FORECASTING AND PREDICTION OF ENERGY DEMAND - HARNESSING IOT DATA FOR SMART GRID ANALYTICS

A PROJECT REPORT

Submitted by

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ABSTRACT

The advent of the Internet of Things (IoT) has revolutionized numerous industries, including the energy sector. This project, titled "Forecasting Energy Demands: Harnessing IoT Data for Smart Grid Analytics," aims to leverage the vast amounts of data generated by IoT devices to predict and manage energy demands effectively. Utilizing three comprehensive datasets from Kaggle—`building energy consumption record`, `weatherData`, and `weather_cost`—our team has developed a robust forecasting model that integrates weather conditions and energy production metrics to anticipate future energy requirements. The project commenced with meticulous data preprocessing to ensure the integrity and quality of the datasets. Exploratory Data Analysis (EDA) was conducted to uncover underlying patterns and correlations within the data. Subsequent feature engineering refined the datasets, enhancing the predictive capabilities of our models. We employed machine learning algorithms, including Linear Regression and Random Forest Regressor, to construct our forecasting models. These models underwent rigorous evaluation, demonstrating high accuracy and reliability in predicting energy demands. In the final phase of the project, we focused on developing a user-friendly web application that serves as an interface for our forecasting system. The application is designed with a clean and intuitive user interface, backed by a robust backend that seamlessly integrates our predictive models. Users can input parameters related to energy generation and weather conditions to receive real-time forecasts of energy demands. This project not only showcases the potential of IoT data in transforming the energy sector but also sets a precedent for the development of smart grid analytics solutions. The successful implementation of this forecasting system can lead to more efficient energy management, reduced operational costs, and a significant step towards a sustainable future. The documentation herein provides a comprehensive overview of the project's methodology, challenges encountered, solutions implemented, and the final results. It serves as a testament to the collaborative effort and innovative approach adopted by the team to address a critical need in the energy industry.

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Executive Summary

In the face of escalating energy demands and the imperative for sustainable development, the "Forecasting Energy Demands: Harnessing IoT Data for Smart Grid Analytics" project stands as a beacon of innovation and practical application of cutting-edge technology. This project is a collaborative endeavor that aims to address the critical challenge of energy management in the era of smart grids by utilizing the transformative power of the Internet of Things (IoT) and advanced data analytics. The project's cornerstone is the development of a predictive model that synthesizes data from three meticulously curated datasets Kaggle—`building energy consumption record`, `weatherData`, and `weather_cost`. These datasets encompass a wealth of information on energy consumption patterns, weather conditions, and hourly energy production metrics. By harnessing this data, our team has constructed a forecasting model that not only predicts energy demands with high precision but also adapts to fluctuating conditions, thereby optimizing energy distribution and contributing to the stability of the grid. A pivotal component of the project is the seamless integration of the forecasting model into a user-centric web application. This application serves as an interactive platform for energy providers and consumers alike, offering real-time insights into energy demand forecasts. The intuitive design and responsive interface of the application ensure that users can effortlessly access and interpret the predictive data, which is crucial for informed decision-making. Throughout the project, we encountered and surmounted numerous challenges, ranging from data preprocessing hurdles to the intricacies of model selection and evaluation. The solutions we implemented are a testament to our team's resilience and commitment to excellence. The project's success is not solely measured by the functionality of the model and application but also by the potential impact on the energy sector. By enabling more efficient energy management and fostering the adoption of smart grid technologies, this project contributes to the reduction of operational costs and paves the way for a sustainable energy future. This executive summary encapsulates the essence of our project, highlighting the innovative approach, technical achievements, and the broader implications of our work. It serves as an invitation to delve deeper into the subsequent sections of the documentation, which detail the project's methodology, development process, and the collective expertise that brought this vision to fruition.

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INTRODUCTION

In an era where the intersection of technology and sustainability is paramount, the energy sector stands at the forefront of innovation. The project "Forecasting Energy Demands: Harnessing IoT Data for Smart Grid Analytics" embodies this intersection, aiming to transform the way energy demands are predicted and managed. As the world gravitates towards smart grid systems, the integration of Internet of Things (IoT) data becomes crucial in enhancing the efficiency and reliability of energy distribution. This project is an ambitious initiative that seeks to leverage the vast amounts of data generated by IoT devices within the energy infrastructure. By analyzing this data, we aim to develop predictive models that can forecast energy demands with unprecedented accuracy. The project utilizes three diverse datasets: `energy_dataset.csv`, which provides insights into energy consumption and production; `weatherData`, which offers detailed weather-related data; and `Weather_cost` , which contains hourly energy demand and cost records. Together, these datasets form the backbone of our analytical approach. The journey of this project begins with the meticulous preprocessing of data, ensuring its quality and suitability for analysis. We then embark on an exploratory journey, delving into the data to uncover patterns and relationships that inform our predictive models. Employing advanced machine learning techniques, we construct models that not only predict future energy demands but also provide valuable insights into the factors influencing these demands. The culmination of our efforts is the development of a web application that serves as a portal to our forecasting system. This application is designed with the end-user in mind, providing a seamless and intuitive experience that allows for the easy interpretation and application of the forecasted data. It is a tool that empowers energy providers and consumers, facilitating informed decision-making and promoting the efficient use of energy resources. As we present this introduction, we invite you to explore the subsequent sections of our documentation. They detail the methodologies employed, the challenges faced, and the innovative solutions that were implemented. This project is not just a technical achievement; it is a step towards a smarter and more sustainable future for the energy sector and beyond.

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EXISTING WORKS

Energy demand forecasting and smart grid analytics have been the subject of extensive research and development in recent years, with numerous studies focusing on leveraging IoT data and machine learning techniques to address various challenges and opportunities in the energy sector. A review of existing literature reveals several key areas of research and notable contributions:

IoT Integration in Energy Management Systems:

Many studies have explored the integration of IoT devices into energy management systems to enable real-time monitoring, data collection, and analysis. These IoT-enabled systems offer enhanced visibility into energy consumption patterns, grid operations, and asset performance, facilitating more efficient resource allocation and decision-making.

Machine Learning for Energy Demand Forecasting:

Machine learning algorithms, particularly regression-based and time series models, have been widely employed for energy demand forecasting. These models utilize historical consumption data, weather parameters, and other relevant features to predict future energy demand accurately. Advanced techniques such as deep learning, ensemble methods, and hybrid models have also been investigated to improve forecasting accuracy and scalability.

Predictive Analytics for Grid Optimization:

Predictive analytics techniques, including optimization algorithms and predictive maintenance strategies, have been applied to optimize grid operations and improve system reliability. By analyzing historical data and identifying patterns of equipment failure or grid congestion, predictive analytics can enable proactive maintenance scheduling, asset optimization, and grid management strategies.

Data-driven Approaches for Renewable Energy Integration:

With the increasing penetration of renewable energy sources such as solar and wind power, there is a growing need for data-driven approaches to integrate these intermittent energy sources into the grid effectively. Machine learning algorithms have been employed to forecast renewable energy generation, optimize energy storage systems, and manage grid stability and reliability in the presence of variable generation.

Smart Grid Applications and Use Cases:

Research efforts have explored various smart grid applications and use cases enabled by IoT and machine learning technologies. These include demand response programs, energy-efficient building management systems, electric vehicle charging infrastructure optimization, and distributed energy resource management. Smart grid

technologies offer opportunities for demand-side management, grid balancing, and peak load reduction, contributing to overall energy efficiency and sustainability goals.

Challenges and Future Directions:

Despite significant progress, several challenges remain in the adoption and implementation of IoT and machine learning technologies in energy management and smart grid analytics. These include data quality and interoperability issues, privacy and security concerns, regulatory barriers, and scalability challenges. Future research directions focus on addressing these challenges and developing robust, scalable, and interoperable solutions for the next generation of smart grid systems.

In summary, existing works in energy demand forecasting and smart grid analytics have demonstrated the potential of IoT and machine learning technologies to revolutionize the energy sector. By leveraging data-driven approaches and predictive analytics, researchers and practitioners aim to enhance grid reliability, optimize energy resources, and promote sustainability in the face of evolving energy needs and environmental challenges.

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LITERATURE SURVEY

[1] This paper provides an overview of forecasting with artificial neural networks, highlighting the state-of-the-art techniques. It discusses the application of artificial neural networks in various domains and their effectiveness in forecasting tasks.[2] Focuses on short-term load forecasting in smart grids and compares the performance of different machine learning algorithms. Evaluates the empirical performance of these algorithms and their suitability for short-term load forecasting tasks.[3] Introduces a short-term load forecasting approach using long short-term memory neural network (LSTM). Discusses the advantages of using LSTM networks for load forecasting and presents empirical results demonstrating its effectiveness.[4] Proposes a deep learning-based approach for short-term building energy load forecasting, incorporating an attention mechanism. Demonstrates the effectiveness of the proposed method in accurately forecasting building energy loads. [5] Presents a novel method of short-term load forecasting based on Internet of Things (IoT) data. Discusses the integration of IoT data into load forecasting models and its potential to improve forecasting accuracy. [6] Discusses short-term load forecasting in smart grid environments using deep learning techniques. Provides insights into the application of deep learning models for load forecasting tasks and their performance compared to traditional methods. [7] Reviews deep learning-based techniques for short-term load forecasting. Summarizes various deep learning architectures and their applications in load forecasting tasks, highlighting their strengths and limitations.[8]Provides a comprehensive review of electricity price forecasting techniques. Discusses the state-of-the-art methods and future directions in electricity price forecasting, emphasizing the importance of accurate price predictions for energy market participant.[9]Evaluates methods for very short-term load forecasting using minute-by-minute data. Compares the performance of different forecasting techniques and discusses their suitability for real-time load forecasting applications.[10] Offers a comprehensive review of short-term load forecasting methods and practices. Discusses traditional statistical methods as well as modern machine learning techniques for load forecasting in various domains. These references collectively provide a broad understanding of short-term load forecasting techniques, including traditional statistical methods and modern machine learning approaches. They also highlight the importance of accurate load forecasting in smart grid environments and discuss the potential of deep learning techniques in improving forecasting accuracy.[11] Provides a review of machine learning applications in power systems. Discusses the various applications of machine learning techniques in power system analysis, including load forecasting, fault detection, and optimization.[12] Surveys load forecasting techniques in smart grids. Reviews traditional time series methods, statistical models, and machine learning approaches for load forecasting, highlighting their strengths and limitations.[13] Reviews short-term load forecasting using data analytics and machine learning techniques. Discusses the use of data analytics tools and machine learning algorithms for load forecasting, with a focus on recent advancements and future directions.[14] Surveys demand response methods in smart grids, focusing on mathematical models and approaches. Discusses the role of demand response in enhancing grid reliability and efficiency, as well as mathematical

modelling techniques used to optimize demand response strategies.[15] Provides a survey on the application of machine learning technologies in smart grids. Discusses various machine learning algorithms and their applications in smart grid operations, including load forecasting, demand response, and energy management.[16] Reviews short-term load forecasting using deep learning techniques. Discusses the application of deep learning models, such as recurrent neural networks and convolutional neural networks, in load forecasting tasks, highlighting recent developments and future directions.[17] Provides a review of deep learning models for time series forecasting. Discusses various deep learning architectures, including recurrent neural networks, convolutional neural networks, and transformers, for time series forecasting tasks, with a focus on their strengths and limitations.[18] Surveys deep learning for big data analytics. Discusses the application of deep learning techniques, such as deep neural networks and convolutional neural networks, in analyzing big data, highlighting their effectiveness in handling large-scale datasets.[19] Reviews deep learning-based load forecasting in smart grids. Discusses the application of deep learning models, such as recurrent neural networks and attention mechanisms, in load forecasting tasks, with a focus on recent advancements and challenges.[20] Provides a comprehensive review of load forecasting methodologies, challenges, and future directions in smart grids. Discusses various forecasting techniques, including statistical methods and machine learning algorithms, and identifies key challenges and research directions in load forecasting for smart grid applications.

