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# Review on Load Forecasting in Modern Power Systems: Comparative Analysis of Techniques, Challenges, Research Gap and Emerging Trends

Pratima Patel, Prof. Seema Pal
*Department of Electrical Engineering, Jabalpur Engineering College (JEC), Jabalpur, Jabalpur, India*

***Abstract: Accurate prediction of load is a fundamental aspect of planning and operation of power systems. The complexity and uncertainty of load forecasting have been significantly increased due to the evolution of renewable energy sources, the integration of electric vehicles and other innovations associated with the smart grid concept. This work presents a detailed overview of load forecasting techniques that include traditional statistical models, various AI, machine learning, and deep learning models. Load forecasting methods based on statistical models, AI-based methods, deep learning methods,machine learning methods, and Transformer-based architecture is reviewed and analyzed. A comparative analysis of these methods is performed on the basis of category, complexity, strengths, and limitations. The factors affecting electrical load are also studied such as the temperature, humidity, holidays, and economic activity to understand their effect on the accuracy of forecasting. In additionchallenges,research gaps and future direction are discussed. The review aims to help researchers select the most appropriate forecasting technique for their research and to gain a better understanding of the recent developments in the area. It will also help utilities to select effective forecasting methods for better grid management and energy planning.***
***IndexTerms—Loadforecasting,ARIMA,machinelearning,deeplearning,LSTM,Transformer,smartgrid.***

## I. INTRODUCTION

Electrical load forecasting is the task of predicting the electricity consumption of a certain area for a future time period. Accurateforecastingisimportantfortheefficientandreliableoperationofmodernpowersystems,allowingutilitiesandsystem operators to make informed decisions regarding generation scheduling, unit commitment, energy trading and infrastructure investment [1].

The ongoing transition to smart grid architectures, the integration of distributed energy resources (DERs), and the increasing penetration of electric vehicles (EVs) have resulted in a far less predictable and more nonlinear load behavior. The traditional loadprofilesarefurthercomplicatedbytheincreasingdemandresponseprogramsandtheemergenceofprosumersmaking the classical deterministic models less and less useful [2], [3].

Traditional methods for load forecasting have relied on statistical techniques, including regression and Autoregressive Integrated Moving Average models. Despite their computational efficiency, these methods rely on the assumptions of linearity and stationarity, which frequently do not hold in contemporary load scenarios. The availability of high-resolution smart meter data and the development of computational resources have gradually promoted the use of machine learning and deep learning methods. For example, Long Short-Term Memory networks, Convolutional Neural Networks, and Transformer-based models havesetnewaccuracybenchmarkswithMeanAbsolutePercentageErrorvaluesconsistentlybelow2%onbenchmarks[4].

Withthelimitedreviewpapersonvariousaspectsofthistopic[5],[6],[7],thereisarequirementforfurtheranalysison thelatestapproachesinthemodernsmartgridera.Thispapertriestofillthisgapbyprovidingacomprehensivereviewon load forecasting methods from five perspectives, i.e., statistical models, AI-based methods, deep learning methods, machine learning, and hybrid frameworks.

## II. CLASSIFICATION OF LOAD FORE CASTING

The classification of electrical load forecasting is based on different time frames, operational objectives, input features and accuracy requirements . Generally, the load forecasting can be the categorized into three major categories based on the lengthof the forecasting period such as Three types of load forecasting are there, namely, Short-Term Load Forecasting , Medium-Term Load Forecasting , and Long-Term Load Forecasting [8]. Each category has a different and important role to play in the planning and operation of modern power systems.

### *A. Short-TermLoadForecasting:-*

STLF includes predicting how much electricity will be needed in the next hour to seven days. This is the most important category for operations because system operators use its outputs directly for real-time grid management, unit commitment, economic dispatch, spinning reserve allocation, and electricity market bidding [9], [10]. Under conditions of high renewable penetration, wrong short-term forecasts can cause big economic penalties, system imbalances, or even grid instability. The accuracy standards for STLF are usually very high. An acceptable level of accuracy for operational deployment is a Mean Absolute Percentage Error (MAPE) below 3% . However, the rapid and nonlinear variations of load demand arising from changing weather conditions, human behaviors, industrial activity cycles, and the random nature of distributed energy resources (DERs) [11] have made it increasingly difficult to attain this accuracy. Recent advances in deep learning, especially LongShort-Term Memory (LSTM) networks and Transformer architectures, have greatly improved the accuracy of STLF, withstate-of-the-art models reaching MAPE values below 2% consistently on standard benchmark datasets.

### *B. Medium-TermLoadForecasting:-*

MTLF considers forecasting horizons of one week to about one year. It is mainly used for planning maintenance dates of generation units, fuel purchase for thermal power plants, hydro-reservoir management and electricity contract negotiations in deregulatedenergymarkets[12].MTLFusesaggregatedhistoricalloadprofiles,seasonalpatterns,andeconomicindicators as its main inputs, while STLF needs real-time data at a high frequency.Such models need to take into consideration seasonal effects,heating/cooling cycle due to temperature, impact of public holidays,as well as economic influences on the base con-sumptionrate.Models falling under the category of MTLF yield MAPE values inthe range of 3–8% depending on geographical location and the approach taken. Hybrid models combining statistical decomposition methods with deep learning have been successfulinmodelingboththetrendandseasonalitycomponentsofmedium-termload[13].

### *C. Long-TermLoadForecasting:-*

LTLF is the task of long-term electricity load prediction with periods that can be as long as several decades. This type ofload forecasting is paramount for planning of electricity production and transmission capacities, energy policy planning and investments in energy infrastructure projects [14]. Due to the extended prediction periods, LTLF models should account for various macroeconomic indicators like GDP growth, population changes, urbanization rates, and industrialization estimates.

As more electric vehicles become used in transportation and heating/cooling systems get increasingly electrified, the electrificationoftheseprocessesbecomesoneofthemainloaddriversonalong-termbasis.Accordingtostatistics,the globalconsumptionofelectricitybyEVsisprojectedtoreachabout180TWhperyearin2024,upby60%comparedto thepreviousyear,whilethefurtherannualincreaseisexpectedtobeexponentialuntil2035[15].Modelingofthistype of load behavior poses a significant challenge to research,as linear regression models cannot effectively represent nonlinear dependencies [16].

## III. FACTORS AFFECTING ELECTRICAL LOAD

To develop effective electrical load forecasting models, it is essential to have a thorough knowledge about the influencing variables that affect electrical load demand. These influencing variables, along with the selection of input variables, model structure, and forecast horizon, directly depend upon each other. Through an extensive literature survey, it has been found that there exist four major categories of influencing variables, namely weather/climatic variables, economic/demographic variables, calendar/temporal variables,and social/behavioral variables.

### *A. WeatherandClimaticFactors*

The second largest class of load-driving factors is that consisting of weather and climate-related variables. Temperature is known to be the single most influential meteorological factor contributing to electricity demand changes, since it drives directly the use of the heating, ventilation and air conditioning systems (HVAC). The energy loads associated with HVAC make up a dominant share of overall electricity consumption both in households and commercial buildings, especially during the extreme seasons [17]. Empirically, it has been found that temperature alone explains 60–70% of variance in peak load on daily basis, which makes accurate temperature forecasts an essential input to load forecast models.

*B. EconomicandDemographicFactors*

The economic and demographic variables are the key factors that define the baseline and long-term trend of the electricity demand. Gross Domestic Product (GDP), industrial production, per capita income, and economic activities in different sectors areresponsiblefordeterminingthequantityofelectricityconsumedinaparticularregion.Inallthestudiesreviewed,GDP and past load data were found to be the most common factors influencing electricity demand. GDP is used as an input variable in about 29% of all the studies [18].

*C. CalendarandTemporalEffects*

Temporal and calendar variables provide systematic regularity and seasonality to electric demand curves, and would be regarded as incomplete without them. Calendar-related phenomena include weekdays, time of day, seasons, and special dates including holidays.

The electricity load on weekdays is quite different from that on weekends due to different levels of industrial and business activities.The electricityload duringweekdaysexhibits obviouspeaks duringtheearly andlate commutesofworkers [19]. The electricity load on weekends seems to be smoother without obvious peaks. Time of day phenomena include intraday periodicity with consumption peaking at mid-afternoon and early evenings in predominantly residential electricity networksand mid-morning in predominantly commercial grids [20].

