REAL-TIME OPTIMIZATION AND MAINTENANCE OF WIND TURBINE PERFORMANCE USING DIGITAL TWIN TECHNOLOGY

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(The dissertation was submitted in partial fulfilment of the requirements for the B.Sc. (Honors) degree in Information Technology Specialising in Software Engineering)

Department of Information Technology

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DECLARATION

I declare that this is my own work, and this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. Also, I hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute my dissertation in whole or part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as article or books).

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Jenojan P.	IT21355714	

As the supervisor/s of the above-mentioned candidates, I hereby certify that they are conducting research for their undergraduate dissertation under my guidance and direction.

Signature of the supervisor: Date:

(Mr.Vishan Jayasinghearachchi) 28/08/2025

ABSTRACT

Wind energy has emerged as one of the fastest-growing renewable energy sources due to its sustainability, low carbon footprint, and ability to meet increasing global energy demands. However, the widespread adoption of wind power continues to face a critical barrier: **noise pollution** generated by wind turbines. Noise emissions, particularly from aerodynamic interactions between turbine blades and airflow, often lead to community complaints, annoyance, and regulatory challenges. This makes noise management not only a technical issue but also a social and environmental concern, directly influencing public acceptance of wind farm projects.

This research addresses the problem by developing a **digital twin–based framework for wind turbines**, designed to model, predict, and mitigate noise in real time while maintaining optimal power generation efficiency. The digital twin acts as a virtual representation of the physical turbine, integrating aerodynamic simulations, acoustic propagation models, and machine learning algorithms trained on the WEA dataset. The primary focus of the model is on **aerodynamic noise**, which dominates in modern large-scale turbines, while mechanical noise sources are considered secondary due to improvements in direct-drive designs and insulation technologies.

The system introduces **adaptive control strategies**, particularly dynamic blade pitch adjustments, which allow the turbine to respond to environmental changes such as wind speed and atmospheric stability. Unlike traditional static design modifications or operational curtailments, this approach provides a **flexible, data-driven mechanism** for balancing noise reduction with power output. Through simulations and case studies across different wind speed conditions (6 m/s, 9 m/s, and 12 m/s), the model demonstrates its ability to achieve measurable reductions in noise levels without significant loss of energy production. Comparative evaluations against existing operational strategies (SO1 and SO2) confirm that the digital twin framework delivers superior outcomes in managing the noise–power trade-off.

The results highlight the potential of digital twins as a transformative tool in the wind energy sector. Beyond technical performance, such systems can enhance **community acceptance, regulatory compliance, and long-term sustainability** of wind projects. This study not only contributes a novel methodological framework for digital twin–driven acoustic control but also lays the groundwork for future

enhancements through IoT sensor integration, reinforcement learning algorithms, and large-scale deployment in wind farms.

In conclusion, the research demonstrates that **digital twin technology offers a practical, scalable, and innovative solution for wind turbine noise management**, supporting both technical efficiency and social acceptability in the global transition to clean energy.

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My heartfelt thanks also go to **Mr. Janaka of the Ceylon Electricity Board (CEB), Mannar Thambapavani**, for generously sharing his knowledge and granting access to the dataset used in this study. His insights into the operational aspects of wind turbines provided valuable practical context and helped align the research with real-world applications.

I am sincerely grateful to **CDAP** for their collaboration and support in providing the necessary facilities and resources, which greatly contributed to the smooth progress of this project.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
API	Application Programming Interface
CNN	Convolutional Neural Network
dB	Decibel
GPU	Graphics Processing Unit
IEC	International Electrotechnical Commission
IoT	Internet of Things
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
ML	Machine Learning
MLP	Multi-Layer Perceptron
MSE	Mean Squared Error
NLP	Natural Language Processing
PID	Proportional Integral Derivative
PV	Photovoltaic
R^2	Coefficient of Determination
RF	Random Forest
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SCADA	Supervisory Control and Data Acquisition

1. INTRODUCTION

1.1 Background

The global transition toward clean and sustainable energy has become a central focus in addressing the dual challenges of climate change and energy security. Among the array of renewable energy technologies, wind power has emerged as one of the most promising and rapidly expanding sources. Wind turbines, both onshore and offshore, are being deployed on a large scale across the world, forming a critical component of national and international strategies aimed at reducing dependence on fossil fuels, cutting greenhouse gas emissions, and meeting future energy demands. According to the International Energy Agency (IEA), wind energy is expected to continue its upward trajectory, with turbines becoming increasingly larger, more efficient, and cost-effective, allowing for more reliable integration into national energy grids.

Despite these clear advantages, the widespread adoption of wind energy is not without its challenges. While the environmental benefits are significant, practical and social concerns must be addressed to ensure sustainable deployment. Among these, noise pollution from wind turbines has emerged as one of the most persistent and widely debated issues. Unlike visual impacts, which can sometimes be mitigated through careful landscape design or siting strategies, noise is continuous, pervasive, and directly influences the quality of life for nearby residents. Reports from communities situated near wind farms have documented various adverse effects associated with turbine noise, including annoyance, difficulty sleeping, and stress-related health problems. These social impacts can have substantial consequences, such as delaying approvals for new projects, reducing community acceptance, and potentially limiting the pace of wind energy expansion, despite its overarching environmental benefits.

Wind turbine noise originates primarily from two sources: aerodynamic and mechanical. Aerodynamic noise is generated as air flows over turbine blades, particularly at high tip speeds, and includes phenomena such as trailing-edge noise, tip vortex noise, and turbulent inflow noise. Mechanical noise, on the other hand, arises from the internal components of the turbine, such as the gearbox, generator, and bearings, with vibrations propagating through the tower into the surrounding environment. In recent years, advances in turbine engineering have significantly reduced mechanical noise through improved insulation, direct-drive systems, and damping mechanisms. Consequently, aerodynamic noise has become the dominant contributor to acoustic emissions in most modern wind farms. As turbines grow in size to capture more wind energy, the magnitude of aerodynamic noise increases, underscoring the need for innovative approaches to noise management.

1.2 Problem Context

Addressing wind turbine noise requires a nuanced understanding of both its technical and operational dimensions. Existing noise reduction techniques can generally be classified into two main approaches: design-based modifications and operational strategies. Design-based solutions focus on reducing noise at the source by altering blade geometry, implementing serrated trailing edges, or using specialized coatings and damping materials. While effective, these strategies are inherently static and are applied during manufacturing, which limits their ability to adapt to dynamic environmental conditions such as fluctuating wind speeds, turbulence, or atmospheric stability.

Operational strategies, on the other hand, involve modifying turbine operations to minimize noise emissions. These may include reducing rotational speeds, altering blade pitch angles, or temporarily curtailing turbine operation during periods when noise impact on the surrounding community is expected to be high. Although these measures can effectively reduce noise, they often come at the cost of energy production, creating a technical and economic trade-off that must be carefully managed by turbine operators.

A critical limitation of current noise management practices is their reliance on static assessments conducted during or after wind farm construction. Such post-installation evaluations are unable to account for the real-time variability of environmental and operational conditions that influence noise levels, including sudden changes in wind speed, turbulence intensity, or shifts in wind direction. Consequently, noise mitigation efforts remain largely reactive rather than predictive, highlighting a significant gap in the capacity to dynamically balance turbine efficiency with community comfort.

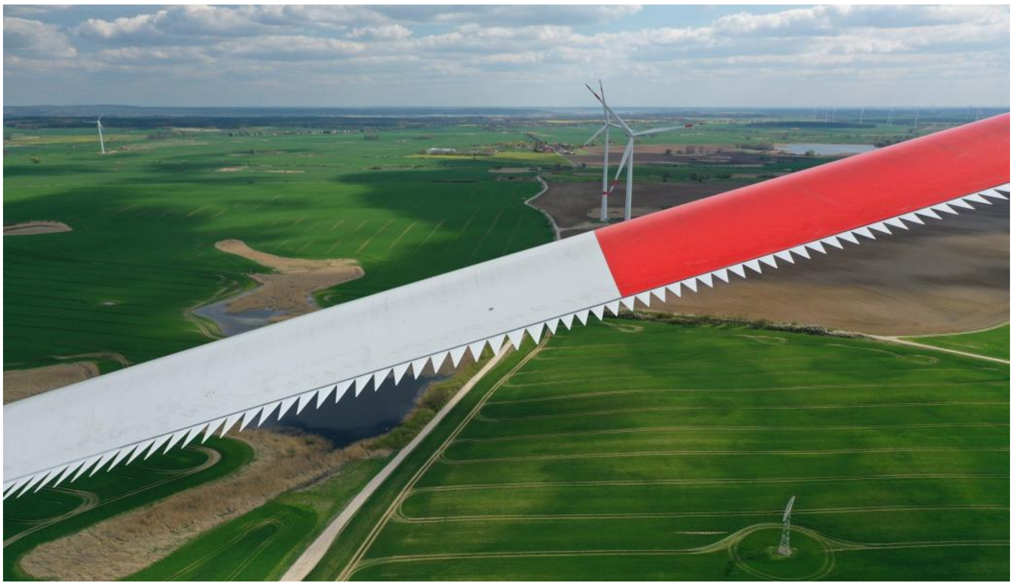


Figure 1-serrated trailing edges

1.3 Digital Twin Approach

In recent years, the concept of the digital twin has emerged as a transformative tool in engineering, manufacturing, and industrial applications. A digital twin is a high-fidelity, virtual representation of a physical system that continuously receives real-time sensor data to replicate the behavior of its physical counterpart. This creates a feedback loop in which simulations, predictions, and optimizations can be performed in a virtual environment and then applied back to the actual system for improved performance.

Applied to wind turbines, a digital twin can integrate turbine dynamics, environmental inputs, and acoustic modeling to simulate and predict noise behavior under a wide range of operational conditions. By combining aerodynamic models, acoustic simulations, and live or simulated sensor data, a digital twin enables adaptive control strategies that can adjust blade pitch, rotor speed, or other operational parameters in real time to minimize noise without significantly compromising power generation. The approach offers several key advantages: continuous monitoring and prediction of noise emissions, the ability to test multiple mitigation strategies virtually before physical implementation, and the capability to dynamically balance energy efficiency with noise reduction based on current operating conditions.

1.4 Research Significance

The development of a digital twin–based system for noise prediction and mitigation carries both technical and societal importance. Technically, it advances turbine design by providing detailed insights into noise generation and enabling the testing of innovative mitigation strategies, such as aerodynamic modifications or advanced damping mechanisms. Operationally, it supports real-time decision-making, ensuring that turbines operate efficiently while maintaining compliance with noise regulations and community expectations. From a societal perspective, reducing the negative impacts of turbine noise enhances public acceptance of wind energy projects, minimizes resistance to new installations, and fosters a more harmonious relationship between renewable energy development and local communities.

Overall, this research aligns with global priorities for renewable energy expansion, sustainable technology adoption, and environmental protection. By integrating cutting-edge digital technologies with wind energy engineering, it presents a practical and forward-looking solution to one of the most persistent barriers to large-scale wind energy deployment. The digital twin approach not only addresses immediate noise concerns but also provides a scalable framework for ongoing improvements in turbine performance, operational efficiency, and community engagement.