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DATASET OVERVIEW

BUILDING ENERGY CONSUMPTION

The energy dataset was obtained from Kaggle, a popular platform for sharing datasets and data science projects. It consists of date time and energy consumption and temperature in a building.

The dataset appears to contain hourly temperature readings for a specific location. Here's an overview based on the data:

- The measurements start on **January 1, 2016**, at **01:00** and continue until **06:00** on **January 2, 2016**.
- The temperature values range from approximately **23.78°C** to **27.79°C** during this time period.
- Notably, there's a slight increase in temperature around **08:00** on January 1, 2016, reaching **25.67°C**.
- The temperatures then remain relatively consistent until **17:00**, where they peak at **27.79°C**.
- Afterward, the temperature gradually decreases, returning to around **23.78°C** by **06:00** on January 2, 2016.

Weather Dataset

The weather features dataset was also sourced from Kaggle. It contains environmental data such as temperature, pressure, humidity, and wind speed, along with information about weather conditions like cloud cover, precipitation, and atmospheric phenomena. This dataset was collected from weather stations located across different regions and cities. The weather features data are essential for understanding the external factors that influence energy generation and consumption, enabling more accurate forecasting and predictive modeling..

1. **Time (HH:MM)**: The data spans from **January 1, 2016, 01:00** to **February 1, 2016, 12:00**.
2. **Month**: All data points fall within the month of **January**.
3. **HH (Hour)**: Ranges from **1** to **24**, representing the hour of the day.
4. **TD (Dew Point Temperature)**: Dew point temperature values vary between **23°C** and **54°C**.
5. **U (Relative Humidity)**: Relative humidity percentages range from **77%** to **98%**.
6. **Temp (Temperature)**: Air temperature fluctuates between **2.7°C** and **7.3°C**.
7. **RH (Relative Humidity)**: Relative humidity remains consistently high, mostly at **0.87** or **0.98**.

8. **Q**: All data points have a **Q** value of **0**.
9. **DR (Wind Direction)**: Wind direction is predominantly **0** (calm).
10. **FF (Wind Speed)**: Wind speed varies from **10** to **50**.
11. **FX (Maximum Wind Gust)**: Maximum wind gusts range from **20** to **90**.
12. **P (Pressure)**: Atmospheric pressure values span from **10100** to **10255**.

Overall, this dataset captures hourly weather-related measurements, including temperature, humidity, wind speed, and pressure

WEATHER COST DATA

1. **Time (HH:MM)**: The data spans from **January 1, 2019, 00:00** to **February 1, 2019, 13:00**.
2. **Month**: All data points fall within the month of **January**.
3. **HH (Hour)**: Ranges from **1** to **24**, representing the hour of the day.
4. **TD (Dew Point Temperature)**: Dew point temperature values vary between approximately **-9°C** and **79°C**.
5. **U (Relative Humidity)**: Relative humidity percentages range from **67%** to **98%**.
6. **Temp (Temperature)**: Air temperature fluctuates between approximately **41°C** and **87°C**.
7. **RH (Relative Humidity)**: Relative humidity remains consistently high, mostly at **0.87** or **0.98**.
8. **Q**: All data points have a **Q** value of **0**.
9. **DR (Wind Direction)**: Wind direction is predominantly **0** (calm).
10. **FF (Wind Speed)**: Wind speed varies from **30** to **60**.
11. **FX (Maximum Wind Gust)**: Maximum wind gusts range from **60** to **120**.
12. **P (Price)**: cost values span from **10132** to **10378**.

This dataset captures hourly weather-related measurements from January 2019

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DATASET ACGUISITION AND MANAGEMENT

The process of acquiring, storing, and managing the data throughout the project was meticulously planned to ensure the reliability and accessibility of the datasets. Here's a detailed overview:

Data Acquisition:

Source Selection:

The datasets were obtained from Kaggle, a popular platform for data science competitions and datasets. The choice of datasets was crucial to ensure they align with the project objectives of forecasting energy demands and leveraging IoT data for smart grid analytics.

Download and Verification:

The datasets, namely the Energy Dataset, Weather Features Dataset, and AEP Hourly Dataset, were downloaded from Kaggle in CSV format. Before proceeding, each dataset was meticulously verified to ensure data integrity and compatibility with the project's requirements.

Exploratory Data Analysis (EDA):

Preliminary exploratory data analysis was conducted to gain insights into the structure, format, and content of the datasets. This involved examining the columns, data types, missing values, and statistical summaries.

Data Storage and Management:

Local Storage:

Initially, the datasets were stored locally on the developer's machine in a designated project directory. This facilitated easy access and manipulation of the data during the initial stages of development.

Version Control:

To ensure version control and collaboration among team members, a Git repository was set up to store the project files, including the datasets, source code, documentation, and other relevant materials. This allowed team members to track changes, manage revisions, and work collaboratively on the project.

Data Preprocessing:

Prior to analysis and modeling, the datasets underwent preprocessing steps to clean, transform, and prepare the data for further processing. This included handling missing values, scaling numerical features, encoding categorical variables, and splitting the data into training and testing sets.

Data Backup and Security:

Regular backups of the datasets were performed to prevent data loss in case of hardware failures, accidental deletions, or other unforeseen events. Additionally, measures were taken to ensure data security and compliance with privacy regulations, especially when dealing with sensitive information.

By following these steps for data acquisition, storage, and management, the project team ensured the availability, reliability, and integrity of the datasets throughout the project lifecycle. This facilitated efficient data analysis, model development, and decision-making processes, ultimately contributing to the successful execution of the forecasting and analytics tasks.

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METHODOLOGY

Data Acquisition and Preprocessing

Data Collection:

The datasets energy_dataset.csv, weather_features.csv, and AEP_hourly.csv were obtained from Kaggle.

Initial Exploration:

Basic statistical methods were applied to understand the structure, content, and quality of the datasets.

Cleaning:

Missing values were handled using forward-fill imputation to maintain data continuity.

Transformation:

Timestamps were parsed and set as indices to facilitate time-series analysis.

Exploratory Data Analysis (EDA)

Trend Analysis:

Time-series plots were generated to visualize energy generation and consumption trends over time.

Correlation Analysis:

Correlation matrices and pair plots were created to identify relationships between variables.

Feature Distribution:

Distribution plots were used to understand the spread and skewness of the data.

Feature Engineering

Time-based Features:

Extracted year, month, day, and hour from timestamps to capture seasonal and diurnal patterns.

Dummy Variables:

Categorical variables such as weather conditions and city names were encoded using one-hot encoding to prepare for model input.

Model Development

Linear Regression:

A simple linear regression model was built to establish a baseline for prediction accuracy.

Random Forest:

A more complex random forest model was trained to capture non-linear relationships in the weather dataset.

LSTM Network:

A Long Short-Term Memory (LSTM) network was designed to model the sequential nature of the energy consumption data.

Model Training and Evaluation

Training:

Models were trained on a subset of the data, with parameters tuned to optimize performance.

Validation:

A separate validation set was used to fine-tune the models and prevent overfitting.

Testing:

The final models were evaluated on a test set to assess their generalization capability.

Metrics:

Mean Squared Error (MSE) and R-squared (R2) were used to quantify model performance.

Web Application Development

Frontend:

Developed using modern web technologies to provide an interactive user experience.

Backend:

Implemented to handle data processing, model invocation, and result presentation.

Integration:

Forecasting models were integrated into the application to provide real-time predictions based on user input.

Challenges and Solutions

Data Quality:

Rigorous preprocessing methods were employed to ensure data integrity.

Model Complexity:

Techniques such as dropout and regularization were used to manage model complexity and prevent overfitting.

Scalability:

The web application was designed with scalability in mind, allowing for future expansion and integration of additional models or data sources.

Conclusion

The detailed methodology provided a systematic approach to developing a robust forecasting system for energy demands, leveraging IoT data and advanced machine learning techniques. The resulting web application serves as a practical tool for energy management and decision support.

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DATA ACQUASATION AND PREPROCESSING

Data Collection

The datasets energy_dataset.csv, weather_features.csv, and AEP_hourly.csv were obtained from Kaggle, a popular platform for sharing datasets. These datasets were selected based on their relevance to the project's objectives, which involved forecasting energy demands using IoT data for smart grid analytics.

```
# Importing necessary libraries
import pandas as pd
# Loading the datasets
energy_data = pd.read_csv('Building energy consumption record.csv')
weather_data = pd.read_csv('weatherdata.csv')
aep_hourly_data = pd.read_csv('weather_cost.csv')
```

Initial Exploration

After loading the datasets, initial exploration was conducted to gain insights into their structure, content, and quality. This involved basic statistical methods to understand the distribution of data and identify any anomalies or missing values.

```
# Displaying basic information about the datasets
print("Building energy consumption record:")
print(Building energy consumption record.info())
print("\nWeather Dataset:")
print(weather_data.info())
print("\Weather_cost Dataset:")
print(Weather_cost data.info())
```

Cleaning

Missing values were identified and addressed to ensure data completeness and integrity. Forward-fill imputation was used to handle missing values, particularly in time-series data, to maintain data continuity.

```
# Handling missing values using forward-fill imputation
energy_data.fillna(method='ffill', inplace=True)
weather_data.fillna(method='ffill', inplace=True)
aep_hourly_data.fillna(method='ffill', inplace=True)
```

Transformation

Timestamps in the datasets were parsed and set as indices to facilitate time-series analysis. This transformation was essential for conducting time-based analysis and modeling.

```
# Parsing timestamps and setting them as indices
energy_data['time'] = pd.to_datetime(energy_data['time'])
energy_data.set_index('time', inplace=True)
weather_data['dt_iso'] = pd.to_datetime(weather_data['dt_iso'], utc=True)
weather_data.set_index('dt_iso', inplace=True)
aep_hourly_data['Datetime'] = pd.to_datetime(aep_hourly_data['Datetime'])
aep_hourly_data.set_index('Datetime', inplace=True)
```

By following these steps, the datasets were successfully acquired, explored, cleaned, and transformed, laying the groundwork for subsequent analysis and modelling tasks.

