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A REVIEW OF RESIDENTIAL ELECTRICITY USAGE PREDICTION TECHNIQUES

Shwetha B.N
Research scholar at Presidency University, Bangalore
shwethabn@presidencyuniversity.in

Dr. Murali Parameswaran
Professor at Presidency University, Bangalore
murali.p@presidencyuniversity.in

Abstract—Residential electricity usage is drastically rising on account of population growth and the utilization of the latest appliances. Electricity demand is the electricity required for power consumption in the residence division. Prediction of residential electrical energy usage is very important to make future power grids more reliable. The load forecasting problem is tougher because of the unpredictability found in the individual residential consumers. Accurate forecasting activities are essential for the planning of electrical resources and for maintaining supply and demand equilibrium. This paper reviews different categories of techniques to forecast residential electricity consumption, which includes both single and hybrid models. There are numerous categories of residential forecasting models like deep learning, machine learning, statistical as well as hybrid techniques. The techniques are further categorized into sub-techniques and into individual models. Each and every category of the model is analyzed in terms of input parameters, output parameters, error type and timeframe of forecasting.

Index Terms— Electricity forecasting, deep learning models, residential area, time series analysis

I. INTRODUCTION

The electricity demand is increasing because of the sharp rise in economic growth and population. The yearly compound growth rate of the demand for power has been close to 8%. India's need for energy has grown over time, possibly resulting in the country's rapid economic growth. [1][2]. The residential field has a tremendous impact on total electric energy expenditure along with reports 27% of worldwide electrical energy usage. The electricity produced by the power plant should be utilized immediately after it is created. Therefore, electricity demand forecasting is a very critical element in the present and future smart grids.

Electricity is consumed both in industrial and residential areas. Electricity consumption in the residential area leads to the electrical energy utilized by all the devices at home. The electricity demand of a single residential house is the energy required for that house. The working of elements like those in lights, airflow controlling, heating and cooling occupants along with characteristics of occupants, ambient weather conditions, characteristics of building, building construction and many other variables affect how efficiently a residential area uses energy. It is quite challenging to accurately judge the consumption of constructions due to the complex circumstance [3].

The idea of forecasting has been around for a while now to estimate future electricity demand. Prediction of the individual residential loads has attracted researchers. In smart grids, smart meter availability has facilitated the creation of unique models for every home was possible Electricity load forecasting is required in both power utility as well as single residential loads. The power utilities should forecast the future electricity demand with very minor forecasting errors, then only it is possible to provide a stable power supply to the residential area without out brakes. The planning and production of power can be managed better in the power utility if the electricity demand is known prior. The residential area forecasting will be helpful in demand-side management of the future smart grids, as it can make the system more reliable [4].

Load forecasting is predicting the future electricity demand. The main concept of time series forecasting is to forecast potential occurrences by analyzing historical patterns so that emerging outcomes to be consistent with past patterns. A step-in forecasting that aids in predicting future values is model fitting to past data [5]. Time series forecasting has many uses, including budgeting assessment, financial sector analysis, market analysis, and sales planning.

The timeframes of load forecasting used are minute, hour, month, year. The factors affecting load forecasting are time, economics, weather [6]. Depending on the data/features available that can be used to influence the forecasting and the amount of time for the prediction, the different types of electric load forecasting could be separated as Short Term, Very Short Term, Long Term, and Medium Term.

Very Short-Term Load Forecasting uses the number of previous hourly loads on that particular day and can be used for a short time period, no more than a few hours. Because economic variables and land don't alter in a brief amount of time, it is unable to use this knowledge [7]. Predicting the next thirty minutes to fifteen days load is the aim of short-term load forecasting. Here, the forecasting process heavily relies on temperature and other climate/meteorological factors. The short-term load forecasting for specific electric consumers will be more crucial in the grid's forthcoming strategy and execution. Because of the significant volatility and doubtful situation, it is very challenging to forecast the electricity need of a single energy consumer, other than the aggregated housing load on a large scale. [8].

The electricity consumption from a few days to months can be predicted using Medium Term Load Forecasting. The climatic conditions and temperature should not be included in the prediction [9]. Long-term Electricity Forecasting is usually used for the timeframe of 1-10 years and it may extend up to many decades. It provides estimates for peak and valley loads on a weekly or monthly basis, which is important for expanding generating, transmitting and distributing systems [10].

Electricity prediction is very essential in power utility as well as residential area. Existing surveys on load forecasting of power utility topics are in-depth analysis of the methods for predicting loads utilizing single as well as combination predictive concepts ,focuses on load forecasting of single models and hybrid models, Corentin Kuster, Yacine Rezgui et al focuses on identifying models suited for current scenario [4], Alfares, Hesham & Mohammad et al gives idea of nine classification of forecasting [11].Currently available studies on predicting building load: Seyedzadeh, S. Rahimian et al introduces ML models used for building forecasting [12]. Hai-Xiang Zhao, Frédéric Magoulès et al concentrates on advanced techniques, quantitative tools, and artificial intelligence techniques to anticipate electricity cost [3]. Deb, C. Zhang at al has analyzed, time series energy consumption forecasts using conventional machine learning algorithms that are reviewed in an evaluation on time series forecasting techniques ways to construct power use [13]. Different from [3] [12] [13], this paper provides a comprehensive overview of 91 research articles with different categories of techniques to forecast residential and building electricity consumption. Each and every category of the model is analyzed in depth in terms of input, output, timeframe and error type. There are numerous categories of forecasting techniques like machine learning models, statistical models, deep learning models, and hybrid models. The remaining part of the paper is organized as Section II, Need for Load forecasting and the system model is discussed in detail. In section III Related works of load forecasting are explained in detail and Dataset sources and simulation tools are explained in section IV. The Section V describes the conclusions of the paper.

