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SURVEY

Toward Holistic Energy Management by Electricity Load and Price Forecasting: A Comprehensive Survey

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ABSTRACT Electricity load and price data pose formidable challenges for forecasting due to their intricate characteristics, marked by high volatility and non-linearity. Machine learning (ML) and deep learning (DL) models have emerged as valuable tools for effectively predicting data exhibiting high volatility, frequent fluctuations, mean-reversion tendencies, and non-stationary behavior. Therefore, this review article is dedicated to providing a comprehensive exploration of the application of machine learning and deep learning techniques in the context of electricity load and price prediction. In contrast to existing literature, our study distinguishes itself in several key ways. We systematically examine ML and DL approaches employed for the prediction of electricity load and price, offering a meticulous analysis of their methodologies and performance. Furthermore, we furnish readers with a detailed compendium of the datasets utilized by these forecasting methods, elucidating the sources and specific characteristics underpinning these datasets. Then, we rigorously conduct a performance comparison across various performance metrics, facilitating a comprehensive assessment of the efficacy of different predictive models. Notably, this comparison is carried out using the same datasets that underlie the diverse methodologies reviewed within this study, ensuring a fair and consistent evaluation. Moreover, we provide an in-depth examination of the diverse performance measures and statistical tools employed in the studies considered, providing valuable insights into the analytical frameworks used to gauge forecasting accuracy and model robustness. Lastly, we devote significant attention to the identification and analysis of prevailing challenges within the realm of electricity load and price prediction. Additionally, we delve into prospective directions for future research, thereby contributing to the advancement of this critical field.

INDEX TERMS Electricity load forecasting, electricity price forecasting, deep learning, machine learning, metaheuristics, smart grids.

I. INTRODUCTION

Electrical energy plays a fundamental role in every economy around the globe [1], [2], [3]. Since every technology of the modern era depends on electricity, a country's prosperity (in terms of economic growth) is highly dependent on its electricity infrastructure, grid, availability, and type of electricity generation (renewable and/or fossil fuel). Therefore, electricity demand has increased in recent years, both in the residential and commercial sectors. On the contrary,

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electricity prices fluctuate when the power grid cannot meet the demand [3], [4], [5]. As a result, numerous studies have been conducted to predict electricity demand and price so that utilities and consumers can efficiently plan electricity generation and consumption, respectively. However, the prediction of the electric load remains a significant challenge for power grids ever since the emergence of electricity [3]. In addition, predicting the electricity price is also one of the fundamental problems for energy consumers because accurate price prediction helps consumers to make decisions, for e.g., which time is suitable for which device (low price) and which time is not suitable for maximum energy consumption because of the high price [6], [7], [8].

As the demand for electricity rises and environmental-energy conflicts evolve, the significance of electricity is growing progressively [1], [9], [10]. Furthermore, due to the fluctuation in electricity load, the price of energy also fluctuates, which also complicates decision-making for energy consumers. Several forecasting approaches have been developed in recent decades based on mathematical or neural network models. Based on the electricity price forecasts, energy consumers can make better decisions regarding energy purchases; in contrast, utilities can make better decisions regarding energy generation and sources based on the electricity load forecasts. Therefore, both load and price forecasting are necessary for each other.

There are several reviews in the literature that discuss deep learning (DL)/ machine learning (ML) use within energy management systems in relation to electricity load and price forecasting [11], [12], [13], [14]. For example, the authors of [11] review studies related to building energy consumption (BEC) prediction using machine learning methods, focusing on the scale of prediction. Another study provides an overview of intelligent load forecasting approaches developed for efficient energy management systems [14]. Here, the forecasting methods were divided into two classes: single and hybrid computational intelligent methods. However, in that paper, only the studies that consider electricity load forecasting (ELF) are examined instead of considering them together with electricity price forecasting (EPF). Nti et al. also conducted a comprehensive study in which they considered seventy-seven articles related to electricity demand forecasting [3]. ML / DL models as well as accuracy metrics are also discussed in their study. A short survey on price and load forecasting is presented in [15] and [16], where the authors reviewed existing studies (within the last four years) related to DL / ML forecasting methods with a primary focus on short-term prediction. In addition, conventional forecasting models for predicting electricity load and price are also examined. A study presented in [17] provides an overview of EPF and presents several guidelines for using state-of-the-art approaches and metrics for EPF with the goal of increasing reliability. In addition, the paper focuses on performance measures that have been adopted in the literature to validate the effectiveness of ML / DL models for EPF. However, discussion related to datasets and their presentation is not addressed in that study. Aslam et al. present a comprehensive overview of energy management systems and discuss in detail how the prediction of load and energy generation (by solar panels and wind turbines) affects energy management in smart grids [1]. They delve extensively into the ML/DL models formulated over the past two decades for load and power generation prediction. Additionally, they make dedicated efforts to explore the nature of data employed in forecasting models, distinguishing between simulated/randomly generated data and real-world data.

Table 2 explains the closely-related studies that review ELF and EPF and shows the novelty of our study. Based on the literature review of existing studies (surveys) [1], [17], [18], and to the best of our knowledge there is no survey/review that focuses on EPF and ELF at the same time, considering the presentation of datasets and performance metrics. Therefore, this study is differentiated by its data-centric view and analysis of performance metrics, along with the ML/ DL models developed for ELF and EPF.

In an energy management system (EMS), demand side management is one of the essential components and enables energy consumers and utility operators to make efficient management decisions regarding energy purchases and generation, respectively. Within this framework, anticipating electricity demand in advance becomes instrumental in reshaping the load profile, ultimately leading to a reduction in the energy demand curve. This dynamic restructuring allows for more efficient energy management and distribution within smart energy systems. In contrast, prior knowledge of electricity prices can help energy consumers to make energy purchase decisions, i.e., consumers can choose to purchase electricity in the low price hour based on EPF. Since ELF and EPF are important components of EMS for both energy consumers and utilities, this study provides a comprehensive overview of DL / ML approaches developed in the recent literature to predict both electricity load and price. This study also presents datasets that have been used in the literature to predict ELF and EPF. Thus, new researchers can follow and reuse the data to develop new prediction applications. In addition, based on critical analysis, the proposed review can serve as a technical guide for selecting efficient and effective prediction approaches. Lastly, this study outlines open research inquiries and suggests future research trajectories within the realm of ELF and EPF.

The remaining paper is organized as follows: Section II describes preliminaries on popular DL-based forecasting models and Section III reviews load forecasting, including both short-term and long-term. Section IV reviews recent studies related to electricity price forecasting. Section V presents critical analysis and observations from this study. Details related to performance matrices and statistical analysis are presented in Section VI. We shed light on recent

TABLE 1. Nomenclature.

Acronym	Definition	Acronym	Definition
AE	Auto Encoder	KEPCO	Korea electric power corporation
AEMO	Australian energy market operator	LM	Load monitoring
AI	Artificial intelligence	LSTM	Long short term memory
ALM	Adaptive learning model	LSTM-EFG	LSTM-enhanced forget-gate
ANN	Artificial neural network	MI	Mutual information
AR	Auto-regressive model	MLP	Multilayer perceptron
ARX	Auto-regressive with exogenous input	MLR	Multiple linear regression
BEC	Building energy consumption	MFE	Multistage forecast engine
BRT	Boosted regression tree	NMAE	Normalized mean absolute error
DE	Differential evolution	NWS	National weather service
DL	Deep learning	NWTC	National wind technology center
DLSTM	Deep LSTM	PDRNN	Pooling-based deep RNN
DNN	Deep neural network	PV	Photovoltaic
DQR	Direct quantile regression	p-WPRF	Probabilistic wind energy ramp forecasting
ELF	Electricity load forecasting	RBMs	Restricted boltzmann machines
EMSs	Energy management systems	Relu	Rectified linear unit
ENN	Elman neural network	RESs	Renewable energy sources
EO	External optimization	RICNN	Recurrent Inspection CNN
EPF	Electricity price forecasting	RNN	Recurrent neural network
ESSs	Energy storage systems	SSA	Singular spectrum analysis
EVs	Electric vehicles	SVRM	Support vector regression machine
EWT	Empirical wavelet transformation	UAVs	Unmanned aerial vehicles
GA	Genetic algorithm	V2G	Vehicles to grid
GABPNN	GA back-propagation NN	WIND	Wind integration national dataset
GBR	Gradient boosting regression	WPD	Wavelet packet decomposition
GRU	Gated recurrent unit	WPF	Wavelet packet filter
HELM	Hysteretic extreme learning machine	WT	Wavelet transform
ICT	Information and communication technologies	WTD	Wavelet threshold denoising
IMFs	Intrinsic mode functions	WTs	Wind turbines

challenges and future directions in Section VII. Finally, Section VIII concludes this survey.

II. PRELIMINARY ON POPULAR FORECASTING APPROACHES

This section discusses in detail several popular forecasting methods that are recently developed in the literature.

A. BASIC MODELS

1) ARIMA

ARIMA is considered as an integration of autoregression and moving average. When a time series has a seasonal trend, the seasonal ARIMA approach is utilized to predict future values. The main advantage of ARIMA is that it can effectively predict stationary time series. However, the major limitation of the model is the assumption of a linear relationship between current and future values. As a result, the performance of the model is not satisfactory for a number of real-world examples, such as financial time series and electricity price series, etc. In real data, it is not necessary that all time-series values are stationary, and to determine whether the series is stationary or not, Augmented Dickey-Fuller (ADF) is performed.

2) SUPPORT VECTOR MACHINE (SVM)

SVM stands out as a widely utilized machine learning model within the realm of supervised learning, capable of addressing both classification and regression challenges. The main difference between a support vector classifier and a support vector regressor is determined by the loss function. The goal of SVM is to discriminate data elements by introducing a hyperplane into the N-dimensional feature space. A hyperplane functions as the decision boundary, distinguishing the data points of one class from those of other classes. Its linearity or nonlinearity depends on the distribution of the data points. Also, kernel tricks can be used to distinguish non-separable elements of the opposite classes. Different kernel features for SVM design selection are linear, non-linear, rbf, sigmoid, etc. Figure 1 shows an example of SVM classification and regression. The main advantage of SVM is its usefulness in high-dimensional space.

