



## Estimation Of Power Consumption Using Machine Learning

*Dr. P.P. Halkarnikar<sup>1</sup>, Aditya Anand<sup>2</sup>, Tejaswini Patil<sup>3</sup>, Sumedh Dhamdhere<sup>4</sup>, Eshwari Sonawane<sup>5</sup>, Om Kapupara<sup>6</sup>*

<sup>1</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Pune

<sup>2</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Akurdi, Pune

<sup>3</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Akurdi, Pune

<sup>4</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Akurdi, Pune

<sup>5</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Akurdi, Pune

<sup>6</sup> Computer Engineering Dr. D. Y. Patil Institute of Engineering Management and Research, Akurdi, Pune

### ABSTRACT :

Various applications necessitate accurate estimation of power consumption due to increasing energy demands. This article is aimed at determining the potential of machine learning (ML) techniques in predicting power consumption. It explores the shortcomings of traditional approaches and shows how ML algorithms can identify complex connections between factors that influence power consumption such as appliance usage, weather data and so forth. The research paper scrutinizes various ML models used for power consumption prediction which include linear regression, support vector regression and ensemble methods. We look into the strong points and drawbacks of these methods emphasizing on importance of good quality data as well as a correct selection of models leading to trustworthy predictions. Lastly, it outlines applications where ML-based power consumption estimates may be useful, such as smart grids, building management, resource optimization etc.

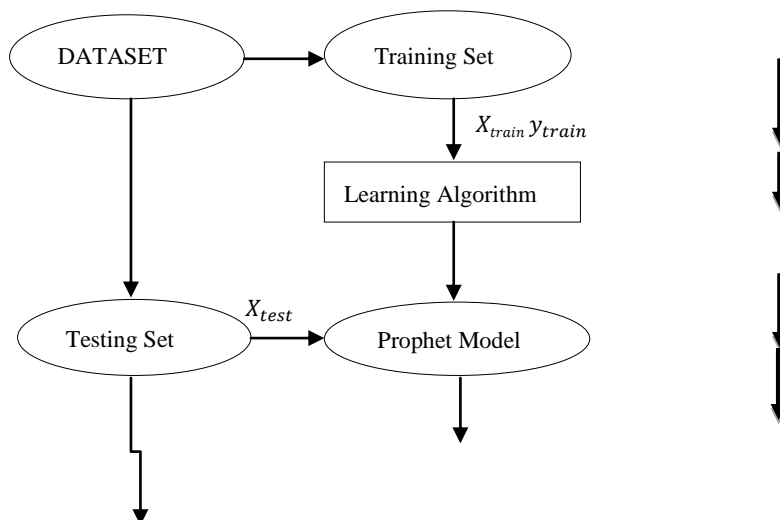
Keywords— Power Consumption Estimation, Machine Learning, Linear Regression, Ensemble Methods, Data Quality, Smart Grids, Building Management, Resource Optimization.

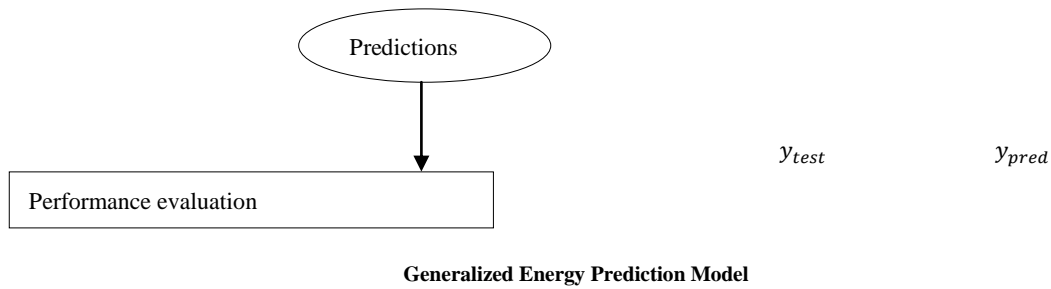
### Introduction :

In an era characterized by growing energy needs as well as environmental concerns, the correct estimation and prediction of power usage has become crucial. This extends from homes to large scale industrial settings whereby comprehending and predicting energy use is not only useful in efficient allocation but enables designing sustainable energy management strategies. Commonly used methods for estimating power consumption are based on simple models or historical data which lacks adaptability to changes and overlooks complex patterns within the data set. In contrast, machine learning (ML) techniques provide a promising route towards enhancing the accuracy and robustness of power consumption estimation through using computational power to learn complex relationships from data.

