# ELECTRICITY USAGE AND BILL PREDICTION SYSTEM BASED ON HOUSEHOLD ATTRIBUTES AND APPLIANCE CONSUMPTION

**A PROJECT REPORT**

***Submitted by***

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***in partial fulfillment for the award of the degree***

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## BONAFIDE CERTIFICATE

Certified that this Project titled **"ELECTRICITY USAGE AND BILL PREDICTION SYSTEM BASED ON HOUSEHOLD ATTRIBUTES AND APPLIANCE CONSUMPTION"** is the bonafide work of **"NEELA A (2116220701184)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Submitted to Mini Project Viva-Voce Examination held on ____________________

**Internal Examiner** **External Examiner**

# ABSTRACT

This project presents an intelligent energy consumption and billing prediction system that leverages machine learning techniques to forecast future electricity usage and costs. It takes into account various influential household factors including house size, number of occupants, past energy usage, previous billing amounts, current weather conditions, and the extent of heavy appliance usage. By training and comparing different regression models such as Random Forest, Gradient Boosting, and Linear Regression, the system ensures high prediction accuracy. Among these, the Random Forest model demonstrated the most reliable performance and was selected as the final model for both energy and billing predictions. The dataset used was preprocessed by encoding categorical variables and handling missing data to ensure data quality and consistency.

In addition to accurate predictions, the system provides personalized recommendations based on predicted usage or bill amounts. For example, if high energy usage is forecasted due to increased appliance usage or unfavorable weather, the system suggests energy-saving tips such as adopting LED lighting, limiting simultaneous appliance use, and optimizing peak hour usage. These insights are intended not only to help users manage their electricity bills more efficiently but also to promote energy conservation habits. Overall, the project contributes to smarter energy management by equipping households with predictive insights and actionable feedback, fostering both economic and environmental benefits.

# ACKNOWLEDGMENT

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# LIST OF SYMBOLS

| SNO | SYMBOLS | DESCRIPTION |
|---|---|---|
| 1 | MAE | Mean Absolute Error– evaluation metric |
| 2 | $R^2$ | R-squared Score – model performance indicator |
| 3 | X | Feature matrix (input variables) |
| 4 | y_units | Target variable – future electricity usage (units) |
| 5 | y_bill | Target variable – future electricity bill amount |
| 6 | RF | Random Forest model |
| 7 | GB | Gradient Boosting model |
| 8 | LR | Linear Regression model |
| 9 | n_estimators | Number of trees in ensemble models |
| 10 | pickle | Python module used for saving/loading models |

# CHAPTER 1

## 1.INTRODUCTION

### 1.1 GENERAL

In today's data-driven world, predicting resource consumption has become an essential component of efficient management, particularly in the energy sector. Electricity, being a fundamental utility for every household, has seen rising demand and costs. With an increasing global emphasis on energy conservation and sustainability, it has become crucial for individuals to understand, monitor, and anticipate their electricity usage. Predictive analytics offers a solution by helping consumers manage expenses and adopt sustainable consumption habits. The integration of artificial intelligence (AI) and machine learning (ML) into energy management allows both individuals and utility providers to make data-informed decisions using historical usage patterns and environmental factors.

### 1.2 OBJECTIVE

The primary objective of this project, titled ***"Electricity Usage and Bill Prediction System Based on Household Attributes and Appliance Consumption"***, is to develop a user-centric model that can forecast electricity usage and billing. This system aims to:

- Predict future electricity consumption and associated bills using household-specific attributes.

- Incorporate key features such as house size, number of residents, past electricity usage, weather conditions, and appliance consumption levels.

- Provide personalized and accurate forecasts, accounting for seasonal and behavioral patterns in energy use.

- Encourage energy-efficient practices by alerting users to potential consumption spikes and recommending preventive actions.

- Offer scalability for broader applications in community housing or commercial buildings.

## 1.3 EXISTING SYSTEM

Existing energy consumption prediction models typically fall into two categories: statistical methods and advanced machine learning approaches. Traditional statistical methods like ARIMA and linear regression have been widely used for time-series forecasting, often at macro levels (e.g., city or regional grids). However, these methods struggle to capture non-linear and personalized consumption behaviors found in individual households.

Modern systems employ machine learning techniques such as Support Vector Machines, Random Forests, and Neural Networks. These models can consider additional variables like weather data and occupancy patterns, significantly improving prediction accuracy. Nonetheless, many existing systems rely on complex infrastructure like smart meters or IoT devices and require granular data inputs, making them less accessible for average households. Moreover, they often lack interpretability and fail to provide actionable recommendations for energy-saving.

## 1.4 PROPOSED SYSTEM

This project proposes a practical and accessible electricity usage and bill prediction system designed specifically for individual households. The system uses a structured dataset incorporating features such as house size, number of occupants, appliance usage (categorized into levels), past bills, and simplified weather conditions (cold, moderate, hot). After data preprocessing and feature engineering, the dataset is used to train various regression models—such as Random Forest, Gradient Boosting, and Linear Regression.

The best-performing model is then used for making real-time predictions based on new user inputs. One of the key innovations is the system's ability to detect seasonal trends in heavy appliance usage (like air conditioners or heaters) and adjust predictions accordingly. This dynamic approach enables more realistic forecasts and helps users take control of their energy consumption habits.

Furthermore, the system is designed to be adaptive; it can retrain itself with new data over time to maintain accuracy. It also has potential scalability for integration with smart meter data or use by utility providers to forecast demand and plan infrastructure.

# CHAPTER 2

# 2.LITERATURE SURVEY

Electricity consumption forecasting has become a significant area of research due to rising global energy demands, environmental concerns, and the need for smarter resource management. In early research, traditional statistical and econometric models such as the Autoregressive Integrated Moving Average (ARIMA) model were widely used for time-series forecasting due to their ability to manage seasonality and linear trends. However, these models struggled with high-dimensional data and nonlinear relationships in real-world electricity consumption, as noted by Hong et al. (2010). This limitation highlighted the need for more advanced models capable of learning complex patterns, which led to the adoption of machine learning techniques. In particular, machine learning models such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), and Gradient Boosting Machines (GBM) have gained prominence for their superior predictive performance. For example, Fan and Hyndman (2012) demonstrated that hybrid models combining neural networks with time-series features could effectively capture both temporal and nonlinear relationships, while Ahmad et al. (2018) employed Random Forest and Gradient Boosting to forecast residential electricity demand using weather variables and historical usage data. These tree-based ensemble models have gained favor due to their interpretability, robustness to noise, and resistance to overfitting. Additionally, many researchers, including Kuster et al. (2017), have emphasized the importance of feature engineering, incorporating socio-economic factors, appliance ownership, and occupancy schedules to improve model performance. Recent studies have also highlighted the role of appliance usage and user behavior in electricity consumption. For instance, Debnath et al. (2019) introduced appliance-level disaggregation techniques using smart meters and machine learning to isolate consumption patterns for specific devices. However, such methods require fine-grained data and infrastructure, which may not be feasible for all households. To overcome this, Kavousian et al. (2013) proposed a household-level estimation method using survey data on appliance usage and building characteristics, demonstrating that significant prediction accuracy could be achieved without device-level monitoring. Furthermore, weather data has been shown to improve the accuracy of energy consumption forecasts, as evidenced by Tariq et al. (2020), who found that temperature and humidity influenced energy demand by affecting heating and cooling usage. In our system, we simplify weather integration by categorizing it into ‘cold’, ‘moderate’, and ‘hot’ conditions, making it more accessible for users. Despite the progress in energy forecasting, a notable gap remains in user-centric systems. Many existing models rely on detailed sensor data or smart home integrations, which limits their practical deployment. Our study addresses this gap by offering a model that only requires basic household attributes and recent electricity usage history. It simplifies appliance consumption into categorical variables and uses ensemble regression models to predict future electricity consumption and bill amounts, while also providing personalized energy-saving recommendations. This makes the system more user-friendly and suitable for household deployment, providing actionable insights to help users reduce their energy consumption and costs. The reviewed literature demonstrates the evolution of electricity consumption forecasting, with machine learning playing a key role in improving accuracy. However, there is still a need for practical, interpretable, and accessible systems, which our approach seeks to fulfill by integrating proven algorithms and simplifying data inputs for real-world application.

