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ORIGINAL CONTRIBUTION

Hybrid Machine Learning-based Short-Term Electricity Price Forecasting in Smart Grids Using Weather, Demand, and Market Data: A Systemic Review

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Abstract— Electricity Price Forecasting (EPF) represents one of the most important areas of activities of smart grid, as it directly affects the economic dispatch, demand responses, risk hedging, and reliability of the systems. Short term EPF is a difficult engineering problem due to the nonlinearity, volatility, and sensitivity to exogenous variables like weather and demand. This article provides a thoroughly structured and comprehensive analysis of hybrid Machine Learning (ML)-based methods of solving problems in short-term EPF and carries out the review of the literature published since 2015 and until 2025. Under the engineering view, the concept of review conceptualizes EPF as a data-driven forecasting pipeline which is composed of data acquisition, preprocessing, feature extraction, model training, and forecasting output. The paper studies the topic of hybrid architectures which combine signal decomposition methods (e.g., EMD, VMD, wavelets), sophisticated learning methods (e.g., CNN-LSTM, attention mechanisms, transformers), and ensemble policies including stacking and quantile regression averaging. These hybrid systems are evaluated on how well they can model temporal dependencies, the cross-feature interactions as well as extreme price behaviors. The review also speaks of formal evaluation practice based on conventional performance measures, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) and probabilistic forecasting measures. The analysis of comparable results of benchmark datasets and real-world electricity markets indicates hybrid models tend to perform better than individual learners in both point and probabilistic forecasting tasks. But the difference in performances between market structures, forecasting horizons (inter and day-ahead), and regime conditions through the use of strong validation procedures including rolling-origin analysis and leakage-free experimental design emerge. Moreover, the paper determines the main issues associated with the real-time implementation such as the complexity of the computation, scalability, and integration with the energy management system. It also points out the increased significance of uncertainty judgment by means of probabilistic forecasting methodology. Although this has been recently improved, the gaps in research have not been closed yet, such as cross-market generalization, transparency in what is available in the decision time and interest in evaluating operation value besides mainstream error measures. Lastly, the paper gives the future research paths on how to establish strong, interpretable and uncertainty aware hybrid EPF frameworks to increase the practical applicability of such models to the current smart grid setting.

Index Terms— Hybrid Machine Learning, Electricity Price Forecasting, Short-term Price Forecasting, Smart Grids, Energy Market Forecasting

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I. INTRODUCTION

The Market prices in liberalized power markets are highly seasonal, nonlinear and hasty sprouts due to variations in demand, generation failure, variability of renewable power and weather [1, 2]. It is thus imperative that the activities of the smart grid such as bidding strategy, unit commitment, demand response, and risk management absolutely require precise short-term Electricity Price Forecasting (EPF), which may fall within the range of intraday to day-ahead [3, 4].

Standard EPF methodologies have been heavily based on statistical and econometric models including autoregressive models with exogenous inputs (ARX), regime-switching models and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. Although these models are successful in modeling linear interactions and volatility structures, in the current electricity markets, they usually cannot model the complex nonlinear interactions and high-dimensional dependencies. On this note, approaches to Machine Learning (ML) and deep learning have received growing popularity because they can be trained to make nonlinear mappings (of heterogeneous data sources) such as variables in the market, demand, and weather-specific features [1, 2, 5].

Nonetheless, it is clear that no single modeling approach can individually explain seasonality, spike in extremes and effect of various exogenous drivers at the same time [6]. This has created the rise of hybrid machine learning systems that combine complementary features like signal decomposition, feature engineering and ensemble learning [7]. These combined methods are especially favorable to the needs of engineering, where high-level performance, interpretability and the measure of uncertainty are the essential parts of decision-making in the real world [8, 9] .

Despite some review reports bringing together the EPF methodologies and benchmarking practices [1, 4, 2], the systematic analysis of hybridization strategies, especially their interplay with weather, demand, and market fundamentals in a smart grid is not exploited.

Therefore, the objectives of present review paper are to address this gap as following:

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- To observe the engineering of data acquisition, preprocessing, and feature construction in weather–demand–market-driven EPF system.
- To categorize and analyze hybrid machine learning architecture, highlighting its structural design and functional advantage.
- To assess the existing practices in both point and probabilistic forecasting, including the use of standard performance metrics and validation protocol.
- To find key limitations, inconsistencies, and open research challenges relevant to the deployment of EPF model in real-world smart grid environment.