II. NEED FOR LOAD FORECASTING AND SYSTEM MODEL

In Energy Management System, forecast for electricity is a extremely crucial component. The global energy demand is increasing, making the energy management system (EMS) more crucial. The first step in developing an EMS management strategy must include energy prediction. The planning and production of power can be managed better in the power utility if the electricity demand is known prior. The power utilities should forecast the future electricity demand with very minor forecasting errors, then only it is possible to provide a stable power supply to the residential area without out brakes. A system that can keep track of, forecast, schedule, learn about, and make judgments about local energy output and consumption is required in future Smart grids. Building energy consumption modeling and forecasting can contribute important data to help demand-side management strategies. Source for concerns like load shedding, valley filling, as well as peak shaving can come from a straightforward routine building characteristic. The predictions will be used in scheduling electrical appliances that facilitate efficient use of electricity usage. Understanding the consumer’s load curve forms can help one better understand consumer behavior. The future electricity usage of residential houses helps the customer to have an idea of electricity expenditures and reduce electricity bills based on dynamic pricing techniques. It would assist users in making well-informed decisions regarding the purchase, daily use, and financial planning for household device purchases.

Fig 1: Steps for building the Load Prediction model

The electricity usage of an individual residential house can be collected from the smart meter. A smart meter is a piece of electrical devices that records information. including current, power factor, electricity usage and voltage levels. In addition, the smart meter can display the power consumed per second, minute, hour, and daily consumption. The backend of the smart meter consists of a database and records the total electricity consumption of individual houses. The raw power consumption information about specific homes can't be used to build a forecasting model, the data may be missing as well as the inappropriateness of the recorded time frames. The data should be passed to the preprocessing task as shown in fig 1.

The data cleaning procedures, such as adding missing values or addressing discrepancies in the data, are performed during data preprocessing. Resampling the data series into hourly, weekly, monthly, and yearly power usage is possible for data series that adhere to the standards for time series. The entire dataset is separated into testing and training categories., to learn from the previous section using train data. The models used for forecasting Electricity load are statistical models, Machine learning, Deep learning and hybrid model. In forecasting the electricity load, a number of performance metric parameters can be used.

As per the resolution of time in prediction weekly forecasting, monthly forecasting, yearly forecasting, daily forecasting authors can consider different metrics Mean Absolute Percentage error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R squared, MBE (Mean Bias Error), Normalized Root Mean Square Error (NRMSE), training period time, testing period time. A general rule for calculating forecasting model accuracy is that it increases with decreasing values of each performance parameter.

III. RELATED WORK

Actual load forecasting has been the subject of a great deal of study. Previously, statistical-based models based on pure statistics and calculations were used for time series analysis to forecast electricity load. Recently, research was conducted in the domain of machine learning models, both machine learning models and deep learning models provide better accuracy of load forecasting. Further, hybrid models provide the best accuracy to forecast electricity consumption. Fig 2 shows the Classification of different categories of load forecasting Techniques

3.1 Statistical model

3.1.1 ARIMA and ARMA: The two statistical models considered are ARIMA and ARMA to forecast electricity consumption of individual house and time period of forecasting used are monthly, quarterly, weekly and daily respectively. The dataset consists of power utilization from 2006 December to 2010 November and has nine attributes and 2,075,259 records [14]. Two groups of time series data were created. The training dataset considered from 2006-12-26 to 2009-12-31 in first group. The test dataset with data from 2010-01-01 to 2010-11-26 was used to determine the best predicting window in second group. The accuracy of model is measured using AIC and RMSE score. The daily, weekly, monthly and quarterly AIC measurement of ARMA 615.33, -11.19,1.64,11.37 and ARIMA 771.54,6.94, -11.91, -0.98 respectively. The results show that ARIMA is well suited for monthly and quarterly forecasting. For weekly and daily forecasting period ARMA model is well suited [15].

3.1.2 Simple linear regression, Multiple regression and Quadratic regression: The household section requires a significant amount of electricity and supports the construction of forecasting models. Here, the models used are Multiple, simple and quadratic regression to forecast daily and hourly power consumption. TxAIRE Research and Demonstration House data is considered as dataset for the year 2013 June. A quadratic regression model can provide better results for shorter time intervals like an hour because HVAC systems contribute significantly to the total energy consumed by buildings and have performance that can be characterized as a second-order polynomial. For a one-hour interval, the RMSE values for simple linear regression, multiple regression, and quadratic regression are 348,348,337[16].

3.1.3 ARIMAX: The building's electricity demand was forecasted using the ARIMAX model, the independent variable measure of occupancy rate, and accuracy of the model main thing. A three-story structure building with laboratories and 81 separate workspaces in eastern Ontario Canada, installed wireless sensors, contact closure sensors, PIR motion sensors, and data relating to overall building occupancy. Data were accessible between midnight on September 30th 2009 to 12th June 2009 till 1 am. The entire dataset Week 2 Day 1 Hour 1 through Week 16 Day 1 Hour 7) was used for the initial model exploration, and a split sample was used to test the model's robustness. The model was then utilized to predict the power draw for the next hours (Week 16 Day 1 Hour 8 and onwards), and the predicted data were contrasted with the actual data for this time period's power consumption. The performance metrics used are RMSE, R squared and MAPE . The RMSE score for the entire week is 16.3, and the prior Monday's score is 23.5[17].

