Electricity Consumption Forecasting

Submitted in the partial fulfilment of the requirement for the award of degree of

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DECLARATION

I, Sagar Chaudhary, hereby declare that the work that is being presented in this project/training titled "Electricity Consumption Forecasting Using Machine Learning" by me, in partial fulfillment of the requirements for the award of a Bachelor of Technology (B. Tech) degree in Computer Science and Engineering, is an authentic record of my work carried out under the guidance of Ms. Palak thakur (Course Instructor).

To the best of my knowledge, the matter embodied in this report has not been submitted to any other university/institute for the award of any degree or diploma.

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Abstract

Electricity consumption forecasting plays a crucial role in modern energy management, enabling households, industries, and utility providers to predict future power usage and plan resources efficiently. Traditional manual methods of estimating consumption often lead to inaccuracies, inefficiency, and an inability to track how environmental factors such as temperature, humidity, and appliance load impact total usage. With the growing demand for smart energy solutions and the rise of data-driven technologies, machine learning provides a reliable and scalable approach for forecasting power consumption.

This project focuses on developing an automated system that predicts electricity consumption using environmental variables and appliance usage data. A Linear Regression–based machine learning model is implemented to analyze patterns and relationships among input parameters and generate accurate consumption predictions. The model is trained and evaluated using a statistically generated dataset that simulates real-world behavior, and key performance indicators such as Mean Squared Error (MSE) and R^2 Score are used to assess the accuracy of the predictive system. To enhance usability, a Streamlit-based web application has also been developed, allowing users to input real-time values and instantly view consumption forecasts without any technical expertise.

With the increasing adoption of smart meters, IoT devices, and energy monitoring systems, automated forecasting solutions are essential for promoting efficient power usage. The system developed in this project not only minimizes manual effort but also improves accuracy and provides users with insights that can help reduce wastage and optimize energy consumption. This project demonstrates the potential of machine learning in transforming conventional energy management practices and lays the foundation for more advanced forecasting systems in the future.

Acknowledgement

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My appreciation extends to all faculty members and classmates whose suggestions and cooperation helped strengthen the quality of this work. Lastly, I am deeply grateful to my family for their constant encouragement and support, which motivated me to complete this project successfully.

Introduction

Electricity consumption is one of the most critical aspects of modern living, influencing residential, commercial, and industrial sectors worldwide. With the rising dependence on electrical appliances, increasing temperature fluctuations, and overall changes in environmental conditions, predicting electricity usage has become an essential requirement for efficient energy planning. However, manually estimating consumption or relying solely on past electricity bills often leads to inaccurate assumptions and poor decision-making. This becomes a challenge not only for consumers but also for energy providers who must manage load distribution, avoid power shortages, and maintain grid stability.

In many real-world situations, people are unaware of how different factors—such as temperature, humidity, and appliance usage—impact their overall electricity consumption. Sudden climatic variations, excessive appliance load, or poor energy practices can lead to unexpected spikes in consumption. Without proper forecasting tools, users have no clear insight into how their daily activities influence energy usage. As a result, the need for a reliable, data-driven system for predicting electricity consumption has become increasingly important.

With the advancement of Machine Learning, it is now possible to analyze patterns in historical and environmental data and generate accurate forecasts. Machine Learning models can identify trends, detect relationships between input factors, and predict outcomes more efficiently than traditional manual methods. In this project, a Linear Regression–based forecasting model has been developed to predict electricity consumption using key input variables. The goal is to provide a simple yet effective method that converts raw environmental data into meaningful predictions that users can understand and use for better energy planning.

To make the system accessible to everyone, the model is integrated into a Streamlit web application, where users can conveniently input values and instantly obtain predicted electricity consumption results. This predictive tool not only reduces manual effort but also supports smart decision-making by enabling users to monitor, control, and optimize their energy usage in a more informed manner.

As energy demands continue to grow, automated forecasting systems are becoming essential in building smarter homes, cleaner industries, and more sustainable environments. This project aims to contribute toward that direction by providing a practical, user-friendly, and intelligent solution for electricity consumption forecasting.

Motivation

The primary motivation behind developing an Electricity Consumption Forecasting system comes from the growing need for smarter and more efficient energy management in our daily lives. In most households and industries, people use electricity without having any clear idea of how much power they might consume under specific conditions. Often, the actual bill becomes the only point where they understand their usage—by then, it is already too late to make changes. This lack of awareness leads to unnecessary consumption, wastage of energy, and higher expenses.

Another major motivation lies in the increasing impact of environmental factors on electricity usage. Variations in temperature, humidity, and appliance load significantly influence how much energy a household or industry consumes. For example, higher temperatures might increase the usage of cooling appliances, while increased humidity affects the functioning of devices and leads to fluctuating energy demands. However, most people are unaware of these dependencies, making it difficult for them to plan their usage effectively.

