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Review

A Review of Electricity Price Forecasting Models in the Day-Ahead, Intra-Day, and Balancing Markets

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Abstract: Electricity price forecasting plays a fundamental role in ensuring efficient market operation and informed decision making. With the growing integration of renewable energy, prices have become more volatile and difficult to predict, increasing the necessity of accurate forecasting in bidding, scheduling, and risk management. This paper provides a comprehensive review of point forecasting models for electricity markets, covering classical statistical approaches both with and without exogenous inputs, and modern machine learning and deep learning techniques, including ensemble methods and hybrid architectures. Unlike standard reviews focused solely on the day-ahead market, we assess model performance across day-ahead, intra-day, and balancing markets, with each posing unique challenges due to differences in time resolution, data availability, and market structure. Through this market-specific lens, the paper merges insights from a broad set of studies; identifies persistent challenges, such as data quality, model interpretability, and generalisability; and outlines promising directions for future research. Our findings highlight the strong performance of hybrid and ensemble models in the day-ahead market, the dominance of recurrent neural networks in the intra-day market, and the relative effectiveness of simpler statistical models such as LEAR in the balancing market, where volatility and data sparsity remain critical challenges.

Keywords: electricity price forecasting; day-ahead market; intra-day market; balancing market; machine learning; deep learning; hybrid models

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1. Introduction

Electricity price forecasting (EPF) plays a fundamental role in energy markets, enabling market participants to optimise trading strategies, mitigate financial risks, and maintain grid stability. However, forecasting with accuracy has become increasingly difficult due to the rapid expansion of renewable energy sources such as wind, solar, and hydroelectric power. This challenge is especially evident in real-time markets such as the intra-day market (IDM) and balancing market (BM), where forecast errors in renewables require real-time corrections [1]. While policy incentives, declining technology costs, and regulatory mechanisms like feed-in tariffs have accelerated renewable adoption [2,3], these energy sources introduce significant variability and uncertainty into electricity markets. Unlike traditional commodities, electricity cannot be stored efficiently, requiring real-time balancing of supply and demand. As a result, short-term price fluctuations are highly sensitive to

renewable generation forecasts, regulatory interventions, and unforeseen disruptions such as generator outages or transmission constraints. These complexities make EPF particularly challenging, as prices exhibit high volatility, non-linearity, and sudden spikes.

1.1. Point Forecasting Methods

EPF approaches can be broadly divided into point forecasts and probabilistic forecasts. Point forecasts generate single-valued predictions that are easy to interpret and support parsimonious predictor–target relationships, typically under the assumption of homoscedasticity. Historically, point forecasting has been dominated by statistical models due to their interpretability and ability to capture temporal dependencies. Classical methods include autoregressive (AR) models, both without and with exogenous inputs (ARX), which have been extended to autoregressive integrated moving average (ARIMA) and its variants with seasonality (SARIMA) and exogenous inputs (ARIMAX). To account for volatility, these are often paired with Generalised AR Conditional Heteroscedasticity (GARCH) models, which model time-varying variance within a linear framework. More recent developments incorporate regularisation techniques to improve generalisation in high-dimensional settings. The Least Absolute Shrinkage and Selection Operator (LASSO) utilises l_1 regularisation to enhance linear regression, while the Lasso-Estimated AR (LEAR) model extends AR frameworks using elastic nets to apply both l_1 and l_2 regularisation. Although these methods remain widely used, they often struggle to capture the non-linearities, regime shifts, and extreme price fluctuations that typify modern electricity markets—particularly those with high renewable energy penetration [4].

To overcome the limitations of traditional statistical models, machine learning (ML) and deep learning (DL) techniques have gained prominence in EPF, offering greater flexibility for modelling complex, non-linear relationships. ML approaches such as Support Vector Machine (SVM), Random Forest (RF), and gradient boosting algorithms (e.g., XGB, LGBM) have shown strong performance in uncovering intricate patterns within market data [5–7]. DL models, particularly recurrent neural networks (RNNs), have been widely adopted in the day-ahead market (DAM) due to their ability to learn hierarchical feature representations and capture temporal dependencies [8,9]. Despite their predictive power, these models often require large datasets, entail significant computational costs, and are prone to overfitting. In response, hybrid approaches that combine statistical, ML, and DL components have gained traction, aiming to exploit the strengths of each paradigm. These integrated models offer a promising path forward, balancing interpretability, computational cost, and accuracy to improve forecasting performance in increasingly volatile and data-rich electricity markets.

1.2. Related Work and Literature Gap

EPF has been extensively studied, with early research focusing primarily on statistical techniques within the DAM. The foundational reviews in [10,11] established the dominance of statistical models, which remained the standard for over a decade. However, these works predate the widespread adoption of ML, DL, and hybrid approaches that integrate non-linear and data-driven techniques to further improve forecasting accuracy. More recent surveys have updated the literature to reflect the growing use of ML and DL in EPF [4,12–14]; yet a critical gap remains: most reviews continue to focus almost exclusively on the DAM, neglecting the increasingly important IDM and BM.

These real-time markets pose unique challenges due to higher temporal resolution and greater sensitivity to renewable energy fluctuations, making accurate forecasting essential for managing supply–demand imbalances in systems with increasing renewable penetration. Given the rapid evolution of forecasting methodologies and the growing

importance of the IDM and BM, there is a growing need for a comprehensive, cross-market review. This paper addresses this gap by examining the progression from classical statistical models to modern ML-based techniques across all three short-term markets. By analysing emerging methodologies and distinct forecasting challenges in the DAM, IDM, and BM, we aim to provide researchers and practitioners with a timely and structured resource for navigating the evolving EPF landscape. The key novelty of this work lies in its comprehensive, methodologically structured review of point forecasting models across all three major short-term electricity markets—day-ahead, intra-day, and balancing—highlighting how model performance and suitability vary with market structure, data requirements, and volatility characteristics.

The structure of this paper is as follows: Section 2 provides a background of electricity spot markets, the DAM, IDM, and BM. In Section 3, we provide an overview of statistical, ML, DL, and hybrid models utilised in EPF. The key findings for predictive models in each spot market are discussed in Section 4. Finally, Section 5 summarises our findings.

2. Background: Electricity Market Structure

EPF is highly dependent on market structure, as different electricity markets operate on distinct time frames (see Figure 1) and temporal granularity, and exhibit varying levels of price volatility. The financial instruments shown in Figure 1, including forwards, capacity markets, and financial transmission rights, are described in more detail in Section 2.4. Short-term electricity markets, including the DAM, IDM, and BM, play a crucial role in electricity trading, each introducing unique forecasting challenges due to differences in market mechanisms, trading frequency, and reliance on real-time data. Understanding these market structures is essential for selecting appropriate forecasting models, as methodologies must be tailored to each market's unique characteristics. This section provides an overview of short-term electricity markets, highlighting their structural differences and the specific forecasting difficulties they present.

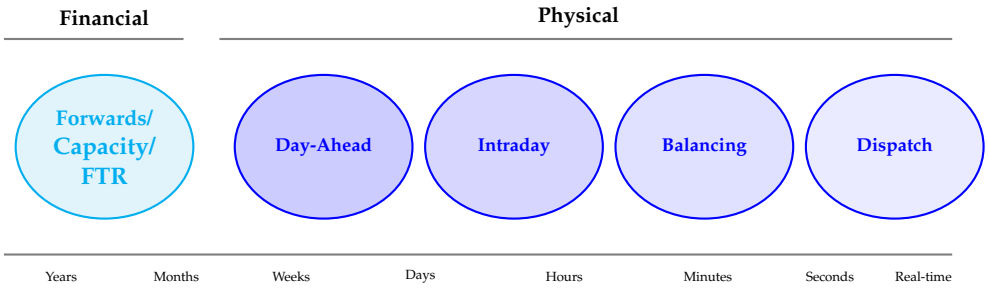


Figure 1. Temporal granularity for each of the relevant markets.

2.1. Day-Ahead Market

The DAM functions as a forward scheduling mechanism in which participants commit to electricity trades one day prior to delivery. Prices and trading volumes are determined through market-clearing auctions based on forecasted supply and demand, typically using optimisation algorithms such as EUPHEMIA in European markets [15,16]. While the DAM displays more stable prices compared to real-time markets, forecasting remains challenging due to the increasing penetration of renewable energy sources, particularly wind and solar. These sources introduce volatility, as their generation depends on weather conditions, complicating both supply and demand forecasts [17].

Early DAM forecasting methods relied on statistical time-series models, due to their ability to capture temporal dependencies. However, these models struggle with non-linear price dynamics and sudden regime shifts. ML and DL approaches have since demonstrated strong performance by capturing complex, non-linear relationships within market data. Techniques such as XGB and LSTM, and hybrid models such as LEAR-DNN, have proven to be stand out performers, improving forecasting accuracy by incorporating multiple influencing factors, including weather conditions, fuel prices, and demand trends [4,18–21].

2.2. Intra-Day Market

The IDM facilitates continuous trading, allowing market participants to adjust their positions in response to real-time fluctuations in supply and demand. Unlike the DAM, where trades are scheduled a day in advance, the IDM operates on shorter time frames, with transactions occurring from a few hours up to 30 min before delivery. This high-frequency trading environment is particularly sensitive to renewable generation variability, unexpected outages, and shifting demand patterns, making accurate forecasting increasingly important [22]. Forecasting in the IDM presents unique challenges due to the need for real-time adaptation to evolving market conditions. Traditional statistical models, while effective for longer time horizons, struggle to capture the higher-frequency, non-stationary nature of IDM price dynamics. In line with the DAM, ML and DL approaches have demonstrated strong performance in processing large datasets, detecting intricate patterns, and effectively incorporating high-resolution temporal data [23–26]. These models integrate diverse real-time data sources, enabling more precise short-term price predictions in high-frequency trading environments, while hybrid approaches that combine statistical and ML-based techniques are being increasingly explored to improve predictive accuracy, model interpretability, and real-time bidding strategy optimisation [26–28].

2.3. Balancing Market

The BM operates in real time, ensuring that electricity supply matches actual system demand. Unlike the DAM and IDM, where trades are scheduled in advance, the BM responds to last-minute supply–demand imbalances, renewable energy fluctuations, and generator outages, making it the most volatile market [1,29]. Operating on extremely short time horizons (5 min), BM EPF is particularly challenging, as BM prices must reflect rapid corrective actions taken by the transmission system operator [30]. While ML and DL models have demonstrated strong forecasting performance in the DAM, and to a lesser extent in the IDM, simpler statistical approaches have proven more effective for BM forecasting due to their ability to handle sharp price spikes without overfitting [31,32]. In contrast, ML and DL models, which excel in capturing complex patterns, often struggle with overfitting, and have difficulty modelling high-frequency fluctuations and sudden regime shifts. To address these limitations, hybrid approaches utilising statistical and ML models are being explored, while real-time data integration, incorporating weather conditions, grid frequency, and system constraints, remains a key focus for improving BM EPF [33,34].

Figure 2 illustrates the aligned trading timelines for the day-ahead, intra-day, and balancing markets, including typical submission times and trading intervals.

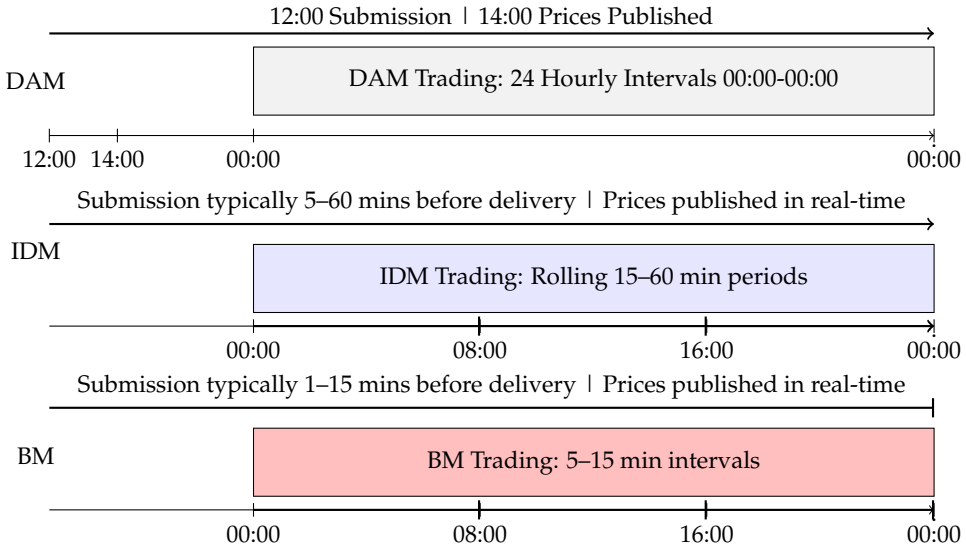


Figure 2. Aligned DAM, IDM, and BM trading timelines, with submission and trading details. Created by the authors based on SEMOpx documentation and European market rules [35,36].