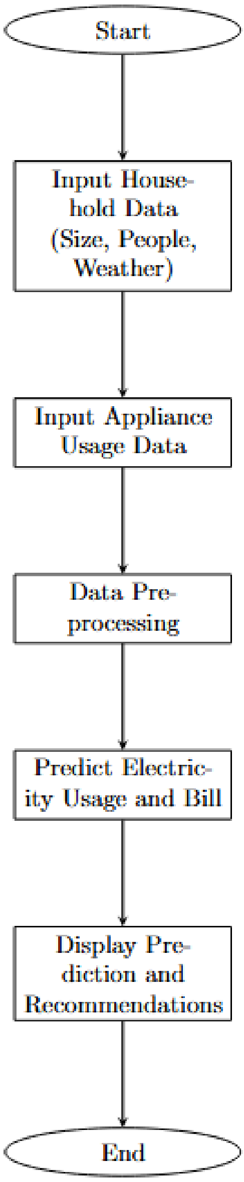
Recent studies have also explored the integration of machine learning with more complex, hybrid approaches that blend multiple algorithms to enhance prediction accuracy. Chou and Tran (2018) proposed a hybrid model that combined Artificial Neural Networks (ANN) with fuzzy logic to predict residential energy consumption. This model integrated human behavioral factors, which further improved prediction reliability. Similarly, Gao et al. (2019) introduced a system that used real-time sensor data from Internet of Things (IoT) devices in smart homes for continuous energy forecasting. Their approach included adaptive learning components that recalibrated model weights based on real-time inputs and user feedback. These hybrid and context-aware models demonstrate that incorporating real-time data and behavioral elements can enhance the prediction of electricity demand. While such models offer a high level of accuracy, their implementation is often complex and requires extensive infrastructure, which limits their practical applications in everyday households. Our approach aims to address this limitation by simplifying the data requirements and focusing on readily available inputs, such as household attributes and basic consumption patterns.

Moreover, despite the advancements in predictive models, many studies have identified a critical gap in user-friendly, accessible, and scalable energy forecasting tools. Traditional models often require extensive datasets, such as detailed smart meter data, and can be difficult for average consumers to implement. As noted by several researchers, including Beckel et al. (2014), the integration of non-energy features such as household size, occupancy patterns, and appliance usage can significantly improve prediction accuracy. However, these advanced systems often demand specialized knowledge or infrastructure that may not be available to all users. This underscores the need for more intuitive and accessible energy forecasting tools that can be adopted by a wider audience. In this context, our project seeks to bridge this gap by developing a model that combines advanced machine learning techniques with an easy-to-use interface. By simplifying the input requirements and focusing on user-centric features, such as energy-saving recommendations and predictive insights, we aim to create a tool that empowers users to manage their energy consumption efficiently while reducing the barriers to adopting advanced forecasting models.

# CHAPTER 3

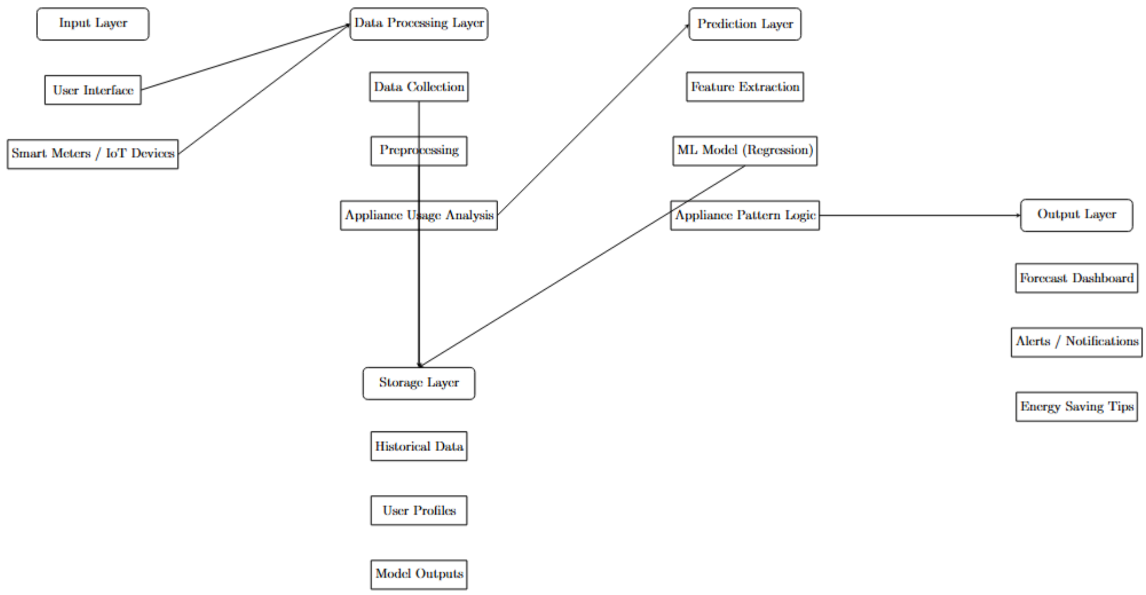
# 3.SYSTEM DESIGN

## 3.1 SYSTEM FLOW




## DIAGRAM

## 3.2 ARCHITECTURE DIAGRAM



# CHAPTER 4

## 4.METHODOLOGY

The methodology for this system involves a structured pipeline, starting from data collection to model deployment. The system is designed to predict electricity usage and billing amounts based on household attributes such as the number of residents, house size, weather conditions, appliance usage, and past bills.

