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# Optimization and Forecasting of Residential Energy Consumption Using Demand Side Energy Management

Ratnottar Jigar[1], Dr. Divyang Vyas
[1]*Research Scholar, Atmiya University*
[2]*Professor, Atmiya University*

***Abstract*—As we enter a more technologically advanced era, the need for power is growing quickly. Nevertheless, because of an energy shortage, future generation's growth fails to keep up with the consumption. Therefore, managing loads will be crucial to addressing an approaching energy issue. Both the energy provider and customer base may benefit from the adoption of Demand Side Energy Management (DSEM). Reduced electricity bills help the consumer and the utility by lowering the highest demand periods. This study proposes using machine learning techniques to develop demand-side energy management programs for residential consumers. Electric load demand is predicted for the next day by the created load prediction models. The present study investigates several machine learning algorithms, including linear regression, random forest, decision tree, multilayer perceptron and the XGBoost regressor, to determine the volume of energy utilized in household management design. This paper uses $R^2$, MAE and RMSE indicates for monitoring the model's performance.**

***Index Terms*—Demand Side Energy Management, Machine Learning, Sustainable Innovations, Ecological Solution, Smart Grid**

## I. INTRODUCTION

Electric utilities encounter challenges in designing, operating, and controlling enormous energy systems to provide high-quality, secure, and cost-effective electricity to customers [1]. Restructuring power system management in the residential sector is crucial for the country's economy and better control of electricity usage and environmental impact, paving the way for sustainable development. A smart grid works to manage electricity demand cost-effectively by integrating and exchanging information amongst all concerned stakeholders [2]. Prediction of demand is crucial for commercial decision-making in various areas, including manufacturing, commerce, medical services, and transportation. Precise projections of demand reduce supplies, saves operational costs, increases client satisfaction, and improves the supply network stability. Artificial Intelligence (AI) has improved demand forecasting using machine learning [3], deep learning, and other computer techniques that handle large volumes of structured and unstructured data, resulting in more accurate predictions. This study emphasizes only on residential dwellings due to their significant impact on total energy consumption.

This paper provides an in-depth examination of ML approaches [4] for calculating energy consumption in residential areas, using MSE, RMSE and $R^2$ as critical evaluation indicators. The main objective is to determine which models that deliver the most precise estimates of energy usage in dwellings by comparing them to these measurements.

The findings from this research can be used to estimate future electricity demand and allocate resources effectively, as well as to satisfy global sustainable development goals.

Finally, by conducting a comprehensive analysis of various machine learning designs, the current study aims to advance the field of residential building energy consumption prediction. Section II of the manuscript discusses several DSEM techniques [5]. Section III focuses further on the dataset. Section IV describes the proposed methodology. Section V describes the findings and how the machine learning model executed on the dataset. The results of the research are presented in Section VI.

## II. TYPES OF DSEM

DSEM interventions can be adopted by either suppliers or the consumers. Consumers are able to minimize their energy consumption or move their demand to off-peak hours to save money. DSEM strategies are classified into two types: energy reduction and load shifting. DSEM can be used by both residential and industrial customers [5].

### *A. Energy Reduction Method*

It's additionally recognized as the ecologically friendly way. The primary focus is saving electricity. In order to do this, we will need to use energy-efficient gadgets. Saving electricity is an aspect of the energy efficiency strategy. Fig 1 demonstrate the load management techniques.

*B. Load Management Method*

This process involves controlling a network's load to balance electricity supply and demand. Electricity pricing and usage habits are intimately connected. Variations in load patterns can help save money on electricity, which is one of DSEM's key goals. Load management strategies include three types: load shifting, valley filling, and peak clipping.

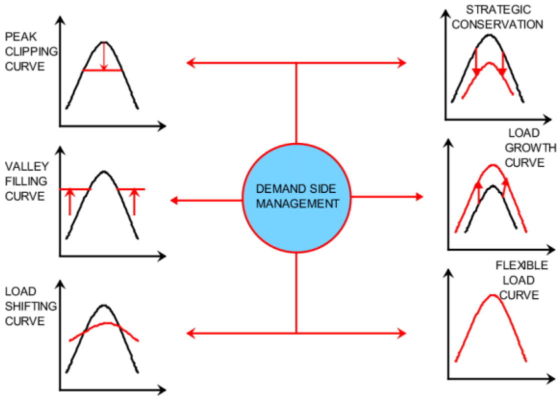


Fig. 1 Load Management Techniques

*1) Load Shifting*

Load shifting is the motion of traffic at various hours of everyday. DSEM algorithms with load transfer strategies successfully decrease excessive system patterns of demand. It schedules smart home devices during high and not busy demand periods. The aim is to increase system effectiveness by limiting supply and demand to the least feasible proportions.