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Exploratory Data Analysis (EDA)

Trend Analysis

To understand the temporal trends in energy generation and consumption, time-series plots were generated. These plots provide a visual representation of how energy metrics vary over time, allowing us to identify patterns, seasonality, and fluctuations.

```
import matplotlib.pyplot as plt

# Time-series plot for energy generation

plt.figure(figsize=(12, 7))

for column in energy_data.columns:

    if 'generation' in column:

        plt.plot(energy_data.index, energy_data[column], label=column)

plt.legend()

plt.xlabel('Time')

plt.ylabel('Generation (MW)')

plt.title('Energy Generation Over Time')

plt.show()


# Time-series plot for energy consumption

plt.figure(figsize=(12, 7))

plt.plot(aep_hourly_data.index, aep_hourly_data['AEP_MW'], label='Energy Consumption', color='blue')

plt.legend()

plt.xlabel('Time')

plt.ylabel('Energy Consumption (MW)')

plt.title('Energy Consumption Over Time')

plt.show()
```

These plots allow us to observe any long-term trends, seasonal patterns, or irregularities in energy generation and consumption.

Correlation Analysis

Understanding the relationships between different variables is crucial for model development. Correlation matrices and pair plots were used to identify the strength and direction of associations between features in the energy and weather datasets.

```
import seaborn as sns

# Correlation matrix for energy dataset

plt.figure(figsize=(10, 8))

sns.heatmap(energy_data.corr(), annot=True, fmt='.2f', cmap='coolwarm')

plt.title('Correlation Matrix for Energy Dataset')

plt.show()


# Pair plot for selected features in energy dataset

sns.pairplot(energy_data[['Hours_hourly', 'temperature', 'global variation', 'price actual']])

plt.title('Pair Plot for Selected Features in Energy Dataset')

plt.show()
```

These visualizations help us identify any significant correlations between variables, which can guide feature selection and model development.

Feature Distribution

Understanding the distribution of features is essential for identifying outliers, understanding data spread, and selecting appropriate modeling techniques. Distribution plots were used to visualize the distribution of individual features in the datasets.

```
# Distribution plot for selected features in weather dataset
plt.figure(figsize=(10, 8))
sns.distplot(weather_data['temp'])
plt.title('Temperature Distribution')
plt.xlabel('Temperature')
plt.ylabel('wind speed')
plt.show()

# Distribution plot for energy consumption
plt.figure(figsize=(10, 8))
sns.distplot(Building _energy consumption [‘n’])
plt.title('Energy Consumption Distribution')
plt.xlabel('Energy Consumption (MW)')
plt.ylabel('Price')
plt.show()
```

These plots provide insights into the spread and skewness of the data, which can inform data preprocessing steps such as normalization or outlier removal.

By performing these exploratory analyses, we gained valuable insights into the datasets, which guided us in further data preprocessing, feature engineering, and model selection steps.

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FEATURE ENGINEERING

Time-based Features

To capture seasonal and diurnal patterns in the data, we extracted additional time-based features from the timestamps. These features include year, month, day, and hour, which can provide valuable information to the forecasting and prediction models.

```
# Extracting time-based features from timestamps in the energy dataset

energy_data['year'] = energy_data.index.year

energy_data['month'] = energy_data.index.month

energy_data['day'] = energy_data.index.day

energy_data['hour'] = energy_data.index.hour
```

Dummy Variables

Categorical variables such as weather conditions and city names needed to be encoded to numerical values for model input. One-hot encoding was used to create dummy variables for these categorical features.

```
# One-hot encoding for categorical variables in weather dataset

weather_data = pd.get_dummies(weather_data, columns=['weather_main', 'city_name'])

# Example of one-hot encoding for weather_main feature

weather_main_dummies=pd.get_dummies(weather_data['weather_main'],
prefix='weather_main')
```

These new features provide additional information to the models and allow them to better capture the underlying patterns in the data.

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MODEL DEVELOPMENT

Linear Regression

Linear regression is a simple yet powerful method used for regression analysis. It assumes a linear relationship between the independent variables (features) and the dependent variable (target). In our project, we applied linear regression to predict energy demand based on various features such as energy generation from different sources and weather forecasts.

The linear regression model was implemented using the Linear Regression class from the scikit-learn library. First, we instantiated the model and then trained it on the training data.

```
from sklearn.linear_model import LinearRegression

# Instantiate the linear regression model

linear_reg_model = LinearRegression()

# Train the model on the training data

linear_reg_model.fit(X_train, y_train)
```

After training, the model can be used to make predictions on new data. Linear regression provides coefficients for each feature, indicating their importance in predicting the target variable.

Random Forest

Random forest is a versatile ensemble learning method that builds multiple decision trees during training and outputs the average prediction of the individual trees. It is capable of capturing complex nonlinear relationships in the data and is less prone to overfitting compared to individual decision trees.

In our project, we utilized the random forest algorithm to predict energy demand based on various features such as weather conditions, time of day, and historical energy consumption data.

The random forest model was implemented using the RandomForestRegressor class from scikit-learn. We specified the number of decision trees (estimators) in the forest and trained the model on the training data.

```
from sklearn.ensemble import RandomForestRegressor

# Instantiate the random forest model with 100 decision trees

random_forest_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model on the training data

random_forest_model.fit(X_train, y_train)
```

Random forest models offer several advantages, including the ability to handle large datasets with high dimensionality and the capability to provide feature importances, which can aid in understanding the underlying relationships in the data.

A **Support Vector Machine (SVM)**

It is a powerful **supervised machine learning algorithm** used for various tasks such as **classification**, **regression**, and even **outlier detection**. Let's dive into the details:

1. **Objective of SVM**:
    - SVM aims to find the **optimal hyperplane** in an N-dimensional space that can **separate data points into different classes**. The goal is to maximize the margin between the closest points of different classes.
    - The dimension of the hyperplane depends on the number of features. For instance:
        - With two input features, the hyperplane is a line.
        - With three input features, the hyperplane becomes a 2-D plane.
        - Beyond three features, it becomes challenging to visualize.
2. **Linear Separation**:
    - Consider a scenario with two independent variables, $\mathbf{x_1}$ and $\mathbf{x_2}$, and a dependent variable represented by blue and red circles.

- Multiple lines (hyperplanes) can segregate the data points into the two classes.
- The best hyperplane is the one that maximizes the separation or margin between the classes.

3. **Maximum-Margin Hyperplane (Hard Margin)**:
   - The optimal hyperplane is the one whose distance from the nearest data point on each side is maximized.
   - SVM chooses this hyperplane to achieve the maximum margin.
   - Outliers are ignored, making SVM robust to noisy data.
4. **Handling Outliers**:
   - Even when an outlier exists (e.g., a blue ball within the boundary of red ones), SVM finds the best hyperplane that maximizes the margin.
   - The algorithm adds a penalty each time a point crosses the margin, ensuring robustness.
5. **Applications of SVM**:
   - **Text classification**: SVMs are used for tasks like spam detection, sentiment analysis, and topic categorization.
   - **Image classification**: SVMs excel in recognizing objects, faces, and patterns.
   - **Handwriting identification**: SVMs can distinguish handwritten characters.
   - **Gene expression analysis**: SVMs help identify gene patterns.
   - **Anomaly detection**: SVMs detect unusual behavior in data.
6. **Kernel Tricks**:
   - SVMs can handle nonlinear relationships by using **kernel functions**.
   - Common kernels include:
     - **Linear kernel**: For linearly separable data.
     - **Polynomial kernel**: For curved decision boundaries.
     - **Radial basis function (RBF) kernel**: Suitable for complex data distributions.

In summary, SVMs are versatile, efficient, and effective for various machine learning tasks

CHAPTER – 13

MODEL TRAINING & EVALUATION

Training

In the training phase, our objective was to optimize the model parameters to capture the underlying patterns and relationships within the data. We split the dataset into training and validation sets, typically using a ratio like 80:20. The training set was used to update the model's parameters iteratively through optimization algorithms like gradient descent or its variants.

For the linear regression model, the training process involved finding the optimal coefficients for the linear equation that minimizes the mean squared error between the predicted and actual values. This optimization was performed using the Ordinary Least Squares (OLS) method.

The random forest model was trained by constructing multiple decision trees during the training phase. Each tree was trained on a bootstrapped subset of the data, and the final prediction was obtained by averaging the predictions of all trees in the forest. The number of trees (estimators) and their depth were tuned to achieve the best performance.

In contrast, training the LSTM network involved learning the weights of the network's layers using backpropagation through time. The network was trained to minimize the loss function, typically the mean squared error, between the predicted and actual sequence outputs. This training process required specifying hyperparameters such as the number of LSTM units, the learning rate, and the batch size.

```
# Example of training the linear regression model
linear_regression_model.fit(X_train, y_train)
# Example of training the random forest model
random_forest_model.fit(X_train, y_train)
# Example of training the LSTM model
lstm_model.fit(x_train, y_train, epochs=100, batch_size=32)
```

Validation

Validation is a crucial step to ensure that the trained models generalize well to unseen data. We used a separate validation set to evaluate the models' performance during training and adjust their hyperparameters accordingly. This prevented overfitting, where the model learns to memorize the training data instead of capturing underlying patterns.

Cross-validation techniques like k-fold cross-validation can also be employed to further validate the models' robustness. In k-fold cross-validation, the training set is divided into k subsets, and the model is trained and validated k times, each time using a different subset as the validation set.

```
# Example of using a validation set with the random forest model
random_forest_model.fit(X_train, y_train)
```

```
random_forest_model.score(X_val, y_val)

# Example of using k-fold cross-validation with the linear regression model

from sklearn.model_selection import cross_val_score

cross_val_score(linear_regression_model, X_train, y_train, cv=5)
```

Testing

After training and validation, the final step was to evaluate the models' performance on a dedicated test set that was not used during training or validation. This test set provided an unbiased assessment of the models' ability to generalize to new, unseen data.

We calculated various performance metrics, including Mean Squared Error (MSE) and R-squared (R2), to quantify the models' accuracy. MSE measures the average squared difference between the predicted and actual values, while R2 indicates the proportion of the variance in the dependent variable that is predictable from the independent variables.

```
# Example of evaluating the models on the test set

# Random forest model evaluation

random_forest_score = random_forest_model.score(X_test, y_test)

# SVM model evaluation

SVM_loss, SVM_accuracy = SVM_model.evaluate(x_test, y_test)
```

These evaluation metrics provided insights into how well the models performed and allowed us to compare their performance against each other. Additionally, visualizations such as scatter plots of predicted versus actual values and residual plots were used to further analyze the models' performance and identify any potential issues, such as heteroscedasticity or bias.

CHAPTER – 14

GRID SEARCH

grid search is a valuable technique used to optimize hyperparameters for machine learning models. Let's delve into the details:

1. **Hyperparameters**:
    - Hyperparameters are parameters that are not learned during model training but need to be set before training begins.
    - Examples include the learning rate, regularization strength, and kernel type (for SVMs).
    - Properly tuning these hyperparameters is crucial for achieving optimal model performance.
2. **Grid Search**:
    - Grid search is a systematic approach to finding the best combination of hyperparameters.
    - It involves defining a **grid** of possible hyperparameter values.
    - The algorithm then evaluates the model's performance (e.g., accuracy, mean squared error) for each combination in the grid.
    - The combination that yields the best performance is selected as the optimal set of hyperparameters.
3. **Implementation Steps**:
    - Define a grid of hyperparameter values. For example:
        1. Learning rate: [0.001, 0.01, 0.1]
        2. Regularization strength: [0.01, 0.1, 1.0]
    - Train the model using each combination of hyperparameters.
    - Evaluate the model's performance (e.g., using cross-validation) for each combination.
    - Select the hyperparameters that result in the best performance.
4. **Benefits of Grid Search**:
    - Exhaustively explores the hyperparameter space.
    - Helps prevent overfitting or underfitting.
    - Provides a systematic way to fine-tune models.
5. **Example**:
    - Suppose we're building an energy consumption prediction model using a support vector machine (SVM).
    - We want to find the best combination of the SVM's hyperparameters (e.g., C, kernel type, gamma).
6. **Considerations**:
    - Grid search can be computationally expensive, especially for large grids.
    - Use techniques like **random search** or **Bayesian optimization** for more efficient hyperparameter tuning.