II. METHODS AND SEARCH STRATEGY

To achieve a reviewed methodology, the review utilizes a systematized and replicable approach because of the predefined principles of Electricity Price Forecasting research (EPF) [2]. It aims at systematic identification, screening and synthesizing research work that is interested in hybrid machine learning methodologies of short term EPF in context of smart grids. The extensive literature search has been carried out in the major scientific databases, such as Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and arXiv to have a wide coverage of peer-reviewed and preprint studies. The search strategy used methodology and domain-specific keywords such as electricity price forecasting, day-ahead and intraday price, hybrid machine learning, ensemble, stacking, decomposition, like VMD, EMD, and wavelet transform, and deep learning models, such as CNN-LSTM, attention, and transformer. Furthermore, probabilistic forecasting terminologies were also introduced including quantile regression and distributional modelling to encompass the uncertainty-conscious methods.

A. Data sources and search protocol

The widespread scope of the review is between January 2015 and December 2025 with the hasty development of hybrid and deep learning techniques within the recent years. Previous seminal literature, especially [1], is present to give a theoretical and methodological background. The databases chosen were done so that it is not restricted to one specific field in terms of engineering, energy systems as well as machine learning. The search terms were formulated so as to include both methodology and application-focused research to guarantee that the search targets the innovations in both scholarly literature and practice in the electricity markets.

B. Inclusion and exclusion criteria

The selection of studies included a set of literature pertaining to short-term forecasting horizons (typically between intraday and 48-hours ahead) and express use of exogenous variables including weather conditions, electricity demand, renewable generation or cross-market characteristics. Studies that used hybrid models, such as decomposition-based, model-coupled or ensemble models, were only considered. Moreover, to achieve feasible applicability and scientific rigor only those studies that provide quantitative assessment findings on actual electricity market data like PJM, Nord Pool or EPEX were considered. Reviewed studies were eliminated when their subject was long-term forecasting, they did not have adequate methodological disclosures, or did not present reproducible appraisal guidelines, including well-defined divisions of information or timetables of feature availability.

C. Screening and data extraction

The first screening was done according to the titles and abstracts, and the full-text discussion of interested studies was done. Each of the chosen papers was curated by extracting important information, namely, the hybrid model structure, input variables including market, weather, and demand variables, the target electricity market, forecasting horizon, evaluation measures, and major conclusions. The literature synthesis is done by taking a thematic approach, where emphasis is given on the aspect of hybridization of forecasting accuracy, robustness and generalization as opposed to presenting the studies in a chronological manner.

D. Engineering-oriented framework and taxonomy

In order to enhance the engineering component of this review, a single conceptual framework and taxonomy hybrid EPF models are presented. Figure 1 provides a taxonomy that divides hybrid approaches into large families, such as decomposition-based models, model coupling and feature fusion methods, and ensemble and stacking models, as well as spatio-temporal and multi-market learning methods, and probabilistic or distributional hybrids.

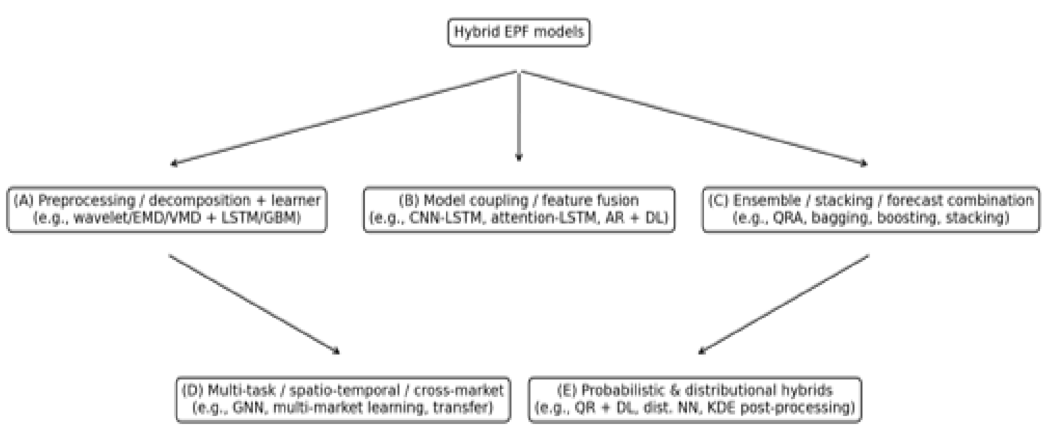

Fig. 1. Taxonomy of hybrid EPF model families

To add to this, Figure 2 provides the conceptual representation of an end-to-end EPF pipeline, which consists of data acquisition, preprocessing, feature engineering, hybrid model training, and forecasting outputs. This pipeline illustrates that heterogeneous data sources (market prices, weather variables, demand signals, etc.) are converted into actions (point forecasts, prediction interval, risk measures, etc.). Also, the framework includes monitoring and retraining functionality to overcome concept drift and regime shifts, as well as it presents the real-world implementation needs of smart grid systems.

