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# Smart City Energy Analytics: A Random Forest-Based Prediction Model

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***Abstract:*** This For energy management, policy planning, and guaranteeing a steady supply of electricity, accurate forecasting of electricity demand is essential. Forecasting models have been greatly enhanced by recent developments in artificial intelligence (AI) and machine learning (ML), which incorporate a variety of independent variables such as weather, economic factors, and historical consumption data. In order to improve forecasting accuracy, this study investigates the combination of machine learning models, specifically artificial neural networks (ANN), and multi-criteria decision-making techniques. A key challenge in electricity demand forecasting lies in selecting relevant input variables. This research employs a systematic approach to identify significant factors impacting demand and applies advanced ML techniques, such as Random Forest, LSTM, and Extreme Learning Machines, to develop robust predictive models. Comparative analysis using performance metrics like RMSE and MAPE demonstrates the effectiveness of AI-driven forecasting approaches. The findings contribute to the evolving landscape of energy demand prediction, aiding in efficient power system planning and optimization.

***Index Terms*** **- Electricity demand forecasting, machine learning, artificial neural networks, multi-criteria decision-making, energy consumption prediction, time-series forecasting, energy management.**

## I. INTRODUCTION

Forecasting electricity demand is essential for energy management, power system design, and policy formation. The accurate prediction of electricity consumption enables utilities and stakeholders to optimize generation, minimize costs, and ensure a reliable power supply. Traditional forecasting models, including statistical and mathematical approaches, have been extensively used; however, the choice of an appropriate model remains a challenge due to the influence of multiple external factors such as meteorological, socioeconomic, and environmental variables [1].

These independent variables play a critical role in enhancing forecasting accuracy, yet their selection remains subjective in many studies, often relying on researchers' expertise rather than systematic approaches [2].

Forecasting electricity demand has changed as a result of recent developments in artificial intelligence (AI) and machine learning (ML), which have produced more reliable and flexible models. Because they can capture complex nonlinear relationships in energy consumption data, techniques like artificial neural networks (ANN), long short-term memory (LSTM), and hybrid models that combine statistical and deep learning methods have become popular [3].

By utilising various model strengths, hybrid models—which combine multiple machine learning techniques—have demonstrated notable gains in predictive performance [4].

The dynamic character of consumption patterns is one of the main obstacles to forecasting electricity demand.
As global electricity demand rises, particularly in industrial and commercial sectors, the need for advanced forecasting methods that incorporate real-time and historical data becomes increasingly vital. The industrial sector is the largest consumer of electricity, with developed nations consuming approximately 43.26% of the world's total electricity consumption, according to recent studies [5].

Given the economic impact of demand fluctuations, accurate forecasting not only aids in optimizing energy production but also prevents financial losses due to overproduction or shortages.By combining machine learning techniques with multi-criteria decision-making methods, this study seeks to enhance electricity demand forecasting. By systematically selecting relevant external factors and employing advanced ML algorithms, this research seeks to enhance forecasting accuracy and provide valuable insights for energy management. Comparative analyses of various forecasting models will be conducted to assess their performance based on key evaluation metrics such as root mean square error (RMSE) and mean absolute percentage error (MAPE). The findings will contribute to optimizing electricity demand prediction strategies, ultimately supporting sustainable energy planning and resource allocation.

## II. OBJECTIVE

The primary objective of this research is to develop advanced forecasting models that accurately predict energy consumption in urban areas by addressing the limitations of traditional time-series methods. In order to provide more accurate and flexible predictions, these models seek to identify intricate, non-linear relationships in energy consumption data.

**Specific objectives include:**

- To overcome the constraints of traditional forecasting models by effectively capturing non-linear dependencies and intricate consumption patterns.
- To improve forecasting accuracy using machine learning techniques that adapt to dynamic and evolving energy trends.
- To analyze the influence of renewable energy integration, technological advancements, and changing consumer behavior on energy demand.
- To develop a robust forecasting tool that supports efficient energy management, grid stability, and strategic resource allocation.
- To create adaptable forecasting models that evolve with the energy landscape, enhancing predictive capabilities for sustainable energy planning and decision-making.

## III. ALGORITHM

This study uses the **Random Forest (RF)** algorithm to improve energy demand forecasting by taking advantage of its capacity to manage missing values, high-dimensional data, and non-linearity. To increase accuracy and generalisation, RF builds several decision trees and aggregates their predictions as an ensmble learning technique.

