PREDICTING WIND TURBINE PERFORMANCE USING MACHINE LEARNING TECHNIQUES

A MINI PROJECT REPORT

Submitted by

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In partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

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ENGINEERING COLLEGE, ALAMATHI ROAD, AVADI, CHENNAI-62

(AN AUTONOMOUS INSTITUTION)

ANNA UNIVERSITY

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ANNA UNIVERSITY

BONAFIDE CERTIFICATE

Certified that this project report of title "**PREDICTING WIND TURBINE PERFORMANCE USING MACHINE LEARNING TECHNIQUES**" is the bonafide work of **HARIHARASUDHARSAN N (113121UG03032), KAVIN S (113121UG03046), ASHWIN JOSH B (113121UG03301),** who carried out the project work under my supervision.

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This project report was submitted for viva voce held on ____________________________
At Vel Tech Multi Tech Dr. Rangarajan and Dr. Sakunthala Engineering College.

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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(HARIHARASUDHARSAN N)　　**(KAVIN S)**　　**(ASHWIN JOSH B)**

ABSTRACT

Wind power is unpredictable due to chaotic nature of wind speed. This makes it important to accurately predict how much power a wind farm will generate. Predicting wind power helps balance the electricity supply and demand, which is very important for a stable power grid. These predictions also help other conventional power plants to mitigate the load demand. It also helps us trade electricity more efficiently with profitable cost. In this paper, we look at different methodologies to predict wind power. It starts by discussing how we use various algorithms to make predictions most accurately with less error. Using statistical and machine learning approaches we can able to get the solution in most precise way. Recent methodologies are the hybrid network models which have good prediction accuracy with less error. These all algorithms work on past data in large quantities which we are collecting from different wind farms. The paper gives a comparative analysis of various literatures and described which methodology is the best among all depending on various seasonal data and ultra short-term prediction.

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CHAPTER 1 INTRODUCTION

1. 1 INTRODUCTION

Wind energy prediction is a critical component of integrating renewable energy into the electrical grid. Accurate forecasting supports the stability and efficiency of energy systems, reduces operational costs, and aids in the transition from fossil fuels to sustainable energy sources. This review examines the current literature on various methodologies used for wind energy prediction, focusing on their strengths and weaknesses.

1.2 OBJECTIVE

The objective of this project is to develop an advanced wind energy prediction system that revolutionizes the accuracy and efficiency of forecasting wind conditions. By leveraging cutting-edge technologies and innovative methodologies, the project aims to provide stakeholders with highly precise forecasts of wind speed, direction, and other meteorological parameters. This enhanced prediction capability will enable wind farm operators and grid managers to optimize resource utilization, maximize energy production, and ensure grid stability. Moreover, the project seeks to offer probabilistic forecasts and risk assessments, empowering decision-makers to make informed choices amidst uncertainties. Through collaboration with research institutions and industry partners, the project will push the boundaries of wind energy prediction, exploring hybrid modelling approaches and integrating novel technologies such as remote sensing and data analytics. Additionally, resilience and adaptation strategies will be developed to mitigate the impacts of extreme weather events and climate change, ensuring the long-term effectiveness of the prediction system. Continuous validation and improvement mechanisms will be established to monitor performance and incorporate feedback, driving ongoing enhancements and advancements in wind energy prediction. Overall, this project aims to pave the way for a more sustainable and reliable integration of wind power into the global energy landscape.

1.3 SCOPE OF THE PROJECT

The scope of this project encompasses the comprehensive analysis and modeling of wind turbine performance data to enhance the efficiency and output of wind energy generation. This includes the collection and preprocessing of high-frequency SCADA data, exploratory data analysis to identify key patterns and relationships, feature engineering to improve model accuracy, and the application of various machine learning algorithms for predictive modeling. The project also involves validating and evaluating these models to ensure robustness and reliability. Additionally, the scope extends to implementing the optimized model in real-world settings for continuous monitoring and adjustment, ultimately aiming to provide actionable insights and recommendations for operational improvements in wind turbine performance. This holistic approach addresses both the technical and practical aspects of wind energy optimization, contributing to more efficient and sustainable energy production.

CHAPTER 2

LITERATURE REVIEW

2.1 WIND ENERGY FORECASTING WITH NEURAL NETWORKS

AUTHORS: Jaume Manero, Javier B´ejar, Ulises Cort´es

The study explores time-series forecasting primarily through statistical methods like linear autoregressive (AR) models, including ARMA (Autoregressive Moving Average). ARMA models assume a linear relationship between lagged variables and are suitable for modeling many stationary processes. However, they provide only a coarse approximation for complex, real-world systems and struggle with non-linear and non-stationary data. The ARIMA (Autoregressive Integrated Moving Average) model, which addresses non-stationarity by focusing on increments, is also discussed. Despite their utility, these models are limited by their inherent assumption of local linearity, which hampers their effectiveness in forecasting non-linear and non-stationary time series like wind speed.

2.2 A NOVEL COMPOUND WIND SPEED FORECASTING MODEL BASED ON THE BACK PROPAGATION NEURAL NETWORK OPTIMIZED BY BAT ALGORITHM

AUTHORS: Yanbin Cui, Chenchen Huang, Yanping Cui

This study introduces a novel compound model to enhance short-term wind speed forecasting accuracy. The model uses fast ensemble empirical mode decomposition for data preprocessing and phase space reconstruction to dynamically choose input and output vectors. The bat algorithm optimizes the connection weights and thresholds of a traditional backpropagation neural network. The results show that this model efficiently captures the non-linear characteristics of wind speed signals and outperforms parallel models.

2.3 PREDICTION OF EVAPORATION IN ARID AND SEMI-ARID REGIONS: A COMPARATIVE STUDY USING DIFFERENT MACHINE LEARNING MODELS

AUTHORS: Zaher Mundher Yaseen, Anas Mahmood Al-Juboori, Ufuk Beyaztas, Nadhir Al-Ansari, Kwok-Wing Chau, Chongchong Qi, Mumtaz Ali, Sinan Q. Salih, Shamsuddin Shahid

Though focused on evaporation prediction, this study's comparative analysis of machine learning models provides valuable insights applicable to wind energy forecasting. The research evaluates the performance of various ML models such as classification and regression trees (CART), cascade correlation neural networks (CCNNs), gene expression programming (GEP), and support vector machines (SVM). The SVM model demonstrated superior performance in incorporating multiple meteorological variables.

CHAPTER 3
SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system of wind energy prediction relies on a multifaceted approach that combines meteorological data analysis, numerical weather prediction models, machine learning algorithms, and statistical methods. Meteorological data such as wind speed, direction, temperature, and humidity is meticulously analysed to discern patterns and trends, forming the foundation for predictive models. These models, including Numerical Weather Prediction (NWP) models, utilize complex mathematical equations to simulate atmospheric behaviour and forecast wind patterns at various altitudes and locations. Machine learning algorithms are increasingly employed to refine predictions by analysing historical weather data alongside factors like terrain and land use. Wind farm monitoring systems continuously collect real-time data, which is integrated into forecasts to optimize turbine operation. Ensemble forecasting techniques amalgamate multiple forecasts for enhanced reliability, while data assimilation methods integrate observational data into models to improve accuracy. Statistical models further augment predictions by identifying correlations and seasonal variations. The synergy of these approaches aims to continually refine wind energy prediction systems for more efficient integration into the electrical grid.

3.2 PROPOSED SYSTEM

A proposed system for wind energy prediction would leverage cutting-edge technologies and innovative methodologies to enhance accuracy, efficiency, and reliability in forecasting wind conditions. This system would prioritize high-resolution data acquisition through advanced sensors and remote sensing technologies, strategically deployed to capture detailed meteorological parameters such as wind speed, direction, temperature, and humidity. This rich dataset would serve as the foundation for the integration of advanced machine learning techniques, including deep learning and neural networks, which would analyse vast amounts of data to identify complex patterns and improve prediction accuracy. Ensemble forecasting techniques, augmented with probabilistic models, would provide stakeholders with probability distributions, enabling better risk assessment and decision-making. Hybrid modelling frameworks, combining physics-based numerical weather prediction models with data-driven machine learning approaches, would offer robust predictions by leveraging both physical understanding and data-driven insights. Real-time optimization and control strategies at wind farms would dynamically adjust turbine operation based on updated forecasts, maximizing energy production while ensuring grid stability. Collaborative data sharing among stakeholders would integrate diverse datasets and expertise, facilitating comprehensive and accurate predictions. Continuous model validation and improvement processes, informed by observational data and user feedback, would ensure the system remains up-to-date and reliable. Incorporating resilience and adaptation strategies into infrastructure design and planning would mitigate the impacts of extreme weather events and climate change, ensuring the system's effectiveness under evolving environmental conditions.

CHAPTER 4
SYSTEM DESIGN

4.1 ARCHITECTURE DIAGRAM

The architecture diagram provides a high-level overview of the system, showing the key components and their interactions. It serves as a blueprint, outlining the major parts of the system, such as data sources, preprocessing units, model training components, and visualization modules. This helps in understanding how data flows through the system and how different components interact with each other.