2.4. Other Electricity Markets

In addition to the DAM, IDM, and BM, several other markets play fundamental roles in the overall trading of electricity. An overview of these markets and their unique characteristics is provided below:

- *Forward market*: Allows participants to hedge positions in DAM, IDM, and BM through contracts-for-difference [37]. Contracts-for-difference enable participants to lock in a strike price, providing protection against price volatility. Forecasting in this market requires predicting long-term price trends and movements.
- *Ancillary markets*: Support the power grid's stability and reliability through services like frequency regulation, spinning reserve, voltage control, and black start capabilities. Accurate forecasting in ancillary markets ensures the availability of resources needed to maintain grid stability. This involves sophisticated models considering real-time operational data and dynamic supply and demand conditions [38].
- *Capacity market*: Ensures sufficient generation capacity to meet peak demand. Capacity providers receive payments for committing to supply electricity or reduce demand during peak periods, incentivising investment in new capacity [39]. Forecasting in the capacity market involves predicting peak demand periods and capacity resource availability.
- *Financial transmission rights auctions*: Manage congestion costs and provide financial hedges against price differences across market zones. Financial transmission rights entitle holders to payments based on price differences between locations. Forecasting in this market involves predicting congestion patterns and price differentials, requiring an understanding of grid operations and transmission constraints [40].

While the forward, ancillary, and capacity markets are integral to the broader functioning of the electricity system, this review focuses exclusively on the DAM, IDM, and BM due to their direct relevance to short-term price volatility, renewable integration challenges, and real-time trading dynamics. Markets oriented toward long-term hedging, such as the forward market and financial transmission rights auctions, are excluded, as their longer time horizons and distinct pricing mechanisms fall outside the primary scope of this study.

3. Predictive Models

Accurate EPF requires models that can effectively capture diverse market dynamics, accommodate high volatility, and adjust to real-time conditions. In this section, we review key predictive models, including statistical, ML, DL, and hybrid approaches, highlighting their application and suitability across each spot market. We begin by discussing statistical models, distinguishing between those that rely solely on historical price data and those that incorporate exogenous inputs. In contrast, ML and DL techniques are evaluated for their strength in modelling complex, non-linear relationships inherent in volatile markets. Drawing on insights from previous reviews [4,10–14,19], we assess the strengths and limitations of these methods while extending the focus beyond the DAM to real-time markets, namely, the IDM and BM, where forecasting challenges are amplified by shorter decision windows and greater volatility.

3.1. Statistical Methods Without Exogenous Inputs

Statistical models that rely solely on historical price data are widely used in EPF to identify underlying patterns such as trends, seasonality, and autocorrelation. Common techniques include AR, ARIMA, GARCH, as well as simpler approaches like naive models and exponential smoothing (ES). These methods have traditionally performed well in relatively stable markets such as the DAM, where price dynamics tend to be more predictable [19,41]. However, in more volatile environments like the IDM and BM, where price shocks and non-linear behaviours are frequent, these models often struggle to maintain forecasting accuracy [31,32,42,43]. In this subsection, we review both simple and advanced statistical methods without exogenous inputs, highlighting their applicability and limitations across different market conditions.

3.1.1. Autoregressive Model

The AR model is a foundational time-series forecasting technique where the dependent variable is regressed against its own lagged values, assuming a linear relationship. An AR model of order p, denoted AR(p), expresses the current value y_t as a linear combination of its p previous values, denoted as

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t, \tag{1}$$

where ϕ_0 is an intercept term, ϕ_i are AR coefficients, and ϵ_t is white noise. AR models are suitable for stationary time series which exhibit a constant mean and variance over time, and serve as a building block for more complex models like ARMA and ARIMA.

AR models are particularly adept at capturing mean-reversion behaviour, a common characteristic in electricity prices. However, in practice, simple AR models often struggle to handle sudden volatility and price shocks, as evidenced by studies in the Indian DAM [44]. To address these limitations, combining AR with volatility models such as GARCH has proven effective in enhancing accuracy in more turbulent settings. While the simplicity of AR models makes them valuable baselines [45], they are frequently outperformed by advanced methods, such as DL models like NBEATSx, that are better equipped to model non-linear price dynamics. Moreover, evidence from Italy's DAM suggests that incorporating external factors via extensions like ARX, in tandem with GARCH, is considerably beneficial for improved forecast performance [46]. In the IDM, AR models demonstrate limited forecasting accuracy due to their inability to capture time-varying cross-hour dependencies [47], but their performance improves significantly when extended with exogenous variables or hybrid approaches [48]. Their performance in the IDM is further improved with regularisation and exogenous variables, often outperforming more complex models [49].

In the BM, AR models remain relatively underexplored, with moderately strong performance, albeit in a short 3-month test period [43]. Overall, we see a trend of AR models underperforming compared to more complex models which utilise exogenous outputs.

3.1.2. Autoregressive Integrated Moving Average Model

The ARIMA model is a widely used time-series forecasting approach that combines three components: the AR term captures temporal dependencies, as outlined in Equation (1); the integrated (I) component achieves stationarity through differencing, $\nabla^d y_t = (1 - B)^d y_t$, to remove trends and ensure constant statistical properties; and the moving average (MA) term models the impact of past forecast errors, $y_t = \theta_0 + \epsilon_t + \sum_{j=1}^{q} \theta_j \epsilon_{t-j}$, where ϵ_t denotes white noise. These components are unified into the ARIMA framework, denoted ARIMA(p, d, q), and expressed compactly as

$$\phi_p(B)\nabla^d y_t = \theta_q(B)\epsilon_t, \tag{2}$$

where $\phi_p(B)$ and $\theta_q(B)$ are polynomials in the backshift operator B. ARIMA has been widely applied in EPF in the DAM, proving effective in handling non-stationary behaviour—such as non-constant mean, variance, and seasonality—as demonstrated in markets like Spain and California [50]. However, its fundamentally linear structure limits its ability to capture non-linear dynamics, such as abrupt price spikes and regime shifts [51]. To overcome these shortcomings, hybrid approaches, such as integrating wavelet transforms with ARIMA, have been proposed to better manage volatility [52]. Despite these enhancements, ARIMA models tend to excel only in linear settings and often require additional techniques to handle complex non-linear patterns effectively [5]. Recent studies have highlighted ARIMA's limitations when compared to advanced models like graph convolutional networks, which can more effectively capture spatial dependencies and intricate non-linear relationships, especially for short-term locational marginal price forecasting [53]. Moreover, incorporating GARCH-type specifications into ARIMA frameworks has been shown to improve forecast accuracy in the DAM, particularly for generating reliable density forecasts [44,46]. In the German IDM, ARIMA models perform well for daily average price forecasting when applied to deseasonalised data, though their accuracy is largely dependent on seasonal adjustments rather than the model's inherent predictive strength [54]. The incorporation of a seasonal component with SARIMA displays improved performance, proving more capable at capturing intra-day price patterns, but its performance remains limited in highly volatile trading periods, where more adaptive models like XGB and LSTM demonstrate superior accuracy [55]. Beyond both the DAM and IDM, ARIMA struggles to capture the real-time dynamics and extreme volatility characteristic of the BM [42], though definitive conclusions are limited by short evaluation periods and the use of the mean absolute percentage error (MAPE), which is unsuitable when prices are frequently close to zero. Furthermore, in the Irish BM we see ARIMA outperformed by both more complex ML and DL models, as well as the statistical model LEAR, across multiple metrics [32]. Overall, ARIMA struggles in all three spot markets, with particularly poor performance in real-time markets, where models with exogenous inputs continue to standout.

3.1.3. Generalised Autoregressive Conditional Heteroscedasticity Model

The GARCH model is utilised in EPF to model time-varying volatility, capturing volatility clustering by allowing the conditional variance to depend on past squared residuals and variances, unlike standard time-series models that assume constant variance. In a GARCH (p, q) model, the time series y_t is typically assumed to follow $y_t = \mu_t + \epsilon_t$, where $\epsilon_t = \sigma_t z_t$, $z_t \sim \mathcal{N}(0, 1)$, and the conditional variance σ_t^2 evolves according to

$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$. Here, α_0 is a constant, α_i captures the impact of lagged shocks, and β_j models the persistence of volatility.

GARCH models have been widely used to model volatility in deregulated electricity markets [44,56]. Extensions such as the k-factor GIGARCH model, which incorporates long memory and stochastic volatility, have demonstrated improved forecasting accuracy in markets like the German DAM [57]. Enhanced versions, including EGARCH and TGARCH, integrate additional market drivers, such as demand fluctuations and renewable energy inputs, to better capture volatility clustering and asymmetry [46]. Moreover, recent studies have shown that GARCH-t models coupled with LASSO feature selection can effectively manage heteroscedasticity and, in some cases, even outperform certain ML approaches in New Zealand's DAM [58]. GARCH models, when applied in isolation, often underperform in EPF due to their limited ability to capture complex market dynamics, and while their use in the IDM and BM remains underexplored, their limitations in the DAM suggest they are unlikely to perform well in more volatile real-time markets without integration with AR-type or ML/DL methods.

3.1.4. Exponential Smoothing Model

ES is a simple yet effective forecasting method that assigns exponentially decreasing weights to past observations, allowing recent data to have more influence on the forecast. Variants like Holt's linear method introduce a trend component, and Holt–Winters extends this to incorporate seasonality, either additively or multiplicatively. More advanced versions, such as TBATS and ES-Transformers, further enhance performance by incorporating trigonometric seasonality, Box–Cox transformations, and ARMA error structures.

Holt's ES has demonstrated strong accuracy in forecasting residential electricity consumption, often achieving a lower MAPE compared to alternative methods [59]. Building on this foundation, recent innovations to ES incorporate Transformer architectures to enhance both long- and short-term forecasting performance [60]. Meanwhile, the TBATS model extends traditional ES by integrating features like trigonometric seasonality and ARMA error components, which has led to improved performance in contexts such as Denmark's DAM and photovoltaic system data [61,62]. However, TBATS can struggle in scenarios lacking external regressors, ending up being outperformed by RNN models, more suited to non-linear settings [63]. Hybrid models that combine ES with additional smoothing and trend techniques, such as SVR-CDSES and Functional ARX (FARX), have also been explored to improve long-term forecasts for energy demand and electricity prices [64,65]. Nonetheless, when applied to volatile markets like the BM, traditional ES methods fall short in capturing rapid price fluctuations, echoing similar limitations observed with ARIMA models [42]. Overall, ES is a simple and interpretable model, but it performs poorly in the BM and, while its application in the IDM remains unexplored, its limited adaptability suggests similarly weak performance in more volatile real-time markets.

3.1.5. Naive Model

A naive model serves as a simple baseline for EPF, typically using the previous t hours of prices to forecast the next t hours or, in seasonal variants, replicate the price from the corresponding period in the previous cycle. Common variants include a random walk approach, where the most recent price is used as the next prediction, and seasonal naive models, which assume that price patterns repeat at fixed intervals (e.g., daily or weekly cycles). However, the definition of a naive model varies across studies, often dictated by the specific market structure, or they are used as a benchmark to evaluate the performance of more complex models. Despite their simplicity, naive models have proven effective in various markets, such as the Lithuanian DAM, where a seasonal naive approach worked well

for seasonal patterns [66]. Naive models remain a widely used benchmark in the IDM, often performing competitively despite their simplicity. In more volatile conditions, augmenting them with LASSO has significantly improved accuracy [67]. Some implementations rely on the most recent price of the corresponding hourly product, demonstrating strong performance and often rivalling more complex statistical methods [68]. In trading applications, they have shown economic value as a competitive baseline [69]. When leveraging DAM prices as predictors, naive models remain a strong reference, though they are typically outperformed by LASSO and ARX [25]. While they perform well under stable conditions, they struggle with sudden price fluctuations and intra-day market volatility [48]. Despite exhibiting significant forecasting errors for daily average and hourly prices, they accurately capture general market behaviour in stable periods [54]. Additionally, in the continuous trading regime, expert linear models show only marginal improvements over naive benchmarks, reinforcing their relevance in real-time markets [70]. In the more real-time BM, naive models remain a valuable baseline, especially for quick approximations, though they are less accurate than models like ARIMA or LEAR [31,32]. A naive baseline remains a popular choice in real-time markets due to their ability to quickly adapt to short-term price fluctuations and leverage strong autocorrelations in high-frequency data, providing a simple benchmark for evaluating more complex models.