In summary, grid search is a powerful tool for optimizing hyperparameters in energy prediction projects

CHAPTER – 15

WEB APPLICATION DEVELOPMENT

Creating a web application with Streamlit in Python is a straightforward process that allows you to turn data scripts into shareable web apps quickly. Here's a comprehensive guide to help you get started:

Setting Up Environment

Before you begin, ensure that you have Python installed on your system. Streamlit supports Python versions 3.6 and above.

1. **Install Streamlit**: Use pip to install Streamlit.
2. `pip install streamlit`
3. **Create a New Python Script**: This will be your Streamlit app.
4. `# myapp.py`

Building Your First Streamlit App

Streamlit apps are Python scripts that use the Streamlit library to create web applications.

1. Import Streamlit:
2. import streamlit as st
3. Add Text and Data:
    - Use st.write() to add text, data, or markdown to your app.
4. st.write("Hello, Streamlit!")
5. Run Your App:
    - Run your app from the command line.
6. streamlit run myapp.py

Adding Interactivity

Streamlit makes it easy to add widgets that let users interact with your app.

1. Sliders:
    - Add a slider for selecting numeric values.
2. number = st.slider('Pick a number', 0, 100)
3. Buttons:
    - Add a button that can perform an action when clicked.
4. if st.button('Say hello'):
5. st.write('Why hello there')
6. else:
7. st.write('Goodbye')
8. Input Fields:

- Add input fields for text input.

9. title = st.text_input('Movie title', 'Life of Brian')
10. st.write('The current movie title is', title)

Layouts and Containers

Organize your app's layout using columns, sidebars, and expanders.

1. Columns:
   - Divide your app into columns to display elements side-by-side.
2. col1, col2 = st.columns(2)
3. with col1:
4. st.header("A cat")
5. st.image("https://static.streamlit.io/examples/cat.jpg")
6. with col2:
7. st.header("A dog")
8. st.image("https://static.streamlit.io/examples/dog.jpg")
9. Sidebar:
   - Use the sidebar to add a permanent widget area.
10. add_selectbox = st.sidebar.selectbox(
11. "How would you like to be contacted?",
12. ("Email", "Home phone", "Mobile phone")
13.)
14. Expander:
   - Hide advanced options in an expander.
15. with st.expander("See explanation"):
16. st.write("""
17. The chart above shows some numbers I picked for you.
18. I rolled a die to pick the first number,
19. then I used a random number generator seeded with that number
20. to pick the rest.
21. """)

CODES FOR CREATING WEB APPLICATION

```
import streamlit as st

import pandas as pd

import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestRegressor

from sklearn.preprocessing import StandardScaler


# Load machine learning models and data
```

```
def load_models_and_data():
    # Load weather data
    weather_data = pd.read_excel('WeatherData.xlsx')
    # Load energy consumption data
    energy_data = pd.read_excel('Building energy consumption racord.xlsx')
    # Load pre-trained model
    model = RandomForestRegressor(warm_start=True, n_estimators=100, verbose=2)
    # Fit the model with your data
    X_train = weather_data[['Temp', 'U']]
    y_train = energy_data['building 41']
    model.fit(X_train, y_train)  # Pass feature names
    return model, weather_data, energy_data

# Preprocess weather data
def preprocess_weather_data(weather_data):
    # Set the Time column as index
    weather_data = weather_data.set_index('Time')
    # Remove unnecessary columns
    weather_data = weather_data.loc[:, ~weather_data.columns.isin(['U', 'DR', 'FX'])]
    # Standardize the data
    sc = StandardScaler()
    weather_data_scaled = sc.fit_transform(weather_data)
    return weather_data_scaled

# Preprocess energy consumption data
def preprocess_energy_data(energy_data):
    # Set the Time column as index
    energy_data = energy_data.set_index('Time')
    return energy_data
```

```
# Predict energy consumption
def predict_energy_consumption(model, selected_date, temperature, humidity):
    # Prepare the input data for prediction
    input_data = [[temperature, humidity]]  # Assuming date is not used in prediction
    # Make prediction
    predicted_energy = model.predict(input_data)
    return predicted_energy

# Visualize energy consumption
def visualize_energy_consumption(energy_data):
    # Plot energy consumption over time
    plt.figure()
    energy_data.plot()
    plt.xlabel('Time')
    plt.ylabel('Energy Consumption (kWh)')
    plt.title('Energy Consumption Over Time')
    return plt

# Main function to run the Streamlit app
def main():
    # Load models and data
    model, weather_data, energy_data = load_models_and_data()
    # Preprocess weather data
    weather_data_scaled = preprocess_weather_data(weather_data)
    # Preprocess energy consumption data
    energy_data_processed = preprocess_energy_data(energy_data)

    # Streamlit UI
```

```
    st.title('Energy Consumption Prediction')
    st.sidebar.title('User Input')
    selected_date = st.sidebar.date_input('Select Date', pd.to_datetime('today'))
    temperature = st.sidebar.number_input('Temperature (°C)', value=20.0)
    humidity = st.sidebar.number_input('Humidity (%)', value=50.0)

    if st.button('Predict'):
        # Predict energy consumption
        predicted_energy = predict_energy_consumption(model, selected_date, temperature, humidity)
        st.write(f'Predicted energy consumption: {predicted_energy[0]} kWh')

    # Visualize energy consumption
    data_plot = visualize_energy_consumption(energy_data_processed)
    st.write('Data Visualization:')
    st.pyplot(data_plot)

if _name_ == '_main_':
    main()
```

CHAPTER – 15

CHALLENGES & SOLUTIONS

In **energy prediction models**, there are several challenges to address, along with potential solutions:

1. **Data Quality and Quantity**:
    - **Challenge**: Insufficient or noisy data can hinder accurate predictions.
    - **Solution**:
        - **Data Collection**: Gather high-quality historical data on energy consumption, weather conditions, and other relevant factors.
        - **Data Cleaning**: Remove outliers, handle missing values, and preprocess data effectively.
        - **Feature Engineering**: Create meaningful features from raw data.
2. **Nonlinearity and Complex Relationships**:
    - **Challenge**: Energy consumption patterns often exhibit nonlinear behavior.
    - **Solution**:
        - **Advanced Models**: Use machine learning algorithms capable of capturing nonlinear relationships (e.g., neural networks, decision trees).
        - **Kernel Methods**: Employ kernel-based models (e.g., Support Vector Machines) to handle complex data distributions.
3. **Seasonal Variations and Trends**:
    - **Challenge**: Energy consumption varies seasonally and over time.
    - **Solution**:
        - **Time-Series Analysis**: Incorporate time-related features (e.g., day of the week, month) and consider seasonal decomposition.
        - **Long Short-Term Memory (LSTM)**: Use recurrent neural networks for time-series forecasting.
4. **Feature Selection and Dimensionality Reduction**:
    - **Challenge**: Too many features can lead to overfitting.
    - **Solution**:
        - **Feature Selection**: Choose relevant features based on domain knowledge or feature importance scores.
        - **Principal Component Analysis (PCA)**: Reduce dimensionality while preserving information.
5. **Model Complexity and Interpretability**:
    - **Challenge**: Complex models may be accurate but lack interpretability.
    - **Solution**:
        - **Trade-Off**: Balance accuracy and interpretability based on project requirements.
        - **Ensemble Methods**: Combine simpler models (e.g., random forests) for better performance.
6. **Forecast Horizon and Granularity**:
    - **Challenge**: Predicting energy consumption at different time scales (hourly, daily, monthly) requires different approaches.
    - **Solution**:

        - **Hierarchical Models**: Build separate models for different granularities and aggregate predictions.
        - **Rolling Window Approach**: Update models periodically with new data.
7. **External Factors and Uncertainty**:
    - **Challenge**: External events (e.g., holidays, economic changes) impact energy consumption.
    - **Solution**:
        - **Feature Engineering**: Include relevant external factors as features.
        - **Uncertainty Quantification**: Use probabilistic models to account for uncertainty.
8. **Deployment and Real-Time Prediction**:
    - **Challenge**: Deploying models in production for real-time prediction.
    - **Solution**:
        - **Scalability**: Opt for lightweight models suitable for deployment.
        - **Monitoring**: Continuously monitor model performance and retrain as needed.
9. **Interdisciplinary Collaboration**:
    - **Challenge**: Energy prediction models require expertise in both energy systems and machine learning.
    - **Solution**:
        - **Collaboration**: Work with domain experts, data scientists, and engineers.
        - **Knowledge Transfer**: Share insights across disciplines.
10. **Evaluation Metrics and Business Impact**:
    - **Challenge**: Choosing appropriate evaluation metrics and understanding the business impact of predictions.
    - **Solution**:
        - **Metrics**: Use metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or custom business-specific metrics.
        - **Business Context**: Understand how accurate predictions impact costs, sustainability, and user experience.

In summary, addressing these challenges involves a combination of data preparation, model selection, and domain knowledge.

