2022c. Past, present, and future of customer engagement. J. Bus. Res 140, 439–458. https://doi.org/10.1016/j.jbusres.2021.11.014.

Liu, H., Shi, J., 2013. Applying ARMA–GARCH approaches to forecasting short-term electricity prices. Energ. Econ. 37, 152–166. https://doi.org/10.1016/j.eneco.2013.02.006.

Liu, L., Bai, F., Su, C., Ma, C., Yan, R., Li, H., Sun, Q., Wennersten, R., 2022. Forecasting the occurrence of extreme electricity prices using a multivariate logistic regression model. Energy 247, 123417. https://doi.org/10.1016/j.energy.2022.123417.

Loi, T.S.A., Ng, J.L., 2018. Anticipating electricity prices for future needs – implications for liberalised retail markets. Appl. Energ. 212, 244–264. https://doi.org/10.1016/j.apenergy.2017.11.092.

Lu, H., Ma, X., Ma, M., Zhu, S., 2021. Energy price prediction using data-driven models: a decade review. Comput. Sci. Rev. 39, 100356 https://doi.org/10.1016/j.cosrev.2020.100356.

Maciejowska, K., Nitka, W., Weron, T., 2021. Enhancing load, wind and solar generation for day-ahead forecasting of electricity prices. Energ. Econ. 99, 105273 https://doi.org/10.1016/j.eneco.2021.105273.

Memarzadeh, G., Keynia, F., 2021. Short-term electricity load and price forecasting by a new optimal LSTM-NN based prediction algorithm. Electr. Pow. Syst. Res 192, 106995. https://doi.org/10.1016/j.epsr.2020.106995.

Meng, A., Wang, P., Zhai, G., Zeng, C., Chen, S., Yang, X., Yin, H., 2022. Electricity price forecasting with high penetration of renewable energy using attention-based LSTM network trained by crisscross optimization. Energy 254, 124212. https://doi.org/10.1016/j.energy.2022.124212.

Moreno, B., López, A.J., García-Álvarez, M.T., 2012. The electricity prices in the European Union. The role of renewable energies and regulatory electric market reforms. Energy 48 (1), 307–313. https://doi.org/10.1016/j.energy.2012.06.059.

Moreno, B., García-Álvarez, M.T., Ramos, C., Fernández-Vázquez, E., 2014. A general maximum entropy econometric approach to model industrial electricity prices in Spain: a challenge for the competitiveness. Appl. Energ. 135, 815–824. https://doi.org/10.1016/j.apenergy.2014.04.060.

Mosquera-López, S., Nursimulu, A., 2019. Drivers of electricity price dynamics: comparative analysis of spot and futures markets. Energ. Policy 126, 76–87. https://doi.org/10.1016/j.enpol.2018.11.020.

Mosquera-López, S., Uribe, J.M., Manotas-Duque, D.F., 2017. Nonlinear empirical pricing in electricity markets using fundamental weather factors. Energy 139, 594–605. https://doi.org/10.1016/j.energy.2017.07.181.

Mukherjee, D., Lim, W.M., Kumar, S., Donthu, N., 2022. Guidelines for advancing theory and practice through bibliometric research. J. Bus. Res 148, 101–115. https://doi.org/10.1016/j.jbusres.2022.04.042.

Neupane, B., Woon, W., Aung, Z., 2017. Ensemble prediction model with expert selection for electricity price forecasting. Energies 10 (1), 77. https://doi.org/10.3390/en10010077.

Nowotarski, J., Weron, R., 2018. Recent advances in electricity price forecasting: a review of probabilistic forecasting. Renew. Sust. Energy Rev. 81, 1548–1568. https://doi.org/10.1016/j.rser.2017.05.234.

Osório, G., Lotfi, M., Shafie-Khah, M., Campos, V., Catalão, J., 2019. Hybrid forecasting model for short-term electricity market prices with renewable integration. Sustainability 11 (1), 57. https://doi.org/10.3390/su11010057.

Panapakidis, I.P., Dagoumas, A.S., 2016. Day-ahead electricity price forecasting via the application of artificial neural network-based models. Appl. Energ. 172, 132–151. https://doi.org/10.1016/j.apenergy.2016.03.089.

Pany, P.K., Ghoshal, S.P., 2015. Dynamic electricity price forecasting using local linear wavelet neural network. Neural Comput. Appl. 26 (8), 2039–2047. https://doi.org/10.1007/s00521-015-1867-2.

Papler, D., Bojnec, S., 2012. Determinants of costs and prices for electricity supply in Slovenia. East Eur. Econ. 50 (1), 65–77. https://doi.org/10.2753/EEE0012-8775500104.

