A
Mini Project Report on

EcoWatt - Power Prediction System

Submitted in partial fulfillment of the requirements
for the degree of
BACHELOR OF ENGINEERING
IN
Computer Science & Engineering
Artificial Intelligence & Machine Learning

by

Soham Waradkar (23206002)
Jay Yadav(23206007)
Pranal Vernekar (23206008)
Manas Jagtap (23206011)

Under the guidance of

Prof. Sayali Badhan

Department of Computer Science & Engineering
(Artificial Intelligence & Machine Learning)
A. P. Shah Institute of Technology
G. B. Road, Kasarvadavali, Thane (W)-400615
University Of Mumbai

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CERTIFICATE

This is to certify that the project entitled **“EcoWatt - Power Prediction System”** is a bonafide work of Soham Waradkar (23206002), Jay Yadav(23206007), Pranal Vernekar (23206008), Manas Jagtap (23206011) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of **Bachelor of Engineering** in **Computer Science & Engineering (Artificial Intelligence & Machine Learning).**

Prof. Sayali Badhan	Dr. Jaya Gupta
Mini Project Guide	Head of Department

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Project Report Approval

This Mini project report entitled **"EcoWatt - Power Prediction System"** by **Soham Waradkar, Jay Yadav, Pranal Vernekar and Manas Jagtap** is approved for the degree of ***Bachelor of Engineering*** in ***Computer Science &Engineering***, (AI&ML) ***2024-25***.

External Examiner: ____________________

Internal Examiner: ___________________

Place: APSIT, Thane

Date:

Declaration

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Soham Waradkar	Jay Yadav	Pranal Vernekar	Manas Jagtap
(23206002)	(23206007)	(23206008)	(23206011)

ABSTRACT

Predicting the power output of wind turbines is essential for improving the efficiency and effectiveness of wind energy systems. This project explores a method for forecasting wind turbine power using machine learning techniques combined with weather data. By analyzing historical data on wind speed, direction, and other relevant factors, we developed a predictive model that estimates turbine power output. We tested our model with data from several wind farms and found that it performed better than traditional methods like linear regression. This work highlights important features that influence power output and includes methods for selecting the most relevant data. Our findings show that the model reduces prediction errors and can be used in real-time to enhance grid management and energy distribution. This project offers insights and tools for future work in wind energy forecasting, aiming to support more efficient use of renewable energy.

Keywords: Prediction,Wind speed,Turbine,Power output

Index

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

As the global focus shifts toward sustainable energy solutions, wind power has become a prominent player in the renewable energy sector. Wind turbines, which harness the kinetic energy of the wind to generate electricity, are a key technology in this transition. However, the inherently variable nature of wind makes it challenging to predict turbine output accurately. The efficiency and reliability of wind power systems depend heavily on the ability to forecast power generation to manage grid stability, optimize energy storage, and ensure a consistent supply of electricity.

Accurate prediction of wind turbine power output involves understanding and modeling the complex interplay between various meteorological factors, including wind speed, direction, and atmospheric pressure. Traditional forecasting methods, such as linear regression, often struggle to capture the dynamic and non-linear relationships between these factors and turbine performance. As a result, there is a growing need for more sophisticated predictive models that can handle the complexity of wind patterns and provide more reliable forecasts.

In this project, we explore the application of advanced machine learning techniques to enhance the accuracy of wind power predictions. Our approach involves developing a model that integrates historical wind data with real-time meteorological information. By analyzing data from multiple wind farms, we aim to identify key variables that significantly influence turbine output and use this information to train a machine learning model. This model is designed to not only predict power output with greater precision but also adapt to changing wind conditions in real-time.

To achieve these goals, we apply various machine learning algorithms, including regression trees, neural networks, and ensemble methods, to determine which approaches offer the best performance. Feature selection techniques are employed to isolate the most relevant predictors from a broader set of data, thus improving the model's efficiency and accuracy.
The effectiveness of our model is evaluated through rigorous testing, comparing its predictions to actual power output data from the wind farms.

Our research also addresses the practical implications of implementing these predictive models in operational settings. By providing more accurate forecasts, our approach can help grid operators better manage energy resources, reduce the likelihood of power imbalances, and make informed decisions about energy storage and distribution. Ultimately, this project aims to contribute to the advancement of wind energy technology by offering a robust tool for predicting turbine power output, thereby supporting the broader goal of optimizing renewable energy systems.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 HISTORY

Wind energy has a long history, dating back to ancient times when windmills were used in places like Persia and medieval Europe for tasks such as grinding grain and pumping water. However, the development of modern wind energy technology, aimed at generating electricity, really took off in the late 20th century. This was driven by the oil crises of the 1970s and 1980s, which highlighted the need for alternative, sustainable energy sources and spurred advancements in renewable energy technologies.

During the late 20th century, wind turbines began to evolve from simple designs into more efficient and powerful systems. The early turbines were quite basic and had limited efficiency. The 1990s saw major improvements as engineers developed larger turbines with better materials and design features. This period also saw an increased emphasis on predicting how much power these turbines could generate, which was crucial for integrating wind energy into the electricity grid effectively.

Initially, predicting wind turbine power output relied on straightforward statistical methods. These methods used historical data on wind speed and direction to estimate future power production. Linear regression models were commonly used, but they had limitations, particularly in capturing complex, non-linear relationships between wind conditions and power output. As the size and number of wind farms increased, more sophisticated forecasting methods became necessary. With the advent of the 21st century, numerical weather prediction models started to play a key role. These models use complex mathematical equations to simulate atmospheric conditions and provide more accurate forecasts by considering a wider range of meteorological data and higher spatial resolutions. While earlier methods like time series analysis were used, they were often limited in their ability to handle non-linear patterns.

Recently, machine learning has transformed wind power forecasting. Techniques like regression trees, neural networks, and ensemble methods have greatly improved the accuracy of predictions. Machine learning can analyze large amounts of historical and real-time data to identify patterns that simpler models might miss. This has made it possible to provide more accurate and timely predictions of wind turbine output.

Feature selection techniques have also been used to focus on the most important variables, which helps improve the efficiency and accuracy of the models. Machine learning methods, which were not available in earlier times, are now essential for making better predictions and managing wind power systems effectively.