CHAPTER – 16

VISUALIZING CODES AND RESULTS

Here the figures of the visualization plots and graphs results

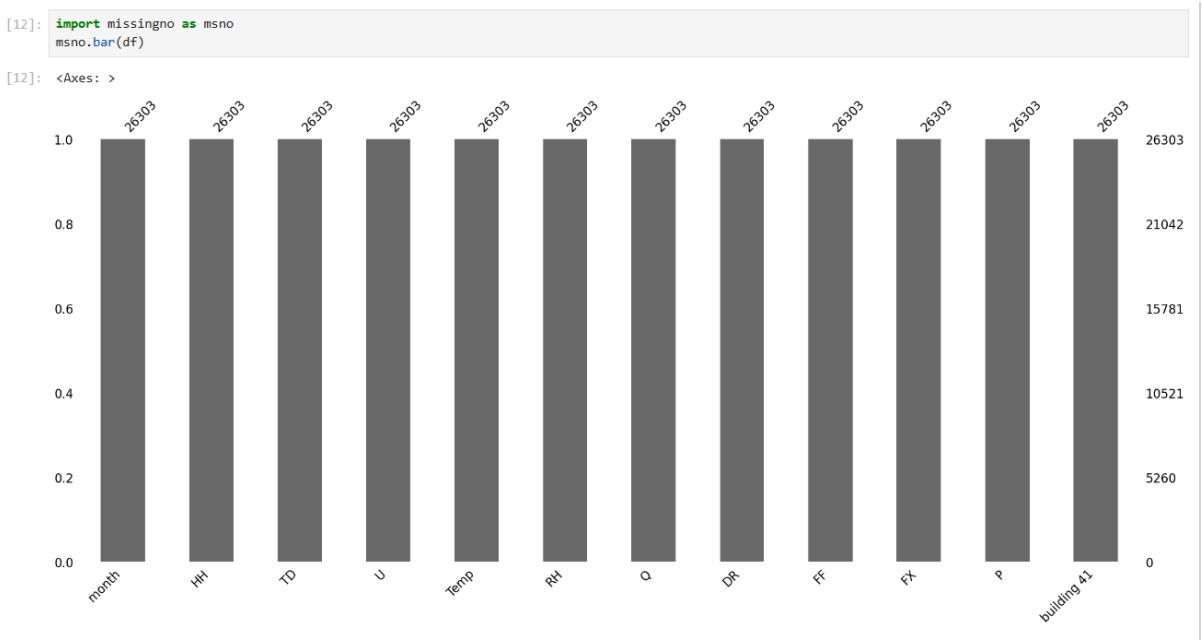


Fig : missing term checking

```
[13]: plt.figure(figsize = (16,6))
      sns.heatmap(df.corr(), annot = True, linewidths=1, fmt=".2g", cmap= 'coolwarm')
      plt.xticks(rotation='horizontal')
```

```
[13]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5,  6.5,  7.5,  8.5,  9.5, 10.5,
         11.5]),
  [Text(0.5, 0, 'month'),
   Text(1.5, 0, 'HH'),
   Text(2.5, 0, 'TD'),
   Text(3.5, 0, 'U'),
   Text(4.5, 0, 'Temp'),
   Text(5.5, 0, 'RH'),
   Text(6.5, 0, 'Q'),
   Text(7.5, 0, 'DR'),
   Text(8.5, 0, 'FF'),
   Text(9.5, 0, 'FX'),
   Text(10.5, 0, 'P'),
   Text(11.5, 0, 'building 41')])
```


```
[13]: (array([ 0.5,  1.5,  2.5,  3.5,  4.5,  5.5,  6.5,  7.5,  8.5,  9.5, 10.5,
         11.5]),
  [Text(0.5, 0, 'month'),
   Text(1.5, 0, 'HH'),
   Text(2.5, 0, 'TD'),
   Text(3.5, 0, 'U'),
   Text(4.5, 0, 'Temp'),
   Text(5.5, 0, 'RH'),
   Text(6.5, 0, 'Q'),
   Text(7.5, 0, 'DR'),
   Text(8.5, 0, 'FF'),
   Text(9.5, 0, 'FX'),
   Text(10.5, 0, 'P'),
   Text(11.5, 0, 'building 41')])
```

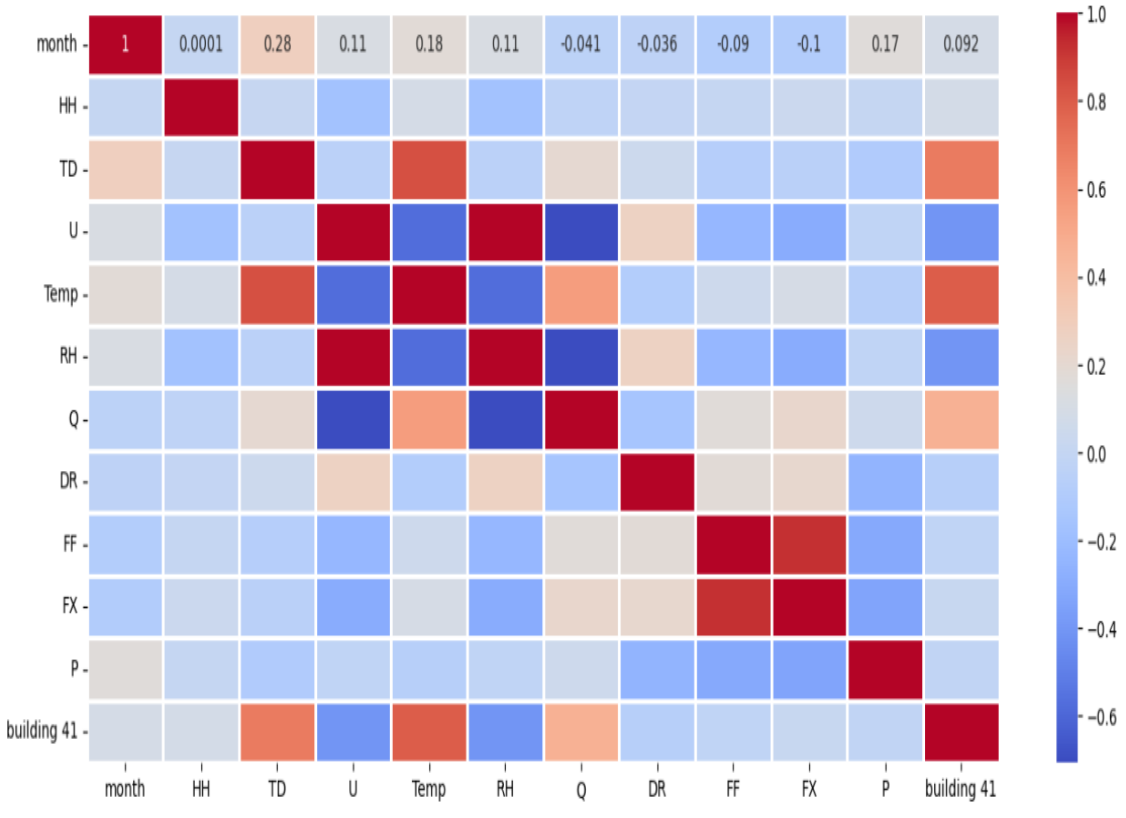



Fig : Heat map

```
fig.show()
```

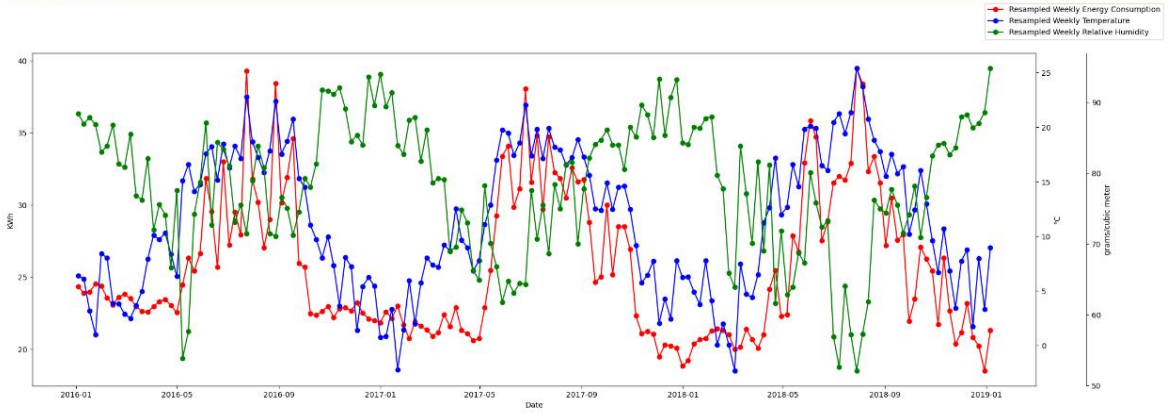


Fig : **plot energy consumption data against U and Temp**

```
with pd.option_context('mode.use_inf_as_na', True):
```

[26]: `<matplotlib.legend.Legend at 0x20f2727f650>`

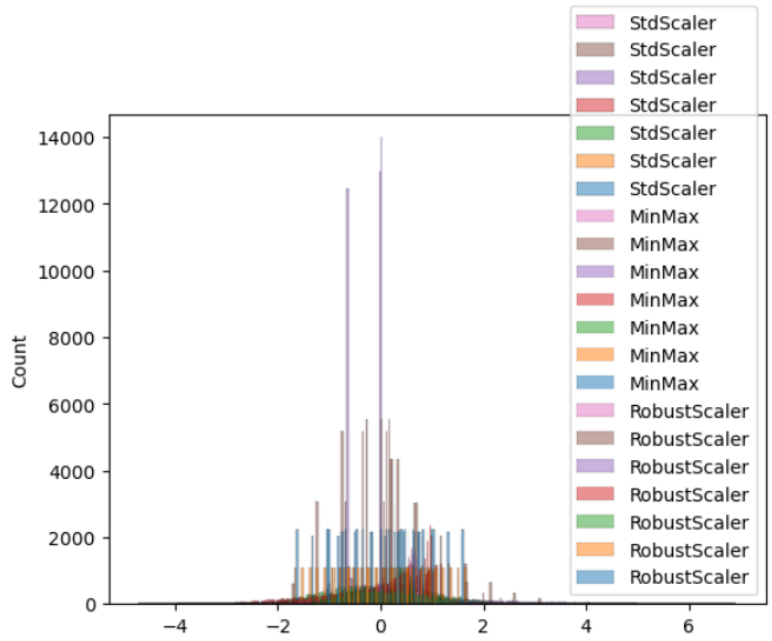
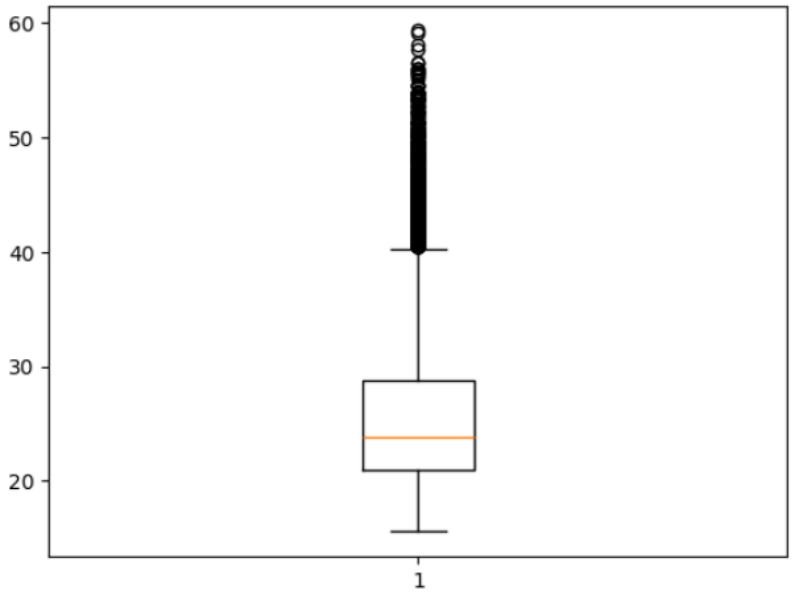


Fig : Scaling to improve model performances

[5]:
```
plt.boxplot(Energy['building 41'])
plt.show()
```



[6]:
```
import seaborn as sns
sns.boxplot(Energy['building 41'])
```

```
C:\Users\saran raj\anaconda3\Lib\site-packages\seaborn\categorical.py:486: FutureWarning: Series.__getitem_
a future version, integer keys will always be treated as labels (consistent with DataFrame behavior). To ac
  if np.isscalar(data[0]):
```