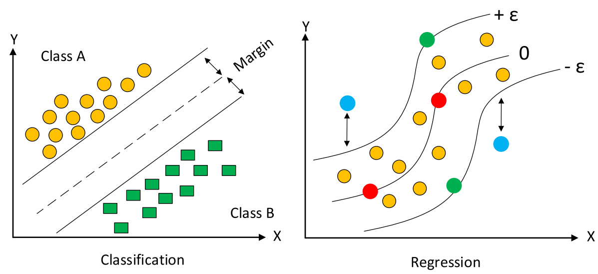

FIGURE 1. SVM classification and regression example.

3) ELM

ELM belongs to a single hidden layer feed forward NN and the main difference between ELM and other NN is that the

TABLE 2. Comparison of the current survey with existing survey/review studies.

Reference	Published year	Reviewed span	BEC/ELF	EPF	DP	PM	Review/survey focus
Amasyali *et al.* [11]	2018	2002-2017	✓	✗	✓	✗	In the context of BEC, with a primary focus on load prediction, the investigation encompasses an analysis of data properties and the data pre-processing techniques employed in the current body of literature.
Wei *et al.* [12]	2018	1986-2017	✓	✗	✗	✗	This paper addresses the energy analysis of buildings and forecasts power consumption via data-driven approaches. Additionally, the study delves into data classification approaches for the management of buildings energy consumption.
Fallah *et al.* [14]	2018	1979-2018	✓	✗	✗	✗	The writers investigate advanced machine learning methods employed in addressing load forecasting challenges. They examine these techniques in terms of classification and assessment to enhance the sustainable functioning of the entire Energy Management System (EMS).
Nti *et al.* [3]	2020	2010-2020	✓	✗	✗	✗	Concentrating on the prediction of electricity demand over the past decade, the study delves into the categorization of applied load forecasting methods across different types. Additionally, the paper explores future directions in the domain of ELF
Arif *et al.* [15]	2020	2016-2020	✓	✓	✗	✗	A short survey on short-term EPF and ELF; ML/ DL along with traditional forecasting methods
Nowotarski *et al.* [17]	2018	2008-2018	✗	✓	✗	✓	EPF by employing ML DL approaches; data pre-processing and classification methods; performance measures
Aslam *et al.* [1]	2021	2000-2021	✓	✗	✓	✗	Solar energy prediction approaches; wind energy prediction methods; ELF; datasets presentation
This study	**2023**	**Upto 2023**	✓	✓	✓	✓	DL-based models for EPF and ELF ; first-of-its-type DP while considering electricity price and load demand forecasting; performance metrics; statistical analysis; open research issues along with future opportunities

parameters (such as hidden nodes, biases, and input weights) can be randomly assigned. This feature makes the learning process fast compared to other NNs. Another important advantage of ELM is that less human intervention is required, i.e., ELM can be used for feature assignment. However, the performance of ELM may degrade when the dimensions and the amount of data are large. Figure 2 presents the structure of ELM.

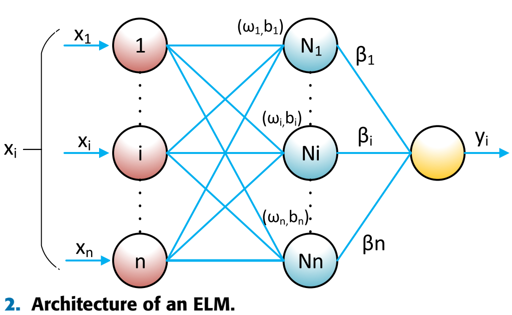

FIGURE 2. Architecture of an ELM.

B. NEURAL NETWORKS

An NN is a complex network consisting of interconnected nodes that resemble the biological structure of neurons. Because of their complex structure, NNs are able to effectively solve analytical problems where typical machine learning methods fail. According to Hykin [19], an NN has the ability to process information similar to the human brain. The learning process in NNs starts with an input data set. The neurons in each layer learn the underlying patterns and information associated with the data, and adjust the weights between the interconnected neurons to improve the learning process. Based on our study of electricity load and time forecasts, NNs are the most efficient algorithms to forecast based on electricity load and price data. However, their applications are not limited to forecasting. Other applications of NNs include preprocessing, clustering methods, etc.

1) LSTM

LSTM, an extended iteration of a recurrent neural network (RNN), finds application in a diverse range of problems according to the source [20]. The main difference between RNN and LSTM is that RNN overwrites the information, while LSTM decides whether to keep or discard the information. It solves the problem of vanishing/exploding gradient in RNNs. The main feature that distinguishes LSTM from other NNs is the memory cells instead of hidden units. This feature allows the LSTM to capture any long-range dependencies in the input data. Figure 3 shows the structure of LSTM NN, which consists of three gates: i) input gate, ii) output gate, and iii) forget gate. The input gate tracks and updates the information in the memory cell. It also decides whether to keep or discard the information. Equation 1 shows the state of the input gate at a given time "t". The output gate tracks the flow of information from the memory cells. Equation 3 shows the state of the output gate at a given time "t". The forget gate tracks the flow of information from the memory cells. Equation 2 shows the state of the forget gate at a given time "t".

$$i_G^t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{1}$$
$$f_G^t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{2}$$
$$o_G^t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{3}$$

In Equation 1,2 and 3 x_t is the input series, h_{t-1} represents the previous hidden state, σ represents the activation function. The activation function for each gate is sigmoid. W represents the weight metrics connecting the input with each gate whereas b represents the bias at each gate.

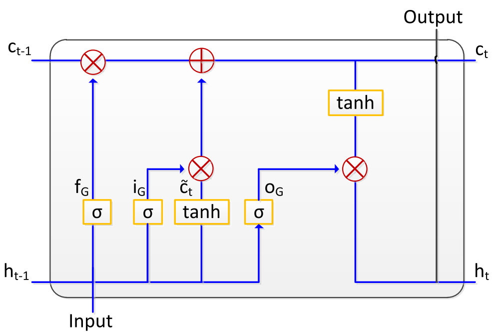

FIGURE 3. Structure of a LSTM cell.

2) GRU

GRU is a modified RNN and a variant of LSTM that it solves the vanishing/exploding gradient problem. Figure 4 shows the structure of a GRU NN. The structure of the GRU consists of a reset gate, an update gate, a memory unit, and a hidden state. The reset gate determines the meaning of the historical information in the previous hidden state and determines how much information needs to be discarded. Equation 4 shows the mathematical equation for updating the reset-gate. The update-gate determines the influence and helps in discarding specific information. Equation 5 shows the mathematical equation for updating the update gate. The training process of GRU is performed by backpropagation and gradient descent.

$$z_G^t = \sigma(\sum_j(W_z x_t) + \sum_j(U_z h_{t-1})) \tag{4}$$
$$r_G^t = \sigma(\sum_j(W_r x_t) + \sum_j(U_r h_{t-1})) \tag{5}$$

In Equation 5 and 4 x_t is the input series, h_{t-1} represents the previous hidden state, σ represents the activation function and W represents the parameters of the input variable.

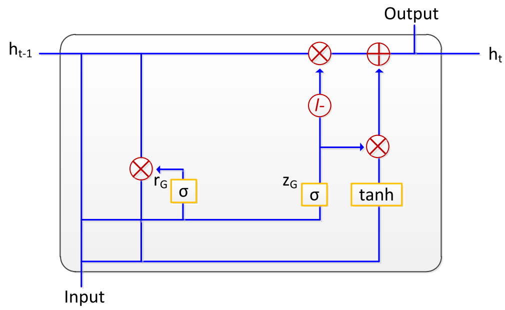

FIGURE 4. Structure of a GRU cell.

3) CNN

A CNN is designed specifically for handling grid-like structures of information, such as images. CNNs have found a wide variety of uses, including but not limited to image classification, time series analysis, video classification, NLP, crowd estimation, and ML. Several studies employing CNN in the field of price prediction have been presented, showcasing intriguing potential [21], [22]. These studies contribute to expanding options for optimizing scheduling BTM operating systems. The paper by Khan et al. [21] suggests an enhanced CNN for price forecasting and electricity load, demonstrating respectable forecasting performance. However, the enhanced CNN, despite its notable performance, appears to be similar to an ordinary CNN, and the specific distinctions are not explicitly explained, except for the use of 1-dimensional input. An alternative strategy suggested in [22] integrates GRU and CNN to produce probabilistic price predictions. Despite leveraging the strengths of both CNN and GRU, which enhances accuracy, the iterative computation process of GRU contributes to an overall increase in computational time costs.

4) GRNN

GRNN is a parallel radial basis function NN based on a one-pass algorithm, and does not require an iterative mechanism to compute the results. GRNN achieves satisfactory results in solving both regression and classification problems. Figure 5 shows the structure of a GRNN, which includes the following layers input, pattern, summation, and output layer. Complete details of GRNN can be found from [1]. Equation 6 represents the mathematical formulation of GRNN.

$$\bar{Y}(X) = E(y|X) = \frac{\sum_j^n (Y_j)[\exp -\frac{(X-X_j)^T(X-X_j)}{2\sigma^2}]}{\sum_j^n [\exp -\frac{(X-X_j)^T(X-X_j)}{2\sigma^2}]} \tag{6}$$

In Equation 6, $\bar{Y}(X)$ represents the weighted average, X represents the input, and X_j represents the corresponding learning sample at the j^{th} neuron. σ represents the smoothing function. It is the most critical parameter of GRNN as the forecasting performance of GRNN depends on σ. If the value of σ is too large, a large number of training samples are considered, and vice versa.

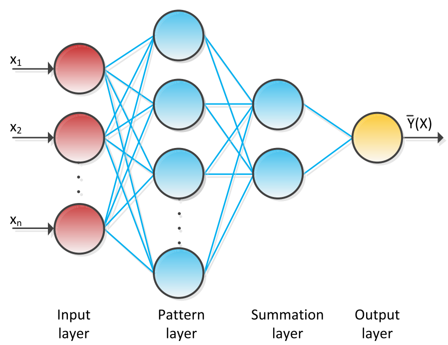

FIGURE 5. Architecture of a GRNN.