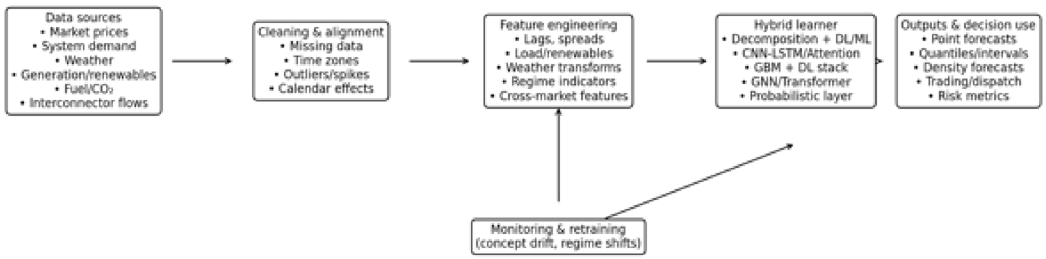

Fig. 2. Taxonomy of hybrid EPF model families

E. Thematic synthesis of the literature

F. Data modalities and feature engineering: Aligning weather, demand, and market signals

A majority of short-term Electricity Price Forecasting (EPF) research formulates electricity prices as a multivariate time series that is enhanced with a large assortment of exogenous factors. The most frequent inputs are lagged prices at various time scales (hourly, daily, weekly), load predictions of the system, renewable generation predictions, weather factors: temperature, wind speed, solar irradiance and humidity [10]. Besides that, calendar effects, fuel prices, CO_2 costs, and interconnections flow limits are often added to model market fundamentals [1, 2, 11]. These non-homogeneous data sources capture the complexity and interdependency of the electricity markets in which the price formation relies not only on the dynamics of the physical systems but also on economics [12].

This greatly depends on the market structure and the horizon of the forecasting. Cross-market prices and interconnector flows can be very successful in enhancing forecasting performance in related and integrated markets, especially in Europe, where common constraints of the system and shared economic drivers are typically observed [11]. In intraday forecasting, imbalance signals and reserve activation mechanisms are likely to dominate predictive performance, with the effects of weather and demand being indirectly carried by imbalance signals [4]. This underscores the need to have context-sensitive feature selection that is dependent on the temporal level and market structure [13].

EPF pipelines that are hybrid often include feature transformations that are domain based to improve the predictive performance [14]. These can be the degree indices of heating and cooling in order to approximate the nonlinear relationships between temperature and demand and the renewable ramp indicators to represent the abruptness of changes in generation as well as the indicators reflecting the regimes of peak load or scarcity [15]. Redundancy and overfitting in using high-dimensional input spaces can be regulated by using feature selection methods like functional ANOVA [11].

One aspect of the EPF modeling that is very critical and yet is sometimes ignored is the data alignment and the elimination of information leakage. Indeed, inputs should be made based on the information at the time of forecasting otherwise inflated model performance may be indicated. Models that are based on stringent assessment standards, as well as rolling-origin validation and careful lag construction, tend to report smaller straightforward gains with intricate models than their counterparts in well-regularized statistical indicators [16, 2]. This highlights the fact that reproducible and real evaluation frameworks are important.

Lastly, price spikes and heavy-tail distributions are characteristics requiring specific precaution to process. Standard methods are logarithmic transformations, robust scaling, clipping outliers, or the explicit modelling of extreme price events [17]. Although previous methods uses ad hoc de-spiking methods, new hybrid frameworks are more likely to solve these problems with decomposition algorithm and probabilistic modeling schemes. However, generalizing hybrid models in the extreme market conditions is a research area that has not been filled yet [4, 18].

TABLE I
COMMON DATA INPUTS AND THEIR ROLES IN SHORT-TERM EPF

Data Source	Typical Variables	Rationale in EPF (synthesis)
Market data	Day-ahead/intraday prices; spreads; imbalance price; volume; cross-market prices	Captures auto-correlation and arbitrage links; cross-market feature represent integration effects [1, 11].
Demand/load	System load; load forecast; regional loads; net load	Proxy for marginal generation and scarcity; major driver of price level and ramps [1].
Weather	Temperature; wind speed; solar irradiance; humidity; precipitation	Influences demand and renewable supply; supports ahead-of-time scarcity signals [2].
Generation/renewables	Wind/solar forecasts; outages; reserves; capacity margins	Represents supply variability and constraints that shape spikes and volatility [4].
Fuels/emissions	Gas/coal prices; CO_2 allowances; heat rates	Maps to marginal cost and merit-order effects; often relevant in thermal-dominated systems [1].
Grid constraints	Interconnector flows; transmission limits; congestion indicators	Important in coupled markets; helps explain price separation [11].