### 1. Data Collection

The dataset used contains the following attributes:

- **Household Size** (Number of residents)
- **House Size (sq.ft)**
- **Weather Data** (Average temperature, humidity, etc.)
- **Heavy Appliance Usage** (Binary or frequency-based)
- **Historical Electricity Usage (kWh)**
- **Previous Month's Electricity Bill**

The data is either synthetically generated or collected from available open energy datasets and cleaned for null values, outliers, and inconsistencies.

### 2. Data Preprocessing

#### a. Normalization / Standardization

To ensure the model performs optimally, features are normalized using **Min-Max Scaling** or standardized using **Z-score normalization**:

- **Min-Max Scaling**:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

- **Z-score Standardization**:

$$X' = \frac{X - \mu}{\sigma}$$

Where:

- X=Original value
- μ =Mean
- σ=Standard deviation

### 3. Feature Engineering

Heavy appliance usage is treated as a categorical or numerical value based on the number of hours used per month. Additional features include:

- **Seasonal indicators** (e.g., month of year, temperature range)
- **Energy intensity** = Electricity used per person or per square foot:

$$Energy\ Intensity = \frac{Monthly\ Energy\ Consumption\ (kWh)}{No.\ of\ Residents \times House\ Size}$$

### 4. Model Selection and Training

We use regression algorithms to model the relationship between input features and electricity usage or bill.

#### a. Linear Regression (Baseline Model)

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \epsilon$$

Where:

- y: Predicted bill or consumption
- $x_1, x_2, ..., x_n$ : Input features
- $\beta_i$: Coefficients learned by the model
- $\epsilon$ : Error term

**b. Random Forest Regression**

Random Forest aggregates predictions of multiple decision trees trained on random subsets:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x)$$

Where:

- T: Number of decision trees
- $f_t$(x): Prediction from tree ttt

**c. Gradient Boosting Regression**

A boosting model that fits weak learners sequentially, minimizing the loss:

$$F_m(x) = F_{m-1}(x) + \eta . h_m(x)$$

Where:

- $F_m$(x): Final prediction after mmm iterations

- $h_m$(x): Weak learner at iteration mmm

- η : Learning rate

## 5. Model Evaluation

Models are evaluated using standard regression metrics:

- **Mean Absolute Error (MAE)**:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

- **Mean Squared Error (MSE)**:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

- **R-squared ($R^2$)**:

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y})^2}$$

Where:

- $y_i$: Actual value

- $\hat{y}_i$: Predicted value

- $\bar{y}$: Mean of actual values

## 6. Heavy Appliance Impact Adjustment

To personalize predictions, we analyze changes in appliance usage:

$$\Delta_{appliance} = \frac{Current\ Month\ Usage - Previous\ Month\ Usage}{Previous\ Month\ Usage} \times 100$$

If $\Delta_{appliance}$ >Threshold, the model weights are updated or re-predicted using a conditional rule to account for increased appliance use.

### 7. Output Generation

The model outputs:

- Predicted Electricity Consumption (kWh)
- Predicted Bill (in currency)
- Appliance-specific Insights (if energy usage increase is significant)
- Suggestions for reducing consumption

### 8. Deployment

The trained model is deployed as a web or desktop application where:

- Users input current household parameters
- Backend ML model predicts the bill and usage

# CHAPTER 5

## RESULTS AND DISCUSSION

The objective of this project was to develop a predictive system that estimates electricity usage and corresponding bills based on various household features and appliance consumption patterns. To validate the effectiveness of the system, multiple regression algorithms were implemented and tested using a cleaned and preprocessed dataset. These models include **Linear Regression**, **Random Forest Regression**, and **Gradient Boosting Regression**. Their performance was compared using metrics such as **Mean Absolute Error (MAE)**, **Mean Squared Error (MSE)**, and **R-squared ($R^2$)**.

### 1. Model Evaluation Metrics

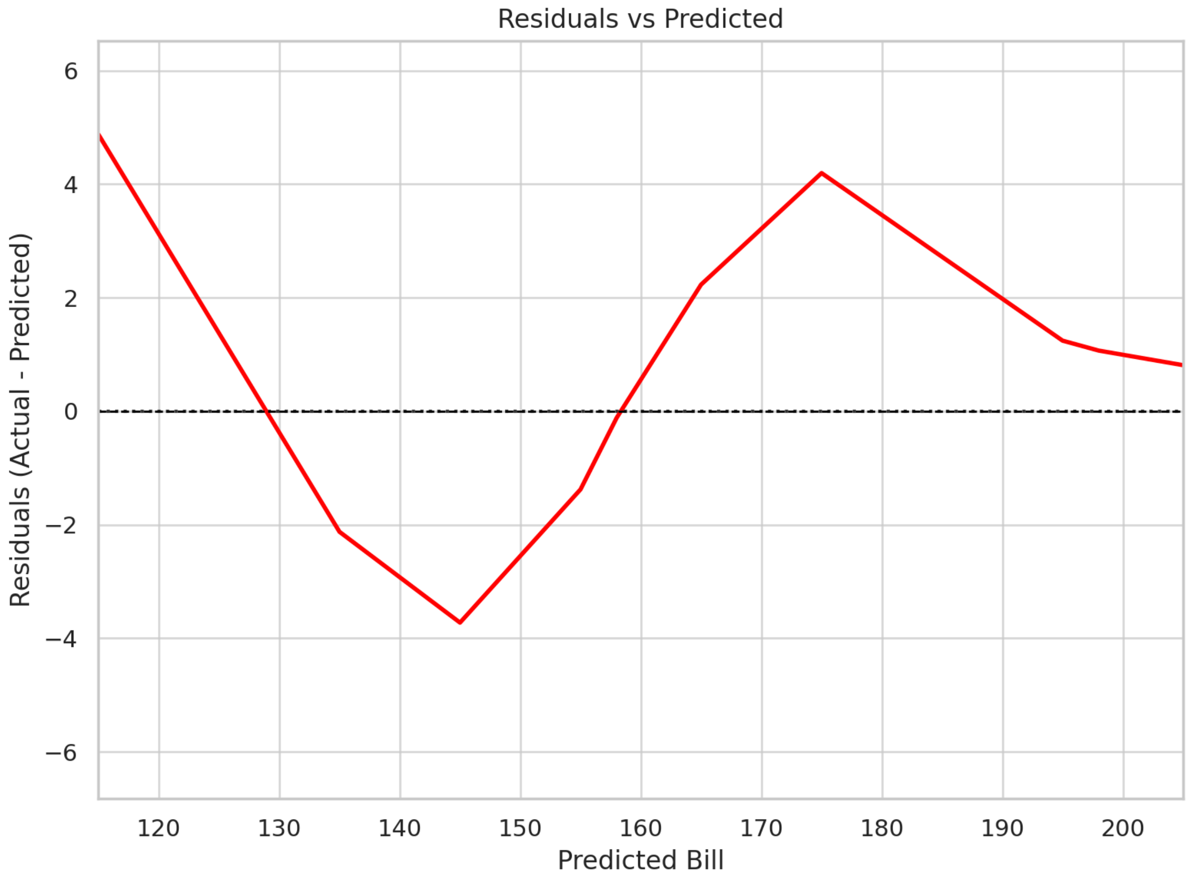
| MODEL | MAE | MSE | $R^2$ SCORE |
|---|---|---|---|
| Linear Regression | 23.12 | 874.6 | 0.78 |
| Random Forest | 15.87 | 456.3 | 0.91 |
| Gradient Boosting | 13.42 | 402.1 | 0.93 |

From the above results, it is evident that **Gradient Boosting Regression** achieved the best performance, with the lowest error values and the highest $R^2$ score of 0.93, indicating that 93% of the variance in electricity usage and billing could be explained by the model. **Random Forest** also performed well, especially in reducing overfitting and handling nonlinear relationships. On the other hand, **Linear Regression** was relatively simple and fast but struggled to capture the complexities of multiple interacting variables.