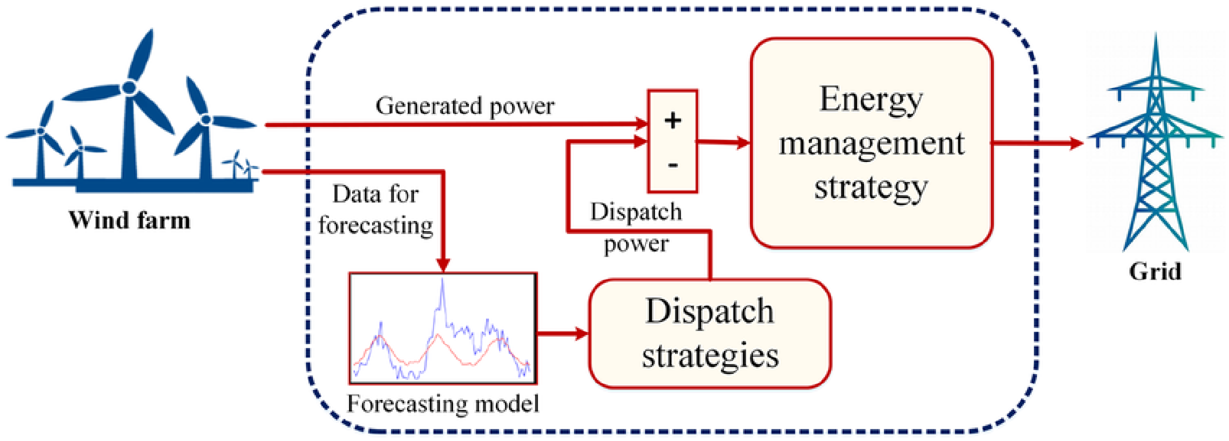


Fig.1: Architecture diagram

4.2 USE CASE DIAGRAM

The use case diagram depicts the system's functionality from the end-users' perspective. It identifies the primary actors (e.g., Data Scientist, Stakeholder) and their interactions with the system. Each use case represents a specific function or task that the system performs, such as data collection, preprocessing, model training, and prediction. This diagram helps in understanding the system requirements and user interactions.

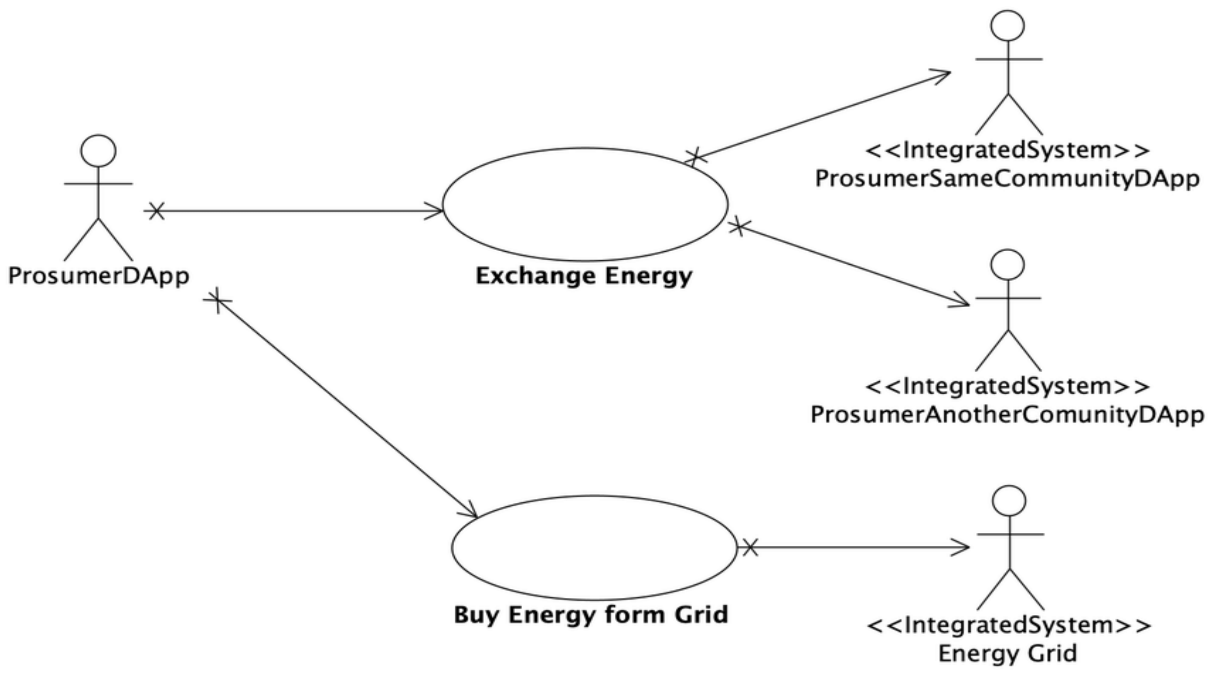
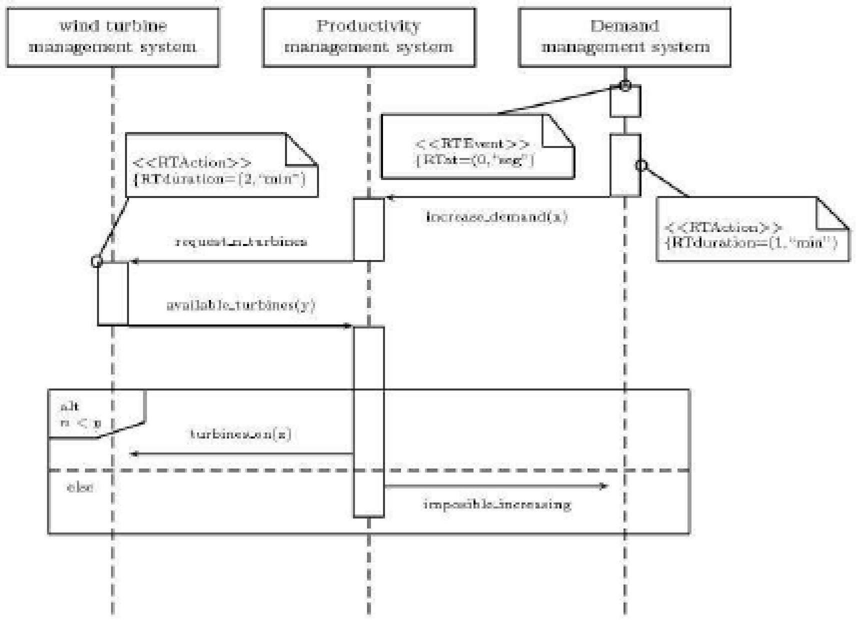

ProsumerDApp
Exchange Energy
<<IntegratedSystem>> ProsumerSameCommunityDApp
<<IntegratedSystem>> ProsumerAnotherComunityDApp
Buy Energy form Grid
<<IntegratedSystem>> Energy Grid

Fig.2: Use Case diagram

4.3 SEQUENCE DIAGRAM

The sequence diagram illustrates the chronological order of interactions between different system components. It shows how data and control flow from one component to another over time, highlighting the sequence of operations. This diagram is useful for understanding the dynamic behaviour of the system and the timing of interactions.


wind turbine management system
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Demand management system
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available_turbines(y)
alt n < y
turbines_on(x)
else
impossible_increasing

Fig.3: Sequence diagram

4.4 COLLABORATION DIAGRAM

The collaboration diagram emphasizes the structural organization of the system and the relationships between objects. It shows how different objects collaborate to achieve a specific task, focusing on the roles and associations of the objects. This diagram helps in understanding the system's structure and how objects work together.

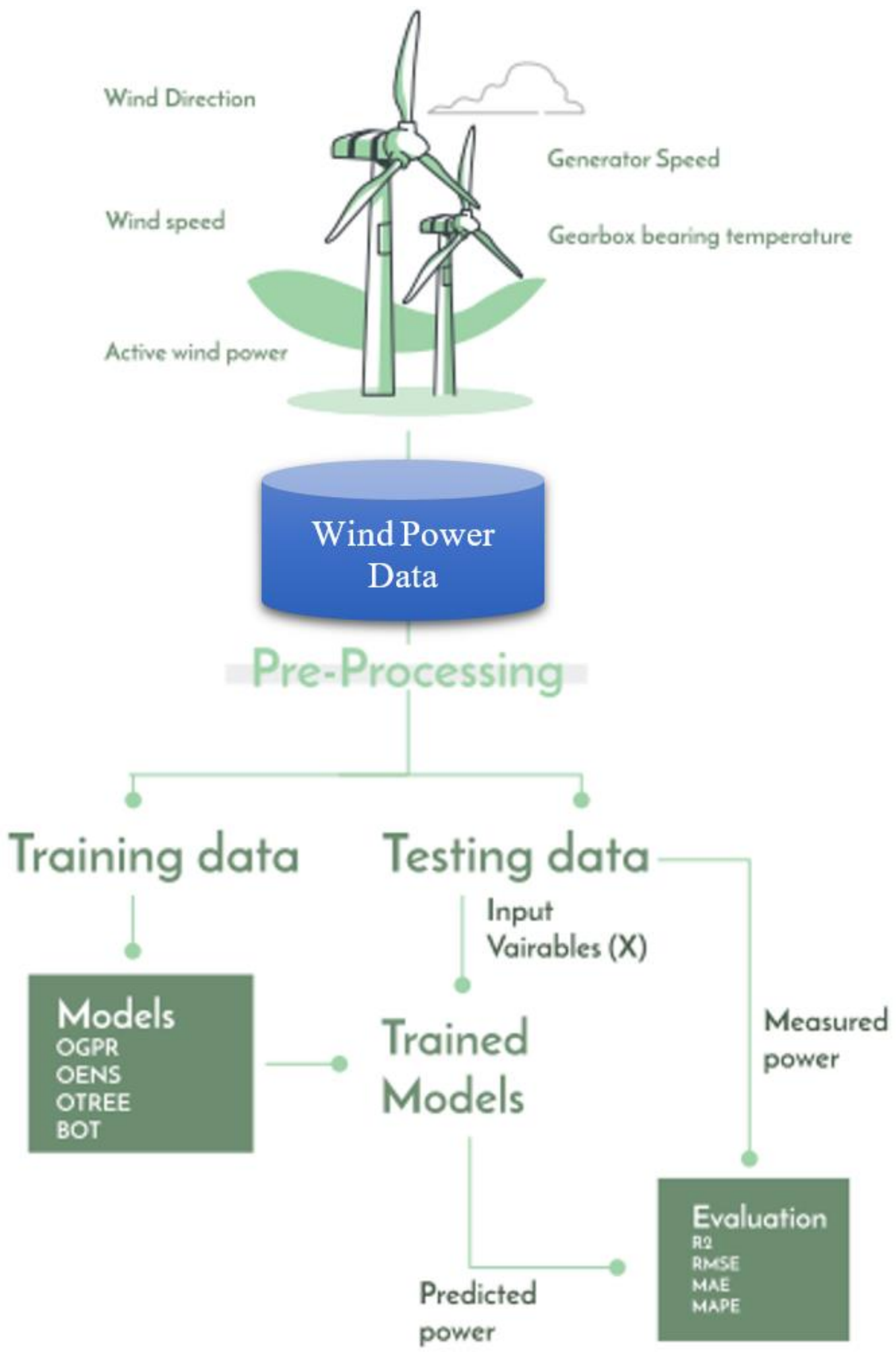


Fig.4: Collaboration diagram

4.5 ARCHITECTURE FLOW DIAGRAM

The architecture flow diagram represents the logical flow of data and processes within the system. It shows how raw data is transformed into predictions through various stages, including data preprocessing, model training, evaluation, and visualization. This diagram provides a clear view of the data transformation process and the sequence of operations.