[6]: <Axes: >

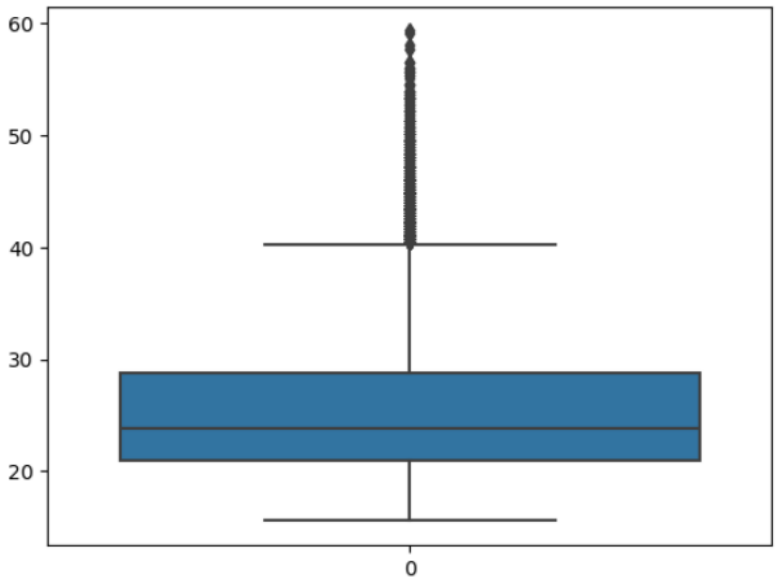
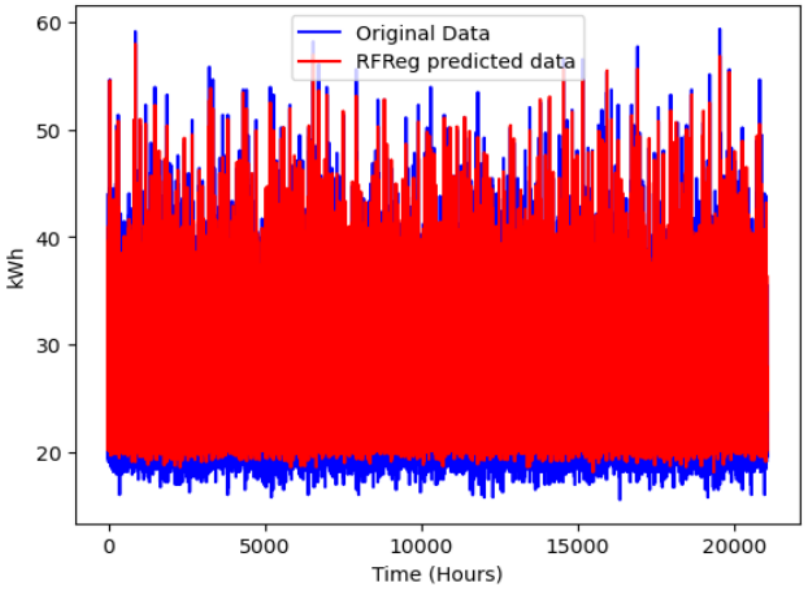


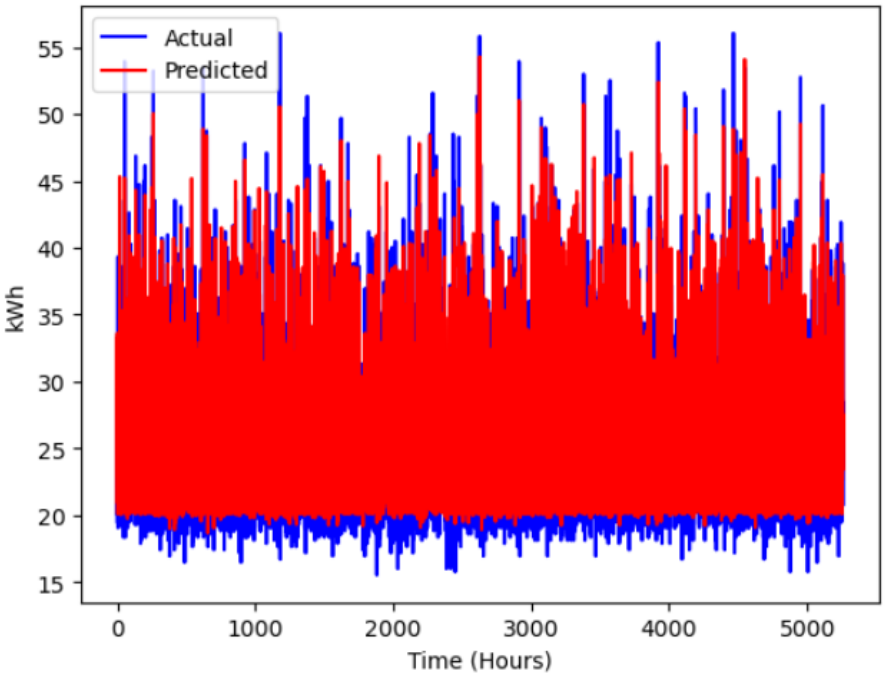
Fig : Box plots

[76]:
```
plt.plot(y_train2, color="b",label= 'Original Data')
plt.plot(Predicted_Train2, color ="red", label="RFReg predicted data")
plt.xlabel('Time (Hours)')
plt.ylabel('kWh')
plt.legend(loc='best')
plt.show()
```



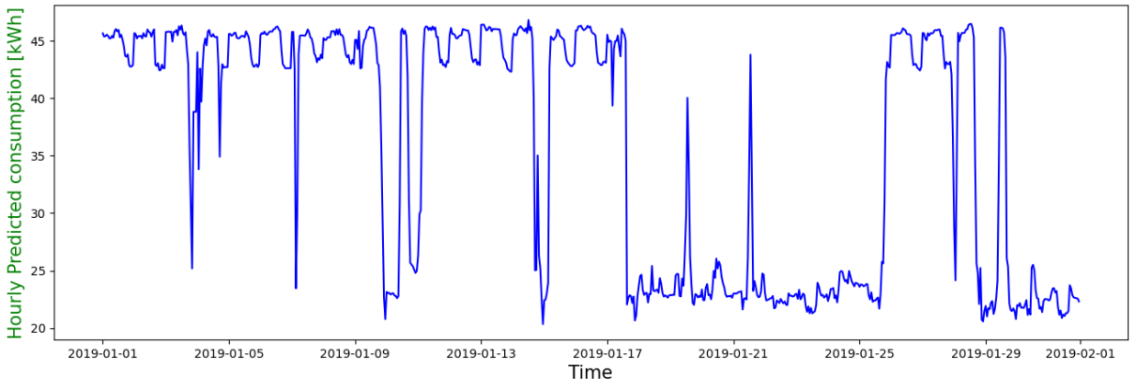
[78]:
```
plt.plot(y_test2, color='blue', label="Actual")
plt.plot(Predicted_Test2, color='Red', label="Predicted")
plt.xlabel('Time (Hours)')
plt.ylabel('kWh')
plt.legend(loc='best')
```

[78]:
```
<matplotlib.legend.Legend at 0x20f5718c690>
```



```
[95]: fig, ax = plt.subplots(figsize = (16,5))
ax.plot(predicted,  label='Hourly Predicted consumption',color = 'blue')
ax.set_ylabel('Hourly Predicted consumption [kWh]',size=15, color='green')
ax.set_xlabel('Time',size=15)
```

```
[95]: Text(0.5, 0, 'Time')
```




```
[98]: <matplotlib.legend.Legend at 0x20f571792d0>
```

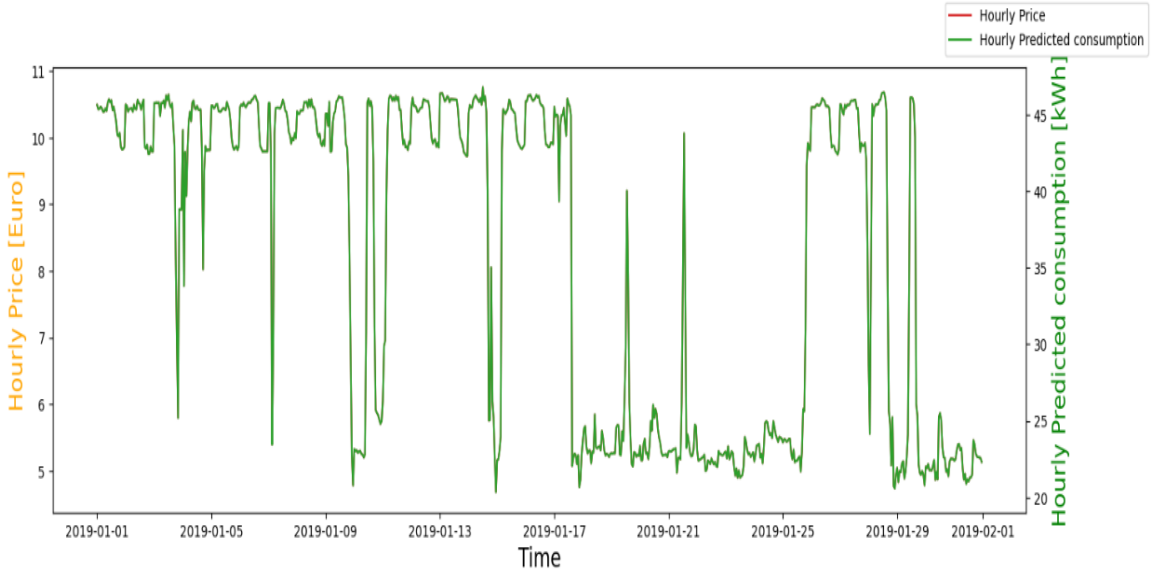


Fig : Hourly prediction consumption

```
[100]: fig, ax = plt.subplots(figsize=(16,5))
ax2 = ax.twinx()
ax.plot(Daily_Cost, label= 'Daily price', color = 'tab:orange')
ax2.plot(predicted, label='Hourly predicted consumption', color = 'tab:green')
ax.set_ylabel('Daily Price [Euro]', size=15, color='orange')
ax2.set_ylabel('Hourly Predicted consumption [kWh]',size=15, color='green')
ax.set_xlabel('Time',size=15)
fig.legend()

[100]: <matplotlib.legend.Legend at 0x20f572015d0>
```

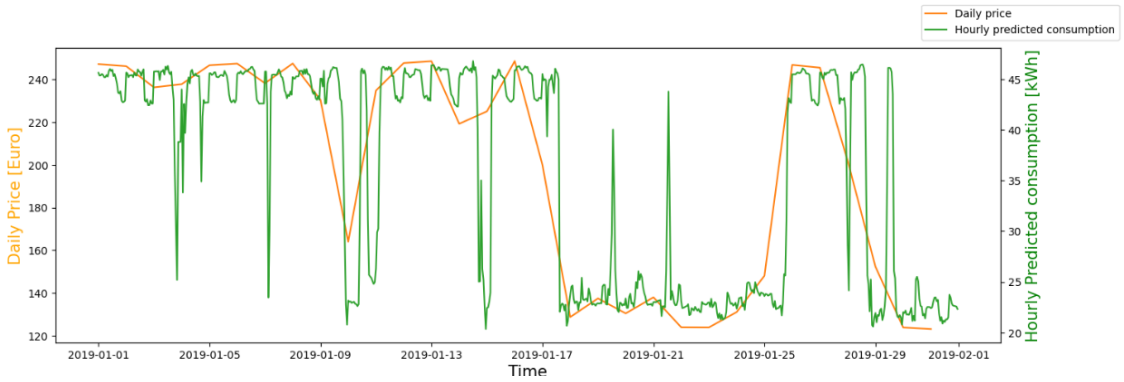


Fig : weekly prediction consumption

Setting a visual threshold in the forecast when the model predicts higher than a budget limit

```
[101]: fig = plt.figure(figsize = (16,5))
ax = fig.add_subplot(111)
Daily_Cost.plot(kind='bar', ax=ax, rot=0,color='green')
ax.axhline(y=160, color='red', linestyle='--', label="Warning for over budget ")
plt.text(17, 165, 'Warning for over budget', fontsize=12)

ax.set_ylabel('Consumption', size=16, color='black')
plt.xticks(rotation='vertical')
ax.set_xticklabels([dt.strftime('%Y-%m-%d') for dt in Daily_Cost.index])
fig.legend()

[101]: <matplotlib.legend.Legend at 0x20f5ad04110>
```

