



Review

# Comprehensive Review on Electricity Market Price and Load Forecasting Based on Wind Energy

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**Abstract:** Forecasting the electricity price and load has been a critical area of concern for researchers over the last two decades. There has been a significant economic impact on producers and consumers. Various techniques and methods of forecasting have been developed. The motivation of this paper is to present a comprehensive review on electricity market price and load forecasting, while observing the scientific approaches and techniques based on wind energy. As a methodology, this review follows the historical and structural development of electricity markets, price, and load forecasting methods, and recent trends in wind energy generation, transmission, and consumption. As wind power prediction depends on wind speed, precipitation, temperature, etc., this may have some inauspicious effects on the market operations. The improvements of the forecasting methods in this market are necessary and attract market participants as well as decision makers. To this end, this research shows the main variables of developing electricity markets through wind energy. Findings are discussed and compared with each other via quantitative and qualitative analysis. The results reveal that the complexity of forecasting electricity markets' price and load depends on the increasing number of employed variables as input for better accuracy, and the trend in methodologies varies between the economic and engineering approach. Findings are specifically gathered and summarized based on researches in the conclusions.

**Keywords:** electricity price; electricity load; electricity price forecasting; wind energy; day-ahead market; intra-day market; balancing power market



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## 1. Introduction

The government-controlled and monopolistic characteristics of the power sector has been changing since the beginning of the 1990s with the introduction of competitive market and deregulation processes [1]. The free-competitive market rules reshape electricity trade, as electricity is a non-storable commodity in economic terms, and its consumption and production require a balance dependent on power system stability [2,3]. In line with these changes, generating electricity from the renewable energy resources, mainly wind and solar powers, is rapidly increasing in the world [4,5]. This increase can be attributed to the environmentally friendly characteristics of renewable energy resources, that can be expressed by increasing energy demand triggering global warming in the world [6].

Energy demand can be supplied by electricity production through wind energy [7]. However, electricity production is affected by weather conditions (e.g., speed of wind, precipitation, and temperature) and industrial activities (e.g., business work hours, weekdays, holidays, weekends, etc.) [1,8]. These elements are particular to the electricity commodity, making it unique and different from other commodities in terms of forecasting related price dynamics. It leads to researchers developing new prediction methods. Besides, in both financial and academic institutions, electricity price forecasts (EPFs) have become a basic information for energy companies and energy researchers in their decision-making systems and agendas [1,9,10].

Various methods have been tried and developed for EPFs through renewable energy, and it will continue as the new techniques are studied [11]. A contribution of this paper to the literature is to analyze the relationship between EPF and wind energy. This paper presents, as scientific novelty, a review on recent trends of EPF techniques considering wind energy and updated references. The advances in EPF and load techniques are comparatively discussed, and it is concluded with the main future works to cover in:

- Short-term, middle-term, and long-term price and load forecasting approaches;
- Simulation, equilibrium, production cost and fundamental models for middle and long terms;
- Statistical, artificial intelligence, and hybrid models in the framework of time series for short terms;
- Moving trends of EPF and load techniques that are in the span of economics and engineering fields;
- Working principles of electricity markets through country-specific examples.

Forecasting methods in electricity market and renewable energy resources have gained a forward acceleration and attracted attention from market participants and decision makers [12]. To this end, the motivation of this paper is to present a comprehensive review for electricity markets considering price and load forecasting mechanisms through wind energy, which is one of the fastest growing renewable energy resources due to a growing wind power integration into the electrical grids [13]. For the determined hypothesis, it is observed that forecasting approaches vary between economic terms (i.e., demand [14], supply [15], profit [16], producer, and consumer surplus [17]) and engineering techniques (i.e., power systems [18,19], optimization [20], control [21], and meta-heuristics algorithms [22,23]). As a methodology, this review follows the historical and structural development of electricity markets (i.e., day-ahead markets, intra-day markets, balancing power markets), price and load forecasting methods, and recent trends in wind energy generation, transmission, and consumption, being a novel contribution to the literature. The difficulties of predicting wind power [24], i.e., wind power has a stochastic nature [25] and its prediction is contingent upon weather conditions, e.g., wind speed; precipitation; temperature, may have some adverse effects on the market operations such as fast fluctuations of wind power and loads in the new designed power grid [18]. Nonetheless, wind energy resource applications require extremely rigorous and accurate data [26].

Findings are discussed and compared through the use of quantitative and qualitative analysis, and they reveal that the complexity of forecasting electricity markets price and load depends on the increasing number of employed variables as input for better accuracy, and the trend in methodologies varies between the economic and engineering approaches, and specifically includes mathematics, statistics, econometrics, and electrical engineering and computer science.

The content of the work is presented as follows: Section 2 presents a literature analysis on electricity market mechanism, components, and instruments, considering the day-ahead market (DAM), or spot market; the intra-day market (IDM), or future market; the balancing power market (BPM), or balance market; price of electricity; and electric load. Section 3 shows the electricity market price and load forecasting through wind energy generation. Section 4 analyzes the forecasting models of the electricity markets through wind energy, where several case studies are considered and discussed.

## 2. Electricity Market Mechanism, Components, and Instruments

### 2.1. Electricity Market: Structure and Components

The short-term electricity market structure includes day-ahead and intraday markets which are often known as “spot markets” [27]. However, these markets’ designs show differences. While DAMs have been coupled for the last few years, IDMs have gained traction by going global from being national [28]. Moreover, DAMs are organized as auctions, whereas IDMs operate as trades and enable market participants to balance demand and supply variations in the short-term to decrease exposure to an imbalance penalty [28,29].

The reason being, DAMs are based on forecasts and forecasts include errors in their nature. Specifically, various and increasing number of parameters, intermittent production from wind power plants can be given as the factors. However, the closer to real-time, the more accurate the forecast is possible. The bilateral basis with continuous trading enables market participants to adjust their last updated positions [27]. In addition to these markets, the eventual balancing of the supply and demand is accomplished by the BPMs, which are regulated by the transmission system operator (TSO). The system stability is provided in the context of security in these markets [30] (see [31,32] for detailed information).