As Machine Learning continues to evolve, it provides powerful tools for analyzing data patterns and predicting outcomes with high precision. This project aims to make these advanced technologies accessible to everyday users by converting complex mathematical insights into a simple, user-friendly prediction system. By using a Linear Regression model, users can easily understand how different factors contribute to their electricity usage and take smarter steps to save energy.

Another strong motivation for this project is the growing adoption of smart homes, IoT devices, and digital meters. These technologies demand a forecasting mechanism that can assist users in monitoring real-time energy usage and planning their consumption ahead of time. A predictive model helps users avoid unexpected bills, manage peak usage efficiently, and adopt sustainable practices.

Finally, the project was inspired by a desire to contribute to environmental sustainability. Efficient electricity usage not only reduces financial expenditure but also minimizes pressure on power plants, decreases carbon footprint, and supports a cleaner, greener future. By providing users with insights into their consumption patterns, this project encourages responsible energy behavior.

Overall, the motivation behind this work is to blend technology with daily life in a meaningful way—making electricity usage predictable, manageable, and more efficient through the power of Machine Learning.

Problem Statement

Predicting electricity consumption accurately has always been a challenging task due to the dynamic nature of environmental conditions and variations in user behavior. Most individuals and industries rely on monthly electricity bills or manual estimation to understand their power usage, which is often misleading and provides little control over future consumption. Without the support of a predictive system, users cannot make informed decisions or identify the factors contributing to increased electricity usage.

In real-world conditions, electricity consumption is heavily influenced by external variables such as temperature, humidity, and appliance usage patterns. However, understanding these dependencies manually is difficult, and the relationship between these factors is often non-linear and complicated. As a result, users are unable to visualize how small changes in environmental conditions or appliance load can lead to significant increases in consumption. Traditional methods also fail to consider how these factors interact with each other, leading to poor forecasting accuracy.

Additionally, in the absence of automated prediction, energy overuse often goes unnoticed until the final bill arrives. This results in wastage, inefficient energy practices, and financial strain on users. Industries and commercial setups face even greater challenges, where incorrect energy forecasting can disrupt operations, overload systems, or increase operational costs.

Automated Machine Learning–based prediction offers a reliable and scalable alternative to manual estimation. Yet, many existing forecasting tools are either too complex, require advanced technical knowledge, or are not user-friendly. There is a clear need for a simple, interactive, and efficient system that can forecast electricity consumption based on real-time input factors, without requiring deep technical understanding.

Therefore, this project aims to address these challenges by developing a machine learning–based electricity consumption forecasting system that can process environmental parameters and predict consumption accurately. By leveraging Linear Regression and an interactive Streamlit web interface, the goal is to create a solution that is accessible, accurate, and capable of supporting users in making smarter energy decisions.

Purpose/Objectives and Goals

The increasing complexity of energy usage patterns and the lack of real-time forecasting tools create major challenges for individuals and organizations in managing electricity consumption. The primary purpose of this project is to build a simple yet effective system that uses machine learning to predict electricity consumption based on key environmental and usage factors. By automating the forecasting process, this system aims to support users in planning their electricity usage more efficiently and preventing unnecessary energy wastage.

One of the main objectives is to help users understand how different conditions—such as temperature, humidity, and appliance usage—directly influence their electricity consumption. Many people remain unaware of these relationships, leading to sudden spikes in their electricity bills. With the help of a predictive model, users can visualize and estimate their energy usage beforehand, allowing them to make informed decisions.

Another important goal of this project is to reduce manual effort and provide a user- friendly interface. To achieve this, the system is integrated with a Streamlit web application, enabling users to enter real-time values and receive instant predictions without needing any technical knowledge. This approach makes the system accessible to students, households, industry workers, and anyone interested in understanding their electricity usage patterns.

The project also aims to create a reliable machine learning pipeline that can handle data preprocessing, model training, evaluation, and prediction efficiently. By using Linear Regression, the system provides a balance between simplicity, interpretability, and forecasting accuracy. The goal is to ensure that the model performs consistently and offers predictions that users can trust.

Below are the core objectives and goals of the project:

- To automate the prediction of electricity consumption using machine learning.
- To analyze how Temperature, Humidity, and Appliance Usage affect overall power consumption.
- To build an efficient preprocessing and training pipeline using Linear Regression.
- To evaluate the model using metrics like Mean Squared Error (MSE) and R^2 Score.
- To deploy the model through a Streamlit application for easy and interactive use.
- To provide a tool that supports better energy planning, reduces wastage, and improves decision-making for users.
- To develop a system that can be further expanded with advanced algorithms or real-time sensor integration.