3.2. Statistical Methods with Exogenous Inputs

Statistical models with exogenous inputs extend time-series models by incorporating external predictors. Models such as ARX, ARIMAX, their variants FARX and SARIMAX, along with transfer function (TF) and copula models, leverage additional information, such as renewable generation, demand forecasts, and fuel prices, to improve accuracy.

3.2.1. ARX-Type Models

ARX models extend the traditional AR-based models from Section 3.1.1 by incorporating exogenous inputs to account for external factors influencing electricity prices. An ARX model of order p, denoted ARX(p), expresses the current value y_t as a linear combination of its p previous values and q exogenous inputs x_t, as follows:

$$y_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j x_{t-j} + \epsilon_t, \tag{3}$$

where ϕ_0 is an intercept term, ϕ_i represents AR coefficients, θ_j represents the coefficients for the exogenous inputs x_{t-j}, and ϵ_t is the error term. The FARX model introduces non-parametric terms, allowing it to model complex, non-linear interactions between variables.

Incorporating exogenous variables like demand and fuel prices improves ARX models' accuracy in DAM [46], while FARX models further reduce errors by integrating weather data [65]. However, ML models generally outperform ARX in capturing complex price dynamics [19]. ARX models have been effectively applied in the IDM, demonstrating strong performance in forecasting price spreads and predicting the direction of price changes, providing economic value in electricity trading [71]. However, their accuracy can be improved by incorporating regularisation techniques such as LASSO, which help mitigate overfitting in high-dimensional settings [25]. ARX models have also been explored for predicting whether intra-day prices will exceed day-ahead prices, though they can be outperformed by other linear models such as LASSO or elastic net in forecasting IDM index values [72]. Further improvements have been demonstrated when ARX models are combined with regularisation techniques to refine parameter selection and improve predictive stability [73]. In the BM, as for AR models we see little attention on the use of ARX models. Regarding the current literature, ARX models perform moderately well [43],

albeit with a short test period and unsuitably chosen MAPE metric. Overall, ARX models improve upon AR models by incorporating exogenous inputs, particularly benefiting IDM forecasting, where demand shifts and fuel prices influence prices. While they enhance accuracy across markets, their edge is less pronounced in DAM, where ML and DL models excel, and in BM, where gains over simpler methods are marginal.

3.2.2. ARIMAX Model

Like ARX, the ARIMAX model extends the ARX with the differenced (I) and MA terms from the ARIMA model in Section 3.1.2. This can be further extended with the addition of seasonal components with SARIMAX, making it ideal for markets with recurring seasonal patterns.

ARIMAX's incorporation of exogenous variables, like demand and renewable energy, results in improved accuracy over ARIMA [46]. The further use of seasonality in SARIMAX models further improves their predictive power, especially in markets with strong seasonal patterns like the Leipzig Power Exchange and European Power Exchange [74], as well as Denmark's DAM [61]. SARIMAX models perform well in capturing external factors but are often outperformed by advanced models like LSTM during market volatility [75,76]. In the IDM, SARIMAX models demonstrated consistent and reliable performance for EPF, outperforming DL approaches and effectively capturing extreme price fluctuation [72]. Though unexplored in the BM, ARIMAX and its variants are likely to outperform ARIMA and AR models due to their ability to incorporate exogenous variables, a feature that has contributed to their success in the DAM and IDM.

3.2.3. LASSO Models

LASSO is a linear regression technique that incorporates L_1 regularisation to enforce sparsity by shrinking some coefficients to exactly zero. This makes it well suited for high-dimensional forecasting problems, such as EPF, where variable selection and model interpretability are important. The LASSO estimate $\hat{\beta}$ is obtained by minimising the penalised least squares objective:

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{t=1}^{T} (y_t - \mathbf{x}_t^\top \beta)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right), \tag{4}$$

where λ controls the degree of shrinkage.

LASSO performs well in the DAM but struggles with collinearity in highly correlated data and is generally outperformed by bagging [48], as well as more complex ML and DL models [77]. LASSO effectively captures the AR intra-day dependency structure of electricity prices, providing strong forecasting performance while mitigating overfitting through automatic parameter selection [47]. It consistently selects key explanatory variables, offering statistically robust insights into market dynamics and improving predictive performance in continuous trading settings [25,78]. However, it struggles with collinearity in highly correlated market data [48], where alternative regularisation methods like Orthogonal Matching Pursuit show promise for improved stability [70]. While LASSO balances complexity and accuracy when combined with bootstrap techniques for probabilistic forecasting [79], it is often outperformed by more complex models like GRU and LSTM, particularly when modelling spread values [68]. Additionally, it demonstrates strong distributional fit but tends to underestimate volatility compared to neural network (NN)-based approaches [80]. LASSO performs well in the DAM and IDM, but it struggles with collinearity, volatility, and spread values, often being outperformed by bagging, ML, and DL models, while in the BM, research remains focused on the LEAR model.

3.2.4. LEAR Models

The LEAR model, introduced as LASSO X in [81], combines AR with elastic net regularisation, enabling automatic lag selection while handling multicollinearity among predictors. Building on the AR structure outlined in Equation (1), where future values are regressed on past lags, LEAR estimates the coefficients β by minimising the penalised loss function:

$$\hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left(\sum_{t=1}^{T} (y_t - \mathbf{x}_t \beta)^2 + \lambda_1 \sum_{j=1}^{p} |\beta_j| + \lambda_2 \sum_{j=1}^{p} \beta_j^2 \right) \tag{5}$$

Here, λ_1 controls the L_1 sparsity penalty, while λ_2 introduces an L_2 penalty from ridge regression, enabling the model to retain correlated predictors while improving robustness.

LEAR remains a stand out performer in the DAM, and a standard baseline for new proposed models, regardless of the proposed model being statistical, ML, DL, or a hybrid approach. In the DAM, LEAR displays strong performance, automating the variable selection and handling of multicollinearity, leading to it outperforming traditional AR models [81]. Careful hyperparameter tuning is crucial for balancing complexity and preventing overfitting, but regardless it has proved a strong performer against top DL architectures in multiple markets [4]. LEAR excels in capturing distribution tails for risk management [82], but combining it with other models like GARCH can further improve accuracy [58]. While effective for probabilistic forecasting [83], LEAR is often outperformed by DL models in the DAM [45,84,85]. In the BM, LEAR shows remarkable results, outperforming more complex ML and DL models, which struggle with overfitting [32,86]. LEAR excels in the DAM as a baseline model, while in the IDM, LASSO remains the preferred choice, with LEAR yet to be tested. Despite outperforming traditional models, LEAR is often surpassed by DL models in the DAM but outperforms more complex ML and DL approaches in the BM.

3.2.5. Transfer Function Model

The TF models the relationship between input variables and price changes, which makes the TF model effective in markets with stable price dynamics and clear external drivers. TF models capture relationships between prices and external variables, and have been shown to improve EPF accuracy in Spain and California [87]. However, they struggle with the high-frequency nature of hourly prices due to linear assumptions. Comparisons show ML and DL models outperform TF models, highlighting the need for non-linear approaches in EPF [19,88]. TF models remain untested in the IDM and BM but are unlikely to perform well due to their volatility.

3.2.6. Copula Model

The copula model provides a flexible framework for capturing the dependence structure between multiple variables, without assuming a specific distribution. Copula models effectively capture multivariate relationships in electricity markets, showing how renewable energy sources, especially wind, affect prices and volatility [89]. A DVINE copula integrated into a spatio-temporal model enhances probabilistic forecasting by addressing non-linear and non-stationary patterns, outperforming baseline models [90]. However, like the TF model, the copula model remains untested in real-time markets, and its weak performance in the DAM suggests it may struggle further.

3.3. Machine Learning Methods

ML models are increasingly utilised for EPF due to their ability to capture complex, non-linear market dynamics without being limited by assumptions of stationarity. The models discussed include K-Nearest Neighbors (KNN), Support Vector Regression (SVR),

RF, XGB, and LGBM. As electricity markets become more volatile, ML models are essential for capturing non-linear patterns and adapting to rapid fluctuations in price dynamics.

3.3.1. K-Nearest Neighbours

KNN is a simple, non-parametric, instance-based learning algorithm. In the context of EPF, KNN predicts the target value y_t by identifying the k most similar past observations in the feature space, typically using a distance metric such as Euclidean distance. For real-valued feature vectors $\mathbf{x}_t, \mathbf{x}_s \in \mathbb{R}^d$, this distance is defined as

$$d(\mathbf{x}_t, \mathbf{x}_s) = \sqrt{\sum_{i=1}^{d} (x_{t,i} - x_{s,i})^2} \tag{6}$$

To prevent features measured on different scales from dominating the distance computation, normalisation to zero mean and unit variance is commonly applied. Once distances are computed, the k nearest neighbours are selected, and the predicted value $\hat{y}_t$ is typically the average of their observed values. The choice of k is critical: small values may lead to overfitting, while large values can over-smooth the data, missing important local patterns.

In the DAM, KNN demonstrates mixed performance, with techniques like SVM and principle component analysis (PCA) improving both accuracy and efficiency [91]. Feature selection methods [92,93] and the inclusion of meteorological data [94] further enhance performance. Despite these improvements, KNN often underperforms compared to advanced ensemble models like RF and XGB due to its sensitivity to neighbour selection and distance metrics [77,86,95,96]. Its accuracy in predicting extreme price peaks can be constrained by dataset imbalances [97]. In the IDM, KNN struggles with rapid price fluctuations and high-frequency dynamics, underperforming against ensemble methods like XGB and DL models [55]. In the BM, research is limited, but KNN's challenges with dataset imbalances remain [97]. Notably, it is outperformed by both more complex ML models and simpler statistical approaches, with a performance gap that is less pronounced in the DAM and IDM [32,86]. Overall, KNN's instance-based approach lacks adaptability to volatile, high-frequency markets, and it is consistently outperformed by ensemble methods.

3.3.2. Support Vector Regression

SVR aims to find a regression function $f(\mathbf{x}_t)$ that predicts the target value y_t within a margin of tolerance ϵ, while maintaining model flatness and minimising prediction error. This is achieved by minimising the norm $\|w\|^2$ of the weight vector w, subject to constraints involving slack variables ξ_t and ξ_t^* that account for deviations beyond the ϵ-insensitive tube. A regularisation parameter C balances the trade-off between model complexity and tolerance to error, influencing the model's ability to generalise. SVR shows mixed performance across electricity markets and is generally outperformed in the DAM by tree-based models such as RF and XGB, with studies in the Australian NEM also reporting weaker results compared to NNs due to limited tunability and less efficient optimisation [98]. However, hybrid approaches such as SOM-SVR and SVR-ARIMA have shown improved handling of non-stationary behaviours [99,100], and radial basis function (RBF) kernels have further enhanced accuracy [19]. Despite these enhancements, SVR still struggles with extreme price spikes [9,101], though it performs competitively in locational marginal price forecasting [102]. In the IDM, SVR achieves moderate accuracy but is often outperformed by tree-based ensembles like XGB and DL models due to its limited ability to adapt to high-frequency price fluctuations [55]. In the BM, SVR performs poorly, as DL models with seasonal attention mechanisms capture extreme price fluctuations more effectively [103]. A broader comparison of ML models highlights SVR's limitations in

handling BM volatility, ranking it the weakest among top statistical and ML methods [32]. Overall, SVR's performance declines from DAM to BM, with hybrid models improving outcomes but still trailing ensemble and DL approaches in real-time markets.

3.3.3. Random Forest

RF is an ensemble learning algorithm that constructs multiple decision trees using bootstrapped subsets of the training data and aggregates their predictions to improve accuracy and robustness. At each split, RF randomly selects a subset of features to determine the best split, reducing correlation among trees and lowering variance. The final prediction is computed as the average of the outputs from all N trees in the ensemble:

$$\hat{y}_t = \frac{1}{N} \sum_{n=1}^{N} T(\mathbf{x}_t; \Theta_n), \tag{7}$$

where $T(\mathbf{x}_t; \Theta_n)$ is the prediction from the n-th tree with parameters Θ_n.

