MONITORING OF INDIVIDUAL HOUSEHOLD ELECTRICAL APPLIANCES AND PREDICTION OF ENERGY CONSUMPTION USING MACHINE LEARNING

Mr.D.Seenivasan[1]
[1]*Assistant Professor, Department of Computer Science and Business Systems*
M.Kumarasamy College of Engineering
Karur, India
email address

Mr.N.Selvam[2]
[2]*Assistant Professor, Department of Electrical and Electronics Engineering*
M.Kumarasamy College of Engineering
Karur, India
selvamn.eee@mkce.ac.in

Mr.G.Naveen[3]
[3]*Student , Department of Electrical and Electronics Engineering*
M.Kumarasamy College of Engineering
Karur, India
naveenchitravali@gmail.com

Mr.R.Sudahar[4]
[4]*Student , Department of Electrical and Electronics Engineering*
M.Kumarasamy College of Engineering
Karur, India
sudhansudahar@gmail.com

Mr.P.Janagan[5]
[5]*Student , Department of Computer Science and Business Systems*
M.Kumarasamy College of Engineering
Karur, India
janagan2020csbs@gmail.com

Ms.S.Dhanushmathi[6]
[6]*Student , Department of Computer Science and Business Systems*
M.Kumarasamy College of Engineering
Karur, India
dhanushmathisa2020csbs@gmail.com

Abstract: **The paper proposes a scalable ensemble approach for forecasting the electricity consumption of households. SVM (support vector machine) based approach is a combination of different machine learning models, including linear regression, decision trees, and random forests, to improve the accuracy of the forecasts. The study was conducted using real-world data from households in the Netherlands, and the results show that the proposed approach outperforms traditional single-model approaches and achieves better accuracy in electricity consumption forecasting. The approach is scalable and can be applied to large datasets, making it suitable for use in real-world applications. SVM (Support vector machine) is a machine learning algorithm for load forecasting Long-term individual household forecasting may be used in a variety of applications, such as determining customer advance payments. Yet, there is a scarcity of literature on this form of forecasting current approaches either focus on short-term projections for individual families or long-term predictions at an aggregated level. To remedy this void, we describe a strategy that forecasts each monthly consumption over the future year using only a few months of consumption data from the current year. Utility providers may use this strategy to forecast any customer's use for the coming year even with limited data. Future forecasting of power consumption of linear regression for power consumption of data. Linear regression algorithm is implemented for future forecasting of data.**

Keywords: Forecasting, Machine learning, SVM, Linear regression, Households appliances, Electricity consumption.

I. INTRODUCTION

Provides background information on the importance of accurate electricity consumption forecasting and the challenges involved in achieving this. The introduction also highlights the need for a scalable and accurate approach to electricity consumption forecasting, particularly for households. The accurate electricity consumption forecasting is essential for ensuring a stable and efficient electricity supply, and for enabling the integration of renewable energy sources into the grid. However, forecasting electricity consumption can be challenging, particularly for households, due to the complexity and variability of household energy use patterns. To address these challenges, the paper proposes a scalable ensemble approach for forecasting the electricity consumption of households. The approach combines multiple machine learning models, including linear regression, decision trees, and random forests, to improve the accuracy of the forecasts. The approach is scalable and can be applied to large datasets, making it suitable for use in real-world applications. Electricity forecasting has been researched for many years and continues to be a critical endeavour. Domestic smart metre deployment permits the collecting of consumption data from individual residences. One way this data might be utilised to produce value is through electricity forecasting. Precise power consumption forecast is important for a variety of applications such as determining customers' advance payments, assisting day-to-day grid operations, and strategic planning of energy system extensions.

Greenhouse gases (GHG) emissions will hold steady or might even increase in developed countries if effective reduction of energy consumption will not be taken (Lomas, 2010), contrary to policy goals aiming a transition towards low carbon economies. The need for energy consumption reduction is also linked to energy supply security and affordability, and climate change strategies. Therefore, increased search for energy efficiency, greenhouse gases emissions reduction and increased share of renewable energy sources, as established in the new European Union goals by 2030 (EC, 2014) requires more decisive action Given the rise of smart electricity meters and the wide adoption of electricity generation technology like solar panels, there is a wealth of electricity usage data available.