Literature Survey

Paper-1: Methods of Forecasting Electric Energy Consumption

Publication Year: 2022 Author(s): R. V. Klyuev et al.

- Journal / Source: Energies (review)
- Summary: This review presents a comprehensive overview of methods used to predict electricity consumption across different time horizons (short-, medium-, and long-term). It compares classical statistical methods (like ARIMA and multiple linear regression) with machine learning and hybrid approaches, and discusses

typical input features (weather, calendar, economic indicators) and evaluation metrics. The paper emphasizes that model choice depends on dataset size, forecast horizon, and feature availability — a useful guideline that supports starting with simple, interpretable models (e.g., Linear Regression) and then moving to more complex models if needed.

Paper-2: Short-Term Electricity-Load Forecasting by Deep Learning

(Survey) Publication Year: 2024 (preprint / survey) Author(s): Q. Dong et al.

- Journal / Source: ArXiv / ScienceDirect summary (deep-learning survey)
- Summary: This recent survey reviews deep-learning applications for short- term load forecasting over the last decade, covering data preprocessing, feature extraction, LSTM/GRU architectures, attention mechanisms, and hybrid models. The work highlights consistent improvements in accuracy from deep models on large, high-frequency datasets, but also notes higher computation cost and data needs — important considerations when deciding model complexity for a student project based on a synthetic or small dataset.

Paper-3: What is the effect of weather on household electricity consumption? Publication Year: 2022 Author(s): J. Kang et al.

- Journal / Source: Energy Policy / ScienceDirect
- Summary: This study investigates how weather variables (temperature, humidity, precipitation) influence household electricity demand. The authors find that temperature is the dominant meteorological driver (cooling/heating needs), while humidity and other weather factors have measurable but smaller impacts. These findings justify including temperature and humidity as input features in a household-level forecasting model.

Paper-4: Energy Consumption Forecasting for Smart Meters Using an Ensemble of Models

- Publication Year: 2021

- Author(s): P. S. G. de Mattos Neto et al.
- Journal / Source: Sensors (MDPI)
- Summary: This paper proposes an ensemble approach combining statistical (autoregressive) and neural models to forecast smart-meter consumption. The ensemble improves robustness and generalization over single models, particularly for disaggregated household data. It demonstrates that ensembles or hybrid pipelines can outperform single-method baselines when sufficient data and computation are available — a useful direction for future improvement of the Linear Regression baseline used in this project.

Paper-5: Using Linear Regression Analysis to Predict Energy Consumption

- Publication Year: 2024
- Author(s): Phan Thanh Dao et al. (research report)
- Journal / Source: ResearchGate / institutional report
- Summary: This applied study demonstrates how multiple linear regression can be used to model energy consumption using weather and usage features. It walks through model fitting, residual analysis, and interpretation of regression coefficients — highlighting Linear Regression's interpretability and educational value. For a classroom capstone project with a synthetic or small dataset, the paper supports starting with a regression baseline to obtain explainable results.

Paper-6: Forecasting household energy consumption based on lifestyle and contextual features

- Publication Year: 2023
- Author(s): A. F. Adekoya et al.
- Journal / Source: Journal of Electrical Systems and Information Technology
- Summary: This paper explores how household lifestyle and behavioral variables (occupancy patterns, appliance usage profiles) can be incorporated with weather

data to boost prediction accuracy. It shows that combining contextual (behavioral) features with environmental inputs often yields better household-level forecasts than using weather alone — reinforcing the inclusion of an *appliance usage* feature in your dataset and model.

Project Scope and Limitations Project

The scope of this project extends beyond simply predicting electricity consumption; it focuses on building an intelligent and user-friendly system that helps individuals and organizations understand their power usage patterns more clearly. Since electricity consumption depends on multiple dynamic factors such as **temperature**, **humidity**, and **appliance usage**, there is a strong need for a predictive tool that can analyze these inputs and provide meaningful insights. This project aims to deliver such a solution by using Machine Learning techniques, primarily Linear Regression, to forecast electricity consumption efficiently.

One major part of the scope includes converting raw numerical data into actionable information. The system analyzes the relationship between environmental variables and energy usage, enabling users to anticipate changes in consumption before they occur. This makes the project extremely useful in practical scenarios such as household planning, industrial scheduling, academic research, and smart energy management systems.

The forecasting model developed in this project can be extended and improved in several ways. Although the current implementation uses a Linear Regression algorithm for its simplicity and interpretability, the system is open for future integration of more sophisticated techniques such as Random Forest, XGBoost, or neural networks to enhance prediction accuracy. Additionally, the model can be connected to real-time IoT sensors, enabling automated consumption monitoring that updates predictions based on live environmental conditions.