G. Hybridization via preprocessing and decomposition: Wavelets, EMD/CEEMDAN, and VMD

The hybrid models based on decomposition rely on the premise that the series of electricity prices can be modeled as a superposition of components of various time scales, such as long-term trends, medium-term oscillations and high-frequency spikes [1]. Wavelet transforms, Empirical Mode Decomposition (EMD/CEEMDAN), and Variational Mode Decomposition (VMD) techniques are typically employed to extract them, and then use them individually as machine learning or deep learning tasks, like support vector regression, gradient boosting, or recurrent neural networks.

More recent papers have shown that decomposition can enhance the stability of models and their ability to predict, especially in markets which are highly volatile and non stationary. It gives the example of hybrid models, a combination of VMD and deep learning architectures, demonstrating promising performance on MISO and Australian National Electricity Market markets. Decomposition-based approaches should however be used with care. When unfocused on test data, that can cause overfitting with improper choice of decomposition parameters. It is suggested by best practices that the determination of decomposition settings in the training data and its verification with rolling-origin evaluation protocols are the necessary measures to make sure that it becomes robust [16, 2].

A second shortcoming is that model interpretability and generalization is a concern as decomposed components can not directly relate to physical processes that are interpretable. To overcome this, performance gains using ablation analysis have been used in the majority of studies to ensure that the gains are maintained under varying market conditions and during various seasonal regimes. Also, decomposition enhances the computational complexity, which might presumptively restrict its use in real-time forecasting processes [4]. All in all, decomposition-based hybrids are specifically suited to non-stationary environments which are highly non-stationary when the design and testing of the hybrids is thoroughly regulated.

H. Architectural hybrids and representation fusion: CNN-LSTM, attention, and transformers

The new architectural models offer the hybrid forms of neural network which are formulated to include the complementary patterns with electricity price data. One of them is a CNN-LSTM architecture in which local temporal and cross-feature hip are compressed with the help of the convolutional neural networks, whereas the long-term dependencies are assessed using the long short-term memory networks. These models are further improved by attention mechanisms which dynamically weight key time steps or features giving the model the ability to conform to sensitive regimes or events.

The documentary evidence shows that hybrid design solutions like CNN-LSTM can deliver a superior result to isolated models in certain regimes of the market and under the assessment conditions, taking the case of day ahead forecasting. Others use linear models, including autoregressive models, alongside deep learning networks as methods of modelling linear and nonlinear contributions respectfully, with the view to enhancing their overall predictive power. This mix is quite in line with the well-known econometric baselines, which are also competitive in the benchmarking of EPF [1, 2].

More recent models that are based on transformers include self-attention models, which use transformers as a drop-in replacement to exploit long-range dependencies without the sequential constraints of recurrent models. Although these models are very effective in certain analyses, they are generally very demanding in terms of large data sets, regularization monitoring, and processor usage [19]. Representation fusion is another type of architecture that extends architectural hybrids, where a representation of various input modalities (historical prices and exogenous variables) is modeled separately, and finally fused together in a layer [20]. This renders it useful in maintaining the statistical characteristic of various data sources and minimizes the chances of information leak in the event of appropriate implementation [2]. In spite of flexibility, such models might be limited in their practical usage because of complexity and tuning issues [16].

I. Ensemble, stacking, and probabilistic hybrids: From QRA to distributional neural networks

The premise of ensemble based hybrid models is to enhance robustness and accuracy through combination of more than one predictor with different error properties. The tradition of forecast combination within EPF has always existed and has been reported to be effective methods in the literature [1]. The most obvious extension of these techniques is the probabilistic forecasting based on Quantile Regression Averaging (QRA) that is used to make the prediction intervals by amalgamating a set of point predictions of several underlying models [3, 4].

Prediction intervals using hybrids based on QRA have been shown to generate well-calibrated predictions and to make use of strong point forecasting models. Nevertheless, they can perform poorly in the presence of distributional changes or in cases when the models used as the base have a high correlation [21]. The most recent developments are the distributional neural networks which directly learn the probability distributions of electricity prices, and hybrid systems which obtain full predictive distributions through the combination of deep learning models with density estimation methods [18]. These methods enhance the uncertainty representation especially in the markets where the price distributions are heavily skewed.

The recent development is the comparison of forecasting performance based on operational value, e.g., trading profitability and system flexibility. Amphetamines in the context of studies with trading simulations reveal that seemingly small positive economic returns can be gained by the improvement of probabilistic calibration, even in cases where the performance of the classical error measures is slight [18]. However, probability EPF has not been standardized seriously with some variations here including quantile choice, density estimation techniques, and measures of performance. It is imperative to have probabilistic predictions that are reliable and sharp as the misguided optimism of forecasting can result in negative working consequences [4].

J. Smart-grid deployment considerations: Drift, explainability, and operational value

The application of EPF models within a smart grid setting generates a new set of issues associated with non-stationarity, interpretability, and usefulness. Structural changes due to rising levels of penetration of renewables, regulatory change, and changing market mechanisms subject electricity markets to concept drift and declining model performance over time. Popular mitigation measures are rolling-window retraining and regime-aware representations, but systematic comparisons of mitigation methods are in their early stages [1, 2, 5].