2.2 LITERATURE REVIEW

[1] “Wind Turbine Power Output Forecasting Using Artificial Intelligence”, Tejas Bhardwaj et. al.(2022)

In this paper, wind turbine power output is predicted using Artificial intelligence (AI) techniques. The AI techniques used for predictions are Machine Learning (ML) algorithm and Deep Learning (DL). In ML, polynomial regression is used and Long Short Term Memory(LSTM) was used in DL. This forecasting is long-term forecasting that uses three years of data collected from NIWE (National Institute of Wind Energy) and the results can be used directly for the planning of energy management. Various environmental factors were taken into consideration for forecasting for better accuracy and results. The AI helps to predict the wind turbine output with high accuracy by considering the linear and non-linear types of dataset. This technique can also be used for the preventive maintenance of wind turbines and before the installation of wind power plants in an unfamiliar place to determine the corresponding wind potential.

[2] “A Comparative Study of Machine Learning Techniques for Wind Turbine Performance Prediction”, S. Muralidharan et. al.(2023)

This paper describes a comparative study of various machine learning techniques for wind turbine performance prediction. The dataset used in this study is obtained from the National Renewable Energy Laboratory (NREL) and contains meteorological data and power output from a wind turbine. The machine learning techniques considered in this study include artificial neural networks (ANN), decision trees (DT), and random forests (RF). The results show that RF outperforms ANN and DT in terms of RMSE and MAE, while ANN outperforms DT and RF in terms of R-squared. Overall, this research demonstrates the effectiveness of machine learning techniques for wind turbine performance prediction and provides insights on the advantages and disadvantages of certain machine learning approaches. The findings of this research can be used to guide wind farm managers in selecting appropriate machine learning techniques for wind turbine performance prediction.

[3] “Real-time power prediction approach for turbine using deep learning techniques”, Lei Sun et. al.(2021)

This paper describes The accurate power forecasting is of great importance to the turbine control and predictive maintenance. However, traditional physics models and statistical models can no longer meet the needs of precision and flexibility when thermal power plants frequently undertake more and more peak and frequency modulation tasks. In this study, the recurrent neural network (RNN) and convolutional neural network (CNN) for power prediction are proposed, and are applied to predict real-time power of turbine based on DCS data (recorded for 719 days) from a power plant. In addition, the performances of two deep learning models and five typical machine learning models are compared, including prediction deviation, variance and time cost. It is found that deep learning models outperform other shallow models and RNN model performs best in balancing the accuracy-efficient trade-off for power prediction (the relative prediction error of 99.76% samples is less than 1% in all load range for test 216 days). Moreover, the influence of training size and input time-steps on the performance of RNN model is also explored. The model can achieve remarkable performance by learning only 30% samples (about 216 days) with 3 input time-steps (about 60 s). Those results of the proposed models based on deep-learning methods indicated that deep learning is of great help to improve the accuracy of turbine power prediction. It is therefore convinced that those models have a high potential for turbine control and predictable maintenance in actual industrial scenarios.

[4] “Short-Term Power Prediction of Wind Turbine Applying Machine Learning and Digital Filter”, Shujun Liu et. al.(2023)

As wind energy development increases, accurate wind energy forecasting helps to develop sensible power generation plans and ensure a balance between supply and demand. Machine-learning-based forecasting models possess exceptional predictive capabilities, and data manipulation prior to model training is also a key focus of this research. This study trained a deep Long Short-Term Memory (LSTM) neural network to learn the processing results of the Savitzky-Golay filter, which can avoid over-fitting due to fluctuations and noise in measurements, improving the generalization performance. The optimum data frame length to match the second-order filter was determined by comparison. In a single-step prediction, the method reduced the root-mean-square error by 3.8% compared to the model trained directly with the measurements. The method also produced the smallest errors in all steps of the multistep advance prediction. The proposed method ensures the accuracy of the forecasting and, on that basis, also improves the timeliness of the effective forecasts.

[5] “Integrated Energy Management and Forecasting Dataset”, K M Karthick Raghunath(2023)

The Integrated Energy Management and Forecasting Dataset is a comprehensive data collection specifically designed for advanced algorithmic modeling in energy management. It combines two distinct yet complementary datasets - the Energy Forecasting Data and the Energy Grid Status Data - each tailored for different but related purposes in the energy sector. The integration of IoT (Internet of Things) technologies in the Integrated Energy Management and Forecasting Dataset significantly enhances its functionality and applicability in real-world scenarios. Sensors across various points in the energy grid and renewable energy sources gather data like energy consumption, production, grid load, and environmental factors (temperature, weather conditions). Sensors within the grid infrastructure also monitor load, distribution, and transmission status. Sensors in solar panels, wind turbines, and traditional power plants (like coal or gas-fired) provide detailed output data. IoT infrastructure ensures that the data is not just accurate but also current, reflecting the latest status of the energy grid and environmental conditions.

[6] “Prediction of Wind Power with Machine Learning Models”, Ömer Ali Karaman(2023)

Wind power is a vital power grid component, and wind power forecasting represents a challenging task. In this study, a series of multiobjective predictive models were created utilising a range of cutting-edge machine learning (ML) methodologies, namely, artificial neural networks (ANNs), recurrent neural networks (RNNs), convolutional neural networks, and long short-term memory (LSTM) networks. In this study, two independent data sets were combined and used to predict wind power. The first data set contained internal values such as wind speed (m/s), wind direction (°), theoretical power (kW), and active power (kW). The second data set was external values that contained the meteorological data set, which can affect the wind power forecast. The k-nearest neighbours (kNN) algorithm completed the missing data in the data set. The results showed that the LSTM, RNN, CNN, and ANN algorithms were powerful in forecasting wind power. Furthermore, the performance of these models was evaluated by incorporating statistical indicators of performance deviation to demonstrate the efficacy of the employed methodology effectively. Moreover, the performance of these models was evaluated by incorporating statistical indicators of performance deviation, including the coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE) metrics to effectively demonstrate the efficacy of the employed methodology. When the metrics are examined, it can be said that ANN, RNN, CNN, and LSTM methods effectively forecast wind power. However, it can be said that the LSTM model is more successful in estimating the wind power with an R2 value of 0.9574, MAE of 0.0209, MSE of 0.0038, and RMSE of 0.0614.

CHAPTER 3

PROBLEM STATEMENT

3. PROBLEM STATEMENT

As the global shift toward renewable energy accelerates, wind power has emerged as a crucial component of sustainable energy portfolios. However, the effectiveness of wind energy is highly dependent on accurate forecasting of wind turbine power output, which remains a significant challenge. Current forecasting methods often struggle to accurately predict short-term power output due to the intricate and dynamic nature of wind patterns. Traditional models fail to account for the complexity of wind behavior, leading to unreliable predictions. Additionally, the high variability of wind conditions, characterized by rapid and unpredictable changes, makes short-term forecasting even more difficult. This variability poses a significant challenge for grid operators, who must balance supply and demand to ensure grid stability.