III. LOAD FORECASTING

Predicting load is essential for efficiently managing and balancing the demand for electricity and power generation. In broad terms, load forecasting involves predicting the anticipated load requirements by employing a systematic approach to define future potential loads based on sufficient quantitative information. This information is subsequently used to inform decisions related to system expansion. Figure 6 depicts the generic steps involved in load forecasting. In this section, recent studies dealing with electricity load forecasting are analyzed and discussed in detail. Table 3 summarizes the load forecasting methods while Table 4 presents the datasets used in those studies.

A. SHORT-TERM FORECASTING

1) HYBRID FORECASTING MODELS

An ARIMA-based load prediction model is developed in [23]. The load data was categorized into six clusters, determined by the hourly load distribution throughout the year. Subsequently, the ARIMA model was applied to forecast the electricity load within each cluster. The effectiveness of this model was validated through real-time experiments. The outcomes indicate that the suggested model demonstrates superior forecasting accuracy in comparison to ARIMA on its own. Based on the accurate forecasts, the management authorities have managed the electricity demand, especially during peak hours. The authors of [24] put forward a hybrid model designed for short-term load prediction, where they employ a stacked denoising auto-encoder (SDA) to refine features extracted from actual electricity load data. Afterward, SVR is fine-tuned to forecast the electricity load for the subsequent day. In a separate investigation detailed in [25], a forecasting model called CLSAF, relying on convolutional (LSTM, is created to improve the precision of short-term residential electricity load predictions. This model incorporates selected autoregressive features. Additionally, three strategies are introduced: the selection of autoregressive features, the choice of exogenous features, and the implementation of a ‘‘default’’ state to prevent overfitting. The experimental outcomes demonstrate the efficiency of the proposed method over its counterparts. In [26], another method for short-term residential electricity load forecasting is developed by fitting a Markov chain mixed distribution model (MCM). This study conducts one-step ahead load forecasting, and the approach is applied to real-time datasets gathered from the Australian power market. Moreover, persistence and quantile regression (QR) models are implemented as benchmark methods and the simulation results confirm the effectiveness of the proposed model. In [27], an improved version of EMD, namely sliding window EMD (SW-EMD), is developed along with a new feature selector (based on Pearson correlation) with the aim of maximizing relevance and reducing redundancy. Then, a hybrid prediction engine based on an improved Elman-NN (IENN) predicts load signal using an intelligent algorithm (metaheuristic-based shark smell optimization (SSO)) to optimize the weights of this prediction engine. Multiple real-time experiments were conducted to demonstrate the effectiveness of the proposed model.

2) ML-EMPOWERED METAHEURISTIC FORECASTING

Fractional ARIMA was used by the authors in [28] along with the modified cuckoo search algorithm for effective short-term energy demand forecasting. The fractional ARIMA model and the enhanced optimization method demonstrate reasonably good accuracy and efficacy in forecasting short-term power loads based on actual power consumption data. Particle swarm optimization (PSO) based multi-fractional brownian motion (FBM) is suggested in [29] for short-term power demand prediction based on the Hurst exponent. A study presented in [30] developed a hybrid model for electricity load forecasting based on metaheuristic-based genetic algorithm (GA) and DL models. In the proposed model, K-nearest neighbors (KNN) extract features from actual load data and then NSGA is used for optimizing the parameters of KNN. In the last step, DBN is employed for load prediction. In citepeng2021effective, IBSA-DRESN is developed, where IBSA is an improved backtracking search optimization (BSA) algorithm. Usually, optimization techniques are best in either exploration or exploitation. In this work, the authors update the BSA by balancing exploration and exploitation. For this purpose, adaptive mutation, niching, and round roulette selection are used. IBSA is used to optimize the parameters of DRESN, an echo state network with a double reservoir to improve its learning ability.

3) BAYESIAN-ENHANCED FORECASTING

For precise short-term power load prediction, the research outlined in [31] introduces a temporal attention-driven encoder-decoder network optimized through Bayesian methods. Built on an encoder-decoder structure using GRU, the model exhibits significant resilience in time series predictions. The inclusion of a temporal attention layer prioritizes key input data features, significantly enhancing load forecasting precision. Finally, to achieve optimal forecasts, the Bayesian optimization approach is employed to validate the hyperparameters of the proposed model. The authors

FIGURE 6. Generic steps of electricity price and demand forecasting.

conduct several experiments on real-time data to confirm the effectiveness of the proposed prediction model over similar approaches.

4) MULTI-STAGE FORECASTING

In [32], the authors present a multi-stage electricity load forecasting model. The approach involves forecasting the electricity load by integrating the forecasted results of the load and the error series. The original data series is partitioned into three segments. The first part is employed for load forecasting, while the remaining parts are utilized for fault series generation and forecasting. To predict the electricity load, the historical series is initially divided into a series of Intrinsic Mode Functions (IMFs) and a residual using Complete Ensemble Empirical Mode Decomposition (CEEMD). Each component is then individually predicted using an enhanced backpropagation neural network. For error series generation, the difference between the actual and predicted forecast values of the second and third sets is computed. After generating the error series, the application of VMD is employed to break down the series into a set of Intrinsic Mode Functions (IMFs) and residuals. Subsequently, each component is predicted using PSO-BPNN. The forecast results of each component and the residual are then summed to obtain the forecast result of the fault series.

B. LONG-TERM FORECASTING

Long-term forecasting of electricity demand plays a critical role for planners and utilities in power generation, expansion planning, and grid development. Overestimation of future electricity demand leads to wastage of electricity and other resources, while underestimation of long-term electricity demand leads to insufficient demand and generation. Thus, there is an exigent and timely need for accurate long-term electricity forecasts in order to use electricity efficiently and avoid blackouts or other losses.

1) HYBRID FORECASTING

A study presented in [33] proposes a method based on a decomposition model for long-term electricity load forecasting. The proposed model uses Spain as a case study for forecasting electricity load until 2030, with electricity consumption data obtained from the Spanish Energy Agency (1970-2012). They also perform several simulations and the results show the effectiveness of the proposed model in terms of accurate electricity forecasting. In this study, a new forecasting strategy is developed using a temporal disaggregation technique that improves existing methods and can incorporate long and short-term features [34]. The performance of this method is compared with a nonlinear autoregressive NN with exogenous inputs in predicting the electricity load in Spain. Simulation results confirm that the newly proposed approach is adaptable enough to be used in a variety of scenarios based on different assumptions about short-term projections and long-term trends. A study presented in [35] proposes long-term electricity load forecasting using a generalized regression NN (GRNN). The GRNN method performs accurate prediction between input and target vectors with minimum error rate [36]. The study also conducts several experiments on real-time datasets and compares the results with benchmark approaches, i.e., cascade forward backpropagation-NN (CFBNN) and feed-forward backpropagation-NN (FFBNN). Another study introduces the utilization of the multiplicative error model (MEM) for long-term power load prediction [37]. Real-world data obtained from a US regional transmission operator was used for the experiments. Directional accuracy and out-of-sample forecasting results during the great recession of 2008 demonstrate the superiority of accounting for volatility.

2) BAYESIAN-ENHANCED FORECASTING

For long-term power load prediction of a specific industrial area while considering energy efficiency scenarios, a novel approach that merges the bottom-up method with hierarchical linear methods is proposed [38]. Moreover, Bayesian inference is used to estimate the model parameters as well as to incorporate uncertainty into the model predictions. A fuzzy-based Bayesian model is developed in [39]. The proposed model uses an econometric methodology to increase the accuracy and reliability of the expert prediction. The fuzzy relation matrix, fuzzy Bayesian formulated prior prediction are three main components of the newly developed model. To address long-term uncertainties, leveraging prior predictions involves amalgamating the benefits of expert experience with other time-based approaches from a probabilistic standpoint. The authors also conduct experiments with real-time data to confirm the effectiveness of the proposed model. The experimental outcome beats compared models, i.e., regression, ARIMA, ANN, exponential smoothing (ES), grey model (GM), and expert prediction (EP).

IV. PRICE FORECASTING

Ever since the deregulation of electricity markets, precise and effective energy price forecasting has emerged as a critical need. The complex dynamics of energy prices, marked by sudden spikes, seasonal variations, and significant volatility, have led to the development of multiple electricity price forecasting models. Despite these efforts, no single model consistently outperforms others due to the challenging nature of these prices. A discrete incremental approach based on FBM was presented for ELF by Deng et al. in [57]. The discrete incremental approach for ELFÂ discretizes the stochastic differential equation triggered by FBM. Using maximum probability estimation, other discrete incremental modeling parameters are assessed. By using price forecasting models, electricity consumers can manage their demand in the low price hours to get the maximum benefit. There are several studies on electricity price forecasting that use DL, ML, or hybrid models that include DL / ML along with the heuristic approaches. In this section, recent studies dealing with electricity load forecasting are analyzed and discussed in detail. Table 5 summarizes the price forecasting methods while Table 6 presents the datasets used in those studies. Furthermore, Figures 7 and 8 offer a visual comparison of several electricity load forecasting approaches (in terms of RMSE and MAE) implemented on two datasets.

1) ENSEMBLE LEARNING

In the study presented in [58], a project is introduced that suggests an electricity price forecasting approach utilizing a heterogeneous ensemble learning technique and a self-adaptive decomposition method. In the pre-processing step, hyperparameter tuning of the complementary empirical ensemble mode decomposition is carried out using the Coyote algorithm, a metaheuristic approach. Subsequently, three approaches SVR, ELM, and GBM are employed for price prediction.

Yang et al. developed an adaptive hybrid method for multi-step electricity price prediction [59]. The proposed adaptive price forecasting method combines the best features of an improved multi-objective sine-cosine algorithm (IMOSCA), variational mode decomposition (VMD) and regularized ELM (RELM) to enhance the performance of deterministic forecasting. They also claimed that, unlike previous studies on price forecasting, the proposed method does not require future information for price forecasting. In the proposed method (VMD-IMOSCA-RELM), VMD is used as preprocessing, since it is a decomposition approach and RELM optimized by IMOSCA is used to predict each component with better stability and accuracy. Several simulations

TABLE 3. Summary of load prediction approaches.