*2) Valley Filling*

Valley filling is a strategy that holds electricity during off-peak hours to boost demand and flatten the load curve. It additionally decreases peak to average ratio (PAR) by promoting mean demand. valley filling adds new loads during off-peak periods.

*3) Peak Clipping*

Peak clipping is a technique for flexible loads like air cooling and room heating. It cuts excessive demand, particularly, Utilization may exceed feeder/transformer temperature limits or system shortages.

## III. DATASET SPECIFICATION

The collection of data employed in this study was obtained from UCI's machine learning archive, and it is accessible for free. It offers data on a family's electric power usage in the French city of Sceaux from 2006 to 2010. The data presented here has been used to create predictions in a variety of accounts. Each data point in the dataset has been collected over a four-year period, from the month of December 2006 to the month of November 2010. Seven parameters were tracked and recorded at one-minute intervals throughout the household. The dataset contains nine characteristics in total, including the measured variables and the date and time information. Tables I and II present the resource metadata and characteristic descriptions, respectively.

| Metadata | Details |
|---|---|
| Name of the Data | Household Power Consumption |
| Place | Sceaux, France |
| Time Duration | 2006 to 2010 |
| Time Interval | 1 Minute |
| No. of Parameters | 9 |
| No. of Datapoints | 2075259 |
| Missing Values | 1.25 % |

Tables I Details of the Metadata

| Variable | Units | Details |
|---|---|---|
| Date | dd/mm/yyyy | Measurement Date |
| Time | hh:mm:ss | Measurement Time |
| Voltage | Volts | Minute-averaged voltage |
| global_intensity | Amperes | House globe minute-averaged electric strength |
| global_active_power | Kilowatts | House globe minute-averaged active strength |
| global_reactive_power | Kilowatts | Household global minute-averaged reactive strength |
| sub_metering_1 | Watt-hour | Energy metering of kitchen, dishwasher, an oven and a microwave |
| sub_metering | Watt-hour | Energy metering |

| | | |
|---|---|---|
| _2 | | of a washing-machine, a tumble-drier, a refrigerator and a light |
| sub_metering _3 | Watt-hour | Energy metering for the electric water-heater and AC |

Table II In depth details of variables

## IV. PROPOSED METHODOLOGY

The most recent experimental approach is to examine the metrics and learn how to utilize machine learning procedures to create a regression model for assessing a home's consumption of energy for utility demand. The present task is done with Python, and the ML code is run in a Jupyter notebook. The structure shown in Figure 2 is utilized to perform the action [6]. In this article, ML algorithms were used on 150000 datapoints and 1000000 datapoints to see what sort of impact is made by modifying the datapoints.

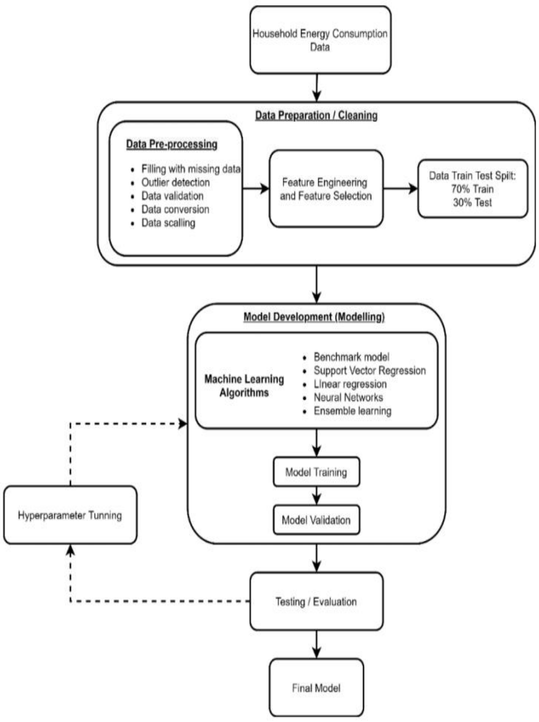


Fig. 2 Proposed Experimental Approach

### A. *Data Pre-processing*

Data cleansing and preparation is a crucial step in the machine learning load prediction method [7]. When unprocessed, unpolished data is used for prediction, the model produces inadequate outcomes. Insignificant data points were eliminated during data collection in order to remove the input properties from the target parameter. The data was then divided into two sets: training and testing. The training set educates the ML models, and the test set confirms their results. 70% of the data is used for learning, and 30% for monitoring. Further the model is also tested for 80% for training data and 20% for testing.