Another major challenge is data integration. Accurately forecasting wind power requires the effective combination of diverse data sources, including historical wind data, real-time weather forecasts, and turbine-specific parameters. However, integrating these data sources in a meaningful way is a significant hurdle. Moreover, achieving a balance between prediction accuracy and computational efficiency is crucial. High-precision models often demand substantial computational resources, which can limit their practicality for real-time applications.

This project aims to address these challenges by developing advanced machine learning models designed specifically for wind power forecasting. By leveraging sophisticated algorithms and integrating diverse data sources, the project seeks to improve the accuracy of wind power predictions while optimizing computational efficiency. Enhanced forecasting capabilities will lead to more reliable energy management, improved grid stability, and a stronger contribution of wind energy to the renewable energy mix. This initiative aims to make wind energy more predictable and efficient, supporting the transition to a sustainable energy future and contributing to global efforts to combat climate change.

CHAPTER 4

EXPERIMENTAL SETUP

4. EXPERIMENTAL SETUP

4.1 Hardware Setup

- Processor: Intel i5 8th gen Or Above
- Ram: 8GB Or Above
- Storage: 256 GB SSD Or Above
- OS: Windows 10 Or Above

4.2 Software Setup

- Visual Studio Code
- Node Package Manager (10.8.3)
- React JS (18.2.0)
- Firebase
- Python Flask (3.0.3)

CHAPTER 5

PROPOSED SYSTEM & IMPLEMENTATION

5. PROPOSED SYSTEM & IMPLEMENTATION

5.1 Block diagram of proposed system

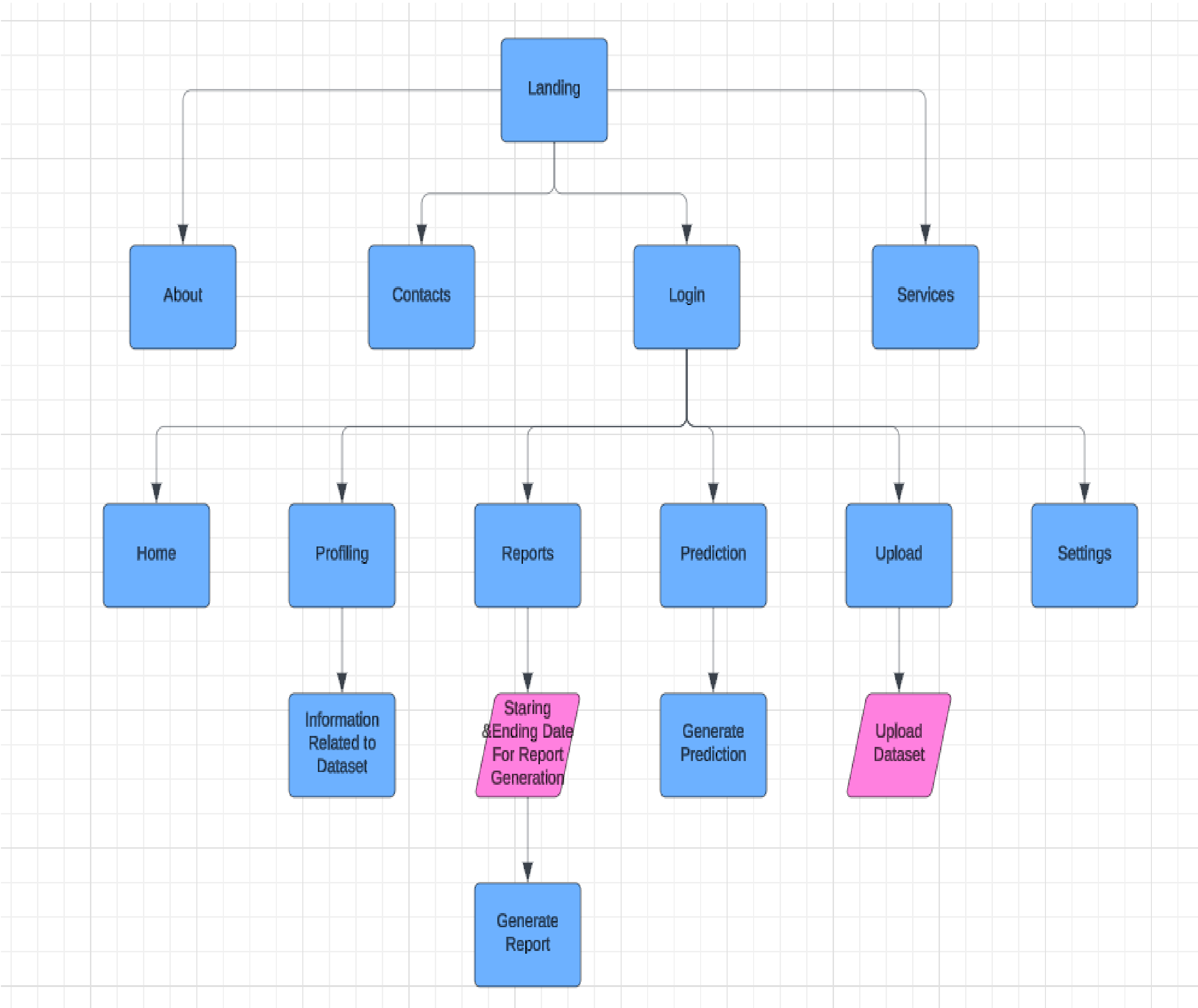


Fig. 5.1: Block Diagram For EcoWatt

5.2 Description of block diagram

- Landing Page: The entry point to the application that directs users to various sections including About, Contacts, Login, and Services.
- About & Contacts: These sections provide general information about the application and allow users to contact support for assistance.
- Login: Provides authentication for users, granting access to further application functionalities like profiling, prediction, and reporting.
- Services: Offers a general overview of the features and benefits of using the application.
- Home: After logging in, users land on the home page where they can access all core functionalities.
- Profiling: Users can manage their profiles, including information about datasets they have uploaded for wind energy predictions.
- Prediction: This feature allows users to generate power predictions based on wind energy datasets by analyzing historical data and weather conditions.
- Reports: Enables users to generate detailed reports on power predictions. Users can specify starting and ending dates for generating these reports, ensuring the data reflects the desired time range.
- Upload: Users can upload new datasets related to wind energy. These datasets are used to enhance prediction accuracy and generate reliable energy forecasts.
- Settings: Users can manage their preferences and configurations within the application.