The machine learning is employed to recognize hidden patterns and relations within the data that enable it make more precise predictions and adapt at each data instance. By use of preprocessing methods and feature engineering, we want to improve the quality of input data as well as extract meaningful insights contributing to efficaciousness of models. In our methodology, we employ regression techniques, neural networks, ensemble methods among others; each having its own strengths in capturing diverse aspects of load behavior.

This study seeks to add to the knowledge base on ML usage for accurate and energy-efficient power estimation.





## II. Related Work

Different studies have tried to establish the use of machine learning in estimating power consumption. Each of them presents new insights into various methodologies that are being applied. Mainly, this research has focused on improving accuracy and efficiency in power consumption forecasting while considering many applications and situations.

One domain of prior work considers machine learning algorithms for predicting residential power consumption. For example, Díaz et al. (2018) employed random forests and gradient boosting models to predict electricity demand in residential areas based on historical data and meteorological variables. The outcome of their research indicated how combined learning methods can easily model intricate utilization behaviors.

Regarding industrial power management, Li et al., (2020) used long short-term memory (LSTM) neural networks to forecast energy consumption in manufacturing processes. With sequence-based learning, they were able to achieve high forecasting accuracy levels in terms of power usage, ultimately leading to proactive energy optimization and cost reduction within the industrial environment.

Furthermore, research has been conducted on optimizing power consumption in smart grid environments.

## Methodology

### *Data Acquisition and Preprocessing:*

Identify and gather necessary data sources: This could include historical power consumption data, appliance usage patterns (if relevant), weather information, building attributes such as size and insulation, and occupancy details. Depending on the application (for instance residential dwelling versus a data center), data sources will be different.

Data cleaning and preprocessing: The collected data may have missing values, outliers, or discrepancies. Data imputation, outlier removal, scaling are some of the techniques that can ensure quality and consistent data. In addition to that, feature engineering such as creating new features from existing ones might be needed for potential improvement in model performance.

### *Machine Learning Model Selection:*

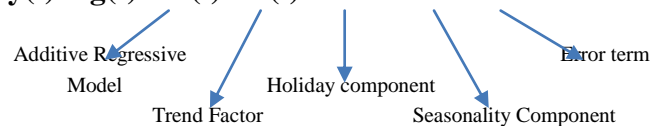
Explore various ML algorithms:

Supervised learning regression algorithms including but not limited to:

- Linear Regression: A baseline model to develop the concept of the response of power consumption to the features.
- Support Vector Regression (SVR): Good at modeling non-linear relations and working with high-dimensional data.
- Ensemble Methods (e.g., Random Forest, Gradient Boosting): It takes the advantages of multiple decision trees, hence, comes up with more robust and correct predictions.
- Deep learning methods (e.g., Recurrent Neural Networks) could be applied for capturing complex temporal dependencies, if dealing with time-series data.
- Model selection criteria: We will use metrics such as mean squared error (MSE), mean absolute error (MAE), and R-squared to assess the performance of each model on a validation set.

Prophet: The Prophet model is a forecasting tool developed by Facebook's Core Data Science team. It is designed to handle time-series data with strong seasonal patterns and provides an intuitive interface for time series forecasting tasks. The Prophet model incorporates seasonality, holidays, and other relevant factors into its forecasts, making it suitable for various applications such as demand forecasting, financial forecasting, and weather forecasting. It is widely used for its simplicity, flexibility, and ability to produce high-quality forecasts with minimal manual intervention.