*D. SocialandBehavioralFactors*

An emerging and highly relevant set of influencing factors are social and behavioral elements, owing to the technological revolution currently affecting the domestic and commercial use of energy. Patterns in lifestyle, culture, occupancy, and the awareness of individuals about the cost of their energy consumption all influence load profiles.

Thegrowingprevalenceofsmarthomes,IoT-enabledappliances,andHEMShasledtotheevolutionofconsumptionbehavior in the domestic space. Real-time monitoring, scheduling, and automation of energy consumption in smart homes mean thatload profiles are now more flexible and difficult to predict than ever.There has been ample evidence that integrating consumer behavior information through IoT into machine learning and XAI systems increases forecast accuracy.

## IV. METHODS OF LOAD FORECASTING

This review systematically analyzes the development of short-term load forecasting (STLF) methods from 2000 to 2025. A total of 72 papers were selected from reputed journals and conferences such as IEEE Transactions, MDPI Energies, Elsevier EnergyandFrontiersinEnergyResearch.Theliteraturereviewedisclassifiedbyforecastingtechniqueasfollows:2papers are reviewed under statistical and classical methods covering ARIMA and Regression based approaches; The 2 papers for SARIMA based seasonal forecasting are included; 3 papers are selected for Artificial Neural Network (ANN) and Fuzzy Logic methods; 2 papers are about hybrid ARIMA-ANN models; 4 papers review Support Vector Machine and Machine Learning techniques; Random Forest and XGBoost methods are selected for 3 papers;6 papers on Long Short-Term Memory (LSTM)anditsvariantssuchasBi-LSTMandGatedRecurrentUnit(GRU),4papersonCNN-LSTMhybriddeeplearningmodels, and 3 papers on Transformer and Attention-based architectures. The rest of the papers are on ensemble methods, federated learning, explainable AI and smart grid applications.

*A. TraditionalStatisticalMethods*

The traditional basis for electrical load forecasting has been the statistical methods due to their sound mathematical basis and ease of understanding. This is because such methodologies rely on the application of known statistical laws in order to predict the link between past loads and various other determinants. Although novel machine learning systems have been developed recently, the conventional approaches still have practical relevance.

*1) Regression Analysis:* Theregression-basedapproachisoneoftheoldestandmostpopularapproachesinload forecasting.

The linear and multiple regression models create mathematical functions that represent the relationship between the electric power load and predictor variables like air temperature, time-related, and calendar variables. Multiple regression models represent the load as a weighted sum of the predictors. It is easy to interpret the coefficients in this case, and computingforecasts becomes faster.

Regression models are still applicable for short and medium term load forecasting for the period 2020-2025. They are especiallysuitableinhybridarchitectureswheretheyarebasicorpre-processingmodels[21].Buttheirlinearityinherent limitstheircapabilitytomodelnon-lineardependenciesandsophisticatedseasonalpatternsinpresent-dayelectricpowergrids.

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2) *TimeSeriesMethods(ARMA/ARIMA/SARIMA):*ForecastinghasbeenwidelyperformedusingmodelssuchasARM and ARIMA models. The ARIMA model is an extension of the Box-Jenkins method. It takes into account autoregressive terms, differencingtermsandmovingaveragetermsinitsconstruction,whichenablesittohandlenon-stationarytimeseriesdata. The Seasonal ARIMA (SARIMA) is an extension of the ARIMA model, by adding the seasonal component to deal with seasonality effects and periodicity in time series data, which is suitable for short-term forecasting with significant seasonality [22]. The ARIMA and SARIMA models assume the linearity and stationarity, which make them not suitable for modeling the non-linearnatureofloadvariations,suddenspikesindemand,oreventheenvironmentalfactorsthatcouldaffecttheprocess.
3) *ExponentialSmoothing:*ExponentialsmoothingalgorithmssuchasHolt-Winterstechniquefindapplicationinmany scenarios where time series data with trend and seasonal elements have to be forecasted. Such forecasting techniques apply exponentiallyweightedaverageonhistoricaldatapoints,thusassigninghighersignificancetomorerecentpoints. Holt-Winters algorithm efficiently models all three elements – level, trend, and seasonality – and is applicable for medium term load forecasting tasks. Due to high efficiency and reliability, exponential smoothing algorithms are widely employed in contemporary forecasting frameworks [23].Unfortunately, just like any other classical model, exponential smoothing fails in handling nonlinear time series data.

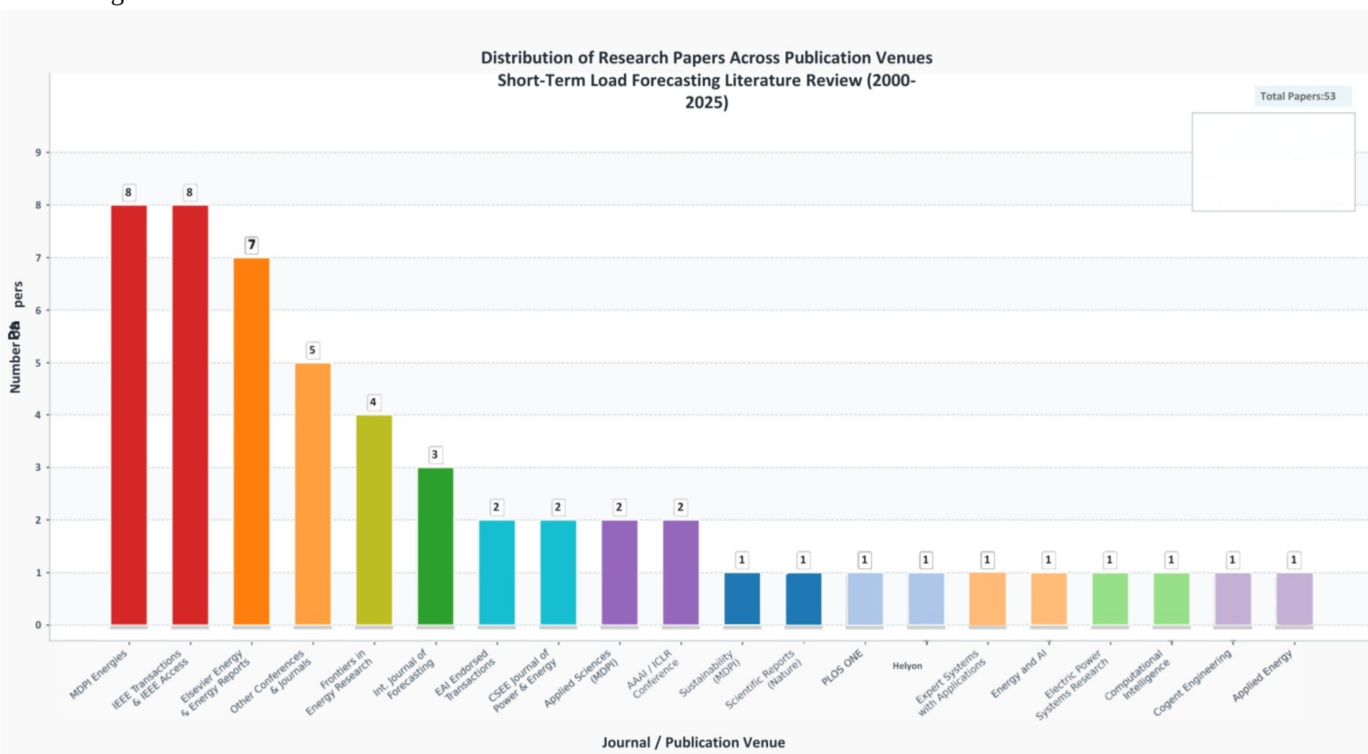


Fig.1.'DistributionofResearchPapersAcrossPublicationVenuesLoadForecastingLiteratureReview(2000–2025)'

4) *KalmanFilter:*TheKalmanFilterisanalgorithmforrecursivelyestimatingstatesfromobservations,whereeachestimate is continually updated as more data becomes available. It performs quite well in applications related to load forecasting because such problems involve evolving states.

Recently, there have been several modifications of the Kalman Filter approach that combine it with other models, providing improved results in terms of short-term forecasting [24]. However, although being a powerful tool, it relies on the assumption that system dynamics are linear and that noise is Gaussian.

### B. *ArtificialIntelligence-BasedMethods*

Due to inadequacies in traditional statistical modeling in modeling non-linear relationships, the use of artificial intelligence (AI) was adopted in load forecasting, starting from the early 1990s.