5.3 Implementation

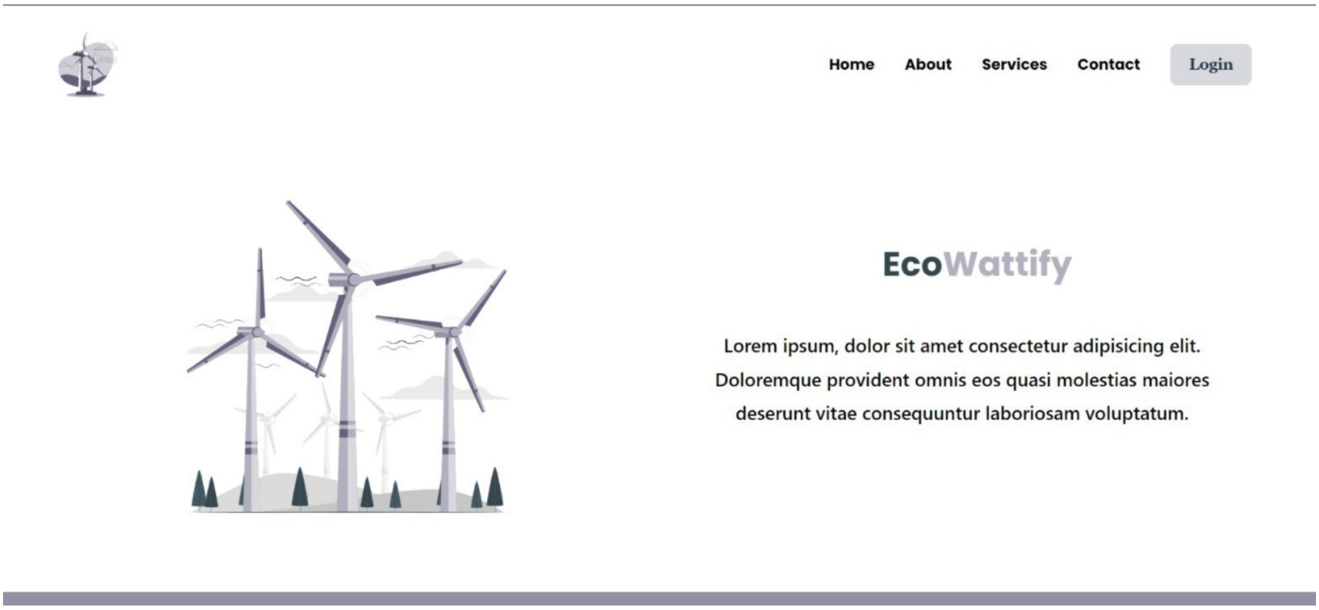


Fig. 5.3.1 Landing

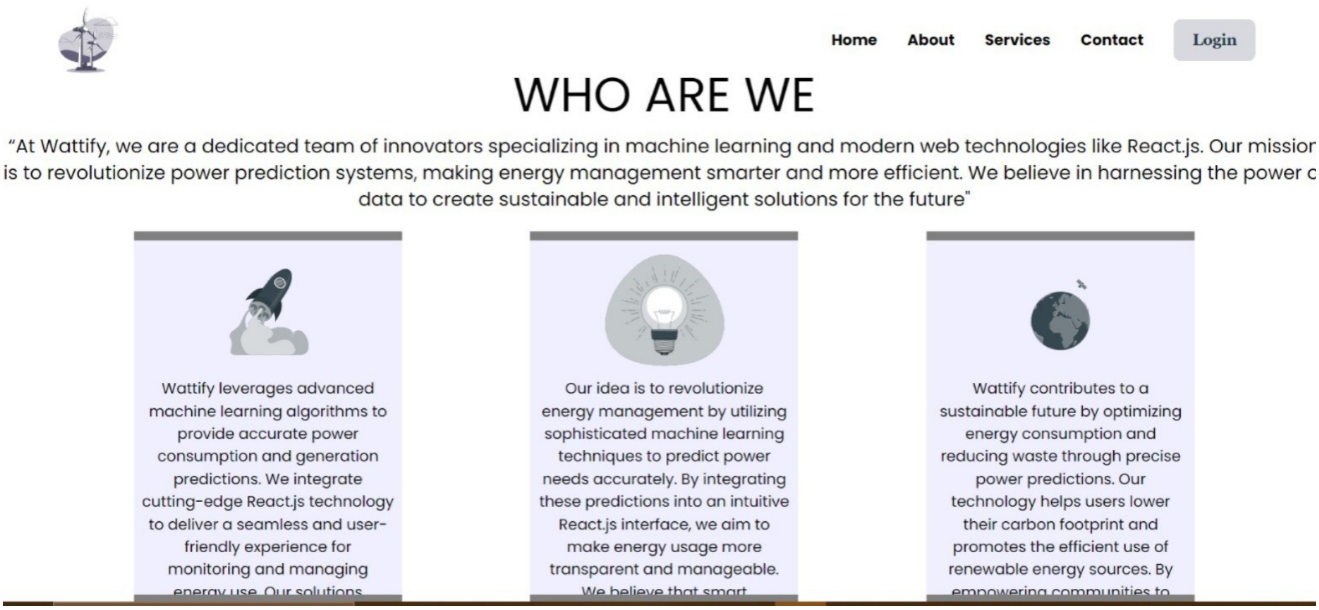


Fig. 5.3.2 About Us

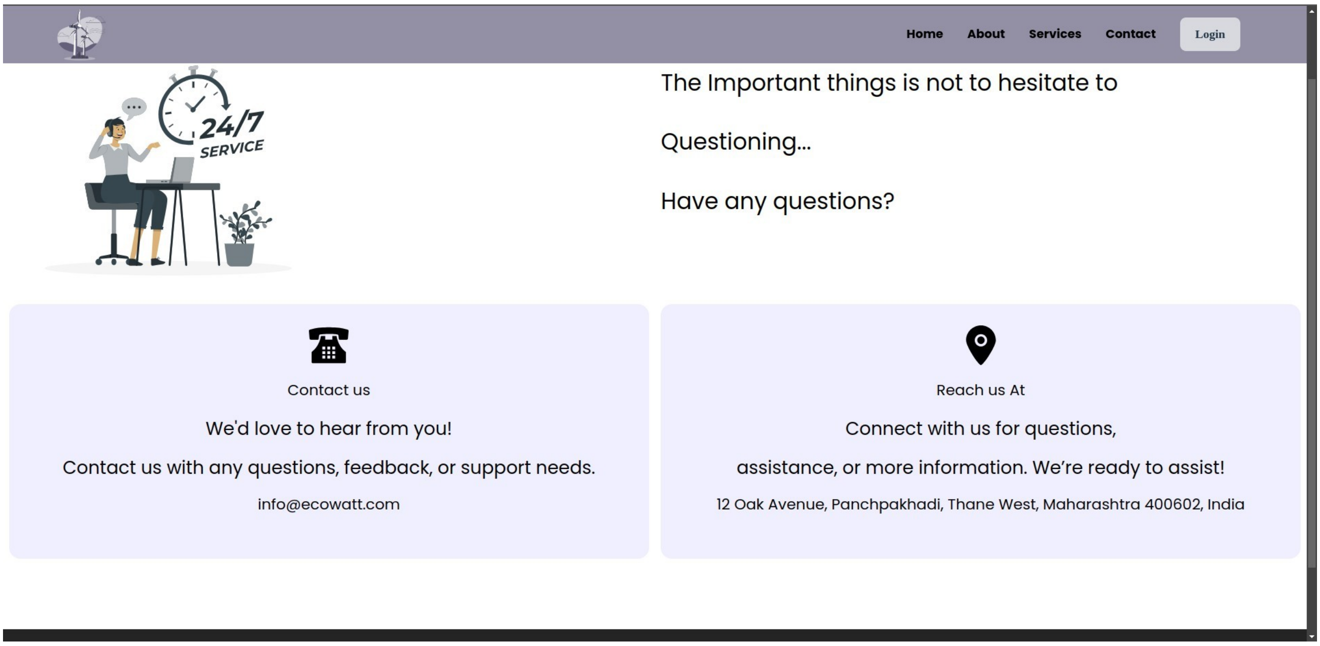


