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Energy Forecasting Models for Power and Telecommunication Infrastructures: A Systematic Review

Tolulope Erinosho[1], KamoliAmusa[1],Abdultaofeek Abayomi[2], Fatai Kazeem[1], Imhade Okokpujie[3], Abolaji Okikiade Ilori[4]

[1]*Department of Electrical and Electronic Engineering, Federal University of Agriculture,Abeokuta, Ogun State, Nigeria*

[2]*Innovation and Advanced Science Research Group (IASRG), Summit University, PMB 4412, Offa, Kwara State, Nigeria*

[3]*Department of Mechanical and Mechatronics Engineering, Afe Babalola University,Ado Ekiti, 360001, Nigeria*

[4]*Department of Electrical and Biomedical Engineering, Faculty of Engineering and Technology, First Technical University, Ibadan, Nigeria*

Abstract: *Energy demand for power and telecommunication infrastructures has risen in recent years owing to technological advancements. The downtimes caused by an inadequate energy supply to critical infrastructure pose a great risk to daily activities. Hence, knowledge of future energy demands is pertinent to minimizing losses and operational costs, while ensuring consistent and reliable services. This article comprehensively reviews different models for predicting energy requirements by power and telecommunication infrastructure. The findings reveal that, while traditional models such as linear regression are simple to implement, models utilizing machine learning (ML) and deep learning (DL) techniques demonstrate superior performance in predicting energy consumption, yielding more precise outcomes. It has also shown that ML and DL models, including long short-term memory (LSTM), convolutional neural networks (CNN), Gated Recurrent Units (GRU), and hybrid architectures, are particularly effective for handling the complexities of long-term forecasting and adaptive systems. Thus, this current study offers valuable insights for academia, researchers, and energy personnel in network planning of the power and telecommunication industries to improve energy efficiency and cost management by analyzing historical data, identifying complex patterns, enabling real-time adaptations, and accurately forecasting their energy requirements. Researchers can also build upon the identified gaps to enhance the existing models and improve productivity.*

Keywords: *Energy, Infrastructures, Machine-Learning, Forecasting, Deep-Learning, Telecommunications*

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I. Introduction

Accurate energy demand predictions help optimize resource allocation, improve system reliability, and reduce operational costs [Ahmad et al. 2022; Granderson et al. 2023].As telecommunication networks expand, energy requirements and consumption management have become major concerns, thus increasing the need for robust forecasting models[Khan et al. 2021;Kumar et al. 2023].Although the population has titled towards mobile telecommunications, Williamset al. (2022) found that the energy requirements for the adoption of new technologies have been grossly overlooked.Tawn and Browell (2022)reviewed the different methods to forecast solar and wind power generation. According to the review, precise wind and solar forecasting increases the value of renewable energy by economically enhancing the dependability and viability of these resources. Efforts to ensure that future energy generation and demand are known beforehand can be observed in these studies [Tawn and Browell 2022].Hence, the focus should be on methods that can be used now and in future research.

Energy forecasting has traditionally used conventional techniques, such as Box-Jenkins and exponential smoothing.However, these methods often struggle with nonlinear patterns and large-scale datasets, which are common in power systems and telecommunications [Rao et al. 2023].However, intelligent machine learning (ML) methods can model nonlinear interactions. These techniques, developed using artificial neural networks (ANNs), fuzzy logic, and support vector machines, outperform the traditional techniques[Ahmadi et al. 2023]. However, the use of deep learning (DL) for Short-Term and Long-Term Forecasting (STLF) is a further development of these techniques [Pin et al. 2020].DL and ML methods have proven to be effective instruments for energy forecasting in recent years [Paige et al. 2022].Since 2015, ML and DL have grown in prominence, according to Google Trends (2024)data. A trend depicting the rise in the popularity of DL and ML is shown in Figure 1, indicating that ML is more popularly utilized.Ahmadet al. (2021)provided a realistic baseline that allowed researchers to compare their efforts in AI, ambitions, standard applications, challenges, and global roles in policymaking.

In a study on load forecasting, Nti et al (2020) critically reviewed previous studies, with a focus on the factors that affect its accuracy. The study showed the prevalence of the adoption of Artificail Neural Networks (ANN) for load forecasting and the challenges that comes with time series analysis.However, the review paper by Alsharef et al (2022) discussed the nonlinearity and complexity of time-series data and how it can be addressed usingautoML and DL frameworks..Arsene and Parisio (2024) applied six new prediction models that work with the principle of Convolutional Neural Networks (CNN) on integrated electrical, heat, and gas network systems to understand the model's effectiveness in multi-energy systems.A. Yang, Li and X. Yang (2019) used least-squares support vector model (SVM) methods to perform commercial and industrial data experiments to test the accuracy of the method for energy forecasting.Other studies have all demonstrated the extensive use of ML and DL methods in energy forecasting [Chinnaraji and Ragupathy 2022;De Real, Dorado and Duran 2020;Huang et al. 2022;Li et al. 2022;Roman-Portabales, Lopes-Nores and Pazos-Arias 2021;Vu et al. 2021].

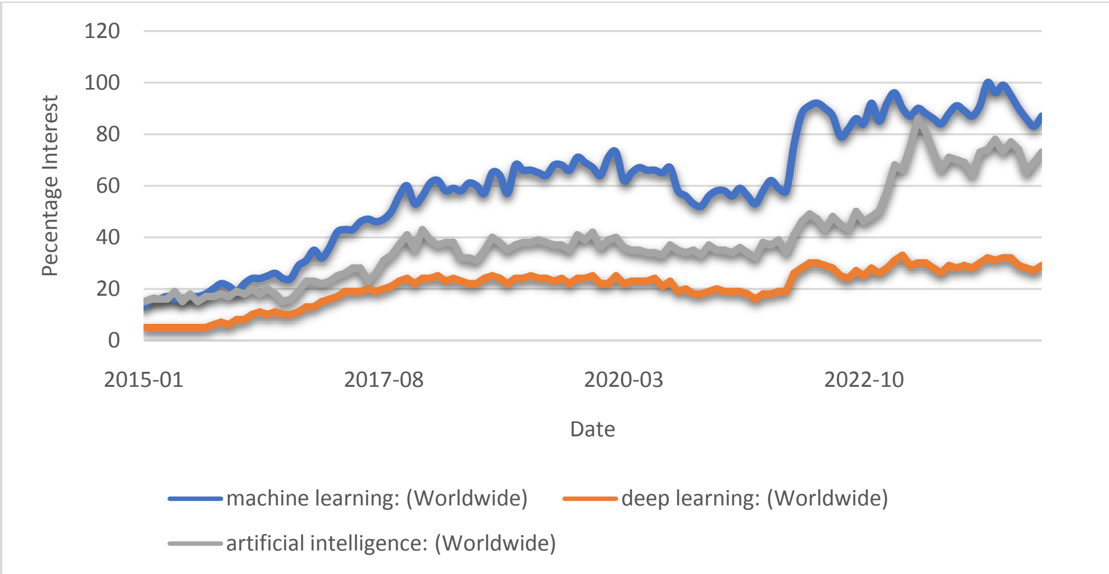

Figure 1: Percentage interest in ML and DL applications [Google Trends (2024)]