**1. Data Preprocessing**

To prepare the dataset for modeling, missing values are handled using mean or mode imputation techniques to ensure data consistency [10]. Numerical features are normalized to bring all variables to a common scale, thereby preventing dominance by features with larger magnitudes [11]. To transform categorical variables into a machine-readable format, one-hot encoding or label encoding are used. Additionally, feature selection is performed to eliminate redundant or irrelevant variables, which enhances model interpretability and efficiency [12].

**2. Model Construction**

The Random Forest model is constructed by training an ensemble of **N** decision trees, each using a randomly selected subset of the training data. At each split within a tree, only a subset of features is considered, a strategy that reduces overfitting and enhances model robustness [13]. The splitting criterion for node division is determined using the **Mean Squared Error (MSE)**, which ensures that the selected splits lead to minimal variance in predictions. The final model consists of multiple trees whose outputs are aggregated to generate more stable and accurate predictions.

**3. Prediction and Aggregation**

The average of the outputs from each decision tree is used to calculate the final prediction for regression tasks. Making effective use of the available data, the Out-of-Bag (OOB) error estimation is used to evaluate model performance without the need for a separate validation set [14]. This method lowers the chance of overfitting while improving the model's capacity to generalise to new data.

**4. Model Evaluation**

To evaluate the model's performance, multiple error metrics are employed, including the **$R^2$ score**, **Root Mean Squared Error (RMSE)**, and **Mean Absolute Error (MAE)**. These metrics offer a thorough evaluation of the model's precision and dependability in predicting energy consumption. Additionally, hyperparameter tuning is performed by optimizing factors such as the depth of decision trees, the number of estimators, and the maximum number of features considered at each split. This optimization process ensures that the model is well-calibrated to capture complex patterns in energy consumption data.

**5. Feature Importance Analysis**

To further enhance the interpretability of the model, an analysis of feature importance is conducted. The contribution of individual features to energy demand predictions is assessed using **Gini importance** or **permutation importance**. This analysis helps identify key drivers of energy consumption, providing valuable insights for decision-makers and energy planners.

## IV. MATHEMATICAL MODEL

Energy demand is predicted using a variety of mathematical models, each with special advantages depending on the data type and forecasting needs.

***1. Linear Regression:***

Based on past consumption and outside variables like the weather, the linear regression model forecasts future energy demand. The model is stated as follows:

$$D(t+h) = \beta 0 + \beta 1 D(t) + \beta 2 T(t) + \beta 3 H(t) + \ldots + \beta n D(t-n) + \epsilon$$

where D(t) represents the energy demand at time t, T(t) and H(t) denote temperature and humidity, respectively, and $\epsilon$ is the error term. This model is simple, interpretable, and works effectively when there is a linear relationship between variables [10].

***2. Autoregressive Integrated Moving Average (ARIMA):***

For time-series forecasting, ARIMA is frequently utilized, particularly in the presence of trends and seasonality. This is the model equation:

$$D(t) = \alpha 0 + \alpha 1D(t-1) + \alpha 2D(t-2) + \ldots + \alpha pD(t-p) + \theta 1\epsilon(t-1) + \theta 2\epsilon(t-2) + \ldots + \theta q\epsilon(t-q)$$

where p represents the autoregressive order, d is the differencing order, and q is the moving average order. This model effectively handles stationarity and seasonality in energy demand [11].

***3. Exponential Smoothing (ETS):***

The Exponential Smoothing (ETS) model is appropriate for short-term forecasting because it gives historical observations exponentially decreasing weights. The following is the equation:

$$St = \alpha Dt + (1-\alpha)St-1$$

where St is the smoothed value at time t, α is the smoothing factor, and Dt represents the observed energy demand. This model adapts well to trends and seasonality [12].

***4. Decision Trees (Random Forest):***

An ensemble-based decision tree model called Random Forest divides data according to feature values. Conditions like these are used to divide the tree nodes:

$$xj < \theta \Rightarrow \text{left child, otherwise right child}$$

where xj is a feature and θ is a threshold. This model performs well with non-linear data, handles high-dimensional datasets, and reduces overfitting through ensembling [13].

***5. Bagging (Bootstrap Aggregating):***

Bagging is a technique used in Random Forest to train multiple decision trees on different bootstrapped samples of the dataset. The bagging process follows:

$$Bk \sim \text{Bootstrap}(D)$$

where Bk represents the bootstrapped sample from dataset D. This technique enhances model stability by reducing variance and improving prediction accuracy [14].

