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SURVEY

Advanced Techniques for Joint Weather and Electricity Demand Prediction Survey

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ABSTRACT Recent advancements in the field of machine learning have exceptionally enhanced the accuracy as well as efficiency of electricity demand and weather forecasting. There is a range of forecasting methods used for predicting electricity demand and weather conditions, including historical approaches like time series analysis and more recently machine learning algorithms. This review aims at summarizing the recent progress that demonstrated a shift from applying simple regression and correlation coefficients to more powerful and flexible algorithms. Findings from the research indicate that Support Vector Regression (SVR), Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) and Multivariate Adaptive Regression Splines (MARS) are better suited for short-term electricity demand forecasting because of the accuracy. Furthermore, novel approaches such as diffusion models for weather prediction are obvious examples of how generative models are capable of handling uncertainty. Linear methods such as Autoregressive Integrated Moving Average (ARIMA) are still useful for short-term prediction and linear moving average, while modern techniques, especially deep learning and hybrid approaches, are better suited for discovering intricate relations and dealing with different predictors. The idea here is to select the best characteristics of different models for modeling in complex situations. However, some of the difficulties remain. These include data quality issues, interpretation of derived models, and high computational complexity.

INDEX TERMS Electricity demand, forecasting methods, machine learning, weather prediction.

I. INTRODUCTION

Weather predictions and prediction of electricity demand play an important role in the administration of effective power systems. While the world is struggling to come to terms with the impacts of climate change and the transitions to cleaner energy systems, the need for accurate forecasts in such areas cannot be overemphasized [1]. Forecasting is critical in energy supply systems to achieve its objectives, ensure grid stability, and integrate renewable energy systems [2]. Likewise, in meteorology, better predictions are central to numerous fields such as farming, transport, and even processing for calamity [3]. The growing complications in energy circuits together with the integration of renewable energy sources demands the development of methods for accurate and highly efficient forecasts.

Various trends that have characterized the development of forecasting methods have included changes in computing power, data gathering practices, and actual computation methods. In the past, traditional statistical techniques like regression, time series, moving average, exponential smoothing, etc., have been used to forecast which are now accompanied by advanced machine learning methods [4]. These forecasting tasks have typically used traditional models

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– Auto-regressive Integrated Moving Average (ARIMA) and Seasonal-ARIMA (SARIMA) - due to their comprehensiveness and ability to detect linear trends and seasonality in historical data [5]. However, since electricity demand and weather patterns are non-linear, the accuracy of such models is restricted by their ability to provide an approximate representation of reality. Such data-based models have the possibility of uncovering non-linear interactions within sections of electricity usage and weather sequences, which in many cases may provide more precise and versatile estimates compared to conventional techniques.

Machine learning (ML) has emerged as a new generation of forecasting tools and has been recognized as possessing the capability to address nonlinear relationship issues within data. Advancements in computational capability and the increase in the availability of data have boosted the use and development of ML methods in the field of forecasting. These methods include Support Vector Machine (SVM), Neural Networks (NN), and Decision Trees, specifically Long Short-Term Memory(LSTM) networks that have significant potential to enhance forecasts performance [6]. These types of models are superior in modelling complex patterns and dependencies that exist in big data with multiple variables; these models are, therefore, ideal for forecasting problems that require interactions with many influencing factors [7].

This paper will review the current literature to illustrate and compare the currently available machine learning approaches to be possibly combined in electricity and weather predictions. The objectives of this study are

- Detect and investigate the efficiency of machine learning techniques e.g. long-term short memory (LSTM) and conventional statistical time series models e.g., ARIMA, SARIMA for precise electrical energy need and weather prediction, emphasizing their strengths, constraints, and pertinence to advanced energy systems.
- Identify the best methodology for forecasting electricity demand and weather conditions and key performance metrics for evaluating forecast accuracy.
- Identify what types of datasets are best suited for various machine learning techniques for better forecasting and how integration and data quality impacts the performance of a forecasting model.
- Identify the main challenges and limitations in applying machine learning techniques to electricity and weather forecasting.
- Explore how recent trends and approaches in machine learning can be practically applied to energy management and suggest future research directions.

The paper is structured as follows: Section I explains the relevance of the forecasts and the application of machine learning for the electricity demand and weather. Section II presents the historical background together with key ideas that are crucial for reviewing the predicted development in more effective forecast methods. Section III presents the review of the literature. Section IV outlines the methodologies including Random Forest (RF), NNs, LSTM Networks, Support Vector Regression (SVR) and the pros and cons of gradient boosting algorithms. Section V discusses key machine learning techniques, the best methodology for forecasting electricity demand and weather, and key performance metrics for evaluating forecast accuracy. It also discusses which kind of data set is suitable for the electricity demand and weather conditions forecasting. Section VI concludes the discussion and potential research directions to enhance forecast accuracy and efficiency, addressing existing challenges and proposing innovative solutions.

II. BACKGROUND AND CHALLENGES

The section discusses how demand for electricity relates to weather information, traditional methods of forecasting, and the challenges encountered in this area.

Electricity demand forecasting is a challenging and highly multifaceted process that requires precise consideration of a broad range of variables, with climate being the most critical of them all. The task requires the forecasting of future demand for electricity by using historical data and several other variables. The problem structure is non-linear because electricity demand is not constant but depends on the demand on a daily basis, weather changes, business and human activities, among others. However, these factors interrelate in complex ways and this just makes the problem of forecasting even more complex when we consider the integration of renewable power generation technologies into the power networks. This issue has been mentioned in a number of works analyzing the difficulties in forecasting in the energy systems, for example, the necessity of utilizing models reflecting nonlinear and multi-factorial dependencies in electricity consumption [1], [2].

This brings about the main issue in the forecasting of electricity demand in the industrial sector who are relying on the continuous supply and distrubution of power for which the demand is a direct function of the unpredicted weather conditions that is influenced by global and regional climatic changes. Weather conditions like temperature, humidity, wind speed, and even cloud cover have a strong influence on energy demands like heating, cooling and lighting [8]. These interactions are complex and non-linear, difficult for traditional statistical methods to characterize faithfully. On the other hand, the machine learning methodologies provide the opportunity to capture complex patterns between the weather data and electricity demand so as to present more precise and stable predictions [9].

The data conventionally used in electricity demand forecasting include prior consumption records, weather conditions (temperature, humidity, wind speed), time of day, day type and seasons. These data are built over time and commonly include additional parameters such as population density, economic activity, and trends on social media that influence consumption patterns [1], [7]. The primary purpose is to use these data to train predictive models to forecast future electricity demand, helping to optimize power generation,cost predictions, grid stability management, and integrate renewable energy more efficiently [10].

A. ELECTRICITY DEMAND FORECASTING

Management of the electricity supply chain management is one of the most important elements of the power system, of which demand forecasting is a crucial part. It is therefore very essential for the utilities since it assists in the planning and management of generation and resources with minimal operational costs incurred. Often, data on past consumption are also used with the other parameters, including time of day, seasons, level of economic activity, and weather. The previous methods of forecasting used in this field include the time series and the regression approach. However, these approaches are not able to integrate dynamic complications that may exist in electricity consumption; this particularly applies in a situation where consumption is dynamically changing due to shifts in technology or changes in social behaviour [10].

B. IMPORTANCE OF WEATHER FORECASTING

The significance of weather prediction cannot be underestimated as it is used in agriculture, transport, disasters, and many other sectors. Weather forecasting provides information that allows key decision makers to minimize risks and better plan how they will use limited resources. For example, farmers require predictions for the appropriate times to cultivate crops and when to harvest them, while the transport sector requires estimates to plan for conditions that better support transport. Other conventional methods of giving the weather information includes the Numerical Weather Prediction (NWP) models which work on physical equations principles. Although these models have evolved, they can be inferior due to strong assumptions and the time required to perform calculations, especially in cases of localized weather events.

Weather acts as an essential factor in predicting electricity demand. Temperature variation, humidity ratios, and wind speen change have a direct effect on electricity for heating and cooling [11]. Therefore, enhancing the reliability of weather prediction is relevant to the reliability of electricity demand forecasting. The impact of weather variables on electricity consumption is a dynamic relationship, such that feedback integrated with instantaneous data for accurate prediction is preferable.