2. BACKGROUND LITERATURE

2.1 Wind Turbine Noise Studies

The issue of noise generated by wind turbines has become increasingly prominent as turbine sizes have expanded and wind energy projects have moved into rural and suburban areas. Larger rotor diameters and taller towers, while beneficial for energy capture, have resulted in increased acoustic emissions, which can directly affect the surrounding environment and local communities. Several studies indicate that at distances ranging from 300 to 500 meters from a wind turbine, average sound levels typically fall within 35–45 dB(A) [1], [2]. While these levels may appear moderate, they are comparable to the ambient noise of a quiet library and can still be disturbing to sensitive populations, especially during nighttime or low-background-noise conditions. At distances around 1,000 meters, the measured sound levels generally decrease to approximately 30–35 dB(A) [3]; however, in rural areas where background noise is naturally low, turbine noise becomes more perceptible, emphasizing the importance of mitigation strategies even at relatively long distances.

Wind turbine noise is broadly categorized into two primary sources: **aerodynamic noise** and **mechanical noise**. Aerodynamic noise arises from the interaction of moving air with the turbine blades, particularly at high tip speeds. This category includes several specific phenomena: trailing-edge noise, which is the dominant contributor in large turbines; tip vortex noise, generated by the swirling vortices at blade tips; and turbulent inflow noise, which results from the interaction of incoming wind turbulence with the blade surfaces. In modern large-scale turbines, particularly those exceeding 2 MW in capacity, aerodynamic noise has become the primary contributor to overall noise emissions [4].

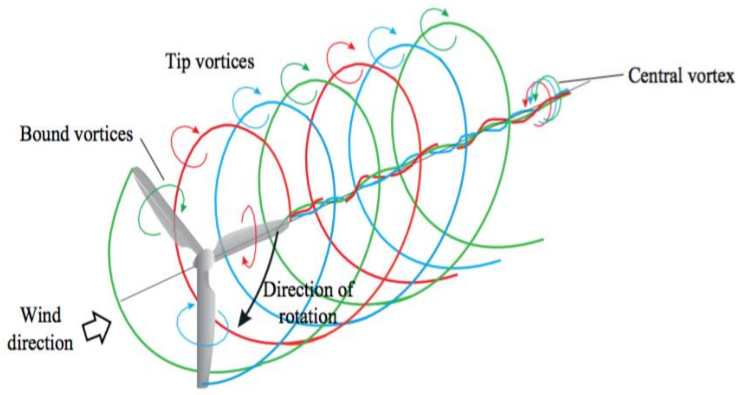


Figure 2-swirling vortices at blade

Mechanical noise, in contrast, originates from internal components of the turbine, such as gearboxes, generators, and bearings. Vibrations produced by these components propagate through the nacelle and tower, eventually radiating into the surrounding environment. Historically, mechanical noise represented a significant portion of turbine-generated sound; however, advances in direct-drive turbine designs, improved insulation, and vibration-damping techniques have largely reduced its contribution [5]. Despite this reduction, the variability of aerodynamic noise remains highly dependent on atmospheric conditions. Field studies demonstrate that during stable nighttime atmospheres with low ambient noise, community annoyance has been reported at sound levels as low as 33–35 dB(A) [6], illustrating that even relatively modest noise levels can have a perceptible impact on residents under certain environmental conditions.

2.2 Noise Mitigation Techniques

Noise mitigation strategies for wind turbines can be broadly divided into two categories: **design-based techniques** and **operational strategies**.

Design-based techniques focus on reducing noise emissions at the source by modifying the turbine's physical components. Common approaches include blade modifications such as serrated trailing edges, curved tips, and the use of porous materials to disrupt turbulent airflow and minimize aerodynamic noise. Surface treatments, including rubber coatings and advanced composite materials, can help attenuate vibrations and reduce the transmission of mechanical noise. Additionally, component redesign, such as adopting direct-drive systems, eliminates the need for gearboxes, effectively removing a significant source of mechanical noise. Field experiments have demonstrated that serrated trailing edges can reduce noise levels by 2–5 dB(A) without causing substantial losses in power output [7], [8]. While effective, these interventions are generally static, meaning they are implemented during the manufacturing stage and cannot adapt dynamically to changing operational or environmental conditions.

Operational strategies, in contrast, rely on modifying the turbine's real-time behavior to minimize noise. Blade pitch control is a widely used method, allowing operators to adjust blade angles to reduce tip speed during sensitive periods, such as nighttime or when turbines are located near residential areas. Rotor speed reduction is another approach, where turbines operate at lower revolutions per minute (RPM) under specific conditions to limit noise emission. Curtailment strategies, which involve temporarily shutting down turbines to comply with regulatory noise limits, can also be employed. Despite their effectiveness, operational strategies often result in reduced energy output, creating a trade-off between noise reduction and power generation [9]. Like design-based techniques, most operational strategies are implemented in a fixed or schedule-based manner and are unable to respond dynamically to real-time environmental changes, limiting their efficiency in adaptive noise management.

2.3 Digital Twin Technology in Wind Energy

In recent years, digital twin technology has emerged as a promising tool for monitoring and optimizing complex engineering systems, including wind turbines. A digital twin is a virtual representation of a physical system that integrates sensor data, simulation models, and analytics to replicate real-world behavior in real time. Within the context of wind energy, digital twins have been primarily applied to structural health monitoring, predictive maintenance, and performance optimization. For example, they can detect fatigue damage in turbine blades or towers, anticipate failures in gearboxes or generators, and optimize operational parameters to maximize energy production [10], [11].

Beyond these applications, digital twins are increasingly being explored for noise prediction and mitigation. By integrating aerodynamic models that simulate airflow patterns with acoustic propagation models that predict how sound travels through the terrain and atmosphere, digital twins provide a platform for real-time analysis of turbine noise. When combined with real-time sensor data from microphones, vibration sensors, and weather instruments, digital twins can continuously adjust operational parameters such as blade pitch or rotor speed to maintain noise levels below regulatory or community-defined thresholds while preserving energy output. Unlike static mitigation methods, digital twins offer a predictive and adaptive approach, allowing operators to proactively manage turbine noise under varying environmental conditions.

2.4 Research Gap

A comprehensive review of the literature reveals several important gaps in current wind turbine noise research. First, the majority of studies focus on static, post-installation assessments rather than real-time, adaptive systems capable of dynamically responding to environmental changes. Second, existing noise mitigation strategies are either design-based, with fixed reductions applied during manufacturing, or operational, with a trade-off between noise reduction and energy efficiency, but rarely both. This creates a persistent challenge in balancing community comfort with turbine performance. Third, although digital twin technology has proven effective in structural health monitoring and performance optimization, its potential for adaptive noise prediction and control remains largely underexplored.

Consequently, there is a clear opportunity to develop a digital twin–based system that can predict wind turbine noise in real time and enable dynamic operational control for optimized noise mitigation. By addressing this gap, the present research seeks to provide an innovative, data-driven solution that integrates modern digital technologies with renewable energy operations, improving both turbine efficiency and community acceptance.

Feature / Focus Area	Oerlemans et al. [5]	van den Berg [6]	Reddy et al. [8]	Negri et al. [9]	Proposed System
Aerodynamic noise identification & quantification	✅	❌	❌	❌	✅
Noise propagation under varying conditions	❌	✅	❌	❌	✅
Noise mitigation strategies	✅ (design-based)	✅ (operational, atmospheric)	❌	❌	✅ (adaptive, real-time)
Digital twin for monitoring & optimization	❌	❌	✅ (fault detection)	✅ (performance optimization)	✅ (noise mitigation)
Real-time adaptive noise control	❌	❌	❌	❌	✅

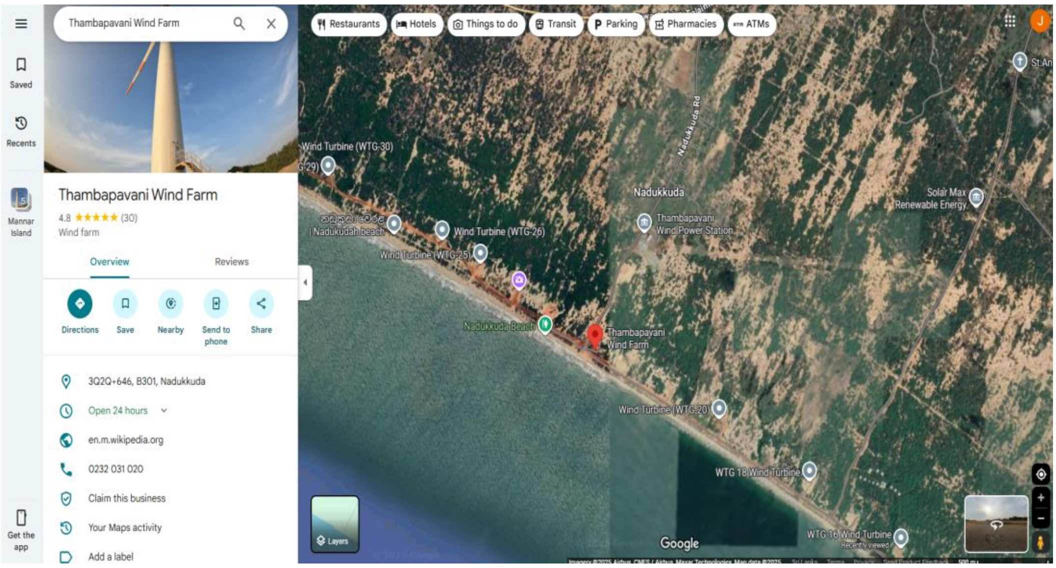
Table 1-Comparison of Research Gap

2.5 Research Problem

Noise pollution remains one of the most persistent and socially sensitive challenges in wind energy development. Unlike urban areas where background noise masks disturbances, rural wind farm locations are often acoustically quiet, making turbine sounds more noticeable. For nearby residents, continuous turbine noise has been linked to annoyance, sleep disruption, and in some cases, health concerns. Such impacts reduce public acceptance of wind projects and have, in several instances, delayed or prevented new installations. Thus, noise is not only a technical issue but also a socio-political barrier to renewable energy expansion.

Traditional mitigation strategies fall into two categories: **design modifications** (e.g., serrated blade edges, porous surfaces) and **operational adjustments** (e.g., reduced RPM, pitch control, curtailment). Design interventions, while helpful, are static and cannot adapt to changing environmental conditions or community sensitivities. Operational strategies are more flexible but involve a direct trade-off with energy production, forcing operators to sacrifice efficiency in order to maintain social acceptance. Furthermore, most noise assessments are conducted post-installation, producing static, reactive insights that fail to capture dynamic variations across weather patterns, wind turbulence, or time of day.

A site visit to the **Thambapavani Wind Power Station** in Mannar, Sri Lanka, highlights these challenges in practice. The farm, with 103.5 MW capacity and Vestas low-noise turbines, operates four turbines in noise-reduction mode near residential areas, shutting them down when wind speeds exceed 9 m/s. While this reduces disturbance, it is reactive and results in significant energy loss—demonstrating the limitations of current practice.



In recent years, digital twin technology has shown great promise in wind energy applications such as predictive maintenance, structural health monitoring, and performance optimization. By coupling real-time sensor data with advanced simulation models, digital twins enable continuous monitoring, predictive

Figure 3-Thambapavani Wind Farm

forecasting, and adaptive decision-making. However, their potential for real-time noise prediction and adaptive control remains largely unexplored. A digital twin could anticipate acoustic impacts under varying conditions and adjust turbine operations proactively, minimizing the need for curtailment while safeguarding energy output.

Problem Statement:

Despite progress in turbine design, operational strategies, and digital technologies, there is still no integrated system capable of predicting, monitoring, and mitigating wind turbine noise in real time without sacrificing efficiency. Current approaches remain static, reactive, or energy-intensive. This study addresses this gap by proposing a digital twin–based predictive framework for adaptive noise management in wind turbines.