3.1.4 Multiple regression: The prediction model to forecast one reliant variable i.e. everyday consumption and 6 explanatory variables including radiation of solar, ambient temperature, speed of wind, relative humidity, type of building and weekday index on the Southwark Campus of London South Bank University, two buildings real-time data was gathered. To predict daily power use, the multiple regression method is employed. Real data consumption for the year 2011 is used to cross-verify predictions of the MR model. By using RMSE, NRMSE, and MAPE, the accuracy is evaluated. The NRMSE for the model's outputs for the administrative building or the academic building are 12% and 13%, respectively [18].

3.1.5 SARIMA: The real data was collected from January 2009 to December 2018 from the UTHM (Malaysian Technical University electricity). The electricity usage of UTHM for the year 2019 may be predicted using the SARIMA method in SPSS, the Box-Jenkins method, and Expert Modeler. The amount of electricity consumed has significantly increased since 2009. Every month, the electricity use varies, and the average amount of power consumed annually was 2830.8958 MWh in 2015, while 951.9013 MWh was consumed annually on average in the least amount of electricity in 2009.

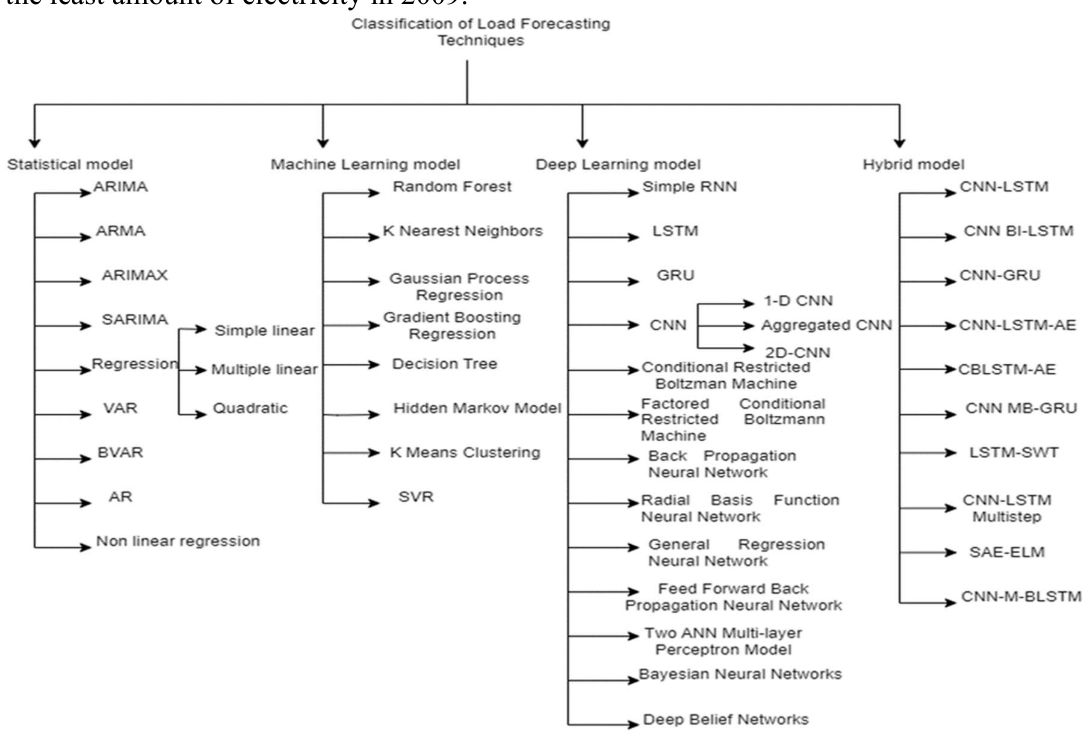

Fig. 2. Classification of different categories of load forecasting Techniques

Seasonality-periodic oscillations can be seen in the monthly UTHM electricity consumption data. The MAPE of the predicted outcome is 8.4% [19].

3.1.6 BVAR: The household energy consumption issues of China are modeled using VAR. The main factors influencing HEC are consuming capacity, population, and structure. BVAR Bayesian inference-based non-restrictive VAR model, is presented to avoid the drawbacks of VAR model exceeding sample size and overfitting. The real time data total sum of HEC of China was used. The China's real HEC for 2009 was 338.43 million tce and the forecast BVAR value was 337.84 million tce, while ARIMA predicts 342.67 million tce. The BVAR model is slightly better than ARIMA model [20].

The statistical models can be used for forecasting residential houses, building, power utilities and others are mentioned below along with the studies in the below table I:

Sl.no	Techniques Used	Related studies in forecasting
1	ARMA	[15],[28],[29]
2	ARIMA	[15],[28]
3	ARIMAX	[17]
4	SARIMA	[19],[25],[26],[30]
5	Simple linear Regression	[16]
6	Non-linear Regression	[22], [23]
7	Multiple Regression	[16],[18],[21],[22],[23]
8	Quadratic Regression	[16]
9	BVAR	[20]
10	VAR	[27]
11	SARMA	[24]
12	AR	[28]

Table I: Different types of statistical models along with related studies in forecasting

3.2 Machine Learning model

3.2.1 Random Forest: To forecast energy consumption of a building on an hourly basis, the author has suggested an ensemble approach, using Random Forest (RF). A collection of several CART (regression) that were trained with random variables and bagging selection make up the ensemble prediction model known as RF.