C. THE RISE OF MACHINE LEARNING IN FORECASTING

Over the recent years, machine learning has emerged as one of the most preferred approaches to the conventional approaches in forecasting weather and electricity demand [12]. Machine learning and its subcategories are (deep learning and reinforcement learning) expressly applicable to dynamic systems where the relationships between variables can be constantly changing, contrasting usual programming, which expects exact directions for each circumstances as machine learning models do not require direct programming, instead, they are built with past data. These models can effectively analyze and process large data sets and incorporate different types of data like sensor input, social media trends, and economic indicators which can improve the accuracy of forecasts [13].

Deep learning approaches like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are exceptionally helpful for examining electricity demand and weather data as they can study spatial models and temporal needs. For illustration, CNNs can acquire spatial connections in weather maps, but RNNs can identify tendencies in the use of electricity in time series. Research have revealed that ML models such as Support Vector Regression (SVR) and Artificial Neural Networks (ANNs) frequently outclass outdated forecasting methods, such as statistical regression models, by delivering more correct and flexible forecasts in composite environments [14].

D. CURRENT TRENDS AND CHALLENGES

The latest developments in machine learning together with forecasting approaches still contain various essential restrictions. Sophisticated models are required to analyze intrinsic non-linear dependencies between weather factors and electricity consumption to achieve effective relationship detection. Data quality continues to be a problematic situation which negatively impacts forecasting model performance because of missing values and outlier events alongside sensor measurement errors.

Machine learning models encounter additional implementation difficulties when used for practical energy management systems because they require handling high computational costs, robust models along with understandable decision-making processes [15]. Accurate prediction has become essential for both the present climate change situation and growing energy usage since these conditions persist.

The primary aim of this review is to highlight how machine learning methods can be effectively used to strengthen the accuracy of electricity demand forecasting and to determine which models are more suited to address the sort of non-linear interactions that are commonly found in the data. Further, it aims at determining datasets that are most appropriate for these machine learning models, investigate the effect of data quality and integration on the forecast accuracy, and highlight the major issues regarding the application of machine learning under the electricity demand and weather forecasting. By focusing on the integration of two domains; electricity demand and weather forecast, it offers insights on how energy management practices can be improved in the best way [14].

III. LITERATURE REVIEW

The application of machine learning approaches in electricity demand and weather forecasting has enhanced traditional methods with new techniques that capture modern energy systems. This section discusses the literature works that are relevant to the field of electricity demand coupled with the weather forecasting especially with the recent development of the ML.

A. ELECTRICITY DEMAND FORECASTING

Research suggests that machine learning has a significant impact on forecasting electricity demand in recent years [16]. Adequate forecasting of electricity demand plays a significant role in the operation of the grid, cost reduction, and energy planning. ARIMA and regression are good examples of models commonly used in the past because they mimic linear patterns in historical data. Initially, ARIMA and multiple regression methods were employed; while these were adequate for short term forecasting under conditions of no change, they were incapable of handling demand that was nonlinear in nature [17].

Thus, recent developments focus on machine learning techniques such as Random Forest (RF) and grade boosting machines (GBMs) for their ability to model non-linear demand dynamics influenced by social and environmental factors [9]. However, due to the dynamics in the demand patterns concerning factors like weather, technology changes, and social trends, ML techniques such as Random Forest, SVR, and NN are fast emerging as important tools.

Al-Musaylh et al. considered the use of SVR, ARIMA and Multivariate Adaptive Regression Spline (MARS) models for short-term electricity demand forecasting in Queensland, Australia [18]. The results showed SVR as the best model for 24-hour forecasts because it produced a Willmott index of 0.890 approx with an MAE of 162.363 MW approx. The experimental data confirm that MARS together with SVR outperform ARIMA as choices for short-term load prediction in this case.

The survey by Imani [19] examines multiple deep learning (DL) prediction approaches within diverse electricity demand forecasting conditions. Their investigation demonstrates three main findings: First, deep learning models display exceptional capabilities in handling temporal dependencies found in consumption behaviors. Secondly, Long Short-Term Memory networks specifically demonstrate strong performance in detecting long-term dependencies that extend from one day to another season. Third, the selection of models for forecasting relies heavily on consumer classes because residential customers require complex architecture due to irregular patterns but industrial customers benefit from simpler models because their patterns are more stable.

B. WEATHER FORECASTING

There has also been a lot of development on the application of machine learning in weather prediction. Guizzi et al. with their research demonstrated that a particular forecast model selection depends on specific weather elements together with forecast horizons showing exponential smoothing models work effectively for temperature forecasting but pressure and humidity measurements exhibit varying behavioral patterns that influence model performance [20].

Naz undertook a study on time series to forecast temperature for the maximum temperatures in Umeåcity of Sweden [21]. The study also compared various ARIMA models to assess the applicability of such classical statistical models in forecasting temperature.

Lam et al. [22] introduced GraphCast as a machine learning system that defeats traditional numerical weather prediction systems while matching their performance on 90% of verification targets for mid-range global weather forecasting. The predictive model operates at 0.25° resolution across the entire globe and concludes calculations in less than a minute yet persists to generate forecasts of hundreds of weather variables over ten days with enhanced precision and computational strength.

The provision of weather information is largely based on NWP models that represent numerical solutions to the physical equations describing the atmosphere's behavior. However, these models have several challenges in terms of computational complexity and local event prediction [3].LSTM networks and CNNs have been adopted widely as they are proved to be more effective than NWPs in forecasting localized climate events like rainfall or heatwaves. Waheed et al. showed that such a model could capture the temporal feature of meteorological data, and better short-term predictions of temperature and precipitation [8].

C. WEATHER FORECASTING ADVANCEMENTS

Scher et al. used deep learning in weather prediction and stated that CNNs are useful systems that can be used to accurately predict other weather phenomena. Their work proved that they are as precise and effective as the numerical weather prediction of the short-range forecast [23].

The deep learning system applied by Grönquist et al. operates to expand low-resolution climate data which leads to predictions of high-resolution weather information [24]. The team gained understanding about how their deep learning system could improve regional weather forecast precision in areas with complex geographical barriers as it valuably established nonlinear patterns between local weather patterns and geographical features that conventional numerical weather prediction models or post-processing methods do not represent efficiently.

Recent advances in ML focus on better predicting weather severity together with improved time accuracy. The application of deep neural networks has shown remarkable success in enhancing ensemble prediction systems based on the findings presented in [25]. The method achieved over 14% better forecast capabilities together with superior results during extreme weather prediction and lower computational costs that needed fewer trajectory calculations compared to conventional ensemble systems.

D. THE FREQUENCY DOMAIN AND TIME SERIES ANALYSIS

Frequency domain has been used as commonly as time series in predicting electricity and weather. Frequency domain techniques were adopted in forecasting the electricity market as recommended by Trapero and Pedregal [26], where a series of data is transformed into frequencies. Essentially, this method was considered extremely helpful in tracking the long-run and short-run electricity prices precisely.

Yan et al. proposed frequency domain decomposition and deep learning for forecasting ultra-short-term solar Photo Voltaic power [27]. Their strategy on the performance of solar power incorporated the frequency domain analysis fused with deep learning to gain high-accuracy predictions for the fluctuations.

Ramos and Oliveira provided a procedure for selecting the correct state space and ARIMA models by using time series cross-validation [28]. Thus, this method is advantageous where there is a need to systematically select the models which are very significant in the case of electricity and weather domains concerning forecasting. Strengthening innovations in state space modeling, Baek provided solutions to predict one-hour electricity loads in South Korea [29]. The study showed how the state space models could capture the temporal patterns of the electricity demand as evidenced by the veracity of the models.

E. RENEWABLE ENERGY INTEGRATION

The integration of renewable energy sources has brought out the need for improving the methods of forecasting. Researchers in [30] have provided several classifications of methods of photovoltaic power forecasting based on ANN, SVR, and RFs; the assessment of such methods shows that this type of forecasting has pros and cons when predicting solar power.

F. ENSEMBLE METHODS AND HYBRID APPROACHES

Organizational methods and combined systems have shown important improvements in the precision of demand forecasts. XGBoost (eXtreme Gradient Boosting) by Chen and Guestrin [31] provides an exceptional tree boosting system delivering impressive scalability and enhanced performance by using sparsity-aware algorithms alongside weighted quantile sketches. XGBoost efficiently processes large-scale electricity demand prediction datasets due to its processing ability of billions of points. Energy forecasting complexity increased when solar and wind power entered the energy sector along with renewable resources.