RF demonstrates strong performance across the DAM, IDM, and BM, as well as in broader energy demand forecasting applications [64]. Its ability to handle multi-output tasks regarding prices and demand was demonstrated in the Spanish DAM [104]. RF effectively captures intricate market dynamics, surpassing traditional statistical models and remaining competitive against state-of-the-art ML methods [19,105]. Unlike models such as SVR, which struggle with overfitting, RF benefits from its ensemble structure, which reduces variance and improves generalisation. Online adaptive variants of RF address concept drift, a key challenge in EPF, by adjusting to evolving market conditions and improving real-time forecasting accuracy [95]. Additionally, hybrid RF models integrating DL components further enhance prediction performance by refining feature extraction and reducing forecasting errors, as demonstrated in the Nord Pool DAM [106,107]. In the IDM, RF maintains competitive accuracy when paired with feature selection techniques but is typically outperformed by gradient boosting models (e.g., XGB, LGBM), which better handle short-term market fluctuations and extreme price spikes [55]. While RF remains a stable and interpretable model, its reliance on bagging rather than boosting results in slightly weaker adaptability in highly volatile intra-day trading conditions. RF is well suited for real-time data streams and financial decision making [108], though it trails behind models like LEAR and XGB in point-based forecasting metrics [32,86]. However, RF remains competitive in financial performance evaluations, often achieving lower trading risk and more stable profit margins than highly sensitive DL models [109]. Additionally, RF's lower computational complexity compared to DNNs makes it a more accessible choice for operational forecasting. RF remains a strong model across the DAM, IDM, and BM, balancing accuracy, interpretability, and scalability. It delivers reliable mid-term forecasts in the DAM, but in the IDM, it lags behind boosting methods in handling short-term volatility. In the BM, RF offers consistent performance with lower computational cost, though XGB and LGBM better capture extreme price fluctuations for EPF.

3.3.4. Gradient Boosting

Gradient boosting algorithms, like XGB and LGBM, are efficient, high-performance algorithms that build ensembles of decision trees sequentially, with each new tree correcting the residuals of previous predictions, with the objective function

$$\text{Obj} = \sum_{t=1}^{n} L(y_t, \hat{y}_t) + \sum_{m=1}^{M} \Omega(f_m), \tag{8}$$

where $L(y_t, \hat{y}_t)$ is the loss function and $\Omega(f_m)$ represents an elastic net to penalise model complexity. Predictions are updated iteratively as $\hat{y}_t^{(m)} = \hat{y}_t^{(m-1)} + \eta f_m(\mathbf{x}_t)$, and the final output is the initial mean point forecast y_0 plus the sum of all tree predictions:

$$\hat{y}_t = y_0 + \sum_{m=1}^{M} \eta f_m(\mathbf{x}_t). \tag{9}$$

While XGB employs level-wise tree growth, LGBM introduces a leaf-wise growth strategy and efficiency features such as Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB), enabling scalability to large datasets.

In the DAM, XGB consistently outperforms models like ARIMA, KNN, and SVR, especially when combined with feature selection techniques or integrated into hybrid frameworks with deep neural networks (DNNs) [107,110], improving wind speed forecasting with historical data [111], and showing high accuracy in capturing key variables like renewable energy penetration [107]. XGB's optimised hyperparameters reduce errors in load forecasting [112], and its robustness is validated in short-term EPF [113]. In the Nord Pool DAM, XGB surpasses models like SVM and RF due to its efficient boosting process [106]. LGBM also performs well, excelling in smart manufacturing [114] and wind power forecasting [115], efficiently handling large datasets. XGB and LGBM also perform well, efficiently handling large datasets and outperforming models like DNN in the Irish DAM [32]. In the IDM, XGB shows mixed results, underperforming simpler regularised models due to challenges with hyperparameter tuning and capturing intra-day dependencies [49]. It performs competitively against the naive benchmark for daily average prices but struggles with short-term price peaks [54]. LSTM models outperform XGB by capturing short-term volatility more effectively [55]. In the BM, both XGB and LGBM perform more consistently, excelling in the UK BM in bidding and risk management [116], though they are occasionally outperformed by simpler models [58]. XGB benefits from incorporating key market variables like net imbalance volume and loss of load probability, though it is often surpassed by DL models in handling extreme price fluctuations, with LGBM performing poorer than the other statistical, ML, and DL models [103]. In the Irish BM, both XGB and LGBM excel, outperforming other ML and DL models [86,109,117], only coming up short to LEAR [32]. Overall, XGB demonstrates strong, versatile performance across the DAM, IDM, and BM, with strengths in hybrid frameworks and real-time market adaptation, though its effectiveness in the IDM is limited by intra-day complexity.

3.4. Deep Learning Methods

Over the past two decades, DL has emerged as a powerful extension of NNs, driven by innovations such as Hinton's efficient training of deep belief networks through greedy layer-wise pretraining [118]. This breakthrough enabled the training of deeper networks beyond traditional models like MLPs, leading to significant improvements in generalisation [119]. DL has since been widely applied across fields like image recognition [120], speech recognition [121], and machine translation [122], with notable success in energy-related applications, particularly wind power forecasting [123,124]. In EPF, DL models such as DNNs, convolutional neural networks (CNNs), LSTMs, and gated recurrent units (GRUs) have proven successful at capturing complex temporal dependencies.

3.4.1. Deep Neural Networks

DNNs are artificial neural networks (ANNs) with multiple hidden layers, allowing them to model complex, non-linear relationships in EPF. For an input vector $\mathbf{x}_t$, each hidden layer l applies a transformation utilising the layer's weight $\mathbf{W}^{(l)}$ and bias $\mathbf{b}^{(l)}$:

$$\mathbf{Z}^{(l)} = \sigma\left(\mathbf{W}^{(l)} * \mathbf{Z}^{(l-1)} + \mathbf{b}^{(l)}\right) \tag{10}$$

where $\sigma(\cdot)$ represents a non-linear activation function. The input layer uses $\mathbf{Z}^{(0)} = \mathbf{x}_t$, with the final prediction typically given by a single-output neuron with linear activation: $\hat{y}_t = \mathbf{W}^{(L)}\mathbf{Z}^{(L-1)} + \mathbf{b}^{(L)}$. Model parameters are learned by minimizing a loss function using stochastic gradient descent or its variants, while overfitting is addressed through techniques such as dropout and L_1/L_2 regularisation to enhance generalisation.

DNNs have shown strong performance in EPF, particularly in the DAM, where they often outperform traditional statistical and ML methods [19]. However, their effectiveness depends on proper hyperparameter tuning, as seen in studies where benchmark constraints limited performance [125–127]. Enhancements such as incorporating inter-market features [6] and training on order book data [128] have improved accuracy. Despite their ability to model non-linear relationships, DNNs do not always outperform simpler models in the DAM, with simpler models such as LASSO and tree-based methods often yielding better point and probabilistic forecasts due to their interpretability and stability [14]. In hybrid frameworks, DNNs perform well in multi-market settings [85], particularly when combined with feature selection techniques like XGB, which improves model efficiency and robustness [110]. In the IDM, while DNNs display some strong performance relative to classical models like LASSO, RNN models such as LSTMs and GRUs outperform them in capturing short-term price fluctuations, particularly when leveraging spread values between day-ahead and intra-day prices [68]. In contrast, in the EPEX IDM, DNNs performed similarly to LSTM-based models but were outperformed by LASSO based models in probabilistic forecasting, underscoring potential challenges of DL in capturing price volatility [80]. In more volatile markets like the BM, DNN models, despite their ability to model non-linear relationships in the DAM, and IDM to a lesser degree, are often outperformed by simpler models such as LASSO and LEAR [32]. This is largely attributed to their tendency to overfit and over-react to price spikes. In addition, tree-based methods such as RF and XGB often yield better point and probabilistic forecasts [31,109]. Overall, DNNs excel in the DAM, outperforming simpler statistical and ML models by capturing complex, non-linear relationships, variable interactions, and temporal dependencies that are difficult to model explicitly. However, in the IDM, they display mixed performance, being outperformed by LSTMs and GRUs, which better handle short-term price fluctuations. In the BM, DNNs are outperformed by simpler, more interpretable models like LASSO, RF, and XGB, which prove more capable of dealing with price spikes and issues surrounding overfitting. While DNNs benefit from hybrid frameworks and feature selection, their computational demands and susceptibility to overfitting present limitations in volatile, real-time markets.

3.4.2. Convolutional Neural Networks

CNNs are a class of DL models originally designed for spatial data but increasingly applied to time-series forecasting due to their ability to extract local patterns and hierarchical features through convolutional operations. A CNN processes an input sequence $\mathbf{x}_t$ by applying a series of convolutional filters across the input to compute feature maps, where the output of each layer is typically computed as in Equation (10). Pooling layers are often used to reduce dimensionality and increase robustness to noise, while fully connected layers translate the extracted features into final predictions.

In the DAM, CNNs have demonstrated strong performance, particularly in feature extraction and capturing non-linear market dynamics [53,129]. Integrating CNNs with dimensionality reduction techniques like PCA has been shown to reduce overfitting and computational costs while maintaining competitive accuracy [129]. CNN autoencoders have also proven effective, outperforming GRUs due to their efficient handling of high-dimensional data [130]. However, CNNs tend to perform slightly worse than DNNs and GRUs in certain EPF applications [19], likely due to their limited ability to capture long-term dependencies without additional mechanisms like recurrent layers. Hybrid CNN architectures have been proposed to address these limitations. For example, combining 1D-CNNs with self-attention mechanisms enhances forecasting accuracy by capturing both local and long-range temporal dependencies [131]. However, these improvements come at the cost of increased model complexity and computational overhead. In the IDM, CNNs effectively capture local temporal dependencies and short-term price fluctuations. However, they are consistently outperformed by attention-based models and LSTMs, which better model intra-day patterns and adapt to market dynamics [55]. CNNs struggle with the high-frequency nature of IDM data, as they lack the sequential memory capabilities inherent in recurrent architectures. In the BM, CNNs have shown weaker performance than other DL models, particularly in the UK market, where they underperform LSTMs, GRUs, and the proposed SA-BiLSTM due to their limited ability to capture seasonality and extreme price spikes, likely stemming from their spatially constrained filter design [103]. Overall, CNNs demonstrate moderate success in the DAM, leveraging their strength in feature extraction to model non-linear patterns. However, their lack of temporal memory mechanisms results in comparatively poorer performance in the IDM and BM, where capturing long-term dependencies and extreme events is crucial. Hybrid architectures that integrate CNNs with recurrent or attention-based layers have shown promise, but their added complexity may limit their practical application in real-time EPF scenarios.

3.4.3. Long Short-Term Memory

LSTM networks, introduced by [132], are a type of RNN designed to capture long-term dependencies in sequential data through a gating mechanism that regulates information flow across time steps. Each LSTM cell maintains two key components: a hidden state $\mathbf{h}_t$, which represents the output at time t; and a cell state $\mathbf{c}_t$, which stores long-term contextual information. The cell state is updated via three gates, the forget gate $\mathbf{f}_t$, input gate $\mathbf{i}_t$, and output gate $\mathbf{o}_t$, which control what information is discarded, updated, and exposed, respectively. The forget gate determines which parts of the previous cell state $\mathbf{c}_{t-1}$ are retained:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \tag{11}$$

The input gate decides which new information is added to the cell state:

$$\mathbf{i}_t = \sigma(\mathbf{W}_i[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \tag{12}$$

The output gate governs the contribution of the current cell state to the hidden state:

$$\mathbf{o}_t = \sigma(\mathbf{W}_o[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \tag{13}$$

The updated cell state is computed by blending retained and new information:

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tanh(\mathbf{W}_c[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \tag{14}$$

Finally, the hidden state $\mathbf{h}_t$ is updated as

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \tag{15}$$

Here, σ denotes the sigmoid activation function, and $\odot$ denotes element-wise multiplication. This gated structure enables LSTMs to retain and update information over long time horizons, making them well suited where temporal dependencies and delayed effects are common.