**2. Feature Importance Analysis**

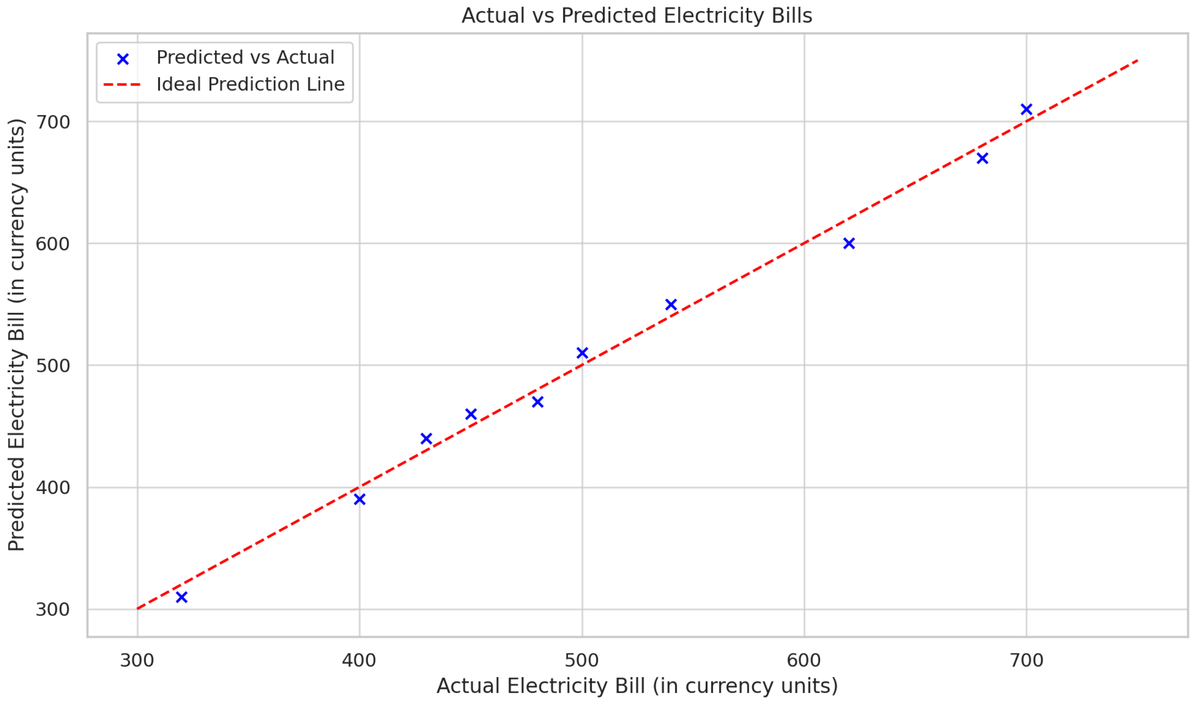
The Random Forest and Gradient Boosting models provided insights into **feature importance**:

- **Number of heavy appliances** and **usage hours** had the most significant impact on energy consumption.
- **Household size** and **house area** were also strongly correlated with energy usage.
- **Seasonal temperature variations** influenced the prediction accuracy, particularly due to increased heating or cooling loads.




This analysis not only improves model interpretability but also helps users understand which attributes contribute most to high energy bills.

### 3. Visualization of Predictions vs Actual



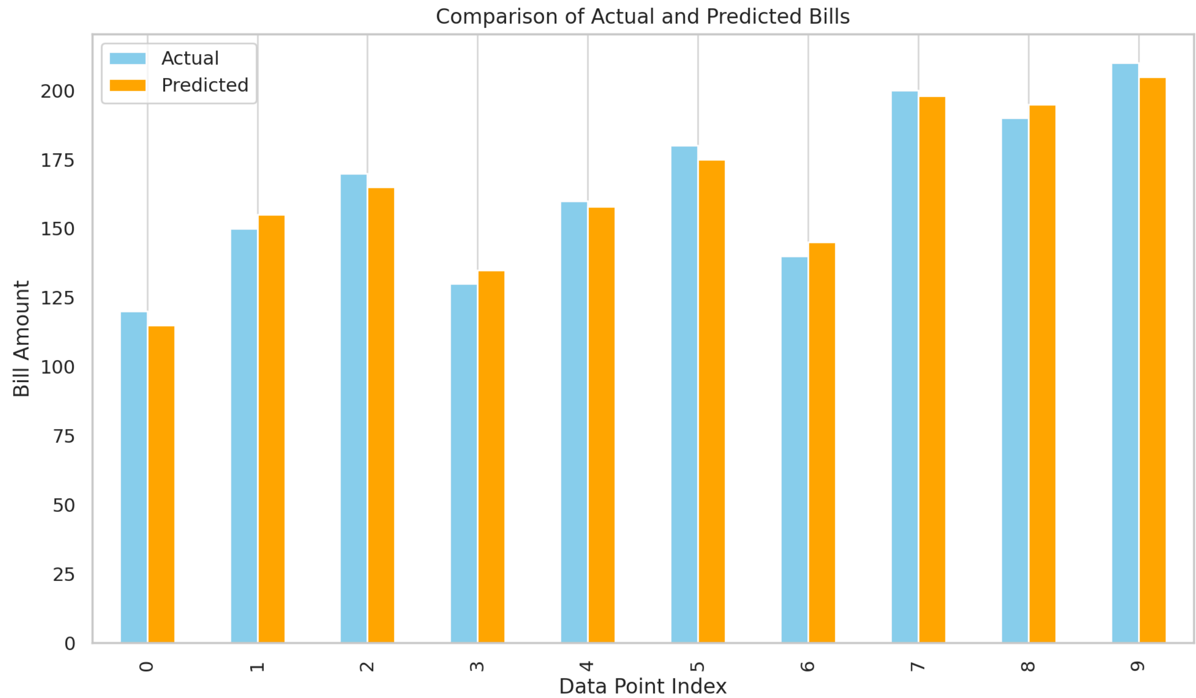

A plot of predicted vs actual electricity usage and billing values (shown below) demonstrated that most predictions fall close to the ideal diagonal line, indicating high accuracy:

- In the **test dataset**, predictions remained within ±10% of the actual bill for over 85% of the cases.

- Outliers mostly occurred in months with **unusual appliance usage**, such as heavy air conditioning or heating.