This is because AI modeling allows for the modeling of complex patterns within data without the need for any specific mathematical modeling.

1) *ArtificialNeuralNetworks(ANN):*ArtificialNeuralNetworks(ANNs)areamongsttheoldestmachinelearningalgorithms applied for load forecasting purposes. Artificial neural networks are universal function approximation models that can capture complex non-linear mappings between inputs and outputs. Input variables usually include past load information, weather conditions and calendar variables.

Theoutputofaneuroncanbeexpressedas:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where$x_i$representsinputfeatures,$w_i$areweights,$b$ isbias,and$f$()istheactivationfunction(e.g.,sigmoid,ReLU). For a multi-layer network:

$$y = f^{(L)}(W^{(L)} \cdot f^{(L-1)}\left(\ldots f^{(1)}\left(W^{(1)}x + b^{(1)}\right)\right)$$

Several works have proven the ability of ANNs to perform load modeling and accurate forecasting [25], [26]. Nevertheless, there are several weaknesses of classical ANNs such as the need for big data sets during training, vulnerability to overfitting, and the vanishing gradient phenomenon.

2) *Fuzzy LogicSystems:*FuzzyLogic Modelsare basedon linguisticvariables andmembership functionsin orderto deal with uncertainties in load prediction.

Afuzzyrulecanbedefinedasfollows:

iF$x_1$is$A_1$,$x_2$is$A_2$Then$y$is$B$

Outputiscalculatedusingweightedsummethod.

$$y = \frac{\sum(i=1)^N \mu_i(x) \cdot y_i}{\sum(i=1)^N \mu_i(x)}$$

$\mu_i(x)$denotesthemembershipfunction.ANFIScombinesneuralnetworksandfuzzylogictoimproveaccuracy[27],[28].

1) *Support Vector Regression (SVR):*Support Vector Regression (SVR) intends to construct a function where the deviation between the prediction and real target values is no more than $\epsilon$.

Theregressionfunctionfollows:

$$f(x) = w^T \phi(x) + b$$

Optimizationproblemfollows:

$$min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right)$$

withconstraintsasfollows:

$$y_i - w^T\phi(x_i) - b \le \epsilon + \xi_i$$
$$w^T\phi(x_i) + b - y_i \le \epsilon + \xi_i^*$$

where $\phi(x)$ represents mapping from input to high-dimensional space, $C$is penalty parameter. SVR has great generalization performance[29],[30]buthassignificantcomputationalcomplexity.

3) *HybridAIMethods:*Inhybridmodeling,anumberofmethodsareusedtogetherinordertoachievehighlevelsof forecasting accuracy. Forinstance,inARIMA–ANNhybridmodeling,

$$y_t = y_t^{(ARIMA)} + y_t^{(ANN)}$$

where:

- $y_t^{ARIMA}$ captureslinearcomponents
- $y_t^{ANN}$ modelsnonlinearresiduals

Suchhybridtechniquesimproveaccuracyandrobustness[31],[32].

*C. MachineLearningMethods*

TraditionalAIalgorithmsforloadpredictionhavecertaindrawbackssuchaslackofscalability,lackofautomatedfeature selection and inaccuracy of the current ML models [33].

1) *RandomForest:* TheRandomForestmodelisanensembleof $T$ trees,eachtreebeingtrainedonabootstrapsampleof the training data. The output $\hat{y}$ is given by averaging the outputs of all individual trees:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(\boldsymbol{x})$$

where $h_t(\mathbf{x})$ representsthepredictionmadebythe $t$-thtreeoninputvector $\mathbf{x}$.RandomForest(RF)reducesvarianceby averaging but keeps low bias to prevent overfitting in single decision trees [34].

Oneofthemostsignificantbenefitsof RFinloadforecastingisitsnaturalfeaturerankingbasedonthemeandecreasein impurity (MDI):

$$FI(j) = \sum_{t=1}^{T}\sum_{s\in S_t(j)} p(s)\cdot \Delta I(s)$$

where the set of splitting criteria on feature $\boldsymbol{j}$ of tree $t$ is denoted as $\boldsymbol{S_t(j)}$, $p(s)$ is the proportion of observations that fall into split $s$, and $\boldsymbol{\Delta I(s)}$ is the reduction in impurity at split $s$ [35]. This approach has been used to identify important input features such as temperature, humidity and calendar-related variables. RF-based methods have resulted in MAPE scores between 1.5and 3% in STLF applications [36].

2) *Gradient Boosting: XGBoost and LightGBM:* Gradient boosting constructs an ensemble of $M$ weak learners sequentially. The model at step $m$ is:

$$F_m(x) = F_{(m-1)}(x) + \eta \cdot h_m(x)$$

where $\eta$ is the learning rate and $h_m(\mathbf{x})$ is a tree fitted to the negative gradient (residuals) of the loss function $\mathscr{L}$ withrespect to $F_{m-1}$:

$$h\_m = \arg \min_{h \sum_{i=1}^{n}\left[-\frac{\partial \mathscr{L}(y_i, F_{m-1}(x_i))}{\partial F_{m-1}(x_i)} - h(x_i)\right]^2}$$

XGBoostaugmentsthisobjectivewithL1andL2regularizationtermstopreventoverfitting:

$$\mathscr{L}^{(m)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \gamma T + \frac{1}{2}\lambda\|w\|^2$$

where $T$ is the total number of leaves,**w**are the weights of leaves, $\gamma$ is the minimum gain threshold, and $\lambda$ is the L2 regularization parameter. Models trained using XGBoost algorithms have demonstrated the lowest MAPE of 2.61% on regional grid data sets . The LightGBM algorithm expands gradient boosting through the leaf-wise growth of trees and Gradient-based One-Side Sampling (GOSS). The algorithm is able to train ten times faster than XGBoost models on large data sets withsimilarperformance[37].Bothalgorithmshavesecuredtoppositionsinthe GEFComenergyforecastingcompetition[38].

3) *k-Nearest Neighbors (kNN):* kNN approximates load by finding the $k$ closest data points to the query point $\mathbf{x}_q$ according to some distance metric like the Euclidean distance:

$$d(x_q, x_i) = \sqrt{\sum_{j=1}^{d} (x_{q,j} - x_{i,j})^2}$$

The weighted prediction is computed as:

$$\widehat{y_q} = \frac{\sum_{i=1}^{k} w_i \cdot y_i}{\sum_{i=1}^{k} w_i}, \quad w_i = \frac{1}{d(x_q, x_i)}$$

*D. DeepLearningMethods:*

Deep learning has become the prevailing approach in load forecasting because of its superior capability of learning complex temporal interactions along with multivariate dependencies in large datasets [39].

1) *Recurrent Neural Networks (RNN):* The processing of the sequence by the RNNs is done using the hidden state $\mathbf{h}_t$ which holds the information regarding time:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b)$$

where $\mathbf{x}_t$ denotes the input data for time step $t$, $\mathbf{W}_h$ and $\mathbf{W}_x$ denote weight matrices, while $\mathbf{b}$ denotes the bias term. Although RNNs are capable of modeling temporal load sequences, they suffer from the problem of vanishing gradients when backpropagating through time (BPTT), which can be mathematically formulated as:

$$\frac{\partial L}{\partial W} = \prod_{k=t}^{T} \left( \frac{\partial h_k}{\partial h_{k-1}} \right) \to 0$$

as $T \to \infty$

This limits their ability to capture long-range load dependencies.

2) *Long Short-Term Memory (LSTM):* The LSTM network [40] eliminates the vanishing gradient by means of three gates, namely: the forget gate $\mathbf{f}_t$, the input gate $\mathbf{i}_t$, and the output gate $\mathbf{o}_t$, defined as

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$\boldsymbol{o_t} = \sigma(\boldsymbol{W_o}[\boldsymbol{h_{t-1}}, \boldsymbol{x_t}] + \boldsymbol{b_o})$$

The cell state $\mathbf{c}_t$ and hidden state $\mathbf{h}_t$ are updated as:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c)$$
$$h_t = o_t \odot \tanh(c_t)$$

where $\sigma(\,)$ is the sigmoid function and $\odot$ denotes element-wise multiplication. LSTM consistently achieves MAPE values below 2% on standard load forecasting benchmarks.