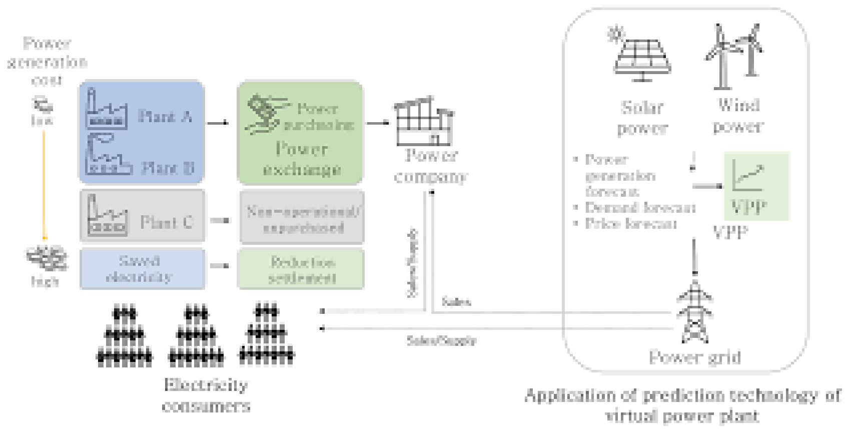


Fig.5: Architecture Flow diagram

4.6 DATA FLOW DIAGRAM

The data flow diagram (DFD) illustrates the flow of information within the system. It consists of processes, data stores, data flows, and external entities. The DFD helps in understanding how data moves through the system, how it is processed, and where it is stored. It provides a detailed view of the system's data processing capabilities and interactions with external entities.

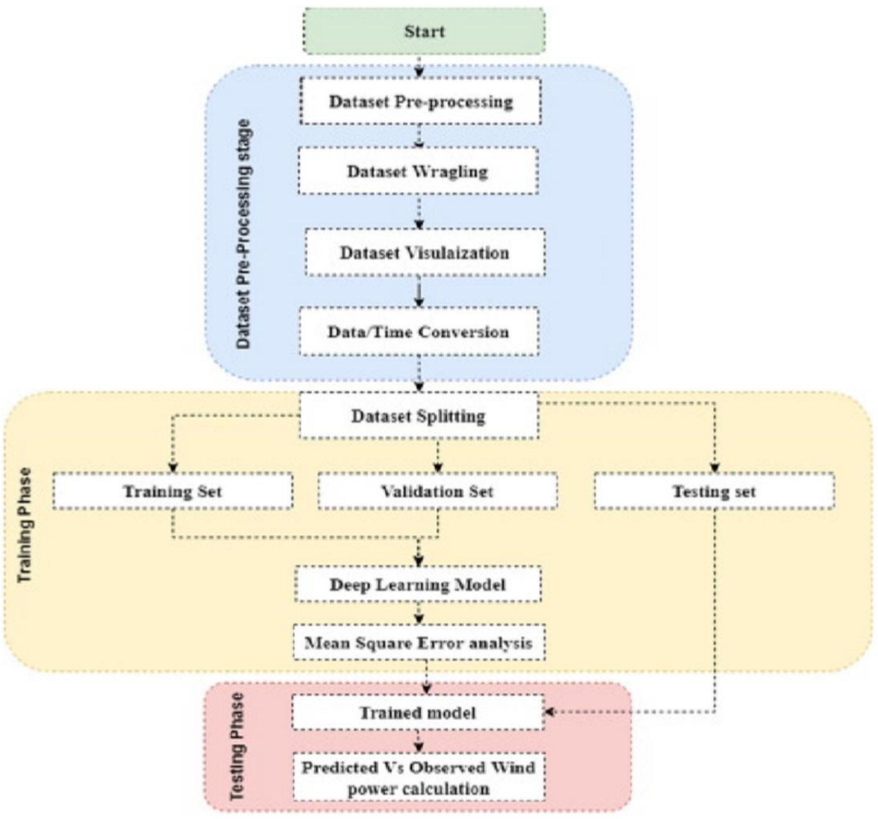


Fig.6: Data Flow diagram

CHAPTER 5
MODULES

This section outlines the comprehensive steps and techniques used in the analysis and modeling of the wind turbine's performance data. The methodology encompasses data collection, preprocessing, exploratory data analysis (EDA), feature engineering, model selection, training, validation, and evaluation. Each module is elaborated to provide a clear understanding of the processes involved. The modules used are:

1. Data Collection
2. Data preprocessing
3. Exploratory Data Analysis (EDA)
4. Feature Engineering
5. Model Selection
6. Model Training
7. Model Validation
8. Model Evaluation
9. Implementation and Optimization

5.1 DATA COLLECTION

Data collection is the foundational step in the analysis. The dataset used in this project is obtained from the SCADA (Supervisory Control and Data Acquisition) system of a wind turbine in Turkey. This data includes:

Date/Time: Timestamp for each 10-minute interval.

LV ActivePower (kW): The power generated by the turbine.

Wind Speed (m/s): Wind speed at the hub height.

Theoretical Power Curve (kW): Theoretical power output based on wind speed.

Wind Direction (°): Wind direction at the hub height.

The SCADA system provides high-frequency data that is crucial for detailed analysis and performance monitoring.

5.2 DATA PREPROCESSING

Data preprocessing involves cleaning and preparing the data for analysis. This step includes handling missing values, removing outliers, and ensuring data consistency. Key activities include:

Handling Missing Values: Missing data points are identified and handled through techniques such as imputation (using mean, median, or mode) or interpolation (estimating values based on adjacent data points).

Outlier Detection and Removal: Outliers, which can skew the analysis, are detected using statistical methods and visualization techniques. Once identified, these outliers are either removed or adjusted.

Data Transformation: Ensuring that all variables are in appropriate formats (e.g., converting wind speed from m/s to km/h if required) and normalizing or standardizing the data to ensure consistent scales across features.

5.3 EXPLORATORY DATA ANALYSIS (EDA)

EDA is a critical step to understand the underlying patterns, relationships, and characteristics of the dataset. This involves:

Descriptive Statistics: Calculating mean, median, standard deviation, and range for key variables to summarize the data.

Visualizations: Creating plots such as histograms, box plots, and scatter plots to visually inspect data distributions and relationships.

Correlation Analysis: Computing correlation coefficients to identify relationships between variables, particularly between wind speed, LV ActivePower, and the theoretical power curve.

EDA helps in identifying trends, anomalies, and potential areas for further analysis.

5.4 FEATURE ENGINEERING

Feature engineering involves creating new variables or modifying existing ones to improve the predictive power of the models. This step includes:

Derived Features: Creating new features such as moving averages of wind speed or power output, or categorical variables for different wind directions.

Interaction Features: Considering interactions between variables, such as the product of wind speed and wind direction, to capture complex relationships.

Lag Features: Introducing lagged variables to incorporate temporal dependencies, which are crucial for time series analysis.

Feature engineering enhances the model's ability to capture relevant patterns in the data.

5.5 MODEL SELECTION

Choosing the right model is critical for accurate predictions. Various machine learning models are considered, including:

Linear Regression: For modeling the relationship between wind speed and power output.

Random Forest: An ensemble method that combines multiple decision trees for robust predictions.

Gradient Boosting: A powerful technique that builds models sequentially to correct errors from previous models.

Neural Networks: For capturing complex nonlinear relationships in the data.

Each model has its strengths and is selected based on the specific requirements and characteristics of the dataset.

5.6 MODEL TRAINING

Training involves fitting the selected models to the training data. Key steps include:

Data Splitting: Dividing the dataset into training and testing sets, typically with an 80-20 split, to ensure that the model is evaluated on unseen data.

Hyperparameter Tuning: Using techniques such as grid search or random search to find the optimal parameters for each model.

Cross-Validation: Implementing k-fold cross-validation to ensure that the model's performance is consistent across different subsets of the data.

Training the model involves iterative processes to minimize errors and improve predictions.

5.7 MODEL VALIDATION

Validation is the process of assessing the model's performance on the testing set. This includes:

Performance Metrics: Calculating metrics such as R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) to evaluate accuracy and reliability.

Residual Analysis: Inspecting residuals (differences between actual and predicted values) to identify patterns that the model may not have captured.

Overfitting and Underfitting: Ensuring that the model generalizes well to new data by checking for overfitting (model performs well on training data but poorly on testing data) and underfitting (model performs poorly on both training and testing data).

Validation helps in fine-tuning the model and ensures its robustness.