Voyant et al. reveals that neural networks alongside support vector regression form traditional machine learning tools although regression trees and random forests and gradient boosting represent newer methods which deliver equivalent prediction results [1]. Research demonstrates that cross-method combinations produce better results particularly in situations involving solar irradiance estimation along with demand forecasting for electricity. Fig. 1 shows the recent machine learning techniques used for electricity demand prediction which extend across different domains starting from time series analysis up to interpretable AI methods.

G. IMPACT OF EXTREME EVENT PREDICTION ON ELECTRICITY DEMAND PREDICTION

The stability of the power grid together with demand management requires strong dependence on the predictions of extreme events. Chen et al. conducted an extensive survey of weather prediction solutions using machine learning with eight effective prediction methods for different time intervals [32]. Authors emphasize that ML shows high power for short-term prediction yet faces substantial barriers for forecasting extreme events because of complex climate phenomena and restricted data accessibility.The comprehension of these methods serves essential objectives in predicting electricity demand during harsh climate events because it affects both power grid stability and distribution resources.

H. LONG-TERM ELECTRICITY DEMAND FORECASTING

The prediction of electricity demand across extended time periods faces distinctive obstacles because it requires handling intricate feedback structures and irregular forecasting patterns which extend over numerous years. Bedi and Toshniwal made substantial progress in the field of long-term forecasting using their customized deep learning framework [33]. The framework included three fundamental breakthroughs as its core features:

- Season-based cluster analysis of monthly consumption data
- LSTM networks with multi-input or multi-output architecture
- Moving window-based active learning

Their model demonstrated superior performance when used for forecasting electricity usage in Chandigarh through historical data analysis which exceeded ANN, RNN and SVR traditional models. The positive results show how deep learning offers solutions to static regions and historically-driven limitations within multi-year electricity demand forecasting.

I. INTERPRETABILITY AND EXPLAINABLE AI

Machine learning methods that predict electricity needs and meteorological conditions provide steady accurate outcomes for both prediction results and their stability. Better model improvements result from the feature of ML models to detect hidden nonlinear patterns in datasets thus creating immense value. Future advancements in hybrid models together with ensemble methods as well as Explainable AI (XAI) have already established promising possibilities within these fields.

AI explainability has been identified as the primary theme in terms of the increasing concerns about 'black box' of different ML systems. Recent improvements in model interpret ability utilized LIME (Local Interpretable Model-agnostic Explanations) together with SHAP (Shapely Additive explanations) capabilities [34]. The LIME technique

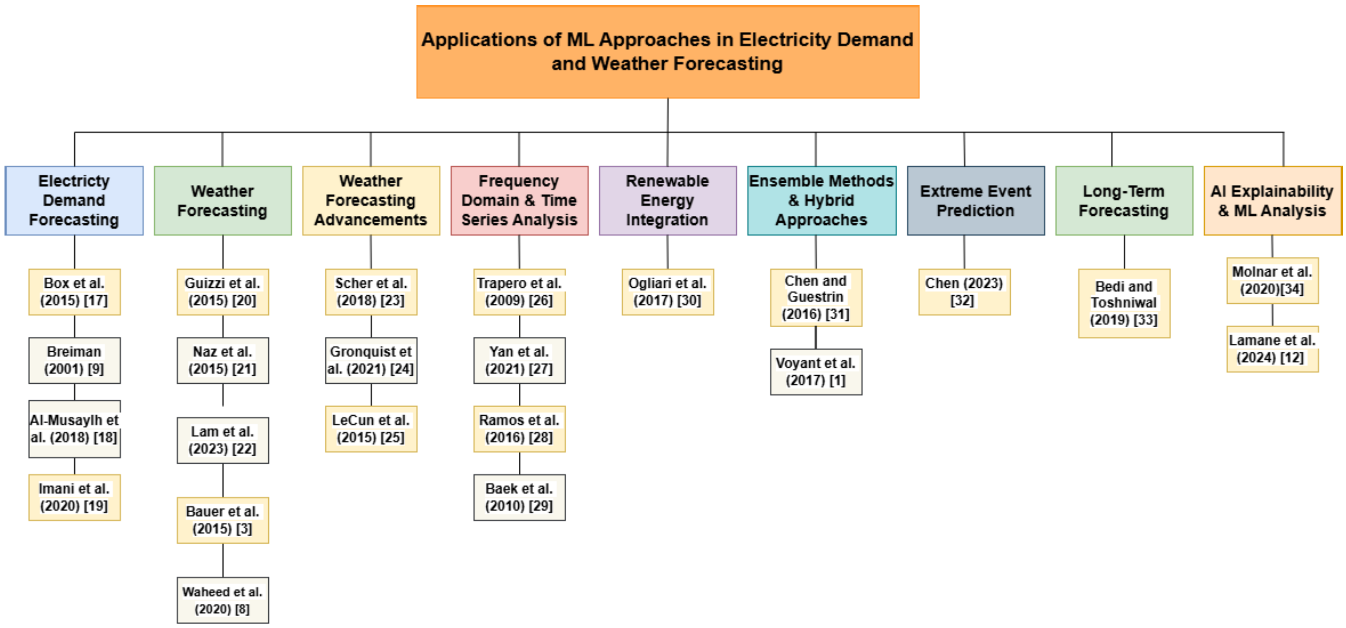

FIGURE 1. Overview of ML applications in electricity demand prediction: A literature review taxonomy by research domain.

generates understandable approximations for how the model operates locally whereas SHAP implements game theory principles to identify feature importance values. This is true especially for stakeholders involved in energy management as precise and quantifiable tools for decision making are very important.

Lamane et al. introduced a new method that integrates suspended sediment concentration forecasting through the combination of machine learning models including random forest, extra trees, XGBoost and CatBoost, and XGBoost with genetic programming [35]. The approach integrated SHAP analysis for promoting interpretation without sacrificing conventional performance assessment metrics in the framework. The research achieved exceptional predictive capabilities at different locations based on performance statistics that demonstrated robust forecasts (NSE: 0.53-0.86, RMSE: 1.20-2.55 g/L, correlation: 0.83-0.91 g/L). The research demonstrated that individual locations needed particular model selection strategies because divergent mathematical models performed best according to locality requirements. The study used SHAP analysis to determine flow and seasonality as the main factors affecting sediment concentration while maintaining high predictive accuracy levels.

The literature review shows the development of electricity demand prediction by machine learning methods. More advanced predictive techniques such as deep learning together with ensemble methods and explainable AI have replaced traditional statistical approaches. Advanced models retain the ability to process non-linear data trends while supporting renewable integration and managing weather event effects. The field progresses through hybrid models combined with explainable AI solutions to achieve better and interpretable predictive results for complex real-world scenarios despite ongoing challenges in finding model interpretability without sacrificing complexity.

Table 1 shows a comprehensive summary of the key research, methods and findings in electricity demand prediction showing how traditional approaches shifted toward advanced machine learning methods. Each domain implies specific methods to resolve demand prediction issues through fundamental contributions to the field. The frequency domain analysis uses time-series decomposition approaches and the renewable energy integration requires prediction of variable generation demand. The combination of several predictive models through ensemble methods improves accuracy while interpretable AI technology provides transparency for forecasting decisions. The table highlights how the methodologies evolve from traditional forecasting approaches to advanced ML techniques, showing the progression of this field towards better prediction systems.

IV. MACHINE LEARNING MODELS FOR ELECTRICITY DEMAND FORECASTING

Machine learning models for electricity demand forecasting can be broadly classified into three primary categories (see Fig. 2). Time series models use ARIMA and SARIMA analyze temporal patterns within historical data. LSTM and GRU neural networks belonging to deep learning utilize neural networks to capture complex sequential dependencies. Random Forest and GBM/XGBoost represent the third category of learning methods that combine different models to achieve better prediction accuracy.

TABLE 1. Literature review summary.