In North Central Florida 2 academic institutes used the method to predict how much power would be used each hour. RF models trained with various parameter settings were contrasted to learn how they impacted the model's capacity to predict consequences. The results demonstrated that RF was not very dependent on the quantity of variables, so employing empirical mtry is preferred as it is faster and more accurate. To evaluate the effect of time-wise data affects model training quality, the RF model was lastly trained using yearly and monthly data. The performance statistic is measured by R2, MAPE, RMSE, and PI (performance index). In terms of prediction accuracy, RF outperformed RT and SVR by 14–25% and 5%–5.5%, respectively, as measured by the performance index (PI)[31].

3.2.2 K nearest neighbors: The energy management system should analyze the necessary electricity required for the residential sector. As per consumer needs electric power will be produced. Based on categorization, the K-Nearest Neighbors classifier is used to predict daily energy use. The technique includes 5 pace collection of data, processing of data, prediction of data, validation of data, and evaluation of performance. The dataset used here is hourly consumption data of five hundred and twenty apartments from Seoul. The 60% training and 40% testing ratio provides the highest accuracy. In the above approach, according to a suitable distance vector, the input feature vector X is categorized using the K-closest vector. They then pick which class to assign vector X to with the help of many of their K nearest neighbors. The K-nearest neighbor algorithm, which is based on distance and the K-nearest neighbor's voting function, uses the Euclidean distance as its metric. The performance metric is measured using sensitivity, ROC value, specificity and kappa statistics [34].

3.2.3 Gaussian Process Regression: For the electrical power predictions for various occupancy activities and weather conditions with various inputs the Gaussian Process Regression algorithms can be used. The findings demonstrate that GPR may provide precise forecasts when a large data set with just a less time that involves complicated energy use patterns is obtained from measurements of actual buildings. The six commercial building energy usage databases were used for data collection and the key parameters were derived by examining their effects on the building's power consumption. To assess the differences between predictions and actual operations, different analyses were conducted using Adjusted R-square, NMBE, RMSE and R squared [36].

3.2.4 Gradient boosting regression tree: The author has developed a novel energy usage prediction model to analyze and foresee how much energy is used by buildings. The forecasting of the data on energy usage is enhanced by the gradient-boosting regression tree method. In the proposed GBRT, which modifies the gradient boosting approach, a regression tree of predefined length is used as the weak classifiers. By modeling the use of heating and cooling, an iron, a microwave, a computer, fluorescent lights, a laundry machine, a water heater, a hair dryer, dimmable lamps, a TV, and a dishwasher, the data relating to the use of energy is created. The three performance indices MAE, MAPE, and RMSE seem to be utilized to assess the efficacy of numerous algorithm designs [38].

3.2.5 Decision tree: Energy demand prediction is built using the decision tree approach. The process creates precise prediction models with tree topologies that resemble flowcharts, allowing users to quickly obtain crucial information, and categorical variables can be predicted as well as classified. By simulating building energy usage intensity (EUI) levels, the approach is used to calculate residential buildings' energy performance indices. The basic steps of this method, which include building a decision tree based on training data and evaluating it based on test data, are supplied. It is employed to anticipate and categories constructing EUI levels in Japanese housing developments. The findings demonstrate that building energy demand levels can be classified and estimated with high accuracy using the decision tree method (ninety-three percent of train data and ninety-two percentage of test data), as well as recognize and grade important building elements [40].

3.2.6 Hidden Markov Model: The author has suggested a hidden Markov model-based method to forecast power usage in household buildings of Korea, the information gathered from advanced electric meters. The dataset employed is power usage smart meter data for a duration of 1 year from Seoul (South Korea). The technique consists of 4 layers Data Acquisition Layer to gather data using devices of IOT, a Markov model is built in the pre-processing layer to execute data transformations, a Markov model is built in the application layer to perform prediction, and the trained HMM is employed to a given chain of observed data to find the best-fitting HMM. For weekly, daily, and weekly data, the forecasting precision used is RMSE metric is 0.46,1.54, and 2.62 respectively. Other metrics utilized include Mean Absolute Deviation (MAD), MAPE, and MSE [42].

3.2.7 K-means clustering algorithm: A smart meter collects the data, which is then sent through pre-processing, aggregation, and filtering steps. In order to segment information and locate clusters, the K-means clustering method is being used. For the forecasting model, SVM is used to approximate the daily load profiles of consumers. Data on electricity use is gathered from the customers as a component of the study. In contrast, the survey data is pre-processed, and a regression model is used to examine how it relates to the segments of the load profile (knowledge extraction). To ascertain whether there are any significant correlations among the survey data as well as the likelihood that a customer will be in a specific cluster, the relationship among the requirement profiles and survey variables was obtained using probit model. The final step involves creating prediction models that will be used to forecast consumer segments based on home characteristics. A one and half year term's worth of data from 4232 Irish families was in use, together with power use at 30-minute intervals and questionnaires asking about prior responses [44]. The precision and balanced accuracy of the forecasting approaches work with various episodes are used to gauge the outcomes. For this implementation, SVM achieves the highest precision of 75.8% [45].