### 2.1.1. Day-Ahead Markets

DAMs are organized markets that are used for electricity trading and balancing activities just one day before the delivery date of electricity, operated by a transmission system operator. DAMs include auctions that are conducted simultaneously 24 h in a day. The market participants are able to adjust their own transaction schedule by selling or buying power with the short-term price forecasts thereby maximizing their profits [33]. The main reasons that DAMs are needed and their purposes are summarized as follows [34]:

- Determining the electrical energy reference price.
- To provide market participants with the opportunity to balance themselves by giving them selling and buying energy options for the next day in addition to their bilateral agreements.
- To provide the system operator with a balanced system the day before.
- To provide the system operator with the opportunity to manage the constraints in the day before, by creating bid zones for large-scale and continuous constraints.

DAMs are developing through institutions, regulations, software and web applications daily. For instance, currently, a DAM software and optimization model on the DAM for the Turkish electricity sector, which has a user-friendly interface design and is amenable to flexibility and improvements, since it is designed and written entirely by the domestic resources, has been completed [35]. Table 1 shows the various DAMs electricity markets over the world.

**Table 1.** Various DAMs in the world.

Country	Name (Year)
UK	England and Wales Electricity Pool (1990)
Norway	Nord Pool (1992)
Sweden	Nord Pool (1996)
Spain	Operadora del Mercado Español de Electricidad (OMEL) (1998)
Finland	Nord Pool (1998)
USA	California Power Exchange (CalPX) (1998)
Netherlands	Amsterdam Power Exchange (APX) (1999)
USA	New York ISO (NYISO) (1999)
Germany	Leipzig Power Exchange (LPX) (2000)
Germany	European Energy Exchange (EEX) (2000)
Denmark	Nord Pool (2000)
Poland	Towarowa Gielda Energii (Polish Power Exchange, PolPX) (2000)
USA	Pennsylvania-New Jersey-Maryland (PJIM) Interconnection (2000)

Table 1. Cont.

Country	Name (Year)
UK	UK Power Exchange (UKPX) (2001)
UK	Automated Power Exchange (APX UK) (2001)
Slovenia	Borzen (2001)
France	Powernext (2002)
Austria	Energy Exchange Austria (EXAA) (2002)
USA	ISO New England (2003)
Italy	Italian Power Exchange (IPEX) (2004)
Czech Republic	Operator Trhu s Electrinou (OTE) (2004)
USA	Midwest ISO (MISO) (2005)
Belgium	Belgian Power Exchange (Belpex) (2006)

Source: Adapted from [1].

The liberalization of the electricity markets in Europe began three decades ago [36]. Before the 1990s, the markets had a monopolistic characteristic and were dictated by governments. This transformation led to electricity generation, transmission and distribution along with the law of supply/demand, which enabled competition and price reductions [37]. It is noteworthy that the DAMs in the world have adapted to this transformation and quickly became larger markets, and some of their names that are mentioned in Table 1 changed due to integrations, where detailed information can be found in [1].

### 2.1.2. Intra-Day Markets

In addition to the currently operating DAM, Ancillary Services, and balancing power market, the intra-day market (IDM) enables near real-time trading and offers market participants the opportunity to balance their portfolios in the short term. The IDM works as a bridge between the DAM and the BPM, and it contributes greatly to sustainability of the whole system.

The functionality of the IDM changes the role of the factors that cause imbalances, such as power plant failures, changes in the production of renewable energy sources, and unpredictable changes in the amount of consumption, as they will be eliminated in a near real time, and the participants will be given the opportunity to balance or minimize the negative or positive imbalances that they may face. Additional trading space will be provided by giving the participants the chance to evaluate their capacities, which they cannot use in the DAM, in the IDM after the closing time of the DAM. It will contribute to the increase of liquidity in the markets. It will also be of significant assistance to the TSO in providing a balanced system prior to real-time balancing.

IDMs are developing daily in terms of institutions, regulations, software, and web applications. The market designs in IDM might strongly deviate between countries [38]. For instance, a new software, named “Intraday Market Software”, on IDM for the Turkish electricity sector was developed and has been in use by Energy Exchange Istanbul (EPIAS) since 2016 [39]. More information can be found in [40] for the German IDM, in [41] for the European IDM, and in [42] for the Swedish IDM.

### 2.1.3. Balancing Power Markets (Balance Markets)

Real-time balancing consists of balancing power market (BPM) and ancillary services. The system operator is provided the spare capacity that can be activated in a couple of minutes (i.e., around 15 min) by the BPM for real-time balancing. Ancillary services provide demand and frequency control services. The balancing market prices are determined hourly based on upward and downward regulating power offers evaluated by the TSO in real-time balancing [43].

Although a market with balanced production and consumption amounts is given to the TSO with the DAM and IDM, there are deviations in real time. For example, if a power

plant is out of service, or when a large amount of consumption causes the plant to stop (start), the balance is disrupted [44]. For instance, on BPM for Turkish electricity sector [45]:

- All market participants participating in the BPM must present their available capacities.
- Balancing units that can receive or load independently in a couple of minutes (around 15 min) are obliged to engage in the BPM.

More information can be found in [46] for the European BPMs.

## 2.2. Electricity Market Instruments through Country-Specific Researches

### 2.2.1. Electricity Price

Electricity prices, or market clearing price (MCP), are determined by the law of supply/demand curves. The place for this is the DAM, which is managed by the system operators of the countries. The system operators gather hourly offers for the following day from sellers and buyers, and the supply/demand curves are analytically built in this way. The intersection of the supply and demand curves gives the MCP. While the buying and selling amounts are named as equilibrium quantities of electricity, the electricity trade volume is determined by multiplication of the equilibrium quantity and MCP. However, forecasting electricity prices is not easy because price series show characteristics such as variance, nonconstant mean, significant outliers, and volatility [47]. The common characteristics of electricity prices can be summarized as follows [1,48,49]:

- Seasonal effects for prices;
- Mean reversion;
- Spikes and volatilities due to changes in fuel price, load uncertainty, outages, market power, and market participant's behavior;
- Correlation between electricity load and price.

More detailed information can be found in [1] for various countries, and in [50] for the Turkish electricity markets, in [51] for the England and Wales electricity markets, in [52,53] for the Nordic electricity (Nord Pool) markets, in [54] for the New Zealand electricity markets, in [55] for Danish electricity markets, and in [56] for the US electricity markets.