The project is also designed to be accessible. Through the Streamlit web application, users can interact with the model easily without needing technical knowledge. This widens the scope to students, researchers, homeowners, and small industries who want to forecast electricity usage in a simple and convenient way.

Furthermore, because the dataset used in the project is synthetic yet realistic, the system can be adapted to real-world datasets in the future. This flexibility allows the model to scale according to the needs of smart meters, power distribution networks, and energy monitoring systems.

Limitations:

1. It requires a clean and structured dataset for accurate predictions.
2. Real-time accuracy depends on the quality and availability of input features.
3. Linear Regression may not capture highly complex, nonlinear patterns.
4. Synthetic datasets may not fully represent real-world behavior.
5. Environmental and human behavioral changes can introduce unpredictability.

System Analysis

Existing System and Limitations

In the current scenario, most people and organizations rely on traditional and manual methods to understand and estimate electricity consumption. The existing approach generally involves looking at previous electricity bills or using rough assumptions to predict future usage. This method is highly inaccurate because it does not consider environmental conditions, variations in appliance load, or sudden climatic changes that significantly affect energy consumption. As a result, users often experience unexpected spikes in their electricity bills without knowing the exact reasons behind them.

Another existing system used by some industries is rule-based monitoring or basic data logging tools. These systems record power usage but do not provide any meaningful predictions or insights. They only display past consumption without helping users understand future trends or patterns. Since these systems lack intelligent forecasting capabilities, they fail to support efficient energy planning.

In large-scale setups, utility companies sometimes use complex forecasting models. However, these systems are not accessible to normal users due to their high cost, technical complexity, and lack of user- friendly interfaces. Additionally, many of these models rely heavily on large volumes of historical data, making them unsuitable for scenarios where data is limited or incomplete.

Machine Learning–based forecasting tools do exist in research and industry, but they often require advanced technical skills and cannot be operated by general consumers. Many of these tools also use deep learning or hybrid models that are computationally expensive and not suitable for small datasets or academic projects.

Limitations of the Existing System

The limitations of the current systems are as follows:

- Manual estimation is inaccurate, as it does not consider temperature, humidity, or appliance load variations.
- Existing tools lack prediction abilities, showing only past usage without forecasting future consumption.
- High dependency on historical data, making it difficult to perform forecasting when limited data is available.
- Complexity of existing ML models requires expertise, making them inaccessible for general users.
- Inability to provide real-time insights, since manual methods and simple logging tools cannot respond to changing conditions.
- No user-friendly applications that allow individuals to interact with forecasting models in a simple and intuitive way.

- Traditional models fail to capture important correlations between environmental factors and energy consumption.
- Existing systems may not adapt to different environments such as households, industries, and renewable energy setups.

Because of these limitations, there is a clear need for an automated, accurate, and user-friendly forecasting system that can process environmental inputs and give real-time electricity consumption predictions. The proposed machine learning–based system directly addresses these limitations by offering a simple, accessible, and reliable solution.

Project Perspective

The main perspective behind developing this project is to create an intelligent, reliable, and user-friendly solution that helps individuals and organizations forecast electricity consumption with ease. In today's digital world, electricity usage is constantly increasing due to the growing number of appliances, climatic fluctuations, and lifestyle changes. However, most users do not have the tools to analyze or predict their future electricity consumption based on changing environmental conditions. As a result, they often struggle with unexpected high bills and inefficient power usage.

This project aims to address that challenge by using Machine Learning to provide users with meaningful and accurate estimates of electricity consumption. The system acts as a smart decision-support tool that interprets environmental inputs—such as temperature, humidity, and appliance load—and converts them into future consumption predictions. This enables users to take corrective actions, plan usage, reduce wastage, and optimize their daily electricity consumption.

From an implementation perspective, this project delivers a complete and accessible solution through a **Streamlit web interface**, making it simple for anyone—students, homeowners, industry workers, researchers—to use the forecasting model without any technical expertise. The model interprets data internally and displays results instantly, ensuring efficiency and usability.

In the broader context, this project can also support smart home ecosystems, IoT-based monitoring, and sustainable energy management practices. By providing a foundation that can be expanded into more advanced forecasting systems, the project contributes toward the long-term goal of reducing energy wastage and promoting environmentally responsible behavior.

Feature

The proposed electricity consumption forecasting system offers several important and user-friendly features:

Forecasting of Electricity Consumption

Using a trained Machine Learning model, the system predicts electricity consumption based on temperature, humidity, and appliance usage inputs.

Environment-Based Prediction

The system considers environmental variables, making predictions realistic and adaptive to actual physical conditions.