This data represents a multivariate time series of power-related variables that in turn could be used to model and even forecast future electricity consumption. Machine learning algorithms predict a single value and cannot be used directly for multi-step forecasting. Two strategies that can be used to make multi-step forecasts with machine learning algorithms are the recursive and the direct methods.

SMART METER

Smart meters are advanced digital devices that are capable of measuring and recording electricity consumption data in real-time. Smart meters can be used to forecast the electricity consumption of households by analyzing patterns and trends in the data.

Smart meters can provide highly granular and detailed data on electricity consumption, which can be used to improve the accuracy of electricity consumption forecasting models. By analyzing the data collected by smart meters, machine learning models can identify patterns in household energy consumption, such as daily and weekly usage trends, and adjust forecasts accordingly.

LONG-TERM LOAD FORECASTING

Long-term load forecasting is an important component of forecasting the electricity consumption of households. Long-term load forecasting is the process of predicting electricity consumption trends over a period of several years, typically ranging from five to twenty years. Here are some methods that can be used for long-term load forecasting:

- Trend Analysis: Trend analysis involves identifying and analysing historical trends in electricity consumption data to forecast future consumption. This method relies on the assumption that historical patterns in electricity consumption will continue into the future.

- Econometric Modelling: Econometric modelling involves analysing the relationship between electricity consumption and economic factors such as GDP, population growth, and income levels. This approach is based on the assumption that changes in economic factors will influence electricity consumption patterns.

- Simulation Models: Simulation models involve building models of the electricity grid and simulating future electricity consumption based on scenarios such as changes in technology, population growth, and policy changes. This approach is useful for long-term planning and can help to identify potential issues or bottlenecks in the electricity grid.

- Machine Learning: Machine learning algorithms such as Artificial Neural Networks (ANNs) can be used for long-term load forecasting. These algorithms can learn complex patterns in electricity consumption data and can make accurate predictions over long time horizons.

- Hybrid Models: Hybrid models can be used to combine the strengths of multiple approaches to improve the accuracy of long-term load forecasting. For example, an econometric model can be combined with a simulation model to forecast electricity consumption based on both economic factors and changes in the electricity grid.

II. RELATED WORK

[1]Understanding households' energy needs is an important matter in the fight against energy poverty. The studies carried out so far in Spain have analyzed the domestic electricity demand, but most of them have not validated it with field investigations, and there is no work specifically for vulnerable house- holds. Thus, the study reported in this paper proposes a bottom- up model to characterize Spanish residential electricity consumption and applies it to an NGO's households-database. This versatile model considers typical electrical appliances and key household parameters, i.e. dwelling and household size, to estimate the theoretical consumption required to meet Spanish- households' electricity needs. On average, the modelled consumption is moderately higher than the actual electricity consumption of the households' sample considered. This difference increases when considering only the households visited by the NGO, which confirms their vulnerability condition.[2] In predicting electricity consumption, deep learning models based on various neural network architectures are widely used. Since many factors affect electricity consumption in reality, it is difficult to deal with statistical approaches, while deep learning models can be trained using enough data in practice. In this paper, we analyze the characteristics of the electricity consumption data according to the contract type and measure the performance of the future electricity consumption prediction by applying the deep learning model. The experimental data show different trends according to the contract types, and it is expected that these differences may affect the learning performance of prediction models. Through the experiment, we check the difference of performance depends on the complexity and configuration of models by contract types.[3] Demand forecasting is a crucial component of supply chain management for revenue optimization and inventory planning. Traditional time series forecasting methods, however, have resulted in small models with limited expressive power because they have difficulty in scaling their model size up while maintaining high accuracy. In this paper, we propose Forecasting orchestra (Forchestra), a simple but powerful ensemble framework capable of accurately predicting future demand for a diverse range of items. Forchestra consists of two parts: 1) base predictors and 2) a neural conductor. For a given time series, each base predictor outputs its respective forecast based on historical observations. On top of the base predictors, the neural conductor adaptively assigns the importance weight for each predictor by looking at the representation vector provided by a representation module. Finally, Forchestra aggregates the predictions by the weights and constructs a final prediction. In contrast to previous ensemble approaches, the neural conductor and all base predictors of Forchestra are trained in an end-to-end manner; this allows each base predictor to modify its reaction to different inputs, while supporting other predictors and constructing a final prediction jointly. We empirically show that the model size is scalable to up to 0.8 billion parameters ($\approx$ 400-layer LSTM). The proposed method is evaluated on our proprietary E-Commerce (100K) and the public M5(30K) datasets, and it outperforms existing forecasting models with a significant margin.[4] This paper proposes a method to assess the active population in households based on the fine-grained electricity consumption data from Non-Intrusive Load Monitoring (NILM) devices. Firstly, a feasibility study on assessing household active population using fine-gained data was carried out. Various indices were then designed to evaluate active population. At last, an evaluation method was proposed in accordance with the proposed indices. The proposed method was applied to the measurement result of population quantity of each resident user. Through the method proposed in this paper, the data of household active population can be obtained, which can provide data support for the customer-oriented service of power grid and development of energy strategy for authorities.[5] The spread of smart home technologies not only brings convenience but also creates various security and