3. RESEARCH OBJECTIVES

The central aim of this research is to design and implement a digital twin–based system for wind turbines that is capable of predicting, monitoring, and mitigating noise in real time, while at the same time ensuring that the energy production efficiency of the turbines is not compromised. Wind turbine noise is increasingly recognized as a factor that influences community acceptance and long-term viability of wind energy projects. By introducing a digital twin framework, this study seeks to create a dynamic platform that not only reflects the operational behavior of wind turbines but also enables the exploration of strategies for adaptive noise control. The outcome of such a system is expected to support decision-making processes in wind farm management by offering insights into optimal trade-offs between energy output and environmental noise constraints.

To support the realization of this broad objective, the study outlines several specific research objectives that are interlinked and progressively build towards the final system. The first step involves conducting a comprehensive literature review that situates the research within the existing body of knowledge. Current scientific and engineering studies on wind turbine noise sources, noise propagation mechanisms, and mitigation techniques are critically examined. This review will not only highlight the physical, aerodynamic, and mechanical origins of turbine noise but also reveal gaps in current mitigation strategies. Identifying these gaps is essential because it establishes the need for a more flexible, real-time, and intelligent solution such as a digital twin.

Following the theoretical foundation, the research focuses on assessing the effectiveness of current noise mitigation strategies deployed in wind farms worldwide. Existing approaches are often design-based, such as blade modifications or nacelle insulation, or operational, such as implementing curtailment strategies at high wind speeds. However, these measures are frequently static in nature and involve trade-offs that directly affect power generation capacity. For instance, shutting down turbines or limiting rotor speeds reduces noise but simultaneously leads to financial and energy losses. By carefully analyzing these limitations, the study positions the digital twin as a method to overcome the rigidity of current strategies, making noise control more adaptive and context-sensitive.

The next objective is to design the architecture of the digital twin system itself. Unlike conventional simulation models, the digital twin integrates multiple components into a single cohesive framework. It is envisioned that the architecture will combine aerodynamic models of turbine operation, acoustic models that simulate noise propagation, and real-time or simulated sensor datasets that provide continuous input. Through this integration, the digital twin will function as a living model that evolves with data and mirrors the behavior of the physical turbine under changing wind and environmental conditions.

Once the framework is established, the study moves towards simulating noise scenarios across a range of operational and environmental settings. These simulations allow the system to capture the relationships between wind speed, blade pitch angle, rotor revolutions, and noise emissions. Importantly, this process facilitates an understanding of how noise propagates under different meteorological conditions such as varying wind directions, turbulence levels, or atmospheric stability states. By running these scenarios, the research will generate a knowledge base that informs both predictive modeling and future mitigation strategies.

Building on the outcomes of these simulations, the study incorporates adaptive control strategies within the digital twin. This means that the system will not only predict noise but will also recommend real-time operational adjustments aimed at reducing it. For example, the system may suggest optimal blade pitch angles or rotor speed modifications for given wind conditions that minimize acoustic emissions while maintaining acceptable levels of power production. Such adaptive features transform the digital twin from a passive monitoring tool into an active decision-support system, directly aligning with the main goal of balancing technical efficiency with environmental responsibility.

Validation of the system is a critical research objective, as any predictive framework must be tested for reliability before it can be recommended for practical use. The predictions generated by the digital twin will therefore be compared with real-world field data, where available, or with validated simulation results from existing studies. This validation process ensures that the outcomes of the digital twin are not only theoretically sound but also practically trustworthy. By aligning predictions with observed data, the system gains credibility as a tool that can support real wind farm operations.

Finally, the research aims to formulate a set of practical recommendations for the deployment of digital twin systems in commercial wind farms. These guidelines will address technical aspects, such as data requirements and computational resources, as well as managerial and policy-related considerations, such as compliance with noise regulations and community engagement practices. By doing so, the study ensures that its contributions extend beyond academic exploration into real-world applicability, offering pathways for wind energy developers, operators, and policymakers to implement solutions that balance the dual goals of renewable energy expansion and community well-being.

4. METHODOLOGY

The methodology adopted in this research follows a structured approach that bridges machine learning techniques with interactive visualization in order to create a digital twin of a wind turbine for noise prediction and monitoring. Since real-time access to IoT data streams from an operational wind farm was not available, the design emphasized the integration of publicly available datasets with a software system capable of simulating live conditions. The resulting architecture combined backend data processing, machine learning prediction, and frontend visualization into a unified framework. This section describes, in detail, the requirement gathering process, the handling of datasets, the system architecture, the development of both backend and frontend modules, the machine learning training pipeline, and the validation of the final system.

4.1 Requirement Gathering and Analysis

The foundation of the project was established through a site visit to the **Thambapavani Wind Power Station**, one of the largest onshore wind farms in Sri Lanka. This field exposure provided first-hand insights into turbine operation, community-level concerns regarding noise, and mitigation measures already in practice. The wind farm consists of a fleet of 33 turbines, with 29 operating under unrestricted conditions and 4 operating under a special mode where they are programmed to shut down when wind speeds exceed 9 m/s. This shutdown strategy is intended to reduce noise impact on nearby residential areas.

Noise limits imposed by local regulations and international guidelines, such as those of the **World Health Organization (WHO)**, were also studied to define the operating thresholds of the system. For example, residential areas are limited to 50 dB during the day and 45 dB during the night, while institutional and commercial zones have slightly higher limits. From the engineering side, the turbines were observed to employ serrated trailing edges on the blades, a feature that reduces aerodynamic noise.

A key observation during the field visit was that, although environmental impact assessments had been carried out before the installation of the turbines, there was **no**

real-time noise monitoring system deployed at the wind farm. Instead, noise checks are conducted only periodically. This presented both a challenge and an opportunity: the absence of a live monitoring network meant that the research would need to simulate such a system, but it also highlighted the importance and potential value of developing a digital twin capable of fulfilling this role.

4.2 Dataset Integration and Handling

Due to the unavailability of live sensor data, the project made use of the **WEA-Acceptance Dataset** published by Leibniz University Hannover. This dataset, designed for wind energy research, contains detailed operational and environmental parameters, including wind speed, wind direction, rotor RPM, blade pitch angle, power output, and noise levels in decibels.

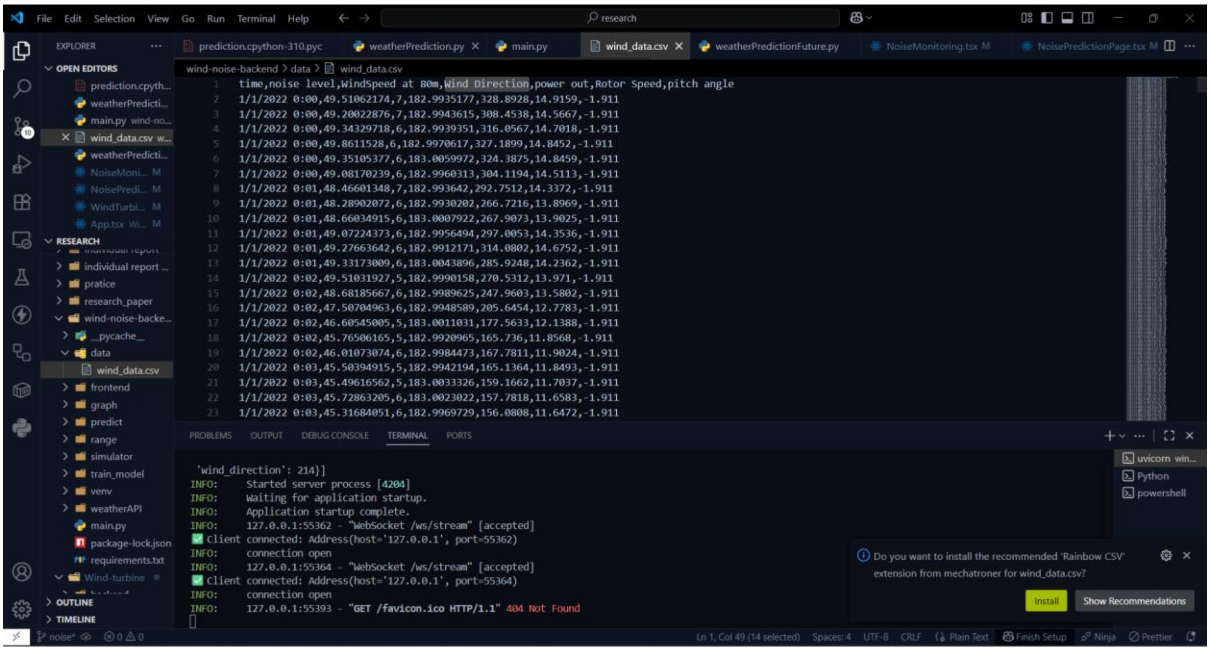


Figure 4-WEA-Acceptance dataset

The dataset was imported into the system and subjected to a preprocessing pipeline developed in Python. This included data cleaning, where missing values were interpolated or removed, and normalization, where values were scaled to fall within comparable ranges. This preprocessing ensured the dataset was suitable for machine learning and also stable for visualization purposes.

To mimic the effect of IoT sensor streams, the dataset was configured to be **released in 30-second intervals**, effectively reproducing the experience of continuous monitoring. These values were handled by the backend and stored in a lightweight database for retrieval. From the perspective of the frontend visualization, the turbine appeared to be operating under live conditions.

To further enhance realism, the system was designed to integrate with external weather data. The OpenWeather API was used to fetch wind speed, direction, and temperature forecasts for any selected site. In the final implementation, users could select a geographic location on a Google Maps interface, which then retrieved the corresponding five-day weather forecast and supplied it to the digital twin. This integration extended the scope of the system from being purely retrospective (based only on the Hannover dataset) to being predictive, enabling it to simulate the impact of future weather conditions on turbine noise and performance.

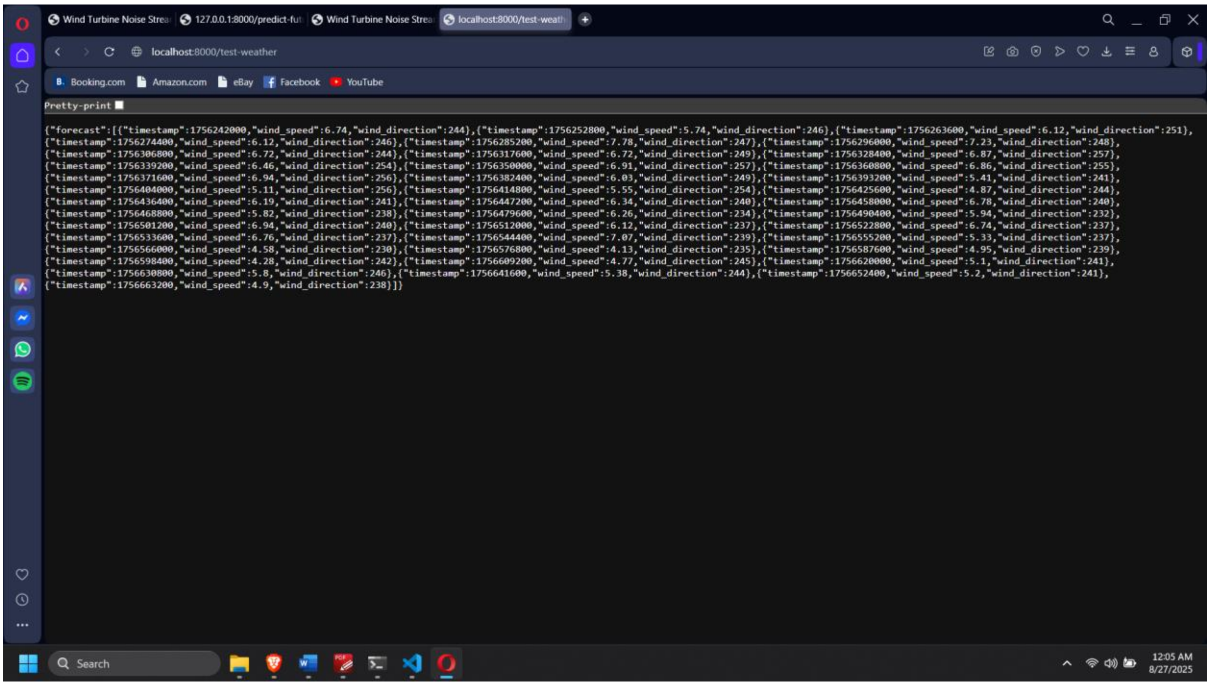


Figure 5-OpenWeather dataset

4.3 System Architecture and Design

The overall architecture of the digital twin was modular, consisting of four interconnected layers: the data source, the backend, the frontend, and the prediction engine. The data source comprised both the Hannover dataset, which was streamed as if it were live sensor input, and the OpenWeather forecast data. The backend, implemented in Python, was responsible for data preprocessing, normalization, and storage, as well as providing a set of RESTful APIs for the frontend.