3.2.8 SVR: For the purpose of increasing the effectiveness of demand-side management, the researcher has taken into account the energy usage of a single household utilizing data from a smart meter. The SVR model is used to forecast each residential's power usage for the hourly and daily timescales. Kilowatt-hours (kWh) of energy were devoured by homes on a one-hour time scale, according to the raw data from smart meters. We acquired previous hourly weather as well as humidity data from a representative of the Canadian government. The dataset goes through various stages, which includes processing of data, exploratory analysis of information, forecasting development, as well as assessment. Regular data granularity produced better prediction results than hourly granularity because single residential customers are unpredictable by nature. If only weekdays were considered for the identical household, the least individual households MAPE error fell to 12.78 for prediction of per day basis and 23.31 for prediction of per day basis [46].

The machine learning models which can be used for forecasting residential houses, building, power utilities and others are mentioned below along with the studies in the below table II:

Sl.no	Techniques Used	Related studies in forecasting
1	Random Forest	[31],[32],[33],[42]
2	K nearest neighbors	[34],[35]
3	Gaussian Process Regression	[36],[37]
4	Gradient boosting regression tree	[38],[39]
5	Decision tree	[40],[41]
6	Hidden Markov Model	[42], [43]
7	K-means clustering algorithm	[45]
8	Support Vector Regression	[46],[47]

Table II: Different types of Machine learning models along with related studies in forecasting

3.3 Deep Learning model

The Deep Neural Networks consist of different hidden layers compared to the machine learning model and Regular neural network. Deep Neural Networks consist of two different types of networks shallow and Deep Neural Networks. Shallow neural networks typically usually contain two to three layers, which restricts their ability to represent complex functions. The neural networks are used with five or more layers and offers more effective algorithms that can boost accuracy.

3.3.1 Simple RNN, LSTM, GRU: The models used in the current approach are LSTM, Simple RNN, and Gated recurrent unit (GRU) to predict day-ahead electrical power. The approach used publicly available AMPds dataset, which consists of 1-year data consumption along with 11 parameters for 21 sub-meters. Each smart meter in this dataset receives 5,25,600 readings annually. The performance metric used to measure short-term load forecasting 1-minute resolution data set are MAPE and MAPE. The LSTM RNN achieves high accuracy compared to GRU and simple RNN and MAPE scores of simple RNN, LSTM and GRU are 0.59,0.24 and 0.343[48].

3.3.2 LSTM: The LSTM RNN framework is used to predict single residential house consumption for short term period. The hyper parameters considered for the LSTM architecture are hidden layers 2, hidden nodes 20, epochs 150. Beginning in 2010, SGSC had accumulated the readings from meter for roughly ten thousand different consumers in New South Wales during the course of the project's four-year development. The three months of data from June 1, 2013, to August 31, 2013, during which all chosen clients have completed 30-minute interval energy usage data. The MAPE summary of LSTM, BPNN, KNN and ELM are listed with different time steps and compared, LSTM/12-time steps provide better Average of MAPE individual forecasts, Average of MAPE Aggregating forecasts and Average of MAPE forecasting and the, percentages are 44.06%,8.64% and 8.58% [49].

3.3.3 Autoencoder: It has dual states—a predictor as well as a projector—that communicate each other and communicate to teach themself what to do to quickly create states on their own without any assistance. In terms of state analysis and the basis for predicted purchase behavior, the forecaster performs better than others. The model can be more accurate since one can change the parameters to regulate the estimated electric energy usage statistics in line with multiple situations. On a total of two million minutes, the data on the use of electricity from 2006 to 2010 are split into train and testing data in a nine: one ratio. It has 3 submeters, each of which corresponds to a different room in the house, and eight attributes [14]. The model uses periods of 15, 30, 45, or 60 minutes when making predictions. The success of the technique is evaluated using three metrics: MSE, mean absolute error, and mean relative error [53].

3.3.4 Aggregated Convolutional Neural Networks: The input considered is individual electricity consumption dataset to predict week-ahead consumption. The difference between basic CNN and aggregated CNN is that ACNN has more no of convolution layers. The parameters used for ACNN are 2 convolution layers, Max pool size 2, Batch size 8, Number of filters 16, no of neurons in the fully connected layer is 200 and the output layer predicts week-ahead values. The electricity used by the house dataset is an array of variables dataset that includes statistics on power use at regular 1-minute intervals from 16 December 2006 (17:24:00) to 26 November 2010 (21:02:00) [14]. The performance metric used is RMSE score, the RMSE was calculated per day of week with ARIMA, BASIC CNN, ACNN model. The overall RMSE score for per week for ARIMA, ACNN, CNN are 405.655, 384.939, 400.145[55].

3.3.5 Conditional Restricted Boltzmann Machine (CRBM) and Factored Conditional Restricted Boltzmann Machine (FCRBM): Two recently created time series predictions of energy usage using stochastic models over various time horizons with various time resolutions are CRBM and FCRBM. A class of machine learning algorithms, including CRBM and FCRBM, seeks to acquire knowledge at different abstraction levels and numerous levels of portrayal. The assessment relies on a standard dataset that includes information on electricity consumption with a 1-minute resolution that was gathered from a residential user over a period of 4 years [14]. One minute resolution, fifteen minutes resolution, hourly resolution, and weekly resolution are the timeframes used for predictions. The results demonstrate that FCRBM outperforms ANN, Support Vector Machine (SVM), Recurrent Neural Networks (RNN), and CRBM for the energy prediction issue under consideration. The efficiency metric used is RMSE score. [58].