privacy concerns among users. Electricity consumption data collected by smart meters is one of the sources of these concerns. The electricity consumption of the appliances working at home made it possible to have information about the private life of the household. This study is aimed to reveal a classification model by using the electricity consumption data obtained as a result of the study conducted in Ireland and the results of the survey study conducted with the households. While the first method in the study aims to access information about private life directly with electricity consumption data, the second method uses the predictions of one private information to improve the results of the prediction of another related information. As a result, it has been concluded that electricity consumption data can be used in the process of obtaining information about private life, and that the use of relationship between two information leads to an improvement in model performance. This study shows one of the obstacles that may occur in the spread of smart houses and has prepared the environment for studies that can be done on the subject of solution.[6] The demand for electricity power consumption (PC) is growing lots due to the upward thrust of hardware and the development of the population. Hence it is mandatory to predict energy to enhance its management and co-operation among the energy utilized in a construction and the power grid. There is a problem for predicting the Energy Consumption Prediction (ECP) due to tremendous problems like climate conditions and the effective behaviour of tenants. We present a keen crossover approach that joins Convolutional Neural Network (CNN) with Gated Recurrent Unit (GRU) method which is a Deep Learning technique through three steps which achieves better prediction results when compared to other existing techniques.[7] Forecasting of a single household electricity consumption (load) would be very useful for home energy management systems. However, the load forecasting of a single household is challenging due to the unpredictability of the individual household consumption behaviour. In this paper, a consumption scenario-based probabilistic load forecasting (PLF) method is developed. An energy consumption scenario analysis is proposed to compute the probability of occurrence of each consumption scenario of an individual household at any future time horizon. Then, the analysed results are integrated with PLF algorithms to provide the load forecasting of an individual household. Case studies are conducted to compare the performance of three conventional PLF algorithms and the performance of these three algorithms integrating with consumption scenario analysis. Results show that the proposed method outperforms the conventional PLF methods.[8] Load forecasting at the household level is challenging because the electricity consumption behavior can be much more variable than those at aggregate levels. The introduction of Advanced Metering Infrastructure (AMI) systems has helped to better forecast the load of an individual household. Since smart meter data is streaming data and there is a need to deal with a massive amount of such data in a real-time fashion, an efficient and fast framework to handle this challenge is required. Deep neural networks like Long Short-Term Memory (LSTM) can be used for this purpose but they take a long time to train. In this paper a novel k-nearest meter-based Echo State Network (ESN) is proposed and experimental results demonstrate that it is a more suitable candidate for load forecasting, since it is much easier to train and has a great deal of accuracy. The model is compared with other time series models like Persistent (PM) and Vector Autoregression (VAR), as well as deep learning models like multi-layer perceptron (MLP), LSTM and a combination of convolutional neural network (CNN) and LSTM (CNN-LSTM). The results show that the proposed model has a significant improvement over all other models on a dataset spanning 4 months, along with a significant reduction in training time compared primarily to deep learning models.[9] Efficient load forecasting is needed to ensure better observability in the distribution networks, whereas such forecasting is made possible by an increasing number of smart meter installations. Because distribution networks include a large amount of different loads at various aggregation levels, such as individual consumers, transformer stations and feeders loads, it is impractical to develop individual (or so-called local) forecasting models for each load separately. Furthermore, such local models ignore the strong dependencies between different loads that might be present due to their spatial proximity and the characteristics of the distribution network. To address these issues, this paper proposes a global modeling approach based on deep learning for efficient forecasting of a large number of loads in distribution networks. In this way, the computational burden of training a large amount of local forecasting models can be largely reduced, and the cross-series information shared among different loads can be utilized. Additionally, an unsupervised localization mechanism and optimal ensemble construction strategy are also proposed to localize/personalize the forecasting model to different groups of loads and to improve the forecasting accuracy further. Comprehensive experiments are conducted on real-world smart meter data to demonstrate the superiority of the proposed approach compared to competing methods.[10] Due to the improvement of population quality of life over the world and the following increase of energy demand in particularly the electricity, it has become necessary to follow the evolution of its consumption. Electricity consumption forecasting is considered as key factor in a process of improving energy efficiency, controlling consumption and reducing costs. The main objective of this paper consist to propose a forecast model for household electricity consumption using XGBoost regressor applied on a dataset which contains data collected from a house situated in Sceaux (Paris, France) between December 2006 and November 2010. The experimental results show that the proposed model achieved a higher performance for forecasting periods, particularly, in hourly and daily granularities in terms of RMSE and MAEP.