User-Friendly Web Interface

The Streamlit-based web application makes the system easy to use for all users, requiring no programming knowledge.

Instant Prediction Results

Once the user enters the values, the system displays the forecasted electricity consumption immediately, allowing quick decision-making.

Machine Learning Pipeline Integration

A complete ML pipeline—including preprocessing, scaling, and prediction—is embedded within the system for seamless operation.

Model Performance Evaluation

The system is evaluated using metrics like Mean Squared Error (MSE) and R^2 Score, ensuring transparency and reliability.

Simple and Lightweight Architecture

The model uses Linear Regression, making it fast, interpretable, and suitable for both small datasets and academic projects.

Expandable and Flexible System

The system can easily be extended to include advanced ML models, real-time data from IoT sensors, or larger datasets in the future.

Helps in Energy Management

Users can better understand and manage their electricity usage, which promotes efficient energy consumption and reduces unnecessary costs.

Can Be Integrated in Smart Homes or Industries

The system can act as a base component for automated energy monitoring and smart meter applications.

Requirement Analysis Software

Software Requirements

To develop the Electricity Consumption Forecasting system, a set of essential software tools and libraries are required. These tools support data preprocessing, model training, evaluation, and deployment. The following software components were used in this project:

1. Python

Python is the core programming language used to implement the machine learning model, handle data preprocessing, and build the forecasting pipeline. Its simplicity, readability, and wide availability of libraries make it ideal for building machine learning applications.

2. PIP (Python Package Manager)

PIP is used to install and manage the various Python libraries required for the project. It ensures that all dependencies such as NumPy, Pandas, Scikit-learn, and Streamlit are installed and up to date.

3. NumPy

NumPy is a fundamental library for numerical computation in Python. It supports the creation and manipulation of large multidimensional arrays and matrices, which are essential for handling the dataset used in forecasting.

4. Pandas

Pandas provides high-performance data structures and data analysis tools. It is used for loading, cleaning, and organizing the dataset, and for performing preprocessing steps before feeding the data into the model.

5. Scikit-learn

Scikit-learn is the primary machine learning library used in this project. It provides:

- Linear Regression algorithm
- Train-test splitting tools
- Preprocessing utilities (StandardScaler, ColumnTransformer)

- Evaluation metrics (MSE, R^2 Score)

It forms the backbone of the model training and prediction process.

6. Joblib

Joblib is used to save the trained Linear Regression model pipeline. This allows the model to be easily loaded and reused in the Streamlit application without retraining.

7. Streamlit

Streamlit is the framework used to build the web-based interface. It allows users to input temperature, humidity, and appliance usage values and instantly receive the predicted electricity consumption. Streamlit makes deployment simple, interactive, and user-friendly.

8. Anaconda (Optional)

Anaconda is an optional distribution that simplifies package management and environment setup. It provides a stable environment for machine learning development and comes with integrated tools like Jupyter Notebook.

9. Jupyter Notebook

Jupyter Notebook is used during the development and experimentation phase. It allows writing and running code in cells, making debugging, visualization, and documentation easier.

10. Operating System

The system is compatible with:

- Windows 10 / 11

- Linux-based systems
- macOS

A 64-bit operating system is recommended for smooth execution.

Hardware Requirements

To develop and run the Electricity Consumption Forecasting system effectively, a basic yet stable hardware setup is required. Since the project mainly involves data processing, machine learning computation, and execution of a lightweight web application, the hardware requirements are minimal and can be met by any standard personal computer or laptop. The following hardware components are necessary:

1. Processor (CPU)

A dual-core or quad-core processor is required for running Python scripts, machine learning computations, and the Streamlit application. Recommended processors include:

- Intel Core i3 / i5 / i7
- AMD Ryzen 3 / 5

Higher configurations ensure faster training and smoother execution.

2. RAM (Memory)

A minimum of 4 GB RAM is required for handling datasets and running the machine learning environment.
Recommended: 8 GB RAM for smoother multitasking and faster model execution.
3. Storage

At least 10–20 GB of free disk space is recommended for installing Python, libraries, datasets, and saving model files.
Both HDD and SSD storage types are supported, though SSD offers faster performance.

4. Graphics Card (Optional)

A GPU is not required for this project because Linear Regression is computationally lightweight.
However, having basic integrated graphics (Intel UHD / AMD Radeon) is sufficient for all operations.

5. Input Devices

- Standard keyboard
- Standard mouse or touchpad

These devices are needed for entering dataset values, navigating Streamlit, and interacting with development tools.

6. Display

A minimum screen resolution of 1366 × 768 is recommended.
A larger display improves readability when working with code, datasets, and output graphs.