### 2.2.2. Electricity Load

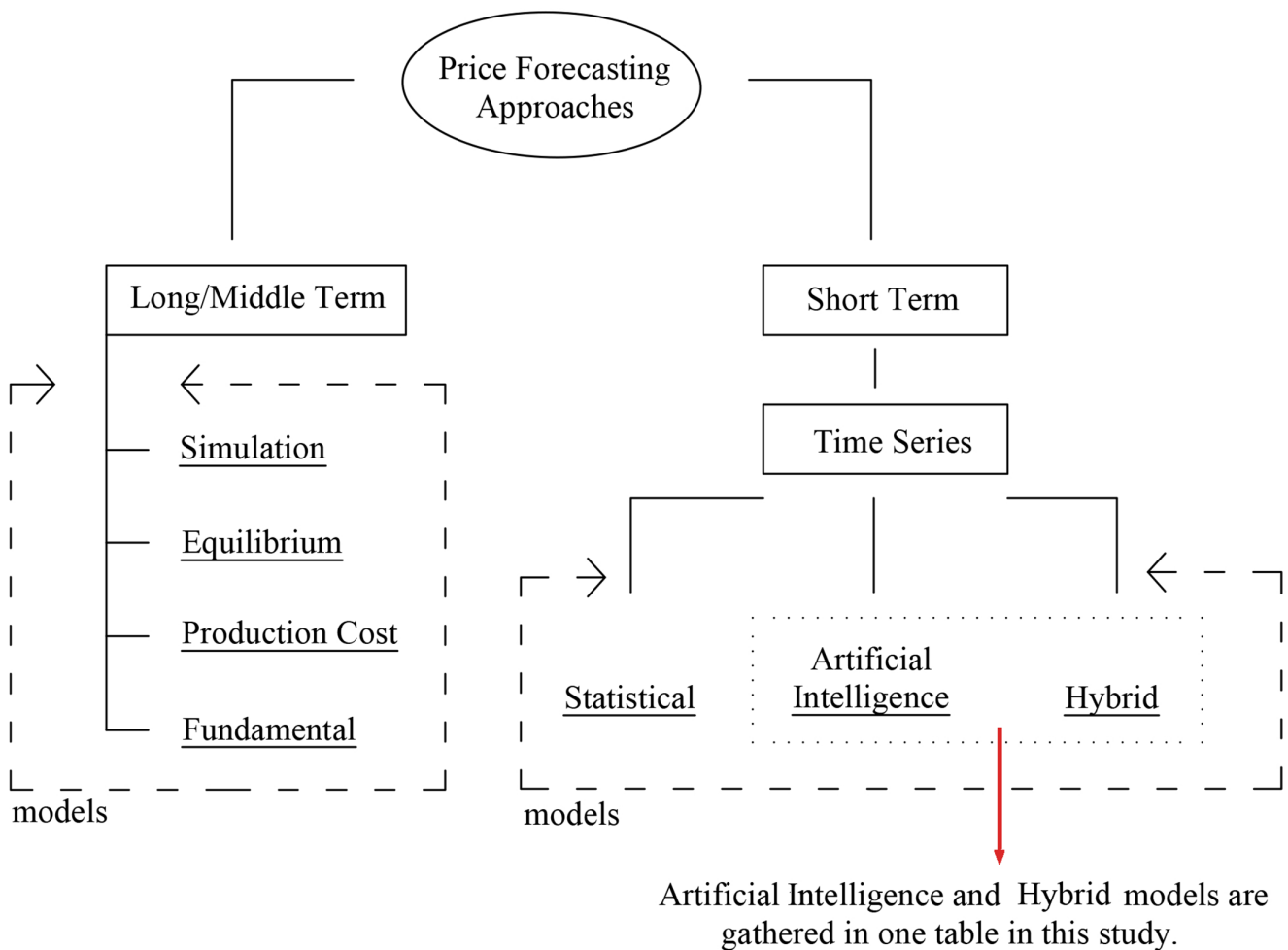
Forecasting the electricity load has been a key role in the operation of power systems, and it includes forecasts on various time scales (i.e., minutely, hourly, and yearly) [57]. Several decisions are based on load forecasts, for instance, reliability analysis, dispatch planning of generating capacity, and operation and maintenance plans for power systems. With the free competition and deregulation of the electric power industry, load forecasting increased its viability and importance all around the world. An accurately predicted load is vital data for the EPF, since market shares, profits, and shareholder value can easily be influenced by forecast errors. Nevertheless, due to the nonstationary and variability of the load series, forecasting procedures of the electric load is increasingly difficult. Time-varying prices, price-dependent loads, and the dynamic bidding strategies of market participants make this complexity [58]. Therefore, more accurate results are needed by more sophisticated forecasting instruments for the electrical power systems and the motivation behind more accurate forecast methods is hidden in the economic effect of the forecast errors [59]. However, a substantial amount of research has been done (see [60,61] for reviews and [58,62,63] for methods and techniques of short-term load forecasting and modeling, respectively).

Moreover, electric power should be stored or consumed very close-after from its generation. The cost of storing electric power is expensive, therefore, electricity markets, through system operators, exist for allocating the transactions between market participants. This mechanism provides a possible distribution of loads, freeing networks will be avoided from excessive loads. This review is focused on renewable energy through wind energy. Weather conditions, e.g., wind speed, precipitation, and temperature, have an important influence on electricity production from wind energy. The countries that supply a considerable share

of electricity demand from wind energy (e.g., Spain, Denmark, Germany [4]) and have wind energy potential (e.g., Turkey) should consider this energy source, mitigating global warming. More details can be found in [1] for various countries, and in [50] for the Turkish electricity markets.

### 3. Electricity Market Price and Load Forecasting through Wind Energy Production

The EPF studies can be categorized in the following two main groups: Long/middle terms and short terms. While long/middle models can be gathered into: simulation, equilibrium, production cost, and fundamental models. Short term models, or time series models, can be gathered into: statistical, artificial intelligence, and hybrid models [64], see Figure 1. This review paper follows the approach presented in [64]. Tables 2 and 3 presents a literature review through statistical models. However, it differs from the mentioned approach by merging the artificial intelligence and hybrid models into one category, as shown in Table 4. Table 5 presents a literature review through middle/long term models on electricity market price and load forecasting through wind energy.



**Figure 1.** A classification for EPF approaches. Source: Adapted from [64].

Various statistical model examples are shown in Tables 2 and 3 (Table 2 contains more simple models, represents the first part of the statistical models and Table 3 contains more advanced models, represents the second part of the statistical models). These models can be gathered in a main title named as time series analysis. Specifically, ordinary least squares (OLS) regressions, autoregressive distributed lag (ARDL) regressions, panel data analysis, vector autoregressive (VAR) analysis, generalized autoregressive conditional heteroskedasticity (GARCH) analysis, multiple linear regressions, auto-regressive with eXternal model



input (ARX) analysis, logit-probit regressions, quantile regressions, autoregression (AR) models, exponential generalized autoregressive conditional heteroskedasticity (eGARCH) analysis, autoregressive moving average model with exogenous regressors (ARMAX) analysis, least absolute shrinkage and selection operator (LASSO) analysis, seasonal component autoregressive (SCAR) analysis, and univariate and multivariate regressions.