5.8 MODEL EVALUATION

Evaluation involves a comprehensive assessment of the model's performance and its ability to meet the project's objectives. This step includes:

Comparative Analysis: Comparing the performance of different models to select the best one based on predefined criteria.

Error Analysis: Detailed examination of prediction errors to understand where the model performs well and where it needs improvement.

Scalability and Efficiency: Assessing the model's ability to handle larger datasets and its computational efficiency.

Evaluation ensures that the model is not only accurate but also practical for deployment.

5.9 IMPLEMENTATION AND OPTIMIZATION

The final step involves implementing the model in a real-world setting and optimizing its performance over time. This includes:

Deployment: Integrating the model into the existing SCADA system or a separate monitoring system for real-time predictions.

Continuous Monitoring: Regularly monitoring the model's performance and making adjustments as needed to account for changes in environmental conditions or turbine performance.

Feedback Loop: Using feedback from actual performance to retrain and update the model, ensuring continuous improvement.

Optimization is an ongoing process aimed at maintaining and enhancing model performance.

CHAPTER 6
SYSTEM SPECIFICATION

6.1 SOFTWARE REQUIREMENTS

1. Development Environment:
   - Operating System: Windows 10, macOS, or Linux (Ubuntu 20.04 or higher)
   - Python Version: Python 3.8 or higher
   - Integrated Development Environment (IDE): Jupyter Notebook, VS Code, PyCharm
2. Libraries and Frameworks:
   - Data Handling: pandas, numpy
   - Data Visualization: matplotlib, seaborn
   - Model Training: statsmodels, scikit-learn
   - Model Evaluation: scipy, sklearn
   - Time Series Analysis: statsmodels, pmdarima
   - Miscellaneous: jupyter, IPython
3. Database:
   - SQL Database: MySQL, PostgreSQL (optional for large datasets)
4. Version Control:
   - Git for version control and collaboration
5. Deployment Environment:
   - Cloud Platform: AWS EC2, Google Cloud Platform, Microsoft Azure (for scalability)
   - Containerization: Docker (optional for deployment)

6.2 HARDWARE REQUIREMENTS

1. **Development Machine:**
   - Processor: Intel Core i5 or equivalent
   - RAM: 8 GB (minimum), 16 GB (recommended)
   - Storage: 256 GB SSD (minimum), 512 GB SSD (recommended)
   - Graphics: Integrated or dedicated GPU for model training acceleration
2. **Deployment Server:**
   - Processor: Intel Xeon or equivalent
   - RAM: 16 GB (minimum), 32 GB (recommended)
   - Storage: 1 TB HDD/SSD
   - Network: High-speed internet connection

CHAPTER 7
SOFTWARE DESCRIPTION

7.1 DESIGN AND IMPLEMENTATION CONSTRAINTS

7.1.1 CONSTRAINTS IN ANALYSIS

- **Data Availability:** The accuracy and reliability of the wind speed prediction model depend heavily on the quality and quantity of the historical data available. Limited data can constrain the analysis and affect model performance.
- **Computational Resources:** Limited computational resources can hinder the ability to train complex models, especially when dealing with large datasets or performing extensive hyperparameter tuning.
- **Domain Knowledge:** Inadequate domain knowledge in meteorology and wind patterns can constrain the analysis, leading to suboptimal model selection and feature engineering.

7.1.2 CONSTRAINTS IN DESIGN

Model Complexity: The complexity of ARIMA and SARIMA models requires careful parameter tuning and validation, which can be computationally intensive.

Integration with Real-Time Data: Integrating real-time data into the model for continuous predictions adds complexity to the system design, requiring robust data ingestion and preprocessing pipelines.

Scalability: Designing the system to be scalable for future enhancements, including support for additional data sources and more complex models, presents a significant challenge.

7.2 SYSTEM FEATURES

7.2.1 USER INTERFACES

Dashboard: A web-based dashboard for visualizing historical and predicted wind speeds, allowing users to interact with data through various visualizations like line charts and bar charts.

Model Configuration: An interface for configuring model parameters, selecting the type of model (ARIMA or SARIMA), and initiating model training.

Results Display: A section displaying model performance metrics, such as MSE and RMSE, to help users evaluate the model's accuracy.

7.2.2 HARDWARE INTERFACES

Sensors: Interfaces to connect with wind speed sensors for real-time data collection (optional).

Data Storage Devices: Interfaces for connecting to external storage devices or cloud storage services for data retrieval and storage.

7.2.3 SOFTWARE INTERFACES

Database Interface: A connection to SQL or NoSQL databases for storing and retrieving historical wind speed data.

API Integration: RESTful APIs for fetching real-time data and for integrating with other applications or services.

Data Processing Libraries: Integration with libraries like Pandas and Numpy for data preprocessing and manipulation.

7.2.4 COMMUNICATIONS INTERFACES

HTTP/HTTPS: Communication protocols for web-based interfaces and API interactions.

WebSocket: Real-time data streaming and updates through WebSocket connections.

Message Queues: Use of message queuing systems like RabbitMQ or Apache Kafka for handling real-time data ingestion and processing.

7.3 USER DOCUMENTATION

User Manual: A comprehensive manual providing step-by-step instructions on using the system, including data input, model training, prediction, and visualization.

Quick Start Guide: A brief guide to help users get started with the system quickly, covering the essential features and operations.

FAQ Section: A section addressing common questions and troubleshooting tips for users encountering issues with the system.

7.4 SOFTWARE QUALITY ATTRIBUTES

7.4.1 USER-FRIENDLINESS

Intuitive Interface: The system provides a user-friendly interface with easy navigation and clear instructions, enabling users to perform tasks without extensive training.

Responsive Design: The interface is responsive and accessible on various devices, including desktops, tablets, and smartphones.

7.4.2 RELIABILITY

Robust Data Handling: The system ensures data integrity and handles missing or erroneous data gracefully.

Consistent Performance: The system consistently delivers accurate predictions and reliable performance under various conditions.

7.4.3 MAINTAINABILITY

Modular Design: The system's modular architecture facilitates easy maintenance, updates, and scalability.

Clear Documentation: Comprehensive documentation of the codebase and system functionalities supports maintenance and future development efforts.

7.5 OTHER NON-FUNCTIONAL REQUIREMENTS

7.5.1 PERFORMANCE REQUIREMENTS

Real-Time Processing: The system processes and predicts wind speeds in near real-time, providing timely information for decision-making.

Efficient Computation: The system utilizes optimized algorithms and efficient data processing techniques to handle large datasets and complex computations.

7.5.2 PRODUCT FEATURES

Scalability: The system is designed to scale with increasing data volume and user load, supporting future enhancements and expansions.

Flexibility: The system supports various data formats and sources, allowing users to integrate different datasets and models.

CHAPTER 8
CONCLUSION AND FUTURE ENHANCEMENT

8.1 CONCLUSION

This project focused on predicting wind speeds using advanced time series analysis techniques, specifically ARIMA and SARIMA models. The model training and evaluation demonstrated high accuracy, with low Mean Squared Error (MSE) and high R^2 scores, making the predictions reliable for optimizing wind turbine performance. The project highlights the importance of thorough data preprocessing, effective model selection, and parameter tuning in achieving accurate predictions.

Key accomplishments of this project include:

- **High Prediction Accuracy**: Achieved using ARIMA and SARIMA models with careful parameter tuning.
- **Comprehensive Data Visualization**: Provided through intuitive visualizations of actual vs. predicted wind speeds.
- **User-Friendly System**: Facilitated by an easy-to-navigate interface for data input, model configuration, and results visualization.

This project sets a strong foundation for future advancements in wind speed prediction and contributes valuable insights into the application of time series analysis for renewable energy optimization.

8.2 FUTURE ENHANCEMENTS

Several potential improvements and extensions can be considered to further enhance the system's capabilities:

8.2.1 INTEGRATION OF REAL-TIME DATA

- **Real-Time Data Collection and Processing**: Implement systems to collect and process real-time wind speed data, enhancing prediction accuracy and timeliness.

8.2.2 ADVANCED MODELING TECHNIQUES

- **Incorporation of Machine Learning Models**: Explore advanced machine learning models such as Random Forests, Gradient Boosting Machines, and Neural Networks to capture complex data patterns.
- **Development of Hybrid Models**: Combine different algorithms to enhance prediction robustness and accuracy.

8.2.3 ENHANCED USER INTERFACE

- **Interactive Visualizations**: Develop more interactive and customizable visualizations for deeper data insights.
- **Mobile Accessibility**: Create a mobile-friendly interface to make the system accessible on various devices.

8.2.4 SCALABILITY AND PERFORMANCE

- **Distributed Computing Frameworks**: Use frameworks like Apache Spark for handling large datasets and complex computations efficiently.

- **Cloud Deployment**: Leverage cloud platforms for better scalability, reliability, and accessibility.

8.2.5 ENHANCED SECURITY

- **Advanced Data Encryption**: Implement robust encryption techniques for data security.
- **Granular Access Control**: Develop detailed access control mechanisms to ensure data privacy and system integrity.