Category	Ref	Techniques	Key Findings
Electricity Demand Forecasting	[17]	ARIMA, Multiple Regression	Effective for short-term forecasting under stable conditions but struggles with non-linear demand patterns.
	[9]	Random Forests (RF), Gradient Boosting Machines (GBMs)	RF and GBMs capture complex demand fluctuations influenced by social and environmental factors.
	[18]	MARS, SVR, ARIMA	MARS outperforms SVR and ARIMA for short-term load forecasting in Queensland, Australia.
	[19]	Deep Learning (DL) Models	DL techniques effectively capture dependencies in electricity consumption patterns across residential and industrial consumer types.
Weather Forecasting	[20]	Forecast Models Selection for Weather Elements	Model choice depends on weather elements and forecast horizon, emphasizing customization.
	[21]	Time Series Analysis, ARIMA	Demonstrates ARIMA's applicability and limitations in temperature prediction.
	[22]	Artificial Intelligence	AI techniques yield results as accurate as traditional numerical weather prediction systems.
	[3]	NWP, CNN, LSTM	CNNs and LSTMs outperform NWP models in localized events, improving computational efficiency.
	[8]	LSTM Networks for Meteorological Data	LSTMs improve short-term temperature and precipitation forecasts by capturing temporal dependencies.
Weather Forecasting Advancements	[23]	Deep Learning with CNNs	CNNs are as accurate as traditional NWP systems for short-range weather forecasting.
	[24]	Deep Learning for Scaling Low-Resolution Climate Data	Uses low-resolution data to produce detailed forecasts via deep learning.
	[25]	CNNs for Spatial Data Processing	CNNs classify satellite imagery for cloud cover and precipitation, improving spatial weather data.
Frequency Domain and Time Series Analysis	[26]	Frequency Domain Analysis	Effective for forecasting electricity prices and monitoring short- and long-term price fluctuations.
	[27]	Frequency Domain Decomposition + Deep Learning	High-accuracy predictions for solar PV power fluctuations, especially ultra-short-term.
	[28]	Time Series Cross-Validation	Enhances model reliability through systematic cross-validation.
	[29]	State Space Models	Captures temporal patterns in electricity demand, providing accurate one-hour load forecasts.
Renewable Energy and Integration	[30]	ANN, SVR, Random Forests	Evaluates methods for photovoltaic power forecasting with respective strengths and weaknesses.
Ensemble Methods and Hybrid Approaches	[31]	Ensemble Method - XGBoost	XGBoost delivers top-tier performance in electricity demand and weather forecasting.
	[1]	Hybrid Time Series + ML	Hybrid methods boost forecasting accuracy.
Extreme Events and Demand Prediction	[32]	RNNs for Heatwave Prediction	RNNs outperform statistical methods in detecting heatwave onset and offset.
Long-Term Forecasting	[33]	Deep Belief Networks (DBNs)	DBNs excel in multi-year electricity demand forecasting compared to traditional methods.
AI Explainability and ML Analysis	[34]	SHAP, LIME	Improves interpretability of ML models, aiding decision-making in energy management.
	[35]	SHAP with Hybrid Models	Enhances prediction accuracy and transparency in sediment dynamics forecasting.

A. TIME SERIES MODELS

Load forecasting is a significant technique used for load prediction [36]. It is a vital challenge in the generation and provision of electricity and many techniques have been developed in the literature for improving the efficiency of electrical load forecasting [37]. The purpose of this section is to discuss the pros and cons of the analyzed models, their further applicability, and the distinctive characteristics of time series models, Deep Learning, and Ensemble Learning based models.

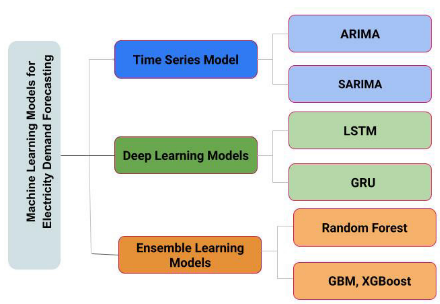

FIGURE 2. Classification of machine learning models for electricity demand forecasting.

1) ARIMA (AUTO REGRESSIVE INTEGRATED MOVING AVERAGE)

ARIMA is a broadly applicable, statistical model for analyzing and forecasting time series data. It is a time series forecasting technique that equips auto regression, integration and moving average elements to forecast the next values of time series which are non-stationary in nature [36]. It has three components. These three components, namely AR, I,

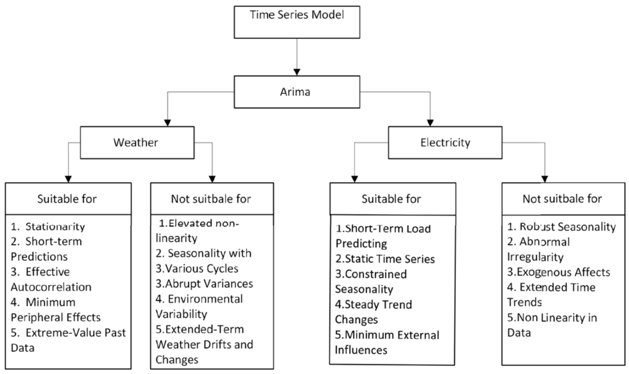

FIGURE 3. **ARIMA model suitability for weather and electricity forecasting scenarios.**

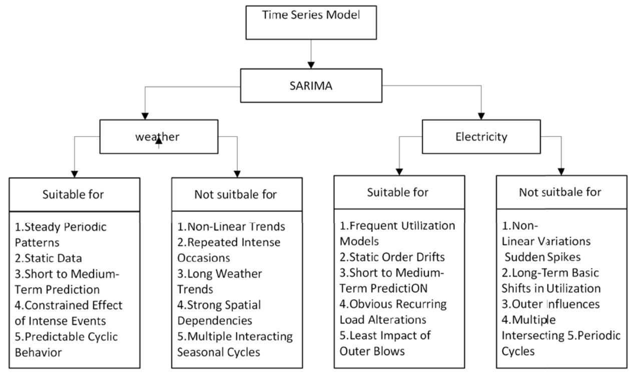

FIGURE 4. **SARIMA model suitability for weather and electricity forecasting scenarios.**

and MA make the ARIMA model capable of performing functionalities which enables the model to capture concepts such as linear relationship as well as time series data tendencies. ARIMA model can be represented normally in its order, which is p for the AR component order, d for the differencing order, and q for the MA component order.

Fig. 3 shows the suitability of the ARIMA model for electricity and weather forecasting.

a: AUTO REGRESSIVE (AR)
In auto regressive (AR) modeling, there exists a dependency between the present and past observation values of p units, representing how the present values are influenced by the past values. The parameter p in the order defines the number of previous observations used for prediction.

b: MOVING AVERAGE (MA)
In Moving Average models, the prediction process is based on a series of previous prediction errors of the order q to predict current values. This model identifies random shocks and short-term fluctuations in the data.

c: INTEGRATION (I)
The integration component (I) corresponds to the number of times (d) a data series needs differentiation to achieve stationary. Difference analysis removes trends along with seasonal patterns by computing differences between consecutive observation values. These three components merge to generate ARIMA(p,d,q) models, and each parameter is responsible for a specific purpose in time series forecasting.

2) SARIMA (SEASONAL ARIMA)
SARIMA,the Seasonal Auto-Regressive Integrated moving average model incorporates both the non-seasonal ARIMA part and the seasonal part [38]. ARIMA models are more commonly used for forecasting and time series analysis while SARIMA models on the other hand are designed specifically for handling seasonal data. This includes seasonal factors for time series data with recurrence in fixed time periods.

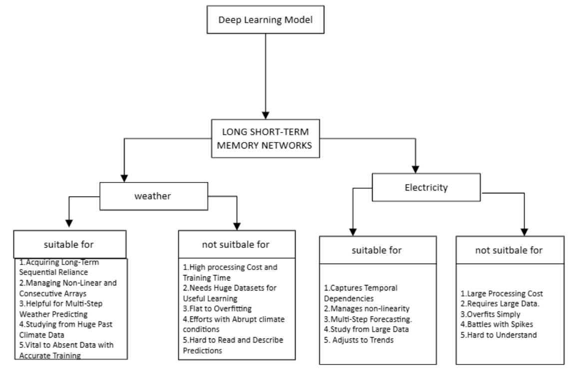

FIGURE 5. **LSTM model suitability for electricity and weather forecasting.**

SARIMA integrates seasonal AR, seasonal MA and seasonal I for capturing seasonal patterns. The seasonal AR terms are the coefficients that speak of the influence of current observation on its lagged observations at fixed seasonal intervals; seasonal MA on the other hand, depicts how the current observation depends on the residuals at seasonal intervals. The component of seasonal integration (I) deals with seasonality by eliminating seasonal trends.