In the DAM, LSTM models have consistently outperformed statistical models, demonstrating strong predictive performance when capturing complex temporal dependencies [18,19,133]. Hybrid architectures, such as CNN-LSTM combinations, have improved accuracy by improving feature extraction [134,135]. However, performance gains often depend heavily on dataset size and the careful selection of hyperparameters [136,137]. In markets like Turkey and New South Wales, LSTMs surpassed GRUs in capturing seasonal and event-driven price fluctuations [138,139]. In the IDM, LSTMs exhibit mixed performance. While outperforming classical models such as ARX in the Turkish IDM [68], LSTMs are often matched or outperformed by GRUs due to the latter's computational efficiency and effective gating mechanisms [140]. In the German IDM, LSTMs demonstrated superior performance for daily average and hourly price forecasting [54], but simpler linear models still outperform LSTMs when intra-day volatility increases [80]. LSTMs similarly produce varied results in the BM. In the Dutch BM, univariate LSTMs outperform their multivariate counterparts and linear regression for short-term forecasts, though performance deteriorates for longer forecasting horizons [141]. In the Irish BM, LSTMs within multi-headed DNN-RNN architectures, struggle to capture short-term price patterns, struggle with overfitting, and are outperformed by statistical models like LEAR [32,109]. Conversely, LSTMs achieve strong results in the UK BM, where non-linear price fluctuations are more effectively captured [103], particularly when implemented with seasonal attention mechanisms like SA-BiLSTM, which enhance the model's ability to track extreme price events. Recent advances in EPF increasingly integrate bidirectional LSTM (BiLSTM) networks into hybrid frameworks that combine multi-stage preprocessing and ensemble learning to capture complex bidirectional temporal dependencies, decompose noisy signals, and adapt to evolving market dynamics—especially in high-volatility, high-frequency settings. These models capture forward and backward temporal dependencies, offering a more comprehensive understanding of market sequences. For example, ref. [101] proposed a CatBoost-BiLSTM hybrid that combines gradient-boosted feature selection with bidirectional recurrent learning, outperforming conventional ML models by improving input relevance and temporal pattern capture. Attention mechanisms further enhance bidirectional learning, as demonstrated by [142], who proposed a BiLSTM attention hybrid with EEMD to improve spike detection and capture non-linear temporal volatility interactions in DAM forecasts, achieving higher accuracy during price anomalies. Overall, LSTM and BiLSTM models demonstrate strong performance in the DAM, particularly when enhanced with hybrid architectures and attention mechanisms. However, their effectiveness in the IDM and BM is mixed, often depending on market volatility, forecasting horizon, and model design.

3.4.4. Gated Recurrent Units (GRUs)

GRUs are a simplified variant of LSTM networks that retain the ability to model long-range dependencies while reducing computational complexity. Unlike LSTMs, which

use separate input and forget gates (see Section 3.4.3, Equations (11–14)), GRUs merge these into a single update gate:

$$\mathbf{z}_t = \sigma(\mathbf{W}_z[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_z) \tag{16}$$

They also introduce a reset gate:

$$\mathbf{r}_t = \sigma(\mathbf{W}_r[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_r) \tag{17}$$

The candidate activation $\tilde{\mathbf{h}}_t$ is computed as

$$\tilde{\mathbf{h}}_t = \tanh(\mathbf{W}_h[\mathbf{r}_t \odot \mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_h) \tag{18}$$

and the final hidden state is updated via

$$\mathbf{h}_t = (1 - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t \tag{19}$$

Here, σ denotes the sigmoid activation function and $\odot$ denotes element-wise multiplication, as in Section 3.4.3. By reducing the number of gates and removing the explicit cell state, GRUs offer a more computationally efficient alternative to LSTMs.

GRUs have achieved superior accuracy over statistical and ML models in electricity markets such as the Turkish DAM [18]. GRUs have also proven effective for short-term EPF tasks [19], with applications showing that integrating GRUs with bagged regression trees improves mid-term forecasting accuracy when handling non-linear market fluctuations [63]. In the New York electricity market, CNN-based models outperformed GRUs, indicating potential limitations when forecasting high-dimensional price patterns [130]. However, GRU models regain their competitive edge in hybrid architectures; for instance, in the Iranian DAM, GRU models combined with stacked autoencoders achieved improved long-term performance [140]. Additional enhancements, such as hyperparameter tuning and hybrid approaches, further bolster performance, as seen in models leveraging periodic pattern extraction techniques [58,143]. Hybrid models combining GRUs with tree-based methods have improved accuracy by dynamically adjusting model weights based on intra-day market patterns [144]. Additionally, ref. [145] introduced a GRU variant with noise-robust training, improving forecast reliability in the DAM, particularly during periods of increased renewable generation. In the Turkish IDM, GRUs achieved the lowest MAE and RMSE, outperforming statistical models and highlighting their suitability for short-term intra-day forecasting [68]. Their computational efficiency, combined with effective learning of hourly price patterns, makes GRUs particularly useful for markets with high-frequency trading. In the British BM, GRUs delivered competitive results but were ultimately outperformed by SA-BiLSTM, which demonstrated superior accuracy due to its seasonal attention mechanisms [103]. Overall, GRUs perform well across all three markets but display mixed results in comparison to other DL architectures. While GRUs outperform LSTMs in computational efficiency and show strong results in the DAM and IDM, they tend to struggle in the BM, particularly during extreme price events, where models with stronger regularisation and more capable of mitigating overfitting perform more reliably.

3.4.5. Temporal Fusion Transformers

Temporal Fusion Transformers (TFTs) are attention-based DL models specifically designed for multi-horizon time-series forecasting, combining recurrent and Transformer-style self-attention layers to capture both short-term dynamics and long-range dependencies. TFTs employ variable selection networks to filter relevant input features and utilise an interpretable multi-head attention mechanism to weigh temporal patterns dynamically. For

each time-step t, the attention score is computed as $\alpha_t = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)$, where Q and K are learned query and key matrices, and d_k is the dimensionality of the key vectors.

TFT models have demonstrated strong performance in forecasting applications, outperforming ARIMA, LSTM, and XGB in photovoltaic power prediction, owing to their interpretability and ability to capture complex temporal relationships via static covariates and dynamic variables [146]. In energy consumption forecasting, TFTs outperform LSTMs and temporal convolutional networks, delivering lower error rates and greater stability in Poland and Nord Pool's DAMs [147,148]. However, these models are prone to overfitting when applied to smaller datasets, necessitating careful regularisation [145]. While TFT applications in the IDM are limited, a study in the Nord Pool market shows their ability to capture short-term price dynamics using domain-specific features like renewable forecasts and cross-border flows [72], though simpler models like LSTM and GRUs often achieve comparable performance in intra-day markets due to the rapid price fluctuations and reduced availability of relevant exogenous predictors. TFT models have shown strong performance in the BM, outperforming LSTM variants and statistical models in forecasting imbalance prices by leveraging adaptive and seasonal attention mechanisms to track extreme price spikes and volatility [103]. Overall, TFTs perform well across each spot market, demonstrating strong results in the DAM and BM due to their flexible handling of dynamic temporal patterns. In the IDM and BM, TFT models remain underutilised, and although they show promise in capturing intra-day dynamics, they are outperformed by other DL models.

3.4.6. DeepAR

DeepAR is a probabilistic forecasting model based on AR RNNs, where each time series is modelled conditionally on its past values and covariates. At each time step t, DeepAR predicts the distribution of the next value y_t given the history y_{t-n} and exogenous inputs $\mathbf{x}_t$ by learning the parameters of a likelihood function, often Gaussian or negative binomial, with the model trained to maximize the likelihood of observed sequences.

DeepAR has proven effective at capturing seasonality and trends, outperforming traditional methods [149]. In DAM EPF, it handles large sets of related time series, though is outperformed by models incorporating heteroscedasticity [145]. In the Nord Pool IDM, DeepAR displays weak performance, being outperformed by LR, ARX, SARIMAX, and TFT [72]. Overall, DeepAR remains largely underexplored in each spot market, with poor results in both the DAM and IDM, with no testing having occurred in any BM to date.

3.4.7. Prophet

Prophet is a decomposable time-series forecasting model designed to capture nonlinear trends with seasonality and holiday effects using a generalised additive model framework. The model expresses the time series as $y_t = g(t) + s(t) + h(t) + \epsilon_t$, where $g(t)$ models the trend, $s(t)$ represents periodic seasonality using Fourier series, $h(t)$ accounts for holiday effects, and ϵ_t is the error term. Prophet automatically detects change points in the trend and fits them using piecewise linear or logistic growth curves, making it especially useful for datasets with strong seasonal components and structural shifts.

In the Italian DAM, Prophet was applied alongside seasonal and trend decomposition using LOESS (STL), improving forecast accuracy by isolating important patterns and reducing noise [150]. Extensions such as Neural Prophet have incorporated DL techniques to handle lagged variables and AR terms, resulting in improved short- and long-term electricity load predictions through better seasonality and trend extraction [151]. Prophet has also been employed for univariate forecasting of exogenous variables, such as weather, where it enhanced real-time EPF performance by effectively modelling both periodic

and non-periodic patterns [97]. Despite these applications, Prophet remains relatively unexplored in the IDM and BM, where higher volatility and shorter forecasting horizons present challenges that the model's simplistic structure may struggle to handle. The model's reliance on predefined seasonal patterns makes it less adaptive to the dynamic price behaviour characteristic of real-time markets, limiting its utility for EPF applications.

3.5. Hybrid Models

Hybrid models integrate statistical, ML, and DL techniques to utilise the complementary strengths of each approach in EPF. These models are particularly effective in capturing the complex, non-linear, and volatile dynamics of electricity markets. By combining the interpretability of linear models, the adaptability of ML, and the sequential learning capabilities of DL, hybrid frameworks offer a flexible and robust forecasting solution.

3.5.1. Statistical Hybrid Models

Hybrid statistical models combine the interpretability of classical time-series techniques with the flexibility and non-linearity of ML or DL components. These models are typically designed to leverage the strengths of AR structures—well suited for capturing linear dependencies—while enhancing adaptability to volatility and non-stationarity through non-linear elements or regularisation schemes. One common class of hybrid models integrates exogenous input models with regularisation techniques. For instance, FARX-LASSO and fARX-EN models extend the ARX framework by introducing LASSO or elastic net regularisation, which help control overfitting and improve predictive robustness in high-dimensional settings [19]. These models retain a linear structure for interpretability, while penalising uninformative inputs and multicollinearity. Another prominent hybrid family includes combinations of linear AR forecasting and conditional variance modelling. The ARIMA-GARCH hybrid remains effective for jointly modelling linear autocorrelation and non-linear volatility, particularly in high-volatility environments like electricity markets with frequent price spikes [44]. These models allow for simultaneous mean and variance forecasting, improving both point and risk-aware forecasts. Statistical–ML hybrids further improve performance by pairing linear decomposition with non-linear learning. Examples include Wavelet-ARIMA with RBF networks (WARIMA-RBF) and Self-Organising Maps with SVR (SOM-SVR). These models decompose the time series into components (e.g., trend, seasonality, noise) and apply non-linear learners to each, capturing both global and local price dynamics [4]. DL has also been integrated with statistical baselines to optimise parameter selection and capture deeper temporal patterns. The DNN–LEAR hybrid, for example, combines DNNs with LASSO–elastic net AR, improving accuracy in DAM EPF while preserving model interpretability through sparse feature selection [4].

Recent contributions have proposed hybrids tailored to specific market or data challenges. In the U.S. DAM and BM (PJM and NYISO), [152] introduced a SARIMA–LSTM model augmented with wavelet decomposition, effectively combining seasonal AR forecasting with LSTM networks to handle both periodic and non-linear structures. In the CAISO market, ref. [153] demonstrated that combining robust PCA for outlier detection with linear regression improves forecast accuracy in heteroscedastic environments. Outside of deregulated markets, ref. [154] proposed a novel hybrid for Cameroon's regulated system: a WOA-GMHES(1,N) model, blending Whale Optimisation Algorithms and Grey Holt ES. This model shows high accuracy under data scarcity conditions, highlighting hybridisation's potential in resource-constrained environments. Overall, statistical hybrid models offer a flexible and modular approach to EPF, allowing researchers to tailor models to specific market conditions—such as volatility, high dimensionality, or data irregularities—by integrating linear structure, regularisation, and non-linear learning in a unified framework.