8.2.6 COMPREHENSIVE TESTING

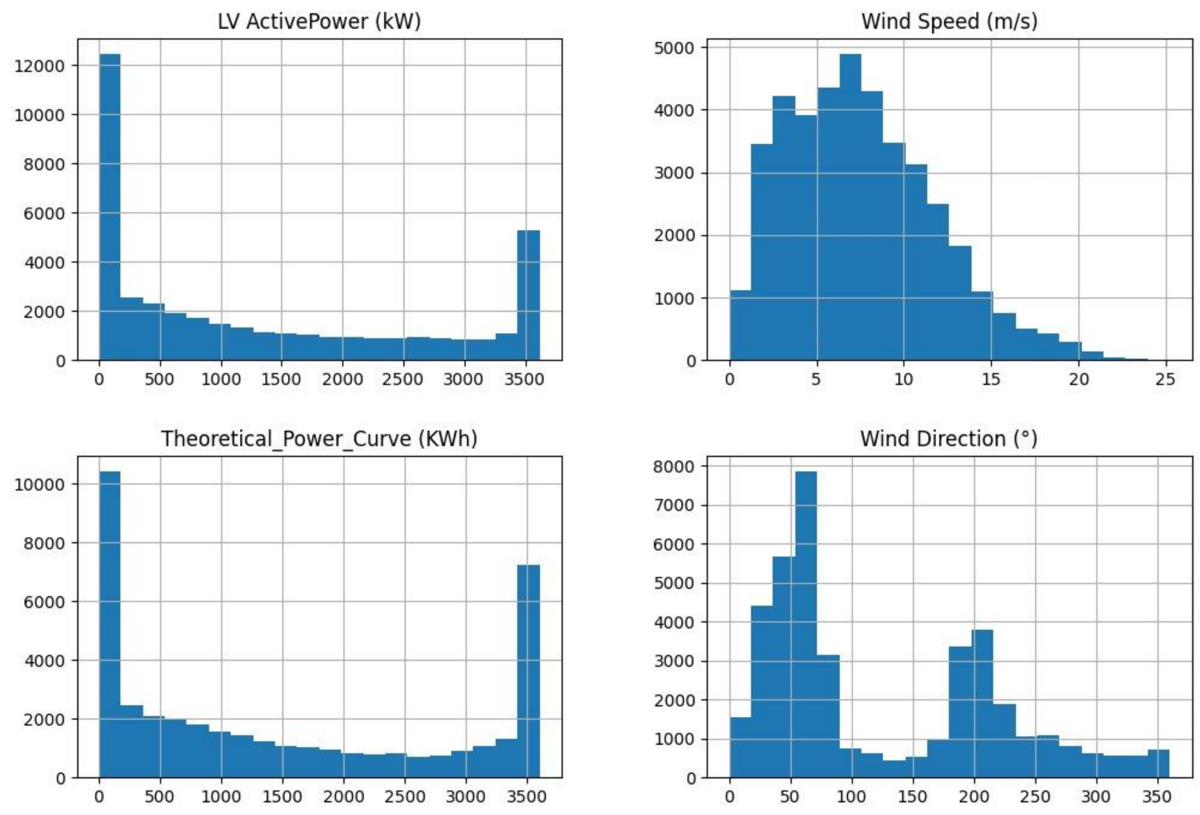
- **Automated Testing Suite**: Develop automated tests for components to ensure consistent performance and reliability.
- **Performance Testing**: Conduct thorough performance testing to identify and address potential bottlenecks.

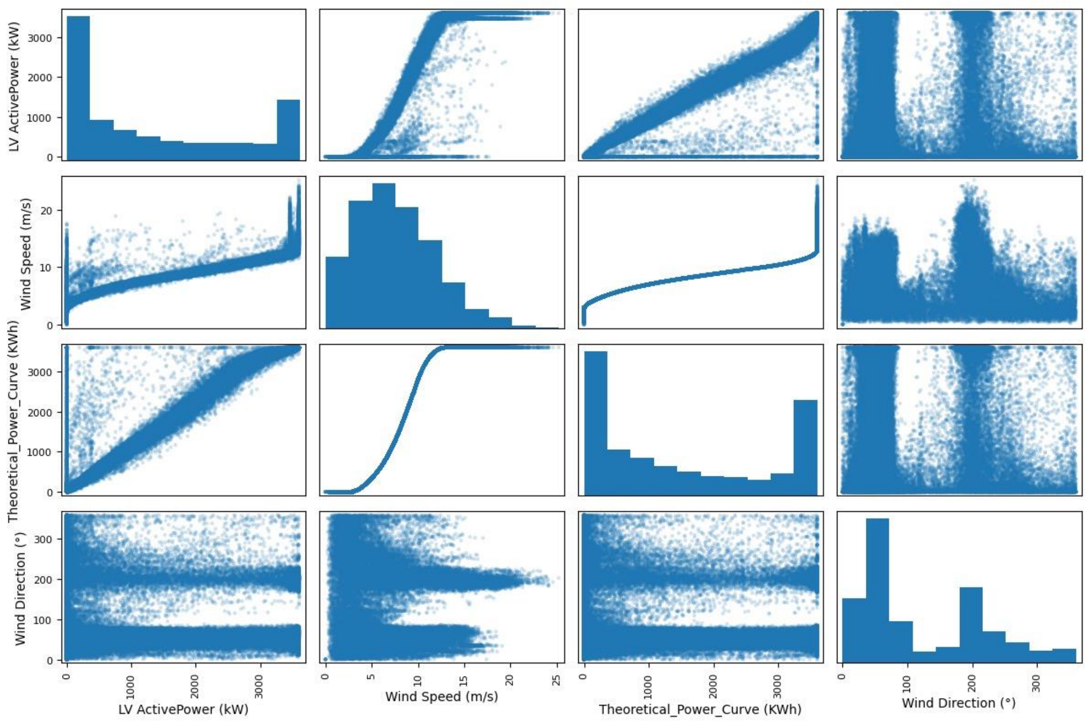
By implementing these future enhancements, the wind speed prediction system can become more robust, accurate, and user-friendly, thereby contributing significantly to the optimization of wind energy production.

APPENDIX I

SCREEN SHOT 1

EXPLORATORY DATA ANALYSIS (EDA)