3) *GatedRecurrentUnit(GRU):* GRU has a simplified structure compared to LSTM by combining the forget and input gates into a single update gate $\mathbf{z}_t$, and an additional reset gate $\mathbf{r}_t$:

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$
$$r_t = \sigma(W_r[h_{t-1}, x_t])$$
$$\boldsymbol{h_t} = (1 - \boldsymbol{z_t}) \odot \boldsymbol{h_{t-1}} + \boldsymbol{z_t} \odot \tanh(\boldsymbol{W_h}[\boldsymbol{r_t} \odot \boldsymbol{h_{t-1}}, \boldsymbol{x_t}])$$

GRU reduces the model parameters by approximately 25% compared to LSTM and achieves similar forecasting accuracy [41]. It is especially suitable for real-time STLF applications because of the lower computational overhead [42].

4) *Convolutional Neural Networks (CNN):*The 1D CNN captures local temporal patterns in load sequences by performing 1Dconvolutionwithasetoflearnedfilters**w**ofkernellength*k*alongthetemporaldimension:

$$z_j^{(l)} = \sigma\left(\sum_{i=1}^{C_{l-1}} \boldsymbol{w}_{ij}^{(l)} * \boldsymbol{x}_i^{(l-1)} + b_j^{(l)}\right)$$

wheredenotes1Dconvolution,$C_{l-1}$isthenumberofinputchannelsatlayer$l$1,and$\mathbf{x}^{(l-1)}$isthe$i$-thfeaturemap.CNNs effectively capture periodic and seasonal patterns in load data and have been applied to both building-level and grid-level forecastingtasks[43],[44].

5) *CNN-LSTM Hybrid Models:*CNN-LSTM hybrid network structures make use of CNN layers for extracting spatial local featuresfromthe input data and LSTM layers to model sequential temporal behavior. For input feature vectors F ∈ R^(T'×d)obtained from the CNN layer, the following is used by the LSTM:

$$\widehat{y_{t+h}} = f_{LSTM}\left(f_{CNN}(X_{t-L:t})\right)$$

where $\mathbf{X}_{t-L:t}$is the input window of size $L$and $h$ is the forecasting horizon. These hybrid architectures have produced MAPEvaluesrangingbetween0.8–1.8%inthecaseofbenchmarkdata,outperformingCNNandLSTMstandalonemodels [45].

6) *Transformer and Attention Mechanism:*Different from the recurrent neural network, the Transformer employs the multi-headself-attention(MHSA)thatcomputesthecorrelationofanytwosequencesatalltimesteps[46]:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

where**Q**,**K**, and**V**representthequery,key,andvaluematrices,respectively,while$d_k$isthekeydimension.Multi-head attention involves performing $H$attention operations in parallel:

$$\text{MHSA}(Q,K,V) = \text{Concat}(\text{head}_1,\ldots,\text{head}_H)W^O$$

Popular Transformer-based architectures for load prediction are Informer which applies ProbSparse attention to reduce the computational cost from $O(T^2)$ to $O(T \log T)$and PatchTST, which patches the input sequence and thus shortens the sequence length [47]. Temporal Fusion Transformers (TFT) combine multi-horizon prediction, variable selection networks, and static covariates encoding within a single neural network [48]. In energy applications,

## E. COMPARATIVEANALYSISOFMETHODS

TableIprovidesacomparisonofthemostsignificantloadforecastingtechniquesdiscussedinthispaperbasedonparameters such as category, complexity, accuracy, merits, and demerits. Out of all the techniques discussed above, deep learning models, especially those using LSTM, CNN-LSTM, and transformers, have been found to be more accurate when it comes to short-range predictions. Nevertheless, they perform better at the expense of increased data needs and computation power. Gradient boostingalgorithmslikeXGBoostcanbeconsideredasanalternativewhenthereisnotenoughdataortransparencyisvital.

TABLEI COMPARISONOFLOADFORECASTINGMETHODS

| Method | Category | Complexity | Strengths | Limitations |
|---|---|---|---|---|
| ARIMA[49] | Statistical | Low | Simple,interpretable | Limitedtolineardata |
| ANN[50] | AI-based | Medium | Capturesnonlinearpatterns | Riskofoverfitting |
| SVR[51] | ML-based | Medium | Workswellonsmalldatasets | Highcomputationalcost |
| Random-Forest[52] | ML-based | Medium | Robustandfast | Limitedtemporalmodeling |
| XGBoost[53] | ML-based | Medium | Highpredictionaccuracy | Requiresfeaturetuning |
| LSTM[54] | DeepLearning | High | Handlessequentialdata | Highcomputationalcost |
| CNN–LSTM[55] | DeepLearning | High | Capturesspatialandtemporal features | Complextraining |
| Transformer[56] | DeepLearning | VeryHigh | Modelslong-rangedependen-cies | Requireslargedatasets |

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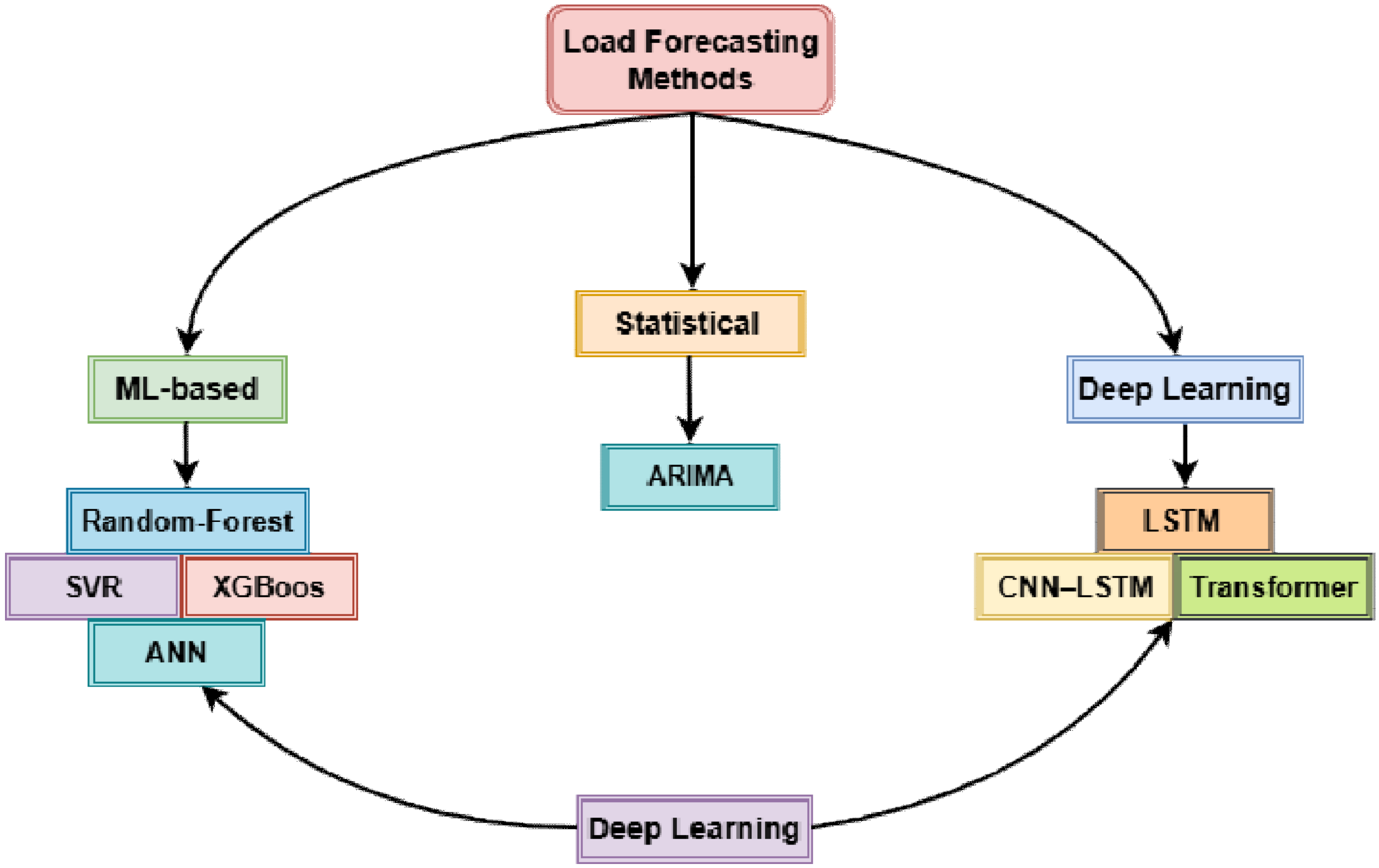



Fig.2.Loadforecastingmethod

### *F. BENCHMARKDATASETS*

Thereproducibilityandcomparabilityofresultsofanyresearchworkrelatedtoloadforecastingdependhighlyontheuseofastandardizeddataset.ThecommonlyusedbenchmarkingdatasetsarementionedbelowintableII.