Fig. 4 shows the suitability of the ARIMA model for electricity and weather forecasting. The SARIMA model is typically represented as (p, d, q) and (P, D, Q, m) where p, d, q, are nonseasonal parameters, and P, D, Q, m are seasonal parameters. ARIMA and SARIMA both models are widely used for analysis of complex patterns in time series data offering beneficial insights for decision making and forecasting.

B. DEEP LEARNING MODELS
1) LONG SHORT TERM MEMORY(LSTM)
LSTM is a type of RNN used for sequence data or for the time series data [39]. This is to avoid the vanishing gradient problem which is a major concern in other RNNs that are created using memory cells that can store info for a long time.

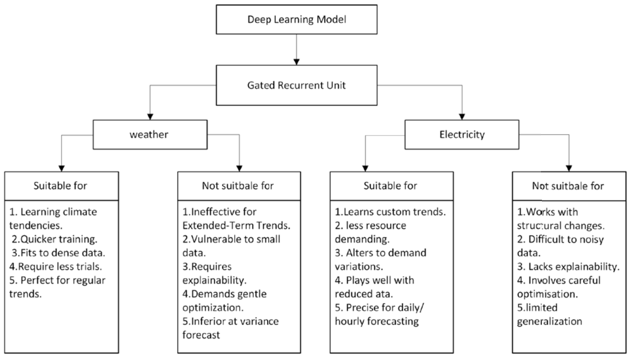

FIGURE 6. **GRU model suitability for weather and electricity forecasting.**

However, this information flow is controlled with the help of input, output, and forget gates that appear from the cell memory Therefore, LSTMs are advantageous while identifying the long-term dependency that is inevitable in any forecasting as it involves use of information from previous steps. Fig. 5 shows the suitability of LSTM model for electricity and weather forecasting.

2) GATED RECURRENT UNITS(GRUs)

Gated Recurrent Units(GRUs) operate in recurrent neural networks to handle temporal sequences in data which makes them ideal for weather and electricity demand predictions [40]. The GRUs maintain simple architecture compared to LSTMs enabling efficient computation which enables fast training at lower resource requirements. GRUs face performance limitations when dealing with long-term dependencies and variance forecasting because they perform less accurately in specific contexts [41]. Fig. 6 shows the suitability of GRU model for electricity and weather forecasting.

3) RANDOM FOREST (RF)

Random Forest is an algorithm of the ensemble learning model used in building decision trees in the training phase and the final output is the majority voting for classification or averaging for regression [42]. Ensemble learning is a strong ML approach that integrate different predictive models to improve the predictive performance and robustness [43]. To overcome overfitting where every tree is built from a subsample of data and features namely bootstrap sample. The final decision is obtained by combining all the results from individual trees hence producing a complete model that addresses all the complexities of data. Fig. 7 shows the suitability of Random Forest models for weather and electricity forecasting.

Table 2 provides a comparative overview of machine learning models, highlighting their strengths, limitations, and applicability to different forecasting scenarios.

C. GRADIENT BOOSTING MACHINES (GBM), XGBoost

XGBoost and GBM are vastly significant methodologies of ensemble learning, which develop models iteratively [44].

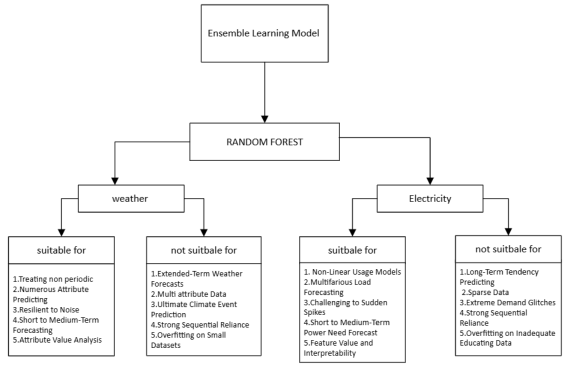

FIGURE 7. **Suitability of random forest models for weather and electricity forecasting.**

Every subsequent model intends to overcome the limitations of previous models and offers excellent accuracy and reliability in dealing with forecasting activities. GBM is a general model while XG Boost has included improvements for its speed and functionality making it highly applicable in machine learning competitions and real life. Fig. 8 shows the suitability of Gradient Boosting models for weather and electricity forecasting.

V. DISCUSSION

A. KEY MACHINE LEARNING TECHNIQUES

Some of the recent research has provided an in-depth understanding of different techniques used in the energy demand and weather forecasting hence combining the strength of the approaches. Among them, Long Short-Term Memory (LSTM) networks have shown the best results, and their performance in terms of predicting peak loads is higher compared to traditional models SARIMAX and their hybrids. Due to their inherent design, LSTMs have significant performance in capturing temporal patterns and are better suited in those environments where the data features are highly volatile and nonlinear [45]. Likewise,Artificial Neural Networks (ANNs) have been used in electricity demand forecasting, with some structures providing higher accuracy than others. This versatility and good performance in different forecasting contexts reinforce the benefits of ANNs [46].

SVR is another technique often used for demand prediction, especially when used in conjunction with other advanced methods of machine learning. Its advantage lies in its ability to capture the interdependence of variables within data [46]. Furthermore, prediction models based on gradient-boosting, including XGBoost, CatBoost, and LightGBM, have been used in energy consumption prediction. CatBoost (Categorical Boosting) serves as a specialized algorithm which belongs to the gradient boosting family to effectively work with categorical features alongside preventing overfitting through its own unique gradient boosting approach. While LightGBM functions as one of the highest performing gradient boosting frameworks that speeds up training time while using less memory than standard gradient boosting

TABLE 2. Machine learning models for electricity demand forecasting.

Technique	Strengths	Limitations	Applicability
ARIMA	Suitable for single-variable time series; easy to interpret.	Assumes linearity and stationarity; struggles with outliers and seasonality.	Best for short-term electricity demand when historical consumption dominates.
SARIMA	Captures seasonal effects better than ARIMA.	Complex to implement; still assumes linearity and stationarity.	Ideal for mid-term forecasting with seasonal variation.
LSTM	Captures long-term, non-linear dependencies with high accuracy.	Needs large datasets; may overfit due to complexity.	Useful for short-to-mid term forecasting with many input features (e.g., climate, economy).
Gated Recurrent Unit (GRU)	Faster training than LSTM; captures dependencies well.	May underperform LSTM on complex sequences.	Preferred when computational resources are limited. Good for short-term forecasting.
Random Forest	Handles non-linear patterns; highlights key features.	Becomes computationally heavy with many trees; less interpretable.	Suitable for short- and medium-term predictions with many variables.
GBM & XGBoost	High accuracy on large datasets; XGBoost is very fast.	Risk of overfitting; interpretability reduces with depth.	Best for short-to-mid term forecasts where speed and accuracy are crucial.

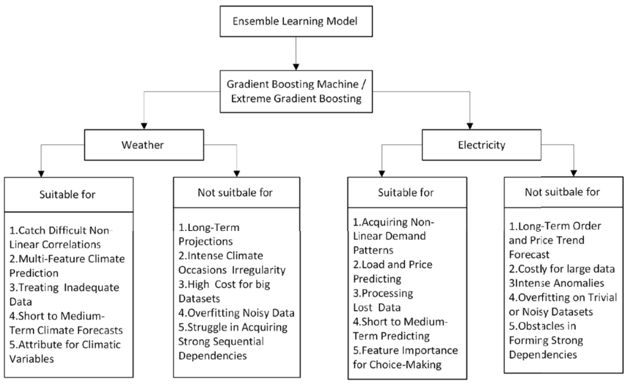

FIGURE 8. Suitability of gradient boosting models for weather and electricity forecasting.

techniques through its tree-based learning algorithms. These methods are particularly effective in the analysis of big data and in identifying nonlinear dependencies, which makes them ideal for solving more complex problems of forecasting [47].