3.3.6 SVM traditional back propagation neural network (BPNN), radial basis function neural network (RBFNN) and general regression neural network (GRNN): In Guangdong, China, a field investigation is conducted to look at the yearly power usage and fundamental performance indicators for residential buildings, such as Thermal inertia, heat transfer coefficient, and heat transfer coefficient of the roof. Lastly, the study's samples, which consist of 59 residential buildings, only have data from 59 of those buildings. The technique's output is the annual power need per square foot of the building area. 50 additional buildings serve as training samples for the prediction model, while nine new structures serve as test samples to assess the model's precision. There are three BPNN layers input, output and hidden. An RBNN's hidden nodes receive each input value unchanged because the links in the input layer are not weighted. In an RBF network, a Gaussian function is commonly used as the transfer function of the hidden layer. Because the connections in the input layer are not weighted, each hidden node in an

RBNN receives each input value without modification. The transfer function of the hidden layer in an RBF network frequently uses a Gaussian function. The functional distance between the input data and the hidden layer's center of basis function is combined with the weights to determine the yield Y for the input. This research uses the RBF as its foundational function. In order to compare models, relative error of testing samples is used as a performance metric, along with MRE and RMSE to estimate the precision of training and testing samples [60].

3.3.7 Feed forward back propagation neural network: The author applied short interval energy forecasting for residences as one of the four different types of layers, along with data acquisition, preprocessing, prediction, and performance assessment. Multiple stores buildings in Seoul, South Korea make up the dataset, which is supplied as input to the acquisition component. The data collection layer receives the collected data as a source of input. To eliminate anomalies in the pre-processing layer, various data cleaning and preprocessing techniques are put into the incoming data. The other two preprocessing phases involve data normalization and calculating variance, mean, skewness, and kurtosis. A feed forward back propagation neural network has been used in the prediction layer to apply normalized data and data with statistical moments. The performance of the suggested technique has been evaluated in the performance evaluation layer using the MAE, MAPE, and RMSE. The timeframes considered are 1 day,2 days, 5 days, and 1 week, as determined by the hourly energy usage prediction results of FFBPN using simple data, normalized data, and statistical data [61].

3.3.8 Two ANN multi-layer perceptron model: The author has discovered that lifestyle factors like social psychology can significantly affect residential energy consumption with the aid of an ANN and living information obtained from 350 households in the Sunyani Municipality. Two ANNs that function in multi-layer perceptron mode is a part of the proposed model. In to choose features and make predictions, backpropagation trained ANNs (BPANN 1) and (BPANN 2), respectively. In this study, the ANN algorithm was used to choose characteristics. By adjusting the weights of the various features, the method aimed to reduce the discrepancy between an estimated value and the real value. The duration is the amount of electricity used on average each day. The results are measured using model's performance was approximated using MSE, RMSE, MAE, and MAPE [63].

3.3.9 Bayesian Neural Networks: The author has provided an enhanced Bayesian Neural Networks (IBNN) approach that includes historical inputs of power data based on a simple feedforward structure. Based on the analysis of correlations between load time delays and impact variables, which takes into account various inputs, the count of invisible neurons, the historical data, time frame of prediction, and requirement of range for sample data, some recommendations on how to select the elements more effectively were given. The efficiency of the enhanced Bayesian Neural Networks model [64] was confirmed using several residential sample datasets from Ausgrid that span an entire year. Demand is forecasted by the first model for the subsequent half-hour, the second for the subsequent hour, as well as the 3rd for the subsequent 24 hours. The BNN 16 model also considered historical data from different time periods, such as 3 months, 1 month, half a year, 9 months, and 1 year. Various ranges of historical data are used from the train group and test group, and the MAPE, MSE, and R precision metrics are applied [65].

The table below shows the different types of deep learning techniques used for prediction residential houses, building, power utilities and others are mentioned below along with the studies in the below table III:

Sl.no	Techniques Used	Related studies in forecasting
1	LSTM	[48],[49],[50],[51]
2	GRU	[48],[52]
3	Auto encoder	[53],[54]
4	CNN	[55],[56],[57]
5	CRBM	[58],[59]
6	FCRBM	[58]
7	BPNN	[60]
8	GRNN	[60]
9	FFBPN	[61],[62]
10	Two ANN perceptron model	[63]
11	BNN	[65],[66]
12	Deep Belief Networks	[67]

Table III: Different types of Deep Learning models along with related studies in forecasting

3.4 Hybrid model

Single techniques for load forecasting frequently have a number of drawbacks, such as low computing effectiveness, high computational complexity, and high mistake rates. To achieve improved accuracy with a low error rate, researchers have been developing hybrid load forecasting approaches and models over time. Hybrid models typically combine two or more distinct methodologies, where each method contributes to the forecasting's increased efficiency and accuracy. The hybrid model can be further classified into machine learning hybrid model (two or more ML models are combined) and deep learning hybrid model (two or more DL models are combined). Further, few popular hybrids model papers are explained in detail.

In general, hybrid models combine two or more separate deep learning algorithms where each technique improves forecasting's accuracy and effectiveness. The existing Deep Learning hybrid models are discussed in the below section.

3.4.1 CNN -LSTM: The prediction of electricity consumption is considered in the resolution of time frame hourly, daily, minutely and weekly and the dataset used is Individual Household Electricity consumption [14]. After reducing the noise and taking the key power's characteristics power's characteristics usage, the CNN layers output is sent as input to the LSTM layer. A layer that is completely connected receives the LSTM layer's final output and quickly creates a forecasted time series of energy use. The suggested CNN-LSTM model provides the better forecasting with precision of RMSE 0.3085, MAE 0.2382, MAPE 31.84 and MSE 0.0952 for weekly consumption prediction. [68].