Nevertheless, ML/DL approaches present challenges due to their more intricate and time-intensive training process compared to regression models [Aslam et al. 2021]. This is attributed to the fact that DL techniques necessitate substantial computing power and extensive data collection [Whang et al. 2023].In power systems and telecommunications infrastructure, accurate energy forecasting is crucial to ensure continued grid stability, effective load balancing, reduced downtime, and the management of integrated renewable energy sources.Hence, this study seeks to perform a comprehensive analysis of energy prediction methods for electrical power and telecommunications systems..The overarching research objectives include establishing the benefits of energy forecasting, ML, and DL methods in energy forecasting, and the potential to improve energy efficiency.

1.2 Methodology

A systematic literature review is a guide to search for relevant literature, define the research gap therein, and investigate it.Consequently, the questions to which this study seeks answers are as follows:

i. Is energy forecasting important? What benefits do ML and DL methods provide for energy forecasting?
ii. Can barriers hinder the use of the ML and DL methods for energy forecasting?

"Energy, Infrastructures, Machine-Learning, Forecasting, Telecommunications and Deep Learning" are the keywords with which the relevant academic literature were searched in Elsevier, Scopus, and Web of Science (WoS) academic databases. Relevant publications were screened by title, abstract, and date within a 10 year period (2015-2024).Figure 2 illustrates the block diagram of the screening process employed in this study.

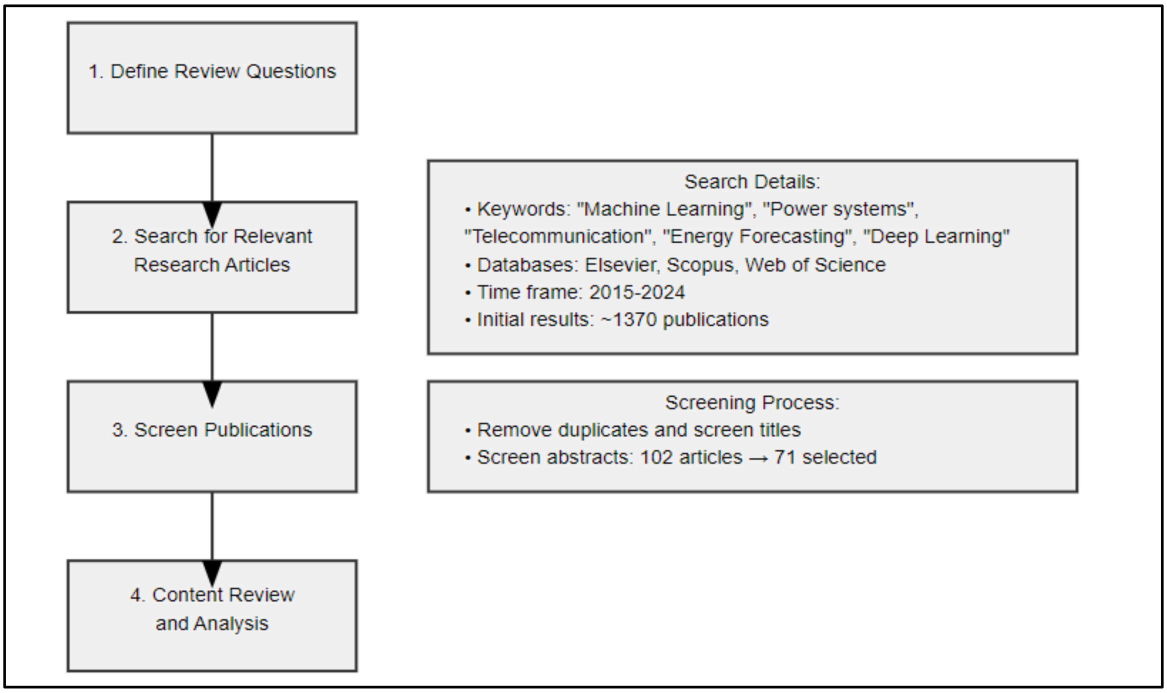

Figure 2: Block diagram of the methodology applied for literature search

II. Previous Studies On Energy Forecasting Methods In Power And Telecommunication Infrastructures

Elucidated in this section are some of the various approaches employed for energy forecasting in telecoms and power systems.

2.1 Traditional energy forecasting techniques in power systems and telecommunications infrastructure.

Several techniques have been utilized for energy forecasting in power and telecommunications systems.Traditional approaches like ARIMA and linear regression, and their shortcomings in modern applications are hereby presented.

Aurnaet al. (2021)conducted time series analysis with the ARIMA and Holt-Winters model to forecast the periodic energy consumption of a study area. However, there is a need for more comprehensive comparisons between the various forecasting models and their applicability in different contexts.Ciulla and D'Amico (2019)on the other hand used the Multiple Linear Regression (MLR) to find correlations within 195 different scenarios. The insufficiency in the overall results prompted the authors to consider a statistical method designed to assist unskilled user in estimating building energy demand.While theproposed method is easy to use, MLR cannot treat nonlinear problems.In another study,Grzegorz (2016) implemented models that required one variable for short-term load forecasting that utilized a single variable, leveraging linear regression and the daily cycle patterns observed in load time series data.However, the local modelling approach, which is beneficial for reducing complexity, may not be generalized well across different periods or conditions.This could lead to poorer performance when forecasting situations that deviate from the historical patterns used to train the model.Barak and Sadegh (2016)in their studysolved the unavailability of the energy consumption dataset in Iran byusing a hybrid model-ARIMA (Auto Regressive Integrated Moving Average)–ANFIS (Adaptive Neuro Fuzzy Inference System) model.However, this method poses a significant risk to the reliability of the models.The study by De Oliveira and Cyrino Oliveira (2018) expanded the use of combined bagging and forecasting methods in the electric energy sector using a combination of ARIMA and exponential smoothing methods.However, the inability of the models to model nonlinear data still limits the effectiveness of the methods employed.However, the research conducted by Clements, Hurn, and Li (2016) demonstrated that a multiple-equation time-series model can rival or even surpass the performance of complex nonlinear and nonparametric forecasting models.However, their use in other regions with different load characteristics or market structures remains untested.Reliance on a linear model may limit the ability to capture intricate patterns in the data.In addition, the model assumed stationarity in the time series data, which differs from real-world scenarios in which load patterns can change due to various external factors.This assumption can lead to inaccurate forecasting results.However, Regmi and Pandey (2015) investigated the energy demand in Nepal's Information and Communication Technology (ICT) sector, focusing on the telecommunications sector using the ridge regression model.The model, although effective in avoiding multicollinearity, may not capture the full complexity of the energy consumption patterns in the ICT sector.In a separate study by Ihedi-Okonkwo and Omosigho (2020) utilized a linear power consumption model to evaluate how the traffic load and instantaneous power consumption of the two base stations selected depend on each other.This is represented by a linear equation, where the power consumption is modelled as a linear combination of the traffic load and a random error term.However, the linear modelling method assumed a constant linear relationship between the traffic load and power consumption, which did not account for the nonlinear dynamics that can occur in real-world scenarios, such as sudden spikes in traffic or varying operational conditions that could lead to different power consumption patterns.