Paschen, M., 2016. Dynamic analysis of the German day-ahead electricity spot market. Energ. Econ. 59, 118–128. https://doi.org/10.1016/j.eneco.2016.07.019.

Paul, J., Lim, W.M., O Cass, A., et al., 2021. Scientific procedures and rationales for systematic literature reviews (SPAR-4–SLR). Int J. Consum Stud. 45, 4. https://doi.org/10.1111/ijcs.12695.

Peña, J.I., Rodríguez, R., 2019. Are EU's Climate and Energy Package 20-20-20 targets achievable and compatible? Evidence from the impact of renewables on electricity prices. Energy 183, 477–486. https://doi.org/10.1016/j.energy.2019.06.138.

Peng, L., Liu, S., Liu, R., Wang, L., 2018. Effective long short-term memory with differential evolution algorithm for electricity price prediction. Energy 162, 1301–1314. https://doi.org/10.1016/j.energy.2018.05.052.

Pereira, J.P., Pesquita, V., Rodrigues, P.M.M., Rua, A., 2019. Market integration and the persistence of electricity prices. Empir. Econ. 57 (5), 1495–1514. https://doi.org/10.1007/s00181-018-1520-x.

Peura, H., Bunn, D., 2021. Renewable power and electricity prices: the impact of forward markets. Manag Sci. 67. https://doi.org/10.1287/mnsc.2020.3710.

Qiao, W., Yang, Z., 2020. Forecast the electricity price of U.S. using a wavelet transform-based hybrid model. Energy 193, 116704. https://doi.org/10.1016/j.energy.2019.116704.

Qiu, X., Suganthan, P.N., Amaratunga, G.A.J., 2017. Short-term electricity price forecasting with empirical mode decomposition based ensemble kernel machines. Procedia Comput. Sci. 108, 1308–1317. https://doi.org/10.1016/j.procs.2017.05.055.

Sandhu, H.S., Fang, L., Guan, L., 2016. Forecasting day-ahead price spikes for the Ontario electricity market. Electr. Pow. Syst. Res 141, 450–459. https://doi.org/10.1016/j.epsr.2016.08.005.

Sapio, A., Spagnolo, N., 2016. Price regimes in an energy island: Tacit collusion vs. cost and network explanations. Energ. Econ. 55, 157–172. https://doi.org/10.1016/j.eneco.2016.01.008.

Shao, Z., Yang, S., Gao, F., Zhou, K., Lin, P., 2017. A new electricity price prediction strategy using mutual information-based SVM-RFE classification. Renew. Sust. Energy Rev. 70, 330–341. https://doi.org/10.1016/j.rser.2016.11.155.

Shao, Z., Zheng, Q., Liu, C., Gao, S., Wang, G., Chu, Y., 2021. A feature extraction- and ranking-based framework for electricity spot price forecasting using a hybrid deep neural network. Electr. Pow. Syst. Res 200, 107453. https://doi.org/10.1016/j.epsr.2021.107453.

Shi, W., Wang, Y., Chen, Y., Ma, J., 2021. An effective two-stage electricity price forecasting scheme. Electr. Pow. Syst. Res 199, 107416. https://doi.org/10.1016/j.epsr.2021.107416.

Shrivastava, N.A., Panigrahi, B.K., 2014. A hybrid wavelet-ELM based short term price forecasting for electricity markets. Int J. Elec Power 55, 41–50. https://doi.org/10.1016/j.ijepes.2013.08.023.

Singh, N., Mohanty, S.R., Dev Shukla, R., 2017. Short term electricity price forecast based on environmentally adapted generalized neuron. Energy 125, 127–139. https://doi.org/10.1016/j.energy.2017.02.094.

Tian, C., Hao, Y., Hu, J., 2018. A novel wind speed forecasting system based on hybrid data preprocessing and multi-objective optimization. Appl. Energ. 231, 301–319. https://doi.org/10.1016/j.apenergy.2018.09.012.

Tschora, L., Pierre, E., Plantevit, M., Robardet, C., 2022. Electricity price forecasting on the day-ahead market using machine learning. Appl. Energ. 313, 118752 https://doi.org/10.1016/j.apenergy.2022.118752.

Voronin, S., Partanen, J., Kauranne, T., 2014. A hybrid electricity price forecasting model for the Nordic electricity spot market. Int Trans. Electr. Energ. Syst. 24 (5), 736–760. https://doi.org/10.1002/etep.1734.

Vu, D.H., Muttaqi, K.M., Agalgaonkar, A.P., Bouzerdoum, A., 2019. Short-Term forecasting of electricity spot prices containing random spikes using a time-varying autoregressive model combined with kernel regression. IEEE T Ind. Inf. 15 (9), 5378–5388. https://doi.org/10.1109/TII.2019.2911700.