The GEFCom2012 and GEFCom2014 competitions provided standard evaluation procedures which helped the field move forward through providing means to compare different models. PJM and ERCOT data sets are popular in North America and havelonghistoricalrecordsthatcanbeusedfortrainingdeeplearningmodels.

## V. CHALLENGES AND RESEARCH GAPS

Though considerable progress has been made in load forecasting methodologies, there remain a number of inherent issuesthat prevent the implementation of effective load forecasting techniques in practical scenarios. This paper will discuss fivemajor categories of open problems.

### *A. DataQualityandAvailability*

However,measurementsoftheloadareoftenmissing,erroneousandcontainoutliersbecauseofsensorandtransmissionfaults[64].Loadmeasurementsinsmartmetersmayhavegapsof1%uptoover15%.Preprocessingstrategiessuchasvariational

TABLEII COMMONLYUSEDBENCHMARKDATASETSINLOADFORECASTINGRESEARCH

| Dataset | Region | Granularity | Features | Access |
|---|---|---|---|---|
| GEFCom2012[57] | Global | Hourly | Hierarchicalelectricityload +weather data (21 zones) | IEEECompetition |
| GEFCom2014[58] | Global | Hourly | Probabilisticload,wind,solar,and price forecasting | IEEECompetition |
| ERCOT[59] | USA(Texas) | Hourly | Zonalload,solarPV,windgeneration data | Public |

| | | | | |
|---|---|---|---|---|
| PJM[60] | USA(East) | Hourly | Multi-zonedemand,peakload,energy forecasts | Public |
| UCIHousehold[61] | France | 1-min/Hourly | Activepower,reactivepower,voltage, sub-metering | OpenSource |
| UCIElectricity[62] | Portugal | 15-min/Hourly | Electricity load of 370 substa-tions (2011–2014) | OpenSource |
| IESOOntario[63] | Canada(Ontario) | Hourly | Provincialelectricitydemand,zonal data | Public |

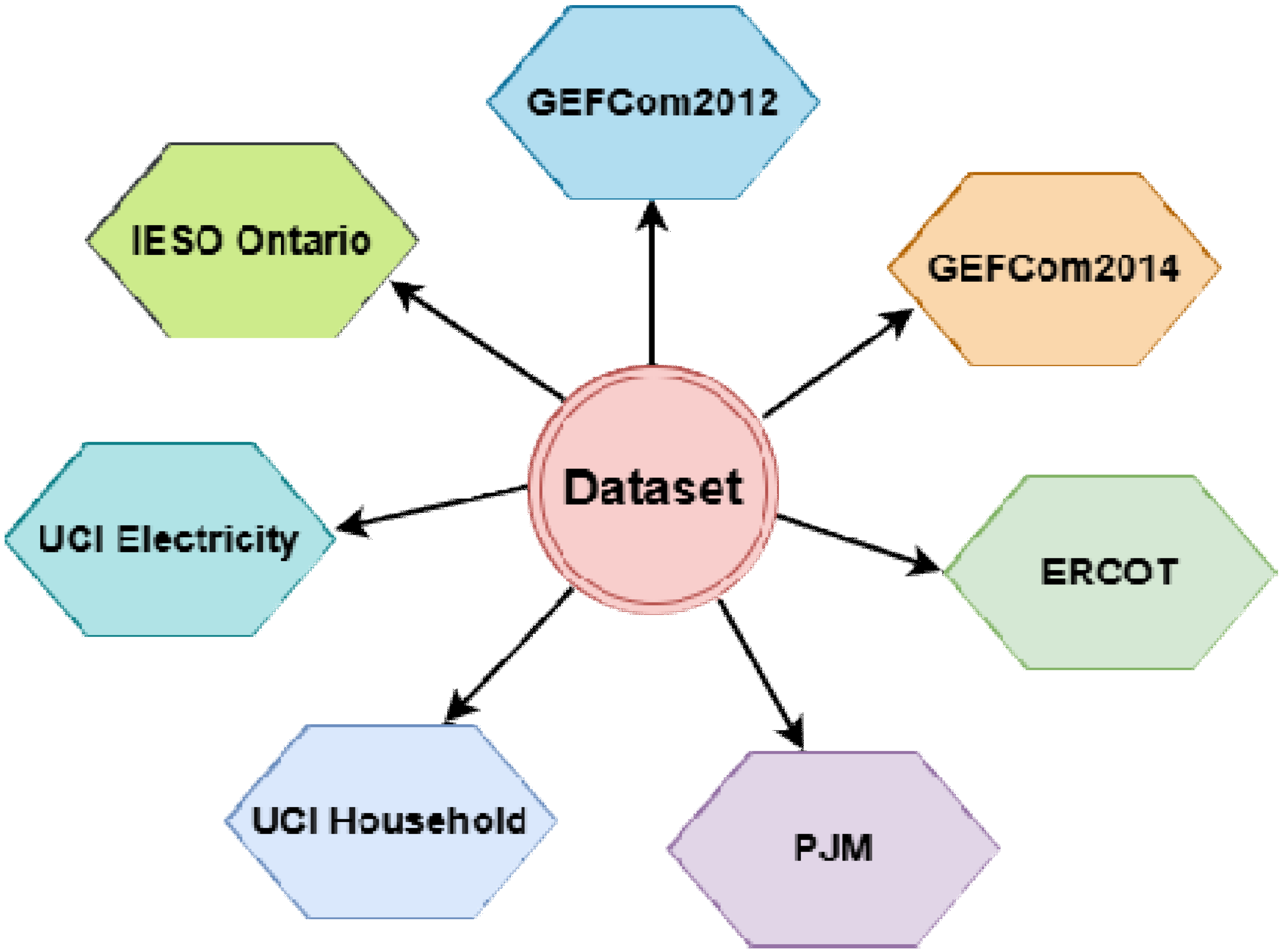


Fig.3.BenchmarkDatasetsinLoadForecasting

autoencoder(VAE)andwaveletdenoisingshouldbecarefullycraftedtoensurethereisnostatisticalbiasintrainingmodels [65].

*B. ModelInterpretability*

Deeplearningmethodshavehighaccuracybutarestilldeepandcannotbeusedinsafety-criticalpowersystems[66].Research is now being undertaken into using XAI methods such as SHAP and LIME. SHAP methods were found to dominate in a recently conducted review of 50 studies (62%), while robust testing of explanation algorithms is still an open research question [67].

### *C. RenewableEnergyIntegration*

Solarandwindintegrationleadstoissuesofintermittencyanddemand-supplyuncertaintythatcannotbefullyaddressedusing only a demand model [68]. Frameworks involving net load forecasting, which combine demand and distributed generation, in additiontoprobability-basedoutputapproachessuchasquantileregressionandBayesiandeeplearning,becomecrucial.

### *D. ComputationalScalability*

Deployment of deep learning algorithms in the restricted settings such as smart metering devices and microgrids involves the application of techniques such as pruning, quantization, and knowledge distillation [69]. Collaborative architecture in which both cloud computing and edge computing are used for performing inference and regular training is one example of such an approach [70].

### *E. PrivacyandDataSecurity*

Smart meters collect detailed consumer behavior data that entails privacy concerns owing to regulations such as GDPR. Although FL offers the ability to train a model collaboratively without exchanging data [71], it has some drawbacks, including non-IID distribution and vulnerability to poisoning attacks on the model [72].

## VI. DIRECTIONS FOR FUTURE RESEARCH

Afewnoveltechniqueshavebeenidentifiedthatwillplayimportantrolesinadvancingloadforecastingmethodologies.

Federated Learning (FL) Federated learning provides a mechanism for collaborative learning using different data sources withoutdisclosinganyprivatedata.Thetechniquecanbeeffectivelyappliedtoutilitynetworksandprosumers.Theperformance of federated learning-based methods is on par with traditional centralised techniques.

Transfer Learning Transfer learning can enhance the forecasting performance when data is not readily available, which is useful for new smart meters and microgrids.