III. PROPOSED WORK

The approach suggested in this work anticipates each home monthly power use one year in advance, needing only historical data from the preceding year, at least from one month. Forecasting electricity consumption is a broad field of study. It is divided into two dimensions: horizon and spatial granularity. The horizon is the predicted amount of time in the future. It might range from a few hours to several years. The spatial granularity is a geographical specification, i.e., consumption of a single appliance or consumption of a whole nation. The sample rate is another important element. SVM (support vector machine) algorithm is implemented for forecasting voltage and current characteristics of the system.

Support Vector Machines (SVMs) are primarily used for classification tasks, but they can be extended for regression purposes. In the context of predicting power consumption, you'd use SVM regression. The SVM is a supervised learning algorithm which can solve the problems of small sample, non-linearity, and high latitude and is more efficient in solving pattern recognition and regression problems. Therefore, it has been widely used in short-term load forecasting.

SVR is an implementation of SVM to predict the continuous-valued output. In SVR, we use the margin the same as SVM. This margin around the target hyperplane signifies the amount of error that is tolerable in prediction The noninvasive load monitoring with household applications is implemented for power consumption system One-minute data from six commonly used household appliances (rice cooker, LED lamp, CFL lamp, water heater, fridge, and ceiling fan) are collected using the DAS

HOUSEHOLD DATA

The sampling frequency of the data acquisition system is 1 Hz (1 data/second). To incorporate the variability of the supply voltage, data from each appliance are collected at different voltages from 210 to 240 V with a 2 V increment per step. This voltage range (210 – 240 V) is selected because the supply voltage to the residence usually remains within this range. The voltages are changed using a single-phase autotransformer (3 kVA, 0 - 250 V, 50 Hz) Therefore, the data length is 60 × 16 = 960 for each appliance for sixteen different voltage levels. During data collection regulator of the ceiling fan was fixed to a particular position. The effect of voltage variability is shown in Fig. 3, which shows the change of power consumption of LED, CFL, water heater (WH), and rice cooker (RC) with a change in supply voltage ranging from 221 to 229 V, and it is found that there exists a significant difference in power consumption for resistive loads e.g. RC and WH while a negligible effect for non-resistive loads for instance CFL and LED. For instance, at 221 V, RC and WH's power consumption is 975 W and 678.4 W, respectively. While the power consumption of RC and WH are 1015W and 728 W, respectively, at 229 V. The power consumption difference of 40 W and 49.6 W have been observed for RC and WH, respectively, by changing supply voltages. The combined power difference of RC and WH is 89.6 W, which is between the fridge's power rating (100 W) and the ceiling fan (80 W). Thus, the supply voltage variation may negatively affect the load classification accuracy if it is not accounted for. For instance, at 229 V, only rice cooker may be misclassified as rice cooker plus LED or CFL as LED and CFL alone have power consumption near about 32 W

SVM ALGORITHM: -

Support Vector Machines (SVM) is a powerful supervised learning algorithm that can be used for both classification and regression tasks. It's particularly useful when dealing with high-dimensional data and complex relationships. For household power consumption prediction, SVM can be used in a regression context. The goal is to predict the power consumption of a household based on various features such as time of day, temperature, number of occupants, etc.

DATA COLLECTION AND PREPROCESSING:-

Gather historical data on household power consumption. This data should include the target variable (power consumption) and features like time, temperature, occupancy, etc.