Fig. 5.3.3 Contacts

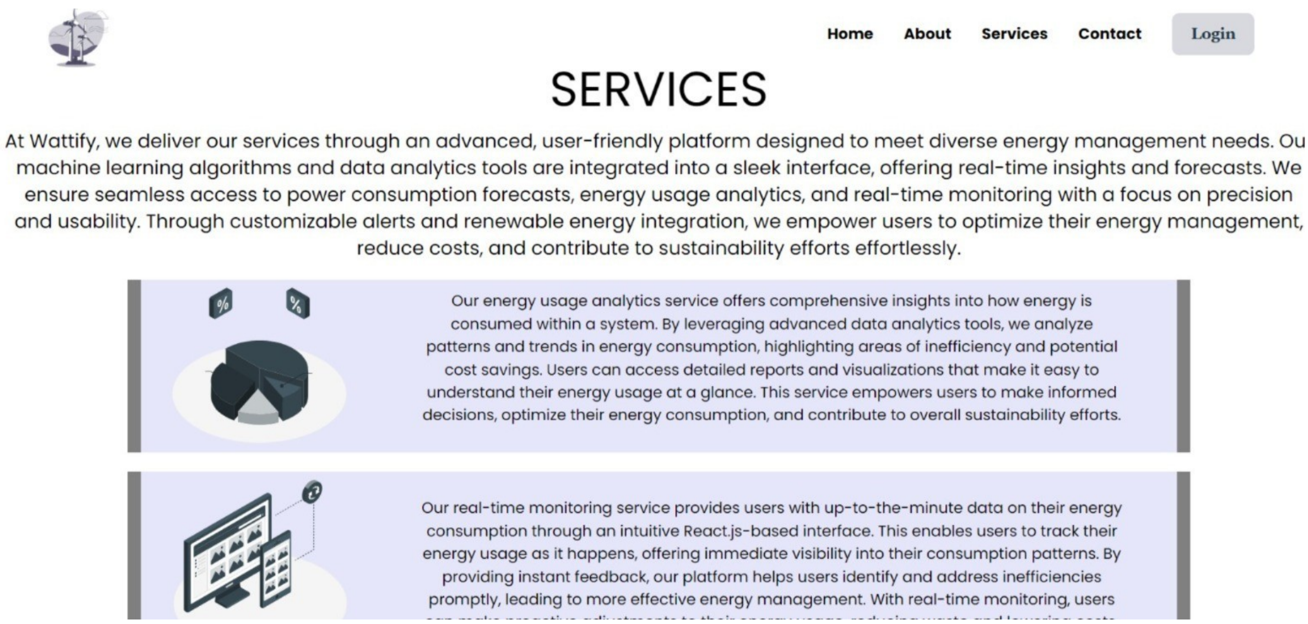


Fig. 5.3.4 Services

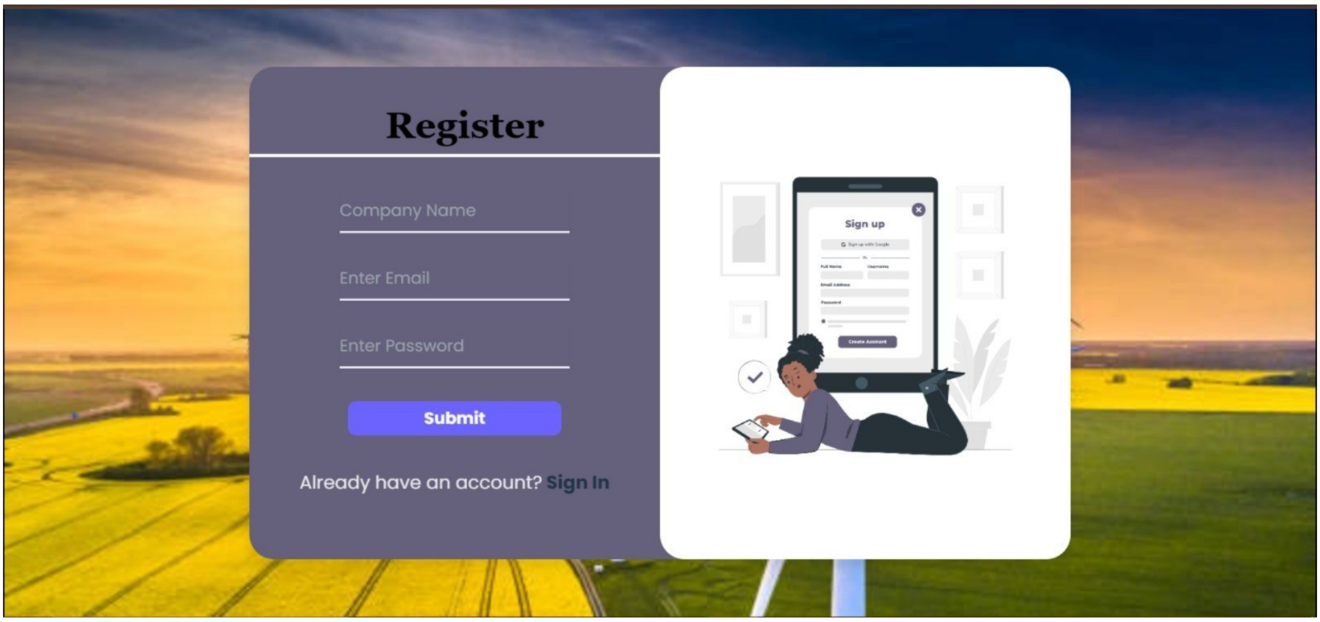


Fig 5.3.5 Register

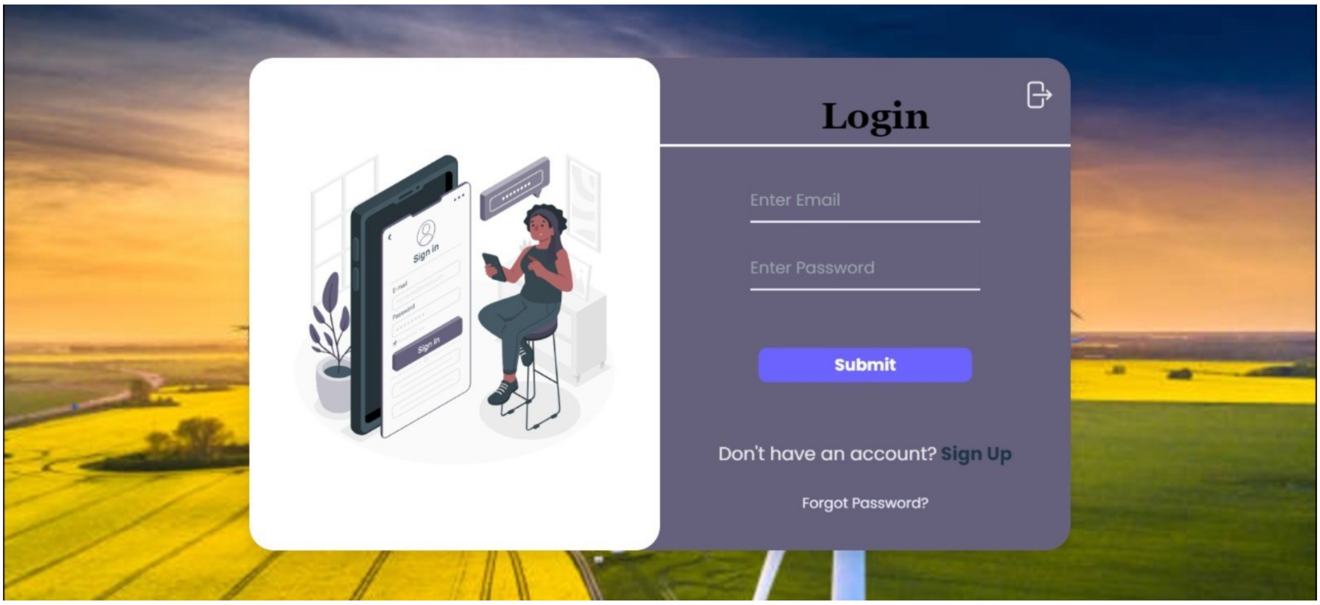