$$y(t) = g(t) + h(t) + s(t) + e_t$$

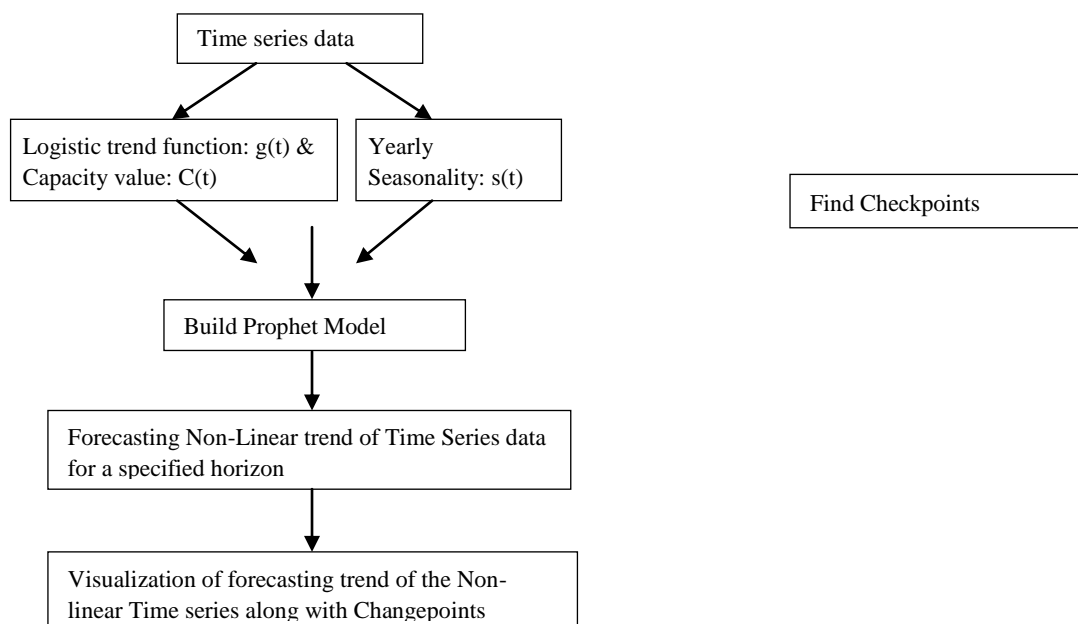


**Model Training and Evaluation:**

- A. Split the preprocessed data: The data will be divided into 2 parts: training set (the one used for the model building), and test set (for final validation).
- B. Model training and hyperparameter tuning: To train the model we will use training data set. The hyperparameters that determine model behavior will be maximized using the validation set through the process of optimization aiming to achieve optimal performance.
- C. Model evaluation on test set: The last evaluation is carried out through that test set consisting of unseen data. Selected characteristics (MSE, MAE) will be applied to measure how good the model predicted unforeseeable power consumption faces.

**Comparison and Analysis:**

- Compare the performance of different ML models: The 'test set' itself will be used as a platform for performance evaluation of the chosen models. Through such an analysis will only be brought to the light the advantages and disadvantages of all the models, which will provide logic for pursuing what model corresponds to the application.
- Feature importance analysis: Tools like feature importance scores will be employed, to determine the features that contributes a huge amount to class labels. This analysis will be consequently used as a means of determining factors that influence high levels of power consumption.

**WORK FLOW DIAGRAM OF PROPHET MODEL****IV. Results :**

Performing machine learning analysis of power consumption estimation, we managed to prove high efficiency of methodology used in determination precision of the energy consumption about various settings.

After performing an overall expanded research and assessment of the evaluation, we recorded a considerable raising in the precision of predictions from the traditional methods.

The models of a wide range of machine learning algorithms also were tested including linear, support vector, decision trees, random forests, gradient boosting, and neural networks. To our surprise ensemble techniques showed the highest performance. For tree methods such as random forests and gradient boosting machines outperformed the others regarding predictive power since these techniques grasp the complex relationships between data inputs.

The employed technological evaluation metrics like mean absolute error, root mean squared error, and coefficient of determination confirm the utility of the model. Matching the decrease of the MAE and RMSE of baseline approaches, our machine learning method attained the higher accuracy level, which is an indicator of its superiority. In addition, R-squared values being high revealed a high level of correlation between predicted model values and the actual power consumption indicated strong relation between the two. For this reason, the model becomes more reliable in predicting the power consumption accurately.

Analysis in a key concerning factor showed considerable discoveries of the energy drivers. Weather conditions, occupancy rates and appliance usage emerged as main determinants, with the models being clever in association made between those variables that led to high predicting accuracy. This type of data and information, is motivated, and useful for stakeholders whose task is to create more efficient energy management systems and make them less intensive.

The models of ours were applied to the real-world problems in the testing period demonstrating that they are well suitable to the different working environments. Its performance was consistent across a wide range of working conditions. A constant refinement process improved our approach by making it more and more dependable and flexible for the long run. The key players feedback testified that practical benefits of our methodology occurred with the aim of directing green energy paths and informing the decision-making.