This overview of various energy forecasting techniques in power systems and telecommunication infrastructure highlights traditional methods and their limitations.The reviewed studies show that energy demand grows alongside ICT development, but linear models often underestimate consumption by omitting factors such as environmental conditions or network configurations.While effective in reducing multicollinearity, ridge regression and logistic growth models also fall short in accurately predicting energy usage owing to limited data and the inability to model nonlinear behaviours.These challenges underscore the insufficiency of traditional models and the need for advanced techniques such as ML/DL, which can handle nonlinearity, adapt to changing conditions, and process more comprehensive data inputs.Table 1 summarizes the traditional methods used in this study.

Table 1: Summary of traditional methods for energy forecasting

Reference	Case Study	Model Used in the Method	Shortcomings
Aurnaet al. (2021)	Energy consumption forecasting for Ohio/Kentucky using time series analysis.	ARIMA and Holt-Winters model.	Lack of comprehensive comparisons with advanced techniques like ML.
Ihedi-Okonkwo and Omosigho(2020)	Evaluating power consumption of base stations based on traffic load using linear regression.	Linear power consumption model.	Fails to account for nonlinear dynamics and factors such as environmental conditions.
Ciulla and D'Amico (2019)	Building energy demand estimation using Multiple Linear Regression (MLR).	Multiple Linear Regression (MLR).	It cannot handle nonlinear problems and is limited to linear relationships.
Grzegorz (2016)	Short-term load forecasting using linear regression univariate models.	Single variable models that are based on linear regression and daily cycles.	Limited generalizability across different time periods and inability to model nonlinear relationships.
Clements, Hurn and Li (2016)	Energy load forecasting in Queensland, Australia	Multiple equation time-series model.	Assumes stationarity in time series data may not adapt to other regions or changing conditions.
Regmi and Pandey (2015)	Estimating energy consumption in Nepal's ICT sector with a ridge regression model.	Ridge regression model and logistic growth model.	Relies on publicly available indicators omits critical data, leading to underestimation.

2.2 Application of advanced techniques in energy forecasting of power systems and telecommunication infrastructure

Following the challenges and limitations of traditional techniques for energy forecasting, the need to adopt advanced methodologies that consider nonlinear dynamics and external factors that affect energy forecasting has been established. Advanced techniques such as the use of ANN, Random Forest, and k-nearest neighbor (kNN) in energy forecasting have been considered. Figure 3 shows the difference between the ML and DL processes, highlighting the exemption of the input feature extraction process in DL models [Ahmad et al. (2021)].

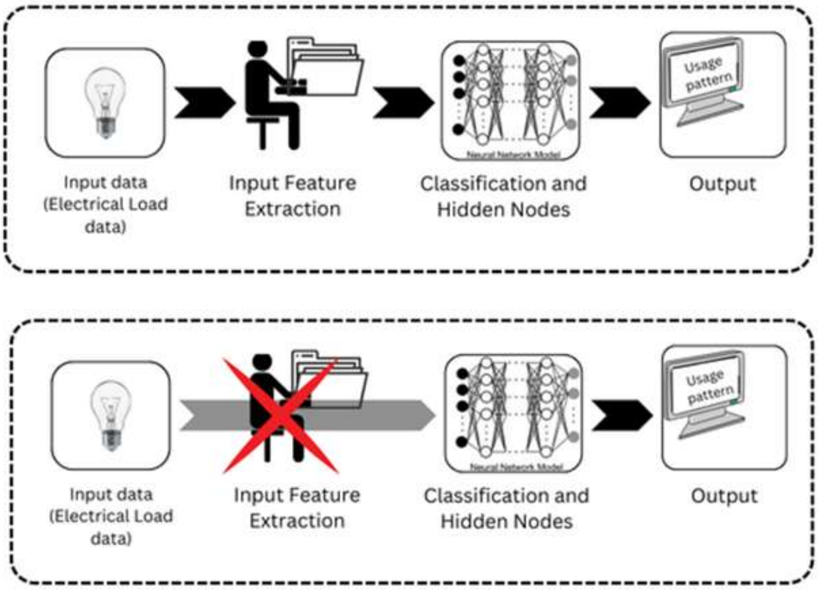

Figure 3: Advanced techniques ML and DL procedures of energy forecasting[Ahmad et al. (2021)]

2.2.1 ML techniques in energy forecasting of power systems and telecommunication infrastructure

Artificial Neural Networks (ANNs) have the capability to estimate a function based on provided input data and corresponding load data, which are utilized as training data [Khwaja, Naeem, and Venkatesh, 2020].An ANN is a mathematical model designed to emulate the structural and functional characteristics of biological neural networks.Chevez and Martini (2024) used ANN models to predict the short- and long-term forecasting hourly energy of a university building simultaneously. The models utilized parallel method of carrying out the prediction of both frequencies.Khwaja, Naeem and Venkatesh (2020) explored ensemble ML with focus bagging and boosting techniques to improve the accuracy of the selected model by testing real data from the New England Pool region.The model effectively enhanced the precision of short-term electricity load forecasts by leveraging ensemble learning with ANNs, offering improvements in both prediction accuracy and error reduction compared to conventional methods.

Supply-demand balance is key to maintaining continuity of electrical energy supply to power systems [Impram, Varbak and Oral. 2020]. According to Mashud and Koprinska (2016), a crucial challenge in the design and management of power systems and energy markets is forecasting the electrical load.Their study introduced an innovative approach to short-term load forecasting by utilizing Advanced Wavelet Neural Networks (AWNN).The AWNN broke down the intricate electricity demand data into components with distinct frequencies that were predicted independently.The combination of wavelet decomposition and NNs proved to be a powerful tool for handling the complexity and nonlinearity inherent in electricity-load time-series data.Alarajet al. (2021) used a Random Forest regressor to predict the energy generated by solar photovoltaic plants based on weather factors.The model was implemented in the MATLAB Simulink environment and demonstrated effective prediction capabilities, thus indicating the utility of the Random Forest model in energy forecasting.Yagli, Yand and Srinivasan (2019)assessed the effectiveness of 68 ML algorithms for forecasting solar energy under different climate zones, sky conditions, and locations. It provides a comprehensive analysis of the model performance and finds significant variations in accuracy across different algorithms. El Maghraouiet al. (2022) focused on using ANN, SVM, Decision Tree and Random Forest to predict energy usage in hotel buildings and concluded that the RF algorithm was the most reliable for predicting energy usage in such environments.Laayati, Bouzi and Chebak (2022) proposed a smart energy management system to improve energy efficiency in open-pit mines using ML.This study developed a monitoring system that optimized the energy consumption and supported predictive maintenance.