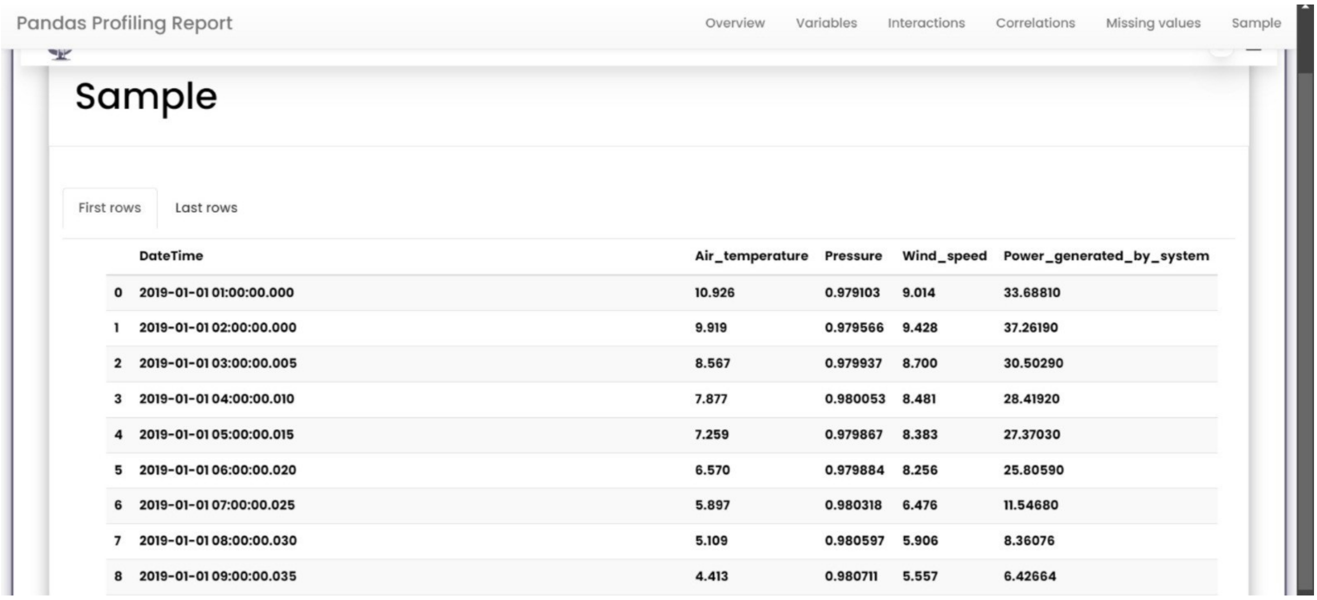


Fig 5.3.6 Login


Pandas Profiling Report   Overview   Variables   Interactions   Correlations   Missing values   Sample