3.5.2. Machine Learning Hybrid Models

ML hybrid models combine diverse predictive algorithms—often spanning tree-based ensembles, NNs, and decomposition techniques—to enhance the accuracy, robustness, and adaptability of EPF. These hybrids are particularly suited to environments with high volatility, non-linear patterns, or limited data interpretability, leveraging the complementary strengths of different ML models. Several hybrid models integrate feature selection, signal decomposition, and non-linear regressors. For instance, ref. [106] proposed a hybrid that combines automatic relevance determination with Extra Trees Regression, effectively capturing the trend, seasonality, and volatility in DAMs by isolating relevant inputs and reducing overfitting through ensemble learning. Similarly, ref. [155] employed a decomposition-enhanced hybrid using variational mode decomposition (VMD) and ensemble empirical mode decomposition (EEMD) with an extreme learning machines optimised by differential evolution. This model excelled in handling non-linear dynamics in markets such as Spain and Australia, outperforming baseline ML and statistical models.

Other hybrid frameworks aim to bridge short- and long-term forecasting capabilities. Ref. [156] developed a Fourier-augmented hybrid that integrates data-driven ML with market-based predictive signals. By applying Fourier analysis, the model isolates dominant frequency components, improving accuracy across both high-frequency volatility and long-term trends, making it particularly effective in balancing signal noise and seasonal price cycles. At the microgrid and household levels, ML hybrids have been used to model consumption patterns influenced by dynamic pricing. Ref. [157] introduced a hybrid based on XGB, optimised for real-time residential demand prediction. By treating electricity price as an exogenous input, the model captures user sensitivity to price signals, significantly improving accuracy for short-horizon load forecasting—critical for demand-response and smart grid applications. In a large-scale DAM context, ref. [110] proposed a three-stage hybrid for Shandong's market in China, integrating a day-similarity algorithm, XGB-based feature selection, and an adaptively optimised DNN. This architecture achieved high accuracy in 96-point forecasting by leveraging historical analogues and deep feature abstraction, illustrating the benefit of combining similarity-based reasoning with supervised learning.

Robustness to data quality issues has also been addressed through hybridisation. The OANQR model by [158] combines outlier detection, VMD, and non-crossing quantile regression, targeting the high volatility and distributional asymmetry of the Singapore DAM. This model produces probabilistic forecasts that remain stable even in the presence of price shocks and data anomalies. Finally, more comprehensive hybrid frameworks incorporate multiple predictive paradigms. Ref. [159] proposed an ensemble architecture that merges RF, SVM, LSTM, ARIMA, and ES. This full-spectrum hybrid leverages strengths from statistical, tree-based, and DL models, achieving state-of-the-art performance across electricity and financial price series. Its ability to adapt to dynamic market conditions highlights the utility of ensemble-of-hybrids strategies in volatile multi-scale forecasting environments. In summary, ML hybrid models excel in scenarios demanding adaptability, high-dimensional learning, and robust treatment of noise or non-stationarity. These architectures are increasingly effective in both aggregate market forecasting (DAM) and granular applications (residential demand), particularly when they combine signal decomposition, advanced feature selection, and optimised non-linear learning.

3.5.3. Deep Learning Hybrid Models

DL hybrid models fuse convolutional, recurrent, and attention-based architectures with statistical and ML techniques to capture complex temporal, spatial, and feature interactions in EPF. These models are particularly adept at managing high-frequency volatility, extracting multi-scale patterns, and improving accuracy through learned representations

and ensemble strategies. Early hybrid designs leveraged CNNs for local pattern recognition and paired them with traditional learners. For instance, the CNN–SVR model applies convolutional layers for feature extraction before regression with SVM, improving short-term EPF accuracy through non-linear kernel adaptation [8]. Similarly, CNN-LSTM hybrids have shown strong performance in the Iranian DAM by capturing both spatial correlations and sequential dependencies [9]. Recurrent hybrid models remain central to DL-based EPF. The GRU–LSTM architecture combines GRUs and LSTM cells to simultaneously model short- and long-term dependencies, improving accuracy in DAM EPF [106]. Extensions of this idea include combinations with trend-aware models: Ref. [151] proposed an LSTM–Neural Prophet hybrid that captures AR trends alongside deep temporal dependencies, while [160] introduced a Prophet–LSTM model optimised with a back propagation NN to improve convergence and reduce forecast error.

Hybrid stacking ensembles have further extended DL models by integrating them into multi-model frameworks. For example, ref. [161] developed a hybrid stacking model combining XGB, CatBoost, LGBM, NODE, GRU, and LSTM, using LASSO as a meta-learner, achieving high short-term accuracy in the Australian DAM by balancing tree-based interpretability and recurrent network flexibility. A similar high-performance framework was proposed by [162], where a CNN–GRU hybrid with attention mechanisms outperformed both standalone DL and Transformer models in the DAM by prioritising relevant temporal features. Attention-based hybrids are gaining traction for their ability to selectively weight key time steps or features. In the Ontario DAM, ref. [131] integrated multi-head self-attention with a 1D-CNN and a mutual information–based feature selection strategy, improving both computational efficiency and accuracy. Similarly, ref. [163] introduced TriConvGRU, a hybrid combining convolutional and recurrent layers to extract multi-scale temporal–spatial features, outperforming statistical and DL models in the same market. Hybrid DL frameworks are also proving useful in real-time markets. In Denmark's DK1 IDM, ref. [55] proposed a model that combines LSTM-based forecasting with a rule-based trading strategy, achieving profitable outcomes by leveraging real-time IDM and DAM price signals for renewable energy trading. Multi-source and multi-market forecasting has benefited from DL hybridisation, as ref. [164] introduced a hybrid for Spain's DAM and derivatives market that combines ANNs for price, wind, and solar forecasts with a temperature-adjusted similar-day demand predictor, achieving accurate 2–10 day forecasts. In the French EPEX DAM, ref. [165] proposed the DF-RNN hybrid, jointly optimising time-series decomposition and sequence forecasting, yielding superior mid- and long-term performance. Cross-market generalisability has been explored through decomposition-based DL hybrids. Ref. [166] introduced a hybrid integrating STL with GRU and LGBM, demonstrating high interpretability and accuracy in both the U.S. PJM frequency regulation BM and the Australian Queensland DAM.

Multi-layered architectures have proven effective, such as a CNN–BiLSTM–AR hybrid from [167] that combines convolutional layers for local pattern extraction, BiLSTM for sequential learning, and an AR component for linear trend reinforcement. Applied to the UK and German DAMs, the model showed notable improvements in forecast accuracy, aided by hyperparameter tuning for architectural balance. Transformer-based hybrids have extended these capabilities, with [168] introducing a Transformer–BiLSTM model that integrates self-attention with bidirectional sequence modelling to capture long-range dependencies and short-term volatility, outperforming standalone LSTM and GRU models in DAM settings. Ensemble bi-forecasting architectures offer a novel path toward interval prediction, with [169] proposing a hybrid for the Australian DAM combining a deep belief network (DBN), BiLSTM, and Improved Complete EEMD with Adaptive Noise, which, using a multiple-input multiple-output structure and a linear operator mechanism,

achieved high-accuracy point and interval forecasts while maintaining interpretability. Ref. [170] developed a hybrid BiLSTM-GRU model that outperformed traditional and DL baselines in forecasting NYISO BM prices by capturing both long- and short-term dependencies. Advanced bidirectional hybrid approaches are also being applied to the BM, where volatility is pronounced. In the British BM, ref. [103] demonstrated that BiLSTM-based ensembles—such as CEEMD–RF–IRSA–BiLSTM and TVFEMD–RF–CNN–ISCA–BiLSTM—achieved superior performance over traditional ML models. These frameworks integrate decomposition (CEEMD, TVFEMD), ensemble learning (RF), optimisation strategies (IRSA, ISCA), and DL, producing highly robust forecasts under dynamic conditions. Advanced hybrid models—particularly those combining BiLSTM with attention mechanisms and signal decomposition techniques—excel at capturing both local fluctuations and global market trends to address complex conditions in DAM and BM. By integrating DL's ability to model non-linearity and long-range dependencies with complementary methods like decomposition (for noise reduction) and structured ensembles (for robustness), these frameworks consistently outperform standalone models, demonstrating superior accuracy in short- and mid-term EPF across diverse market structures.

4. Discussion

EPF has evolved into a multidisciplinary challenge, shaped by growing market complexity, renewable integration, and the demands of high-frequency trading and grid balancing. This discussion aims to connect insights from the preceding review of statistical, ML, DL, and hybrid models across the DAM, IDM, and BM. Rather than evaluating models in isolation, we examine their performance through the lens of market-specific dynamics, forecasting objectives, and methodological trade-offs. Particular attention is given to the suitability of each modelling paradigm under different volatility levels and temporal constraints, as well as the persistent challenges posed by evaluation metric selection and model generalisability.

4.1. Overview

The trends in Tables 1 and 2 show a progression from statistical methods, predominantly used in earlier studies such as [43,44], to more sophisticated ML approaches. However, from 2017 and 2018 onwards, there has been a marked shift toward DL models. These methods have been primarily applied to the DAM and, to a lesser extent, the IDM and BM. Table 3 extends this analysis beyond EPF to include applications in wind power, photovoltaic, and load forecasting, with models like CatBoost-BiLSTM and attention mechanisms showing strong adaptability and success in managing high-dimensional datasets [143].

Focusing in more depth, Table 1, for EPF pre-2020, reveals a clear evolution in methodological approaches and market focus. The DAM dominates the literature, reflecting its central role in electricity trading. Early forecasting efforts primarily relied on statistical models such as ARIMA, ARX, and GARCH, which were effective at capturing linear trends and seasonal patterns. However, these models struggled to handle the increasing non-linearity and volatility brought about by the integration of renewable energy sources. As market dynamics grew more complex and datasets became larger, the focus shifted toward models with built-in regularisation, such as LASSO and LEAR, as well as ML techniques better suited to capturing non-linear price behaviours. From around 2017 onwards, DL models began to emerge, often in hybrid configurations that combined statistical, ML, and DL elements to improve performance and interpretability. While statistical models remained relevant, the broader trend reflects a growing reliance on data-driven non-linear and hybrid approaches to address the increasing volatility and complexity of markets.

Post-2020 EPF sees a clear methodological shift toward hybrid techniques and an expanding focus on real-time markets such as the IDM and BM, as seen in Table 2. While the DAM continues to be widely studied, there is a growing emphasis on addressing the volatility and rapid fluctuations inherent in real-time markets. From 2022 onward, the focus on more real-time markets accelerated, with an increasing number of studies targeting IDM and BM explicitly. However, they remain comparatively underexplored, highlighting a valuable opportunity for future research into unified forecasting frameworks that can support operational decision making across the full spectrum of electricity markets. Statistical and ML models remain popular, but DL architectures like LSTMs and GRUs have gained traction for their ability to capture non-linear dependencies and temporal patterns. More recent studies also introduce Transformer-based architectures and seasonal-trend-aware models, reflecting the field's ongoing evolution toward robust, high-resolution, and real-time predictive approaches. Furthermore, the growing adoption of hybrid models highlights the rising complexity of electricity markets, positioning them as the leading approach for balancing interpretability, accuracy, and adaptability markets.

Table 1. Literature on predictive models for EPF before 2020. Interest in DAM dominates. The ✓ is the approach presented herein.