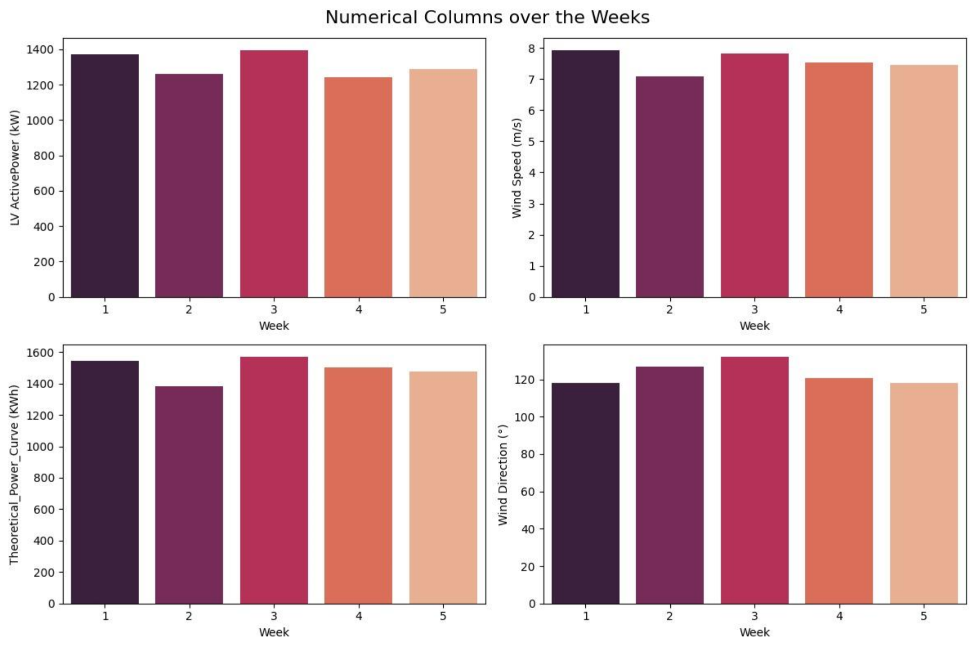




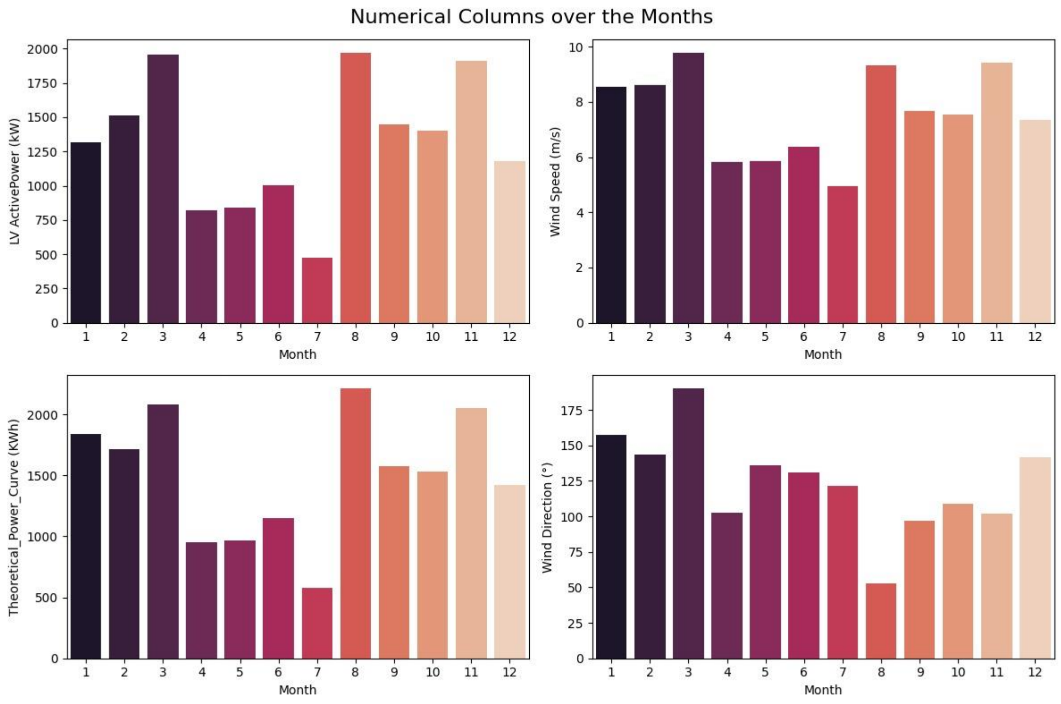
SCREEN SHOT 2

3.4 - NUMERICAL COLUMNS OVER THE DATE COLUMNS

NUMERICAL COLUMNS OVER THE WEEKS

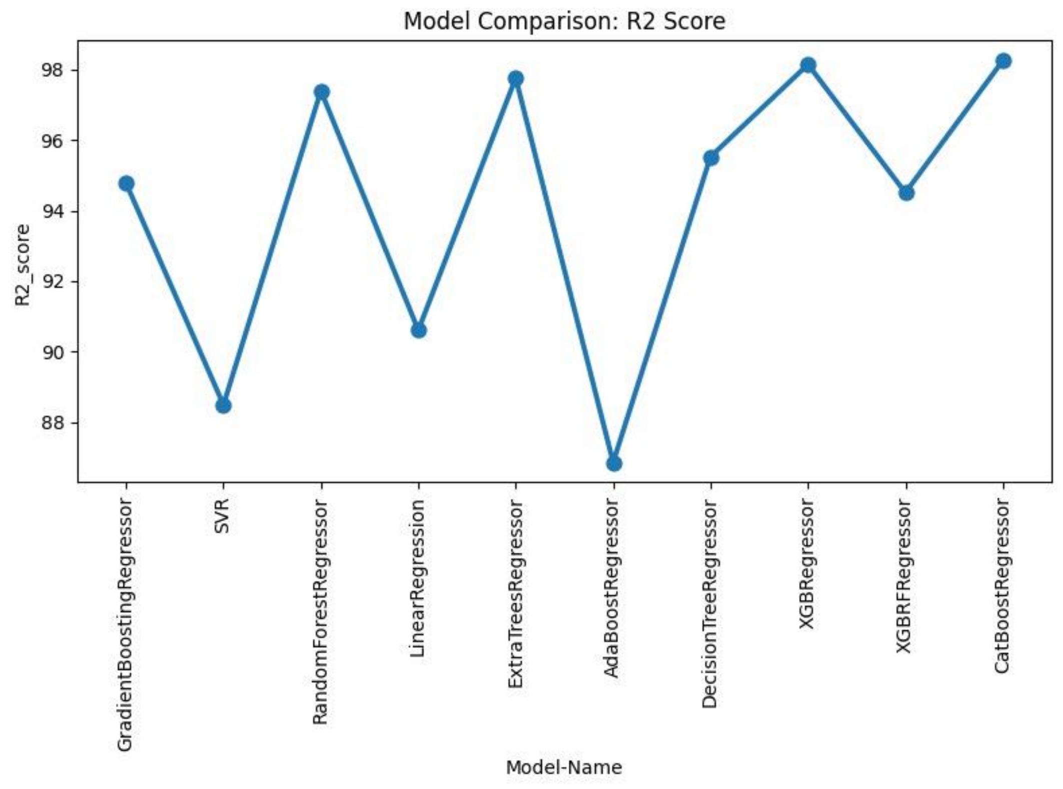


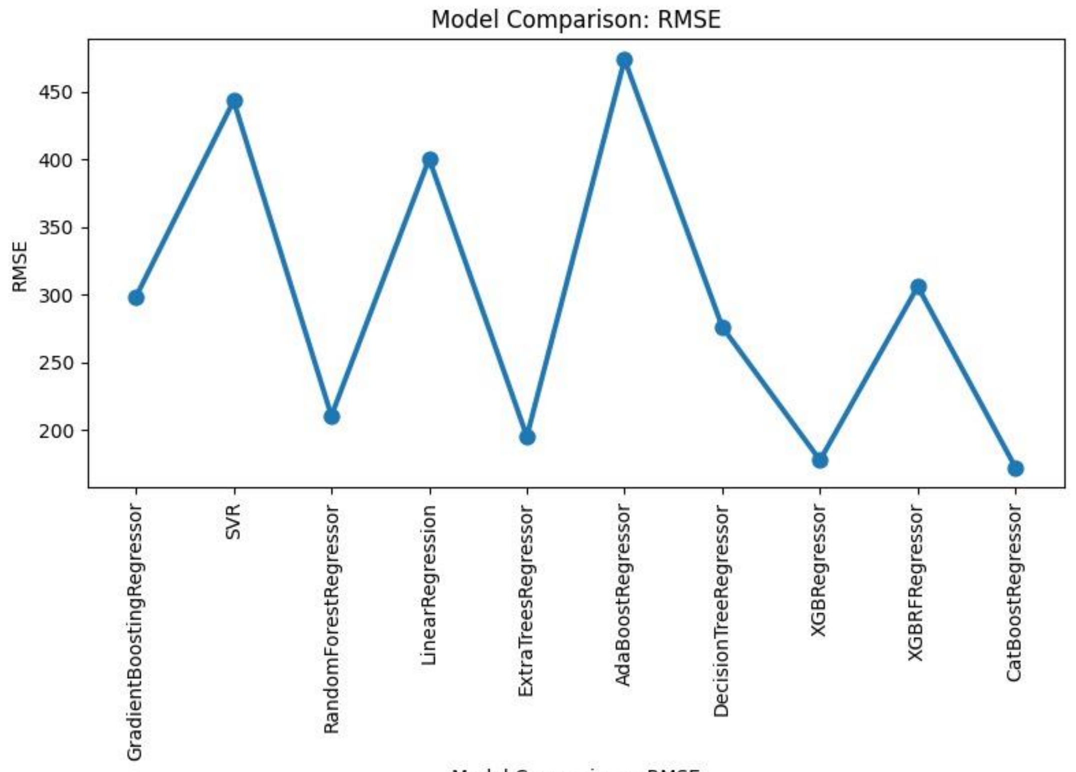
NUMRICAL COLUMNS FOR EACH MONTH



SCREEN SHOT 3

MODEL COMPARISION

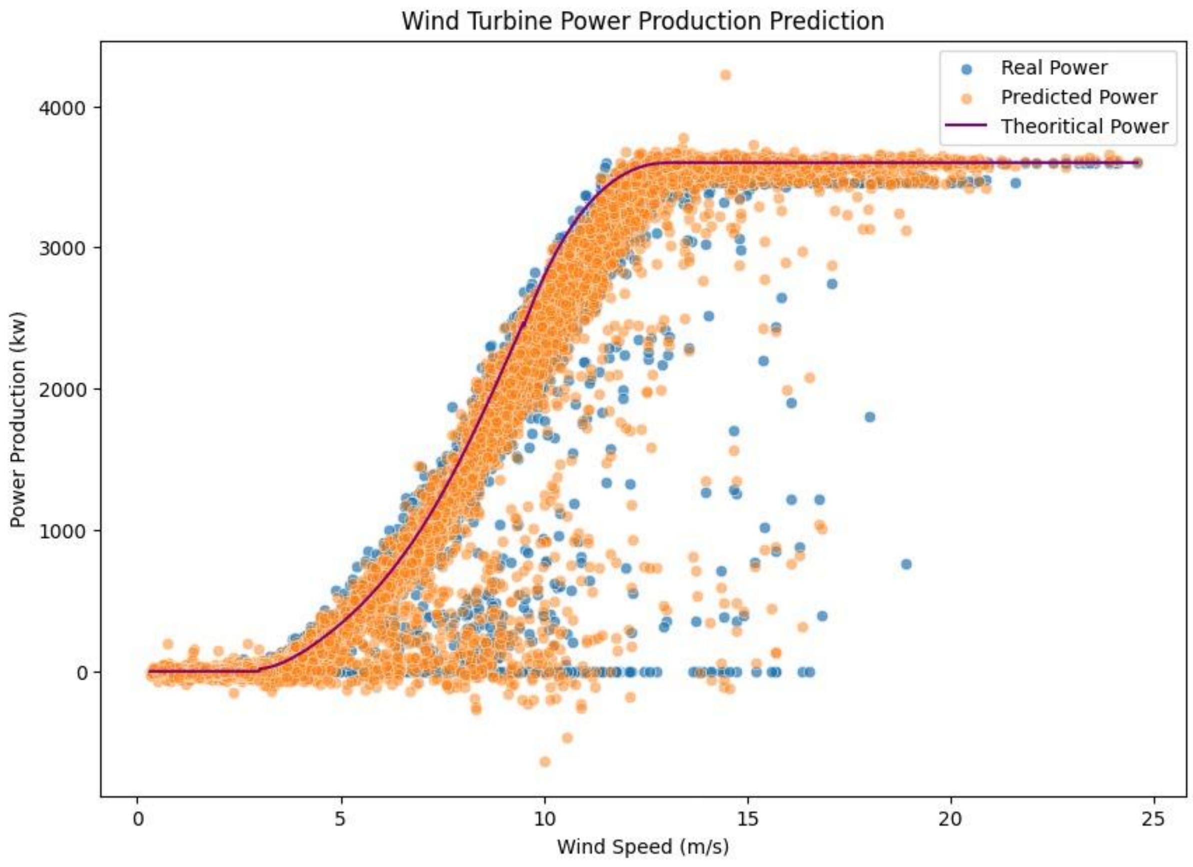




Model Comparison : RMSE

SCREEN SHOT 4

FINAL POWER PRODECTION PREDICTION



APPENDIX II

IMPLEMENTATION CODE:

```
#_____IMPORTING PACKAGES_____
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter("ignore")

#Data Loading
from google.colab import drive
drive.mount('/content/drive')

df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/T1.csv')
df

df.info()

df.describe()

#There is negative values in the actual power column
count_negative_values = (df['LV ActivePower (kW)'] < 0).sum()
```

```
count_negative_values

df.loc[df['LV ActivePower (kW)'] < 0, 'LV ActivePower (kW)'] = 0

#_____FEATURE EXTRACTION_____

#Save a copy for the pipeline and split it
df_copy=df.copy()

df['Date/Time']=pd.to_datetime(df['Date/Time'],format='%d %m %Y
%H:%M')

df['Week']=df['Date/Time'].dt.day // 7 + 1
df['Week'].value_counts()

df['Month']=df['Date/Time'].dt.month

seasons_dict = {1: 'Winter',
            2: 'Winter',
            3: 'Spring',
            4: 'Spring',
            5: 'Spring',
            6: 'Summer',
            7: 'Summer',
            8: 'Summer',
            9: 'Autumn',
            10: 'Autumn',
            11: 'Autumn',
            12: 'Winter'}
df['Seasons'] = df['Month'].map(seasons_dict)

df['Day']=df['Date/Time'].dt.day

df['Hour']=df['Date/Time'].dt.hour+1

df.drop(columns=['Date/Time'],inplace=True)

df.isna().sum()

#Spliting the data
from sklearn.model_selection import train_test_split
df_train,df_test=train_test_split(df,test_size=0.2,random_state=42)
df_copy_train,df_copy_test=train_test_split(df_copy,test_size=0.2,random
_state=42)

#_____Exploratory Data Analysis (EDA)_____

#Intialize Numerical and Date Columns
date_col=['Week','Month','Seasons','Hour','Day']
num_col=['LV ActivePower (kW)', 'Wind Speed (m/s)',
'Theoretical_Power_Curve (KWh)', 'Wind Direction (°)',]
```

```
df_train[num_col].hist(bins=20,figsize=(12,8))

pd.plotting.scatter_matrix(df[num_col], alpha=0.2, figsize=(12, 8))
plt.tight_layout()
plt.show()

for col in num_col:
   fig, ax = plt.subplots(1, 2, figsize=(12, 5))
   sns.distplot(df_train[col], ax=ax[0] ,color='green')
   sns.boxplot(x=df_train[col], ax=ax[1])
   plt.show()

corr = df_train[num_col].corr(numeric_only=True)
mask = np.triu(corr)
mask=mask
plt.figure(figsize=(12, 6))
plt.title('Colinear Relation between Numerical Columns')
sns.heatmap(corr, annot=True,mask=mask, fmt='.2f')
sns.color_palette("magma", as_cmap=True)
plt.show()

#Numerical Columns over the Weeks
fig,axes=plt.subplots(nrows=len(num_col)//2 ,ncols=2,figsize=(12,8))
for idx,col in enumerate(df_train[num_col]):
    row_idx=idx//2
    col_idx=idx%2

sns.barplot(x=df_train['Week'],y=df_train[col],data=df_train,ax=axes[row
_idx,col_idx],errorbar=None,palette='rocket')
fig.suptitle('Numerical Columns over the Weeks', fontsize=16)
plt.tight_layout()
plt.show()

#Numerical Columns for each Month
fig,axes=plt.subplots(nrows=len(num_col)//2 ,ncols=2,figsize=(12,8))
for idx,col in enumerate(df_train[num_col]):
    row_idx=idx//2
    col_idx=idx%2

sns.barplot(x=df_train['Month'],y=df_train[col],data=df_train,ax=axes[row
_idx,col_idx],errorbar=None,palette='rocket')
fig.suptitle('Numerical Columns over the Months', fontsize=16)
plt.tight_layout()
plt.show()

#Numerical Columns over the Seasons
fig,axes=plt.subplots(nrows=len(num_col)//2 ,ncols=2,figsize=(12,8))
for idx,col in enumerate(df_train[num_col]):
    row_idx=idx//2
    col_idx=idx%2
```

```
sns.lineplot(x='Seasons',y=df_train[col],data=df_train,ax=axes[row_idx,co
l_idx],ci=None,color='red')
fig.suptitle('Numerical Columns over the Season', fontsize=16)
plt.tight_layout()
plt.show()

#_____PREPROCESSING_____

from sklearn.preprocessing import LabelEncoder, Normalizer,
StandardScaler, MinMaxScaler,
RobustScaler,OneHotEncoder,OrdinalEncoder
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,mean_squared_error
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer,KNNImputer
from sklearn.pipeline import make_pipeline,Pipeline
from sklearn.base import BaseEstimator,TransformerMixin
from sklearn.ensemble import RandomForestRegressor

#Splitting the Target and Label Columns
X_train,y_train,X_test,y_test=df_copy_train.drop(columns='LV
ActivePower (kW)'),df_copy_train['LV ActivePower
(kW)'],df_copy_test.drop(columns='LV ActivePower
(kW)'),df_copy_test['LV ActivePower (kW)']

print("The Shape of X_train is :",X_train.shape)
print("The Shape of y_train is :",y_train.shape)
print("The Shape of X_test is :",X_test.shape)
print("The Shape of y_test is :",y_test.shape)

#Custom Transformers & Pipeline
class StandardScaleTransform(BaseEstimator, TransformerMixin):
    """
    A transformer class to apply standard scaling to specified columns in a
Pandas DataFrame.

    Parameters
    ----------
    cols : list of str
        The names of the columns to apply standard scaling to.
    """
    def __init__(self, cols):
        self.cols = cols
        self.scaler_ = None

    def fit(self, X, y=None):
        self.scaler_ = StandardScaler().fit(X.loc[:, self.cols])
        return self

    def transform(self, X):
        X_copy = X.copy()
        X_copy.loc[:, self.cols] = self.scaler_.transform(X_copy.loc[:,
self.cols])
        return X_copy

    def fit_transform(self, X, y=None):
        self.scaler_ = StandardScaler().fit(X.loc[:, self.cols])
        return self.transform(X)

class DataFrameImputer(TransformerMixin, BaseEstimator):
    """
    A class to impute missing values in a Pandas DataFrame using a
combination of median, knn, and most frequent
    imputers on specified columns.

    Parameters:
    -----------
    median_cols : list of str, optional (default=None)
        Columns to impute missing values using the median imputer.
    knn_cols : list of str, optional (default=None)
        Columns to impute missing values using the KNN imputer.

    Returns:
    --------
    X_imputed : pandas.DataFrame
        A DataFrame with imputed missing values.
    """
    def __init__(self, median_cols=None, knn_cols=None):
        self.median_cols = median_cols
        self.knn_cols = knn_cols