Ref.	Method(s)	Compared Method(s)	Location	Outcome/observation(s)
[23]	Hybrid of k-means clust. and ARIMA	ARIMA	Chubu University Japan	This work proposes a hybrid model that includes k-means clustering and ARIMA models to predict the electricity load of buildings. Several experiments on real-time data are performed to validate the performance of the proposed method [MAPE is 5.1; and ARIMA: 16.1]
[24]	Hybrid of SSA and SVR	SVR and ANN	California, New York, and Florida	This study deals with short-term electricity load forecasting by developing a hybrid model that combines SSA and SVR approaches. The authors also perform multiple experiments on real-time data from four different locations. The results from experiments confirm the effectiveness of the proposed model over its counterparts [MAPE (for California) is 2.67; SVR: 4.33, and ANN: 4.02]
[30]	NSGA-II-KNN-DBN	NSGA-II-KNN-CNN, DBN, and CNN	Australia	The proposed model combines the best features of one metaheuristic (NSGA-II) and two DL models (KNN and DBN) for electricity load forecasting. Several experiments are also performed on real-time data and results confirm the productiveness of the proposed model over counterparts [MAPE of the proposed method is 5.91; NSGA-II-KNN-CNN: 5.94, DBN: 7.66, and CNN: 8.25]
[26]	MCM model	QR and Persistence	Sydney, Australia	The proposed MCM model is implemented on real-time data taken from Sydney to affirm its productivity. The results from experiments show the higher performance of the proposed method over compared approaches [reliability MAE is 0.02; QR: 0.06, and Persistence: 0.07]
[31]	GRU-based encoder-decoder	Dense, RNN, LSTM, GRU, LstmSeq, GruSeq	Sydney, Australia	The article presents a GRU-based model for electricity load forecasting that is tested on real-time data obtained from the electricity market of the USA. [MAE of proposed method is 458.923; Dense: 504.96, RNN: 512.61, LSTM: 498.83, GRU: 487.91, LstmSeq: 479.05, GruSeq: 478.56, LstmSeqAtt: 475.99, GruSeqAtt: 470.25, and BLstmSeqAtt: 465.48]
[25]	CLSAF	Persistence and ConvLSTM	New York	The proposed method CLSAF and compared approaches are implemented on real-time data to validate the performance of the proposed approach. Results show the higher accuracy of the proposed method [MAPE of the proposed method is 9.8; Persistence: 11.2, ConvLSTM: 10.4]
[27]	EMD-IENN-SSO	ARIMA, SVR, BPNN, RBFNN, WT+BPNN, WT+RBFNN, WT+MI-MI+NN	Ardabil, Iran	This study proposes a hybrid forecast engine that is based on EMD, IENN, Pearson's correlation, and SSO metaheuristic. To check the performance of the proposed method, several experiments are performed on real-time data and the results show efficacy of the proposed model [MAPE of the proposed method is 3.02; ARIMA: 2074, SVR: 15.46, BPNN: 9.48, RBFNN: 8.40, WT+BPNN: 7.43, WT+RBFNN: 6.32, and WT+MI-MI+NN: 4.59]
[35]	GRNN	CFBNN and FF-BNN	Indonesia	This work develops a GRNN-based long-term load forecasting method that uses real-time datasets from Indonesia for experiments. Results affirm that the proposed method has higher performance over its counterparts [MAPE is 0.00; CFBNN: 0.024, and FFBNN: 0.001]
[39]	EP-Fuzzy Bayesian theory	Regression, ARMA, ANN, ES, GM, and EP	China	This article presents a long-term electricity forecasting model based on EP-Fuzyy Bayesian theory and to affirm its productivity, the study shows several experiments and results demonstrate that the newly proposed model has better reliability, flexibility, and accuracy. [MAPE (2010–2016) is 2.35; Regression: 8.77, ARMA: 3.46, ANN: 2.51, ES: 15.24, GM: 5.77, and EP: 5.17]
[33]	Index decomposition	–	Spain	The study develops decomposition based forecasting method that also considers various factors, i.e., GDP, relative energy prices, increasing use of air conditioning, etc.
[38]	Hybrid of bottom-up + hierarchical models	Deterministic approach	Brazil	This paper develops a hybrid forecasting model for industrial area, where several experiments are performed on the pulp and paper industry in Brazil. The results from simulations affirm that the proposed model has higher performance over the compared method [MAPE is 2% lower than the compared approach]
[34]	Temporal dis-aggregation	Non-linear auto-regressive NN	Spain	The proposed temporal dis-aggregation-based forecasting model is implemented on real-time data obtained from the electricity department of Spain. The proposed model shows higher accuracy over counterparts in terms of MAPE [MAPE 3.02% lower than non-linear auto-regressive NN]
[40]	Hybrid of SVM and ARIMA	MLP and ARIMA	Turkey	This study proposes a hybrid algorithm for long-term electricity load forecasting in Turkey. The proposed model is also applied to net electricity consumption till 2022. Several experiments are performed on real-time data, which show that the proposed model beats compared approaches in terms of higher accuracy [MAPE is 0.22; MLR: 9.85, and ARIMA: 0.68]
[32]	Combined of CEEMD-PSO-BPNN and VMD-PSO-BPNN.	BPNN, PSO-BPNN, VMD-PSO-BPNN, ARIMA	USA and Canada	The study proposes a hybrid algorithm for multi-step electricity forecasting. The proposed model uses an error correction strategy to improve the forecasting results and perform several experiments to forecast one, four, six, and eight-step ahead electricity load using the real time data of PJM and Ontario electricity markets. The results of the experiments clearly reveal the superiority of the proposed model over its counterparts in terms of low error values. [lowest MAPE for the step ahead is 0.157, RMSE is 30.949, MAE is 24.360]
[41]	ABPA	BPA, Adj. BPA, Radial basis function NN	Republic of Iraq	The study investigates the model behavior on training and future data. The proposed algorithm is implemented on real time data obtained from the electricity department of the Republic of Iraq. The performance metric shows the superiority of the proposed algorithm over its counterparts.
[42]	IBSA-DRESN	SVR, ESN, RF, BPNN, LSTM, GA-DRESN, DE-DRESN, BSA-DRESN	USA	This study proposes a hybrid algorithm for short-term electricity load forecasting. The authors performed several experiments to train, test, and validate the effectiveness of the presented approach. The results from simulations affirm the higher performance over compared methods. [Mape of the proposed method is 1.3 in one step ahead load forecast and 4.03 in day ahead load forecast.]

TABLE 4. Summary of datasets used for electricity load forecasting.

Ref.	Origin of data	Details about data	Horizon	Time period
[23]	Building energy management system of Chubu University, Japan	The actual dataset contains 30-minute intervals and converted to hourly interval data for one year, and total data points are 8760. [This data is publicly not available]	Hourly	One year (2017–2018)
[24]	Energy and climate departments of California, Los Angeles, New York, and Florida, US	The actual dataset contains one-year data from four different locations. [This data is publicly not available]	Hourly	One year (August 2015–August 2016)
[30]	Five regions of Australia, i.e, NSW, Queensland, South Australia, Victoria, and Western Australia	The real data includes, with 30-minute intervals, total number of data points 315,600; some datasets have smaller data points; however, it is assumed to be same as 325, 600 [43]	30 minutes	18 years (January 1999–December 2016)
[26]	Sydney metropolitan area, Australia	The data is publicly available and contain data of 300 residential consumers; after cleaning of data, it remains for 54 energy consumers and this chooses data of some customers randomly, i.e., consumer numbers 69, 74, 157, 211, and 274 [44], [45]	30 minutes	3 years (July 01, 2010–June 30, 2013)
[31]	American electric power market	The data contains a total of 26,280 data points for three years electricity load that is divided into training and testing data with the ratio of 70% and 30% [46]	Hourly	3 years (January 01, 2017–January 01, 2020)
[25]	National Oceanic and Atmospheric Association, New York	The dataset includes data of 59 individual apartments for three time periods (different seasons) in 2019 [47]	Hourly	3 time periods of 2019, i.e., January 07–February 03, April 01–April 28, and July 15–August 11
[27]	Load demand of three business centers, located in Ardabil, Iran	This data includes load demands of three business centers for one year 2015 to 2016. [This data is publicly not available]	Hourly	One year (August 10, 2915–August 10, 2016)
[35]	Indonesian electricity market	The dataset contains data for nine years from 2000-2008 and the proposed method is implemented to predict for nine years from 2009-2019. [This data is publicly not available]	–	9 years (2000–2008)
[39]	International Energy Agency, China	The dataset contains data for twenty-nine years from 1980-2009, and the newly developed model is implemented to predict for twenty years from 2010–2030. The dataset includes per-capita energy consumption, gross domestic product, urbanization rate, electricity intensity, and industrial structure [48]	–	9 years (2000–2008)
[33]	Red Electrica de Espana S.A	The database comprises nearly 42 years of data, encompassing a breakdown of 22 non-residential uses along with residential use throughout the entire period.	–	42 years (1970–2012)
[38]	Brazilian Institute of Geography and Statistics	The complete dataset contains annual data of the Brazilian industrial sector ranging from 1995 to 2016 and the dataset explanations are given in [49]	–	22 years (1995–2016)
[34]	Red Electrica de Espana S.A	The dataset contains the period 1996–2014, where 6900 observation per day are included [50]	Hourly	19 years (1996–2014)
[40]	Electricity department of Turkey	The dataset is obtained from 6 different sources, i.e., historical population data from 1970–2017 [51], electricity import and export amounts [52], installed capacity and gross electricity generation data [53], [54], and Turkey's net electricity consumption data [55]. From whole data, 85%, 11%, and 4% of data are used for model training, testing, and validation, respectively	–	47 years (1970–2017)
[32]	PJM electricity market and Ontario Power System (IESO)	The PJM electricity market consists of historical load data of thirteen states and the District of California whereas, IESO comprises of electricity load data of Ontario (Province of Canada). [56]	Hourly	About 3 months.
[41]	Electricity department of the Republic of Iraq	This data set includes monthly electricity load demand from 2011 to 2020. The data contains electricity load consumption of industrial, residential, governmental and agriculture sectors. [This data is publicly not available]		
[42]	North-America and PJM electricity market	The PJM electricity market consists of historical load data of thirteen states and the District of California. The authors also considered time and temperature information associated with these datasets. [56]	Hourly	North America (November 1 1989 to June 30, 1990, November 1 1990 to June 30, 1991). PJM (January 1 2011 to December 31, 2011.)

with two different real-time datasets are also run to validate the performance of the adaptive VMD-IMOSCA-RELM model. The results show higher performance for multi-step forecasting compared to the benchmark approaches, i.e., (RELM, MOSCA RELM, IMOSCA-RELM, and adaptive VMD-RELM).