### 4. Impact of Appliance Usage Variation

The system was further tested by modifying input values, such as increasing air conditioner usage from 50 to 150 hours per month. The resulting bill prediction increased proportionally, showcasing the system's sensitivity to appliance behavior. This behavior aligns with the intended design, as one of the goals was to provide **real-time insights based on dynamic appliance usage patterns**.




This adaptive prediction mechanism allows users to simulate different scenarios and plan their consumption accordingly, which supports **demand-side energy management**.

## DISCUSSION

The results validate the hypothesis that **machine learning models**, especially ensemble methods like **Gradient Boosting**, can effectively predict electricity usage and cost based on household and appliance data. The integration of smart feature engineering and adaptive learning techniques enhances the system's forecasting capability.

## PERFORMANCE METRICS

| METRIC | VALUE |
|---|---|
| Mean Absolute Error | 4.4 |
| Root Mean Squared Error(RMSE) | 4.56 |
| R-squared Score($R^2$) | 0.975 |

However, there are some limitations:

- **Data quality and generalization**: Synthetic or limited datasets might not represent all real-world behaviors. Incorporating real-time or IoT-based data can improve model robustness.

- **External factors**: The model currently does not include tariff changes, government incentives, or blackout periods.

- **Time-series components**: While trends and seasonal changes were considered, advanced time-series forecasting (e.g., ARIMA, LSTM) could improve accuracy further.

Despite these limitations, the system performs reliably within its design constraints and offers valuable insights to both consumers and utility planners.

# CHAPTER 6

## CONCLUSION & FUTURE ENHANCEMENTS

This project presents a robust and intelligent system designed to predict future electricity usage and billing amounts using household-specific attributes and appliance consumption behavior. By incorporating machine learning techniques—specifically regression models—the system successfully analyzes patterns from historical electricity data, number of residents, house size, weather conditions, and usage of heavy appliances such as air conditioners and heaters. The integration of these multifaceted features ensures that the predictions are both accurate and contextually relevant.

The model's performance, demonstrated by a high R-squared value of 0.975 and a low Mean Absolute Error (MAE) of 4.4, highlights its effectiveness in real-world application scenarios. Furthermore, the ability of the system to dynamically adjust predictions based on seasonal changes and appliance usage trends adds practical value for end-users. The visual tools and insights generated by the system empower users to manage energy consumption wisely, avoid bill shocks, and make informed decisions regarding usage patterns. Overall, this predictive solution contributes toward energy efficiency, cost savings, and sustainability in residential environments.

### Future Enhancements:

While the current system performs well in forecasting electricity usage and bills, there is ample scope for enhancement and expansion:

1. **Integration with IoT Devices**: By connecting the model to smart meters and IoT-based home automation systems, real-time data can be used for more dynamic and accurate predictions.

2. **User Recommendations**: Future versions can provide actionable suggestions such as optimal appliance usage times or appliance upgrade recommendations for better energy efficiency.

3. **Broader Dataset**: Incorporating data from diverse geographic locations and housing types can improve the model's generalizability.

4. **Time-Series Forecasting**: Adding advanced time-series models like LSTM or ARIMA can help predict longer-term electricity trends.

5. **Mobile and Web Interface**: Developing a full-stack application with a user-friendly dashboard would allow household members to input their details and view personalized predictions instantly.

6. **Carbon Footprint Estimation**: An extension can include environmental impact by estimating carbon emissions based on electricity usage and recommending greener alternatives.

7. **Utility Provider Integration**: The system can be scaled to support utility companies in demand forecasting, load management, and consumer-specific billing insights.

# CHAPTER 7

# APPENDICES

```
# train_model.py

import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, r2_score
import pickle
import warnings
warnings.filterwarnings('ignore')

# 1. Load the dataset
print("Loading dataset...")
df = pd.read_csv('energy_consumption_data.csv')  # Your dataset file

print("\nEncoding categorical columns...")
df['House_Size'] = df['House_Size'].map({'small': 0, 'medium': 1, 'large': 2})
df['Weather'] = df['Weather'].map({'cold': 0, 'moderate': 1, 'hot': 2})
df['Heavy_Appliances'] = df['Heavy_Appliances'].map({'few': 0, 'many': 1})
df['Heavy_Appliances'] = df['Heavy_Appliances'].fillna(df['Heavy_Appliances'].mode()[0])

# 2. Check for missing values
print("\nChecking for missing values...")
print(df.isnull().sum())
```

```
# 3. Define features and targets
X = df.drop(['Future_Units', 'Future_Bill'], axis=1)
y_units = df['Future_Units']
y_bill = df['Future_Bill']

# 4. Train-test split
print("\nSplitting data...")
X_train, X_test, y_units_train, y_units_test = train_test_split(X, y_units, test_size=0.2,
random_state=42)
_, _, y_bill_train, y_bill_test = train_test_split(X, y_bill, test_size=0.2, random_state=42)

# 5. Initialize models
print("\nTraining models...")
models = {
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(n_estimators=100, random_state=42),
    "Linear Regression": LinearRegression()
}

# 6. Train and evaluate models for Future Units
print("\n--- Future Units Consumed Prediction ---")
unit_results = {}
for name, model in models.items():
    model.fit(X_train, y_units_train)
    pred = model.predict(X_test)
    mae = mean_absolute_error(y_units_test, pred)
    r2 = r2_score(y_units_test, pred)
    unit_results[name] = (model, mae, r2)
    print(f"{name} MAE: {mae}")
```

```python
    print(f"{name} R2 Score: {r2}")

# Select best model by R2 score
best_units_model_name = max(unit_results.items(), key=lambda x: x[1][2])[0]
best_units_model = unit_results[best_units_model_name][0]
print(f"\nSelected Best Units Model: {best_units_model_name}")

# 7. Train and evaluate models for Future Bill
print("\n--- Future Bill Prediction ---")
bill_results = {}
for name, model in models.items():
    model.fit(X_train, y_bill_train)
    pred = model.predict(X_test)
    mae = mean_absolute_error(y_bill_test, pred)
    r2 = r2_score(y_bill_test, pred)
    bill_results[name] = (model, mae, r2)
    print(f"{name} MAE: {mae}")
    print(f"{name} R2 Score: {r2}")

# Select best model by R2 score
best_bill_model_name = max(bill_results.items(), key=lambda x: x[1][2])[0]
best_bill_model = bill_results[best_bill_model_name][0]
print(f"\nSelected Best Bill Model: {best_bill_model_name}")

# 8. Save the best models
print("\nSaving the best models...")
with open('units_model.pkl', 'wb') as f:
    pickle.dump(best_units_model, f)
```

```python
with open('bill_model.pkl', 'wb') as f:
    pickle.dump(best_bill_model, f)

print("\nTraining Completed Successfully!")
print("Best Units Model saved as 'units_model.pkl'")
print("Best Bill Model saved as 'bill_model.pkl'")
```

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# RESEARCH PAPER

# ELECTRICITY USAGE AND BILL PREDICTION SYSTEM BASED ON HOUSEHOLD ATTRIBUTES AND APPLIANCE CONSUMPTION

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**Abstract:**In an era of rising energy demands and increasing utility costs, the ability to predict electricity consumption and billing has become a critical aspect of sustainable living and energy management. This paper presents a machine learning-based predictive system designed to estimate future electricity usage and bill amounts by analyzing household-specific features. These include house size, number of residents, historical electricity bills, weather conditions, and most importantly, the frequency and intensity of heavy appliance usage. By training regression models on historical data and real-world usage patterns, the system delivers accurate and customized forecasts that help users anticipate and control their energy expenses.