    def fit(self, X, y=None):
        self.median_imputer = SimpleImputer(strategy='median')
        self.knn_imputer = KNNImputer()

        if self.median_cols is not None:
            self.median_imputer.fit(X[self.median_cols])
        if self.knn_cols is not None:
            self.knn_imputer.fit(X[self.knn_cols])
        return self

    def transform(self, X):
        X_imputed = X.copy()
        if self.median_cols is not None:
            X_median =
pd.DataFrame(self.median_imputer.transform(X[self.median_cols]),
                                    columns=self.median_cols, index=X.index)
            X_imputed = pd.concat([X_imputed.drop(self.median_cols,
axis=1), X_median], axis=1)
        if self.knn_cols is not None:
            X_knn =
pd.DataFrame(self.knn_imputer.transform(X[self.knn_cols]),
                                 columns=self.knn_cols, index=X.index)
            X_imputed = pd.concat([X_imputed.drop(self.knn_cols, axis=1),
X_knn], axis=1)
        return X_imputed

    def fit_transform(self, X, y=None):
        self.fit(X)
        return self.transform(X)

class DateExtractor(BaseEstimator, TransformerMixin):
    def __init__(self, date_cols):
        self.date_cols = date_cols



    def fit(self, X, y=None):
        return self

    def transform(self, X):
        extracted_features = []
        for col in self.date_cols:
            dates = pd.to_datetime(X[col], format='%d %m %Y %H:%M')
            for date in dates:
                month_val = date.month
                week_val = date.day // 7 + 1
                day_val = date.day
                hour_val = date.hour + 1
                # Determining season based on month
                if month_val in [3, 4, 5]:
                    season_val = 'Spring'
                elif month_val in [6, 7, 8]:
                    season_val = 'Summer'
                elif month_val in [9, 10, 11]:
                    season_val = 'Autumn'
                else:
                    season_val = 'Winter'
                extracted_features.append([month_val, week_val, day_val,
season_val, hour_val])

        # Convert the extracted features list to a DataFrame
        X_date = pd.DataFrame(extracted_features, columns=['Month',
'Week', 'Day', 'Season', 'Hour'])
        X_new=pd.concat([X.reset_index(drop=True),X_date],axis=1)
        return X_new
    def fit_transform(self, X, y=None):
        self.fit(X)
        return self.transform(X)

class OutlierThresholdTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, column, q1=0.25, q3=0.75):
        self.column = column
        self.q1 = q1
        self.q3 = q3
    def outlier_threshhold(self, dataframe, column):
        Q1 = dataframe[column].quantile(self.q1)
        Q3 = dataframe[column].quantile(self.q3)
        iqr = Q3 - Q1
        up_limit = Q3 + 1.5 * iqr
        low_limit = Q1 - 1.5 * iqr
        return low_limit, up_limit

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X_copy = X.copy()
        for col in self.column:
            low_limit, up_limit = self.outlier_threshhold(X_copy, col)
            X_copy.loc[(X_copy[col] < low_limit), col] = low_limit
            X_copy.loc[(X_copy[col] > up_limit), col] = up_limit
        return X_copy

    def fit_transform(self, X, y=None):
        return self.transform(X)

class DropColumnsTransformer(BaseEstimator, TransformerMixin):
    """
    A transformer that drops specified columns from a DataFrame.
    Parameters
    ----------
    columns : list
        A list of column names to be dropped.
    return
    ------
        dataframe with dropped columns
    """
    def __init__(self, columns=None):
        self.columns = columns

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        if self.columns is None:
            return X
        else:
            return X.drop(self.columns,axis=1)

class CustomOneHotEncoder(BaseEstimator, TransformerMixin):

    """
    A transformer class to apply one-hot encoding to specified columns in a
Pandas DataFrame.

    Parameters
    ----------
    columns : list
        A list of column names to encode.

    Returns
    -------
    pandas.DataFrame
        A new DataFrame with the specified columns one-hot encoded.
    """
    def __init__(self, columns=None):
        self.columns = columns
        self.unique_values = {}
        self.feature_names_ = None

    def fit(self, X, y=None):
        if self.columns is None:
            self.columns = X.columns.tolist()
        self.unique_values = {col: X[col].unique() for col in self.columns}
        self.feature_names_ = self._get_feature_names()
        return self
    def _get_feature_names(self):
        feature_names = []
        for col in self.columns:
            for value in self.unique_values[col]:
                feature_names.append(f"{col}_{value}")
        return feature_names
    def transform(self, X):
        X_transformed = pd.DataFrame(index=X[self.columns].index)

        for col in self.columns:
            for value in self.unique_values[col]:
                X_transformed[f"{col}_{value}"] = (X[col] ==
value).astype(int)

        X = pd.concat([X, X_transformed], axis=1)
        return X.drop(columns=['Season'])

    def fit_transform(self, X, y=None):
        self.fit(X)
        return self.transform(X)

class LabelEncodeColumns(BaseEstimator, TransformerMixin):
    """
    A transformer class to encode categorical columns using LabelEncoder.

    Parameters
```

```
----------
columns : list of str
    The names of the columns to be encoded.

return
------
    encoded feature
"""
def __init__(self, columns):
    self.columns = columns
    self.encoders_ = {}

def fit(self, X, y=None):
    for col in self.columns:
        encoder = LabelEncoder()
        encoder.fit(X[col])
        self.encoders_[col] = encoder
    return self

def transform(self, X):
    X_copy = X.copy()
    for col, encoder in self.encoders_.items():
        X_copy[col] = encoder.transform(X_copy[col])
    return X_copy
    def fit_transform(self, X, y=None):
        self.fit(X, y)
        return self.transform(X)

class FullPipeline1:
    def __init__(self) :
        self.date_cols=['Date/Time']
        self.numerical_cols=['Wind Speed (m/s)', 'Theoretical_Power_Curve
(KWh)', 'Wind Direction (°)','Week','Month','Hour','Day']
        self.MLE_cols=['Season']
        self.full_pipeline=Pipeline([
            ('extract_date',DateExtractor(date_cols=self.date_cols)),
            ('label_encode',