The frontend was developed using **Three.js**, a JavaScript library that allowed the creation of an interactive 3D model of a wind turbine. This visualization dynamically reflected the operational state of the turbine, with the rotor RPM, pitch angle, wind vane, and anemometer responding in real-time to data received from the backend. In addition to the 3D model, the frontend contained interactive dashboards with charts displaying wind speed, pitch angle, noise levels, and power output, all updated every thirty seconds to match the simulated streaming rate.

A central element of the architecture was the **prediction engine**. Hosted on the backend, this component processed user inputs (such as wind speed, wind direction, and acceptable noise thresholds) and generated corresponding outputs, including predicted noise levels, expected power generation, and recommended pitch angle adjustments. By feeding these predictions back to the frontend, the system allowed users to experiment with operating strategies in a safe, simulated environment.

4.4 Development of Frontend and Backend

The frontend was designed as a **dual-interface system**. The first interface functioned as a monitoring dashboard, displaying turbine operation in real time with both graphical charts and a 3D visualization. The second interface served as a control dashboard, where users could input custom wind conditions or select forecasted weather scenarios from weather chart , and then view predicted turbine behavior under those circumstances.

The backend acted as the bridge between datasets, machine learning models, and the frontend visualization. It was responsible for implementing the **scheduler** that streamed dataset values every 30 seconds, preprocessing incoming data, and exposing multiple APIs for both real-time monitoring and prediction. The backend also integrated the trained machine learning models, enabling the system to deliver predictions on demand.

A lightweight relational database was incorporated into the backend to manage structured storage of raw dataset values, processed data, forecasts, and model predictions. This ensured persistence and efficient retrieval. The schema contained tables for raw input, normalized processed data, forecast values from the OpenWeather API, and historical predictions, making the system both extensible and maintainable.

4.5 Machine Learning Model Training

The predictive capacity of the digital twin was established using supervised machine learning models trained on the Hannover dataset. The selected input features included wind speed, wind direction, rotor RPM, and blade pitch angle, while the output variables were aerodynamic noise (in dB) and power output (in kW). The dataset was pre-processed and divided into training and testing subsets, following an 80–20 split, to ensure robust model evaluation.

Multiple algorithms were implemented and benchmarked, including **Linear Regression, Multi-Layer Perceptron (MLP), Random Forest Regression, and Extreme Gradient Boosting (XGBoost)**. Model performance was assessed using Mean Squared Error (MSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). Among the tested models, **Random Forest and XGBoost consistently achieved the highest predictive accuracy ($R^2 \approx 0.91$), demonstrating strong capability in capturing the nonlinear interactions between aerodynamic and operational parameters**. The MLP also performed competitively, though it required careful tuning of hyperparameters. In contrast, Linear Regression provided only baseline performance, with a negative R^2, confirming its limitations for modeling complex turbine behavior.

The final system integrated the best-performing models into the backend for real-time prediction. In addition, an optimization module was developed to recommend blade pitch settings under varying wind conditions. This allowed the digital twin not only to predict noise and power but also to suggest operational strategies that balance power generation with community noise thresholds. In this way, the system extends beyond passive monitoring, serving as an intelligent decision-support tool for adaptive wind turbine management.

4.6 Summary

In summary, the methodology combined requirement gathering, dataset-driven simulation, frontend–backend system design, database integration, and machine learning model development into a coherent framework for building a digital twin of a wind turbine. The absence of live IoT data was compensated for by adopting a dataset streaming strategy, which ensured realistic behavior in the frontend visualization. The use of machine learning enabled predictive modeling of noise and power output, while the integration of external weather forecasts extended the system into a proactive tool. Together, these elements established a robust methodology for addressing the challenge of wind turbine noise mitigation in a digitally simulated environment.

5. SYSTEM ARCHITECTURE & DESIGN

The system architecture and design of a digital twin for wind turbine noise prediction and mitigation play a critical role in ensuring accurate, real-time monitoring and adaptive control. The architecture integrates multiple components, including the data source, backend processing, machine learning–based prediction engine, and the frontend visualization system. The design also incorporates a database for data storage and retrieval, API communication for modular integration, and user interfaces for monitoring and control. The overall architecture aims to simulate live turbine operations, predict noise emissions, and recommend optimal operational strategies while maintaining energy efficiency.

5.1 Overview of System Architecture

At a high level, the digital twin system follows a modular architecture consisting of four primary layers:

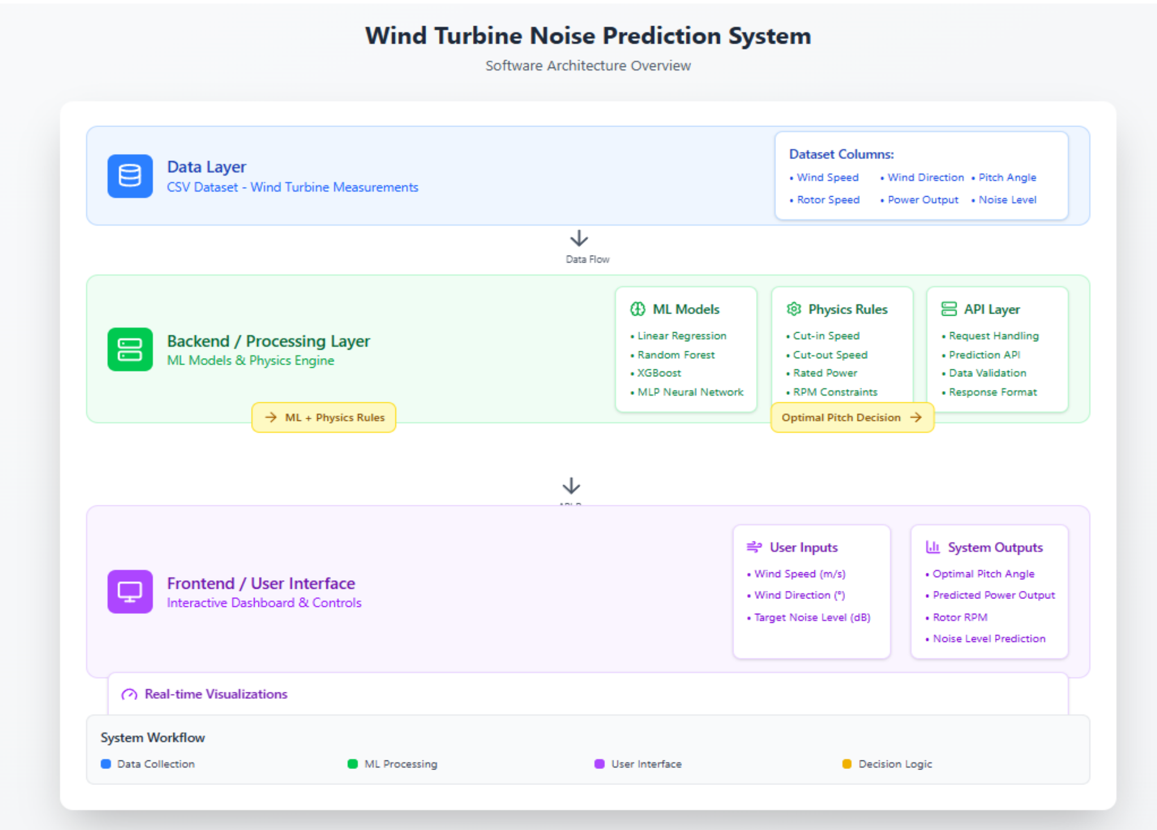


Figure 6-Overview of Software Architecture

1. **Data Source Layer**

   The data source layer simulates real-time sensor inputs for wind turbines. Since direct IoT access at the wind farm was unavailable, the Hannover WEA-Acceptance dataset was used. Key parameters such as wind speed, wind direction, rotor RPM, blade pitch angle, noise level, and power output are streamed at intervals of ten seconds to mimic live sensor readings. This dataset forms the foundation of both real-time monitoring and predictive modeling.

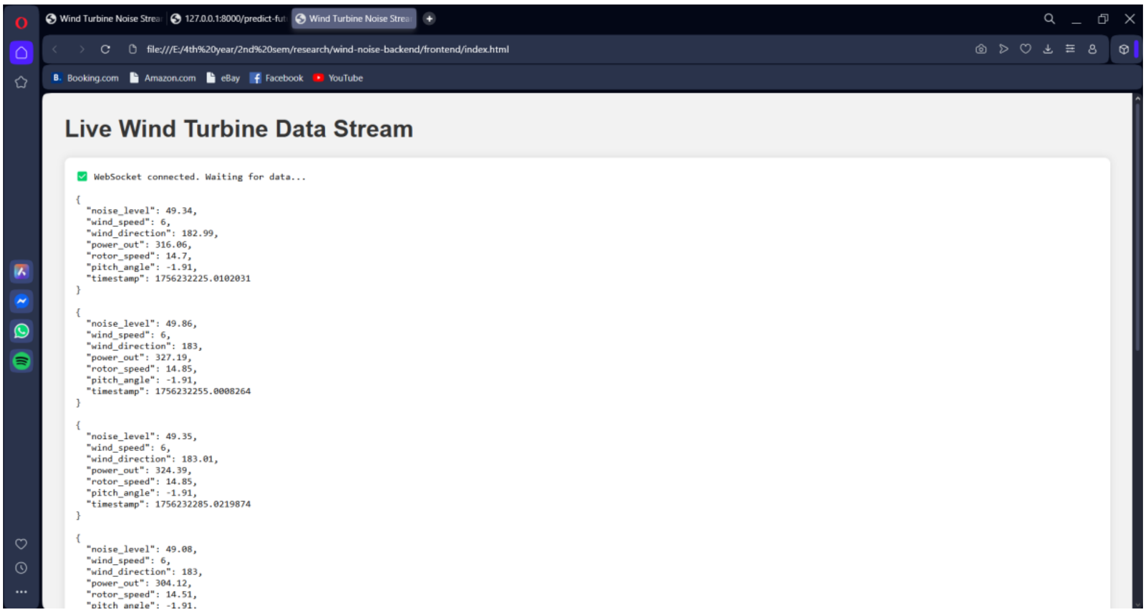


Figure 7-Data streaming timeline

2. **Backend Layer**

   The backend serves as the central processing unit of the digital twin. Implemented in Python, it handles data preprocessing, storage, and delivery to the frontend through REST APIs. Preprocessing tasks include cleaning, normalization, and handling missing or inconsistent data values. The backend also hosts the machine learning models responsible for predicting turbine noise and power output based on current wind conditions and operational parameters.