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Nogales et al. 2002 [87]	✓				✓			
Contreras et al. 2003 [50]	✓				✓			
Sansom et al. 2003 [98]		✓			✓			
Cuaresma et al. 2004 [51]	✓				✓			
Conejo et al. 2005 [52]	✓				✓			
Knittel et al. 2005 [56]	✓				✓			
Zhou et al. 2006 [171]	✓				✓			
Fan et al. 2007 [99]		✓		✓	✓			
Garcia et al. 2008 [88]	✓				✓			
Diongue et al. 2009 [57]	✓				✓			
Lin et al. 2010 [172]	✓	✓			✓			
Che et al. 2010 [100]	✓	✓		✓	✓			
Jakavsa et al. 2011 [74]	✓				✓			
Mei et al. 2014 [108]	✓	✓					✓	
Klaeboe et al. 2015 [43]	✓				✓		✓	
Poplawski et al. 2015 [42]	✓	✓					✓	
Ziel et al. 2016 [47]	✓					✓		
Uniejewski et al. 2016 [81]	✓				✓			
Girish et al. 2016 [44]	✓				✓			
Feijoo et al. 2016 [91]	✓	✓			✓			
Gonzalez et al. 2016 [104]	✓	✓			✓			
Yang et al. 2017 [5]	✓	✓		✓	✓			
Lago et al. 2018 [19]	✓	✓	✓	✓	✓			
Rita et al. 2018 [66]	✓		✓		✓			
Ugurlu et al. 2018 [18]	✓		✓		✓			
Kuo et al. 2018 [138]		✓	✓	✓	✓			
Chinnathambi et al. 2018 [133]			✓		✓			
Jiang et al. 2018 [173]	✓		✓	✓	✓			
Chang et al. 2018 [139]	✓		✓	✓	✓			
Zhang et al. 2018 [174]	✓			✓	✓			
Kath et al. 2018 [69]	✓					✓		
Zhu et al. 2018 [136]		✓	✓		✓			
Johannesen et al. 2019 [94]		✓			✓			
Zhou et al. 2019 [137]		✓	✓	✓	✓			

Table 1. *Cont.*

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Xu et al. 2019 [7]	✓		✓	✓	✓			
Zahid et al. 2019 [8]		✓	✓	✓	✓			
Chang et al. 2019 [175]			✓	✓	✓			
Zahid et al. 2019 [8]		✓	✓	✓	✓			
Atef et al. 2019 [125]		✓	✓		✓			
Luo et al. 2019 [126]	✓		✓		✓			
Lago et al. 2019 [6]			✓	✓	✓			
Karabiber et al. 2019 [61]	✓		✓		✓			
Johannesen et al. 2019 [94]		✓			✓			
Schnurch et al. 2019 [128]	✓	✓	✓		✓			
Oksuz et al. 2019 [68]	✓		✓			✓		
Uniejewski et al. 2019 [25]	✓					✓		
Maciejowska et al. 2019 [71]	✓				✓	✓		
Ali et al. 2019 [92]		✓			✓			
Schnurch et al. 2019 [128]	✓	✓	✓		✓			

Table 2. Literature on predictive models for EPF after 2020. Real-time markets begin to attract attention. The ✓ is the approach presented herein.

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Marcjasz et al. 2020 [67]	✓					✓		
Lucas et al. 2020 [116]		✓					✓	
Khan et al. 2020 [129]			✓		✓			
Narajewski et al. 2020 [78]	✓					✓		
Li et al. 2021 [21]	✓	✓	✓	✓	✓			
Lago et al. 2021 [4]	✓		✓	✓				
Kara et al. 2021 [105]		✓			✓			
Ozen et al. 2021 [48]	✓				✓			
Wang et al. 2022 [95]		✓			✓			
Lehna et al. 2022 [75]	✓		✓	✓	✓			
Narajewski et al. 2022 [31]	✓		✓	✓			✓	
Tschora et al. 2022 [82]	✓	✓	✓		✓			
Xie et al. 2022 [107]		✓	✓		✓			
Zhang et al. 2022 [101]	✓	✓	✓	✓	✓			
Meng et al. 2022 [135]		✓	✓	✓	✓			
Yang et al. 2022 [53]	✓		✓	✓	✓			
Kotsias et al. 2022 [72]	✓	✓	✓			✓		
Iqbal et al. 2022 [63]	✓	✓	✓	✓	✓			
Beltran et al. 2022 [96]	✓	✓	✓	✓	✓			
Jkedrzejewski et al. 2022 [14]			✓		✓			
Alkawaz et al. 2022 [106]	✓	✓		✓	✓			
Rezaei et al. 2022 [140]			✓	✓	✓			
Yang et al. 2022 [130]	✓	✓	✓	✓			✓	
Serafin et al. 2022 [79]	✓					✓		
Heidarpanah et al. 2023 [9]		✓	✓	✓	✓			
Bille et al. 2023 [46]	✓			✓	✓			
Xiong et al. 2023 [144]			✓	✓	✓			
Kapoor et al. 2023 [58]	✓	✓	✓	✓	✓			
Marcjasz et al. 2023 [83]	✓		✓	✓	✓			
Olivares et al. 2023 [45]	✓		✓	✓	✓			
Gunduz et al. 2023 [84]	✓		✓	✓	✓			
Stefenon et al. 2023 [150]			✓		✓			

Table 2. *Cont.*

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Poggi et al. 2023 [54]	✓					✓		
Molin et al. 2023 [141]	✓		✓				✓	
Yang et al. 2024 [85]	✓		✓	✓	✓			
Kilicc et al. 2024 [55]	✓	✓	✓	✓		✓		
Ghimire et al. 2024 [176]		✓	✓	✓		✓		
Bozlak et al. 2024 [76]	✓		✓	✓	✓			
Lisi et al. 2024 [65]	✓			✓	✓			
Kitsatoglou et al. 2024 [77]	✓	✓	✓	✓	✓			
Peng et al. 2024 [97]		✓	✓				✓	
Huang et al. 2024 [110]		✓	✓	✓	✓			
Pourdaryaei et al. 2024 [131]			✓		✓			
Shi et al. 2024 [145]		✓	✓	✓	✓			
Englund et al. 2024 [49]	✓	✓				✓		
O'Connor et al. 2024 [32]	✓	✓	✓		✓		✓	
Uniejewski et al. 2024 [73]	✓				✓			
Bozlak et al. 2024 [76]	✓		✓		✓			
Yang et al. 2024 [85]	✓		✓		✓			
Deng et al. 2024 [103]		✓	✓	✓			✓	
Jiang et al. 2024 [148]	✓		✓		✓			
Guo et al. 2024 [152]	✓	✓	✓	✓	✓			
Nyangon et al. 2024 [153]	✓				✓			
Sapnken et al. 2024 [154]	✓		✓	✓	✓			
Chen et al. 2024 [161]		✓	✓	✓	✓			
Laitsos et al. 2024 [162]			✓	✓	✓			
Ehsani et al. 2024 [163]	✓	✓	✓	✓			✓	
Mubarak et al. 2024 [167]	✓	✓	✓	✓	✓			
Khan et al. 2024 [168]		✓	✓	✓	✓			
Nie et al. 2024 [169]		✓	✓	✓	✓			
Hajigholam et al. 2024 [170]	✓	✓	✓	✓			✓	
Nickelsen et al. 2025 [70]	✓					✓		
Agakishiev et al. 2025 [80]	✓		✓		✓			
O'Connor et al. 2025 [86]	✓	✓			✓		✓	
O'Connor et al. 2025 [109]	✓	✓	✓		✓		✓	
Chen et al. 2025 [158]			✓	✓	✓			
Yan et al. 2025 [165]	✓	✓	✓	✓	✓			
Cu et al. 2025 [166]		✓	✓				✓	

Table 3. Literature on predictive models used outside of EPF or with EPF. When papers look at EPF and external fields, they unilaterally look at the DAM with the external market. The ✓ is the approach presented herein.

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Zhu et al. 2018 [136]		✓	✓					✓
Ali et al. 2019 [92]		✓			✓			✓
Mujeeb et al. 2019 [127]	✓	✓	✓	✓	✓			✓
Ashfaq et al. 2019 [93]		✓	✓	✓	✓			✓
Cai et al. 2020 [111]	✓	✓	✓					✓
Salinas et al. 2020 [149]	✓	✓	✓		✓			✓
Rafi et al. 2021 [113]	✓	✓	✓					✓
Memarzadeh et al. 2021 [134]			✓	✓	✓			✓
Lopez et al. 2022 [146]	✓	✓	✓					✓
Ishak et al. 2022 [59]	✓							✓
Cantillo et al. 2022 [102]		✓						✓
Arrieta et al. 2022 [90]	✓			✓				✓

Table 3. *Cont.*

Reference	Statistical	ML	DL	Hybrid	DAM	IDM	BM	Other
Durante et al. 2022 [89]	✓				✓			✓
Qinghe et al. 2022 [112]	✓	✓	✓✓	✓				✓
Suvarna et al. 2022 [114]		✓	✓	✓				✓
Lopez et al. 2022 [146]	✓	✓	✓					✓
Shohan et al. 2022 [151]			✓	✓				✓
Bashir et al. 2022 [160]	✓		✓	✓				✓
Woo et al. 2022 [60]	✓		✓	✓				✓
Gellert et al. 2022 [62]	✓	✓	✓					✓
Seyed et al. 2023 [115]	✓	✓						✓
Nazir et al. 2023 [147]			✓					✓
Rao et al. 2023 [64]	✓	✓	✓	✓				✓
Gomez et al. 2023 [142]	✓	✓	✓	✓	✓			✓
Parizad et al. 2024 [157]		✓	✓		✓			✓
Zhang et al. 2024 [143]			✓					✓
Williams et al. 2025 [159]	✓	✓	✓	✓				✓
Belenguer et al. 2025 [164]	✓				✓			✓

The literature summarised in Table 3 highlights the dominant approaches in cross-domain forecasting, where EPF is paired with applications such as wind power, load, photovoltaic, and consumption forecasting. Notably, in all cases where EPF is considered, the focus is exclusively on the DAM, reflecting the lower barrier for entry towards forecasting the market. A significant number of these studies employ hybrid models to capture the complex, non-linear, and temporal patterns common across domains, underscoring the overlapping characteristics of effective EPF, and settings with similar predictors.

4.2. Forecasting Methods

The landscape of EPF is shaped by a diverse range of modelling techniques, each with varying strengths depending on market structure, volatility, and data availability. This section categorises these methods into three groups—statistical, ML, and DL models—highlighting their roles, performance, and suitability across the DAM, IDM, and BM.

4.2.1. Statistical Models

In the evolving landscape of EPF, classical statistical models such as AR, ARIMA, and GARCH continue to serve as valuable benchmarks but often fall short in capturing the full complexity of modern markets. AR and ARIMA models are particularly effective in structured environments like the DAM, where they capture mean reversion and linear trends, especially when extended with exogenous inputs (ARX, ARIMAX) or volatility models (GARCH). However, they have seen a decline in rankings with the prevalence of ML and DL models, which are proving more capable of modelling markets that are growing increasingly complex, where non-linearities, regime shifts, and price spikes are more prevalent. ES methods, including TBATS and ES-based hybrids, offer simplicity and interpretability but tend to underperform in volatile or real-time conditions unless enhanced by architectures like the ES Transformer. While enhancements like SARIMAX, hybrid wavelet-based extensions, and regularisation improve accuracy, these models are generally outperformed by ML and DL approaches, which better capture cross-hour dependencies, non-linear dynamics, and price volatility. Regularised models like LASSO and LEAR excel in the DAM and IDM due to their robustness and feature selection capabilities. LEAR, in particular, emerges as a strong contender in the BM, outperforming more complex

models by avoiding overfitting—a common issue for both ML and DL methods in short, noisy datasets. TF and copula models, while theoretically appealing for capturing complex dependencies, remain largely untested in real-time markets and have shown limited success, even in the DAM. The widespread use of naive models as benchmarks, especially in the IDM and BM, reflects their practical utility in real-time forecasting due to their simplicity and responsiveness, though their accuracy lags behind more advanced methods. Overall, the literature indicates that while statistical models still hold relevance—particularly in hybrid structures—the future of EPF lies in flexible, data-driven models that integrate exogenous inputs, capture temporal dynamics, and adapt to the increasingly volatile nature of electricity markets.

4.2.2. Machine Learning Models

In the DAM, ML models like KNN, SVR, RF, and XGB show varied performance, with KNN often struggling due to its sensitivity to neighbour selection and dataset imbalances, which hinder its ability to capture extreme price peaks. In contrast, ensemble models like RF and XGB excel, proving more capable at handling complex market dynamics. RF, in particular, stands out for its strong performance across the DAM, IDM, and BM, showing the ability to capture multi-output tasks and adapt to evolving market conditions through online variants. XGB performs well in capturing key variables like renewable energy penetration but faces challenges in the IDM due to difficulties with hyperparameter tuning, intra-day dependencies, short-term price fluctuations, and extreme volatility, where DL models like LSTM or GRU show superior performance in capturing short-term volatility. XGB excels in the BM [116], particularly for bidding and risk management, though it is sometimes outperformed by simpler models like LEAR [32]. Overall, while RF and XGB deliver strong performance in both the DAM and real-time markets, their adaptability to capturing intra-day volatility and extreme price movements remains limited compared to DL models, reinforcing the growing dominance of hybrid and data-driven approaches in EPF.