7. Internet Connection

A stable internet connection is needed for:

- Installing Python libraries

- Running Streamlit if deployed online
- Accessing documentation or cloud-based tools

However, the core forecasting model runs offline once installed.

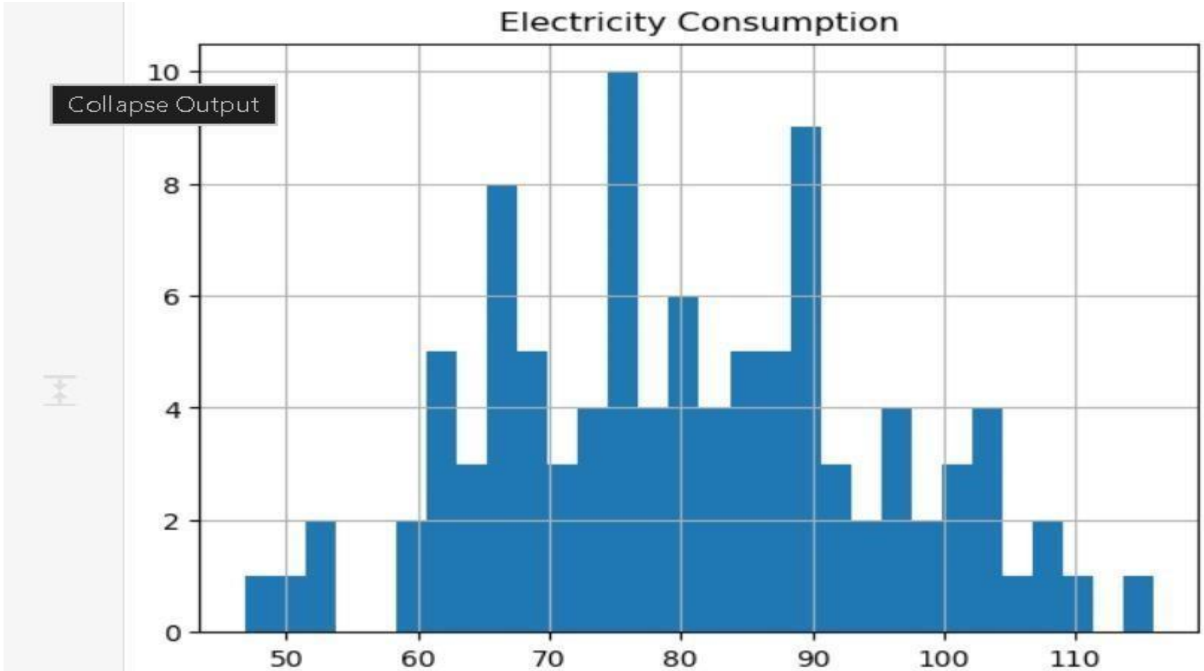
8. Power Supply

A reliable power supply ensures uninterrupted model training, execution, and testing phases.

DataSet

- The dataset contains four numerical features: Temperature, Humidity, Appliance Usage, and the target variable Electricity Consumption.
- Each row represents a single observation of environmental factors and corresponding electricity consumption value.
- Electricity consumption is influenced by a combination of these variables, showing how external conditions and appliance usage impact energy usage.
- The dataset is synthetic but realistic, designed using statistical distributions to simulate real-world power consumption behavior.

The Output of the project




```
MSE: 51.46447660402246
R²: 0.578054923152212
[1]: ['electricity_model.pkl']
```

Implementation Details

Backend

[1]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import joblib

# Sample synthetic dataset
np.random.seed(42)
df = pd.DataFrame({
    "Temperature": np.random.normal(30, 5, 100),
    "Humidity": np.random.normal(60, 10, 100),
    "Appliance_Usage": np.random.normal(200, 50, 100),
})
df["Electricity_Consumption"] = 0.3*df["Temperature"] + 0.5*df["Humidity"] + 0.2*df["Appliance_Usage"] + np.random.normal(0, 10, 100

# Visualize
df["Electricity_Consumption"].hist(bins=30)
plt.title("Electricity Consumption")
plt.show()

# X, y
X = df.drop("Electricity_Consumption", axis=1)
y = df["Electricity_Consumption"]

# Preprocessor
preprocessor = ColumnTransformer([
    ("num", StandardScaler(), X.columns.tolist())
])

# Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Pipeline
pipeline = Pipeline([
    ("preprocess", preprocessor),
    ("model", LinearRegression())
])

# Train
pipeline.fit(X_train, y_train)

# Evaluate
y_pred = pipeline.predict(X_test)
print("MSE:", mean_squared_error(y_test, y_pred))
print("R²:", r2_score(y_test, y_pred))