Dalal et al. (2023) proposed a hybrid forecasting model called TLIA (Transferring long short-term memory into an artificial neural network (TLIA) for energy forecasting.The model integrates LSTM and ANN, leveraging transfer learning to enhance performance by preventing backpropagation modifications in the LSTM layers while updating the ANN layers.The model tested on six datasets significantly outperformed the other seven datasets, thus making it highly efficient for volatile energy market forecasting.Consequently, Lee and Cho (2022) evaluated SARIMAX with SVR, LSTM, and ANN models for peak load forecasting in Korea, and demonstrated that hybrid models, particularly those combining time series and ML, achieved superior performance in energy forecasting compared to individual models.Alhendi et al. (2023) focused on short-term load and price forecasting using an Artificial Neural Network (ANN) integrated with an Enhanced Markov

Chain (ANN-MC) model.he ANN-MC model demonstrated superior performance compared to conventional ANN models, achieving better results across various metrics, including Mean Absolute Percentage Error (MAPE) and Mean Prediction Error (MPE).Although the ANN-MC model showed a higher computational time and a greater risk index than the ANN model, it consistently provided more accurate forecasts.Dinesh, Makonin and Bajic (2019) applied ANNs to forecast power usage in individual houses using non-intrusive load monitoring.The model demonstrated significant accuracy in capturing the characteristics of the houses selected for the study. In contrast, Baba (2022) evaluated a self-tuned ANN-based adaptable predictor using two practical examples, incorporating the k-means clustering algorithm and a genetic algorithm to enhance the performance of selected local solar units.

Falkenberg et al. (2018)in their study addressed the energy consumption challengein mobile communication systems like LTE and 5G by introducing a novel data-driven model that predicted uplink TX-power using ML techniques.The RF model is among the ML techniques used to analyze the relationship between passive indicators, such as velocity, data rate, and TX-power.The model was trained using empirical data from driving tests conducted in a public cellular network. The Random Forest model outperformed the other methods, achieving a mean average error (MAE) of 3.166 dB.The accuracy of the model remained stable even when a limited set of features was used, indicating its robustness for long-term power estimations.AlShafeey and Csaki(2024) described how data from a 2 MW grid-connected wind turbine were used to train Artificial Neural Networks (ANN), Support Vector Machines (SVM), and K-Nearest Neighbors (K-NN).The hybrid model showed better prediction accuracy for both short- and long-term energy estimates.Table 2 summarizes the papers reviewed on ML techniques for energy forecasting.

Table 2: Summary of MLmodels for energy forecasting

References	Case Study	Findings	Model	Prediction Frequency	Industry
AlShafeey and Csaki(2024)	Wind energy forecasting using hybrid ANN, SVM, and K-NN models	The hybrid model showed superior performance in both short- and long-term wind energy forecasting	Hybrid ANN, SVM, and K-NN	Short-term and long-term	Power Systems
Alhendi et al. (2023)	Short-term load and price forecasting for New England	ANN-MC model outperformed conventional ANN models in load forecasting	ANN with Enhanced Markov Chain	Short-term	Power Systems
Dalal et al. (2023)	Hybrid forecasting for volatile energy markets	TLIA model outperformed other models, improving accuracy and reducing processing time	TLIA (Hybrid of LSTM and ANN)	Not specified	Power Systems
El Maghraouiet al. (2022)	Energy consumption prediction in hotel buildings	Random Forest was the most reliable for predicting energy usage in hotel environments.	Random Forest	Not specified	Power Systems
Laayati, Bouzi and Chebak (2022)	Energy management in open-pit mines	A smart energy management system optimises energy consumption.	ML (not specified)	Not specified	Power Systems
Lee and Cho (2022)	Peak load forecasting in Korea	Hybrid models combining SARIMAX with SVR, LSTM, and ANN performed best	SARIMAX, SVR, LSTM, and ANN (Hybrid)	Peak load (not specified)	Power Systems
Baba (2022)	ANN-based adaptable predictor for energy forecasting	Self-tuning ANN-based model improved accuracy through Hebbian law and clustering algorithms	ANN with a self-tuning mechanism	Not specified	Power Systems
Khwaja et al. (2020)	Short-term electricity load forecasting (STLF) in New England	Bag-BoostNN outperformed single ANNs, reducing errors and improving prediction accuracy	Bag-BoostNN (Ensemble of ANNs)	Short-term	Power Systems
Yagli, Yand and Srinivasan (2019)	Solar energy forecasting across different climate zones	Significant variation in accuracy across algorithms, highlighting model	Various ML algorithms	Not specified	Power Systems

		importance.			
Dinesh, Makonin and Bajic (2019)	Power usage forecasting in individual homes	ANNs accurately forecasted power usage in homes using non-intrusive load monitoring.	Artificial Neural Networks (ANN)	Not specified	Power Systems
Yuan et al. (2018)	Seasonal hourly electricity consumption in Japan	High predictive accuracy across seasons with R^2 values above 0.95	Feedforward ANN	Seasonal hourly	Power Systems
Falkenberg et al. (2018)	Energy consumption prediction in LTE/5G mobile systems	Random Forest achieved a mean average error (MAE) of 3.166 dB in predicting uplink TX-power	Random Forest	Long-term	Telecommunication
Mashud and Koprinska(2016)	Very short-term load forecasting in Australia and Spain	AWNN model showed superior performance in multi-step forecasting compared to ARIMA	Advanced Wavelet Neural Network (AWNN)	Very short-term	Power Systems

2.2.2 Deep learning techniques for energy forecasting in electrical power systems and telecommunication infrastructure

Because traditional ANNs have been around for more than a decade and are well established, they have been widely reported in the literature for energy forecasting.However, deep ANN architectures have since emerged, providing fresh insights and occasionally improving the performance.This review considered the use of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) (such as Long Short-Term Memory (LSTM) and gated recurrent units (GRU)), Auto-encoders, Stacked Auto-encoders (SAEs), and Stacked Denoising Auto-encoders (SDAEs) in energy forecasting.CNNs are designed to process two-dimensional data and are particularly effective for feature extraction.These are composed of completely linked layers, pooling layers, convolution layers, and activation functions.Variants include 1D-CNN and 2D-CNN, which are based on the structure of the input data [Kiranyazet al.,2021].Consequently, Rafi, Deeba and Hossain (2021) used an encoder-decoder architecture that combined a CNN and an LSTM.The CNN block processes the input data, which are then flattened and used as input for the LSTM unit, followed by a dense layer for output.The model was noted for its performance in handling long-sequence time-series data and achieving lower error metrics compared to other models.Aurangzeb et al. (2021)in their study used CNN layers arranged in a pyramidal architecture for electrical load forecasting. Pyramidal architecture typically allows for hierarchical feature extraction, with lower layers identifying fundamental patterns and higher layers capturing more abstract representations. In this context, energy customers were grouped into clusters based on their consumption patterns using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm.