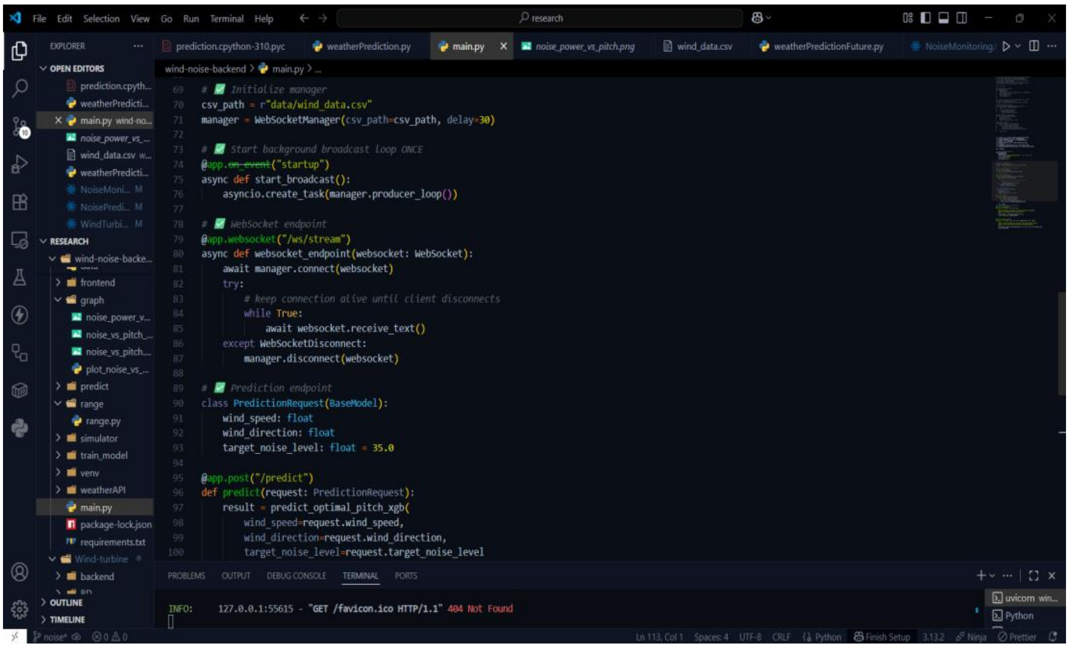


Figure 8-Backend Layer

3. **Prediction Engine**

   The prediction engine is integrated with the backend and uses trained machine learning models to forecast noise levels, power output, and optimal blade pitch angles. It receives wind speed, wind direction, and user-defined noise thresholds as input, and outputs recommended operational parameters. This engine supports both real-time predictions and short-term forecasting using weatherdata obtained from APIs such as OpenWeatherMap, enabling up to five-day predictive capability.

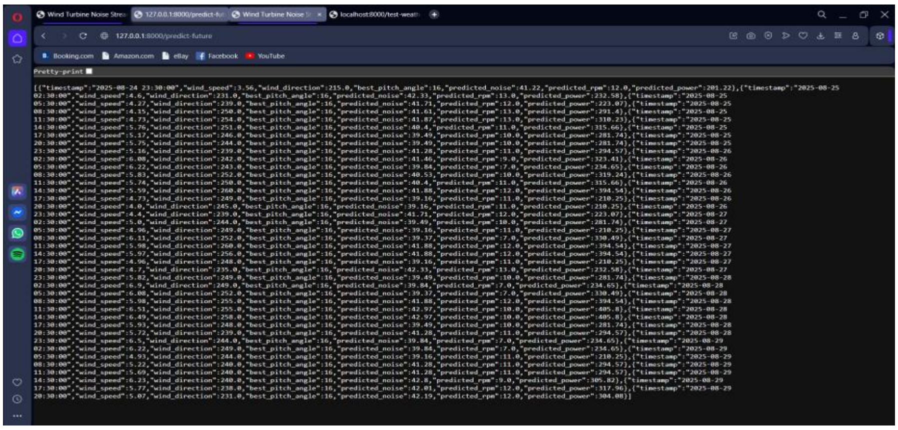


Figure 9-Predicted data set

4.Frontend Layer

The frontend layer provides a visual interface for monitoring turbine operations and interacting with the prediction engine. Implemented using Three.js for 3D visualization and charting libraries for performance monitoring, the interface dynamically displays the turbine rotor, pitch angle, wind vane orientation, and real-time noise levels. Users can explore various operational scenarios, visualize predicted outcomes, and make informed decisions on turbine management.

The system architecture is depicted in Figure 4. The figure illustrates the flow of information from the simulated data source to the backend, through the prediction engine, and finally to the frontend interface.

5.2 Backend Design

The backend architecture is designed to support both real-time simulation and predictive analysis. It is modular to allow scalability and integration with additional turbines, datasets, or predictive models in the future. The primary components include:

Data Preprocessing Module: Cleans incoming dataset streams, handles missing values, and normalizes features for consistent model input.

Prediction Module: Hosts the machine learning models for predicting noise levels, power output, and optimal pitch angles. It can handle real-time requests from the frontend or batch forecasts for multiple turbines.

API Layer: RESTful APIs expose backend functionalities to the frontend, allowing dynamic data retrieval and predictive output delivery. Key endpoints include *@app.post("/predict"), @app.get("/test-weather"), @app.get("/predict-future"), and @app.websocket("/ws/stream")*

The backend design ensures data integrity, computational efficiency, and flexibility for future enhancements, including the integration of live weather APIs for forecasting purposes.

5.3 Frontend Design

The frontend interface is designed to be both interactive and informative, providing stakeholders with a real-time view of turbine operations. Key components of the frontend include:

3D Turbine Visualization: Using Three.js, the turbine rotor, blades, and supporting structures are rendered dynamically. Blade pitch and rotor speed are updated in real time according to dataset or predictive model inputs.

Interactive Charts: Real-time charts display wind speed, noise levels, power output, and pitch angles. Users can observe trends and correlations between operational parameters and acoustic emissions.

User Control Panel: Allows users to input custom wind conditions, select noise thresholds, and request predictions or short-term forecasts.

Geolocation Integration: Google Maps API enables users to select specific turbine locations, providing localized predictions based on wind conditions and terrain features.

The frontend communicates with the backend through API calls, ensuring seamless data flow and dynamic updates of both visualizations and predictive outputs.

5.4 Summary

The system architecture and design for the wind turbine digital twin integrate multiple layers, ensuring accurate simulation, predictive capability, and interactive visualization. The backend efficiently preprocesses data, runs machine learning models, and serves information through APIs. The frontend provides a comprehensive monitoring interface, while the database ensures secure and structured storage of operational and predictive data. By combining these elements, the system achieves dynamic noise prediction, optimal operational recommendations, and scalability for future enhancements, including multi-turbine integration and advanced forecasting.

6.MACHINE LEARNING MODEL DEVELOPMENT

6.1 Dataset Description

The dataset utilized for this research is the **WEA-Acceptance Dataset** provided by Leibniz University Hannover [10]. This dataset was selected because it provides a comprehensive set of parameters relevant to wind turbine operations and noise emissions, making it suitable for developing a machine learning model for noise prediction and operational optimization.

The dataset includes the following parameters:

Parameter	Description
Wind Speed (m/s)	Measures the velocity of wind at the turbine location
Wind Direction (°)	Indicates the direction from which the wind is blowing
Noise Level (dB)	Recorded acoustic emissions from the turbine
Rotor RPM	Rotational speed of the turbine blades
Power Output (kW)	Electrical energy generated by the turbine
Blade Pitch Angle (°)	Angle of the blades relative to wind direction

Table 2-: Information about the measurements

Exploratory analysis of the dataset shows that wind speeds vary from 3 m/s to 16 m/s, while noise levels typically range from 43 dB to 67 dB depending on turbine operation and environmental conditions. Visualizations, such as histograms and scatter plots, were created to understand the distribution of parameters and their relationships. For example, scatter plots between wind speed and noise levels indicate a strong positive correlation, highlighting the relevance of wind speed as a key predictive feature.

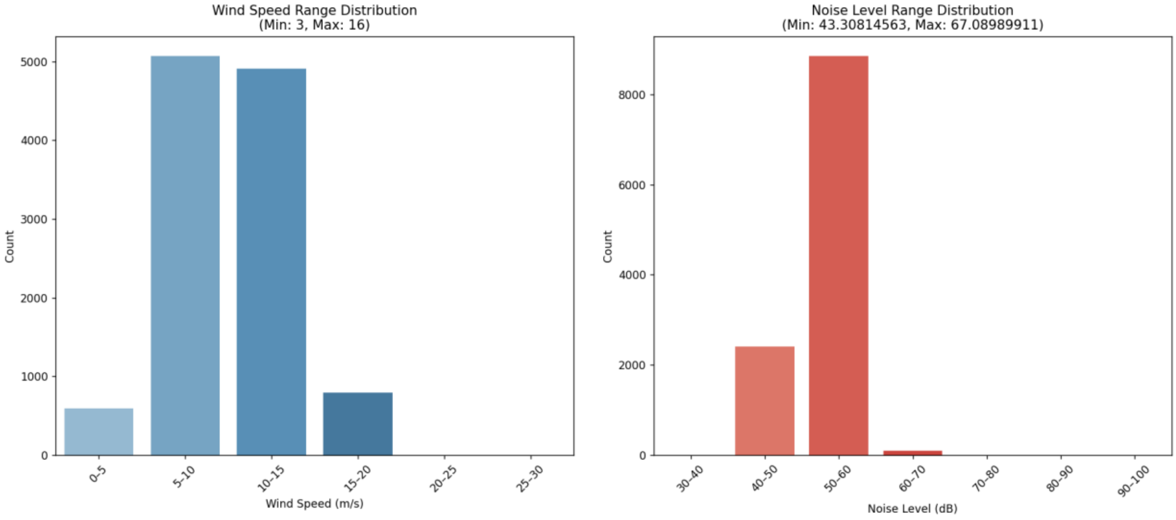


Figure 10-Distribution of Wind Speed and Noise Level with Min/Max Values

6.2 Data Preprocessing

Data preprocessing is a critical step to ensure the quality and reliability of the machine learning model. The following preprocessing steps were performed:

Handling Missing Values:

Any missing entries in wind speed, noise level, or other parameters were imputed using median values to preserve dataset integrity.

Normalization:

Continuous features such as wind speed, rotor RPM, and power output were normalized using Min-Max scaling to bring all values into a 0–1 range. This step prevents any single feature from dominating the model training due to its scale.

Outlier Detection and Removal:

Outliers were identified using the Interquartile Range (IQR) method. Values lying outside 1.5 times the IQR were treated as anomalies and either corrected or removed. For example, sudden spikes in noise levels unrelated to turbine operation were excluded to avoid skewing predictions.

Data Segmentation:

The dataset was divided into training (80%) and test (20%) sets to ensure unbiased evaluation of the model.

6.3 Feature Selection and Importance Analysis

Feature selection is essential for improving model performance and interpretability. Correlation analysis and feature importance techniques were employed to identify the most relevant predictors of noise and power output.