The importance of explainability has grown with the stakes of the decisions in the electricity markets being high. Interpretable models including gradient boosting with feature attribution methods (e.g., SHAP) are transparent in terms of model behavior, whereas deep learning models may be based on either an attention mechanism or a post hoc explanation mechanism. Causal and graph methods of improving interpretability are also discussed in recent studies, especially in the context of many-node or interconnected markets.

The assessment of operational value is also another important factor. The conventional measures of error like MAE or RMSE fail to describe the economic performance of forecasting models. Existing literature that includes the application of the trading and risk-based measurements suggests that any change in increasing probabilistic calibration can be associated with disproportionately greater economic rewards than the marginal enhancement on the point forecasting [18]. Last but not the least, the questions of reproducibility and benchmarking are now major issues in EPF studies. Access to open datasets and universal assessment models, including epftoolbox, make consistent comparisons, which are leakage-free, and aid in deciding whether more complex models are worth the added complexity [2].

TABLE II
COMPARATIVE STRENGTHS AND LIMITATIONS OF MAJOR HYBRID EPF STRATEGIES (SYNTHESIS)

Hybrid strategy	Typical components	Strengths	Limitations / risks
Decomposition + learner	Wavelet/EMD/CEEMDAN/VMD + SVR/GBM/LSTM/BiLSTM	May denoise and separate time scales; can improve spike handling and stability	Mode selection sensitivity; potential leakage/overfitting; added compute overhead
Architectural fusion	CNN-LSTM; attention-LSTM; AR + DL; multi-branch fusion	Learns local + long-range dependencies; integrates exogenous channels	Hyperparameter sensitivity; requires larger datasets; interpretability challenges
Ensemble / stacking	Bagging/boosting; stacking; QRA; forecast averaging	Robustness across regimes; often strong general-purpose performer	Correlation among base models; calibration depends on protocol
Probabilistic hybrids	Quantile loss; QRA; distributional NN; density post-processing	Supports risk-aware decisions; can capture heavy tails and higher moments	Evaluation not standardized; density assumptions; computational complexity
Spatio-temporal / transfer	Multi-market learning; GNN; transfer learning	Shares information across zones; may help sparse markets and congestion modeling	Data alignment complexity; changing coupling relationships; limited stability evidence

III. DISCUSSION

A. Patterns of evidence

The literature is also consistent where hybridization forms performance gain by overcoming certain limitations of particular modeling methods. Techniques of decomposition can help to deal with non-stationary noise and multi-scale variability of price series of electricity, and autoregressive components are effective to meet the linear relationships of price series and seasonal patterns [22]. State-of-the-art deep learning models, such as attention and transformer-based models, allow identifying patterns of relevance in time and regime-specific behaviour. In addition, ensemble and stacking methods are better robustness tools that combine models with complementary error structures which tend to lead to improved point forecasts as well as better-calibrated probabilistic forecasts. All these combined imply that the hybrid models can be especially well-suited to reflect the complex, nonlinear, and heterogeneous nature of electricity market [1, 18, 2].

B. Contradictions and conditional findings

Although hybrid and deep learning models are said to have many benefits, they are not necessarily more superior, and their performance can mostly be limited to the experimental design and data features. Competitive or even strong performance on the calendar effect and information flow across markets have been demonstrated to be realized using well-specified regularized linear models as long as essential characteristics (such as calendar effects and cross-market information) are engineered [2, 23, 24]. In addition, unrealistic assumptions that have been used in some studies claiming large performance gains, include exogenous variables that would not exist at the forecasting horizon or random data splits that neglected temporal causations, and therefore leak information [16, 25, 26, 27]. These aspects underscore the need to have stringent evaluation procedures and plausible data assumptions in the evaluation of model performance [28].

C. Research gaps

There are a number of critical research issues that are still to be addressed in hybrid EPF models development and implementation. A main problem is the poor knowledge of multi-market transferability and domain adaptation especially in those environments where market structures and connections are changing over time. A different difficulty is the systematic test of the performance of models in extreme conditions, in case of lack of supply, intervention of the regulator, or change of the policies. Moreover, it is necessary to enhance the interpretability of the models and bring the predictions closer to the decision-making demands such as measures of cost-benefit analyses and risk assessment. Lastly, more information should be provided on the availability of feature, but more so on whether exogenous variables like weather and demand are predicted or assumed to be known when the prediction is made.

D. Weaknesses of the literature analyzed

The present EPF literature has a great diversity with respect to datasets, forecasting time, measures of evaluations, and experimental procedures, making it difficult to compare and meta-analyze. Numerous researches target one market or a narrow time frame, which may restrict the applicability of their results. Moreover, most negative or inconclusive findings are not reported consistently and that may create publication bias. Since the conditions in electricity markets change terribly quickly, the performance of models in historical data cannot necessarily be applicable to the future, and it is crucial to constantly check and renew forecasting models [29].