3.4.2 CNN BI-LSTM: In the first module two CNNs pull important data from a number of variables in the individual household energy consumption (IHEPC) dataset [14] and timeframes of hourly, daily, minutely, and weekly power consumption are considered. Then, two Bi-LSTM layers of Bi-LSTM module use the previously mentioned data in addition to time series trends on both sides, including backward states and forward states, to make forecasting. After that, it is passed to two fully connected layers, then used to forecast the future consumption of electric energy. The MAPE, RMSE, MSE, MAE, and best values for the model CNN BI-LSTM are 21.28, 0.220, 0.049 and 0.177 and for weekly consumption [71].

3.4.3 CNN-GRU: The model has two phases: the training phase and the refining of the data. Raw data can be processed using a variety of preprocessing techniques in the data refinement phase and during the training phase CNN features were collected from the dataset and passed to GRUs (Gated Recurrent Units), that is chosen as the best and found to have improved sequence learning skills after thorough testing. The approach is an efficient replacement for the existing approaches in terms of the accuracy of prediction and operational complexity. The approach produced excellent results with, MAE, MSE and RMSE values of 0.33 and 0.22, 0.47 using two different data sets, AEP [73] and IHEPC [14]. The methodology is used to predict the hourly use of power [74].

3.4.4 CNN-LSTM-AE: The model is a fusion of CNN, LSTM and autoencoder model to forecast the future residential electric power usage. The dataset is passed through several preprocessing steps to remove repeated values, outliers, and missing values in order to produce better prediction results. CNN layers that are used to extract spatial characteristics have been fed into it LSTM-AE and the endmost forecasting is made using a dense (fully connected) layer. Using the IHEPC dataset [14], the hybrid model acquired the smallest values of MSE, MAE, and RMSE, which are 0.19, 0.31, and 0.47 for hourly consumption and Using data from Korean commercial buildings, the model obtains 0.01 ,0.0003 and 0.01 an of RMSE, MSE and MAE and for hourly consumption [77].

3.4.5 CBLSTM-AE: The CBLSTM-AE framework can precisely forecast how much energy will be used in various building types, including both commercial and residential locations in various nations and the framework was tested on the customer smart boxes. The architecture consists of an autoencoder (AE) with bidirectional long short-term memory (LSTM), Convolutional neural network (CNN), and bidirectional LSTM BLSTM. The LSTM layers and AE-BLSTM are utilized for forecasting, and the CNN layer collects significant features from the dataset. The dataset utilized is the University of California, Irvine's individual household electric power usage dataset [14]. The forecasting period under consideration is 4 weeks, with different input window sizes of 7, 14, 21, and 28 days. According to the results, computation time is improved by 56% and 75.2% and mean squared errors (MSE) increased from 80% and 98.7%. The system was evaluated using smart boxes on real customers [79].

3.4.6 CNN MB-GRU: The refinement of raw electricity consumption data is done in the initial step and the second step starts with the merging of multilayer bidirectional gated recurrent unit (MB-GRU) and Convolutional neural network (CNN) into a hybrid model. IHEPC [14] and AEP [73] datasets were used in this analysis to forecast short-term load. The features are extracted by CNN layers and MB-GRU is used to learn the relationships between the data on electricity use. The model's short-term prediction accuracy for the IHEPC dataset was 0.29, 0.42 and 0.18 MAE, RMSE, and MSE respectively. The model reduced errors for both the appliances load prediction (AEP) dataset MAE (1%) and RMSE (2%) and the individual home electricity consumption prediction (IHEPC) dataset (MAE (4%), MSE (4%) and (RMSE) [80].

3.4.7 LSTM-SWT: The model combines stationary wavelet transform (SWT) method and an ensemble LSTM. The LSTM forecasting accuracy may be enhanced by the SWT's reduction of volatility and expansion of data dimensionality. The suggested method's forecasting performance is further improved by the ensemble LSTM neural network. The energy consumption data, which is Open-source was gathered using remote sensors installed in five separate family homes in London, United Kingdom (UK), as part of the project known as UK-DALE [81]. The data is then used to test the accuracy and reliability of the method. The 2015 one-year energy consumption data is split into train and test 3 months' worth of data is used for testing, whereas 9 months of data are provided for training. The average of five houses for 5 minutes time step was calculated using RMSE, MAPE, and MBE, and the results were 0.0092, 6.8789, and 0.0033[82].

3.4.8 CNN-LSTM for multistep forecasting:
The multi-step prediction is used to provide good latent period for bidding of power. The hybrid model is encouraged for use in real-world applications using the k-step power prediction method. The dataset consists of the energy usage statistics from 5 homes in London, UK, published by Kelly and Knottenbelt [81]. The proposed CNN-LSTM for multistep forecasting outperforms the existing model on five homes consumption dataset. The data used to predict power use points to future times of 5, 10, and 5,000 minutes. For the five tested homes, the CNN-LSTM framework outperforms LSTM by 13.1%, 48.8%, 2.4%, 33.2%, and 14.5%, respectively, using MAPE as the error measure [83].