Correlation Analysis: Pearson correlation coefficients were computed between features and target variables (noise level and power output). Wind speed and blade pitch angle exhibited the highest correlation with noise levels, while rotor RPM and wind speed strongly influenced power output.

Feature Importance: Using a Random Forest model, feature importance scores were calculated. Wind speed was consistently the most influential parameter, followed by pitch angle and rotor RPM. These findings guided the selection of input variables for the final machine learning model.

Visualizations such as heatmaps and bar charts were generated to clearly demonstrate feature importance and interdependencies.

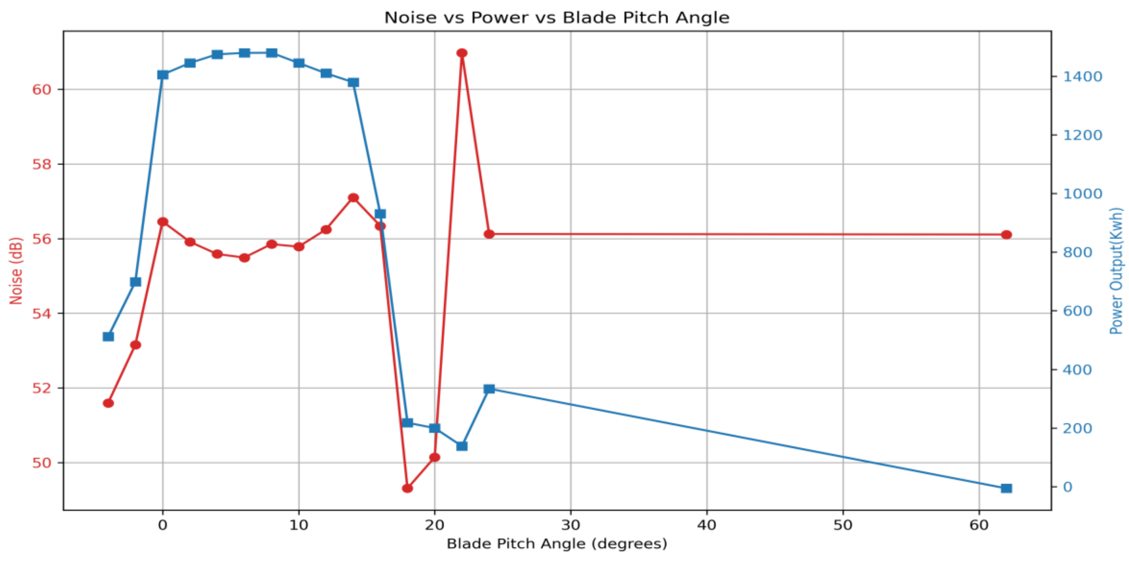


Figure 11-Noise vs Power vs Blade Pitch Angle relations

6.4 Machine Learning Model Choice

Several machine learning algorithms were evaluated for predicting wind turbine noise levels, power output, and optimal blade pitch angles. These included Linear Regression, Random Forest Regression, XGBoost Regression, and Multi-Layer Perceptron (MLP). **Linear Regression** served as a simple baseline model, offering interpretability and suitability for capturing linear relationships, but it is limited in handling complex non-linear interactions. **Random Forest Regression** was selected as the primary model due to its strong balance of accuracy, robustness, and interpretability. It effectively captures non-linear patterns, mitigates overfitting, and provides insights into feature importance, making it ideal for the diverse operational conditions of wind turbines.

XGBoost Regression was also implemented as a high-performance alternative. It offers robustness to noisy data and occasionally achieved slightly higher predictive accuracy than Random Forest, although this came at the cost of increased computational requirements. **Multi-Layer Perceptron (MLP)**, a deep learning model, was included to capture highly complex, non-linear relationships. While MLP demonstrated competitive performance, it required careful feature scaling, hyperparameter tuning, and longer training times, making it less practical for real-time predictions in the current system.

By evaluating all four models, the research ensured a comprehensive understanding of predictive performance across both traditional and advanced machine learning approaches. Random Forest Regression ultimately provided the best combination of predictive reliability, efficiency, and interpretability, making it the core model integrated into the digital twin system. Linear Regression, XGBoost, and MLP remain as supplementary models for comparative analysis and potential future enhancements.

6.5 Model Performance Evaluation

To validate the digital twin predictions, four models—Linear Regression, MLP, Random Forest, and XGBoost—were compared using MSE, MAE, and weighted R^2 metrics for power, rotor speed, and noise. Linear Regression showed poor performance with high errors and a negative weighted R^2 of -5.63. The MLP improved accuracy but was still less reliable than ensemble methods. Random Forest and XGBoost performed strongly, with Random Forest achieving an MSE of 22,462 for power and a weighted R^2 of 0.91, slightly outperforming XGBoost. Consequently, Random Forest was selected for generating all subsequent predictions, ensuring accuracy in the digital twin outputs.

Model	**MSE Power**	**MSE RPM**	**MSE Noise**	**MAE Power**	**MAE RPM**	**MAE Noise**	**R^2 (Weighted)**
Linear	1,750,589	52.91	142.25	1,259.92	6.95	11.39	-5.63
MLP	40,248	1.95	5.70	131.72	0.87	1.70	0.85
Random Forest	22,462	0.99	3.05	89.15	0.52	1.17	0.91
XGBoost	23,884	1.07	3.35	98.34	0.60	1.27	0.91

Table 3-ML Model Performance Comparison

7.SYSTEM IMPLEMENTATION

7.1 Overview

The system implementation of the digital twin for wind turbine noise prediction and monitoring involved the integration of three main components: the backend, the frontend, and the prediction engine. Each component was designed to work seamlessly with the others to ensure real-time monitoring, accurate prediction, and interactive visualization. The implementation phase translated the architecture and methodology into a fully functional system capable of simulating turbine behavior, predicting noise levels and power output, and recommending optimal blade pitch angles.

7.2 Backend Implementation

The backend of the system was developed using **Python** due to its versatility in data processing, machine learning integration, and API development. The backend handles multiple crucial tasks:

Data Preprocessing: Incoming dataset values, streamed from the simulated WEA dataset, are cleaned, normalized, and prepared for prediction. Missing values are imputed, outliers are handled, and scaling is applied to ensure the model receives consistent inputs.

Machine Learning Integration: The Random Forest model trained in Chapter 6 is loaded into the backend. It receives input features such as wind speed, wind direction, and blade pitch angle, and outputs predicted noise levels and power output.

API Development: A RESTful API was developed to enable communication between the backend and the frontend. Key endpoints include:

@app.websocket("/ws/stream")– streams turbine operational data every 30 seconds.

@app.post(“/predict”)– accepts input parameters and returns predicted noise, power output, and recommended blade pitch.

@app.get("/predict-future")– provides access to past turbine performance for visualization.

@app.get("/test-weather") – Retrieves current weather data from OpenWeather API for the turbine site.

This modular backend architecture ensures scalability, maintainability, and easy integration with additional features such as OpenWeather API data for future wind forecasts.

7.3 Frontend Implementation

The frontend was developed using **Three.js** for 3D visualization, complemented by charting libraries (e.g., Chart.js) for real-time data representation. Key aspects of frontend development include:

3D Turbine Model: A dynamic 3D model represents the turbine. Rotor RPM, blade pitch, and wind direction are animated based on the real-time data received from the backend. The model provides a realistic visual representation of turbine operation under varying environmental conditions.

Charts and Graphs: Real-time charts display wind speed, rotor RPM, power output, and noise levels. Users can compare current turbine performance with community noise thresholds through intuitive visual cues.

User Interaction: The frontend interface allows users to input desired parameters, such as wind speed and noise thresholds, and request predictions for optimal turbine operation.

Google Maps Integration: Users can select turbine locations using Google Maps API. The selected latitude and longitude are sent to the backend to fetch local wind forecasts via the OpenWeather API for predictive modeling.

The frontend was designed with usability in mind, providing clear visualizations for operators and researchers to make informed decisions regarding turbine noise and power output.

7.4 System Integration

Integration involved connecting the backend, frontend, and database to function as a cohesive digital twin platform:

Backend APIs were tested with the frontend to ensure correct data streaming and real-time updates.

The ML model predictions were validated against historical WEA dataset entries to confirm reliability.

Interactive frontend elements, including the 3D turbine model and charts, were synchronized with API outputs to create a smooth user experience.

Integration of Google Maps API and OpenWeather API ensures that future wind predictions can feed into the system for proactive noise and power management.

8. RESULTS

8.1 Overview

The results chapter presents the outcomes of implementing the digital twin system for wind turbine noise prediction and adaptive control. The developed system integrates real-time data streaming, machine learning–based noise prediction, and interactive visualization to evaluate turbine performance under a variety of operating and environmental conditions.

The evaluation focuses on three key aspects. First, the accuracy of the machine learning model is assessed by comparing predicted noise levels against field measurements and validated datasets. This step ensures that the model can reliably capture the complex relationship between wind speed, rotor dynamics, and noise generation.

Second, case studies are presented for selected wind speed scenarios (6 m/s, 9 m/s, and 12 m/s). These scenarios illustrate how the digital twin responds to different operating conditions, highlighting its capability to provide dynamic noise predictions. For each case, the system provides insights into both the expected noise levels and the associated power output, offering a practical understanding of the balance between community comfort and energy production.

Third, the noise–power trade-off is analyzed. While traditional approaches at Thambapavani rely on simple shutdown strategies for turbines at higher wind speeds to reduce noise impact, the digital twin introduces a more adaptive alternative. By simulating pitch control and rotor speed modulation, the system demonstrates how noise can be reduced without fully shutting down turbines, thereby minimizing energy loss.

Finally, the system's visualization and real-time interface are presented, showcasing interactive dashboards where operators can monitor noise predictions, turbine states, and recommended adaptive strategies. These outputs provide an accessible platform for decision-making, bridging technical insights with operational usability.

Overall, the results demonstrate that the digital twin framework offers a feasible and innovative approach for managing wind turbine noise in Sri Lanka, particularly for wind farms such as Thambapavani where current mitigation methods remain limited to shutdown strategies.

8.2 Result

The digital twin framework successfully predicted wind turbine performance metrics under different operational scenarios. The model evaluation confirmed that the Random Forest model provided the most reliable predictions among the tested approaches, ensuring that subsequent results are accurate and robust.

Key predicted values from the Random Forest digital twin include a maximum power output of **1498.43 kW**, occurring at the **rated wind speed of 11.0 m/s**. The predicted noise levels range from **47.18 dB to 57.09 dB**, and with pitch control, the maximum power is achieved at a **6.0° pitch angle**, demonstrating the significance of pitch optimization in turbine operation.

Analysis of the generated graphs reveals important trends:

- **Noise vs Wind Speed:** Noise generally increases with wind speed, stabilizing near 57 dB at higher speeds.