The combination of different forecasting methods through hybrid approaches has produced favorable results in recent academic research. Various approaches use multiple methods which allow participants to achieve beneficial aspects from different systems as they work together to overcome each approach's individual drawbacks. A dual phase predictive method using double exponential smoothing integrated with NN is shown to be superior to individual forecasting approaches in terms of accuracy measures [48]. However, traditional time series forecasting models including ARIMA and SARIMA serve as fundamental building blocks for analysis but encounter difficulties when analyzing non-stationary data as well as complex nonlinear data patterns. The models achieve best results with autocorrelation coefficients and moving averages under situations where data demonstrates significant historical relationships (high historical behavior) and when forecast periods is relatvely short (small forecast span).

Research on machine learning methodologies demonstrates important trends in their application to forecasting solutions. LSTM models have proved themselves to be a significant tool for time series analysis; however, their effectiveness must be evaluated in context with other machine learning methods. The Research findings show that different predictive models excel in different scenarios, thus emphasizing that one should choose the methodology considering specific forecasting requirements instead of a universal approach [39]. Different key factors have been responsible for shaping advancements in forecasting techniques. First and foremost, the implementation of complex forecasting models became possible as computational resources have become more accessible. Secondly, growing complexity of energy systems because of renewable source integration requires forecasting systems which are adaptable to changing conditions. Thirdly, access to diverse data sources enables better forecast accuracy with the integration of multiple variables.

These developments have led to several important observations:

1) MODEL SELECTION TRADE-OFFS

The strength of different forecasting methods depends on what specific forecasting conditions exist. The forecasting capability of ARIMA works best when applied to time series that demonstrate strong historical patterns and short prediction horizons while LSTM networks deliver enhanced results when identifying long-term dependencies together with nonlinear correlations. Such diverse forecasting performance outcomes show why different methodologies need to be matched to individual forecasting needs.

2) DATA INTEGRATION CAPABILITIES

Modern forecasting approaches have shown remarkable potential in integrating multiple data streams. This capability is particularly valuable in energy management, where factors

TABLE 3. Comparison of forecasting methodologies.

Methodology	Approach	Complexity	Applicability
LSTM	Captures temporal dependencies and non-linear patterns.	High	Short-term and peak load forecasting.
ANNs	Learns complex relationships via layered architecture.	High	Common in load forecasting.
SVR	Uses hyperplanes and kernels.	Moderate	Works well with limited data.
Gradient Boosting	Combines weak learners to boost accuracy.	Moderate–High	Robust across diverse tasks.
Hybrid Methods	Combines strengths of several methods.	Very High	Ideal for complex or volatile data.
Time Series Models	Uses past values and error terms.	Low–Moderate	Suitable for stable historical patterns.

such as weather conditions, social events, and economic indicators can significantly impact electricity demand [49]. The ability to incorporate diverse data sources has enhanced both the accuracy and reliability of forecasts. Modern forecasting techniques demonstrate remarkable success in combining various data sources. The capability proves essential in energy management, where different factors like weather conditions, social events and economic indicators influence demand of electricity. Forecast accuracy and reliability improved because of inclusion capabilities with various data sources. Use of different data sources in forecasting enhances both accuracy levels and establishes reliable results.

3) COMPLEXITY VERSUS PRACTICALITY

The implementation and maintenance of complex models becomes challenging but these models deliver better accuracy levels compared to simpler models. Deciding between simple and complex models requires balancing theoretical performance against the practical factors like data availability, computational resources and operational demands.

Implementing machine learning for forecasting applications is more than technological advancements. This development represents a basic fundamental shift in managing energy challenges and policy developments. This shift is characterized by:

- Better flexibility in handling different data types
- Better ability to capture complex relationships
- Improved adaptability to changing conditions
- Better integration of domain knowledge with data-driven insights

However, every machine learning method fails to demonstrate dominance as the perfect solution for electricity demand forecasting. The benefits and drawbacks of each approach make them appropriate for different applications depending on specific conditions. Modeled on this understanding, hybrid approaches now become more popular as these approaches use their respective strengths while addressing their individual limitations.

The methodologies vary in terms of approach, level of complexity, and versatility for use in electricity and weather predictions. It can also be seen from Table 3 that there is no single machine learning algorithm that may be termed the best in electricity demand forecasting, since each of them has its advantages and disadvantages. For instance, although the ARIMA model is ideal for short-term prediction majorly based on past consumption, the LSTM proves ideal for long-term relations and non-linearity.

The future of forecasts in energy management will depend on smart implementations of different approaches based on specific constraints and requirements. This suggests that advancements in the field of forecasting in energy management require the advancement of individual algorithms alongside better tools for selecting and merging different methodologies.

B. BEST METHODOLOGY FOR FORECASTING ELECTRICITY DEMAND AND WEATHER CONDITIONS

Choosing the right type of machine learning technique for forecasting the electricity demand as well as the weather conditions involves evaluating the models and how accurately big data will be handled. With regard to the present study, some machine learning methods have been promising, and among them, Random Forest has been cited as the best-performing algorithm.

Although we have discussed several methods of machine learning for forecasting the electricity demand and climatic conditions, Random Forest was determined to be the most useful [50]. This allowed the model to reach a good forecast accuracy and identified important parameters such as the temperature of mains water and the dry temperatures in the outdoor environment. In terms of forecasting, the robustness of this method and the precision of outcomes that are acquired make this strategy technically and operationally feasible. Others include SVM, RF, GB, and NN, especially in a dual phase where the data is preprocessed using data-driven double exponential smoothened before feeding it to the input of the neural network. This leads to a considerable decrease in the error margin of the forecasts, which proves the effectiveness of the integrated application of several models [48].

Moreover,load forecasting performances in the models that comprise two or more algorithms are higher than the performances of particular algorithms. For example, in case of electricity demand forecasting, different configurations of Artificial Neural Networks (ANN) have been used, including specific settings that have been shown to perform better in different contexts as evidenced by [46]. Table 4 shows a comprehensive analysis of different ML techniques used for electricity demand forecasting. The table indicates that all methodologies have their strengths, ability to forecast, key predictors and specific application domains, thus showing the versatility of every methodology for various forecasting situations.

TABLE 4. Performance and applications of ML methods.

Method	Strengths	Accuracy	Key Predictors	Applications
Random Forest	Robust, reduces overfitting	Good	Temperature, water temperature	Short- and medium-term forecasts
Neural Networks	Handles non-linear data	Varies	Weather data, past load	General electricity demand prediction
Hybrid (ANN + Smoothing)	Combines methods for better accuracy	High	Weather-related factors	Complex demand forecasting
SVR	Works well with small datasets	Competitive	Historical load data	Suitable for short-term forecasts
Gradient Boosting	Handles high-dimensional data	High	Weather and social data	Effective for load/consumption prediction

The success of these methodologies can be attributed to several specific features like ensemble learning, handling non-linearity, integrating weather variables and advanced modeling techniques.

Ensemble Learning: Random Forest applies the method of ensemble learning which means that in order to make the decision, it uses multiple decision trees. This approach is useful in capturing interaction between variables and as such is highly suitable for dynamic systems.

Handling Non-Linearity: Neural Networks are useful when other methods are applied simultaneously because of the NN's ability to recognize the non-linear relationship, which is typical of electricity demand and weather data. This makes them able to learn from large data sets meaning they can adapt to dynamics in consumption.

Integration of Weather Variables: Random Forest and to a certain extent, Neural Networks, are better at considering the integration of weather factors, temperature, and solar irradiance, which are crucial to load forecasting [48]. This integration allows models to take into account the consequences of external conditions with regard to electricity consumption e.g tempertaure integration, solar irradiance effects and combined weather patterns.

Advanced Modeling Techniques: Innovations, for example, component-wise estimation procedures that decompose demand into deterministic and stochastic components enhance the capability of the models to capture complex demand behaviour [51]. Moreover, the use of feature selection and multiple criteria optimization has improved the accuracy and stability of the forecasts [52].

Thus, the decision concerning the choice of the best technique again depends on the given context of the forecasting and data available to the analyst. As machine learning algorithms improve in the future, more state-of-the-art modeling approaches and additional influencing factors can be included to make the predictions more precise and realistic to aid the proper management of the power system and the market.

1) PERFORMANCE METRICS FOR EVALUATING FORECAST ACCURACY

Choosing the right key performance indicators is vital for assessing the quality of the prediction models. Fig. 9 shows the key performance metrics for evaluating forecast accuracy.