E. Case study: Experimental verification of the real-world electricity market

In the effort to prove that hybrid machine learning models are practically applicable to short-term Electricity Price Forecasting (EPF), the current section provides a representative case study with reference to a real-world electricity market information. It aims at demonstrating the use of hybrid EPF frameworks in implementation, evaluation, and comparison in real-life operating environments.

F. Dataset description

In the case study, publicly available electricity market data related to EPF research are taken into consideration such as the PJM (Pennsylvania-New Jersey-Maryland) market and the Nord Pool day-ahead market. These markets have gained ample research because of their data transparency, various price dynamics, as well as exogenous variable availability.

The datasets usually involve the hourly costs of electricity and exogenous inputs like the load on the system, the weather conditions (temperature, speed of wind and sunlight), and calendar effects. The data of each market are structured to form a multivariate time series that spans several years to represent seasonal variations, demand and alterations in the market structure.

G. Experimental setup

The definition of the forecasting task is the 24-hour day ahead price forecasting. A rolling-origin evaluation framework subdivides the dataset into sub-datasets which are trained on time-varying moving historical window and tested on the future time periods. This means that it is realistic in evaluation and it does not leak information and this is appropriate in the practice of EPF benchmarking.

The features of inputs are lagged prices, predicted system load, weather variables, and calendar. To be able to make the construction of features only on the available information at the time of the forecasting, feature construction is restricted to the kind of information available in the real-life situation where the forecasting is to be produced. The preprocessing of data is performed to exclude outliers in the data by normalization, processing missing values and optional transformations like a logarithmic scaling of data.

H. Model configuration

An exemplary hybrid modeling design is adopted which consists of decomposition, deep learning, and ensemble. Specifically, the case study takes into account decomposition-based hybrid model where the model first decomposes the price series with the help of Variational Mode Decomposition (VMD). The resulting components are then modelled by a CNN-LSTM structure so that it can elaborate both the local time dynamics and the long-run dependencies. There is the ultimate prediction made through the amalgamation of component level predictions.

As these establish comparatively reliable benchmark models, one might compare a regularized linear model (such as an ARX or lasso regression) and a pure deep learning model (such as LSTM). Such a comparison is possible to estimate the incremental value that hybridization can deliver.

I. Evaluation metrics

The standard point forecasting measures such as RMSE, MAE, and MAPE are used to measure model performance along with the probabilistic measures as appropriate. Moreover, analysis is done in various seasons and market environments to evaluate strength. Rolling-origin evaluation makes sure that the performance measures do not represent an overly optimized result in forecasting premises.

IV. FINDINGS AND COMPARATIVE ANALYSIS

Feedback of the literature has been consistent to show that hybrid models are more effective compared to individual models in terms of accuracy and robustness. Decomposition-based hybrids can be especially useful in the non-stationarity and price spikes, whereas architectural hybrids help to capture nonlinear dependencies. Ensemble techniques also achieve the role of increasing stability by anti-correlated model prediction.

The extent of improvement in performance though differs among markets and evaluation context. Even in other instances, the well-tuned linear models can be competing especially in cases where feature engineering is is well-done. The given observation emphasizes the necessity of strict benchmarking and the necessity to address practical aspects, including the cost of the computation and interpretation of the model.

A. Practical implications

Considering engineering context, the case study reveals that hybrid EPF models could be successfully implemented in smart grid practice in real-life scenarios as long as proper data preprocessing and feature selection and evaluation processes are observed. Exogenous variables like weather and demand have a great impact on forecasting performance since integration is highly effective, whereas forecasting strength in uncertain market dynamics is greater with hybridization. However, to be put into practical use, it is important to pay attention to such issues as computational efficiency, model maintenance, and integration with the current energy management systems. Specifically, decomposition-based and deep learning models can create more extra latency and resource needs and should be weighed against the advantages of increased forecasting.

V. CONCLUSION AND FUTURE DIRECTIONS

This review has made a detailed look, on hybrid machine learning methods in short-term Electricity Price Forecasting (EPF) with specific focus on combing weather, demand and market variables within smart grid settlements. It was found in the analysis that hybrid models provide a great benefit in terms of capturing non-linear, complex, and non-stationary behavior of electricity prices. These models are capable of improving predictive accuracy as well as robustness with carefully designed models where complementary components are combined, including signal decomposition, enhanced neural architectures and ensemble or probabilistic post-processing are used, and are in effect developed and tested using realistic, leakage-free conditions.