Preprocess the data. This may involve handling missing values, scaling numerical features, and encoding categorical variables.

FEATURE EXTRACTION:-

Identify relevant features that might affect power consumption. Consider creating new features or transforming existing ones (e.g., creating time-based features like hour of the day, day of the week).

SPLIT DATA: -

Split your dataset into training and testing sets. The training set is used to train the SVM model, while the testing set is used to evaluate its performance.

SELECTING THE SVM KERNEL:-

Choose an appropriate kernel function. For regression tasks, the Radial Basis Function (RBF) kernel is often a good choice.

MODEL TRAINING:-

Train the SVM regression model on the training data. The model will learn to predict power consumption based on the selected features.

MODEL EVALUATION:-

Use the testing set to evaluate the model's performance. Common regression metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R2) score.

HYPERPARAMETER TUNING:-

Fine-tune hyperparameters like the regularization parameter (C) and the kernel parameters. This can be done using techniques like cross-validation.

PREDICTION AND DEPLOYMENT:-

Once you're satisfied with the model's performance, you can deploy it to make real-time predictions. Remember that the effectiveness of SVM, like any machine learning algorithm, depends heavily on the quality of your data and feature engineering. Additionally, you may want to compare SVM with other regression algorithms like Random Forests or Gradient Boosting to see which performs best for your specific dataset. Lastly, keep in mind that this is a high-level overview. The actual implementation and fine-tuning will require programming and data science skills, as well as a good understanding of SVM and regression techniques.

ADVANTAGE

- Improved Accuracy
- Scalability
- Flexibility

FUTURE FORECASTING

DATA COLLECTION:-

Gather historical data on power consumption for different appliances. This data should ideally cover a significant time period, including various seasons and usage patterns.

DATA PREPROCESSING:-

Clean and preprocess the data. This may involve handling missing values, removing outliers, and normalizing the data.

FEATURE SELECTION:-

Identify relevant features that can impact power consumption. These may include variables like time of day, day of the week, weather conditions, and special occasions (e.g., holidays).

TIME SERIES ANALYSIS:-

Since power consumption data is often time-dependent, consider using time series analysis techniques. This might involve decomposing the time series, checking for seasonality, trends, and autocorrelation.

MODEL SELECTION:-

ARIMA (Autoregressive Integrated Moving Average): Good for stationary time series data. Exponential Smoothing (ETS): Suitable for data with trend and/or seasonality. Prophet: Developed by Facebook, designed for forecasting with daily observations that display trends and seasonality.

MODEL TRAINING AND VALIDATION:-

Split the data into training and validation sets. Train the model on the training data and validate its performance on the validation set. Adjust hyperparameters as needed.

MODEL EVALUATION:-

Use appropriate metrics to evaluate the performance of your model. For time series forecasting, common metrics include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE).

MODEL TESTING:-

Once you are satisfied with the model's performance, you can apply it to forecast future power consumption.

MONITORING AND UPDATING:-

Continuously monitor the model's performance and update it as needed, especially if there are significant changes in usage patterns or external factors that affect power consumption.

DEPLOYMENT:-

Integrate the forecasting model future forecasting analysis the error accuracy.

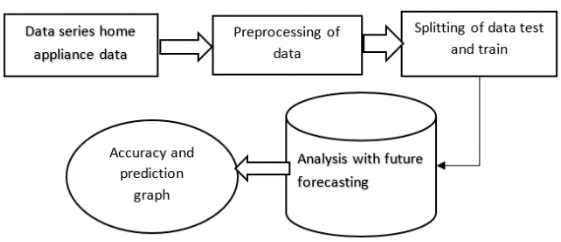


Figure: future forecasting analysis

Here we describe the future forecasting of household appliance and power consumption analysis the forecasting purpose Power consumption forecasting analysis involves predicting future energy usage based on historical data and relevant factors. Here are some steps you can take to conduct a power consumption forecasting analysis.

DATA COLLECTION:-

Gather historical data on power consumption. This data should include records of energy usage over a significant time period, preferably with a high temporal resolution (e.g., hourly or daily data points).

DATA PREPROCESSING:-

Clean and preprocess the data. This may involve handling missing values, removing outliers, and normalizing the data.

EXPLORATORY DATA ANALYSIS (EDA):-

Conduct exploratory data analysis to gain insights into the patterns and trends in the data. This may include visualizing the time series data, identifying seasonality, trends, and potential external factors that could influence power consumption.