### B. *ML Model Design*

Various ML techniques were applied throughout the algorithm development phase to train and provide load predicting algorithms for the whole day prior to the time. Furthermore, a basic persistence-based benchmark design is created to serve as a standard against which the ML models are evaluated. XGBoost, RF, LR, DT, and MLP are among the forecasting methods identified in this study.

### C. *Prediction Model Evaluation*

The proposed forecasting models' outcomes are measured using a variety of evaluation metrics. Because each metric focuses on different aspects of forecasting, using many assessment metrics provides useful information about the model's effectiveness and accuracy. Table III depicts the forecasting evaluation criteria used in this experiment.

| Metrics | Equation |
|---|---|
| $R^2$ | $R^2 = 1 - \frac{RSS}{TSS}$ |
| MAE | $\frac{1}{n}\sum_{i=1}^{n}\left\lvert y_{predict,i} - y_{data,i}\right\rvert$ |
| RMSE | $\sqrt{\frac{\sum_{i=1}^{n}(y_{predict,i} - y_{data,i})^2}{n}}$ |

Table III Assessment Metrics

## V. RESULTS AND FINDINGS

The measurement factors used for evaluating each model's performance are $R^2$, RMSE, and MAE. RMSE is a metric for determining how well a model forecasts a value. It is typical to decide whether the model is legitimate.

A lower RMSE number indicates that the strategy is the best match for the data and forecast its result with greater accuracy. MAE is a measure that decides the average variance in the planned and actual outcomes.

$R^2$ is a metric that indicates the degree of precision about fitting of a model.

Predictions of proposed model is shown in Table IV and Figure 3. Findings shows that Random Forest algorithm plays an important role for assessment parameters.

RMSE and MAE value for random forest is low amongst the all ML model and the $R^2$ value is best fit for the random forest. xGB algorithm also shows the best fit value for given assessment parameters, where MLP algorithm does not fit for the designed model. Proposed model is assessed by applying 150000 datapoints and 1000000 datapoints.

The results show that once the datapoints are changed, it affects the result of proposed ML algorithms.

| ML algorithms | RMSE | | MAE | | $R^2$ | |
|---|---|---|---|---|---|---|
| | 1.5 lakhs | 10 lakhs | 1.5 lakhs | 10 lakhs | 1.5 lakhs | 10 lakhs |
| LR | 0.050 | 0.041 | 0.030 | 0.026 | 0.998 | 0.998 |
| DT | 0.040 | 0.037 | 0.016 | 0.014 | 0.999 | 0.998 |
| RF | 0.031 | 0.027 | 0.013 | 0.011 | 0.999 | 0.999 |
| MLP | 0.314 | 0.058 | 0.309 | 0.050 | 0.942 | 0.997 |
| xGB | 0.030 | 0.029 | 0.016 | 0.016 | 0.999 | 0.999 |

Table IV Forecasting Results

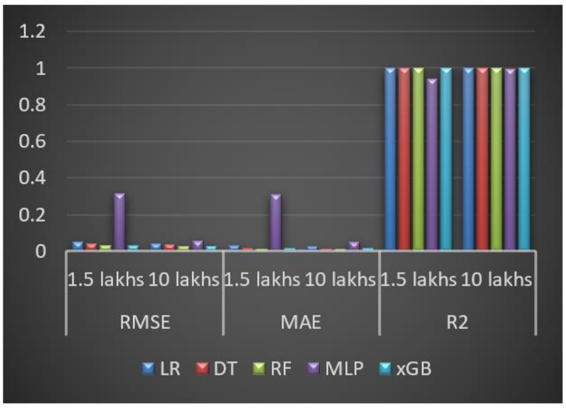


Fig. 3 Comparison of Evaluation Metrics for Proposed ML Algorithms

## VI. CONCLUSION

The study analyzed the way efficiently the aforementioned machine learning models forecasted energy usage for a specific dataset. $R^2$, RMSE, and MAE were among the metrics used to evaluate the models. The load forecasting algorithms established are designed to calculate the power consumption of electric loads 24 hours in advance. even more informative amenities, such as weather variables, may be added to the dataset, or beyond analysis of features can take place on the data that is currently available to improve the models' effectiveness.

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