The researches have shown that a number of hybrid model families are always performing well in different market environments. They are preprocessing and decomposition-based, architectural hybrids (CNN-LSTM and attention-based models and distributions) and ensemble or probabilistic models (Quantile Regression Averaging (QRA)) and distributional neural networks. Effectiveness, however, is strongly contingent on how they are engineered in terms of features and the model as it is developed along with how what they strive to represent correlates with the existing physical and economic processes on electricity markets.

In the future, the focus of research should be on several directions that are paramount to the enhanced pragmatically applicable hybrid versions of EPF models. There should be more standardization in the description of experimental setups especially in the aspect of availability of input features at the moment of forecasting so that there can be reproducibility and appropriate comparison. More efforts are also needed to enhance multi-market transferability and domain adaptation more so in dynamically changing market environments. Moreover, the creation of strict probabilistic forecasting schemes with adequate scoring guidelines and operational metrics based on value is also critical. By incorporating physical system constraints and market regulation in hybrid models, their reliability and interpretability may be improved, and the growth and development of explainable artificial intelligence should be central to the establishment of trust and possibilities of implementation in practical smart grid applications. Last but not least, the availability of open benchmark datasets and standardized toolboxes will probably enhance reproducibility and allow to gain a better understanding of the scenarios, in which adding complexity to a model can give meaningful performance improvements.

VI. STATEMENT AND DECLARATION

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Author declares that no specific funding was received for this research from any funding agency in the public, commercial, or not-for-profit sectors.

B. Competing interests

Author declares that there are no competing financial interests or personal relationships that could have appeared to influence the work reported in this manuscript.

C. Author contributions

AR solely conceived and designed the study, conducted the data collection and analysis, and wrote and revised the manuscript. AR approved the final version of the manuscript.

D. Ethical approval

Author confirms that the study was conducted in accordance with relevant ethical standards and guidelines. Where applicable, informed consent was obtained from all participants involved in the study.

References

[1] R. Weron, “Electricity price forecasting: A review of the state-of-the-art with a look into the future,” *International Journal of Forecasting*, vol. 30, no. 4, pp. 1030-1081, 2014.

[2] J. Lago, G. Marcjasz, B. De Schutter, and R. Weron, “Forecasting day-ahead electricity prices: A review of state-of-the-art algorithms, best practices and an open-access benchmark,” *Applied Energy*, vol. 293, p. 116983, 2021. doi: https://doi.org/10.1016/j.apenergy.2021.116983

[3] T. Hong, P. Pinson, S. Fan, H. Zareipour, A. Troccoli, and R. J. Hyndman, “Probabilistic energy forecasting: Global energy forecasting competition 2014 and beyond,” pp. 896–913, 2016.

[4] J. Nowotarski and R. Weron, “Recent advances in electricity price forecasting: A review of probabilistic forecasting,” *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 1548-1568, 2018.

[5] I. Goodfellow, Y. Bengio, A. Courville, and Y. Bengio, *Deep learning*. MIT press Cambridge, 2016, vol. 1, no. 2.

[6] W. Li and D. M. Becker, “Day-ahead electricity price prediction applying hybrid models of lstm-based deep architectures considering market coupling,” *Energy*, vol. 239, p. 121763, 2021. doi: https://doi.org/10.1016/j.energy.2021.121543

[7] S. Ghimire, T. Nguyen-Huy, R. C. Deo, D. Casillas-Pérez, A. M. Ahmed, and S. Salcedo-Sanz, “Novel deep hybrid model for electricity price prediction based on dual decomposition,” *Applied Energy*, vol. 395, p. 126197, 2025. doi: https://doi.org/10.1016/j.apenergy.2025.126197

[8] Y. Xu, J. Li, H. Wang, and P. Du, “A novel probabilistic forecasting system based on quantile combination in electricity price,” *Computers & Industrial Engineering*, vol. 187, p. 109834, 2024. doi: https://doi.org/10.1016/j.cie.2023.109834

[9] S. Makridakis, E. Spiliotis, and V. Assimakopoulos, “Statistical and machine learning forecasting methods: Concerns and ways forward,” *PloS one*, vol. 13, no. 3, p. e0194889, 2018. doi: https://doi.org/10.1371/journal.pone.0194889

[10] Z. Qu, M. Gao, Y. Liu, H. Lv, J. Sun, M. Li, W. Liu, and M. Cui, “Probability prediction method of short-term electricity price based on quantile neural network model,” *Journal of Electrical Engineering & Technology*, vol. 15, no. 2, pp. 547-559, 2020. doi: https://doi.org/10.1007/s42835-020-00357-1

[11] J. Lago, F. De Ridder, P. Vrancx, and B. De Schutter, “Forecasting day-ahead electricity prices in Europe: The importance of considering market integration,” *Applied Energy*, vol. 211, pp. 890-903, 2018. doi: https://doi.org/10.1016/j.apenergy.2017.11.098