The studies concentrating on merit-order effect for wind power on electricity market price are viable among researchers. Positive merit order effects were found with OLS analysis and time series regressions for Italy [31,65] and for US (California) [66], with time series analysis for Australia [67], and Germany [68], and with ARDL model and demand/supply framework for Australia [69,70], and with quantile regression model for Germany [71] and for US (California) [72]. A different type of time series analysis with panel data analysis through fixed effect regression was applied in [31] for Germany, and a dampening effect of wind power with reduced forecasting errors, which led to decreased price volatility. The VAR model was applied in [42] for Sweden with Granger causality analysis (i.e., unit root tests and impulse-response functions), and it was shown that the prices in the IDMs responded to wind power forecast errors. The same model was applied in [73] for Denmark, Sweden, and Finland. It was found that wind forecast errors did not affect price spreads in locations with large amounts of wind power generation. Studies for Germany [74,75] and Australia [76] with GARCH and eGARCH models showed that an increase in wind generation decreased the prices and increased the price volatility. A multiple linear regression model was applied for Germany's electricity markets [32,77], which showed that 15 min scale helped significantly to reduce imbalances in intraday trading, and a considerable share of spot price variance was explained by fundamental modelling. The ARX models, which are linear models, were applied for Germany [30,78], Poland [78], European countries, and the US [79], and the findings supported more accurate EPPs in the mentioned electricity markets. The ARMAX model was applied for Germany, where it showed that wind energy generation decreased market spot prices [80]. The AR models were applied for Denmark, Finland, Norway, and Sweden, and the used models were better performed compared to commonly-used EPF models [81,82]. The LASSO models were applied for Denmark, Finland, Norway, and Sweden, Germany, and the European Countries, and they demonstrated that LASSO models lead to better performance compared to the typically considered EPF models [83–85]. The SCAR models were applied for Denmark, Finland, Norway, and Sweden, where the SCAR models significantly outperformed the autoregressive benchmark [86]. The multivariate and univariate models were applied for the European countries and some guidelines were provided to structuring better performing models [87].

**Table 2.** Statistical models (first-part) on electricity market price and load forecasting through wind energy.

Author (s)	Data/Period	Country	Method (s)	Findings
Clo et al. (2015), [65].	GME/2005–2013	Italy	Time series (OLS) analysis	The merit-order effect for wind power was found.
Cludius et al. (2014a), [67].	AEMO/2011–2013	Australia	Time series regression analysis	The merit-order effect for wind power was found.
Cludius et al. (2014b), [68].	EEX/2008–2016	Germany	Time series regression analysis	The merit-order effect for wind power was found.
Csereklyei et al. (2019), [69].	NEM/2010–2018	Australia	ARDL model	The merit-order effect for wind power was found.
Forrest and MacGill (2013), [70].	AEMO and NEM /2009–2011	Australia	Econometric analysis techniques (a supply/demand analysis for electricity markets)	The merit-order effect for wind power was found and wind generation had an impact on the MCPs.

Table 2. Cont.

Author (s)	Data/Period	Country	Method (s)	Findings
Gianfreda et al. (2016), [31].	ENTSO-E/ 2012–2014	Italy	Time series regression analysis	It was found that wind generation power induced high imbalance values.
Gürtler et al. (2018), [88].	ENTSO- E/2010–2016	Germany	Panel data analysis (fixed effect regression)	It was found that there were dampening effects of wind power on MCPs, however this effect started to decrease after 2013.
Hu et al. (2018), [42].	Nord Pool FTP server and ENTSO- E/2015–2018	Sweden	VAR framework (Granger causality tests and impulse response functions)	It was found that intraday prices responded to wind power forecast errors.
Koch and Hirth, (2019), [32].	ENTSO-E and TSO/2012–2017	Germany	A multiple linear regression model	It was shown that the 15 min scale became common in intraday trading and helped significantly to reduce imbalances.
Maciejowska (2020), [71].	EPEX and ENTSO-E/ 2015–2018	Germany	Quantile regression model	It was found that wind energy generations had a negative effect on the MCPs.
Pape et al. (2016), [77].	ENTSO-E, EEX, EPEX/2012–2013	Germany	Multiple linear regression models (Fundamental price modeling)	It was shown that the used models well explained the spot price variance.
Serafin et al. (2019), [89].	Nord Pool, PJM/2013–2018	Denmark, Finland, Norway, and Sweden	Quantile Regression Averaging and Quantile Regression Machine	It was shown that QRM was both more efficient and had more accurate distributional predictions.
Spodniak et al. (2021), [73].	ENTSO-E, Nord Pool/2015–2017	Denmark, Sweden, and Finland	VAR model	It was found that wind forecast errors had no impact on price spreads in locations with a big amount of wind power generation.
Westgaard et al. (2021), [72].	LCG Consulting, OASIS/ 2013–2016	US (California)	Quantile regression	Wind generation had a negative effect on electricity prices.
Woo et al. (2016), [66].	CAISO/ 2012–2015	US (California)	OLS Regression	It was found that trading efficiency could be enhanced by DAM forecasts.
Ziel and Steinert, (2018a), [90].	EPEX/2012–2015	Germany and Austria	Time series models (supply/demand curves)	It was found that using the law of supply/demand curve yields realistic patterns for electricity prices and leads to promising results.
Ziel and Weron, (2018b), [87].	EPEX, Nord Pool, BELPEX/ 2011–2013	European Countries	Multivariate and univariate models.	More powerful variables identified and guidelines were provided for better performing models.
AEMO: Australia Energy Market Operator ARDL: Autoregressive distributed lag models BELPEX: EPEX Spot Belgium DAM: Day-ahead market EEX: The European Energy Exchange ENTSO-E: European Network of Transmission System Operators for Electricity			EPEX: The European Power Exchange GME: Gestore dei Mercati Energetici MCPs: Market clearing prices NEM: The Australian National Electricity Market's	PJM: The Pennsylvania–New Jersey–Maryland Interconnection OLS: Ordinary least squares QRM: Quantile regression machine VAR: The vector autoregressive



**Table 3.** A literature review through statistical models (second-part) on electricity market price and load forecasting through wind energy.