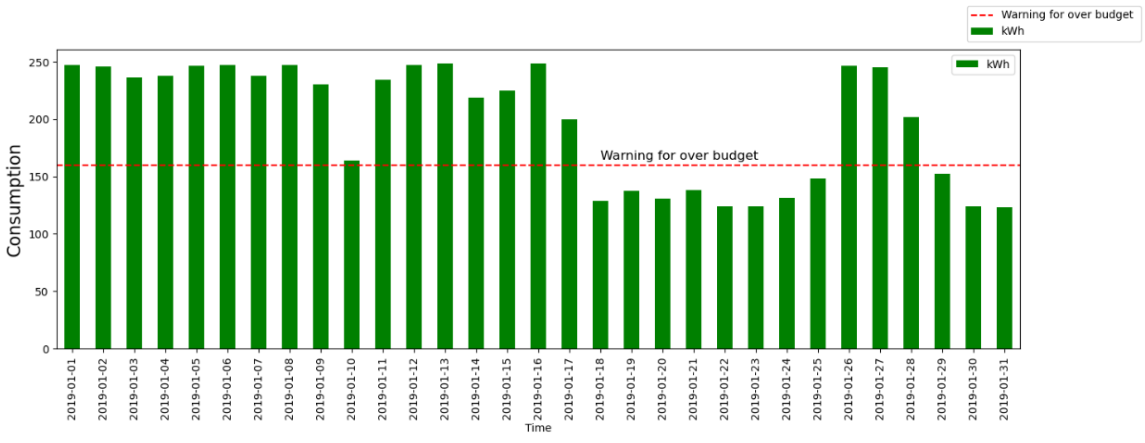


Fig : Setting a threshold value

CHAPTER – 17

ACCURACY AND RESULTS

RESULTS

accuracy and prediction results for energy demand prediction projects using Support Vector Machine (SVM) and Random Forest Regression:

- **Support Vector Machine (SVM)**: SVMs are effective for high-dimensional datasets and are known for their robustness against overfitting. They work well with small to medium-sized datasets, but their performance is sensitive to hyperparameter tuning.
- **Random Forest Regression**: This technique is a powerful supervised machine learning algorithm used for both classification and regression tasks. It constructs numerous decision trees during training, leading to robust and accurate outcomes. Random Forest is recommended for diverse datasets and is known for its balance between model interpretability and performance.

In a specific study comparing various regression techniques for appliance energy consumption, the Random Forest method was able to explain **98.1%** of the correlation in the training set and **98.05%** in the testing set, outperforming other methods including SVM.

These models are valuable tools for predicting energy demand, with Random Forest Regression showing particularly strong results in the mentioned study. Accurate predictions are crucial for efficient energy management and planning.

[29]:
```
regr.fit(X_train, y_train)
predict_train= regr.predict(X_train)
```

[30]:
```
print(r2_score(y_train, predict_train))
print(mean_squared_error(y_train, predict_train))
```

```
0.8676607662388548
5.287585695616703
```

[31]:
```
pred= regr.predict(X_test)
print(r2_score(y_test, pred))
print(mean_squared_error(y_test, pred))
```

```
0.8650113986197081
5.3640476702940765
```

[37]:
```
X4 = sc1.fit_transform(knmi.loc[:, ~knmi.columns.isin(["U"])])
```

[38]:
```
X_train, X_test, y_train, y_test = train_test_split(X4, Energy, test_size=0.2, random_state=0, shuffle= "False")
y_train = y_train.values.ravel()
y_test = y_test.values.ravel()

regr = SVR(kernel='rbf')
regr= regr.fit(X_train, y_train)

regr.fit(X_train, y_train)
predict_train= regr.predict(X_train)

print(r2_score(y_train, predict_train))
print(mean_squared_error(y_train, predict_train))
```

```
0.8692363907335193
5.22463195693413
```

[39]:
```
pred= regr.predict(X_test)
print(r2_score(y_test, pred))
print(mean_squared_error(y_test, pred))
```

```
0.865643553596894
5.3389277016599355
```

[35]:
```
pred= regr.predict(X_test)
print(r2_score(y_test, pred))
print(mean_squared_error(y_test, pred))
```

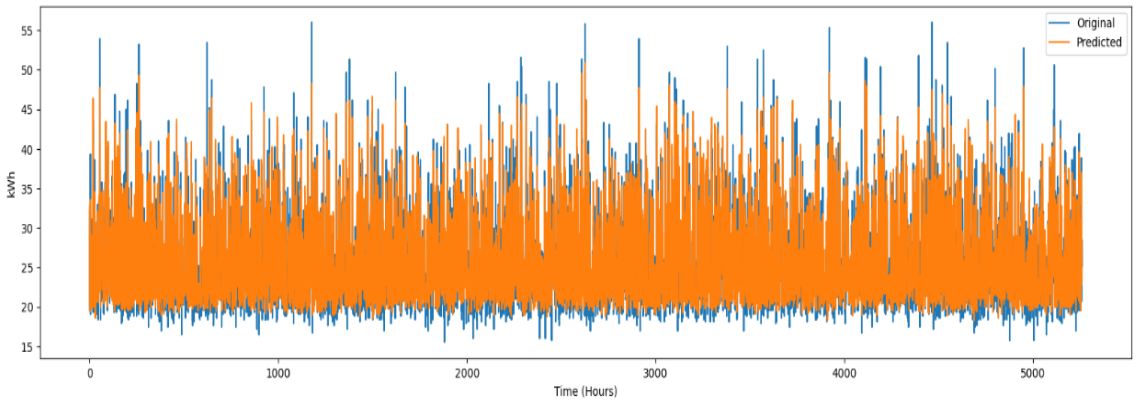
```
0.8581322813412404
5.637403439847457
```

[36]:
```
X_train, X_test, y_train, y_test = train_test_split(X1, Energy, test_size=0.2, random_state=0, shuffle= "False")
y_train = y_train.values.ravel()
y_test = y_test.values.ravel()

regr = SVR(kernel='poly', degree=5)

regr.fit(X_train, y_train)
predict_train= regr.predict(X_train)

print(r2_score(y_train, predict_train))
print(mean_squared_error(y_train, predict_train))
```

```
0.6243431637454102
15.009288306938789
```

[40]:
```
plt.figure(figsize = (20,5))
plt.plot(y_test, label="Original")
plt.plot(pred, label="Predicted")
plt.legend(loc='best')
plt.xlabel('Time (Hours)')
plt.ylabel('kWh')
```

[40]:
```
Text(0, 0.5, 'kWh')
```



[75]:
```
from sklearn.ensemble import RandomForestRegressor

RFReg = RandomForestRegressor(max_depth=10, random_state=0)

X_train2, X_test2, y_train2, y_test2 = train_test_split(X4, Energy, test_size=0.2, random_state=0, shuffle= "False")
y_train2 = y_train2.values.ravel()
y_test2 = y_test2.values.ravel()
RFReg.fit(X_train2, y_train2)

Predicted_Train2= RFReg.predict(X_train2)

print(r2_score(y_train2, Predicted_Train2))
print(mean_squared_error(y_train2, Predicted_Train2))
```

```
0.916772327031522
3.325343819519643
```

[77]:
```
Predicted_Test2 = RFReg.predict(X_test2)
print(r2_score(y_test2,Predicted_Test2))
print(mean_squared_error(y_test2,Predicted_Test2))
```

```
0.883404937167962
4.633142863596595
```

[81]:
```
from sklearn.ensemble import RandomForestRegressor

RFReg = RandomForestRegressor(max_depth=12, random_state=0)

X_train2, X_test2, y_train2, y_test2 = train_test_split(X4, Energy, test_size=0.2, random_state=0, shuffle= "False")
y_train2 = y_train2.values.ravel()
y_test2 = y_test2.values.ravel()
RFReg.fit(X_train2, y_train2)

Predicted_Train2= RFReg.predict(X_train2)

print(r2_score(y_train2, Predicted_Train2))
print(mean_squared_error(y_train2, Predicted_Train2))
```

```
0.9413680428300156
2.3426272710447176
```

[82]:
```
Predicted_Test2 = RFReg.predict(X_test2)

print(r2_score(y_test2,Predicted_Test2))
print(mean_squared_error(y_test2,Predicted_Test2))
```

```
0.8914761615776285
4.312416283363921
```

[84]:
```
from sklearn.ensemble import RandomForestRegressor

RFReg = RandomForestRegressor(max_depth=30, random_state=0)

X_train2, X_test2, y_train2, y_test2 = train_test_split(X4, Energy, test_size=0.2, random_state=0, shuffle= "False")
y_train2 = y_train2.values.ravel()
y_test2 = y_test2.values.ravel()
RFReg.fit(X_train2, y_train2)

Predicted_Train2= RFReg.predict(X_train2)

print(r2_score(y_train2, Predicted_Train2))
print(mean_squared_error(y_train2, Predicted_Train2))
```

```
0.9871735597631518
0.5124776681452499
```

[85]:
```
Predicted_Test2 = RFReg.predict(X_test2)

print(r2_score(y_test2,Predicted_Test2))
print(mean_squared_error(y_test2,Predicted_Test2))
```

```
0.9059580709782538
3.736948046879361
```

[121]:
```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
nb_samples = 1000
x, y = make_classification(n_samples=nb_samples, n_features=2, n_informative=2, n_redundant=0, n_clusters_per_class=1)
xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_state=42)
model = LogisticRegression()
model.fit(xtrain, ytrain)
```