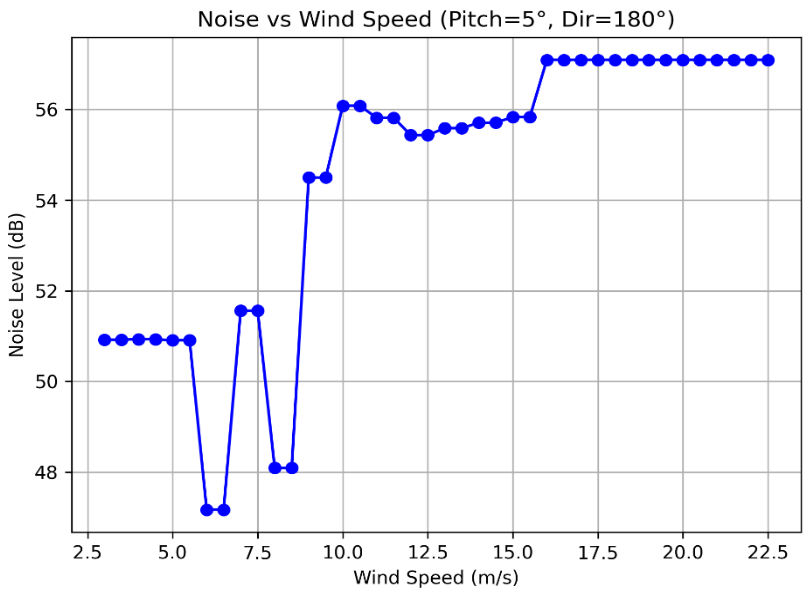


Figure 12-Predicted noise levels vs. wind speed

The predicted noise levels exhibit a nonlinear trend with increasing wind speed. At low speeds (3–6 m/s), noise remains low and stable (~47–51 dB), indicating minimal aerodynamic turbulence. Between 7–10 m/s, noise rises noticeably (~51.5–56 dB) as blade aerodynamics intensify. From 11–15 m/s, levels stabilize around 55–56 dB, reflecting consistent but elevated turbulence. Beyond 16 m/s, noise peaks at ~57 dB and plateaus, showing that further increases in wind speed do not significantly amplify overall noise. This highlights a noise ceiling effect at high wind speeds.

Noise vs Pitch Angle: Increasing the pitch angle slightly reduces noise beyond the optimal operating range.

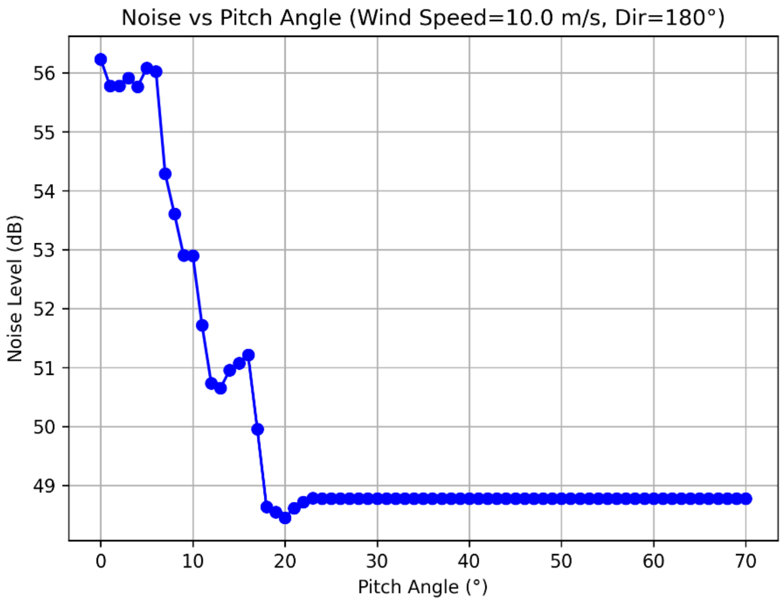


Figure 13-Predicted noise levels vs. pitch angle at 10 m/s wind speed

Analysis of aerodynamic noise across blade pitch angles (0°–70°) at 10 m/s wind speed shows that noise is highest at low pitches (~56 dB at 0°–6°) and decreases steadily as pitch increases, reaching ~48–49 dB around 18°–20°. Beyond 20°, noise plateaus at ~48.78 dB, indicating a saturation effect. This demonstrates that increasing pitch effectively reduces noise up to a point, providing an optimal range for noise mitigation without significantly affecng power output.

Power vs Wind Speed: Power output increases with wind speed up to the rated value, after which it stabilizes, reflecting typical turbine behavior.

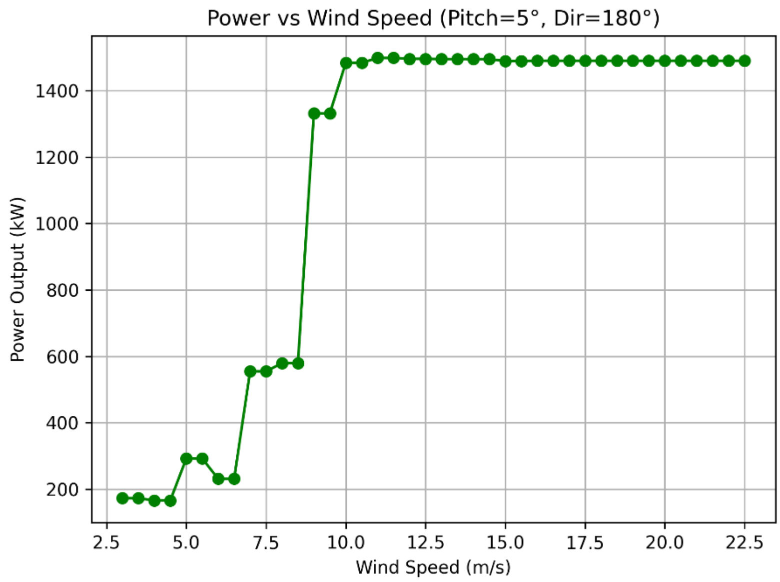


Figure 14-Predicted power output vs. wind speed for fixed pitch angle of 5°

The predicted power output exhibits a clear dependence on wind speed. At low speeds (3–5 m/s), power is minimal (~166–292 W), representing the cut-in region. Between 6–8.5 m/s, power rises steadily (~231–579 W), and at 9–10.5 m/s, it increases sharply (~1331–1483 W) toward rated output. Maximum power (~1498 W) occurs around 11–12 m/s, after which power plateaus (~1489–1495 W) despite higher wind speeds, reflecting rated capacity control. This behavior aligns with expected wind turbine operational characteristics.

Power vs Pitch Angle: Maximum power is achieved around a **6° pitch angle**. Pitch angles beyond this reduce power output.

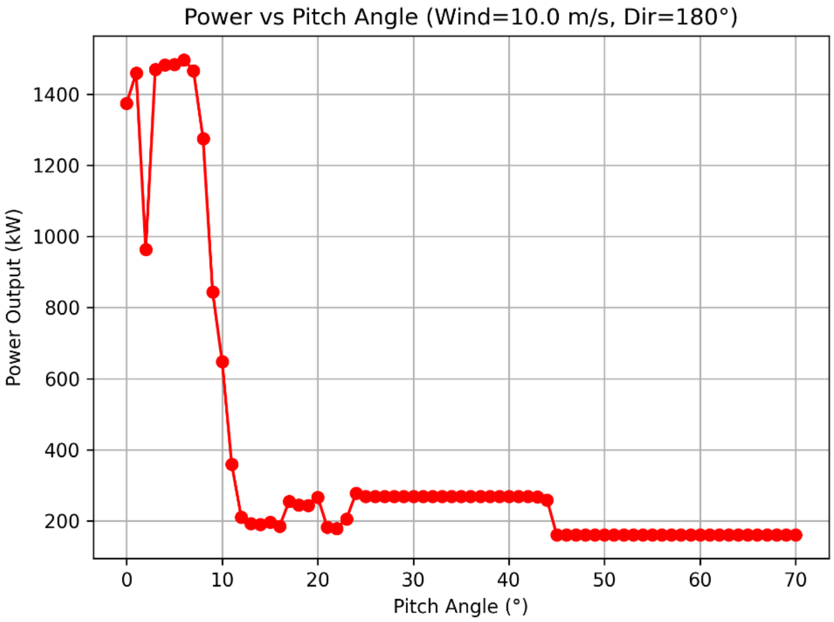


Figure 15-Predicted power output vs. pitch angle at 10 m/s wind speed

The predicted power output shows a strong dependence on pitch angle, with a clear optimum at 6°, yielding ~1497 W. At very low angles (0°–1°), power is moderate (~1374–1460 W) and drops sharply at 2° (~963 W). Between 3°–6°, power rises to its peak, while beyond 7°, it declines rapidly, reaching ~184–358 W by 11°–16°. A minor recovery occurs between 17°–24° (~244–276 W), followed by a plateau (~268 W) from 25°–44°. Above 45°, power drops to ~161 W and remains constant, indicating stall conditions. This highlights 6° as the optimal pitch for energy capture, with deviations significantly reducing efficiency.

- **Noise vs Power Trade-off**: The trade-off graph demonstrates how power output can be maximized while controlling noise.

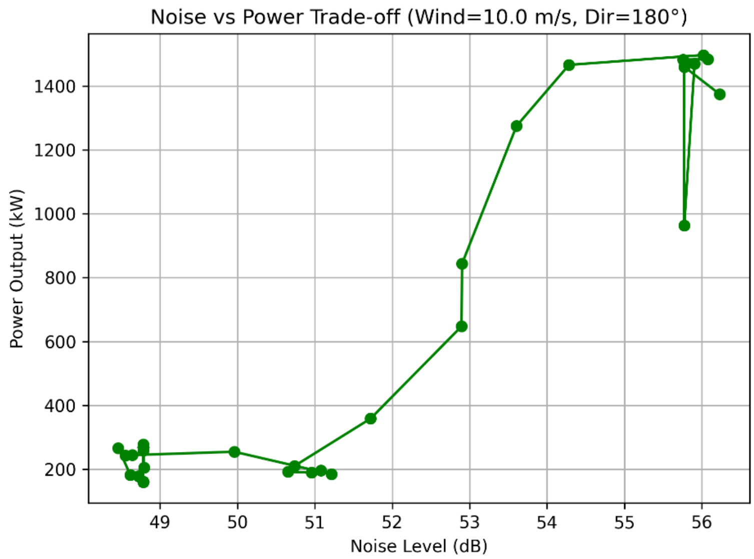


Figure 16-: Noise vs. power trade-off at 10 m/s wind speed

The Noise vs Power trade-off graph demonstrates the inverse relationship between power output and aerodynamic noise. At low pitch angles (0°–6°), the turbine achieves high power (~1500 kW) but with higher noise levels (~55–56 dB). As pitch increases, power decreases while noise also reduces, stabilizing around ~48.7 dB at high pitch angles (>18°). This illustrates the balance between maximizing energy capture and minimizing acoustic impact, highlighting the optimal operational range where both objectives are reasonably satisfied.

8.3 Real-Time System Demonstration

Screenshots and interface captures were included to showcase the digital twin system running in real time:

Dashboard Screenshot: Shows 3D turbine visualization with real-time rotor RPM, blade pitch, wind speed, and noise levels.