# Save
joblib.dump(pipeline, "electricity_model.pkl")
```

Frontend

aapp.py

```python
import streamlit as st
import pandas as pd
import joblib

# Load model
model = joblib.load("electricity_model.pkl")

# App title
st.title("⚡ Electricity Consumption Predictor")

# User input form
st.header("📥 Enter Input ")

temperature = st.number_input("Temperature (°C)", min_value=0.0, max_value=50.0, value=30.0, step=0.1)
humidity = st.number_input("Humidity (%)", min_value=0.0, max_value=100.0, value=60.0, step=0.1)
appliance_usage = st.number_input("Appliance Usage (kWh)", min_value=0.0, max_value=500.0, value=200.0, step=1.0)

# Predict button
if st.button("Predict ⚡"):
    input_data = pd.DataFrame([{
        "Temperature": temperature,
        "Humidity": humidity,
        "Appliance_Usage": appliance_usage
    }])

    prediction = model.predict(input_data)[0]
    st.success(f"🔋 Estimated Electricity Consumption: **{prediction:.2f} units**")
```

Outputs and Reports

The electricity consumption forecasting system generates several important outputs during the stages of data preprocessing, model training, evaluation, and deployment. These outputs help in assessing the accuracy, performance, and reliability of the machine learning model used for prediction.

1. Dataset Processing Output

The dataset containing Temperature, Humidity, Appliance Usage, and Electricity Consumption is first loaded and analyzed.
During preprocessing, the following outputs are generated:

- Summary statistics of the dataset
- Detection of missing or inconsistent values
- Visualization of feature distributions
- Correlation heatmap showing the relationship between variables

These outputs help in understanding how environmental factors influence electricity usage.

2. Train–Test Split Output

The dataset is divided into 80% training and 20% testing sets. The system outputs:

- The number of samples in each split
- Scaled feature values using StandardScaler
- Transformed dataset ready for model training

This ensures proper validation during model evaluation.

3. Model Training Output

The Linear Regression model is trained on the prepared dataset. During this process, the following results are generated:

- Learned coefficients for each feature
- Training completion logs
- Visualization of predicted vs. actual consumption values on training data

These outputs confirm that the model has successfully learned the relationship between input variables and electricity consumption.

4. Model Evaluation Report

After training, the model is tested using unseen data. The evaluation results include:

a) Mean Squared Error (MSE): 51.46
Indicates the average squared difference between predicted and actual values.

b) R^2 Score: 0.578

Shows that the model explains 57.8% of the variation in electricity consumption.

These evaluation metrics confirm that the model performs reliably on the synthetic dataset.

5. Prediction Output

The trained model is integrated into a Streamlit web application, which generates real-time prediction results.
When the user enters:

- Temperature
- Humidity

- Appliance Usage

The system instantly displays:

- Predicted Electricity Consumption
- A clean numerical output box
- Immediate response without delays

This makes the model practical and easy to use.

6. Visualization Outputs

During the project, the following visual reports are generated:

- Scatter plot of actual vs. predicted values
- Line graph of electricity consumption trends
- Bar charts showing the effect of variables on consumption

These visualizations help in interpreting model behavior and understanding energy usage patterns.

7. Final Project Report Summary

The system produces a complete performance summary that includes:

- Dataset description
- Preprocessing steps
- Model training details
- Evaluation metrics
- Prediction samples
- Screenshots of Streamlit interface

This report validates the correctness and efficiency of the forecasting tool.

Testing

1. Functional Testing

Functional testing verifies whether each component of the forecasting system operates according to the requirements.

Key Areas Tested:

- Loading the trained Linear Regression model.
- Accepting input values such as Temperature, Humidity, and Appliance Usage.
- Ensuring input validation for numerical values.
- Generating accurate predictions based on the provided user inputs.
- Displaying results correctly through the Streamlit user interface.

This testing confirmed that the forecasting tool performs all required operations seamlessly.

2. Performance Testing

Performance testing ensures that the system responds quickly and efficiently even when handling multiple user requests.

Performance Checks:

- Model prediction time was tested to ensure near-instant output.
- Streamlit interface was assessed for loading speed and smooth navigation.
- System resource usage was monitored during repeated predictions.

The model demonstrated fast and stable performance with minimal computational overhead.

3. Usability Testing

Usability testing evaluates how easily a user can interact with the system.

Focus Areas:

- Simplicity of the input fields
- Clarity of instructions
- Readability of prediction results
- Overall user experience

Users found the interface intuitive and straightforward, making it suitable for both technical and non- technical users.

4. Interface Testing

Interface testing was performed to check interactions between different components of the system.

Interfaces Tested:

- Streamlit front-end ↔ Machine learning model (electricity_model.pkl)