Physics Informed Neural Networks (PINNs) Physics informed neural networks combine physics and machine learning to obtainmoretrustworthymodels.Theyperformespeciallywellinforecastingwhenthecasesareuncertainorunseen.

Probabilistic Forecasting Differing from point based forecasting, probabilistic approaches produce predictive distributions, andalotofresearchhasgoneintovarioustechniquessuchasquantileregressionandBayesianmodels.

FoundationModelsforTimeSeries Foundation models like TimesFM, Moirai and Chronos can achieve zero-shot and few-shot forecasting.

## VII. CONCLUSION

Thepaperoffersanoverviewofthecurrentstateofartinloadforecastingmethods.StatisticalmodelssuchasARIMA and regression have been compared to more modern architectures such as LSTM, Transformer, CNN–LSTM, and CNN. The modern methods reflects the influence of data availability and computational resources.

Fromtheresultsofthecomparativeanalysis,itcanbeconcludedthatdeeplearningarchitecturesarethemostaccuratemodels forshort-termforecasts,whilegradientboostingmodelscanbeconsideredacompromisebetweenaccuracy,explainability,andcomputationalcosts.Thus,thechoiceofaforecastingalgorithmdependsonspecificforecastingtasks.

This review also emphasizes that weather conditions, seasonal variations, holidays and socio-economic parameters have a significantimpactontheelectricalloadandshouldbetakenintoaccountwhileselectinganappropriateforecastingmodel for accurate predictions. Despite the impressive results achieved, there are still unresolved issues related to data quality, explainability of models, integration of renewable sources, and data protection. Future forecasting models will critically need novel approaches like federated learning, transfer learning, and probabilistic forecasting.

## REFERENCES

[1] Q.Ma,D.Wu,andX.Luo,"Areviewofdeeplearning-basedpowerloadforecastingmethods,"*InternationalJournalofNetworkDynamicsandIntelligence*, vol. 4, no. 4, pp. 100027, 2025.

[2] H.-Y.Su,T.-Y.Chen,andY.-H.Lin,"Towardsimprovedloadforecastinginsmartgrids:Arobustdeepensemblelearningframework,"*IEEETransactionson Smart Grid*, 2024, Early Access.

[3] F.Yang,X.Fu,Q.Yang,andZ.Chu,"Decompositionstrategyandattention-basedlongshort-termmemorynetworkformulti-stepultra-short-termagricultural power load forecasting," *Expert Systems with Applications*, vol. 238, pp. 122226, 2024.

[4] B. Zhong, "Deep learning integration optimization of electric energy load forecasting and market price based on the ANN–LSTM–Transformer method," *Frontiers in Energy Research*, vol. 11, pp. 1292204, 2023.

[5] Z. Xu, H. Wang, Y. Zhang, T. Liu, and K. Chen, "PhaCIA-TCNs: Short-term load forecasting using temporal convolutional networks with parallel hybridactivatedconvolutionandinputattention," *IEEETransactionsonNetworkScienceandEngineering*,vol.11,no.1,pp.427–438,2024.

[6] B.Peng,J.Zuo,X.Gong,Y.Li,W.Wu,andY.Li,"Short-termelectricityloadforecastingforcommunityresidentsbasedonfederatedlearningconsidering privacy protection," *EAI Endorsed Transactions on Energy Web*, vol. 11, 2024.

[7] Y. Wang, N. Gao, and G. Hug, "Personalized federated learning for individual consumer load forecasting," *CSEE Journal of Power and Energy Systems*,vol. 9, no. 1, pp. 326–330, 2023.

[8] F.Dewangan,A.Y.Abdelaziz,andM.Biswal,"Loadforecastingmodelsinsmartgridusingsmartmeterinformation:Areview,"*Energies*,vol.16,no. 3, pp. 1338, 2023.

[9] S.RyuandY.Yu,"Quantile-Mixer:Anoveldeeplearningapproachforprobabilisticshort-termloadforecasting,"*IEEETransactionsonSmartGrid*,vol. 15, no. 2, pp. 2237–2250, 2024.

[10] A. Wan, Q. Chang, A. L. B. Khalil, and J. He, "Short-term power load forecasting for combined heat and power using CNN-LSTM enhanced by attentionmechanism," *Energy*, vol. 282, pp. 128274, 2023.

[11] B.S.Vardhan,M.Khedkar,I.Srivastava,andS.K.Patro,"Impactofintegratedclassifier-regressionmappedshort-termloadforecastingonpowersystem management in a grid-connected multi-energy system," *Electric Power Systems Research*, vol. 230, pp. 110222, 2024.

[12] G.Dudek,P.Piotrowski,andD.Baczyn´ski,"Forecastinginmodernpowersystems:Challenges,techniques,andemergingtrends,"*Energies*,vol.18,no. 14, p. 3589, 2025, doi: 10.3390/en18143589.

[13] J. Liu, Z. Hou, and T. Yin, "Short-term power load forecast using OOA optimized bidirectional long short-term memory network with spectral attentionfor the frequency domain," *Energy Reports*, vol. 12, pp. 4891–4908, 2024.

[14] Y. Zhang and W. Chen, "Empowering data-driven load forecasting by leveraging long short-term memory recurrent neural networks," *Heliyon*, vol. 10,no. 24, pp. e40934, 2024.

[15] International Energy Agency, "Global EV Outlook 2024," IEA, Paris, France, Tech. Rep., 2024. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2024

[16] S.Rallabandi,"AIdrivencapacityplanninginlargescaleinfrastructure:AcomparativeanalysisofLSTMnetworksandtraditionalforecastingmethods,"*InternationalJournalofScientificResearchinComputerScience,EngineeringandInformationTechnology*,vol.10,no.6,pp.950–962,2024.

[17] M.Turkog˘lu,B.Erkmen,Y.Eren,O.Erdinc¸,andI.Ku¨c¸u¨kdemiral,"IntegratedapproachesinresilienthierarchicalloadforecastingviaTCNandoptimalvalley filling based demand response application," *Applied Energy*, vol. 360, pp. 122722, 2024.

[18] B.Biswal,S.Deb,S.Datta,T.S.Ustun,andU.Cali,"Reviewonsmartgridloadforecastingforsmartenergymanagementusingmachinelearningand deep learning techniques," *Energy Reports*, vol. 12, pp. 3654–3670, 2024, doi: 10.1016/j.egyr.2024.09.056.

[19] G. K. Ediga, P. S. Arya, P. A. Tomar, S. Tyagi, A. Mittal, and M. I. Habelalmateen, "Smart energy management: Real-time prediction and optimizationfor IoT-enabled smart homes," *Cogent Engineering*, vol. 11, no. 1, p. 2390674, 2024, doi: 10.1080/23311916.2024.2390674.

[20] J. Moon, M. Maqsood, D. So, S. W. Baik, S. Rho, and Y. Nam, "Advancing ensemble learning techniques for residential building electricity consumptionforecasting: Insight from explainable artificial intelligence," *PLOS ONE*, vol. 19, no. 11, p. e0307654, Nov. 2024, doi: 10.1371/journal.pone.0307654.

[21] S.Khan,"Short-termelectricityloadforecastingusinganewintelligence-basedapplication,"*Sustainability*,vol.15,no.16,p.12311,2023,doi: 10.3390/su15161231.

[22] Y. Wang, J. Wang, G. Zhao, and Y. Dong, "Application of residual modification approach in seasonal ARIMA for electricity demand forecasting: A casestudy of China," *Energy Policy*, vol. 48, pp. 284–294, 2012.

[23] R.Hachache,M.Labrahmi,A.Grilo,A.Chaoub,R.Bennani,A.Tamtaoui,andB.Lakssir,"Energyloadforecastingtechniquesinsmartgrids:Across-country comparative analysis," *Energies*, vol. 17, no. 10, Art. no. 2251, 2024.

[24] L.D.X.Ribeiro,"AdaptiveKalmanBasedForecastingforElectricLoadandDistributedGeneration,"Ph.D.dissertation,UniversityofBras´ılia,Bras´ılia,Brazil, 2017.

[25] A.I.Arvanitidis,D.Bargiotas,A.Daskalopulu,V.M.Laitsos,andL.H.Tsoukalas,"Enhancedshort-termloadforecastingusingartificialneuralnetworks," *Energies*, vol. 14, no. 22, p. 7788, 2021, doi: 10.3390/en14227788.