## V. PROPOSED METHODOLOGY

There are five primary stages to the proposed electricity demand forecasting system:

1. User authentication and registration: Before using the system's features, users must log in or register. This improves user management and guarantees safe access to data.

2. Data Pre-Processing: To deal with missing values, normalise features, and eliminate inconsistencies, raw energy consumption data is preprocessed. This stage guarantees the quality of the data for subsequent analysis [16].

3. Relevant features are extracted, including temperature, humidity, historical energy consumption, and time-based characteristics (e.g., hour, day, season). These characteristics aid in raising demand forecasting models' accuracy [17].

4. Random Forest classification: A Random Forest (RF) classification model is trained using the extracted features to classify energy demand into various levels (e.g., low, medium, high). Because of its ability to withstand non-linearity and feature importance analysis, RF is selected [18].

5. Forecasting Electricity Demand: Using the trained model, the last phase entails forecasting future electricity demand. Energy providers can optimise grid operations and resource allocation with the help of the forecasting output.

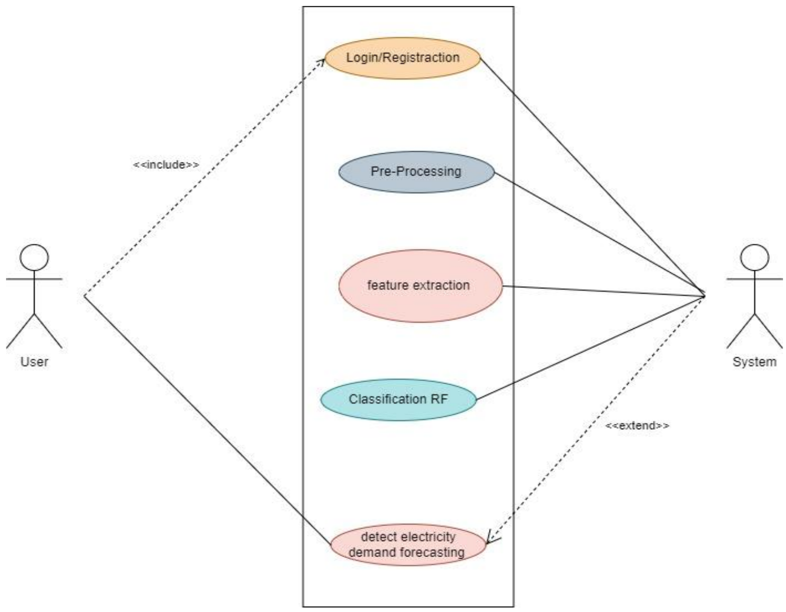


Fig 1. Use Case Diagram

## VI .IMPLEMENTATION MODEL

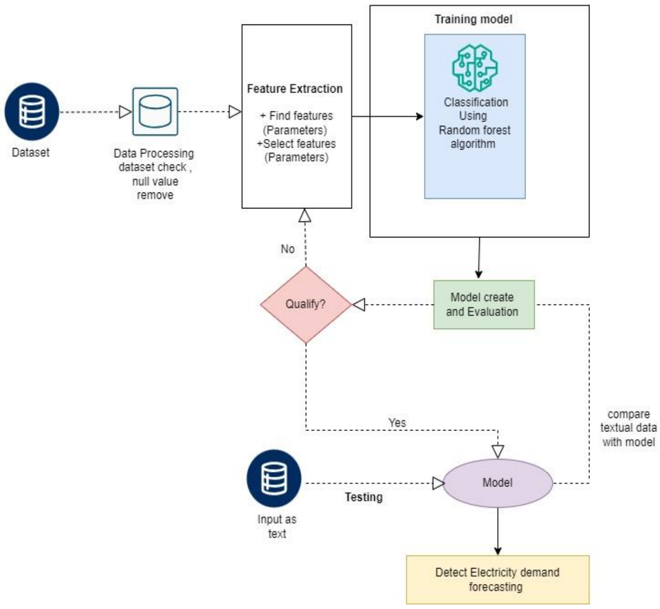


Fig 2. System Architecture

Data preprocessing, feature extraction, model training, evaluation, and testing are all integrated into a methodical pipeline that forms the basis of the electricity demand forecasting implementation model. The proposed method uses machine learning techniques, namely the Random Forest (RF) algorithm, to increase forecasting accuracy.
The steps that make up the methodology are as follows:

***1. Data Acquisition and Preprocessing***
Data on electricity consumption is gathered in the first stage from a variety of sources, such as weather databases, smart meters, and historical load records. The data is cleaned using preprocessing techniques, which include handling missing values, normalising numerical features, and eliminating noisy or redundant data. Furthermore, outlier detection techniques are used to guarantee that the model receives high-quality input [19].