Sample

First rows   Last rows

	DateTime	Air_temperature	Pressure	Wind_speed	Power_generated_by_system
0	2019-01-01 01:00:00.000	10.926	0.979103	9.014	33.68810
1	2019-01-01 02:00:00.000	9.919	0.979566	9.428	37.26190
2	2019-01-01 03:00:00.005	8.567	0.979937	8.700	30.50290
3	2019-01-01 04:00:00.010	7.877	0.980053	8.481	28.41920
4	2019-01-01 05:00:00.015	7.259	0.979867	8.383	27.37030
5	2019-01-01 06:00:00.020	6.570	0.979884	8.256	25.80590
6	2019-01-01 07:00:00.025	5.897	0.980318	6.476	11.54680
7	2019-01-01 08:00:00.030	5.109	0.980597	5.906	8.36076
8	2019-01-01 09:00:00.035	4.413	0.980711	5.557	6.42664

Fig. 5.3.7 Profiling

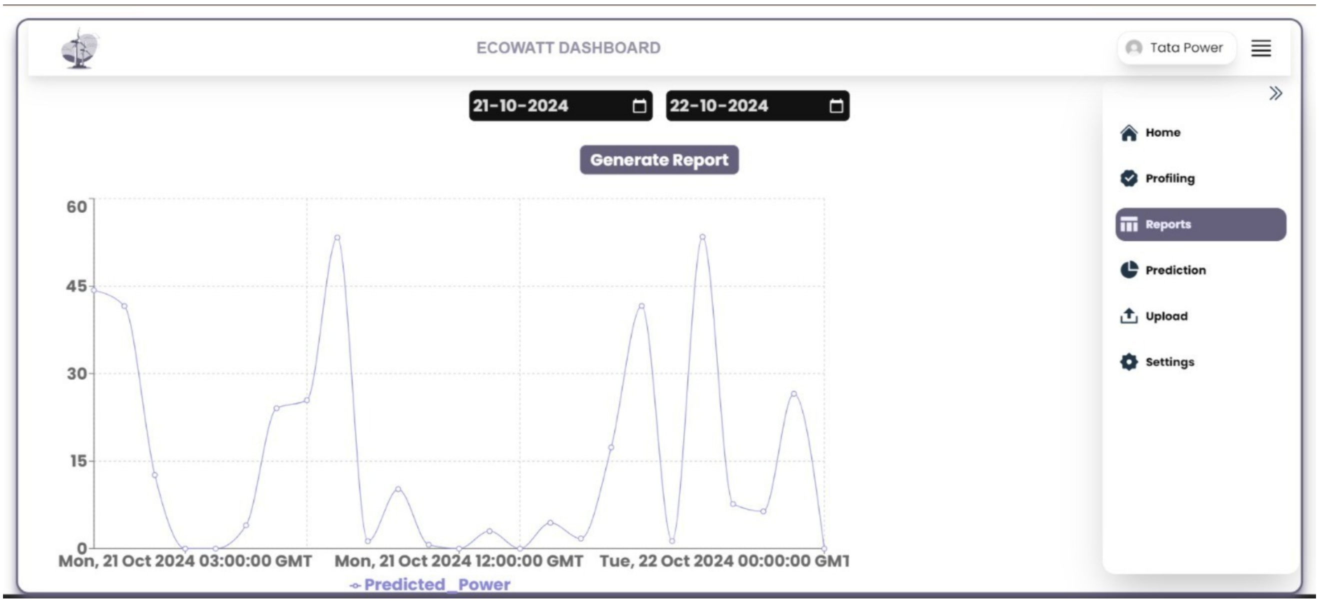
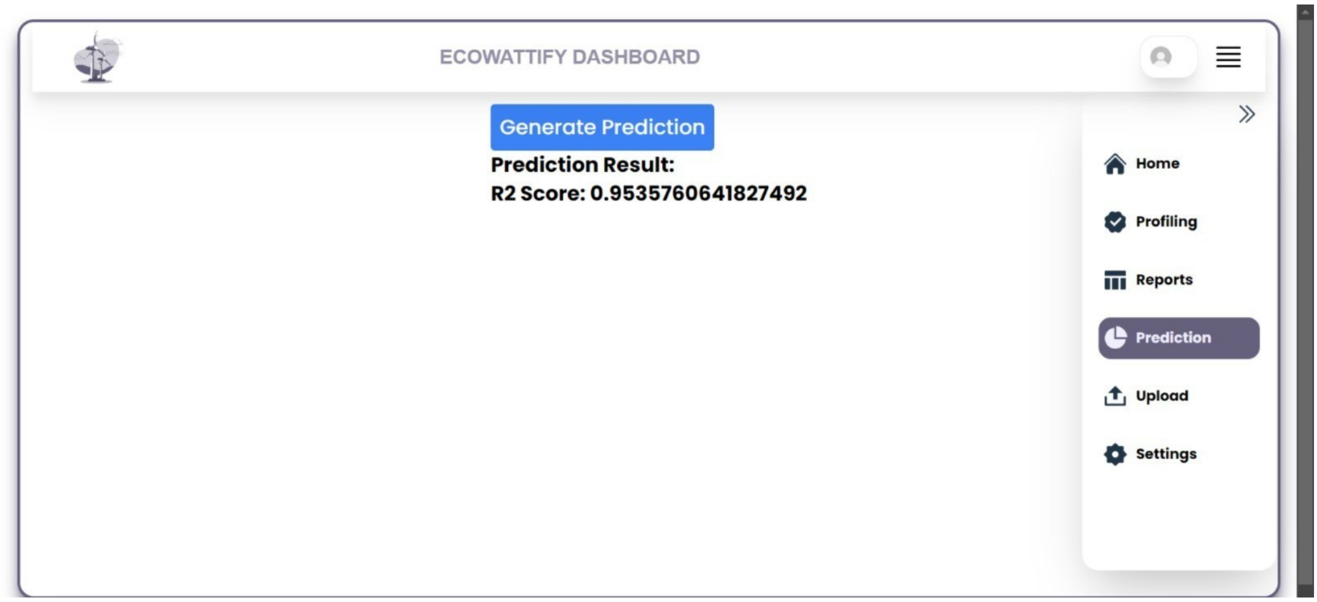
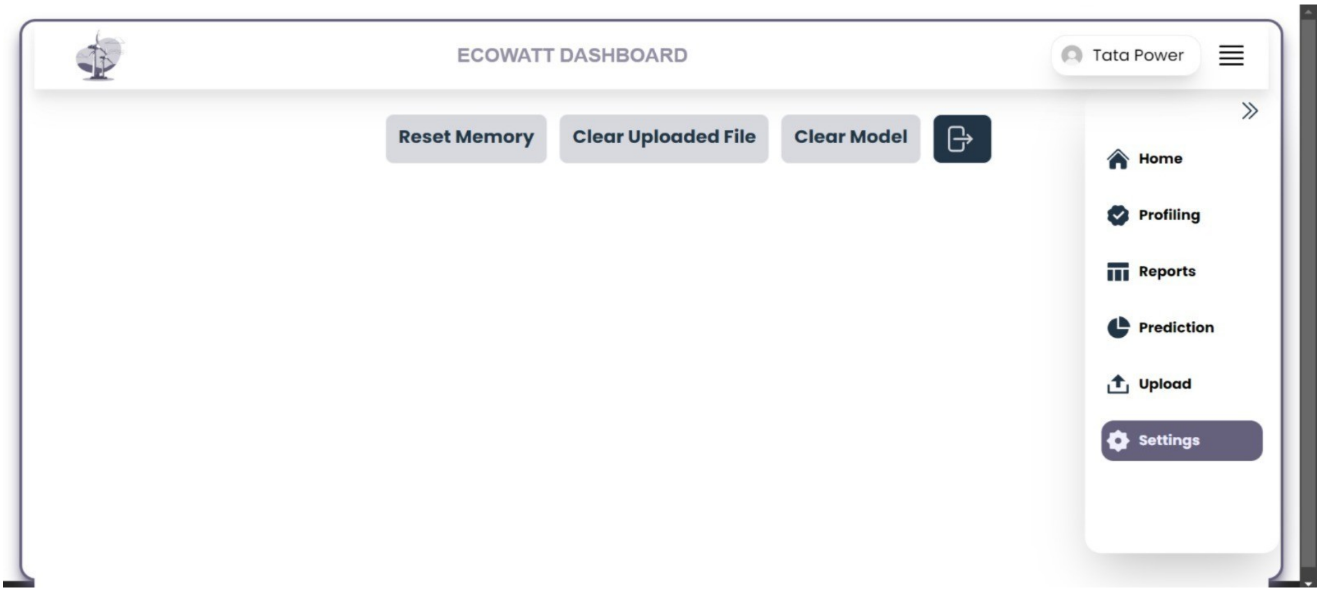