3.4.9 SAE-ELM:The hybrid model takes into account individual advantages and combines stacked autoencoders (SAEs), which extract building energy consumption features with the extreme learning machine (ELM), which predicts the accurate prediction solutions. The extreme deep learning model's input variables are identified using the partial autocorrelation analysis method.The website https://trynthink.github.io/buildingsdatasets/ was used to download the actual building energy usage data. The data was gathered from a single commercial center building in Fremont, California, once every fifteen minutes. The forecasting time frames are 30 and 60 minutes, and the performance metrics used are MAE, MRE, and RMSE. The present architecture provides improved accuracy compared to support vector regression (SVR), the generalized linear model (GLM) and backward propagation neural networks (BPNN) [84].

3.4.10 CNN- M-BLSTM: The CNN and M-BLSTM are combined in 3 steps using the intelligent hybrid methodology. The pre-processing and data organization methods are integrated in the initial stage the suggested methodology to clean up the data and eliminate anomalies. In order to properly learn the sequence pattern, the order in which cleaned data is supplied into the above network in the second stage, which uses a deep neural network. The actual and predicted data series are compared in the third stage, and the prediction is evaluated using error metrics. In this study, IHEPC, a data set from the UCI machine learning library was used [14]. A powerful routine for 60 minutes was used to evaluate the suggested approach to predict the following 60 minutes. For the 10-fold cross-validation on a dataset of each individual family, the minimum rate of MSE, RMSE, MAE, MAPE, and MBE are 0.3193, 0.5650, 0.3469, 0.2910, and 0.03286[86].

The table below shows the different types of hybrid techniques used for prediction residential houses, building, power utilities and others are mentioned below along with the studies in the below table IV:

Sl.no	Techniques	Related studies in forecasting
1	CNN-LSTM	[68],[69],[70]
2	CNN BI-LSTM	[71],[72]
3	CNN-GRU	[74],[75],[76]
4	CNN-LSTM-AE	[77],[78]
5	CBLSTM-AE	[79]
6	CNN MB-GRU	[80]
7	LSTM-SWT	[82]
8	CNN-LSTM for multistep forecasting	[83]
9	SAE-ELM	[84],[85]
10	CNN- M-BLSTM	[86]
11	R-CNN and ML-LSTM for multi step forecasting	[87]

Table IV: Different types of hybrid models along with related studies in forecasting

IV. DATA SOURCES AND SIMULATION TOOLS FOR RESEARCH:

The datasets considered for the research are usually the power consumption of the residential house. Smart grid technology development and the introduction of smart meters, individual house energy consumption data can be easily collected. The datasets used for residential forecasting are mentioned in the below table V.

The majority of the papers frequently use the UCI machine learning repository's Individual Household Electric Power Consumption dataset. The dataset includes four years' worth of multivariate time series data on the energy use of each individual house. The dataset includes 2075259 records that were gathered from a single house in Sceaux, France, which is 7 kilometers from Paris. From December 2006 to November 2010, a 47-month period, was used to compile the records. Table VI lists the seven variables that make up the multivariate dataset found in the UCI machine learning repository.

Sl.no	Dataset	Dataset link or paper
1	Individual household electric power consumption	https://archive.ics.uci.edu/ml/datasets/individual+household+ electric+ power+ consumption
2	Appliance's energy prediction	https://archive.ics.uci.edu/ml/datasets/Appliances+ energy+ prediction
3	UK-DALE dataset	domestic appliance level electricity demand and whole-house demand from five UK homes
4	PRECON	Pakistan residential electricity consumption dataset
5	TxAIRE Research and Demonstration	http://www.uttyler.edu/txaire/houses
6	Data from the Commission for Energy Regulation	http://www.ucd.ie/issda/data/commissionforenergyregulationcer
7	AMPds	A public dataset for load disaggregation and eco-feedback research
8	Ausgrid	https://www.ausgrid.com.au/Industry/Innovation-and-research/ Data-to-share/Solar-home-electricity-data

Table V: Data set table

The most frequently used data set in the majority of existing works is the dataset from the UCI machine learning repository Electric Power Consumption of Individual house is mentioned in the below Table VI.

Variable	Description	Units
Global_active_power	The total active power utilized at	Kilowatts
	Home	
Global_reactive_power	The total reactive power utilized at	Kilowatts
	Home	
Voltage	Average voltage	Volts
Global intensity	Average current intensity	Amps
Sub_metering_1	Active energy for pantry	watt-hours of active
		Energy
Sub_metering_2	Active energy for washing clothes	watt-hours of active
		Energy
Sub_metering_3	Active energy for climate control	watt-hours of active
	Systems	Energy

Table VI: Individual household electric power consumption Data set

Simulation Tools:

The simulation tools used to carry out the research of predicting electricity consumption are listed below in table VII.

Sl.No	Tool	Package
1	MATLAB	Neural Network Toolbox
2	MATLAB	Statistics and Machine Learning Toolbox
3	Python	Scikit-learn libraries
4	R Studio	Forecast package

Table VII: Simulation Tools along with package name

V. CONCLUSIONS

This article provides a review of various models used in forecasting the electricity needs of a residential house. A residential community's electricity load has the characteristics of wild fluctuations, complicated influencing factors, and challenging forecasting. Load forecasting is very essential, it has been very challenging to find a good forecasting model, which provides better accuracy. There has recently been a lot of study in the field of machine learning models, which improve the accuracy of load forecasting. Further, hybrid models provide the best accuracy to forecast electricity consumption. The techniques are further categorized into sub-techniques and into individual models. Each and every category of the model is analyzed in terms of parameters taken as input and also output, error type as well as timeframe involved in forecasting. For the future work, our work will involve building a model which provides the best accuracy in load forecasting.

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