2) ML EMPOWERED METAHEURISTIC FORECASTING

In a study presented in [60], an electricity pricing prediction model was proposed based on a multi-objective (MO) grey wolf optimizer (GWO) and a dual decomposition strategy. The proposed method, namely the improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN)- VMD-MOGWO-ELMAN NN (ICEEMDAN-VMD-MOGWO-ENN), consists of four modules: pre-processing, optimization, prediction and evaluation. The MO-GWO is adapted to provide simultaneous improvements in stability and accuracy. The dual decomposition strategy reduces the drawbacks of the individual decomposition method by improving the prediction performance of the proposed system. Finally, an evaluation module is incorporated to confirm the proposed system's productivity. In terms of both stability and accuracy, the simulation results demonstrate that the proposed system surpasses the performance of the compared methods. In [61], Wang et al. developed a price prediction algorithm using a hybrid of ML and evolutionary methods, namely hybrid selection, extraction and classification (HSEC). To eliminate the redundancy of features, they proposed a hybrid of random forest and relief F methods, and then the integration of principal component analysis and kernel function was utilized for feature extraction. Finally, a hybrid of support vector machine (SVM) and differential evolution (DE) is developed for price prediction classification.

Zhang et al. developed a hybrid feature selection (HFS) approach, namely (HFS-CSS), based on cuckoo search metaheuristic, SVM, and singular spectrum analysis (SSA) methods for short-term electricity pricing forecast [62]. In the first step, they use SSA to extract appropriate parameters from the time series of electricity price; furthermore, cuckoo search is also used to generate optimal features to construct an SVM-based short-term EPF model. Simulations are also used to validate the proposed method's performance. The data is acquired from the electricity market in New South Wales (NSW), Australia.

A study [63] combines the best features of VMD, SAPSO metaheuristic, SARIMA, and DBN. In this method, the SAPSO-optimised VMD adaptively extracts various components from the current electricity price data. Then, irregular features are extracted from the price data by the DBN which is also optimised by SAPSO. Moreover, the proposed hybrid adaptive method is able to adjust its parameters based on the behavior of the input data. The authors also perform several simulations to confirm the effectiveness of the method compared to its counterparts, and the results show its effectiveness. Another work presented in [64] also proposed a multi-step electricity price forecasting approach for energy market management. In this work, a new outlier robust hybrid scheme for energy forecasting is developed based on outlier robust ELM (ORELM) and three different algorithms. After adopting a metaheuristic-based chaotic sine-cosine method (CSC) for preprocessing, a novel feature selector is proposed to build the ideal features for energy price forecasting. Several experiments were conducted using real-time price data from the electricity market in Singapore and Australia to confirm the productivity of the proposed hybrid ORELM-based algorithm. The results confirm that the proposed method is more powerful than its counterparts.

3) HYBRID FORECASTING

The research in [65] introduces a multilayer gated recurrent unit (GRU) for electricity price forecasting, utilizing real-time pricing data from the Turkish day-ahead market. Through various experiments comparing the performance to existing forecasting methods such as Naive, Markov, CNN, ARIMA, LSTM, and ANN, the GRU scheme demonstrates enhanced productivity based on MAE.

In a different study, [66] proposes a hybrid approach for electricity price prediction, combining wavelet transform (WT), kernel ELM (KELM) with self-adaptive particle swarm optimization (SAPSO), and an auto-regressive moving average (ARMA). This method utilizes SAPSO to determine optimal kernel parameters for KELM. The ARMA model forecasts stationary series, while the SAPSO-KELM model predicts non-stationary series. Multiple simulations validate the enhanced accuracy of the proposed hybrid method compared to existing models.

A DNN-based hybrid model for short-term electricity price prediction is developed in [67]. The developed hybrid model, namely SEPNet, combines the best features of three algorithms, namely, CNN, VMD, and GRU. To validate the performance of the proposed model, they perform experiments on data from four different seasons. The proposed method shows efficacy over counterparts, i.e., LSTM, CNN, VMD-CNN, BP, and VMD-ELMAN. Yang et al. [68] develop a hybrid deep learning model to select the efficient forecasting model in short-term electricity price forecasting. This model combines the best features of three algorithms, i.e., VMD, ELM and Sine Cosine Algorithm (SCA). In this work, the VMD is used to decompose the non-stationary and non-linear electricity price series. Afterward, an updated Chaotic CSA (CSCA) algorithm is used to optimize the parameters of ELM. In this work, The leave-one-out optimization strategy is used to tune the parameters of the ELM. The optimal model is selected using an optimal model selection index by considering MSE, RMSE, MAPE, Theil's inequality coefficient, and Index of Agreement (IA). The authors of [69] also developed a hybrid method to forecast the electricity price that combines the best features of six individual methods, including metaheuristics. The SSA method reduces the noise from real data; then, Jordan NN (JNN), echo state network (ESN), and least square SVM (LS-SVM) are adapted to intermediate forecasting; two metaheuristics PSO and simulated annealing are employed for parameters optimization. In order to affirm the productiveness of this hybrid model, several simulations have been performed and results affirm its efficacy over individual approaches, i.e., JNN, ESN, and LSSVM.

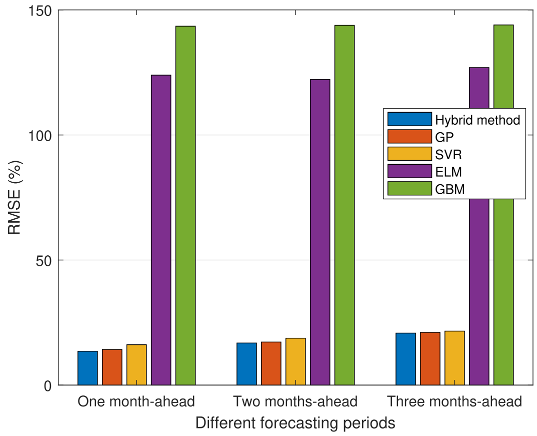

FIGURE 7. Comparison of several electricity price forecasting approaches (in terms of RMSE) implemented on the same dataset [58].

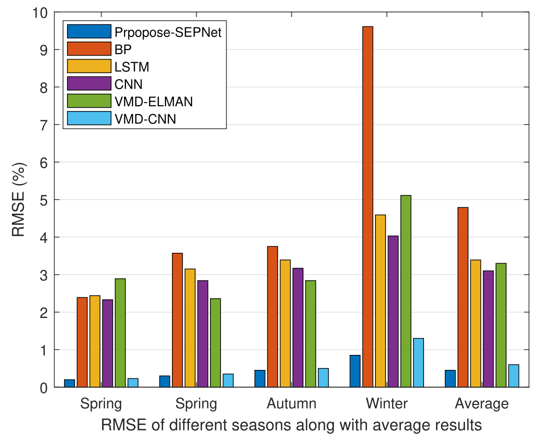

FIGURE 8. Comparison of several electricity price forecasting approaches (in terms of RMSE) implemented on the same dataset [67].

4) MULTI-STAGE FORECASTING

Khan et al. [70] proposed a multi-stage (three-stage) short-term electricity pricing prediction method. This EEMD-ELM model first divides the electricity price series into a limited number of IMFs. The authors used a hit-and-trial method to determine the number of IMFs. Afterward, ELM is used to forecast the individual, non-stationary series. Lastly, all the forecasting results of the individual series are merged to form the overall results. The proposed model showcases high performance over benchmark models, i.e., RNN, SVR, MLP, and ELM. The authors analyzed the results by investigating the performance of the model over three data sets of the Australian electricity market.

Shi et al. [71] presented a Two-stage Electricity Price Forecasting model (TSEP) to predict the occurrences of spikes in day-ahead price forecasting. In the first stage, historical electricity price data is analyzed to classify the price data into normal prices and spikes. In the second stage, variance stabilization transformation and DNN are utilized to forecast the occurrence of spikes. As the occurrence of spikes in electricity price data is not very common, to improve the forecasting accuracy, this work increases the number of spikes intentionally by using the Borderline-Synthetic Minority Oversampling Technique (SMOTE). Borderline-SMOTE is an updated SMOTE. SMOTE uses a K-nearest neighbor algorithm to randomly generate new data samples of the minor class. These samples are merged with the historical price data to remove the class imbalance problem.

V. DISCUSSION AND OBSERVATIONS

In this study, we examine recent research focused on electricity load and price forecasting for efficient energy management. In the majority of these studies, researchers have put forward solutions employing ML/ DL methodologies. Each approach comes with its own strengths and weaknesses when addressing the ELF and EPF, making it challenging to identify the accurate model. This difficulty arises because there is no standardized benchmark dataset, and many researchers utilize their proprietary data, often generated randomly. Additionally, the research codes are typically not accessible online, further complicating the comparison of algorithm performance.

Nonetheless, based on the studies we have examined, we can draw several noteworthy observations concerning ELF and EPF. A significant proportion of these studies employ some basic ML or DL models for predicting electricity load and prices. Furthermore, most studies only deal with residential load prediction; however, the industrial load has a huge impact on the electric grid and energy management systems. Also, electricity load prediction for the commercial sector is missed, even if it is a big energy consumer, especially day time. Additionally, nearly all these studies incorporate mathematical models and various forms of linear programming to solve the prediction problem in the energy domain, which proves to be efficient in such types of problems. Finally, based on the performance analysis of various models, we found that hybrid models are more efficient than non-hybrid models. Typically, researchers combine ML/DL models with metaheuristic approaches to enhance prediction accuracy, and this review highlights that approximately 15% of the examined models fall into the hybrid category for EPF and ELF prediction.