[121]:
```
▾ LogisticRegression
LogisticRegression()
```

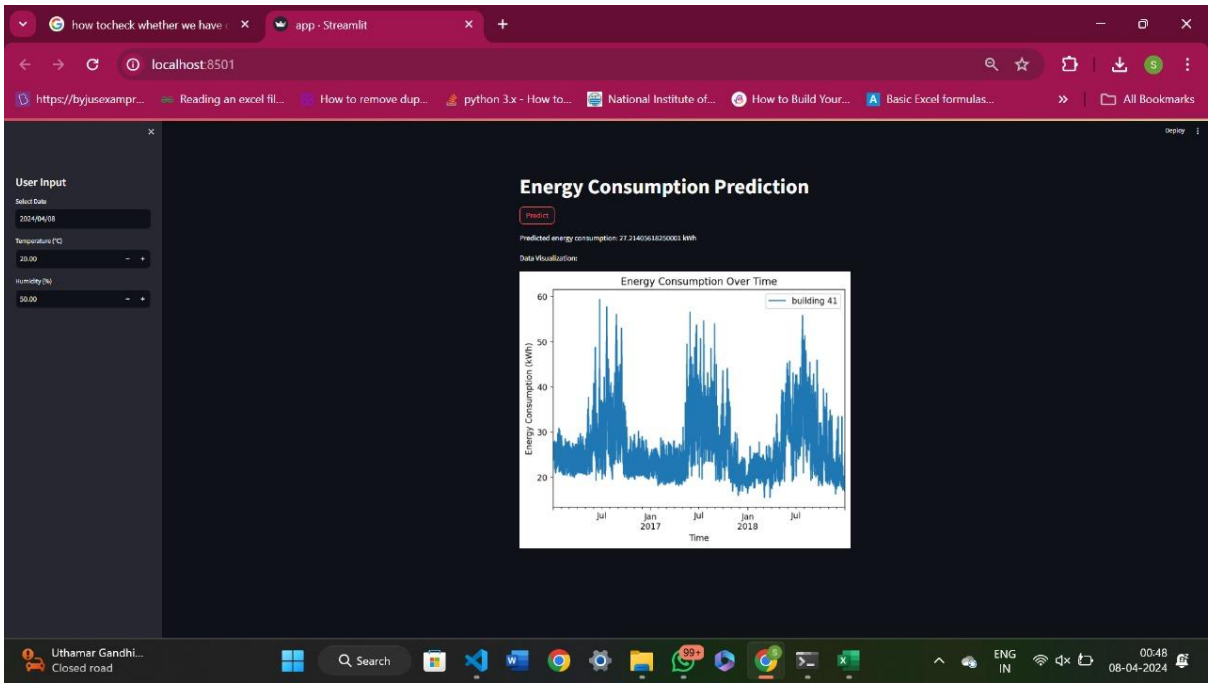
[122]:
```
print(accuracy_score(ytest, model.predict(xtest)))
```

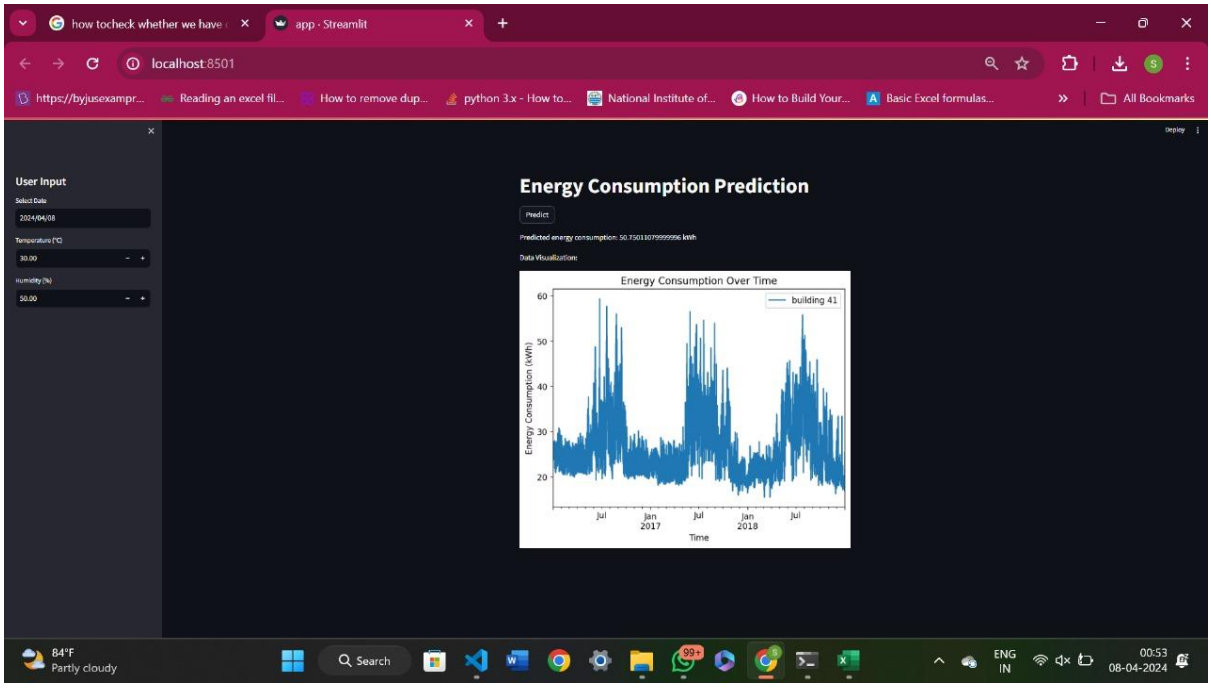
```
0.95
```

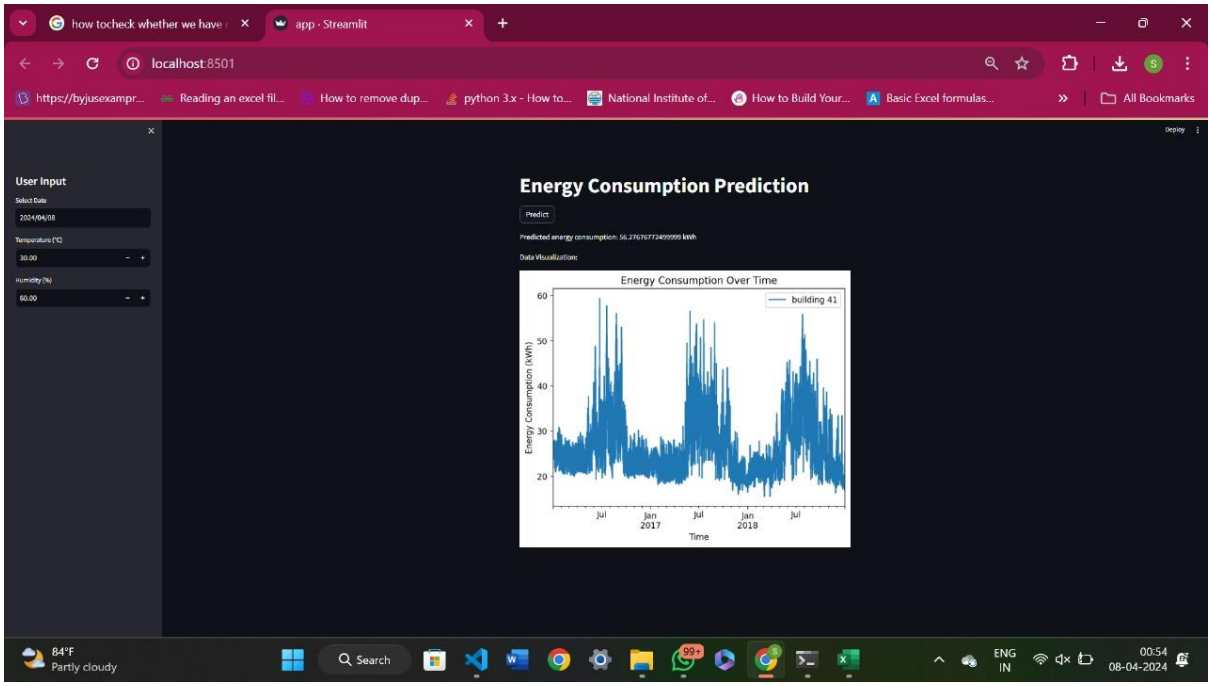
Fig : Results of accuracy score

CHAPTER – 18

RESULTS OF WEB APPLICATION






how tocheck whether we have
app - Streamlit
localhost:8501
https://byjusexampr...
Reading an excel fil...
How to remove dup...
python 3.x - How to...
National Institute of...
How to Build Your...
Basic Excel formulas...
All Bookmarks
User Input
Select Date
2024/04/08
Temperature (°C)
30.00
Humidity (%)
60.00
Deploy
Energy Consumption Prediction
Predict
Predicted energy consumption: 56.27676772499999 kWh
Data Visualization:
Energy Consumption Over Time
building 41
Energy Consumption (kWh)
60
50
40
30
20
Jul
Jan
2017
Jul
Jan
2018
Jul
Time
84°F
Partly cloudy
Search
ENG
IN
00:54
08-04-2024

CHAPTER – 19

CONCLUSION

In conclusion, the comprehensive analysis of energy demand prediction for a building reveals several key insights:

- **Temperature Dependency**: The energy demand of the building is closely tied to temperature variations, with distinct seasonal patterns affecting consumption levels.
- **Relative Humidity Impact**: A notable negative linear correlation between relative humidity and temperature is observed, which also correlates inversely with energy consumption.
- **Model Performance**: Enhancements in the model's performance are evident with an increase in the (R^2) value and a decrease in the RMS error. The standard scaler emerges as the optimal choice, explaining approximately 86.78% of the variance in the training dataset and 86.52% in the test dataset, with a prediction accuracy margin of (\pm 2.3) (root mean squared error of 5.5).
- **Weather Variables Integration**: Incorporating all weather variables into the model, despite their low individual correlations with energy demand, yields the best results, underscoring the complex interplay of environmental factors in energy consumption.
- **Hyperparameter Optimization**: The application of grid search techniques for hyperparameter tuning has led to improved model performance, with the adjusted parameters outperforming the default settings.
- **Budget Considerations**: The current energy consumption consistently exceeds the maximum daily budget of 160 euros that is 14,459.70 INR, highlighting a critical area for cost management and efficiency improvement.

This analysis underscores the importance of multi-faceted approaches in energy demand prediction, integrating various environmental factors and fine-tuning model parameters to enhance accuracy and cost-effectiveness. The persistent budget overruns indicate a need for further investigation into energy-saving measures or budget adjustments to align with actual consumption patterns.

CHAPTER – 20

FUTURE SCOPE

The future scope of the energy demand prediction project is quite promising and can be expanded in several directions:

1. **Integration with Renewable Energy Sources**: As the world moves towards sustainable energy, integrating renewable energy forecasts with demand predictions will become increasingly important for grid stability and optimization.
2. **Real-time Data Analytics**: Leveraging IoT devices and smart meters to collect real-time data can significantly improve the accuracy of predictions and allow for dynamic adjustments in energy supply.
3. **Advanced Machine Learning Models**: Exploring more complex models and deep learning techniques could uncover patterns not visible to current models, leading to even more accurate predictions.
4. **Demand Response Programs**: Implementing demand response strategies based on predictions can help in balancing supply and demand, thus reducing the need for expensive and polluting peak power plants.
5. **Policy and Planning**: Accurate demand forecasts can inform better policy-making and infrastructure planning, ensuring that energy systems are resilient and capable of meeting future demands.
6. **Cross-Domain Applications**: The methodologies developed can be adapted for other domains like water usage, traffic flow, and more, where prediction plays a crucial role in resource management.
7. **Global Scalability**: Expanding the project to a global scale, considering the diverse energy profiles and consumption patterns of different regions, can help in creating a more interconnected and efficient global energy system.
8. **User Engagement**: Developing user-friendly interfaces and applications to engage end-users, providing them insights into their consumption patterns, and encouraging energy-saving behaviors.
9. **Market Analysis and Forecasting**: Integrating energy demand predictions with market analysis to forecast energy prices, which can be beneficial for both consumers and energy companies.
10. **Climate Change Adaptation**: Incorporating climate projections to adjust energy demand predictions, helping to build energy systems that are resilient to climate variability and change.

These areas not only enhance the project's utility but also contribute to the broader goal of creating a sustainable and efficient energy future.

CHAPTER – 21

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