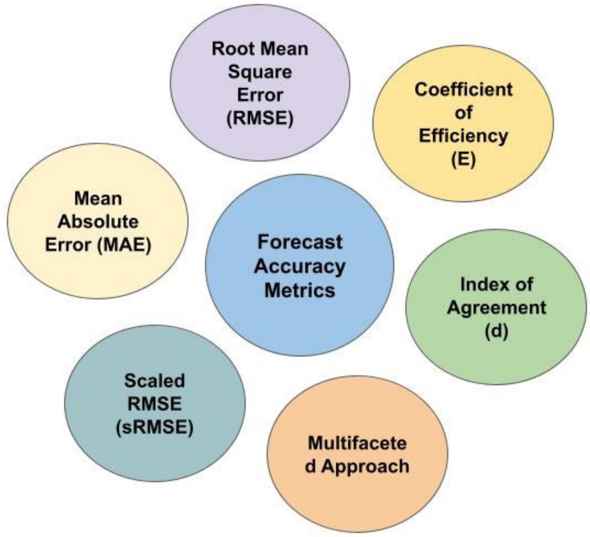

FIGURE 9. Key performance metrics for evaluating forecast accuracy.

Root Mean Square Error (RMSE): Quantifies the mean size of errors in a set of predictions, thus giving an idea of how 'far off' the predictions are from actual values.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Mean Absolute Error (MAE): Expresses the mean of the absolute deviations between forecasted and actual values, providing a quick and easy method of assessing the accuracy of the forecast.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

caled RMSE (sRMSE): A measure that can be less dependent on the scale and can contribute to a better assessment of the model's accuracy in terms of its ability to recognize shifts in variance.

$$\mathrm{sRMSE} = \frac{\mathrm{RMSE}}{\sigma_y} \tag{3}$$

Coefficient of Efficiency (E): Used to determine how closely the predictions of the models match up to the observed

TABLE 5. Metrics for evaluating ML models in electricity demand forecasting.

Metric	Strengths
RMSE (Root Mean Squared Error)	Widely used; penalizes large errors.
MAE (Mean Absolute Error)	Simple and interpretable; less sensitive to outliers.
sRMSE (Scaled RMSE)	Detects changes in model variance.
sPIS (Scaled PIS)	Compares models across varying scales.
Coefficient of Efficiency (E)	Measures predictive power relative to observed mean.
Index of Agreement (d)	Captures agreement between predictions and observations.
Multifaceted Evaluation	Combines qualitative and quantitative criteria.

data with higher values closer to 1 being preferred.

$$E = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{4}$$

Index of Agreement (d): Checks or estimates how well-anticipated values approximate the actual values and give information about the model's robustness to outliers.

$$d = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(|y_i - \bar{y}| + |\hat{y}_i - \bar{y}|\right)^2} \tag{5}$$

Multifaceted Approach: The research shows that boosting reliability through forecast accuracy measurements requires changing original metrics while attempting to remove outlier data when feasible [53]. Using quantitative statistical error metrics along with qualitative expert assessments and pattern analytics enables a detailed forecast model evaluation by detecting anomalies and interpreting local patterns while checking practical usability at the expense of longer analytical processes [54].

Table 5 the characteristics of a set of metrics that can be applied to ML models in electricity demand forecasting. These metrics offer a holistic approach to performance evaluation besides being unique in their way thus making a strong model evaluation.

C. SUITABLE DATASETS FOR MACHINE LEARNING TECHNIQUES

Machine learning has been found to hold much potential in the prediction of weather and electricity, and there are various datasets for various algorithms. The following types of datasets are particularly suitable for different forecasting methodologies.

Historical Electricity Demand Data is important so that the models can be trained to be able to predict future electricity demand. This dataset enables algorithms to understand patterns and trends of usage over time. Artificial Neural Networks(ANNs) work well at modelling non-linearities in the demand patterns, while a Random Forest model performs better than a linear model by addressing the interactions between variables [55].

Weather Data is another important component as all the environmental variables like temperature, humidity, wind speed, and even solar irradiance have a direct correlation with the electricity demand. The decision tree models include CART, XGBoost and AdaBoost which revealed a higher percentage of classification when the demand is forecasted by the weather factor [56]. Moreover, the Linear Regression algorithm gives satisfactory results with deterministic regression functions regarding the weather information.

Table 6 provides a classification of various types of data sets which have been used for electricity demand forecasting with the most suitable algorithms.

Other factors like Economic Indicators such as electricity tariffs as well as demographic characteristics also impact electricity consumption and should be taken into consideration while modelling. Linear regression algorithms are also useful in the decision-making process, especially Support Vector Regression(SVR) which gives good results when economic indicators are included among the parameters.

Furthermore, Solar Power Generation Data is essential for the models addressing the problem of power demand in relation to renewable electricity generation. The incorporation of the solar generation data can enhance the prediction accuracy once an ensemble model that combines several algorithms such as the Random Forest and XGBoost is used [55], [57].

1) IMPACT OF DATA QUALITY AND INTEGRATION

The quality and relevance of selected raw data matter considerably in the performance and accuracy of the forecasting models. It becomes extremely relevant concerning the data quality problem; for example, in photovoltaic power forecasting – the difference in the absolute error with the help of high-quality data can be reduced by approximately 3.25% than the costs incurred in cases that include low-quality data [58]. This has shown the importance of the quality of data that is used in preparing data for use in creating a predictive model.

Moreover, there is a positive effect on the performance and a negative one on the bias with the correct alignment of source-target similarity in the field of time series forecasting and source diversification leads to enhancement of the performance and variability estimation [59]. It also can be observed that the human judgment involved in the integration with computational analytics also can lead to the improvement of the accuracy of forecasting, where machine learning with the assistance of humans has been found to be one of the most efficient integration types [60]. For example, the hybridization of ANN with time series models such as ARIMA gives a higher forecast accuracy than the utilization of artificial neural networks alone [61]. This research emphasizes the significance of data quality, variety, and integration techniques as aspects that can enhance the performance of forecasting models in various disciplines.

Table 7 shows different datasets used in electricity demand forecasting, key variables, suitable techniques, and effects on forecasting accuracy. This table shows what kinds of data play a role in forecasting and why it is crucial to apply a suitable method to each type of data.

TABLE 6. Dataset types and suitable algorithms.

Dataset	Description	Best Algorithms
Historical Demand	Captures usage patterns over time; useful for training time-series models.	ANNs, Random Forest
Weather Data	Includes temperature, humidity, wind speed, and irradiance; strongly affects load.	Decision Trees, Linear Regression
Economic Indicators	Tariffs, income, and population influence long-term demand.	SVR, Linear Regression
Solar Generation	Links renewable supply variability with demand forecasting.	Random Forest, XGBoost

TABLE 7. Dataset types and their role in forecasting.

Dataset	Key Variables	Techniques and Impact
Historical Demand	Past electricity usage data	ANNs, Random Forests; capture trends and seasonality
Weather Data	Temperature, humidity, solar irradiance, wind	XGBoost, Decision Trees, Regression; improves short-term accuracy
Economic Indicators	Tariffs, GDP, income	SVR, Regression; influence long-term demand
Solar Generation	Solar output, capacity	Random Forest, XGBoost; aids in integrating renewables

Hence, the suitability of the data sets for different machine learning techniques bears considerable importance to determine the power requirement and climate conditions. The quality of data used in the models also enhances the accuracy and reliability of the business forecasting models, besides the numbers, and the ways through which these variables diversify and are integrated. Thus, with the extension of machine learning, the use of historical and environmental data as well as data concerning the economic conditions will remain the core elements in the development of effective forecasting solutions for the new conditions in the sphere of energy.

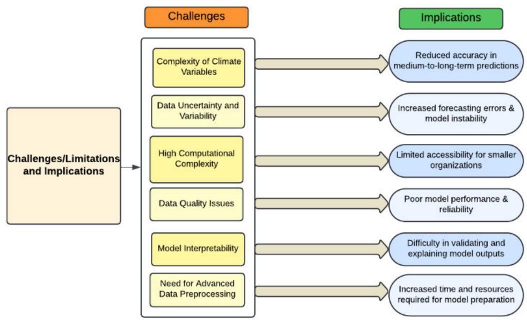

FIGURE 10. Challenges/Limitations of ML techniques and implications.