Overall, it is crucial to emphasize that a limited number of studies have ventured into the development of models with the capability to self-adapt, self-evolve, and self-tune in order to address complex scenarios [1]. This underscores the ongoing necessity to pioneer such methodologies to contend with the diverse facets of EPF and ELF prediction. These emerging methods should not only harness the power of Explainable AI but also explore techniques such as growing and pruning models, along with leveraging transfer learning, to further advance the state of the art in this field.

VI. PERFORMANCE METRICS AND STATISTICAL ANALYSIS

In this section, we discuss the common performance metrics and statistical tests that were performed in the recent literature.

TABLE 5. Summary of methods used for electricity price forecasting.

Ref.	Method(s)	Compared Method(s)	Location	Outcome/observation(s)
[65]	Multi-layer GRU	Markov, Naive, ARIMA, CNN, ANN, and LSTM	Turkey	It is observed from simulation results that the proposed multi-layer based GRU has higher performance for electricity price foresting in terms of MAE that is 5.71. On the other hand, MAE for Markov, Naive, ARIMA, CNN, ANN, and LSTM are 8.04, 7.95, 7.89, 7.29, 9.82, 6.37, and 5.91, respectively.
[61]	HSEC	Decision tree, Naive Bayes, SVM, and DE-SVM	England	Simulation results demonstrate that the proposed hybrid framework is an efficient method for electricity price forecasting. The proposed method achieves more than 90% accuracy that is a higher percentage as compared to benchmark approaches.
[58]	Hybrid of metaheuristic and ML approaches	GP, SVR, ELM, and GBM	Brazil	The authors of this work propose a hybrid of metaheuristic and ML models to forecast electricity prices in the Brazilian market. Simulation results indicate that the proposed method attains superior performance in terms of minimizing errors. [RMSE of the proposed method: 13.55; GP: 14.27, SVR: 16.17, ELM: 123.92, and GBM: 143.48]
[59]	Hybrid adaptive VMD-IMOSCA-RELM	RELM, MOSCA RELM, IMOSCA-RELM, and Adaptive VMD-RELM	Two study area: Queensland & NSW, Australia	In this study, a multi-step forecasting model is constructed, encompassing one-step, two-step, and four-step predictions, through the introduction of an adaptive VMD-IMOSCA-RELM method. Extensive simulations are conducted using two datasets sourced from distinct areas of Australia. The outcomes reveal that the proposed method exhibits superior performance, particularly in terms of minimizing errors. [MAE of the proposed method (Data A and one-step forecasting): 5.05; RELM: 37.01, MOSCA-RELM: 37.12, and AVMD-RELM: 5.25]
[64]	Hybrid	Persistence, ELM, RELM, ORELM, and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN-ORELM)	Two study area: Singapore and Australia	The authors of this paper propose a hybrid algorithm for electricity price forecasting. Experimental results indicate the effectiveness of the proposed method compared to alternative approaches. [MAE of proposed method (Data A and one-step forecasting): 0.76; Persistence: 7.571, ELM: 7.12, RELM: 3.66, ORELM: 0.98, and CEEMDAN-ORELM: 3.85]
[62]	HFS-CSS	SARIMA, LASSO, TBATS, MI-SVM, RESVM, ANN, and RANN	NSW, Australia	This work proposes a hybrid algorithm based on cuckoo search and DL approaches. They tested their proposed model along with benchmark approaches on real-time data taken from the electricity market of NSW. [MAPE of proposed method (for the month of March): 1.61; SARIMA: 3.65, TBATS: 2.38, LASSO: 2.76, SVM: 2.35, MI-SVM: 2.37, RESVM: 2.40, ANN: 2.47, RANN: 2.69, MI-ANN: 2.51, and RENN: 2.52]
[60]	ICEEMDAN-VMD-MOGWO-ENN	ARIMA, GRNN, ENN	NSW, Australia	The proposed ICEEMDAN-VMD-MOGWO-ENN hybrid method has higher performance over counterparts in term of forecasting effectiveness [Forecast accuracy of the proposed method: is 0.97; ARIMA: 0.90, GRNN: 0.89, and ENN: 0.91]
[66]	WT-ARMA-SAPSO-KELM	KELM, ARMA, W-ARMA-BP, and W-ARMA-LSSVM	Australia and Spanish	The proposed method and compared methods are implemented on real-time data taken from Pennsylvania-New Jersey-Maryland (PJM), Australian and Spanish electricity markets and results show the effectiveness of newly developed method [MAPE of proposed method (Spanish market 26-02-2009): is 5.87; KELM: 10.24, ARMA: 21.11, W-ARMA-BP: 15.33, and W-ARMA-LSSVM: 12.59]
[63]	VMD-SAPSO-SARIMA-DBN	LSSVM, Wavelet NN (WNN), ARIMA, SAA, IAA, and MAH	Australia and Spanish	This work develops a hybrid method based on DL and metaheuristic methods and its performance is compared with state-of-the-art methods. Results demonstrate the efficacy of proposed model [MAE of proposed model (Spanish market Feb 12-18): is 0.39; LSSVM: 4.17, WNN: 2.09, ARIMA: 2.20, SAA: 1.23, IAA: 1.11, and MAH: 1.16]
[67]	SEPNet	LSTM, CNN, VMD-CNN, BP, and VMD-ELMAN	New York, US	The hybrid model proposed outperforms other compared methods, demonstrating superior accuracy [RMSE of proposed SEPNet model (spring season): is 0.20; BP: 2.39, LSTM: 2.44, CNN: 2.33, VMD-ELMA: 2.89, and VMD-CNN: 0.23]
[69]	Hybrid of ML models and meta-heuristics	JNN, ESN, and LSSVM	Australia electricity market	In this study, a hybrid model is formulated by amalgamating six existing models, encompassing both machine learning and metaheuristic methods, for short-term electricity price forecasting. Simulation results distinctly indicate that the proposed method exhibits superior performance compared to individual approaches [The MAPE of the proposed method is 6.57; JNN: 7.37, ESN: 11.51, and LSSVM: 7.99]
[70]	EEMD-ELM	RNN, SVR, MLP, ELM	Australia electricity market	This study develops a three stage forecasting model. i.e.,First EEMD method is employed to decompose the electricity price series. Afterwards, ELM is employed to forecast individual series. Lastly, the forecasting results are combined to present the superiority of the model. [The MAPE of the]
[68]	VMD-CSCA-ELM	CSCA-ELM, EMD-CSCA-ELM, CEEMD-CSCA-ELM	Electricity market of Australia	This study develops a hybrid forecasting model based on DL and a metaheuristic approach. Results demonstrate the superiority of the developed model in terms of MAPE, MAE, RMSE, Index of agreement, and inequality coefficient.
[71]	TSEP (SMOTE+VST+ANN)	DNN, SVM, Borderline SMOTE-SVM	Austrian Energy Exchange, ENTSOE	This study develops a two-stage price forecasting model by classifying the electricity price data as spike and normal price. The efficiency of the presented model is shown by outperforming its counterparts in terms of F1 score, sMAPE, and MAE.

TABLE 6. Summary of datasets used for electricity price forecasting.

Ref.	Origin of data	Detail	Horizon	Time period
[65]	Turkish day ahead market, Turkey	The dataset consists of hourly-based data for three years [72]	Hourly	Three years (January 01, 2013–December 31, 2015)
[61]	ISO New England Control Area	The dataset 50,000 real-time hourly data instances of electricity price for five years. [73]	Hourly	Five years (January 01, 2010–December 31, 2015)
[58]	Brazil's commercial and industrial energy price data	The complete dataset contains observation of 289 months that is divided into 70% for training and 30% for testing [74]	Hourly	289 months (April 1996–December 2019)
[59]	Electricity market of Australia	Both datasets contain 1440 instances for thirty days, where data of 25 days is used for training and remaining for testing [43]	30 minutes	one month (June 01, 2016–June 30, 2016)
[64]	Electricity markets of Singapore and Australia	This study uses 6 datasets that contains data, 48 data points per day, for thirty days, where data of 25 days is used for training and remaining for testing [43] [75]	30 minutes	Four months based on different seasons: December 2016, April 2017, July 2017, and November 2017.
[62]	Electricity market of NSW, Australia	This study uses datasets of four seasons (summer, winter, spring, and autumn), 48 data points per day. Data for thirty days is used for each season and data of 20 days is used for training and remaining for testing [43]	30 minutes	Four months of 2013 based on different seasons
[60]	Electricity market of NSW, Australia	This study generated random data for four seasons that includes 912 total data points for 19 days and next data of 12 days is used to forecast the data for one day [43]	30 minutes	Not given, as they generate random data
[66]	Electricity markets of Australia and Spain	This study uses data from two markets for the years of 2004 and 2006, where data of 29/ 30 days of each month is used for training and the data of last day is used for validation [76]	30 minutes	Years of 2004 and 2006
[63]	PJM, Spanish, and Australian Electricity markets	This study uses data from three markets for the year of 2018, where 80% data is used for training and 20% of data is utilized for validation [72]	Hourly	2018
[67]	Electricity price data of New York, US	The work uses data of four years taken from the electricity market of New York, US; where the data of three years (2015-2017) is used for training and the data of last year is employed for testing [77]	Hourly	2015-2018
[69]	Electricity market of NSW, Australia	The work uses data of 20 weeks (January 31, 2011 to July 04, 2011); where, the first 19 weeks are used for model training and the last one week is adapted for model testing [72]	30 minutes	January 31, 2011 to July 04, 2011
[70]	Electricity market of NSW, Vic and QLD, Australia	The works uses data of three months (January 2018 to March 2018); where, any eight seven weeks data can be used to for model training and the remaining one week is employed for testing. [72]	Half hourly	January 1, 2018 to March 31, 2018
[68]	Electricity market of NSW, QLD, and Singapore	This study uses data from four markets, where the data of 25 days is used for training and the data of the last 5 days is utilized for testing [76] [75]	Half hourly	January 2018, April 2018 and November 2019
[71]	Energy exchange Austria	This study uses electricity load data and price data from Energy Exchange Austria and day ahead wind and solar forecast data from ENTSOE [78]	Hourly	January 02, 2012 to September 21, 2019 and September 22, 2016 to September 21, 2019

A. PERFORMANCE METRICS

Based on an extensive literature review, there is no single criterion for evaluating forecasting models. However, to better assess the accuracy of forecasting models, a number of performance indicators have been used in the literature to determine which model is more appropriate. Since these metrics represent a summary of the error distribution, it is imperative to select the most appropriate metrics to evaluate the accuracy of the forecasting models. For example, when dealing with outliers, the RMSE is more sensitive than the MAE. Similarly, Theil's coefficient of inequality is useful to evaluate the generalizability of the forecasting models. Table 9 provides an overview of the most commonly used performance measures. Here, F_i denotes the i^{th} predicted value, F_{avg} denotes the average predicted value, A_i denotes the i^{th} actual value, A denotes the average value in the dataset, and N denotes the total number of instances in the test dataset.