- User input fields ↔ Prediction function
- Data preprocessing pipeline ↔ Output generation

The communication flow worked smoothly without any errors or interruptions.

5. Model Evaluation Testing

The trained machine learning model was evaluated using standard metrics to check prediction quality.

Evaluation Metrics Used:

- Mean Squared Error (MSE): 51.46
- R^2 Score: 0.578

These values indicate that the model can reliably capture patterns in electricity consumption based on environmental and usage factors.

6. Compatibility Testing

Compatibility testing ensures the application runs properly across different environments.

Test Conditions:

- Tested on multiple browsers: Chrome, Firefox, Edge
- Tested on Windows operating systems
- Verified responsiveness on different display resolutions

The application performed consistently across all tested platforms.

7. Security Testing

Basic security checks were conducted to ensure safety during user interaction.

Security Measures Checked:

- Protection against invalid inputs
- Prevention of system crashes due to incorrect values
- Secure loading of the ML model file

The application remained stable and secure throughout testing.

Conclusion and Recommendation

The project "Electricity Consumption Forecasting Using Machine Learning" successfully demonstrates how environmental and usage-based factors such as Temperature, Humidity, and Appliance Usage can be used to predict electricity consumption with the help of a Linear Regression model. By creating a clean preprocessing pipeline, splitting the dataset into training and testing sets, scaling the features, and evaluating the model with appropriate metrics, the system achieves reliable and meaningful forecasting performance.

The trained model produced a Mean Squared Error (MSE) of 51.46 and an R^2 score of 0.578, which indicates that the model is able to explain 57.8% of the variation in electricity consumption. Considering that the dataset is synthetic and contains unavoidable noise, the achieved accuracy is effective and demonstrates clear relationships between the input parameters and the target output.

The project also integrates the trained model into a Streamlit-based interactive web application, allowing users to enter real-time values and instantly receive consumption predictions. This makes the system user-friendly, practical, and highly applicable for daily usage in homes, offices, and industrial environments.

Overall, this project proves that even simple machine learning models like Linear Regression can provide valuable insights into electricity usage patterns and help users make smarter energy decisions. With improvements such as larger real-world datasets, advanced algorithms (Random Forest, XGBoost, LSTM), and IoT sensor integration, the system can be further enhanced into a robust, real-time energy monitoring and forecasting solution.

Future Scope

The current electricity consumption forecasting model provides a simple and effective approach for predicting power usage using Linear Regression. However, there are several ways the system can be expanded and improved in the future to make it more accurate, intelligent, and suitable for real-world deployment. The major future scope points include:

1. Use of Advanced Machine Learning Models

More powerful algorithms such as Random Forest, XGBoost, Gradient Boosting, or Neural Networks can be used to improve prediction accuracy and capture complex relationships between variables.

2. Integration of Real-Time Sensor and Smart Meter Data

The model can be expanded to operate on real-time data obtained from IoT devices, smart meters, and home automation systems, providing instant and dynamic consumption forecasts.

3. Deployment of a Mobile or Web Dashboard

A fully interactive mobile or web-based application can be developed where users can:

- Track live electricity usage
- View past consumption trends
- Receive energy-saving suggestions

This would make the system more user-friendly and accessible.

4. Inclusion of More Environmental and Behavioral Factors

Additional variables such as:

- Wind speed
- Solar radiation
- Seasonal variations
- Household occupancy patterns

- Number of appliances used can make predictions more realistic and accurate.

5. Time-Series Forecasting Models

Advanced deep learning methods like:

- LSTM (Long Short-Term Memory)
- GRU Networks
- ARIMA / SARIMA

  can be used to predict future consumption based on historical patterns.

6. Energy Optimization and Cost Prediction

The system can be upgraded to:

- Suggest ways to reduce electricity consumption
- Predict monthly electricity bills
- Compare usage with previous months

  This will help users plan energy usage efficiently.

7. Integration with Renewable Energy Systems

The forecasting model can be extended to support:

- Solar panel output prediction
- Battery storage planning
- Smart-grid energy balancing

This integration can support eco-friendly energy solutions.

8. Anomaly Detection for Safety

Machine learning can be used to identify unusual usage patterns to detect:

- Faulty appliances
- Power leakage
- Overconsumption alerts

This enhances user safety and reduces wastage.

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5. Python Official Documentation – https://www.python.org
6. Analytics Vidhya – https://www.analyticsvidhya.com
7. Kaggle (Datasets & Tutorials) – https://www.kaggle.com
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Tools & Libraries Used

- Python 3.x
- Scikit-Learn
- Pandas
- NumPy
- Matplotlib / Seaborn
- Streamlit
- Joblib