Shen et al. (2021)proposed a two-dimensional CNNto extract features from the matrix in the load forecasting part of the study. After learning the reshaped time-series features, the prediction was completed by combining the temporal convolutional network (TCN) with a fully connected layer.The Eastern Electricity Market in Texas validated the model's performance.Another study reported by Andriopoulos et al. (2021) found that CNNs perform more accurately when historical data are scarce.Comparing CNN-based models to LSTM algorithms, the study demonstrated that they offer a competitive substitute for STLF problems by taking advantage of the temporal locality of load time series, akin to how image processing uses spatial locality.A novel probabilistic load forecasting technique based on CNNs was developed in the study [Huang, Li, and Zhu (2020)].The method proposed to construct a discrete load probability distribution (LPD) for training samples is called load-range discretization (LRD).Most of the actual loads in the case study fell within the 70–90% confidence level range for particular prediction intervals, indicating the efficacy of the suggested approach.RNNs can retain information throughout the time steps and are well-suited for sequential data.Because they can identify temporal connections in data, they are very helpful for time-series forecasting [Wang et al. (2020)].Long Short-Term Memory (LSTM), a type of Recurrent Neural Network (RNN), was developed to address the vanishing gradient problem, allowing it to effectively learn and retain long-term dependencies.. They work well for identifying patterns and trends in time series data. Although they have fewer parameters and simpler architecture, GRUs resemble LSTMs. They are frequently employed for load forecasting and can assist in capturing dependencies in sequential data [Abumohsen, Owda A and Owda M. (2023)].

Farsi et al. (2021) proposed a novel model combining Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures to assess their effectiveness in short-term load forecasting (STLF). The model was evaluated using two datasets: hourly electricity consumption data from Malaysia and daily load consumption data from Germany.Previous consumption data are parameters for predicting the load one step ahead.The architecture of the model features two distinct paths: the CNN path is responsible for extracting features from the input data, whereas the LSTM path captures long-term dependencies.The outputs from these two paths are then merged, and a fully connected layer along with an additional LSTM layer is employed to process the combined output and generate the final load predictions.Altunkaya and Yilmaz (2020) estimated hourly load demand by analyzing the past 24 h of consumption data alongside weather variables, including temperature and humidity, in Kenya from 2016 to 2020.Deep learning algorithms, specifically Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU), were employed to develop the forecasting models, among which the RNN model emerged as the most effective when examined based on the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).Xuan et al. (2021) presented a Convolutional GRU (CGRU) hybrid network (multitask learning with homoscedastic uncertainty) HUMTL and an ensemble approach based on Gradient Boosting Regression Trees (GBRT), which were employed to forecast various types of loads, leading to the development of a multi-energy load prediction model for Renewable Integrated Energy Systems (RIES).It incorporates three Gated Recurrent Units (GRUs) with distinct structures, enabling the model to learn different energy features to varying extents, thus fulfilling the prediction requirements for diverse load types.HUMTL leveraged homoscedastic uncertainty to enhance the optimization of prediction tasks across these load types.Compared to other forecasting models, the proposed HUMTL-CGRUG model demonstrated superior capability in approximating the evolution patterns of various load types, further exploring the temporal and spatial correlations among multi-energy loads, and delving deeper into the interconnections between different energy systems.

The study reported in Gurses-Tran, Flamme and Monti (2020) introduced a Recurrent Neural Network (RNN) designed to predict day-ahead time-series and forecast intervals for residual loads by utilizing load profiles and meteorological variables.The model was trained and validated by using data sourced from a regional distribution system in southern Sweden.Two recently created stochastic models, the Factored Conditional Restricted Boltzmann Machine (FCRBM) and the Conditional Restricted Boltzmann Machine (CRBM), were examined byMocann et al. (2016) for the purpose of time-series prediction of energy consumption.An individual residential customer’s one-minute resolution electric power usage data for nearly four yearsserved as the benchmark dataset for the assessment.The findings demonstrated that FCRBM outperformed ANN, Support Vector Machine (SVM), Recurrent Neural Networks (RNN), and CRBM for the energy prediction problem resolved in this study.AEs are used for the unsupervised learning of efficient coding.They consist of an encoder that compresses the input and decoder that reconstructs it.Variants include stacked autoencoders (SAEs) and stacked denoising autoencoders (SDAEs), which enhance the robustness of the model by adding noise during training [Jahangir et al. (2020)].SAEs are composed of multiple layers of AEs stacked on top of each other, allowing deeper feature extraction and representation learning.SDAEs are a type of SAE that add noise to the input data during training, which helps the model learn more robust features and improves generalization.

The research reported by Peng et al. (2019) proposed a hybrid model for electrical load forecasting combining Stacked Autoencoders (SAE) and Extreme Learning Machines (ELM) to enhance prediction accuracy.The SAE extracted deep features from the time-series data layer by layer, whereas the ELM, known for its fast training and high-performance approximation, was applied to each layer's output.The model then integrates the outputs of these ELMs by using linear regression to generate the final prediction.The approach was tested on two real-world datasets, and the results were compared to those of various models, including SAE, ELM, Backpropagation Neural Networks (BPNN), Multiple Linear Regression (MLR), and Support Vector Regression (SVR).The hybrid model consistently outperformed the others, achieving lower error rates across metrics, such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).The hybrid model demonstrated better accuracy and robustness in predicting electrical loads, highlighting the effectiveness of combining deep and fast learning algorithms for complex time-series data.To improve the prediction accuracy of power load forecasting in smart grids, Ke et al. (2019) presented a short-term electrical load forecasting technique that combines SAE and GRU neural networks.A multilayer GRU model was used to forecast upcoming electricity loads.By obtaining fewer prediction errors and improved precision in a short process time, the experimental findings showed that the SAE-GRU model significantly outperformed Support Vector Machines (SVM) and standard GRU.This study demonstrated the potential of the model for useful applications in real-time power supply management and highlighted its efficiency and robustness.