Author (s)	Data/Period	Country	Method (s)	Findings
Ketterer (2014), [74].	EEX and ENTSO-E/2006–2012	Germany	GARCH model	Wind power generation had a positive effect on decreasing the wholesale electricity price; however, increased its volatility.
Kyritsis et al. (2017), [75].	Phelix Day Base, EEX, and ENTSO-E/2010–2015	Germany	GARCH-in-Mean model	It was found that wind power Granger cause of MCPs and the volatility of electricity prices were increased by wind power generation
Maciejowska et al. (2019), [78].	TGE, PSE, EPEX SPOT and ENTSO-E/2016–2017	Germany and Poland	Econometric models (i.e., ARX and probit)	It was shown that the price spread could be forecasted by ARX and probit models.
Maciejowska et al. (2021), [30].	EPEX and ENTSO-E/2015–2019	Germany	Econometric models (ARX)	It was shown that variables that were forecasted gave biased results; however, they could be corrected with regression models.
Marcjasz et al. (2018), [81].	Nord Pool, PJM Interconnection and EPEX/2013–2018	Denmark, Finland, Norway, and Sweden	Autoregression Models	It was the extended model of Hubicka et al. (2019), [91] analysis with much longer datasets.
Mwampashi et al. (2021), [76].	NEM/2011–2020	Australia	eGARCH model	It was found that wind generation increase decreased daily prices and increased price volatility
Nowotarski et al. (2014), [79].	Nord Pool, EEX, and PJM/1998–2012	European Countries and US	ARX model (Constrained least squares regression)	The findings supported more accurate results and the used models were well performed for EPFs in the electricity markets.
Paraschiv et al. (2014), [80].	EEE, TSO, Bloomberg/2010–2013	Germany	ARMAX model	It was found that wind energy generation decreased market spot prices.
Uniejewski et al. (2016), [82].	GEFCom, Nord Pool/2011–2013	Denmark, Finland, Norway, and Sweden	Autoregression (ridge regression; stepwise regression, LASSO; elastic net) models	The used models performed well in comparison to previous preferred EPF models.
Uniejewski and Weron (2018), [83].	Nord Pool, PJM/2013–2017	Denmark, Finland, Norway, and Sweden	LASSO models	It was shown that LASSO models performed well in comparison to previous preferred EPF models.
Uniejewski et al. (2019a), [86].	GEFCom, Nord Pool/2013–2015	Denmark, Finland, Norway, and Sweden	SCAR models	SCAR models significantly outperformed the autoregressive benchmark.
Uniejewski et al. (2019b), [84].	EPEX/2015–2018	Germany	LASSO models	Some recommendations were provided for very short-term EPF with LASSO models.
Ziel, (2016), [85].	EPEX/2009–2014	European Countries	Time series model -Linear regression (LASSO)	It was shown that the LASSO forecasting technique performed well.

Table 3. Cont.

Author (s)	Data/Period	Country	Method (s)	Findings
ARMAX: Autoregressive moving average model with exogenous regressors ARX: Auto-regressive with eXternal model input EEX: The European Energy Exchange GARCH: A generalized autoregressive conditional heteroskedasticity model eGARCH: An exponential generalized autoregressive conditional heteroskedasticity) model			ENTSO-E: European Network of Transmission System Operators for Electricity EPEX: The European Power Exchange EPF: Electricity price forecasting LASSO: The least absolute shrinkage and selection operator	NEM: The Australian National Electricity Market's PJM: The Pennsylvania–New Jersey–Maryland Interconnection SCAR: The Seasonal Component AutoRegressive

The first part of the statistical models that are shown in Table 2 are closer to the research perspective of the fields of economics, and the traditionally used regression models by OLS (i.e., the difference between actual and predicted values are squared), VAR (i.e., the causality relationships), quantile regressions (i.e., the nonlinear relationships between electricity prices and variables are possible), and univariate and multivariate models (i.e., multivariate models are accepted as more accurate than the univariate ones but each approaches have its own advantages or disadvantages). However, when the number of regressors become large, these models were insufficient and, thereby, linear models via LASSO [92], ARX [93], SCAR (introduced by [94] and built on the ARX framework), GARCH [95–98] and eGARCH (i.e., proposed by [99]), and ARMAX [100] models were preferred, as it is shown in the second part of the statistical models with Table 3. Therefore, to obtain more accurate findings, statistical models should be more advanced and, since the complexity increases, artificial intelligence and hybrid models are required for more accurate and sensitive forecasts that are shown in Table 4. However, this time the subject becomes closer to the research perspective of the engineering field.

Various artificial intelligence and hybrid/ensemble models on electricity market price and load forecasting through wind energy examples are shown in Table 4. These models can be gathered in a main title named as time series analysis. Specifically, ensemble learning methods for Austria [101], deep neural networks analysis for Germany [102] and US (New York) [103], sensitivity analysis for Mexico [104], and deep learning models for US (New York) [105] can be given as country-specific examples. General findings for the studies showed that the proposed method could provide an effective forecast.

**Table 4.** A literature review through artificial intelligence and hybrid/ensemble models on electricity market price and load forecasting through wind energy.

Author (s)	Data/Period	Country	Method (s)	Findings
Bhatia et al. (2021), [101].	ENTSO-E/2015–2016	Austria	A real-time hourly resolution model (ensemble learning model)	The developed forecasting model showed more consistency, accuracy, and validity.
Bublits et al. (2017), [106].	EPEX, ENTSO-E/2011–2015	Germany	Agent based modelling and multiple regression analysis	The effect of renewable energy prices has been as half low as the coal and carbon prices on electricity prices in Germany in the duration of analysis.
Li and Becker (2021), [102].	Nord Pool, ENTSO-E, Thomson Reuters Eikon/2015–2019	Germany	LSTM deep neural networks	It was shown that feature selection is useful for more accurate forecasts.

Table 4. Cont.