[26] R.K.Shiwakoti,C.Charoenlarpnopparut,andK.Chapagain,"Adeeplearningapproachforshort-termelectricitydemandforecasting:AnalysisofThailand data," *Applied Sciences*, vol. 14, no. 10, Art. no. 3971, 2024.

[27] A.TehlanandV.Kumar,"Fuzzylogicbasedloadforecasting,"*InternationalJournalofAppliedEngineeringResearch*,vol.11,pp.6625–6626,2016.

[28] J. Chakravorty, S. Shah, and H. N. Nagraja, "ANN and ANFIS for short term load forecasting," *Engineering, Technology & Applied Science Research*,vol. 8, no. 2, pp. 2818–2820, Apr. 2018.

[29] L.Hu,L.Zhang,T.Wang,andK.Li,"Short-termloadforecastingbasedonsupportvectorregressionconsideringcoolingloadinsummer,"in*Proc.Chinese Control and Decision Conference (CCDC)*, pp. 5495–5498, Aug. 2020, doi: 10.1109/CCDC49329.2020.9164387.

[30] "Financialforecastingwithmultivariateadaptiveregressionsplinesandqueengeneticalgorithm-supportvectorregression,"*IEEEAccess*,vol.7,

[31] pp.91862–91873,2019,doi:10.1109/ACCESS.2019.2927277.

[32] O.Ezugwu,C.Opata,A.Dimeze,C.Ogbuka,andC.Nwosu,"DevelopmentofahybridARIMA-ANNmodelforenhancedelectricloadforecastingaccuracy," in *Proc. 1st International Conference/Exhibitions of the Department of Mechatronic Engineering, University of Nigeria, Nsukka*, Feb. 2025.

[33] M.Asiri,G.Aldehim,F.Alotaibi,andM.M.Alnfiai,"Short-termloadforecastinginsmartgridsusinghybriddeeplearning,"*IEEEAccess*,pp.1–1,Jan. 2024, doi: 10.1109/ACCESS.2024.3358182.

[34] M. Abumohsen, A. Y. Owda, and M. Owda, "Electrical load forecasting using LSTM, GRU, and RNN algorithms," *Energies*, vol. 16, no. 5, pp. 2283,2023.

[35] B. Singh, "Seasonal electrical load forecasting using machine learning techniques and meteorological variables," *International Journal of Robotics andControl Systems*, vol. 4, no. 3, pp. 1092–1108, 2024.

[36] T.Osgonbaatar,P.Matrenin,M.Safaraliev,I.Zicmane,A.Rusina,andS.Kokin,"Short-termelectricalloadforecastingbasedonXGBoostmodel,"*Energies*, vol. 18, no. 19, pp. 5144, 2025.

[37] U. Singh and S. Vadhera, "Random forest and XGBoost technique for short-term load forecasting," in *Proc. IEEE Int. Conf. Sustainable Technology forPower and Energy Systems (STPES)*, 2023, pp. 1–6.

[38] X.Chen,Y.Li,andZ.Wang,"Short-termloadforecastingbasedonCEEMDAN-FE-ISSA-LightGBMmodel,"*FrontiersinEnergyResearch*,vol.11,pp.1111786,2023.

[39] D.Yang,J.-E.Guo,Y.Li,S.Sun,andS.Wang,"Short-termloadforecastingwithanimproveddynamicdecomposition-reconstruction-ensembleapproach," *Energy*, vol. 263, pp. 125609, 2023.

[40] K.Ullah,M.Ahsan,S.M.Hasanat,M.Haris,H.Yousaf,andS.F.Raza,"Short-termloadforecasting:Acomprehensivereviewandsimulationstudywith CNN-LSTM hybrid approach," *IEEE Access*, vol. 12, pp. 111858–111881, 2024.

[41] M.Waheedandothers,"Datadrivenlongshort-termloadprediction:LSTM-RNN,XG-Boostandconventionalmodelsincomparativeanalysis,"*Computational Intelligence*, vol. 41, no. 3, pp. e70084, 2025.

[42] Y.Bao,"Deeplearning-drivenhybridmodelforshort-termloadforecastingandsmartgridinformationmanagement,"*ScientificReports*,vol.14,no.1,pp.13720,2024.doi:10.1038/s41598-024-63262-x

[43] S.Jangandothers,"Comparativeanalysisofdeeplearningtechniquesforloadforecastinginpowersystemsusingsingle-layerandhybridmodels,"

[44] *InternationalTransactionsonElectricalEnergySystems*,vol.2024,pp.5587728,2024.doi:10.1155/2024/5587728

[45] S. M. Hasanat, K. Ullah, H. Yousaf, and Z. Zahid, "Enhancing load forecasting accuracy in smart grids: A novel parallel multichannel network approachusing1DCNNandBi-LSTMmodels,"*InternationalJournalofEnergyResearch*,vol.2024,pp.2403847,2024.doi:10.1155/2024/2403847

[46] S.Li,M.Chen,D.Zhang,andY.Wang,"PowergridloadforecastingusingaCNN-LSTMnetworkbasedonamulti-modalattentionmechanism,"

[47] *AppliedSciences*,vol.15,no.5,pp.2435,2025.doi:10.3390/app15052435

[48] J. Gong, Z. Qu, Z. Zhu, H. Xu, and Q. Yang, "Ensemble models of TCN-LSTM-LightGBM based on ensemble learning methods for short-term electricalload forecasting," *Energy*, vol. 318, pp. 134757, 2025.

[49] H. Zhou, S. Zhang, J. Peng, S. Zhang, J. Li, H. Xiong, and W. Zhang, "Informer: Beyond efficient transformer for long sequence time-series forecasting,"*Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, pp. 11106–11115, 2023.

[50] Y. Nie, N. H. Nguyen, P. Sinthong, and J. Kalagnanam, "A time series is worth 64 words: Long-term forecasting with transformers," in *Proc. Int. Conf.Learning Representations (ICLR)*, 2023.

[51] B. Lim, S. O. Arık, N. Loeff, and T. Pfister, "Temporal fusion transformers for interpretable multi-horizon time series forecasting," *International Journalof Forecasting*, vol. 37, no. 4, pp. 1748–1764, 2021.

[52] G.N.,"Short-termloadforecastingusingARIMAmodelforKarnatakastateelectricalload,"*InternationalJournalofEngineeringResearchandDevelopment*, vol. 13, no. 7, pp. 75–79, Jul. 2017.

[53] A.Alqaysi,A.Bozkurt,andY.Ates¸,"Electricalloadforecastingbasedonartificialneuralnetworkin Iraq,"in*Proc.10thInternationalCongressonEngineering, Architecture and Design*, Apr. 2023.

[54] Z.Hu,Y.Bao,andT.Xiong,"Electricityloadforecastingusingsupportvectorregressionwithmemeticalgorithms,"*TheScientificWorldJournal*,vol. 2013, Art. no. 292575, 2013, doi: 10.1155/2013/292575.

[55] C.-H.Wu,Y.-T.Tseng,W.-F.Lo,andY.-H.Haung,"Forecastingrenewableenergygenerationusingrandomforestanalysis,"in*Proc.InternationalAssociation for Management of Technology 2025 (IAMOT 2025)*, Montreal, Canada, Jun. 2025.

[56] H. I. Beloev, S. R. Saitov, A. A. Filimonova, N. D. Chichirova, O. E. Babikov, and I. K. Iliev, "Short-term electrical load forecasting based on XGBoostmodel," *Energies*, vol. 18, no. 19, Art. no. 5144, 2025.

[57] S.Bouktif,A.Fiaz,A.Ouni,andM.A.Serhani,"OptimaldeeplearningLSTMmodelforelectricloadforecastingusingfeatureselectionandgeneticalgorithm: Comparison with machine learning approaches," *Energies*, vol. 11, no. 7, Art. no. 1636, 2018.

[58] M.Alhussein,K.Khursheed,andS.Haider,"HybridCNN-LSTMmodelforshort-termindividualhouseholdloadforecasting,"*IEEEAccess*,vol.8,pp.180544–180557,2020,doi:10.1109/ACCESS.2020.3028281.

[59] S.Huang,C.Yan,andY.Qu,"Deeplearningmodel-transformerbasedwindpowerforecastingapproach,"*FrontiersinEnergyResearch*,vol.10,Art. no. 1055683, 2023, doi: 10.3389/fenrg.2022.1055683.