Fig. 5.4.8 Reports



5.3.9 Prediction



5.3.10 Settings

5.4 Advantages

Enhanced Accuracy: ML models can analyze complex patterns and relationships in historical wind data, leading to more accurate predictions of wind power output compared to traditional methods.

Real-Time Forecasting: By integrating real-time weather data and turbine-specific parameters, ML algorithms can provide timely and dynamic forecasts, which are crucial for operational decisions and grid management.

Adaptability: ML models can continuously learn from new data, allowing them to adapt to changing wind patterns and improve predictions over time, enhancing their reliability and precision.

Optimized Resource Allocation: Accurate wind power forecasts enable better planning and resource management, including more efficient scheduling of maintenance and better utilization of wind energy in the grid.

Improved Grid Stability: Reliable predictions help in maintaining grid stability by allowing for better integration of wind power into the energy mix, reducing the risk of power imbalances and outages.

Cost Efficiency: By minimizing errors in power forecasts, ML models can help reduce operational costs and increase the financial viability of wind energy projects.

Advanced Data Integration: ML can effectively combine various data sources, including historical data, weather forecasts, and turbine performance metrics, to provide a comprehensive view of wind power potential.

Scalability: ML algorithms can be scaled to handle large datasets from multiple wind farms, making them suitable for both small and large-scale wind energy operations.

Predictive Maintenance: Accurate forecasts allow for predictive maintenance of turbines, identifying potential issues before they lead to failures, thus extending the lifespan of equipment and reducing downtime.

CHAPTER 6

CONCLUSION

6. CONCLUSION

Conclusion:

Accurate wind power forecasting is crucial for the effective management of wind energy and its integration into the power grid. The development of advanced machine learning models holds the potential to significantly enhance the accuracy of wind turbine power output predictions. By leveraging sophisticated algorithms and integrating diverse data sources such as historical wind data, real-time meteorological forecasts, and turbine-specific parameters this project aims to address the limitations of traditional forecasting methods.

The anticipated improvements in forecasting accuracy will enable better decision-making for energy management, leading to optimized turbine operation and grid stability. Enhanced predictions will facilitate more efficient scheduling of maintenance activities, reduce operational uncertainties, and help in balancing supply and demand more effectively. As a result, wind energy can be utilized more efficiently, contributing to a more stable and reliable power system. This advancement will support the broader adoption of renewable energy and aid in the transition towards a sustainable energy future.

Future Scope:

To build on the improvements made in wind power forecasting with machine learning, future research should focus on real-time applications. Testing the developed models in live operational settings will be essential to assess their performance and make necessary refinements. Additionally, incorporating additional data sources, such as satellite imagery and advanced remote sensing, could further enhance the accuracy of predictions by providing more detailed information on wind conditions.

Evaluating the long-term effects of enhanced forecasting on grid stability and energy efficiency will also be crucial. This involves understanding how improved predictions impact operational strategies and maintenance planning. Furthermore, exploring advancements in machine learning techniques and adapting models for different wind farm types and geographic regions will ensure broader applicability and effectiveness. These steps will help refine wind power forecasting and support more efficient use of wind energy.

REFERENCES

[1] “Wind Turbine Power Output Forecasting Using Artificial Intelligence”,Tejas Bhardwaj, Sumit Mehenge & B. Sri Revathi, International Virtual Conference on Power Engineering Computing and Control: Developments in Electric Vehicles and Energy Sector for Sustainable Future (PECCON), 2022

[2] “A Comparative Study of Machine Learning Techniques for Wind Turbine Performance Prediction”, S. Muralidharan, S.Parthasarathy, Deepa A & Jermin Jersha, International Conference on Smart Engineering for Renewable Energy Technologies (ICSERET), 2023

[3] “Real-time power prediction approach for turbine using deep learning techniques”, Lei Sun, Tianyuan Liu, Yonghui Xie, Di Zhang, Xinlei Xia, Elsevier BV, 2021

[4] “Short-Term Power Prediction of Wind Turbine Applying Machine Learning and Digital Filter”, Shujun Liu, Yaocong Zhang, Xiaoze Du, Tong Xu & Jiangbo Wu, Applied Sciences, 2023

[5] “Integrated Energy Management and Forecasting Dataset”, K M Karthick Raghunath, International Conference on Sustainable Computing and Smart Systems (ICSCSS), 2024

[6] “Prediction of Wind Power with Machine Learning Models”, Ömer Ali Karaman, Applied Sciences, 2023