B. STATISTICAL SIGNIFICANCE

In electricity load and price forecasting, two or more forecast series are often analyzed to determine the superiority of one series over another. Generally, performance criteria such as MAE, MAPE, etc. are used to evaluate the best forecasting model. However, these performance criteria say nothing about the statistical significance of the results provided by a prediction model. Statistical significance means that the predictive accuracy of a model is not due to sampling error or chance. A number of tests are available to assess statistical significance, e.g., two-tailed test, the Wilcoxon rank test, etc., as can be seen in Tables 7 and 8, which list statistical tests and metrics used in electricity load and price forecasting studies, respectively. However, in this section, we focus only on the Die-bold Mariano (DM). As can be seen from Table 8, DM is the most commonly used test for electricity load and price forecasting. The main advantage of DM is that it accounts for sampling variability in average losses. Generally, the test is performed at a 95% significance level. The null hypothesis for the DM test states that the competing forecasting models have the same forecasting ability, whereas according to an alternative hypothesis, the forecasting ability of the competing models is different. If f_i and f_j are the two forecasts and γ_k denotes the autocovariance. The DM test can be represented as follows:

$$DM = \frac{1}{\sqrt{\frac{\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k}{n}}} \tag{7}$$

VII. CURRENT CHALLENGES AND FUTURE RESEARCH DIRECTIONS

In this section, we highlight the current challenges and future research opportunities related to DL / ML and electricity load/price forecasting in smart grids. A pictorial presentation can be seen in Figure 9.

A. ENERGY BIG DATA ANALYTICS

Nowadays, Big Data analysis in the energy field is one of the most important research areas to which the research community must pay special attention. With the advent of wireless communication, sensor technologies, and IoT-based metering systems, huge amounts of data is being generated, e.g., data on load demand, power generation data, electricity price data, weather data, etc. The accessibility of big data in the energy sector to the industry and research community can open new opportunities to improve the efficiency of smart microgrids. The authors in [79] provide a holistic vision for managing Big Data resources in the energy sector, encompassing power generation, power distribution, transformation, and demand-side management. At the end, they have taken an in-depth look at smart data sources and their characteristics. Recent studies highlighted in [80] and [81] utilize big data analytics approaches for effective electrical load and electricity price forecasting. Nonetheless, there remains an urgent need to enhance the adoption of Big Data Analytics approaches in load and price prediction to enhance the performance of energy management systems in smart grids.

B. TRANSFER LEARNING

Transfer learning (TL) is a new technique that can help in energy management systems in smart grids. Basically, TL transfers knowledge from an area with sufficient knowledge to an area with insufficient knowledge to reduce the time and effort required for a new learning process. As stated in [82] and [83], the transfer of knowledge from a certain domain to another domain that has no importance here must be avoided. The concept of TL can enhance the productivity and performance of DL-based price and load forecasting methods. Since historical data is used for training and testing, the knowledge gained from training can be used at different stages of building the forecasting model instead of training it again. In this way, the model works more efficiently and lot of resources can be saved. In recent literature [84], [85], [86], [87], there are some studies that use TL to improve the performance of prediction models. However, there are still opportunities to use it commercially and in industry.

C. GROWING AND PRUNING DL MODELS

Growing and pruning (G&P)-based DL approaches can also enhance the performance of price and electricity load forecasting models. An architecture of DL is created with the bare minimum of neurons and hidden layers in G&P-based forecasting models. Using the growing technique, neurons and new hidden layers are later added to the model. On the other hand, the maximum number of neurons and hidden layers are first included in the architecture of DL model; then the number of neurons and hidden layers are excluded using the pruning approach. G&P-based models repeat three main operations until achieving higher accuracy [88]: 1) model training, ii) modification of weights based on G&P criteria, and iii) model retraining. In the last decade, the field of G&P in DL methods has gained much attention from researchers and several studies have discussed its productivity in various fields, including medical service improvement [89], self-care activities [88], and speech and emotion recognition [90]. Therefore, the application of G&P-based DL methods in electricity price and load forecasting is still an open opportunity for the research community and industry.

D. EXPLAINABLE AI

Many existing load and price prediction algorithms are based on "black-box" methods that are not easy for non-technical people to understand [91], [92]. This is especially difficult for small utilities, which frequently lack the necessary technical know-how and AI expertise. A few studies proposed the use of explainable ML schemes to design forecasting algorithms

TABLE 7. Summary of statistical tests and performance metrics used in electricity load forecasting methods.

Ref.	Method(s)	Test	Test details	Performance metrics
[23]	Hybrid of k-means clustering and ARIMA	None	-	MAE, MSE, MAPE
[24]	Hybrid of SSA and SVR	None	-	MAPE
[30]	NSGA-II-KNN-DBN	None	-	MAPE,CRPS
[26]	MCM model	None	-	Reliable MAE, Normalized CRPS, Prediction Interval Normalized Width
[31]	GRU-based encoder-decoder with temporal attention mechanism	None	-	MAE, RMSE, MAPE, R, NRMSE, SMAPE
[25]	CLSAF	Two-tailed, unequal variances	p-values are computed to investigate the effect of forecasting accuracy in diurnal pattern of the load data.	CV
[27]	EMD-IENN-SSO	None	-	MAPE, NMAPE, RMSE, NRMSE, σ^2
[35]	GRNN	None	-	MSE, MAD, MAPE
[39]	EP-Fuzzy Bayesian theory	None	-	Percentage Error, MAE, MAPE, RMSE
[33]	Index decomposition methodology	None-		Analysis
[38]	Hybrid of bottom-up and hierarchical models	None	-	Electricity consumption
[34]	Temporal disaggregation approach	None	-	MAE, MAPE
[40]	Hybrid of SVM and ARIMA	None	-	MSE, RMSE, MAPE
[32]	Combined forecast results of CEEMD-PSO-BPNN and VMD-PSO-BPNN.	None	-	MAE, MAPE, RMSE, U1
[41]	ABPA	None	-	MSE, MAPE
[42]	IBSA-DRESN	Wilcoxon signed rank Test	At 5% significance level, the proposed algorithm shows better performance as compare to the benchmark algorithms	RMSE, MAE, MAPE

in order to address this situation [93]. These approaches are centered on understandability and interpretability in order to increase user confidence in the obtained outcomes. Developing such explainable AI forecasting approaches will assist users in comprehending and gaining access to fair and transparent explanations of the applied algorithms and their outcomes [94].

E. EFFECTS OF ELECTRIC VEHICLES AND VEHICLE TO GRID (V2G)

Electric vehicles (EVs) can be charged using a grid-connected socket, however, large-scale grid connection for charging of EVs will have significant grid impacts [95], especially if many EVs are charged at the same time, which will aggravate the peak load and off-peak difference, increase the maximum power load, and increase the difficulty in the power grid optimization [96], [97]. Considering the effects of EV charging during electrical load forecasting will minimize the impact of charging on the power grid induced by associated electric vehicles and give a reference for optimizing power grid management [98]. Traditional load and pricing forecasting methods rely heavily on previous data and related influence variables. However, due to the fact that the EV industry is still in its early phases, there is little actual historical data on EVs. The estimate of charging load for EVs is mostly based on driving behavior and statistics analysis of existing fuel vehicles. As a result, forecasting the load and price with increasing EV charging can be difficult. Forecasting methods must take into account when consumers charge, how quickly they charge, and where they charge, among other things.

TABLE 8. Summary of statistical tests and performance metrics used in electricity price forecasting methods.

Ref.	Method(s)	Test	Test details	Performance metrics
[65]	Multi-layer GRU	DM	The authors repeatedly compute the p-value in DM test by changing the number of features for shallow and deep networks.	MAE
[61]	HSEC	None	-	Accuracy
[58]	Hybrid of metaheuristic and ML approaches	DM	Results of DM shows that in more than 95% case, the proposed approach is better as compared to the counterparts	sMAPE, RMSE, R^2, OWA
[59]	Hybrid adaptive VMD-IMOS-CA-RELM	DM	The outcomes illustrate that the performance of the proposed model is superior over counterparts at a 1% significant level.	MAE, RMSE, MAPE and U1
[64]	Hybrid	None	-	MAPE, MAE, RMSE, U1, IA
[62]	HFS-CSS	DM	The DM test results show that models used in this work are statistically different and reject the null hypothesis.	IMAPE and sMAPE
[60]	ICEEMDAN-VMD-MOGWO-ENN	DM, grey relational analysis, Forecasting effectiveness	DM test shows, at 1% significant level, the performance of the proposed model is better as compared to the benchmarks algorithms. Similarly, grey relational analysis and Forecasting effectiveness values of the proposed models indicate the effectiveness of the proposed model.	AE, MAE, RMSE, MAPE, U1, U2
[66]	WT-ARMA-SAPSO-KELM	None	-	MAPE, wMAE, MAE, RMSE, U1,U2
[63]	VMD-SAPSO-SARIMA-DBN	DM	At 1% significant level, the highest value is achieved by the proposed model, and the null hypothesis is rejected	MAE, MAPE, RMSE
[67]	SEPNet	None	-	MAPE, RMSE
[69]	Hybrid of ML models and meta-heuristics	None	-	MAE, MAPE, MSE
[70]	EEMD-ELM	DM	The proposed model achieves the highest value for the DM test and rejects the null hypothesis.	MSE, MAE, MAPE, RMSE
[68]	VMD-CSCA-ELM	DM	At 1% significant value, the proposed model achieves the minimum and maximum values in DM test	MAE, RMSE, MAPE, U1, IA
[71]	TSEP (SMOTE+VST+ANN)	DM	At 1% value, the proposed model has higher predictive accuracy.	sMape, MAE, F1 score, Precision, Recall