Author (s)	Data/Period	Country	Method (s)	Findings
May et al. (2022), [104].	CONAGUA, CENACE, AND CRE/2017–2018	Mexico	Artificial Intelligence Techniques (Sensitivity Analysis)	It was found that the effects of the variables fluctuated due to consumption market conditions.
Nowotarski and Weron, (2018), [107].	GEFCOM/2011–2013	-	Neural network and autoregression	The study was an update of EPF techniques of Weron (2014), [108].
Osorio et al. (2015), [109].	Portuguese TSO (REN)/2007–2008	Portugal	Hybrid evolutionary-adaptive method	A new hybrid method was tested and reduce the uncertainty of wind power predictions.
Yang and Schell, (2021), [103].	NYISO/historical data	US (New York)	Deep neural networks	It was displayed that TL improved accuracy across all network representations.
Yang and Schell, (2022), [105].	NYISO/historical data	US (New York)	Deep learning model	The deep learning model was developed and it was shown that it performed well on time series for EPF.
Zhang et al. (2012), [110].	NSW/2006	Australia	WT, ARIMA and LSDVM	It was shown that the preferred method performed well on EPF.
ARIMA: Autoregressive integrated moving average CENACE: Natural Center for Energy Control CONAGUA: Natural Water Commission CRE: Energy Regulatory Commission ENTSO-E: European Network of Transmission System Operators for Electricity			EPEX: The European Power Exchange LSSVM: Shrinkage and selection operator least squares support vector machine	NYISO: The New York Independent System Operator GEFCOM: The Global Energy Forecasting Competition NSW: New South Wales TSO: Transmission system operator WT: Wavelet transform

The need for artificial intelligence models comes from the non-linear characteristics of electricity price. Since the large number of time series models have linear predictors, the time series techniques lack the ability to capture the behavior of the price signal [64]. Neural [47] and fuzzy neural networks [111] are proposed due to solving this problem. Nonetheless, due to functional relationship of electricity price with time and the nature (characteristics) of electricity price, it is a time variant signal; therefore, neural and fuzzy neural network solutions may not be sufficient for precise forecasting results [64], and it needs hybrid models, which are the combination of non-linear and linear modelling capabilities occurs.

Hybrid models have a very complex forecasting structure, including several algorithms for decomposing or cluster data, feature selection, combined forecasting models, and heuristic optimization [112]. The most commonly preferred decomposition method is the wavelet transform [113–122]. Other decomposition studies that used empirical mode are given in [123–129]. The most widely preferred feature selection methods are the correlation analysis are presented in [118,123,130–132], and the mutual information method in [121,123,130,133–135]. The algorithms for the clustering data are based on: (1) k-means [136,137]; (2) enhanced game [136]; (3) self-organizing maps [114,136,138]; and (4) fuzzy [121,139]. Combined forecasting models for hybrid models that build on more than one method are very common. Some examples can be found in [114,116,124,135,140,141]. The heuristic optimization studies can be found in [126,131,133,139]. The major problems in employing hybrid model are [112]: (1) The proposed methods avoid to be compared with well-build models; (2) the used data sets are small; (3) lack of analysis of the effect of selecting different components.

Various middle/long term models on electricity market price and load forecasting through wind energy examples are shown in Table 5. These models can be gathered by time series analysis. Specifically, a case study for US (Texas) [142], the sensitivity analysis through scenarios for Australia [143], balancing the cost of electricity demand

with large amount of wind energy for Australia [144], data analysis techniques through electricity demand models for Australia [145], WILMAR model through scenarios for Ireland and Great Britain [146]. Monte Carlo simulations for Mykonos (Greece) and La Ventosa (Mexico) [147], and for Denmark [148]. Simulations with stochastic and robust optimization for China [149], a market equilibrium model for China [150]. A modelling demand response utility function for Iran [151], and a dispatch model for Colombia [152] can be given as country specific examples.

**Table 5.** A literature review through middle/long term models on electricity market price and load forecasting through wind energy.

Author (s)	Data/Period	Country	Method (s)	Findings
Baldick (2012), [142].	ERCOT empirical data	US	Case study for Texas	Cost predictions are developed for using wind energy to mitigate CO <sub>2</sub> emissions.
Banaei et al. (2021), [4].	Game theory data	-	The supply function model (pricing models)	Results showed that the applied method reduced the market players profit that depended on uncertainties.
Bell et al. (2017), [143].	WRF data/2015	Australia	The sensitivity analysis through scenarios	The average wholesale spot price in the NEM decreased due to the increase in wind power generation.
Blakers et al. (2021), [144].	NEM/2006–2010	Australia	Balancing the cost of electricity demand with high levels of wind energy	It is found that wind energy generation led deployment on the MCP, but it was modest.
Cutler et al. (2011), [145].	AEOM/2008–2010	Australia	Various data analysis techniques through electricity demand models	Wind power generation became a significant secondary influence (the relationship is inverse with spot prices) after electricity demand on spot prices.
Denny et al. (2010), [146].	AIGS	Ireland and Great Britain	WILMAR model through scenarios	It was found that the increased interconnection reduced both average prices and the volatility of those prices in countries.
Elfarra and Kaya (2021), [147].	Akdağ et al. (2010), [153]/2008–2009	Mykonos (Greece) and La Ventosa (Mexico)	Annual energy production through Monte Carlo simulations	The PDFs (i.e., spline based) produced minimum fitting error
Ji et al. (2021), [149].	Simulation forecast data	China	Simulations with stochastic and robust optimization	The validity and superiority of the recommended models were shown in case studies.
Khosravi et al. (2022), [148].	WF power generation and West Denmark electricity markets	Denmark	Stochastic scheduling, simulations with Monte-Carlo method	Increase in the profit was observed from the wind power management method.
Liu and Xu (2021), [150].	CMDC/2013	China	A market equilibrium model	The impact of wind power development on the spot market price results were explored for both long and short terms.
Niromandfam et al. (2020), [151].	Ordoudis et al. (2016), [154].	Iran	Modelling demand response utility function	It was shown that the proposed demand response utility function improved the wind generation profit in the DAM.

Table 5. Cont.

Author (s)	Data/Period	Country	Method (s)	Findings
Perez and Garcia-Rendon, (2021), [152].	Provided by the authors through the XM data/2018–2019	Colombia	Dispatch model	New bid prices in the market were determined by the firms through the structural model.
AEMO: Australia Energy Market Operator AIGS: All Island Grid Study CMDC: The China Meteorological Data Service Center DAM: Day-ahead market ERCOT: The electric reliability council of Texas			MCP: Market clearing price NEM: The Australian National Electricity Market PDFs: Probability density functions	WILMAR: A stochastic unit commitment model WRF: Mesoscale numerical weather prediction system

The long/middle term models include simulations (i.e., Monte Carlo simulations), market equilibrium models, production cost models, and fundamental models such as game theoretical approaches. The duration is longer or at least the considered period is middle-term in these models. They have remarkable theoretical contributions to the development of the EPF models by using economics terminology and approaches. Table 6 gives the main pros and cons of the reviewed methods and techniques based on the references that are given with Tables 2–5. Additionally, the last row of Table 6 shows the error comparison of the models that are selected among Tables 2–5.