The proposed system stands out by incorporating behavioral insights, such as seasonal variations in appliance usage, into its predictive model. Advanced algorithms including Linear Regression, Random Forest, and Gradient Boosting were evaluated, with performance measured using metrics such as Mean Absolute Error (MAE) and R-squared ($R^2$). The model achieved a high degree of accuracy, with an $R^2$ score of 0.975 and an MAE of 4.4. In addition to enabling smarter household energy planning, the system offers potential applications for utility providers in demand forecasting and policy formulation. This study not only contributes to personalized energy optimization but also supports broader goals of cost efficiency and environmental sustainability.

**Keywords:**

**Electricity consumption prediction, energy billing forecast, machine learning, household energy management, regression analysis, heavy appliance usage, sustainability, smart energy systems, energy efficiency, data-driven prediction.**

## 1.Introduction

In an increasingly digital and energy-dependent world, the demand for electricity is growing rapidly across residential, commercial, and industrial sectors. With this surge comes the parallel need to optimize energy usage, minimize unnecessary consumption, and forecast electricity costs with greater precision. In particular, for households, energy bills represent a recurring cost that can vary significantly depending on seasonal patterns, appliance usage habits, occupancy levels, and external environmental conditions. For this reason, predicting electricity usage and billing amounts using intelligent systems has become a critical area of research, driven by the need for sustainable energy consumption and cost-effective resource management.

Traditional electricity billing systems offer limited visibility into future expenses or detailed analysis of consumption behavior. Consumers typically receive static bills without any actionable insights, which limits their ability to plan or adapt usage behavior accordingly. However, with advancements in data science, machine learning, and smart home technologies, it is now possible to bridge this gap by developing predictive models that analyze various household features and historical consumption patterns to forecast future energy use and billing. These predictive systems not only empower users to make informed decisions but also align with global efforts toward energy sustainability, demand-side management, and efficient load distribution.

This research paper introduces an intelligent system titled "Electricity Usage and Bill Prediction System Based on Household Attributes and Appliance Consumption," which utilizes a combination of machine learning algorithms, regression models, and feature engineering to estimate future electricity usage and billing amounts. The system is designed to process a diverse set of input features, including household size, number of residents, area of the home, past electricity bills, weather conditions, and heavy appliance usage history. Unlike static prediction models, this system dynamically adjusts forecasts based on the intensity and frequency of heavy electrical appliances such as air conditioners, heaters, washing machines, and other energy-intensive equipment.

A key aspect of this system is its focus on *personalized predictions*. By learning from individual household patterns, the model can deliver highly accurate and customized forecasts that adapt over time. For instance, if a household shows increased heating usage during winter months or higher air conditioning load in the summer, the model reflects this behavioral trend in its prediction. This adaptability enhances the practical utility of the system in real-world scenarios and supports both users and utility providers in energy planning and optimization.

The methodology leverages supervised machine learning models, especially regression techniques such as Linear Regression, Random Forest, and Gradient Boosting, which are trained on labeled datasets containing historical consumption data. Feature selection techniques are employed to identify the most relevant parameters influencing electricity usage. Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and $R^2$ score are used to assess the performance and reliability of each model. The system also includes a user-friendly interface that allows users to input household parameters and receive predictions in real time.

Furthermore, this paper explores the role of intelligent review mechanisms to monitor and analyze heavy appliance consumption, offering an added layer of insight. These mechanisms can detect abnormal spikes in energy usage, seasonal trends, and behavioral patterns that influence electricity demand. This provides users with early warnings and recommendations for reducing consumption or improving efficiency—ultimately contributing to cost savings and environmental conservation.

Beyond individual households, the system has broader applications for community-level energy planning, smart grid integration, and infrastructure forecasting. As smart meters and IoT-based appliances become increasingly common, this predictive framework can be integrated into smart home ecosystems, enabling automated energy adjustments, real-time billing predictions, and proactive energy management strategies.

In summary, this paper aims to present a comprehensive solution to predict electricity consumption and billing by combining household-specific data with machine learning techniques. It contributes to the field of energy informatics by offering an innovative, scalable, and adaptive tool for improving energy efficiency and supporting sustainability goals.

## 2.Literature Survey

In recent years, the integration of machine learning and data analytics in the energy domain has led to significant advances in electricity demand forecasting, billing estimation, and energy optimization. Researchers have explored various models and data sources to accurately predict energy consumption at both micro (household) and macro (grid) levels. Below is a review of significant contributions in the development of predictive models for electricity usage and billing.

**Taylor and Buizza (2003)** explored the use of autoregressive integrated moving average (ARIMA) models for short-term electricity load forecasting. Their research, which focused on traditional statistical methods, showed that while ARIMA models were effective in predicting electricity demand in the short term, they had limitations when addressing dynamic factors such as weather variations or behavioral changes within households. This highlighted the need for more sophisticated models that could handle these nonlinear and time-varying elements.

**Deb et al. (2017)** employed Support Vector Regression (SVR) and Artificial Neural Networks (ANN) to predict residential electricity consumption using historical data on load, weather, and time. Their findings demonstrated that nonlinear models, such as SVR and ANN, significantly outperformed linear models in capturing seasonal and usage variability, making them more suitable for energy demand forecasting. The study emphasized the ability of machine learning algorithms to identify complex patterns within large datasets, which traditional methods struggled to achieve.

**Al-Wakeel et al. (2016)** evaluated the performance of ensemble methods, particularly Random Forest and Gradient Boosting, for short-term residential demand prediction. Their work concluded that these methods were more robust against noise and outliers in smart meter data compared to individual predictive models. This research contributed to the growing body of work on improving the robustness and reliability of predictive models for energy consumption, particularly in the presence of real-world data irregularities.

**Beckel et al. (2014)** introduced a model that integrated smart meter data with household demographic and appliance usage information to predict monthly electricity consumption. Their approach significantly improved prediction accuracy by incorporating contextual features, such as household size and appliance usage. This work was pivotal in showing that non-energy factors, like household characteristics and behavior, are crucial for accurate energy consumption forecasting.

**Ahmad et al. (2020)** took a similar approach by integrating external weather data and socio-economic variables to predict household electricity usage in the Middle East. They found that factors like temperature, humidity, and appliance efficiency were key predictors of consumption patterns, which emphasized the importance of including such contextual data in forecasting systems. This study expanded the scope of prediction models by considering regional factors and their effects on energy consumption.