4.2.3. Deep Learning Models

DL models have made significant strides in EPF, particularly in the DAM, where they consistently outperform statistical and ML models, proving more capable at capturing complex, non-linear relationships and temporal dependencies. DNNs excel in multi-market settings when combined with feature selection techniques like XGB, improving both model efficiency and robustness. However, their performance can be hindered by hyperparameter tuning challenges, and despite their power, simpler models such as LASSO and tree-based methods often provide superior forecasts due to their interpretability and lower computational cost. In the IDM, while DNNs show some strong performance, they are frequently outperformed by RNNs like LSTMs and GRUs, which handle short-term price fluctuations more effectively. This is particularly evident in real-time markets, where DL models struggle to adapt to rapid price changes without more advanced attention mechanisms. In the BM, DL models often lag behind ML models, and simpler statistical models due to persistent issues capturing the extreme volatility and sudden price spikes characteristic of these markets, leading to consistent overfitting. Despite their strong performance in the DAM, the lack of adaptability in real-time, high-volatility markets limits the broader application of DL models in the IDM and BM. Simpler models with built in regularisation prove to be better suited for capturing short-term volatility in these markets, although potential remains for statistical-DL hybrid models which remain underexplored in the BM. Overall, while DL models are powerful tools for modelling non-linear dynamics

in the DAM, their performance in the IDM and BM is mixed, often requiring enhancements such as attention mechanisms or hybrid architectures to fully leverage their potential.

4.2.4. Hybrid Models

Hybrid models have emerged as a powerful class of tools in EPF, addressing the limitations of standalone statistical, ML, and DL models. Statistical hybrid models, such as ARIMA-GARCH and FARX-LASSO, effectively combine the linear interpretability of AR frameworks with enhanced handling of volatility, non-stationarity, and multicollinearity through the integration of regularisation techniques and conditional variance modelling. These models are particularly effective in structured markets like the DAM, where periodicity and large datasets support decomposition-based approaches. Similarly, statistical–ML hybrids, including combinations like WARIMA-RBF and SOM-SVR, apply non-linear learners to decomposed components of the time series, achieving improved accuracy through multi-resolution learning. More recent innovations extend hybridisation to incorporate PCA, evolutionary algorithms, and attention mechanisms, demonstrating versatility even in data-scarce or noisy environments. In ML/DL hybrids, architectures exploit the complementary strengths of tree-based ensembles, RNNs, and signal decomposition methods to model non-linearities and short-term volatility across all market types. ML-based hybrids, such as XGB with adaptive DNNs or ensemble frameworks integrating RF, SVM, and ARIMA, have shown exceptional performance in DAM settings. These models leverage feature selection, Fourier/wavelet decomposition, and robust regularisation to improve generalisability and interpretability. DL hybrid models push these boundaries further by fusing CNNs, LSTMs, GRUs, and attention mechanisms into complex multi-layered or ensemble-based systems capable of tracking high-frequency patterns and structural shifts in the IDM and BM. Notably, BiLSTM-based hybrids integrated with decomposition techniques and meta-heuristic optimisation strategies have demonstrated state-of-the-art performance in volatile, real-time markets such as the British BM. Hybrid models consistently outperform standalone approaches across markets, especially when addressing market-specific challenges like seasonality, noise, data sparsity, and regime shifts. Their ability to balance accuracy, interpretability, and adaptability has established them as the dominant paradigm in DAM and IDM forecasting. However, applications in BM remain underexplored, representing a key opportunity for future research.

4.3. Input Data Requirements and Model Sensitivities

The effectiveness of electricity price forecasting models is closely tied to the quality and availability of input data. Classical statistical methods, particularly univariate models like AR or ARIMA, primarily rely on historical price data and tend to be relatively robust to missing values or incomplete datasets, making them suitable when exogenous inputs are limited or unavailable. In contrast, models such as ARX, SARIMAX, and LEAR extend these frameworks by incorporating exogenous variables—including demand forecasts, renewable generation, and fuel prices—which enhances accuracy but increases sensitivity to data quality. Machine learning models, including tree-based ensembles like XGB and LGBM, generally require extensive and well-structured feature sets; while they are more flexible in handling missing data through internal mechanisms such as imputation or feature importance weighting, their performance still depends on the relevance and completeness of input features. Deep learning models, particularly recurrent architectures like LSTM and GRU, demand large volumes of high-quality, multivariate time-series data to effectively capture temporal dynamics. These models are highly sensitive to missing or noisy inputs, often requiring careful preprocessing such as normalization, interpolation, and feature engineering. Consequently, the choice of forecasting model must consider not

only predictive performance but also the feasibility of obtaining the necessary input data, especially in real-time markets where data granularity and timeliness are critical.

4.4. Forecasting Across the Day-Ahead, Intra-Day, and Balancing Markets

The DAM remains the most extensively studied and methodologically mature among electricity spot markets, largely due to its structured nature, longer forecasting horizon, the availability of multiple public datasets, and relatively lower dependence on high-frequency or real-time exogenous variables. Statistical models such as AR, ARIMA, and seasonal variants have historically performed well in this context, especially when enhanced with exogenous inputs, volatility models like GARCH, or regularisation techniques such as LASSO, ridge, and elastic nets. ML models, particularly tree-based ensembles like XGB and RF, also demonstrate strong and consistent performance in the DAM, balancing accuracy and computational efficiency. DL methods—especially RNN variants such as LSTM, GRU, and hybrid CNN-LSTM architectures—outperform statistical approaches by capturing long-term dependencies and complex non-linear patterns, particularly when integrated with attention mechanisms and decomposition techniques. The DAM's relatively stable temporal structure allows these models to capitalise on seasonality and trend information, making it an ideal environment for methodological innovation and benchmarking.

In contrast, the IDM presents greater forecasting challenges due to its high-frequency nature, limited lead time, and susceptibility to short-term volatility driven by renewables, load fluctuations, and market trading behaviour. Many models that perform well in the DAM struggle in the IDM, particularly time-series models like ARIMA and SARIMA, which lack the flexibility to respond to fast-changing conditions. While ML models such as XGB and LASSO have found moderate success, their performance is often hindered by difficulties in capturing intra-day dependencies and abrupt price changes. DL models like LSTM and GRU perform better in this space, particularly when paired with feature selection or hybrid decomposition methods. The lack of consistently available high-resolution exogenous data further limits model performance in the IDM, underscoring the need for models that can adapt rapidly with minimal prior information. The BM is the least studied and most volatile of the three, with very short forecasting horizons and a high degree of unpredictability due to its inherent stochastic nature, diminishes the effectiveness of many conventional approaches. Simpler models like naive benchmarks often perform competitively by capitalising on strong autocorrelations in real-time prices. Hybrid approaches and DL models with attention mechanisms—particularly BiLSTM-based ensembles and Transformer hybrids—are beginning to show promise in the BM by capturing rapid price spikes and noise patterns more effectively. Notably, statistical models like LEAR consistently outperform more complex DL architectures, likely due to their robustness, lower tendency to overfit, and better handling of sparse and volatile data. While hybrid and DL-based models are advancing, the BM still lacks methodological consensus, with contrasting model performance, proving an attractive avenue for future research.

4.5. Regional Trends in Model Usage

While electricity price forecasting methodologies are broadly applicable, their deployment often reflects regional market characteristics, regulatory structures, and data availability. For instance, SARIMAX and TBATS models have seen notable application in European markets such as Denmark and Germany, where strong seasonal patterns and structured DAM environments favour statistical approaches. In contrast, markets like the Irish and British balancing markets favour simpler models such as LEAR and naive baselines due to their robustness in high-volatility, low-data settings. In New Zealand, GARCH models with feature selection have outperformed some ML models, likely due

to their capacity to model volatility in deregulated markets with limited real-time data. Meanwhile, advanced DL and hybrid methods are more frequently explored in research on the Chinese, Iranian, and North American markets, where larger datasets and more computational resources are available. These regional trends suggest that model selection is often shaped less by universal performance and more by local constraints, including data resolution, market rules, and integration of renewables.

4.6. Evaluation Metrics—Persistent Issues

The selection of evaluation metrics in EPF continues to present methodological challenges, particularly when applied uniformly across markets with varying volatility, time resolution, and regulatory conditions. Commonly used metrics such as mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) offer simplicity and interpretability but fall short in capturing the nuanced demands of different forecasting environments. MAE, while less sensitive to outliers than MSE, is scale-dependent and under-penalises large errors—an issue in volatile markets like the BM, where sudden price spikes can have significant financial consequences. MSE, by contrast, exaggerates the impact of extreme deviations, which may overstate model deficiencies in high-variance settings, where even accurate models occasionally miss rare events. Both metrics also obscure the comparative effectiveness of models across different market contexts due to their unstandardised nature. MAPE, despite its popularity in industry, performs poorly when actual prices approach zero, which frequently occurs in real-time and high-renewable-penetration markets. This results in undefined or disproportionately inflated error values, rendering the metric unreliable. The symmetric MAPE (sMAPE) attempts to address this instability but introduces interpretational difficulties of its own. The relative MAE (rMAE), which compares model performance to a benchmark such as a naive or LASSO model, offers more informative context for evaluation, especially in the IDM and BM, where simple models often provide strong baselines. However, its usefulness hinges on the appropriateness of the benchmark, which varies substantially across studies. The weighted MAE (WMAE) introduces the possibility of assigning economic or operational importance to certain observations, such as peak-hour prices, but its limited adoption in academic work highlights a disconnect between research practice and operational priorities. A persistent issue across the literature is the uniform application of these metrics regardless of the forecast horizon, data granularity, or intended use of the forecast, whether for trading, scheduling, or regulatory compliance. For example, using the same metrics to evaluate more stable DAM forecasts and volatile IDM and BM forecasts fails to account for the different risk profiles and error tolerances involved. Until a more context-sensitive and application-aware framework is widely adopted, the evaluation of EPF models will remain fragmented and potentially misleading, hindering the development of robust, transferable, and operationally relevant forecasting solutions.

5. Conclusions

This review has mapped the evolution of EPF methodologies, with a focus on the DAM, IDM, and BM. The field has progressed from early reliance on linear statistical models, such as ARIMA, ARX, and GARCH, to ML, DL, and hybrid architectures capable of modelling complex, non-linear market dynamics. While the DAM remains the most thoroughly studied and methodologically developed market, the IDM and BM have gained increasing attention due to their operational relevance in real-time forecasting, particularly in the context of renewable integration and system flexibility. Our analysis highlights that no single class of models consistently outperforms others across all market contexts. However, hybrid approaches, combining the interpretability of statistical models with the adaptability

of ML and DL, frequently demonstrate strong performance. These frameworks, particularly when enhanced with decomposition techniques, feature selection, attention mechanisms, and ensembles, offer a balance between accuracy and flexibility. However, they often come with added complexity, higher computational demands, and reduced transparency, which can limit their deployment in operational settings. Significant challenges remain, particularly in volatile and data-scarce environments, including the IDM and BM.

Statistical models, while efficient and interpretable, struggle to capture regime shifts and rapid fluctuations. DL models, including LSTM, GRU, and Transformer-based architectures, require large volumes of high-quality data and are prone to overfitting in low-data or high-noise environments. Additionally, the inconsistent availability of high-frequency exogenous variables, such as renewable generation forecasts, demand anomalies, and cross-border flows, limits forecasting accuracy and generalisability across market types and geographies. Compounding these issues is the lack of standardisation in back-testing and real-time evaluation protocols, with inappropriate use of metrics like MAPE limiting the evaluation and comparison of models. These challenges are exacerbated by the lack of standardised benchmarks, open datasets, and reproducible code for hybrid models, creating additional barriers for testing these approaches across different geographies or market types, particularly when transitioning from DAM to real-time applications.

Looking ahead, the future of EPF lies in the development of models that are not only accurate but also scalable, interpretable, and robust across diverse market structures. Improving model performance in the IDM and BM, integrating higher-resolution exogenous data, and adapting successful hybrid strategies from DAM, load, and photovoltaic forecasting represent valuable directions. Equally important is the creation of standardised benchmarking frameworks, the availability of open datasets, and systematic multi-market validation to facilitate practical deployment. As electricity markets grow increasingly decentralised, data-driven, and renewable-centric, robust forecasting will remain fundamental to facilitating efficient trading, reliable system operations, and agile market design.

In parallel with methodological advances, the use of forecast price values continues to expand across electricity markets. Promising applications include strategic bidding in wholesale and balancing markets, real-time dispatch optimisation, and portfolio risk management. In retail and prosumer contexts, forecast prices support demand-side response, tariff design, and local energy trading. Additionally, system operators and aggregators are increasingly leveraging forecasted prices for congestion management, reserve allocation, and ancillary service scheduling. As market mechanisms grow more dynamic and decentralised, the integration of accurate and interpretable price forecasts into operational decision making will be essential for achieving flexibility, efficiency, and resilience across electricity systems.

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