Table 6. Main pros and cons of the reviewed methods based on the references in Tables 2–5.

Pros and Cons of the Reviewed Methods	Statistical Models (First-Part)	Statistical Models (Second-Part)	Artificial Intelligence and Hybrid/Ensemble Models	Middle/Long Term Models
Prons-1	Models allows the use of data by converting them from hourly to daily, which reduce unwanted and excessive noise. Their implementation are easy.	Conditional heteroscedasticity models truly explain the volatilities in prices (i.e., seasonality, mean reversion, and jumps). Dynamic effects can be considered.	These models display improved forecasting performance in terms of consistency, accuracy, and statistical tests). High-frequency electricity price data forecasts are possible.	More realistic modes can be possible to visualize the market players' behaviours (i.e., risk management preferences).
Prons-2	Model allows omitting variables which their inclusion in regressions may generate an endogeneity problem. They are wide-spread preferred models.	The negative electricity prices can be included into the models, which helps to conduct analysis without shifting or cutting off the series.	Private information and imperfect market structure (i.e., oligopolies) can be included and represented with these models.	Theoretical economic models (i.e., Nash Equilibrium conditions) can be implemented with simulations.
Prons-3	Models allows to control the seasonal effects by introducing time dummies.	The causality tests can be implemented in the context of multivariate during off-peak hours, peak hours, and all hours.	These methods are capable of learning lon-term dependencies. They cen control how information is abandoned or memorized throughout time.	Strategical behaviours of the market participants can be modeled and simulated.
Prons-4	Binary variables for the weekend can be included in models.	More accurate estimations of load and wind with these models might improve EPF.	These models are reliable and robust for the system's complexity. Specifically, the ensemble methods have better results than their individual equivalents.	Parametric and nonparamatric methods can be simultaneously implemented.
Prons-5	Yearly, monthly, daily, and hourly dummies can be used to control for systematic demand changes.	These models (i.e., ARX) can utilize both the information on system forecasts and actual past realizations of these variables.	Decision-making strategies can be done with these model and these models can be implemented for other regions to improve EPF efficiency.	Seasonal effects can be simulated effectively.



Table 6. Cont.

Pros and Cons of the Reviewed Methods	Statistical Models (First-Part)	Statistical Models (Second-Part)	Artificial Intelligence and Hybrid/Ensemble Models	Middle/Long Term Models
Cons-1	There can be a lack of certainty on estimations of net effects for individual consumers. Estimated prices can be different (i.e., higher) than observed spot market prices.	The stochastic nature of weather conditions causes the volatilities of wind power. This effects electricity prices electricity price spikes occur.	The decision-making rules are difficult to validate. The implementations might be time-consuming.	The models might be case dependent and different findings can be obtained for other situations.
Cons-2	The differences in wind load profiles can affect the hours of the day and electricity prices can be dependent on these changes.	Mean absolute errors might not work properly when the models with more variables are considered.	These methods have a significantly increased computational burden.	Prediction of wind power effect on prices is difficult due to the wide range of factors (i.e., uncertain demand, several contingencies depend on long-term forecasting intervals).
Cons-3	Many of the variables tend to show near-unit root, or autoregressive properties; therefore, lags of the variables should be included into the models.	The system of equations need many parameters and the estimation of the coefficients are relatively difficult or complex.	Irrelevant assumptions might block or decrease the performance of the estimator.	If the computation time increases with problem size, this might weaken the solution capability of the concentrated problem.
Cons-4	Possible endogeneity problems cause from either omitted variables or reverse causalities (i.e., the aggregate or average electricity demand).	ARMA type models are bounded by the assumption of constant variance that yields inconsistency through volatility.	Various open-source software platforms might be needed, so that any researchers can implement the codes as benchmarks in their individual studies.	
Error comparison of the models	-	Lasso (Ziel, 2016) [85], MAAPE (%): 6.604, RMSE: 2.715, MAE: 1.819	Ensemble learning model (Bhatia, 2021) [101], MAAPE (%): 5.132, RMSE: 2.156, MAE: 1.385	-

Note: The last row of Table 6 shows the comparison of the Lasso and Ensemble learning models in terms of mean arctangent absolute percentage error (MAAPE), mean absolute error (MAE), and root mean squared error (RMSE).

#### 4. Discussion of Forecasting Models on Electricity Markets

Electricity price and load are determined by day-ahead, intra-day, and balancing markets all around the world; however, research shows that, although its data are usually publicly available, market clearing price forecasting is more complex (i.e., fuel prices; equipment outages; and the nature of the market clearing price depends on the hourly loads creates this complexity [155]) than the load price forecasting.

Forecasting the electricity market's prices is needed as a result of the dynamic features of markets, moving from deregulated to regulated form, that cause price volatility. Thereby, well performed MCP estimation and its confidence interval prediction may help power producers and its utilities when submitting bids in cases that are more risk-free (i.e., they can adjust their producers' supply and profits) [155]. Moreover, with reliable daily price forecasting, energy service companies or producers are able to lay out better financial contracts or bilateral ones. The complexity of forecasting electricity markets price and load is also dependent on the increasing number of employed variables as input for better accuracy [64,112]. Thereby, the trend in methodologies moves to more sophisticated instruments, such as hybrid models, as shown and discussed in this review.

In addition to the explanation of operating principles of the electricity market, it is understood from the papers examined in this review that renewable energy resources should be preferred, transforming the structure of electricity markets for better environment conditions with low-carbon levels. Incentives and supply security can be the instruments for all countries [156].

Many methods and models have been developed for the EPF of markets for the last two decades. As a result of the stochastic and nonlinear nature of statistical models and price series, autoregression, moving average, exponential smoothing, and their variants [33,157] have shown to be insufficient [49]. The artificial intelligence models are able to capture non-linearity and complexities and flexible [47,158–160].

Artificial neural networks are outstanding for short-term forecasting, and they are efficiently applicable for electricity markets [161], being more accurate and robust than autoregressive (AR) models. The research [48] uses artificial neural network models to display the strong impact of electricity price on the trend load and MCP. Singhal and Swarup [48] apply artificial neural network models to study the dependency of electricity price in MCP and electricity load. Wang et al. [159] implement a deep neural network model to forecast the price in US electricity markets, differently from conventional models of neural networks. This model supports vector regression. On the other hand, since the price series are volatile, the neural network models have potential to lose the properties of the value of prices [64]. Moreover, neural networks are not convenient for too short-term predictions, since they need high training time. As a result of the aforementioned issues, artificial intelligence models have handicaps in perfect price forecasting [108].