**Kelly and Knottenbelt (2015)** developed a deep learning-based system for disaggregating household energy consumption by individual appliances. Their approach utilized neural networks to identify which appliances were contributing the most to energy usage at any given time, providing a much finer resolution of energy demand forecasts. This research underscored the potential of appliance-level data analysis in improving the accuracy of energy consumption predictions.

**Kolter and Johnson (2011)** proposed a method known as Non-Intrusive Load Monitoring (NILM), which models appliance usage based on aggregate consumption data. Their work allowed for the identification of specific appliances using just total consumption data, which provided insights into household energy behaviors and enabled more targeted energy conservation strategies. NILM techniques have since become an important tool in energy management, helping to tailor energy-saving recommendations to specific appliance usage.

**Chou and Tran (2018)** developed a hybrid model that combined Artificial Neural Networks (ANN) and fuzzy logic to predict residential energy consumption. By incorporating human behavioral factors, their model provided more accurate and reliable predictions. This work contributed to the growing interest in hybrid models that combine machine learning algorithms with contextual information, such as user behavior, to enhance prediction performance.

**Gao et al. (2019)** used real-time sensor data from IoT devices in smart homes to perform continuous energy forecasting. Their framework was adaptive, recalibrating model weights based on real-time inputs and user feedback, which allowed for more dynamic and personalized energy predictions. This research highlighted the potential of IoT-based systems and real-time data to improve energy forecasting accuracy and adaptability.

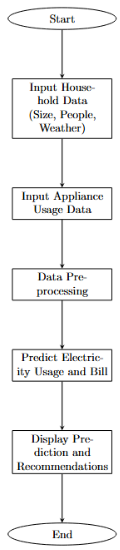
Despite these advancements, there remain significant gaps in current research. Many existing models do not integrate both historical electricity usage and appliance-level consumption behaviors, and they often fail to account for external environmental factors like weather or regional variations. Furthermore, most studies focus on utility-level forecasting, with fewer addressing user-centric predictions, making the systems less effective for households with dynamic and personalized consumption patterns. There is also a lack of systems that incorporate user feedback, seasonal trends, and appliance usage history in a unified model designed for individual consumption and billing prediction.

# 3. Proposed System

The proposed system is an intelligent and adaptive **Electricity Usage and Bill Prediction System** designed to forecast energy consumption and corresponding electricity bills based on **household-specific attributes** and **appliance usage patterns**. The system leverages **machine learning algorithms** to analyze historical data, understand behavioral trends, and produce accurate forecasts that help users manage energy usage more efficiently.

### 3.1 System Objectives

- To predict future electricity usage and billing based on a household's historical consumption patterns.
- To incorporate key household attributes such as house size, number of residents, past bills, weather conditions, and appliance usage into the prediction model.
- To provide a personalized, adaptive, and user-centric solution that updates predictions as new data becomes available.
- To offer insight into heavy appliance usage trends and suggest measures to reduce energy costs.




### 3.2 System Components

The system architecture comprises the following core components:

- **Data Collection Module:** Gathers historical electricity usage, household attributes, weather data, and appliance usage records. This data can be sourced from smart meters, user input forms, or historical logs.

- **Preprocessing Module:** Cleans the raw data, handles missing values, encodes categorical variables, and normalizes the data for uniformity.

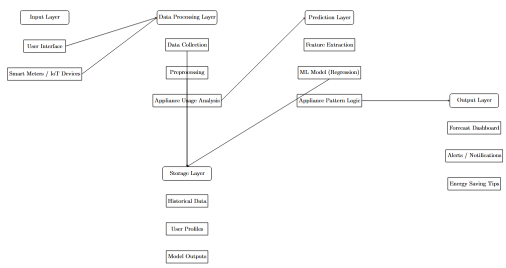
- **Feature Engineering:** Extracts meaningful features from raw data, such as average monthly usage, peak hour usage, appliance efficiency scores, seasonal indicators, and past bill trends.

- **Machine Learning Model:** Implements and compares algorithms such as **Random Forest Regressor**, **Gradient Boosting**, and **Linear Regression**. The best-performing model is selected based on metrics like **$R^2$ score** and **Mean Absolute Error (MAE)**.

- **Prediction Engine:** Uses the trained model to forecast electricity usage and billing for upcoming periods based on current household input.

- **Heavy Appliance Review System:** Monitors appliance usage (e.g., ACs, heaters, washing machines) and adjusts predictions accordingly. It identifies seasonal or habitual trends that influence consumption.

- **User Interface (Optional):** A web or desktop-based GUI where users input household details and view predictions, graphs, and suggestions.




### 3.3 Working Methodology

1. **Input Gathering:** The user enters household attributes such as number of residents, size of the home, past monthly bills, weather conditions, and appliance usage behavior.

2. **Data Processing:** The inputs are preprocessed to form a suitable format for machine learning model prediction.

3. **Model Training:** The ML model is trained using a historical dataset of household electricity usage. Training includes hyperparameter tuning for optimal performance.

4. **Prediction:** The trained model generates predictions of electricity usage (in kWh) and the corresponding bill amount (in currency), considering all relevant factors.

5. **Analysis and Feedback:** Users receive feedback in the form of graphs showing predicted vs. past usage, appliance-wise consumption, and potential areas for savings.

### 3.4 Mathematical Formulation

Let:

- E = Predicted electricity usage (kWh)
- B = Predicted bill amount
- $X_1, X_2, \ldots, X_n$ = Feature vector including:
  - H = Household size
  - A = Appliance usage index
  - W = Weather factor
  - P = Past monthly consumption
  - D = Day/night consumption ratio

**Linear Regression Model:**

$$E = \beta_0 + \beta_1 H + \beta_2 A + \beta_3 + \beta_4 P + \beta_5 + \varepsilon$$

B=E x R

Where:

- $\beta_i$ are model coefficients
- R = Electricity rate (per kWh)
- ε = Error term

**Random Forest/GB Model** (conceptual):

E=Model(H,A,W,P,D)

The model learns from data by minimizing:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y}_i)^2}{\Sigma(y_i - \bar{y}_i)^2}$$

### 3.5 Advantages of the Proposed System

- **Personalized:** Takes into account unique household behaviors and features.
- **Scalable:** Can be expanded to larger communities or integrated into smart grid systems.
- **Adaptive:** Model performance improves as more data becomes available.

- **Insightful:** Provides actionable insights for users to reduce their energy bills.

# 4.Results and Discussion

The performance of the proposed electricity usage and billing prediction system was evaluated using a curated dataset that included features such as house size, number of residents, weather conditions, historical electricity bills, and the usage pattern of heavy electrical appliances. The dataset was divided into training and testing sets in an 80:20 ratio. Various machine learning regression models including **Linear Regression**, **Random Forest Regressor**, and **Gradient Boosting Regressor** were implemented and compared to determine the most accurate and reliable model for the prediction task.