***2. Feature Extraction and Selection***
A key component of enhancing the model's predictive performance is feature extraction. In this step, important factors that affect electricity demand are chosen, including temperature, humidity, time of day, and past consumption patterns. The system reduces dimensionality while identifying the most pertinent attributes by using statistical techniques such as Principal Component Analysis (PCA) and correlation analysis. The robustness of the model is guaranteed and overfitting is avoided with a feature set that is well-optimized [20].

***3. Model Training Using Random Forest***
The extracted features serve as inputs to train the **Random Forest (RF) classification model**. RF is chosen due to its ability to handle large-scale datasets, mitigate overfitting through ensemble learning, and provide high accuracy in classification and regression tasks. The training phase involves:

- Splitting the dataset into training and validation sets (e.g., 80%-20% ratio).
- Building several decision trees according to various data subsets.
- Aggregating results from individual trees to form the final prediction.

The trained model learns the patterns in energy consumption and establishes a mapping function between input features and electricity demand levels [21].

***4. Model Qualification and Evaluation***
Metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 score are used to assess the model's performance during the evaluation phase that follows training. The pipeline returns to feature selection and training for additional improvements if the model's accuracy falls short of the required thresholds. A thorough evaluation procedure guarantees that the finished model is trustworthy and appropriate for predicting applications in the real world.

***5. Forecasting and Testing***
The model is put to use for testing with fresh or real-time input data after it passes evaluation metrics. The trained model is fed unobserved textual or numerical data during the testing phase, after which it identifies or forecasts the amounts of electricity consumption. Businesses, politicians, and energy suppliers can utilise the final product to make decisions about operational planning, load balancing, and energy saving.
The suggested implementation model greatly improves forecasting accuracy and dependability by utilising Random Forest's capability and including sophisticated feature selection algorithms.

VII. RESULTS

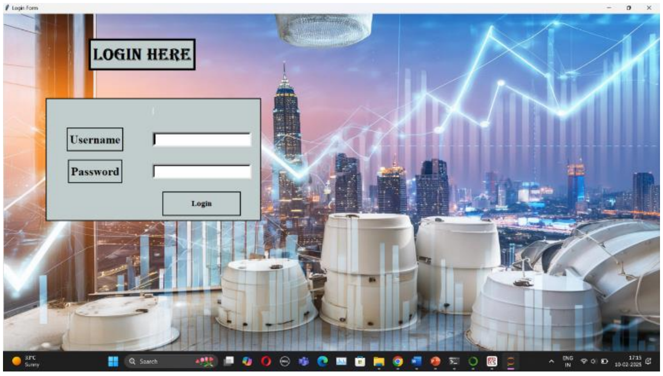


Fig 3 : Login Page

This figure represents login page.

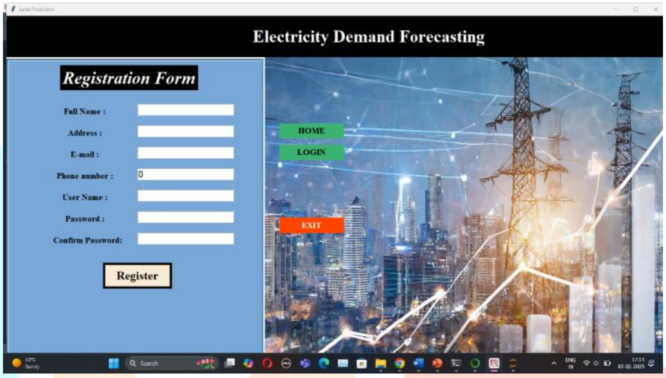


Fig 4 : Registration page

This figure represents registration page.