Wang, D., Gryshova, I., Kyzym, M., Salashenko, T., Khaustova, V., Shcherbata, M., 2022. Electricity price instability over time: time series analysis and forecasting. Sustainability 14 (15), 9081. https://doi.org/10.3390/su14159081.

Wang, D.Y., Luo, H.Y., Grunder, O., Lin, Y., Guo, H., 2017. Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm. Appl. Energ. 190, 390–407. https://doi.org/10.1016/j.apenergy.2016.12.134.

Wang, J., Yang, W., Du, P., Niu, T., 2020. Outlier-robust hybrid electricity price forecasting model for electricity market management. J. Clean. Prod. 249, 119318 https://doi.org/10.1016/j.jclepro.2019.119318.

Weron, R., 2014. Electricity price forecasting: a review of the state-of-the-art with a look into the future. Int J. Forecast. 30 (4), 1030–1081. https://doi.org/10.1016/j.ijforecast.2014.08.008.

Windler, T., Busse, J., Rieck, J., 2019. One month-ahead electricity price forecasting in the context of production planning. J. Clean. Prod. 238, 117910 https://doi.org/10.1016/j.jclepro.2019.117910.

Xu, Y., Zhang, X., Meng, P., 2022. A novel intelligent deep learning-based uncertainty-guided network training in market price. IEEE T Ind. Inf. 18 (8), 5705–5711. https://doi.org/10.1109/TII.2021.3136564.

Yan, X., Chowdhury, N.A., 2014. Mid-term electricity market clearing price forecasting: a multiple SVM approach. Int J. Elec Power 58, 206–214. https://doi.org/10.1016/j.ijepes.2014.01.023.

Yang, H., Schell, K.R., 2021. Real-time electricity price forecasting of wind farms with deep neural network transfer learning and hybrid datasets. Appl. Energ. 299, 117242 https://doi.org/10.1016/j.apenergy.2021.117242.

Yang, H., Schell, K.R., 2022. GHTnet: Tri-branch deep learning network for real-time electricity price forecasting. Energy 238, 122052. https://doi.org/10.1016/j.energy.2021.122052.

Yang, W., Wang, J., Niu, T., Du, P., 2019. A hybrid forecasting system based on a dual decomposition strategy and multi-objective optimization for electricity price forecasting. Appl. Energ. 235, 1205–1225. https://doi.org/10.1016/j.apenergy.2018.11.034.
Yang, W., Wang, J., Niu, T., Du, P., 2020. A novel system for multi-step electricity price forecasting for electricity market management. Appl. Soft Comput. 88, 106029 https://doi.org/10.1016/j.asoc.2019.106029.
Yang, W., Sun, S., Hao, Y., Wang, S., 2022. A novel machine learning-based electricity price forecasting model based on optimal model selection strategy. Energy 238, 121989. https://doi.org/10.1016/j.energy.2021.121989.
Yang, Z., Ce, L., Lian, L., 2017. Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA and kernel-based extreme learning machine methods. Appl. Energ. 190, 291–305. https://doi.org/10.1016/j.apenergy.2016.12.130.
Zhang, J., Tan, Z., Yang, S., 2012. Day-ahead electricity price forecasting by a new hybrid method. Comput. Ind. Eng. 63 (3), 695–701. https://doi.org/10.1016/j.cie.2012.03.016.
Zhang, J., Zhang, Y., Li, D., et al., 2019b. Forecasting day-ahead electricity prices using a new integrated model. Int J Elec. Power 105, 541–548. https://doi.org/10.1016/j.ijepes.2018.08.025.
Zhang, J., Tan, Z., Wei, Y., 2020. An adaptive hybrid model for short term electricity price forecasting. Appl. Energ. 258, 114087 https://doi.org/10.1016/j.apenergy.2019.114087.
Zhang, T., Tang, Z., Wu, J., Du, X., Chen, K., 2022. Short term electricity price forecasting using a new hybrid model based on two-layer decomposition technique and ensemble learning. Electr. Pow. Syst. Res 205, 107762. https://doi.org/10.1016/j.epsr.2021.107762.
Zhang, X., Wang, J., Gao, Y., 2019a. A hybrid short-term electricity price forecasting framework: cuckoo search-based feature selection with singular spectrum analysis and SVM. Energ. Econ. 81, 899–913. https://doi.org/10.1016/j.eneco.2019.05.026.
Ziel, F., Steinert, R., 2018. Probabilistic mid- and long-term electricity price forecasting. Renew. Sust. Energy Rev. 94, 251–266. https://doi.org/10.1016/j.rser.2018.05.038.