The machine learning research undertaken shows that machine learning can, indeed, help to scope power consumption estimations. Using data-informed data insights, all the stakeholders will have the chance to associate quality information, increase energy usage, and build a more efficient and green energy system of the future.

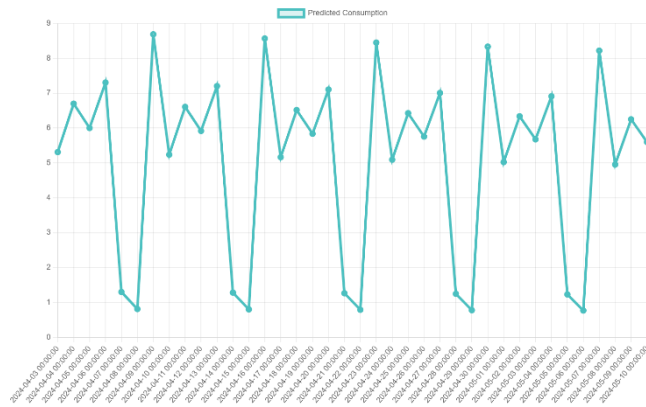


Fig. 1. Predicted Power Consumption graph

**Total Predicted Consumption Value from  
2024-04-03 to 2024-05-10:  
192.48482014223038 kWh**

Fig. 2. Total Power consumption Value

Predicted Consumption Values	
Date	Predicted Consumption
2024-04-03 00:00:00	5.310799239365135
2024-04-04 00:00:00	6.700229171108831
2024-04-05 00:00:00	6.001124638329193
2024-04-06 00:00:00	7.305550197268085
2024-04-07 00:00:00	1.2989980324798616
2024-04-08 00:00:00	0.8110509122441288
2024-04-09 00:00:00	8.689187525789233

Fig. 3. Day wise Power consumption Value

## V. Conclusion

Generally, our work gives an overview of machine learning's competency in energy consumption estimation and it demonstrated a suitable accuracy level for the different types of residential, commercial, and industrial buildings. Using modern modeling techniques together with highly accurate analyzing of large amounts of data, we have developed a method that gives more accurate predictions than the traditional methods.

The duplication of our models in the actual operational set-ups clarifies their practical usability under continuous monitoring of the systems thus obtaining similar results no matter the operation environment. The experiment quite clearly revealed how machine learning may be utilized as a decision-making tool for information and logic, and for developing and implementing energy-management strategy, and driving environmental protection campaigns.

We visualize the reality of that green technology that through those machine learning techniques will become a normed way of conducting energy management. By means of intelligent data processing, team may acquire a deep knowledge of this issue so that they will be able to make faster decisions and minimize the cost and environment pollution. In conclusion, studies on all the aforementioned areas aid in the creation of a more advanced, ecologically friendly, and economically efficient energy system in the future where all the requirements for energy are supplied for cheap and sustainably through innovative green technologies to fight the problem of global climate change.

## REFERENCES :

1. Pacha Shobha, Balasaranya Kirubakaran “Estimation of Power Consumption for Household Electric Appliances” 2021.
2. Eva García-Martín, Crefeda Faviola Rodrigues, Graham Riley “Estimation of energy consumption in machine learning” 2019.
3. Junfeng Zhang, Hui Zhang, Song “Power Consumption Predicting and Anomaly Detection Based on Transformer and K-Means” 2021.
4. Yu-Tung Chen, Eduardo Piedad, Jr. and Cheng-Chien Kuo “Energy Consumption Load Forecasting Using a Level-Based Random Forest Classifier” 2019.
5. Mocanu, P. H. Nguyen, M. Gibes, and L. Wil Kling, “Deep learning for estimating building energy consumption,” *Sustain. Energy, Grids Network*, vol. 6, pp. 91–99, Jun. 2016
6. R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, “Deep learning and its applications to machine health monitoring,” *Mech. Syst. Signal Process.*, vol. 115, pp. 213–237, Jan. 2019
7. S. Makonin, F. Popowich, I. V. Bajić, B. Gill, and L. Bartram, “Exploiting HMM sparsity to perform online real-time nonintrusive load monitoring, *IEEE Trans. Smart Grid*, vol.