Relying on a sole forecasting electricity price model may fail in the treatment of network features in the short term. In those circumstances, hybrid models can be a better alternative for price forecasting. An example of a hybrid model which is a composition of a stochastic approach with a neural network model is given in [135]. Ghayekhloo et al. [136] show hybrid models that include game theoretic approaches. Signal decomposition methods are also used in hybrid models such as empirical mode decomposition and wavelet transform; the examples are given in [115,162,163]. Although the performance is significantly improved by those models, the computational cost can be disadvantageous [101].

## 5. Conclusions

The power industry is rapidly growing all over the world, and renewable energy resources are one of the most vital components in electricity production. Besides, renewable energy has environmentally friendly features (i.e., a considerable reduction of emission helps to mitigate global warming). To this end, increasing wind energy utilization is a challenge to provide electricity power for electricity markets. For the last two decades, the electricity market mechanisms have been faced with regulation procedures designed by decision and policy-making processes. The competition is the key factor to decreasing the cost of electricity and reliably meeting-demand solutions. However, the price spikes and price volatilities, due to various environmental and business factors, are the handicaps of this commodity. These handicaps encourage researchers to produce more effective instruments, techniques, and solutions.

This review paper gathers the latest electricity price and load forecasting techniques and discusses their strengths and weaknesses. Nevertheless, electricity trading markets are becoming more sophisticated, with novel types of contracts in the bilateral transactions or organized markets due to an existing free market competition rule. The independent transmission system operators for each specific market have the responsibility of controlling the entire transmission networks. The price mechanism operates with market clearing price, which is obtained by the law of supply and demand curves that are determined in the day-ahead markets. The price deviations caused by supply and demand forces are corrected in balancing power markets by transmission system operators. Moreover, the intra-day markets are functioning as a bridge between the day-ahead markets and balancing markets. Market participants, who do not sell their entire power or do not take their positions in the day-ahead markets, have the alternative to sell or buy the needed power in the intra-day markets.

As a methodology, this review paper follows the historical and structural development of electricity markets, price and load forecasting methods, and recent trends in wind energy generation, transmission, and consumption. The findings that are based on the considered studies in this review reveal that:

The merit order effect is found for wind power generation, which means that wind power decreases wholesale price of electricity, however, it increases its volatility.

The volatility of wind power is induced by the stochastic character of weather conditions; therefore, both the parametric and non-parametric techniques might be needed in

the calculations. Moreover, this indirectly effects the market clearing prices; however, the volatility of electricity prices is driven by the market design.

Technically, the models can be calibrated by transforming data, known as variance stabilizing transformation, which yields more accurate predictions along with less spikes and lower variation features of data.

As the EPF and load methods tend to be explained more dimensionally (i.e., hybrid methods including deep learning and artificial intelligence), the performance of the methods increase in terms of accuracy, stability, and consistency. Besides, both the linear and the non-linear nature of electricity price data can be observed in this way.

The regulatory interventions due to Covid-19 pandemic and the carbon pricing mechanism might have an adverse effect on electricity price dynamics. However, inventions of new vaccines and pills and prevalent use of renewable energy sources (i.e., wind and solar energy) will lessen the unpredicted effects of Covid-19 and carbon emissions.

Nevertheless, extreme weather events that are related with climate change seem a barrier for electricity market participants through wind energy production in the near future. Therefore, future studies may consider those facts and propose new forecasting techniques and improvements for better market operations. As a practical solution proposal, a cooperation between government, energy producers, manufacturers, and researchers in developing countries might lead to the start of arrangements whereby produced power can be directly delivered to energy-intensive factories, such as fertilizer factories (i.e., fertilizer industry require significant electricity in the world). Therefore, energy transfer losses can be prevented and, with special agreements, the manufacturers can benefit from these arrangements as a means of production cost reduction and wind farm owners can benefit from the utilization of produced electricity without any restriction. As a theoretical solution proposal, research has demonstrated that a large installed capacity of wind energy might reduce wind power variability. Thereby, smooth wind generation could be possible by utilizing storage optimization systems and flexible electricity interconnections (i.e., high voltage direct current systems with voltage source converters operating for wind farms).

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## Nomenclature

AEMO	Australia Energy Market Operator
AIGS	All Island Grid Study
APX	Amsterdam Power Exchange
AR	Autoregression
ARDL	Autoregressive distributed lag
ARMAX	Autoregressive moving average model with exogenous regressors
ARX	Auto-regressive with eXternal model input
Belpex	Belgian Power Exchange
BPM	Balancing power market
CalPX	California Power Exchange
CMDC	The China Meteorological Data Service Center
CRE	Energy Regulatory Commission
DAM	Day-ahead market
EEX	European Energy Exchange
eGARCH	Exponential generalized autoregressive conditional heteroskedasticity
ENTSO-E	European Network of Transmission System Operators for Electricity
EPFs	Electricity price forecasts
EEX	European Energy Exchange
EPEX	European Power Exchange
EPIAS	Energy Exchange Istanbul
ERCOT	The electric reliability council of Texas
EXAA	Energy Exchange Austria
GARCH	Generalized autoregressive conditional heteroskedasticity
GEFCom	Global Energy Forecasting Competition
GME	Gestore dei Mercati Energetici
IDM	Intra-day market
IPEX	Italian Power Exchange
LASSO	Least absolute shrinkage and selection operator
LPX	Leipzig Power Exchange
LSSVM	Shrinkage and selection operator least squares support vector machine
MCP	Market clearing price
MISO	Midwest ISO
NYISO	New York ISO
NEM	Australian National Electricity Market
NSW	New South Wales
NYISO	New York Independent System Operator
OLS	Ordinary least squares
OMEL	Operadora del mercado español de electricidad
PJM	Pennsylvania-New Jersey Maryland Interconnection
PolPX	Polish Power Exchange
QRM	Quantile Regression Machine
SCAR	Seasonal component autoregressive
TSO	Transmission system operator
UKPX	UK Power Exchange
VAR	Vector autoregressive
WILMAR	A stochastic unit commitment model
WRF	Mesoscale numerical weather prediction system

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