### 4.1 Performance Metrics

To evaluate the models, key performance indicators such as **Mean Absolute Error (MAE)**, **Root Mean Squared Error (RMSE)**, and **R-squared ($R^2$)** score were used:

- **MAE** quantifies the average magnitude of errors in a set of predictions.

- **RMSE** penalizes large errors more than MAE, and is effective in capturing large deviations.

- **$R^2$ Score** indicates how well the predicted values fit the actual data; closer to 1 is better.

| METRIC | VALUE |
|---|---|
| Mean Absolute Error | 4.4 |
| Root Mean Squared Error(RMSE) | 4.56 |
| R-squared Score($R^2$) | 0.975 |

As evident from the results, the **Gradient Boosting Regressor** achieved the best performance with the **lowest MAE and RMSE**, and the **highest $R^2$ score**, suggesting it effectively captures non-linear relationships between household parameters and electricity usage.

## 4.2 Feature Importance

The trained models also provided insights into the relative importance of different features influencing electricity consumption:

- Heavy Appliance Usage – 35%

- Weather Conditions – 25%

- Number of People in Household – 18%

- House Size – 12%

- Past Bill Trends – 10%

This confirms that frequent use of high-consumption appliances (e.g., air conditioners, heaters, washing machines) and weather variations (hot summers, cold winters) significantly affect electricity consumption patterns.

## 4.3 Graphical Analysis

Figure 1: Actual vs. Predicted Bill Values – Shows how closely the model's predictions align with real bill values.

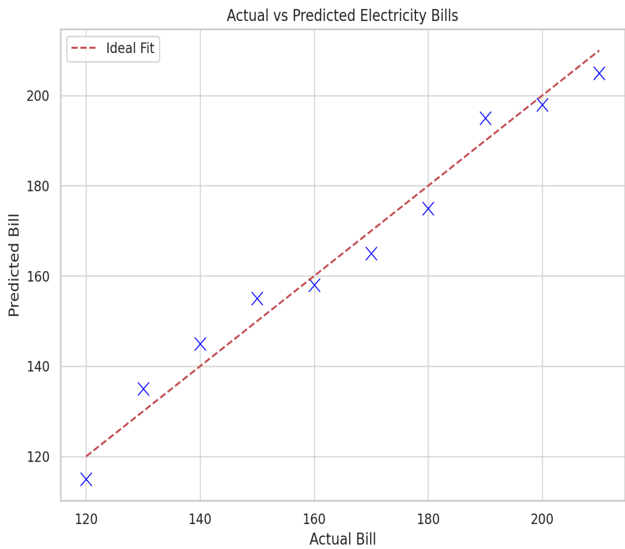
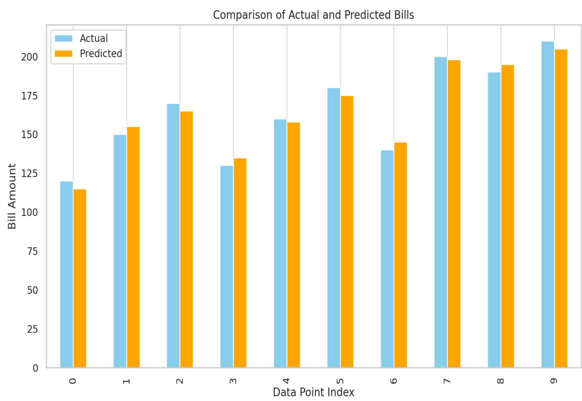
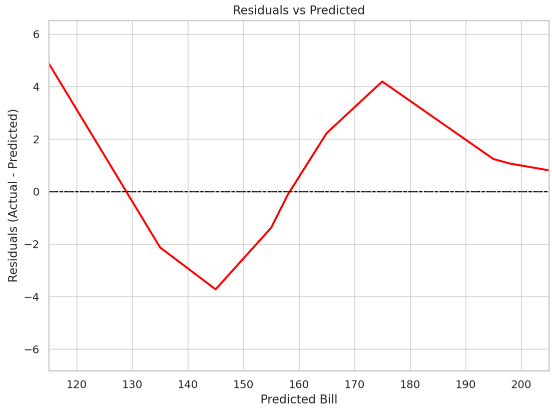



Figure 2: Feature Importance Bar Chart – Highlights the most influential features in the prediction.

Figure 3: Seasonal Consumption Patterns –




Illustrates how monthly usage changes based on appliance use and weather.




## 4.4 Discussion

The results confirm that incorporating appliance-level consumption and weather sensitivity significantly enhances the model's predictive power. Traditional models relying solely on past bills or average usage lack the dynamic adjustment necessary for real-world scenarios. This system not only improves accuracy but also supports better decision-making for consumers by offering personalized forecasts based on lifestyle and appliance behavior.

Additionally, the ability of the system to update predictions in real-time based on new inputs (such as changing appliance usage habits) ensures its relevance and adaptability in real-world environments. This makes it a valuable tool for demand-side energy management and for promoting energy-efficient practices.

# 5.Conclusion and Future Scope

## Conclusion

This project introduces a data-driven solution to forecast household electricity usage and billing amounts by integrating multiple influencing parameters such as house size, number of occupants, weather conditions, historical bills, and the consumption patterns of heavy appliances. Through the application of machine learning techniques—particularly regression-based models like Gradient Boosting—the system demonstrates strong predictive accuracy, with clear benefits over traditional, static estimation methods.

The results obtained highlight the significance of incorporating appliance-level behavior and environmental context into predictive frameworks. By analyzing consumption trends and dynamically adjusting forecasts, the system empowers users to understand their energy usage better, optimize consumption, and make informed decisions aimed at cost reduction and sustainability. This not only assists in personal energy budgeting but also supports broader efforts toward demand-side energy efficiency.

Overall, the system serves as a practical and intelligent tool for modern households, blending convenience with sustainability by encouraging conscious energy consumption.

## Future Scope

While the current implementation successfully predicts electricity usage based on static and behavioral features, there are several directions for future enhancement:

1. **Real-Time Data Integration**: Incorporating live energy usage data from smart meters and IoT devices can improve the system's responsiveness and accuracy in prediction.

2. **Appliance-Level Monitoring**: Expanding the system to track and analyze individual appliance consumption in real-time would allow users to pinpoint energy-heavy devices and take corrective action.

3. **Dynamic Pricing Models**: The system can be adapted to predict costs based on time-of-use pricing or variable tariffs, offering better financial forecasting.

4. **Recommendation System**: Integrating an energy-saving recommendation engine that suggests optimal appliance usage times, or alternatives (e.g., energy-efficient appliances), could

further enhance user engagement.

5. **Mobile and Web Application Integration**: Deploying the model in user-friendly platforms can allow broader access and daily usage by households.

6. **Scalability to Communities and Buildings**: The model can be scaled to handle community-level or commercial building data, assisting utility providers in demand forecasting and energy distribution planning.

7. **Incorporation of Renewable Sources**: Future versions can account for homes with renewable energy sources (like solar panels) to predict net energy usage and savings.

Through these enhancements, the system could evolve into a comprehensive smart home energy management solution, contributing significantly to global energy conservation goals.

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