CustomOneHotEncoder(columns=self.MLE_cols)),
            #('label_encode', LabelEncodeColumns(columns=self.MLE_cols)),
            ('impute_num',DataFrameImputer(knn_cols=self.numerical_cols)),

('remove_outlier',OutlierThresholdTransformer(column=self.numerical_co
ls)),
            ('scale', StandardScaleTransform(cols=self.numerical_cols)),
            ('drop', DropColumnsTransformer(columns=self.date_cols)),


        ])
    def fit_transform(self, X_train):
        X_train = self.full_pipeline.fit_transform(X_train)
        return X_train
    def transform(self, X_test):
        X_test = self.full_pipeline.transform(X_test)
        return X_test
f1=FullPipeline1()
X_1_train_f1=f1.fit_transform(X_train)
X_1_test_f1=f1.transform(X_test)

X_1_train_f1.head()

#_____FEATURE IMPORTANCE_____

#Create and train a Random Forest regressor
model=RandomForestRegressor(random_state=42)
model.fit(X_1_train_f1,y_train)
feature_importance=model.feature_importances_
#Create a DataFrame to associate feature names with their importances
feature_importance_df=pd.DataFrame({'Feature':X_1_train_f1.columns,'I
mportance':feature_importance})
#Sort feature by importance
feature_importance_df=feature_importance_df.sort_values(by='Importanc
e',ascending=False)

feature_importance_df

plt.figure(figsize=(10, 6))
plt.barh(feature_importance_df['Feature'],
feature_importance_df['Importance'])
plt.xlabel('Feature Importance')
plt.ylabel('Feature Name')
plt.title('Feature Importance')
plt.show()

#_____MODELING_____

from sklearn.metrics import r2_score,mean_squared_error
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.ensemble import
RandomForestRegressor,ExtraTreesRegressor,AdaBoostRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor,XGBRFRegressor
from sklearn.model_selection import RandomizedSearchCV
from catboost import CatBoostRegressor

model_name=[]
r2score=[]
rmse=[]
models=[
    GradientBoostingRegressor(random_state=42),
    SVR(),
    RandomForestRegressor(random_state=42),
    LinearRegression(),
    ExtraTreesRegressor(random_state=42),
    AdaBoostRegressor(random_state=42),
    DecisionTreeRegressor(random_state=42),
    XGBRegressor(random_state=42),
    XGBRFRegressor(random_state=42),
    CatBoostRegressor(random_state=42,verbose=False)
]

for model in models:
    model.fit(X_1_train_f1 , y_train)
    y_pred = model.predict(X_1_test_f1)
    model_name.append(model.__class__.__name__)
    r2score.append(str(r2_score( y_test , y_pred ) * 100 ))
    rmse.append(str(mean_squared_error( y_test , y_pred,squared=False )))

models_df = pd.DataFrame({"Model-Name":model_name, "R2_score":
r2score ,'RMSE':rmse})
models_df = models_df.astype({"R2_score": float, "RMSE": float})
models_df.sort_values("R2_score", ascending = False)

#Plot Model Scores
plt.figure(figsize=(8,6))
sns.pointplot(x='Model-Name',y='R2_score',data=models_df)
```

```
plt.xticks(rotation=90)
plt.title('Model Comparison: R2 Score')
plt.tight_layout()
plt.show()

plt.figure(figsize=(8,6))
plt.xlabel('Model Comparison : RMSE')
sns.pointplot(x='Model-Name',y='RMSE',data=models_df)
plt.xticks(rotation=90)
plt.title('Model Comparison: RMSE')
plt.tight_layout()
plt.show()

#Final model
fm=CatBoostRegressor(random_state=42)

#Prepare a set of hyperparameters to search over
param_grid = {
    'learning_rate': np.linspace(0.01, 0.3, 10),
    'iterations': [100, 200, 300, 400, 500],  # Equivalent to n_estimators
    'depth': [3, 5, 7, 9],  # Equivalent to max_depth
    'subsample': np.linspace(0.5, 1.0, 6),
    'colsample_bylevel': np.linspace(0.5, 1.0, 6),  # Equivalent to
colsample_bytree
    'l2_leaf_reg': np.linspace(0.01, 1.0, 10),  # Equivalent to reg_lambda
    'min_child_samples': [1, 5, 10, 15],  # Equivalent to min_child_weight
}

#Create the GridSearchCV object and specify the number of folds for
cross-validation
from sklearn.metrics import make_scorer
def rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

rmse_scorer = make_scorer(rmse, greater_is_better=False)
random_search = RandomizedSearchCV(estimator=fm,
param_distributions=param_grid, n_iter=50, scoring=rmse_scorer ,
n_jobs=-1,error_score='raise')

#Fit the RandmoizedSearch object to your training data:
random_search.fit(X_1_train_f1, y_train, verbose=False)

#Inspect the best parameters and score:
best_params = random_search.best_params_
best_score = random_search.best_score_
print('Best Parameters: ', best_params)
print('Best RMSE: ', best_score)

#Use the best parameters to re-train your model and make predictions on
the test data:
best_model = CatBoostRegressor(**best_params)
```

```
best_model.fit(X_1_train_f1, y_train,verbose=False)
y_pred = best_model.predict(X_1_test_f1)

import joblib
joblib.dump(f1, 'one_hot_pipeline.pkl')

joblib.dump(best_model, 'one_hot_model.pkl')

y_test1=y_test.to_numpy()

#Evaluate the performance of the best model using your preferred metric
r2 = r2_score(y_test1, y_pred )
print('R2 Score: ', r2)

sample_data = {
    'Date/Time': ['31 12 2018 23:10'],
    'Wind Speed (m/s)': [11.404030],
    'Theoretical_Power_Curve (KWh)': [3397.190793],
    'Wind Direction (°)': [80.502724]
}
f_data = pd.DataFrame(sample_data)
f_data1=f1.transform(f_data)
best_model.predict(f_data1)

#Cross-Validation Scores
```

```
cross_val=cross_val_score(best_model,X_1_test_f1,y_test,scoring=rmse_
scorer ,cv=20,verbose=False)

print(cross_val)


plt.figure(figsize=(8, 6))

plt.plot(cross_val)

plt.title("Cross Validation Scores")

plt.ylabel("Score")

plt.xlabel("Fold")

plt.xticks(np.arange(0,20))

plt.tight_layout()

plt.show()


print(cross_val.max())


data_new = pd.DataFrame({'LV ActivePower (kW)': y_test})

data_new['Predictions'] = y_pred

data_new["Theoretical_Power_Curve (KWh)"] =
df["Theoretical_Power_Curve (KWh)"]


data_new.head()


#_____PLOT PREDICTED/REAL/THEORITICAL POWER_____


# Visualizing real, theoritical and predicted power production

plt.figure(figsize=(10,7))
```

```
sns.scatterplot(x=df['Wind Speed (m/s)'], y=data_new['LV ActivePower (kW)'],alpha=0.7, label= 'Real Power')

sns.scatterplot(x=df['Wind Speed (m/s)'], y=data_new['Predictions'], alpha=0.5, label='Predicted Power', marker='o')

sns.lineplot(x=df['Wind Speed (m/s)'], y=data_new["Theoretical_Power_Curve (KWh)"], label='Theoritical Power',color='purple')

plt.title('Wind Turbine Power Production Prediction')

plt.ylabel('Power Production (kw)')

plt.legend()
```

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