FEATURE SELECTION/ENGINEERING:-

Identify relevant features that may impact power consumption. These can include variables like time of day, day of the week, weather conditions, occupancy, holidays, and special events.

TIME SERIES ANALYSIS:-

Apply time series analysis techniques to understand the underlying patterns in the data. This may involve decomposing the time series into its components (e.g., trend, seasonal, and residual components) using methods like moving averages, exponential smoothing, or Fourier transforms.

MODEL SELECTION:-

Choose an appropriate forecasting model based on the characteristics of the data. Common models for power consumption forecasting include:

ARIMA (AutoRegressive+- Integrated Moving Average): Suitable for stationary time series data. Exponential Smoothing (ETS): Effective for data with trend and/or seasonality. Prophet: A forecasting tool developed by Facebook that handles daily observations with seasonality and trends.

Machine Learning Models (e.g., Random Forest, Gradient Boosting): Can be used for more complex modeling and capturing non-linear relationships.

MODEL TRAINING AND VALIDATION:-

Split the data into training and validation sets. Train the chosen model on the training data and validate its performance on the validation set. Adjust hyperparameters as needed.

MODEL EVALUATION:-

Use appropriate metrics to evaluate the performance of your model. Common metrics include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and others.

MODEL TESTING:-

Apply the trained model to forecast future power consumption. Compare the forecasted values with actual observations to assess the accuracy of the model.

MONITORING AND UPDATING:-

Continuously monitor the model's performance and update it as needed, especially if there are significant changes in usage patterns or external factors that affect power consumption.

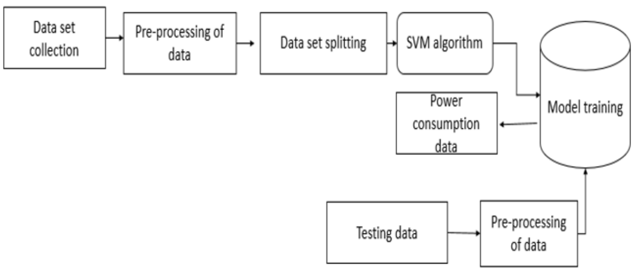
INCORPORATING EXTERNAL FACTORS:-

Consider including external factors like weather forecasts, occupancy schedules, and other contextual information to improve the accuracy of the forecasts.

REPORTING AND VISUALIZATION:-

Present the forecasting results in a clear and understandable manner using visualizations and reports. This helps in communicating the findings to stakeholders. Remember that the success of your forecasting analysis will depend on the quality of the data, the appropriateness of the chosen model, and the incorporation of relevant features and external factors. Additionally, it's important to periodically re-evaluate and update the forecasting model as conditions change over time.

BLOCK DIAGRAM FOR PREDICTION:-



In this above block diagram is describes the electricity power consumption for individual load power consumption dataset contains electricity data voltage ,current ,power factor ,power consumptions of individual electrical load in the home ,first we need to load the data set then we need to preprocess the dataset from this we can the preprocessed output ,we need the splitting the dataset using training and testing of dataset using machine learning models we need to load the model using model training of dataset ,after loading of dataset the input dataset the divided into two parts and dividing using SVM (support vector machine algorithm) training of dataset ,the individual load is going to on and off based on individual load we can analysis the power consumption of the system.