Meanwhile, in a study by Sujan et al. (2022), Random Forest, Long Short-Term Memory (LSTM), Deep Neural Networks (DNNs), and Evolutionary Trees were employed as base models in an ensemble-based approach. Two distinct ensemble models were proposed, combining the predictions of the base models using Gradient Boosting and Extreme Gradient Boosting (XGB). The ensemble models were evaluated using a standard electricity consumption dataset collected at regular intervals over a nine-year period.The experimental results showed that the proposed ensemble model significantly reduced the training time of the second layer within the ensemble framework when compared with the standard method, with even better accuracy.This study recorded a reduction in the RMSE by an approximate value of 39%.Somu, Raman and Ramamrithan (2021) presented a k-CNN-LSTM hybrid model, which was designed to perform cluster analysis of energy usage patterns and other complex features with nonlinear relationships that affect energy usage and long-term dependencies. Upon testing, k-CNN-LSTM outperformed the other variants of standard energy demand forecast models considering well-known quality metrics, demonstrating its suitability for energy consumption forecast problems.Wang et al. (2019)in their research categorised deep learning models into four main types namely deep belief networks (DBN), stacked auto-encoders (SAE), deep recurrent neural networks (DRNN), and other models like convolutional neural networks (CNN) and extreme learning machines (ELM). The study also discussed data preprocessing techniques such as wavelet decomposition and empirical mode decomposition, which help improve the accuracy of these models while Rahman, Srikumar and Smith (2018) developed and optimised novel deep recurrent neural network (RNN) models and analysed the performance of the model for distinct types of electricity consumption patterns. Subsequently, imputation was performed on a dataset of electricity usage that included segments with missing values using deep neural networks.The proposed RNN sequence-to-sequence models predicted the load profiles of commercial buildings with a smaller relative error than a traditional multilayered perceptron neural network.In addition, the proposed model did not yield any additional accuracy when compared to the multilayered perceptron model for estimating the aggregate power usage in residential buildings.The SDAE was utilized for short-term electric load forecasting in a different investigation [Liu, Peyun and Zyu (2019)].Pre-training was performed layer-wise in the SDAE approach, which helped prevent problems, such as gradient vanishing and overfitting. Simple Auto-Encoders (AE) and conventional Back Propagation (BP) neural networks were compared with SDAE's performance. Significant progress was made, as evidenced by the prediction error being reduced from 3.66% (BP) and 6.16% (AE) to 2.88% with SDAE. This illustrates how SDAE may effectively capture nonlinear interactions and enhance forecast accuracy in contexts with complicated data.

In the research study reported by Kim, Lee and Hwangbo (2024), the authors tested the use of the variational auto-encoder (VAE) method to create multiple feasible samples and utilized Bidirectional Long Short-Term Memory (Bi-LSTM) networks to build a demand forecasting model for renewable electricity demand. Using RMSE, MAE, MAPE, and R-square evaluation metrics, the suggested forecasting model was compared to GRU, LSTM, ANN, DNN, SVR, and ARIMA. The findings demonstrated that the VAE-Bi-LSTM-based forecasting model performed better than the other models, with average decreases in RMSE, MAE, and MAPE values of 33.7%, 41.4%, and 39%, respectively. Furthermore, among RNN-based forecasting models, the VAE-Bi-LSTM model was identified as the most optimal network based on information criteria results. Finally, Aslam et al. (2021) carried out a literature review on forecasting renewable energy generation and usage using DL models. Thesereviewed studies demonstrated the application of DL models in renewable energy generation and usage forecastingfrom various perspectives and horizons[Aamasyali and El-Gohary (2018);Fallah et al. (2018);Jha et al. (2017);Mohanty et al. (2017);Shamshurband, Rabczuk and Chan (2019);Wei et al. (2018)]. Table 3 shows the summary of the papers reviewed on the use of deep learning techniques for energy forecasting.

Table 3: Summary of deep learning models for energy forecasting

References	Case Study	Findings	Model Type	Frequency
Kim, Lee and Hwangbo (2024)	Renewable energy in South Korea	the forecasting model is the most effective network among RNN-based models.	VAE-BiLSTM	Not specified
Sujan et al. (2022)	Electricity consumption dataset (500,000 values over 9 years)	XGB-based ensemble model reduced training time by a factor of 10, with a 39% reduction in RMSE	Stacking Ensemble Model (Random Forest, LSTM, Deep Neural Networks, Evolutionary Trees, XGB)	Short-term
Rafi, Deeba and Hossain(2021)	Not specified	Lower error metrics compared to other models	Encoder-Decoder (CNN-LSTM)	Short term
Somu, Raman and Ramamrithan (2021)	Real-time building energy consumption data (IIT-Bombay, India)	k-CNN-LSTM provided an accurate energy demand forecast, capturing spatiotemporal dependencies	k-CNN-LSTM	Not specified
Shen et al. (2021)	Eastern Electricity Market of Texas	Model performance verified	2D-CNN with Temporal Convolutional Network (TCN)	Unspecified

Farsi et al. (2021)	Malaysia and Germany electricity consumption	Effective in short-term load forecasting	Parallel LSTM-CNN Network (PLCNet)	Short-term
Xuan et al. (2021)	Renewable Integrated Energy Systems	Superior capability in approximating load patterns	Convolutional GRU (CGRU) with HUMTL	Not specified
Andriopoulos et al. (2021)	Not specified	CNNs achieve better accuracy with limited historical data	CNN	Short-term
Huang, Li and Zhu (2020)	Not specified	Effective in generating Load Probability Distribution	CNN with Load Range Discretization	Unspecified
Altunkaya and Yilmaz(2020)	Konya, Turkey (2016-2020)	RNN model most effective based on error metrics	RNN, LSTM, GRU	Hourly
Gurses-Tran, Flamme and Monti (2020)	Southern Sweden regional distribution system	Effective in predicting day-ahead residual loads	RNN	Day-ahead
Peng et al. (2019)	Two real-world datasets (unspecified)	Outperformed other models with lower error rates	Hybrid SAE-ELM	Not specified
Ke et al. (2019)	Smart grid data	Outperformed traditional forecasting models	Hybrid SAE-GRU	Short-term
Liu, Peijun and Zyu (2019)	Not specified	Reduced prediction error compared to BP and AE.	Stacked Denoising Auto-Encoder (SDAE)	Short-term
Rahman, Srikumar and Smith (2018)	electricity usage for the Public Safety Building in Salt Lake City, Utah	The models demonstrate lower relative error compared to traditional multi-layered perceptron neural networks in predictingcommercial building's load profiles	RNN	hourly
Wang et al. (2016)	Not specified	Outperformed standalone LSTM-RNN model	LSTM-RNN with time correlation modification	Day-ahead