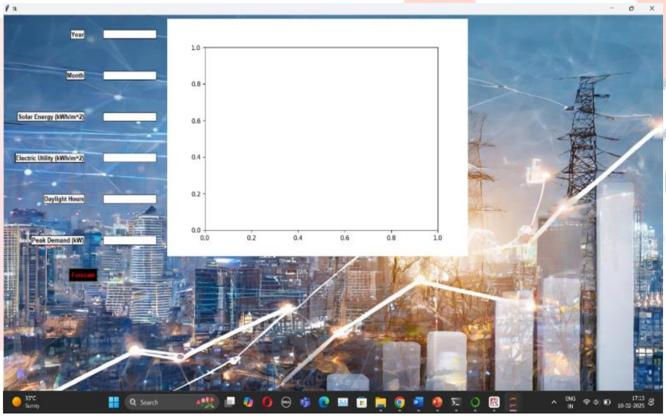


Fig 5 : Output page

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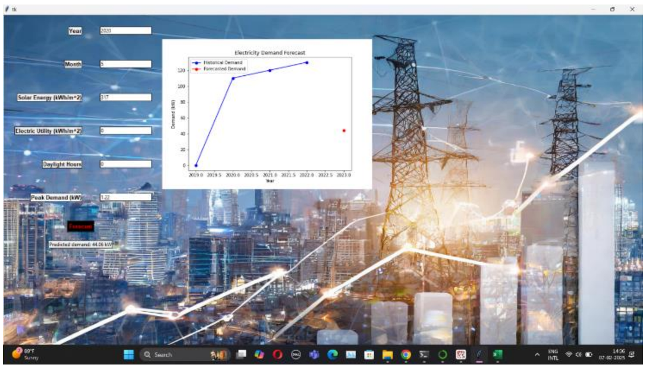


Fig 6 : Output page

This figure represents output page.

## VIII.CONCLUSION

Electricity demand forecasting is essential for efficient energy distribution, minimizing waste, and addressing resource scarcity. While various forecasting methods exist, selecting relevant independent variables remains a challenge. Multi-criteria decision-making techniques, such as the ELECTRE I method, improve variable selection by considering key factors like temperature and seasonal patterns.

Recent research emphasizes AI-driven forecasting models, with neural networks and ensemble methods like random forest outperforming traditional statistical models. Hybrid approaches and probabilistic forecasting are gaining traction, offering improved accuracy. However, gaps remain in benchmarking models and studying underrepresented regions like Africa, where electricity demand modeling is limited.

Smart buildings and urban energy systems require computationally efficient models, with gradient boosting regressor (GBR) showing promise. Future research should explore deep learning, hybrid models, and optimized forecasting for different time horizons. By integrating advanced AI techniques and expanding research to diverse contexts, electricity demand forecasting can support more sustainable and efficient energy management worldwide.

## IX. APPLICATIONS

Forecasting energy demand is crucial for efficient energy use and sustainability in grid management, policymaking, and renewable energy integration. Machine learning techniques, particularly Random Forest (RF), have significantly improved forecasting accuracy, making them valuable tools in modern energy systems.

1. ***Load Forecasting and Grid Management:*** Grid stability and energy supply and demand balance depend on precise load forecasting.

2. RF-based models analyze historical consumption, weather conditions, and economic indicators to generate precise short- and long-term forecasts [22]. These models help grid operators optimize resource allocation, reduce power disruptions, and enhance energy distribution efficiency.

3. ***Renewable Energy Integration:*** Variability in power generation is brought about by the growing reliance on renewable energy sources like solar and wind. RF models help mitigate this unpredictability by analyzing complex relationships between weather patterns and energy demand [23]. This enables better coordination between conventional and renewable energy sources, enhancing grid stability and efficiency.

4. ***Optimizing Energy Efficiency:*** Businesses, households, and industries can minimize inefficiencies by forecasting energy demand using RF-based models. These models identify peak demand periods and suggest load management strategies, leading to better energy conservation [24]. Smart grids and intelligent buildings leverage RF models for real-time energy monitoring, enabling automated adjustments in lighting, heating, and cooling systems to enhance efficiency and reduce operational costs.

5. ***Policy Planning & Decision Support:*** Governments and energy regulators rely on accurate demand forecasts to develop energy policies, infrastructure expansion plans, and pricing strategies. RF-driven models incorporate socioeconomic and environmental factors, aiding policymakers in predicting future energy demands and implementing data-driven strategies for sustainable energy management [25]. These models support demand-side management initiatives, renewable energy investments, and urban planning.

## X. FUTURE SCOPE

In order to improve prediction accuracy, future studies in energy demand forecasting can concentrate on combining hybrid machine learning models, real-time data processing, and uncertainty quantification. Forecasting performance can be enhanced by combining Random Forest with support vector machines or deep learning. Furthermore, more accurate demand forecasts can be made by utilising IoT data and big data analytics. Energy management will be further optimised with the integration of energy storage and real-time decision support systems for smart grids. In addition to improving reliability in managing demand fluctuations, probabilistic forecasting techniques and risk management strategies can guarantee a more sustainable and effective energy system.

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