IV. EXPERIMENTAL RESULTS

```
voltage,current,power,powerfactor,lable
224.70212151670725,0.9342822457888884,78.91012326025407,1.5314219586855702,59
226.1313998518,2.891065771687509,77.90238832564793,0.612823908505828,29
220.76019519431242,0.08459660974292327,77.6138308437194,1.6700018279826654,38
227.5814348327893,0.8760894653783974,78.8107971932105,1.9291372697186526,49
225.6023374473958,0.4185797750823712,77.73956434610476,1.3491268891861135,58
225.9749298357076,0.23483136765416524,77.52215088522206,0.030522465656503295,32
223.9727325024608,2.363107494424891,79.57286949911382,0.1347569591658928,26
222.19821346809061,1.322157649924229,77.84349514855222,0.313137673093266,55
224.43111852319907,2.7107515835096243,76.35671700700105,0.7900647560873348,0
223.7008056157927,0.24747297115409994,76.03493205890486,0.5884921843385817,17
224.75128220226912,1.1231995499882583,79.27980503224259,1.9007474898190786,4
222.26656322273163,2.5499584366010466,76.22672267714597,1.6856896969978674,38
227.26405041531967,1.085819465918684,78.91114187567315,1.1147822068045579,52
226.9710293356698,2.257543165322249,75.29124291598964,1.7494769106169414,29
227.25004506478186,1.4052921176104993,75.66794398728075,1.4226667339727004,45
222.97854017088926,1.1671057189501317,78.00000685174861,1.4315812960693182,33
225.42813396639488,1.7665763719804146,79.78264135768352,1.039115357912925,51
226.23335195945987,1.0553657985599272,76.16009642177488,1.4516843091518703,54
228.66253554643222,0.6521151693279978,77.21441179402183,1.771183092409746,20
221.17122563231172,1.8285992824872865,76.18329816924113,1.3470356951735778,25
222.58308640261822,0.5272956293323078,79.22888571545593,1.5652327358684048,42
223.47130147539622,1.098966819735417,77.6417211728664,1.9358143575399736,61
228.0609477278132,0.21307419956195084,78.04440734579137,0.2178801793480849,47
227.16727351604652,2.197638548034977,77.18528089957184,0.23621160172630118,19
226.67333557389586,1.2961183367534888,78.01963965060492,0.43367094739763057,17
222.44651688994495,0.5091090070193532,76.31151888648311,1.1141617064092224,39
223.11984017178753,1.9661108204006854,77.3330596295496,1.7955827672849725,36
227.32506814782104,0.3438782794747467,78.30054060197773,1.9285204484831622,3
229.16736331896487,2.7121656259870592,76.4395653298269,1.1660554385348867,34
222.1024658784014,2.461044686982699,78.74739619201615,1.9536715433845522,50
```

Figure: voltage, current power, power factor, label

The dataset contains the details about voltage, current ,power ,power factor ,label is consider of input dataset UCI Machine Learning Repository: Dataset Name: Individual household electric power consumption Description: This dataset contains measurements of electric power consumption in one household with a one-minute sampling rate over a period of almost 4 years. Link: UCI Repository - Household Power Consumption.

Figure: Load Prediction and Accuracy

	A	B	C	D	E
1	voltage	current	power	powerfact	lable
2	224.7021	0.934282	78.91012	1.531422	59
3	226.1314	2.891066	77.90239	0.612824	29
4	220.7602	0.084597	77.61383	1.670002	38
5	227.5814	0.876089	78.8108	1.929137	49
6	225.6023	0.41858	77.73956	1.349127	58
7	225.9749	0.234831	77.52215	0.030522	32
8	223.9727	2.363107	79.57287	0.134757	26
9	222.1982	1.322158	77.8435	0.313138	55
10	224.4311	2.710752	76.35672	0.790065	0
11	223.7008	0.247473	76.03493	0.588492	17
12	224.7513	1.1232	79.27981	1.900747	4
13	222.2666	2.549958	76.22672	1.68569	38
14	227.2641	1.085819	78.91114	1.114782	52
15	226.971	2.257543	75.29124	1.749477	29
16	227.25	1.405292	75.66794	1.422667	45
17	222.9785	1.167106	78.00001	1.431581	33
18	225.4281	1.766576	79.78264	1.039115	51
19	226.2334	1.055366	76.1601	1.451684	54
20	228.6625	0.652115	77.21441	1.771183	20
21	221.1712	1.828599	76.1833	1.347036	25
22	222.5831	0.527296	79.22889	1.565233	42
23	223.4713	1.098967	77.64172	1.935814	61

After loading of dataset, we should preprocessing of dataset using null values removing rows and column.