III. Comparative Analysis Of ML And DL Techniques

Machine Learning (ML) and deep learning (DL) techniques offer robust alternatives to conventional methods, especially for nonlinear data, complex systems, and long-term forecasting. These models handle large datasets better and can capture patterns in energy consumption, particularly in dynamic environments such as telecommunications infrastructures and power grids.ML techniques reviewed in this study demonstrated significant strength in modelling complex nonlinear relationships as Random Forests (RF) and Support Vector Machines (SVM) have been shown to model complex nonlinear relationships common in modern energy systems. The different case studies presented in the papers reviewed showed how ML models excel at processing large datasets with many features, making them ideal for energy demand forecasting in both power systems and telecommunications infrastructure. As stated in the current review study, ANN models can adapt to changes in external factors that affect energy demand, improving their predictive accuracy over time as new data becomes available [Roman-Portabales, Lopes-Nores and Pazos-Arias(2021)]. However, these models require significant data preprocessing and longer training times than existing methods. Unlike traditional models, ML models such as RF are ensembles of decision trees,with their complexity increasing as the number of trees growsand their interaction, making it hard to interpret individual decisions.Reviewed studies [Falkenberg et al. (2018);Khwaja, Naeem and Venkatesh (2020)] showed the introduction of Bag-BoostNN, an ensemble of Artificial Neural Networks (ANNs), which demonstrated higher accuracy in short-term electricity load forecasting compared to conventional methods and Random Forest to predict uplink transmission power in mobile communication systems.

Additionally, deep learning models, such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), demonstrated exceptional capability in processing sequential data and capturing long-term dependencies in time series, rendering them highly efficient for energy demand forecasting.Studies reviewed in this paper showed case studies where these models were either used aloneor combined and their performance in the selected application areas indicated.CNNs are powerful in extracting features from multi-dimensional data, which is useful in energy systems where input data is complex.DL models demonstrated their scalability and ability to handle massive datasets, providing better results in systems with large amounts of data, such as smart grids and IoT-based telecommunication networks. However, DL models are computationally intensive and require significant processing power and very large datasets to perform effectively. These models are prone to overfitting if not properly regularisedparticularly when there is insufficient data to train them effectively. Farsi et al. (2021) demonstrated the effectiveness of a hybrid LSTM-CNN model in short-term load forecasting for electricity consumption in Malaysia and Germany, outperforming ML models just as Xuan et al. (2021) used Convolutional GRU (CGRU) to improve load forecasting accuracy in renewable integrated energy systems, leveraging both temporal and spatial correlations.Table 4 shows the summary of the comparative analysis carried out on the different methods reviewed in this current study.

Table 4 :Overview of the comparative analysis conductedon the different hybrid methods

Method	Model Types	Strength	Limitations	Application
Traditional methods	ARIMA, Linear regression, Holt-Winters model	Simple, easy to implement and interpret	Limited scalability and struggle with nonlinear data	Short-term forecasting with relatively stable data
ML models	Random Forest, SVM, k-NN, ANN,	Can handle nonlinear data, adaptable to changing external factors	Requires more computational resources and can be hard to interpret	Medium-term forecasting with complex, nonlinear relationships
Deep Learning models	LSTM, SAE, CNN, GRU	It can capture long-term factors and is effective with very large data.	Computationally expensive and also has a high risk of overfitting	Large-scale and long-term forecasting, especially with dynamic datasets

It can be deduced from the comparative analysis that while traditional models are being replaced by more advanced techniques,such as the ML and DL models used in the reviewed studies, there are severally challenges comfronting the full implementation. Some of these lows and suggested way out are discussed in the ensuing section.

IV. Challenges In The Application Of ML And DL Models For Energy Forecasting In Power And Telecommunications Infrastructures

Despite the numerous benefits of ML and DL over the traditional approaches in the prediction and analysis of power and telecommunication systems, there are several setbacks facing the implementation. One of the major challenges in applying ML and DL models to energy forecasting is the lackof consistent and high-quality data. Power and telecommunications infrastructure often lacks sufficient data granularity, particularly in underdeveloped regions, such as Africa, making it difficult to capture intricate patterns in energy usage. Variations in data formats and standards across different systems and regions further complicate data integration, whereas missing or noisy data can significantly degrade the model performance and accuracy [Forootan et al. (2022)]. Additionally, the dynamic nature of telecommunications energy demand, influenced by fluctuating traffic loads, weather, and operational conditions, introduces complexities that are not easily captured by traditional and local data preprocessing techniques. Data privacy concerns, especially in telecommunications, also hinder data sharing because energy data are often intertwined with sensitive operational information [Liu et al. (2021)]. Therefore, to address data-related challenges, it is essential to establish robust data-collection and standardization practices. Integrating IoT devices and sensors into power and telecommunications infrastructure can facilitate continuous and reliable data collection). Synthetic data generation techniques such as Generative Adversarial Networks (GANs) can be employed to augment training datasets, particularly when real data are scarce [Arruda et al. (2022)]. Additionally, federated learning and encryption methods can ensure data privacy while enabling collaborative modeling efforts across organizations [Qi et al. (2021)].

Also, the inherent complexity of energy systems poses challenges in the development of accurate ML and DL models. Telecommunications infrastructures experience dynamic energy consumption owing to fluctuating user demand, network maintenance schedules, and variable traffic loads, which are difficult to model accurately. For power systems, the high dimensionality of data, encompassing numerous interdependencies such as generation, transmission, and the end-user side distribution, often leads to overfitting, particularly when the training data are limited or biased [Agular and Antonio (2021)]. Furthermore, although powerful, DL models are frequently perceived as “black boxes,” making it difficult for domain experts to interpret their predictions or validate their reliability [Chen et al. (2023)]. The development of hybrid models that combine ML/DL approaches with traditional domain-specific physical models can improve accuracy by capturing both statistical patterns and system dynamics [Raahman et al. (2021)]. Transfer learning, which leverages pretrained models, can enhance efficiency by minimizing the requirement for extensive training on new datasets [Tan et al. (2018)]. Explainable AI (XAI) techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), can improve model interpretability, enabling domain experts to validate predictions and build trust in AI solutions

Furthermore, training and deploying ML and DL models for energy forecasting requires substantial computational resources, particularly when applied to large-scale power grids or real-time telecommunications networks. DL models, with their deep architectures, require significant processing power and memory, leading to high training times and costs. For real-time applications, such as energy optimization in telecommunication base stations, latency is a critical issue. Many existing models fail to meet the demands of real-time decision-making, which is important for maintaining operational efficiency and reliability [Bousdekis et al.

(2021)].Optimizing the computational efficiency is critical for real-time applications. Edge computing, which processes data closer to the source, can reduce the latency and bandwidth requirements Lightweight DL architectures, such as MobileNet, or model compression techniques, can further enhance efficiency. Employing cloud-based platforms offers flexible and economical solutions for training and deploying ML/DL models.