D. CHALLENGES AND LIMITATIONS OF MACHINE LEARNING TECHNIQUES

The ML algorithms are popular in electricity and weather prediction; however, one should remember that any method has its advantages as well as its drawbacks. One primary challenge is the climate variables, and the factors involved in the availability and constraints of data in medium to long-term forecasting. Although ML is useful in short-term forecasting, it does not capture the climate characteristics that characterize long-term structures [32].

In terms of renewable energy forecasting, traditional methods are generally outperformed by ML and deep learning algorithms in terms of short-term predictions. Nevertheless, they face difficulties rooted in uncertainty and variability in data. For example, errors and uncertainties in input information may result in incorrect forecasts and such factors as high computational intensity may negatively influence the implementation of these models [62].

Furthermore, many-application development expands to manage more uncertainty in electricity markets, further research is needed to better tap into it [63]. Some of the pre-processing techniques include anomaly detection, normalization and clustering which provide high efficiency to machine learning models as per the forecasting made on renewable energy and at the same point, add a next level of new complexity to the modelling.

Fig. 10 shows the key limitations of using ML for forecasting including, but not limited to high complexity, poor data quality, or low interpretability that could lead to either lesser accuracy or increased errors.

E. IMPACT OF COMPUTATIONAL REQUIREMENTS, MODEL INTERPRETABILITY AND DATA QUALITY

Computational requirements, model interpret-ability and data quality have a significant impact on the practical implementation of machine learning techniques. Forecasting accuracy greatly depends on data used in the analysis and prediction processes. Techniques like data denoising, outlier detection, and imputation have proven very effective in extracting meaningful information from incomplete or noisy datasets [64].

Furthermore, model interpretability is also important. The black-box property of many deep-learning models can obstruct user trust and acceptance. Therefore we must develop methodologies that improve on the interpretability of predictions made by these models [64]. Interpretable machine learning techniques help identify key features leading to a reduction in dimensionality while maintaining good data quality for major attributes [65].

The main issues and difficulties of utilizing machine learning approaches for electricity demand forecasting or in the broadly defined power system area are summarized along with descriptions and consequences of the main challenges to illustrate that the accuracy of the forecast is challenging.

In conclusion, the use of the application of the machine learning methods has vast possibilities in changing electricity and weather prediction and like any other machine learning technique it has the pros and cons associated with it. Nevertheless, there are some drawbacks to every of these approaches that are computational requirements, model interpretability and data quality in terms of their proper implementation. These challenges must be addressed to enhance the effectiveness of ML-based forecasting applications, as such, ongoing research activities are going to have a significant impact on the future advancement of this field.

F. PRACTICAL IMPLICATIONS AND RECOMMENDATIONS

1) PRACTICAL IMPLICATIONS

The application of the advanced methods of ML in the forecasting environment has far-reaching implications for energy management, and consequently policies. They can increase energy efficiency in various energy systems and advance the accuracy of forecasts in every one of them. More precisely, in terms of electricity demand forecasting, renewable energy generation prediction and energy price forecasting [66], it is observed that the Deep Learning models are more suitable than the other types of models.

These developments have practical implications.

a: IMPROVED GRID OPERATION

Enhancement of the forecasts enables the grid operators to forecast the demand variation impacts on efficiency and cost saving.

b: PLANNING ENERGY IN AN EFFICIENT MANNER

Forecasting provides the basis for resource management that enables energy companies to minimize wasteful use of resources while, at the same time, preparing for future demands for energy.

c: BETTER INTEGRATION OF RENEWABLE ENERGY SOURCES

This will be realised through advanced use of ML models to enhance the balance management of variable renewable electricity generation like wind and solar by addressing generation prediction accuracies.

However, there remain some limitations to it. Some of these challenges are; data privacy/ security, and lack of availability of specialized professionals to harness it to optimum benefits [67]. Future research directions can include the construction of a dependable M2L physical model for integration with renewable power and Smart Grids, accommodative to variability and uncertainty and model interpretability [62].

2) RECOMMENDATIONS FOR FUTURE RESEARCH AND DEVELOPMENT

Concerning future work and development for enhancing the precision and efficiency of electricity and weather forecasts, there are a few domains that need to be concentrated on.

a: INTEGRATION OF ADVANCED MODELS

Conventional methods of forecasting should be complemented by more sophisticated machine learning models like Enhanced Convolutional Neural Networks (ECNN) for accurate short-term weather parameters prediction. This is critical in order to predict competently or forecast accurately the supply and demand schedule or power [68].

b: FOCUS ON STOCHASTIC FORECASTING

Since wind energy is stochastic, the deterministic and probabilistic model of wind power forecasting should be built [69].

c: ADDRESSING DATA PRIVACY AND CYBERSECURITY

For future research, better frameworks framing the details of data privacy and cybersecurity need to be applied to protect the data while using it for prediction.

d: SUPPORTIVE REGULATORY FRAMEWORKS

There must also be enabling policies that will drive the use of ML technologies in energy forecasting by the policy makers, foster collaboration between academia and industries.

e: INVESTMENT IN TRAINING

To maintain and improve the capability to utilise such complex forecasting methods, it is therefore necessary to further invest in developing human capital with knowledge in AI and ML [67].

The use of advanced technologies such as ML in the conventional approaches of forecasting electricity load and climatic factors has significant impacts in the energy sector and policy formulation. These methodologies will improve the grid management systems, energy plans and also assist in integrating renewable power sources as their predictive accuracy is improved. In future studies, the present problems should be solved concurrently with the development of flexible models to deal with ever-changing energy systems.

VI. CONCLUSION

The use of modern machine learning tools to predict electricity demand and weather conditions is the manifestation of great change in the energy field. The better performance of some of the models like Random Forest and LSTMs shows the possibility of more accurate predictions in both energy consumption and generation to improve the implementation of renewable energy in the current grid system. However, there are still concerns regarding data quality, the huge computation demands required for some of the models, and the interpretability of the results for training model users.

Possible future work should focus on the construction of models that are accurate and resilient enough to account for the emerging characteristics of energy systems, coupled with strict confidentiality and security management of data. Working closely with other related stakeholders including researchers, policymakers and other players within the energy industry, the application of machine learning for modeling, management of the grid systems and sustainable energy can easily be put into practice within the most efficient manner.

As electricity demand forecasting continues to advance, emerging trends and research gaps are shaping the future of this field. This section discusses these trends and identifies future directions.The generative models include Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs) that have demonstrated some effectiveness in different applications of forecasting. These models can produce artificial data that looks like the original data on realistic parameters thus improving the accuracy of the forecast models. The advancement of technologies also help in getting new data from smart meters and IoT devices in real-time and these also help in making the accuracy of the forecast better. With regard to forecast data, past consumption and climate data can be used in the same ways as in other contexts, and with predicted data streams, to enhance the success rates of the models over time and changing states. Machine learning techniques such as ensemble methods that involve a convergence of different models are being adopted widely in electricity demand forecasting. The use of ensemble models can provide better and more accurate forecast outcomes by relying on the varying strengths of the techniques in question. Some machine learning techniques have been proven to yield good results in short-term forecasting, but more study has to be done on the use of these techniques for medium and long-term forecasting. Mitigating issues like the failure to capture the dynamics of economic and demographic factors will prove imperative in the formulation of long-term strategies As weather conditions are being altered due to climate change it is now critical to determine the role played by climate on electricity usage. Forecast models that can address the influence of climate change on demand over period lengths is an important research direction.With a rise in the complexity of machine learning models, there is a greater demand for XAI. Thus, creating methods that will help to gain some understanding of how those models work will improve trust, understanding, and, therefore, applicability in such problem domains which are real-world in nature.

The future, therefore, is in the combination of these advanced technologies with traditional methodologies in electricity demand forecasting. Addressing the gaps in areas such as medium to long-term forecasting, climate change impact assessment, and explainable AI will enable researchers and practitioners to create even better, more efficient, and understandable models for the transition to sustainable energy systems.

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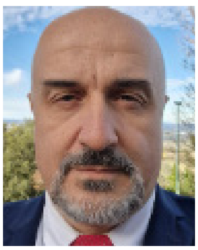

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