[12] F. Cordoni, “A comparison of modern deep neural network architectures for energy spot price forecasting,” *Digital Finance*, vol. 2, no. 3, pp. 189-210, 2020. doi: https://doi.org/10.1007/s42521-020-00022-2

[13] T. Gneiting and M. Katzfuss, “Probabilistic forecasting,” *Annual Review of Statistics and Its Application*, vol. 1, no. 1, pp. 125-151, 2014. doi: https://doi.org/10.1146/annurev-statistics-062713-085831

[14] H. Mubarak, A. Abdellatif, S. Ahmad, M. Z. Islam, S. Muyeen, M. A. Mannan, and I. Kamwa, “Day-ahead electricity price forecasting using a cnn-bilstm model in conjunction with autoregressive modeling and hyperparameter optimization,” *International Journal of Electrical Power & Energy Systems*, vol. 161, p. 110206, 2024. doi: https://doi.org/10.1016/j.ijepes.2024.110206

[15] R. J. Hyndman and G. Athanasopoulos, *Forecasting: principles and practice*. OTexts, 2018.

[16] L. Tschora, E. Pierre, M. Plantevit, and C. Robardet, “Electricity price forecasting on the day-ahead market using machine learning,” *Applied Energy*, vol. 313, p. 118752, 2022. doi: https://doi.org/10.1016/j.apenergy.2022.118752

[17] O. Llorente and J. Portela, “A transformer approach for electricity price forecasting,” *arXiv preprint arXiv:2403.16108*, 2024.

[18] G. Marcjasz, B. Uniejewski, and R. Weron, “On the importance of the long-term seasonal component in day-ahead electricity price forecasting with NARX neural networks,” *International Journal of Forecasting*, vol. 35, no. 4, pp. 1520-1532, 2019. doi: https://doi.org/10.1016/j.ijforecast.2017.11.009

[19] M. S. Rahman and H. Reza, “Hybrid deep learning approaches for accurate electricity price forecasting: A day-Ahead US energy market analysis with renewable energy,” *Machine Learning and Knowledge Extraction*, vol. 7, no. 4, p. 120, 2025. doi: https://doi.org/10.3390/make7040120

[20] F. Ziel and R. Steinert, “Probabilistic price forecasting in day-ahead electricity markets: A LASSO-based approach,” *Energy Economics*, vol. 75, pp. 391-402., 2018. doi: https://doi.org/10.1016/j.eneco.2015.08.005

[21] B. Uniejewski and R. Weron, “Regularized quantile regression averaging for probabilistic electricity price forecasting,” *Energy Economics*, vol. 95, p. 105121, 2021. doi: https://doi.org/10.1016/j.eneco.2021.105121

[22] C. Monteiro, I. J. Ramirez-Rosado, and L. A. Fernandez-Jimenez, “Probabilistic electricity price forecasting models by aggregation of competitive predictors,” *Energies*, vol. 11, no. 5, p. 1074, 2018. doi: https://doi.org/10.3390/en11051074

[23] G. Moschogianni, “Pathways to team performance and reduction of silence behaviour: Exploring the role of benevolent leadership through moderating impact of corporate social responsibility,” *Journal of Management Practices, Humanities and Social Sciences*, vol. 9, no. 2, pp. 93-106, 2025.

[24] H. Gulzar, “Motivation as the link: Mediating effects of intrinsic and extrinsic drives on student success,” *Journal of Advanced Research in Social Sciences and Humanities*, vol. 1, pp. 94-106, 2025.

[25] A. Aguir, “Post-covid monetary policy challenges in emerging economies: Revisiting the effectiveness of inflation targeting,” *Pakistan Journal of Life and Social Sciences (PJLSS)*, vol. 23, no. 1, 2025.

[26] A. Bano, E. B. Hafiz, and S. H. Hamzah, “Unlocking activity in inactive children: A gender-based comparison of three physical training interventions,” *Journal of Management Practices, Humanities and Social Sciences*, vol. 9, no. 3, pp. 158-174, 2025.

[27] T. Rui, A. Bano, and F. A. Jam, “Beyond fandom: Investigating the role of identity-based motivation and customer engagement in shaping sports consumer evangelism,” *International Journal of Consumer Studies*, vol. 50, no. 1, p. e70164, 2026.

[28] A. Miraki, P. Parviainen, and R. Arghandeh, “Electricity demand forecasting at distribution and household levels using explainable causal graph neural network,” *Energy and AI*, vol. 16, p. 100368, 2024. doi: https://doi.org/10.1016/j.egyai.2024.100368

[29] R. Sevlian and R. Rajagopal, “A scaling law for short term load forecasting on varying levels of aggregation,” *International Journal of Electrical Power & Energy Systems*, vol. 98, pp. 350-361, 2018. doi: https://doi.org/10.1016/j.ijepes.2017.10.032