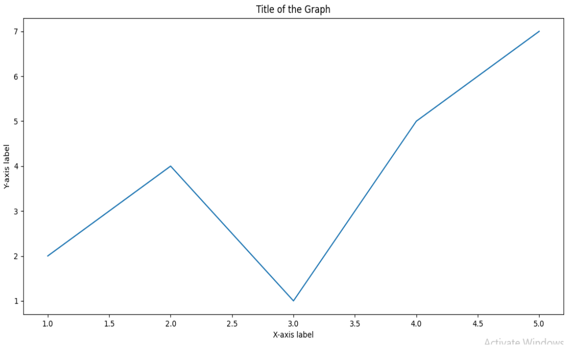


Figure: Accuracy Graph

Accuracy: 0.9500000000000001

UserWarning: X does not have valid feature nar

	Days	Forecasted Power Consumption
0	101	1026.010909
1	102	1026.456868
2	103	1026.902826
3	104	1027.348785
4	105	1027.794743
5	106	1028.240702
6	107	1028.686661
7	108	1029.132619
8	109	1029.578578
9	110	1030.024536
10	111	1030.470495
11	112	1030.916454
12	113	1031.362412
13	114	1031.808371
14	115	1032.254329
15	116	1032.700288
16	117	1033.146247
17	118	1033.592205
18	119	1034.038164
19	120	1034.484122
20	121	1034.930081
21	122	1035.376040
22	123	1035.821998
23	124	1036.267957
24	125	1036.713915
25	126	1037.159874
26	127	1037.605833
27	128	1038.051791
28	129	1038.497750
29	130	1038.943708

Figure: Forecasting Power Consumption

This is forecasting power consumption for 30 days for future forecasting power, power consumption of 30 days for future forecasting power consumption.

V. CONCLUSION

In conclusion, forecasting household electricity consumption requires collecting and analysing historical data on electricity usage, identifying factors that affect consumption, building a predictive model, testing the model, and refining it to improve its accuracy. By using this approach, homeowners can gain insights into their electricity consumption patterns, plan for energy-efficient upgrades, and adjust usage to save money on utility bills. It is important to note that forecasting electricity consumption is an ongoing process, and homeowners should regularly review and refine their models to account for changes in household behaviour and external factors that may affect energy usage, The power consumption of household appliances can vary widely depending on factors such as the type of appliance, its size, age, and usage patterns. Additionally, different regions may have variations in voltage and frequency, which can affect power consumption.

VI. REFERENCES

[1] S. Mian Qaisar and F. Alsharif, "Signal Piloted Processing of the Smart Meter Data for Effective Appliances Recognition", Journal of Electrical Engineering & Technology, vol. 15, pp. 2279-2285, 2020.

[2] T. Ahmad, H. Zhang, and B. Yan, “A review on renewable energy and electricity requirement forecasting models for smart grid and buildings,” Sustain. Cities Soc., vol. 55, Apr. 2020, Art. no. 102052

[3] K. Bandara, H. Hewamalage, and R. Godahewa, “A scalable ensemble of global and local models for long-term energy demand forecasting,” in Proc. 41st Int. Symp. Forecast. 2021.

[4] T. Ahmad, H. Zhang and B. Yan, "A review on renewable energy and electricity requirement forecasting models for smart grid and buildings", Sustain. Cities Soc., vol. 55, Apr. 2020.

[5] X. Shao, C. S. Kim and P. Sontakke, "Accurate deep model for electricity consumption forecasting using multi-channel and multi-scale feature fusion CNN-LSTM", Energies, vol. 13, no. 8, pp. 1881, 2020.

[6] K. Bandara, H. Hewamalage and R. Godahewa, "A scalable ensemble of global and local models for long-term energy demand forecasting", Proc. 41st Int. Symp. Forecast., 2021.

[7] W. Chen, P. Wei and Y. Peng, "Impacts of climate change on monthly electricity consumption: A case of tianjin china", Pol J Environ Stud, vol. 30, no. 5, pp. 3927-3941, 2021.

[8] Y. Gao, Y. Ruan, C. Fang and S. Yin, "Deep learning and transfer learning models of energy consumption forecasting for a building with poor information data", Energy Build, vol. 223, pp. 110156, Sep. 2020

[9] X. M. Zhang, K. Grolinger, M. A. Capretz and L. Seewald, "Forecasting residential energy consumption: Single household perspective", Proc. 17th IEEE Int. Conf. Mach. Learn. Appl., pp. 110-117, 2019.

[10] K. F. al Miraz, K. Biswas and R. Y. Rudra, Forecasting Electricity Demand of Bangladesh and its relation with physical and natural variables using group method of data handling model, 2021.

[11] W. Wu. “IEEE CIS Technical Challenge 2020 Git Hub Repository.” 2020.

[12] K. Bandara, R. Godahewa, and H. Hewamalage. “IEEE CIS Technical Challenge 2020 Git Hub Repository.” 2020. [Online]. Available:

https://github.com/rakshitha123/IEEE_CIS_Comp