In addition, the incorporation of ML and DL models into existing energy management systems is another significant hurdle. Most power and telecommunications infrastructure is built on legacy systems that are not designed to interface with modern AI-based solutions [Saravanan et al. (2024)]. Ensuring the interoperability between these systems requires significant customization, which can be both costly and time-consuming. Furthermore, the lack of standardized frameworks for implementing AI solutions in these domains creates barriers to their widespread adoption.To overcome integration challenges, ML and DL models should be designed as modular systems that can easily interface with the existing energy management frameworks. The development of standardized APIs and protocols can facilitate seamless communication between legacy systems and AI solutions. Pilot projects can be used to demonstrate the feasibility and benefits of integration before full-scale deployment, thus encouraging stakeholder buy-in.

Furthermore, energy-forecasting models often depend on historical data to forecast future consumption patterns. However, these patterns are influenced by external factors such as weather changes, policy shifts, and unexpected events. In power systems, renewable energy sources like solar and wind are highly weather-dependent, introducing variability that must be accounted for in forecasting models [Bloomfield et al. (2022)]. Similarly, telecommunications infrastructure experiences energy demand spikes during adverse weather conditions or emergencies, which are difficult to predict accurately. Policy and regulatory constraints also impact the deployment of AI solutions, as they may require adherence to local guidelines that are not universally applicable [Birol (2022)].Building adaptive models that update in real time using new data can help address the impact of changing external factors. Incorporating exogenous variables such as weather conditions, economic indicators, and policy changes into forecasting models can enhance their robustness and accuracy. Dynamic modeling approaches, such as reinforcement learning, can also be explored to account for system variability and uncertainties.

Lastly, a critical gap in the effective application of ML and DL models for energy forecasting is the inadequacy of domain expertise among the AI developers. Without a deep understanding of the operational nuances of power and telecommunications systems, models may fail to capture key variables or interdependencies, leading to suboptimal performance [Saravanan et al. (2024)]. This disconnection between AI development and domain knowledge often results in solutions that are not fully aligned with the practical requirements of the field.Collaboration among AI developers, energy engineers, and telecommunications specialists is crucial for bridging the gap between technology and domain expertise. Capacity-building programs, including workshops and training sessions, can equip stakeholders with the skills required to understand and effectively implement ML/DL solutions. Cross-disciplinary research initiatives can also drive innovation by combining insights from various fields.

Engaging regulatory bodies to align AI solutions with local guidelines can facilitate smoother implementation. Developing policies that support innovation, while ensuring compliance with safety and operational standards, is essential. Open data initiatives and benchmarking efforts can further promote transparency and encourage the development of best practices.

Investing in research and development is critical for advancing ML and DL applications in energy forecasting. Custom solutions tailored to the unique needs of power and telecommunications infrastructure can address specific challenges and unlock new opportunities. Open-source platforms can foster collaboration and accelerate the development of innovative solutions.

V. Conclusion

This paper has presented a review of traditional, ML and DL models that are used to tackle the problems in energy forecasting for different case studies.Academic literature from2015 to 2024 extracted from popular databases were used to retrieve related research articles that utilsed ML approaches such as Artificial Neural Networks, Random Forest, Support Vector Mechanism, k-nearest neighbour (k-NN) and DL approaches including Convolutional Neural Networks, Recurrent Neural Networks, long short-term Memory, Gated Recurrent Unit, Auto-encoders, Stacked Auto-encoders and Stacked Denoising Auto-encoders for energy forecasting. This current review has demonstrated that ML and DL models, including LSTM, CNN, GRU, and hybrid architectures are well-suited for handling the complexities of long-term forecasting and adaptive systems, as they outperform traditional methods in various case studies, such as the PLCNet model and the Bag-BoostNN model. Given the benefits and increased interest in application of energy forecasting, this review will serve as a source reference for researchers and engineers interested in load forecasting based on traditional, ML and deep learning methods to guide them in their tasks towards an informed decision.Consequently, our findings offer valuable insights for both academia and industry engineers in the power and telecommunication space on how to advance the implementation of ML and DL models for improved productivity. Researchers can build upon the identified gapsin existing systems and modelsand explore unsupervised learning, hybrid models for energy forecasting studies and applications. For industry practitioners in the telecommunication sector where energy demands continue to escalate with the advancements in 5G and other wireless technologies,implementing these advanced models can lead to improved energy management and cost savings.

VI. Recommendation For Future Directions

Energy forecasting continues to rapidly evolve, driven by several emerging trends with significant potential to impact future research and applications. Integrating access to real-time data streams from smart grids and telecommunication networks can create new possibilities for responsive energy forecasting. For instance, Edge AI enables machine learning models to operate at the edge of networks, offering near real-time forecasting with reduced latency. This is particularly crucial for telecommunication infrastructures, where energy demands fluctuate unpredictably due to dynamic traffic loads. Falkenberg et al. (2018) demonstrated how edge computing enhances energy optimization in such contexts, especially in areas with limited computational resources. Future research could explore lightweight and robust deep learning models optimized for edge devices, such as IoT nodes and mobile base stations.

Federated Learning (FL) technology also presents a promising avenue, enabling decentralized model training across multiple devices. This approach enhances privacy, reduces centralized data requirements, and allows for more personalized and context-aware predictions. Although FL integration in energy forecasting remains in its early stages, its potential to revolutionize smart grid and telecommunication applications warrants further exploration.

Hybrid models, which combine the strengths of machine learning (ML) and deep learning (DL) techniques, are gaining traction. For example, the PLCNet model by Farsi et al. (2021) leveraged CNN for feature extraction and LSTM for sequential data handling, achieving improved forecasting performance. Similarly, models integrating physical-based and data-driven approaches can better handle the variability of renewable energy sources, as seen with physics-informed neural networks (PINNs). Meanwhile, unsupervised learning techniques provides additional opportunities, particularly in contexts with scarce labeled data. Techniques such as autoencoders can uncover complex data features, improving adaptive forecasting for sectors like 5G and IoT-enabled networks [Liu, Peijun and Zyu (2019)]. Expanding these methods to handle adaptive forecasting across diverse systems, including renewable-integrated grids is considered a promising direction.

In addition, emerging technologies, such as Explainable AI (XAI) and Quantum Machine Learning (QML) are poised to reshape the field. XAI enhances transparency, making energy forecasting models more interpretable for regulatory and operational stakeholders. Meanwhile, QML offers unprecedented computational capabilities, enabling large-scale energy forecasting for systems such as national grids and global telecommunications.

Finally, there is a pressing need to establish standardized, open-access benchmark datasets of varied energy sources and mix, for an efficient energy forecasting in power and telecommunication systems. Such datasets would facilitate comparative studies, improve model evaluations, and accelerate advancements across academia and industry, particularly in energy related tasks.

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