F. EDGE COMPUTING OR ON-DEVICE AI

Geo-distributed equipment and devices are typically linked to fog or cloud data centers, which make centralized decisions and provide control orders for smart grid computing [99]. Nonetheless, it has many flaws, including heterogeneous environments, security and privacy concerns, and limited bandwidth resources [100]. In this context, edge computing shifts the frontier of computation applications away from centralized nodes and toward the communication network's outskirts [101], [102]. Edge computing puts computing resources closer to end users and sensors to do data analytics for smart grid decisions. It benefits from its ability to effectively lessen system latency, reduce the load on cloud computing centers, achieve better scalability and availability, and maintain data security and privacy. Because of these capabilities, edge computing is gaining attraction in academics and industry. The necessity of incorporating edge computing in smart grids will become clear as the requirement for smart grids to interact with millions of dispersed energy resources and electrical demands grows in the near future. This is especially true for the power distribution network, which is currently unprotected, uncontrolled, and uncommunicated with the power system. However, with this novel edge computing technology, many of the existing ML and DL-based schemes need to be upgraded accordingly.

G. INTEGRATION WITH HEATING NETWORK

In extensive urban settings, district heating systems serve as a prevalent means of heat distribution, typically comprising a district heating network powered by a combined heat and power plant. These plants primarily produce useful heat, a constant requirement in district heating systems. Consequently, actual electricity generation is contingent upon the prevailing heat demand [103]. Notably, there have been dynamic fluctuations in electricity prices. Achieving precise hourly predictions of heat load in the day-ahead horizon is

TABLE 9. Summary of the performance metrics used in ELF and EPF. [Note: N shows the number of data points, F_i is the i^{th} forecasted value, A_i is the i^{th} actual value, and avg shows the average value].

Metric(s)	Equation	Details
Mean Absolute Error (MAE)	$\frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert$	Commonly used in scale dependent accuracy measurement; efficient for comparing different models on the same data; sensitive to outliers;
Mean Square Error (MSE)	$\frac{1}{N}\sum_{i=1}^{N}(F_i - A_i)^2$	Most commonly used performance metric; scale dependent; more sensitive to outliers as compare to MAE;
Individual Mean Absolute Percentage Error (IMAPE)	$(\frac{\lvert F_i - A_i\rvert}{A_i}) \times 100\%$	Scale independent performance metric; useful when comparing performance of models on different data;
Mean Absolute Percentage Error (MAPE)	$\frac{1}{N}\sum_{i=1}^{N}\frac{\lvert F_i - A_i\rvert}{A_i} \times 100\%$	Most commonly used performance metric; scale independent performance metric; useful when comparing performance of models on different data; sensitive to outliers;
Symmetric MAPE (sMAPE)	$\frac{1}{N}\sum_{i=1}^{N}(IMAPE_i - MAPE)^2$	MAPE can not be applied if the actual load values are 0. sMAPE removes this shortcoming by introducing a lower and upper bound on the load values;
Root Mean Square Error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert^2}$	Most Commonly used performance metric due to its statistical properties; scale dependent; very sensitive to outliers;
Normalized Root Mean Square Error (NRMSE)	$\frac{1}{max(F) - min(F)}\sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert^2}$	Effective to evaluate the degree to which data variate;
Pearson Correlation Coefficient (R)	$\frac{\sum_{i=1}^{N}(F_i - F_{avg})(A_i - A_{avg})}{\sqrt{\sum_{i=1}^{N}(F_i - F_{avg})^2(A_i - A_{avg})^2}}$	Measures linear dependency between the actual and predicted values;
Theil's inequality coefficient (U1)	$\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert F_i - A_i\rvert^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert F_i\rvert^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}\lvert A_i\rvert^2}}$	Use to assess the generalization ability of forecasting models;
Theil's inequality coefficient (U2)	$\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}((A_{i+1} - F_{i+1})/A_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}((A_{i+1} - F_i)/A_i)^2}}$	Use to assess the generalization ability of forecasting models;
Continuous Ranked Probability Score (CRPS)	$\frac{1}{N}\sum_{i=1}^{N}\int_{-\infty}^{\infty}(F_i(x) - A_i(x))dx$	Measures the sharpness and reliability of the prediction interval; compares the probabilistic and deterministic forecasts;
Coefficient of Variation (CV)	$\frac{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(F_i - A_i)^2}}{A_{avg}}$	Normalized metric; effective if load values are zero;

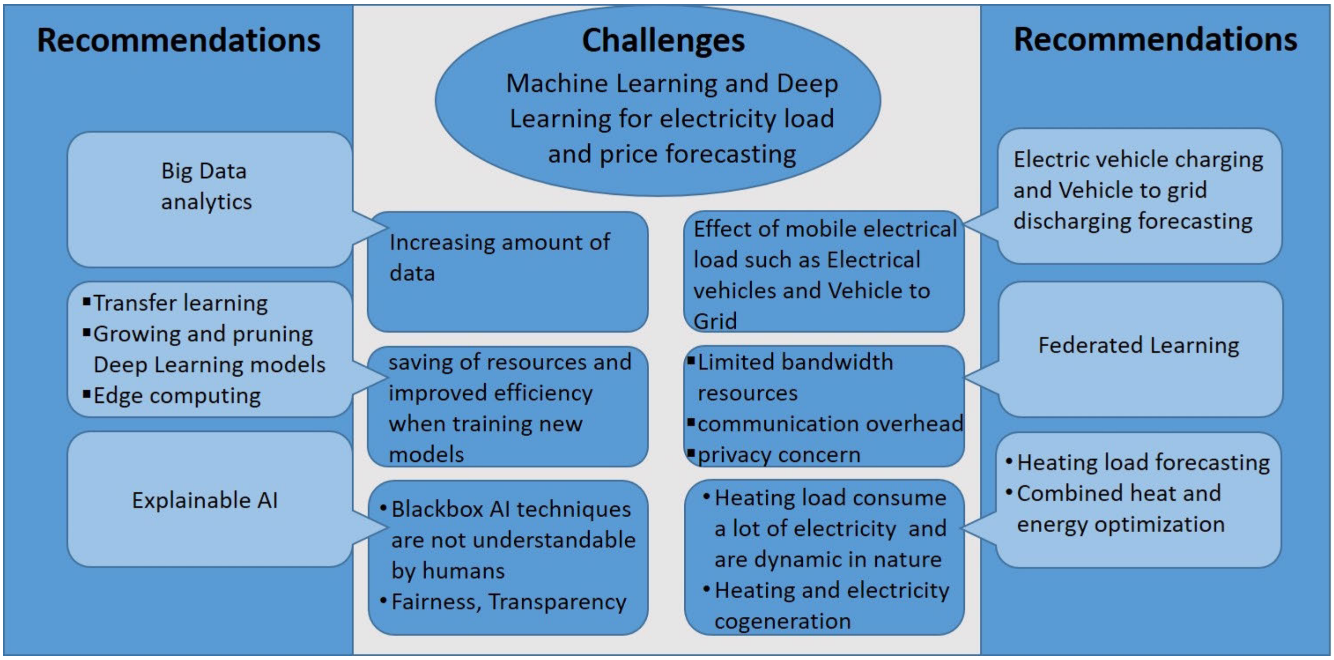

FIGURE 9. Primary challenges and recommended future directions related to future smart grid.

crucial for optimizing and planning the production of both heat and electricity in co-generation units. Consequently, the significance of heat load forecasting parallels that of electric load forecasting, necessitating forecasting models that encompass both electrical load and price, along with heat load [20]. Nevertheless, forecasting hourly heat demand on a large urban scale poses a challenging task. The heat required for building heating primarily hinges on weather data, whereas domestic hot water consumption is closely linked to consumer behavior throughout the day and week [104].

H. DISTRIBUTED FORECASTING METHODS

Conventional machine learning methods for load forecasting entail a central server that performs machine learning training [105]. The disadvantage of this method is that all data gathered from various devices is sent to a central server, which introduces security and privacy challenges, strains communication networks, and necessitates huge and efficient computational resources (centralized). To deal with this, distributed forecasting methods should be focused. One such distributed method is the federated learning [106], [107] method for electrical load prediction with smart meters that can train a ML model in a distributed fashion without requiring participants to provide any local information [108]. In the federated learning technique, a global machine learning model is distributed across multiple devices pertaining to individual smart meters, and each device upgrades its local copy of the collaborative model utilizing data locally.

VIII. CONCLUSION

To reduce uncertainty and overcome energy crises, recent developments in the electrical market necessitate accurate load and price forecasts. This study provides an in-depth look at Machine Learning and Deep Learning models for energy load and price predictions. Several methods for electrical load and price forecasting are discussed in this work, including short-term and long-term forecasting models. Furthermore, the fundamental strategies and datasets employed by each method are addressed. To show the performance of each method, performance metrics for all load and price forecasting approaches (that are studied in the study) based on the same datasets are presented in the form of bar graphs. With respect to price forecasting, different forecast periods (e.g., one month ahead, two months ahead, and three months ahead) are compared. The study concludes that deep learning models are effective in predicting non-linear, non-stationary, high-frequency, and high-volatility data. Moreover, deep learning models are effective compared to machine learning; however, hybrid deep learning models provide the best prediction accuracy. Furthermore, this study discusses some key issues associated with the application of ML and DL for load and price forecasting, as well as some recommendations that can serve as the foundation for future research initiatives for scholars in this field.

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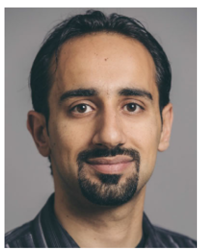

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