[60] T. Hong, P. Pinson, and S. Fan, "Global energy forecasting competition 2012," *International Journal of Forecasting*, vol. 30, no. 2, pp. 357–363, 2014.doi: 10.1016/j.ijforecast.2013.07.001

[61] T. Hong, P. Pinson, S. Fan, H. Zareipour, A. Troccoli, and R. J. Hyndman, "Probabilistic energy forecasting: Global energy forecasting competition 2014and beyond," *International Journal of Forecasting*, vol. 32, no. 3, pp. 896–913, 2016. doi: 10.1016/j.ijforecast.2016.02.001

[62] R.Bryce,G.Buster,K.Doubleday,C.Feng,R.Ring-Jarvi,M.Rossol,F.Zhang,andB.-M.Hodge,"SolarPV,windgeneration,andloadforecastingdataset for ERCOT 2018: P.E.R.F.O.R.M.," National Renewable Energy Laboratory, Golden, CO, USA, Tech. Rep., 2023. doi: 10.2172/1972698

[63] PJMInterconnection,"2024Long-termloadforecastreport,"PJM,Audubon,PA,USA,Tech.Rep.,2024.[Online].Available:https://www.pjm.com/library/reports-notices/load-forecast

[64] G.He´brailandA.Be´rard,"Individualhouseholdelectricpowerconsumption[Dataset],"*UCIMachineLearningRepository*,2006.doi:10.24432/C58K54

[65] A.Trindade,"Electricityloaddiagrams2011–2014[Dataset],"*UCIMachineLearningRepository*,2015.[Online].Available:https://archive.ics.uci.edu/dataset/321

[66] IndependentElectricitySystemOperator(IESO),"Ontariohourlyelectricitydemanddata,"IESO,Toronto,ON,Canada,2024.[Online].Available:https://www.ieso.ca/en/Power-Data/Data-Directory

*[67]* C.Termritthikunandothers,"Electricityloadforecastingusinghybriddatasetswithlinearinterpolationandsyntheticdata,"*Eng.,Technol.&Appl.Sci.Res.*,vol.14,no.6,pp. 17931–17938,2024.doi:10.48084/etasr.8577

[68] X.Li,Y.Chen,D.Zhao,andZ.Wang,"Identificationandcorrectionofabnormal,incompletepowerloaddatainelectricityspotmarketdatabases,"*Energies*,vol.18,no.1,pp.176,2025.doi:10.3390/en18010176

[69] L. Baur, K. Ditschuneit, M. Schambach, C. Kaymakci, T. Wollmann, and A. Sauer, "Explainability and interpretability in electric load forecasting usingmachine learning techniques – A review," *Energy and AI*, vol. 16, pp. 100358, 2024. doi: 10.1016/j.egyai.2024.100358

[70] V.ArabzadehandR.Frank,"Afour-dimensionalanalysisofexplainableAIinenergyforecasting:Adomain-specificsystematicreview,"*MachineLearning and Knowledge Extraction*, vol. 7, no. 4, p. 153, 2025, doi: 10.3390/make7040153.

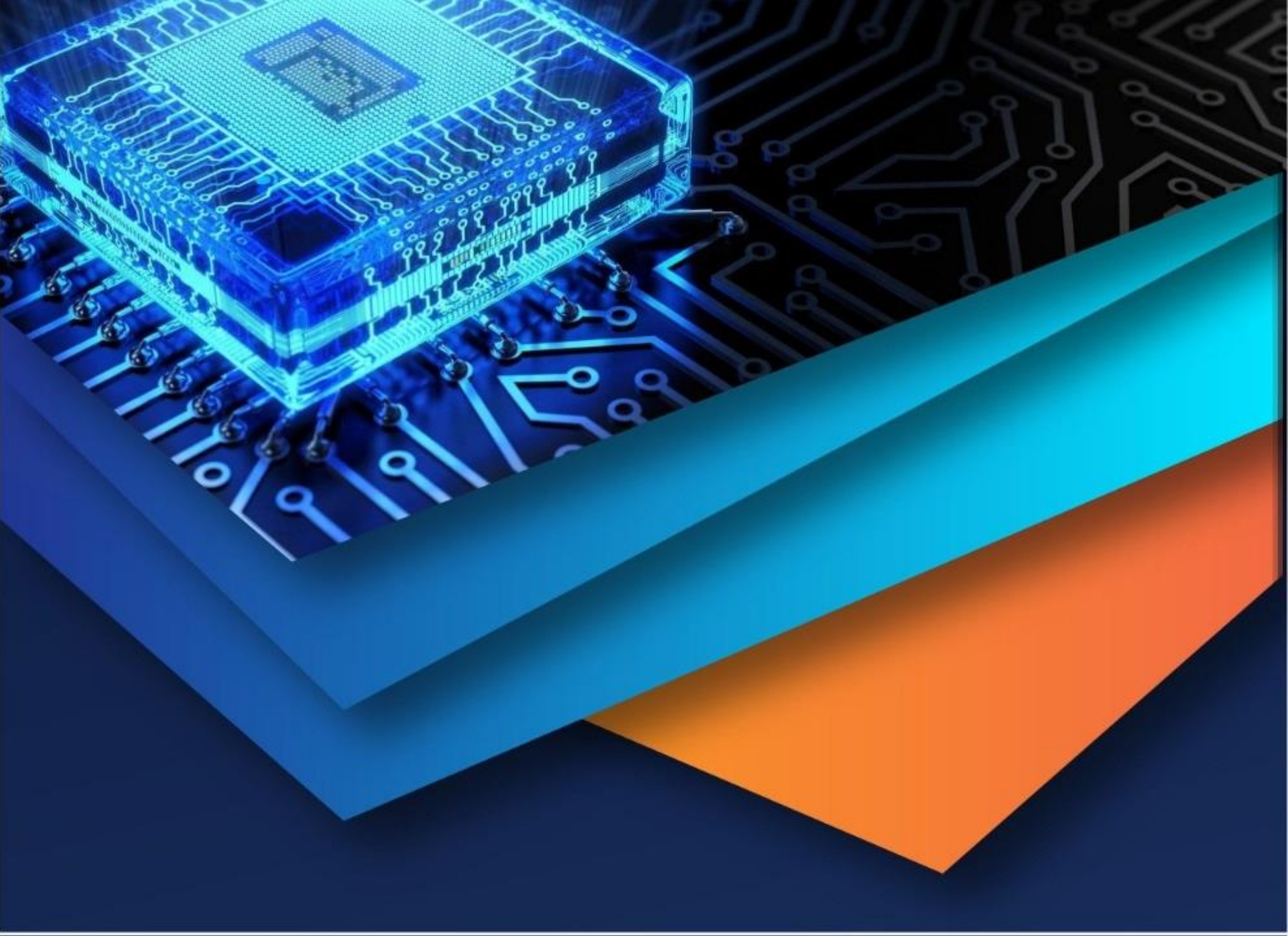
[71] M.A.A.Sarker,B.Shanmugam,S.Azam,andS.Thennadil,"Enhancingsmartgridloadforecasting:Attention-baseddeeplearningwithfederatedlearning and XAI," *Intell. Syst. Appl.*, vol. 23, pp. 200422, 2024. doi: 10.1016/j.iswa.2024.200422

[72] C.Feng,Y.Wang,Q.Chen,Y.Ding,G.Strbac,andC.Kang,“Smartgridencountersedgecomputing:Opportunitiesandapplications,”*Adv.Appl.Energy*,vol.1,pp.100006,2021.doi:10.1016/j.adapen.2020.100006

[73] A.X.WangandJ.J.Li,“Anovelcloudedgecollaborationbasedshorttermloadforecastingmethodforsmartgrid,”*Front.EnergyRes.*,vol.10,pp.977026,2022.doi:10.3389/fenrg.2022.977026

[74] B.Peng,J.Zuo,X.Gong,Y.Li,W.Wu,andY.Li,“Short-termelectricityloadforecastingbasedonfederatedlearningconsideringprivacyprotection,”*EAIEndorsedTrans.EnergyWeb*,vol.11,2024.doi:10.4108/ew.6007

[75] Y.Wang,N.Gao,andG.Hug,“Personalizedfederatedlearningforindividualconsumerloadforecasting,”*CSEEJ.PowerEnergySyst.*,vol.9,no.1,pp.326–330,2023.doi:10.17775/CSEEJPES.2021.08300



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