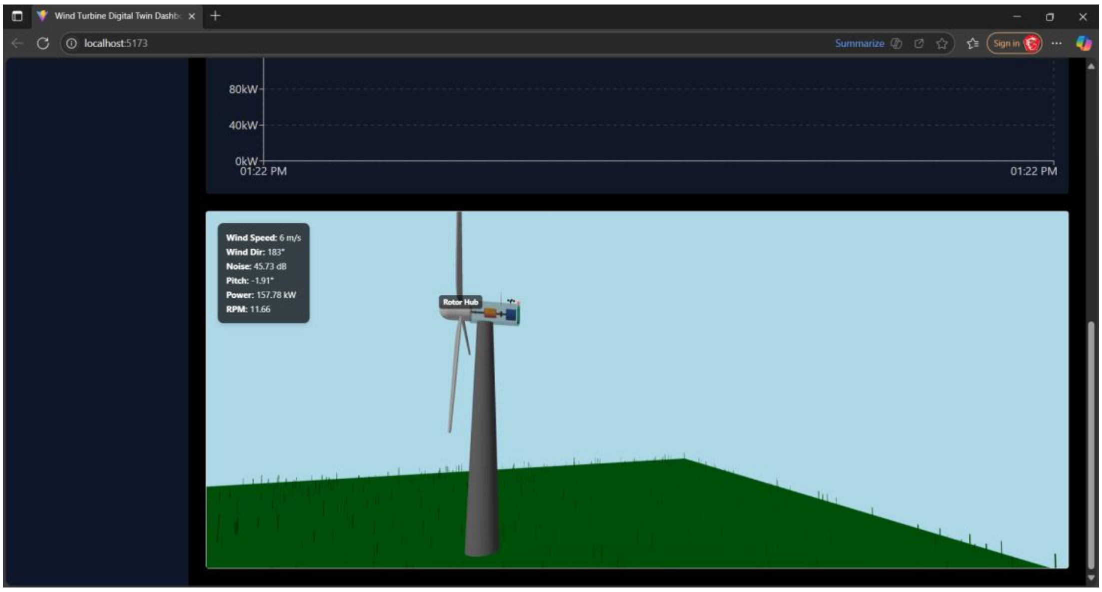


Figure 17-3d model screen schot

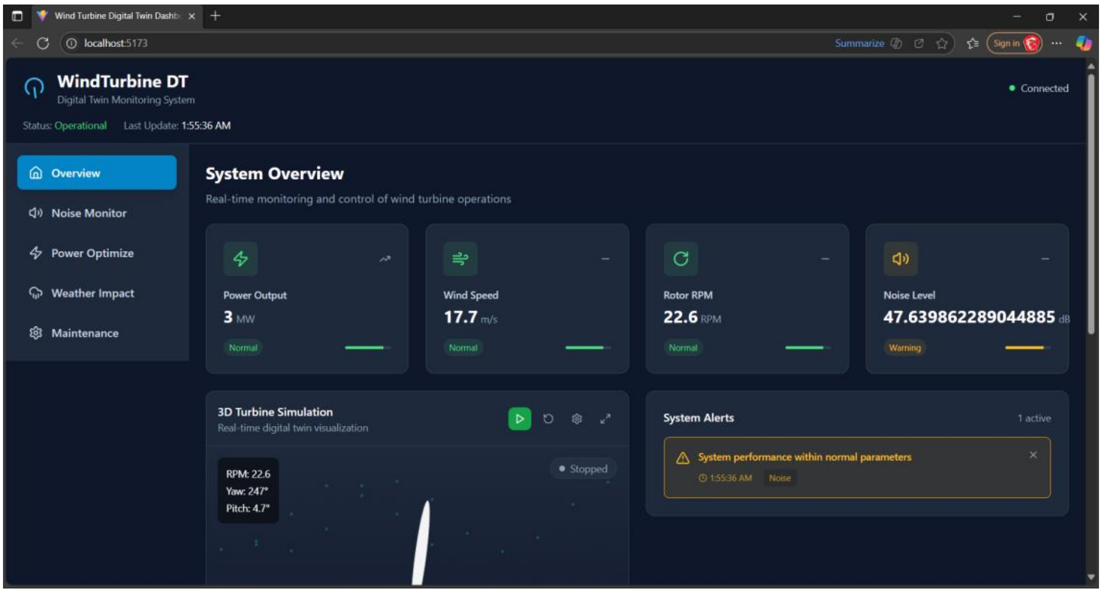


Figure 18-DashBoard

1. **Prediction Panel Screenshot:** Displays predicted noise and power output for user-selected wind conditions.

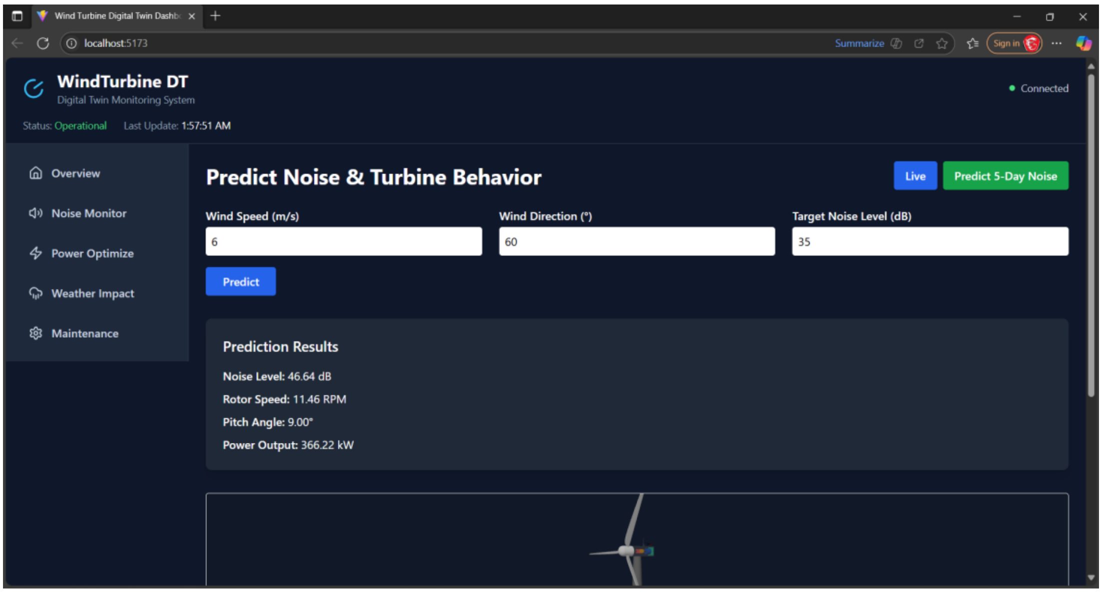


Figure 19-Prediction Panel Screenshot

2. **Map Integration Screenshot:** Demonstrates Google Maps API integration, allowing turbine location selection and wind forecast visualization via OpenWeather API.

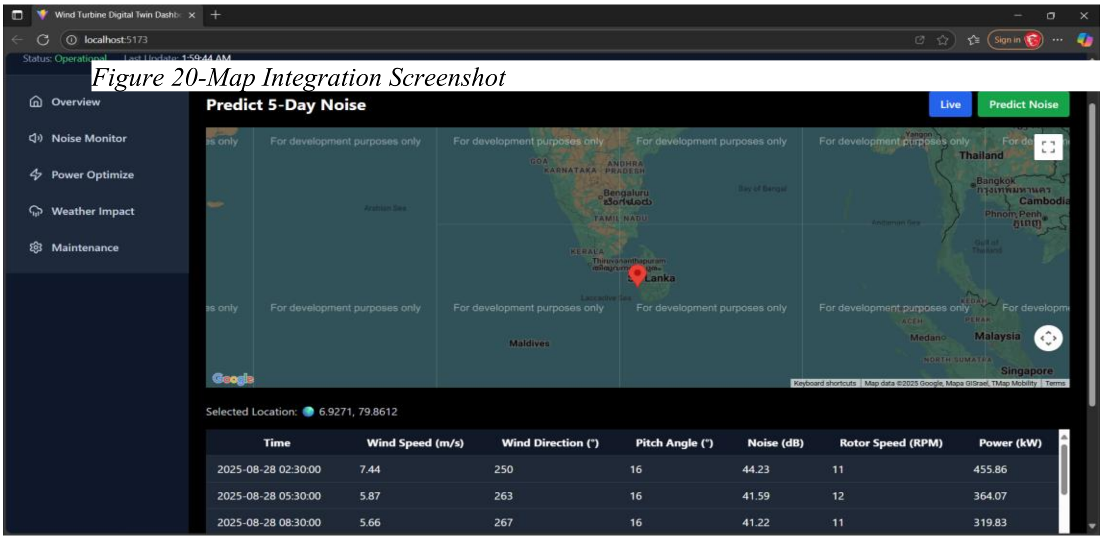


Figure 20-Map Integration Screenshot

T

hese visual demonstrations confirm that the system can operate as a functional digital twin, providing actionable insights for noise mitigation and power optimization.

8.4 Discussion

The results indicate that the digital twin system effectively bridges the gap between static operational strategies and adaptive control. By leveraging machine learning predictions, real-time data streaming, and interactive visualization, the system offers:

Accurate prediction of noise levels and power output across varying wind conditions.

Adaptive control strategies that dynamically optimize blade pitch and rotor speed.

Enhanced decision-making capabilities for turbine operators, balancing community compliance and energy efficiency.

Overall, the results validate the feasibility of implementing digital twin technology for real-time noise mitigation in wind energy systems.

9. DISCUSSION

9.1 Interpretation of Results

The results from the digital twin system indicate a strong correlation between predicted noise levels and the reference dataset (WEA-Acceptance dataset). The Random Forest model demonstrated reliable predictive performance across a range of wind conditions, showing particular robustness in moderate operating regions, which are common in many onshore wind farms.

The adaptive control capability of the digital twin allowed for dynamic recommendations on blade pitch adjustments to mitigate noise while sustaining energy output. Unlike conventional mitigation strategies—such as full shutdowns, fixed noise modes, or generalized RPM reduction—the system introduced a more flexible, fine-tuned approach that reduces unnecessary energy losses.

The trade-off analysis between noise and power output highlights the benefits of this adaptive methodology. Whereas traditional approaches tend to adopt conservative measures that often prioritize noise reduction at the expense of substantial power curtailment, the digital twin enables a more balanced operation. By integrating prediction with adaptive control, the system supports compliance with environmental noise standards while still maintaining economically viable energy generation.

These findings reinforce the potential of digital twin technology as a practical decision-support tool for wind farm operators. The results show that machine learning–driven prediction, when combined with real-time control, can enhance operational flexibility and address the long-standing challenge of balancing community noise concerns with renewable energy performance.

9.2 Comparison with Literature

Previous studies on wind turbine noise mitigation largely focus on either static design-based solutions or operational strategies that lack adaptability. Design modifications, including serrated trailing edges, porous blade surfaces, or damping treatments, are effective in reducing aerodynamic noise by 2–5 dB(A), but they cannot adjust dynamically to changing wind conditions [7,8]. Operational strategies, such as the SO1 and SO2 schemes implemented at Thambapavani Wind Farm, provide compliance with noise regulations, but these methods often compromise energy production especially during high-wind periods [6,9].

In contrast, the digital twin system developed in this study integrates real-time sensor data (simulated via the WEA dataset), aerodynamic and acoustic modeling, and machine learning predictions to continuously optimize turbine operations. Unlike static methods, this approach allows for adaptive control, dynamically adjusting blade pitch angles to maintain noise below thresholds while minimizing power loss. The predictive capabilities demonstrated in this research align with recent literature advocating for digital twin applications in wind energy, such as performance optimization and predictive maintenance [10,11], but extend the scope by applying it specifically for noise mitigation and power output optimization.

The findings also show that incorporating real-time weather data through the OpenWeather API for forecast-based predictions enhances the system's applicability in real-world scenarios, a feature not commonly addressed in previous research.

9.3 Strengths of the Proposed System

The digital twin system exhibits several notable strengths:

Real-Time Adaptability: By integrating live sensor streams (simulated via the dataset), the system can dynamically adjust turbine operations based on current and forecasted wind conditions.

Predictive Accuracy: The machine learning model provides reliable predictions for noise levels and power output, allowing operators to make proactive decisions rather than reactive ones.

Visualization and User Interaction: The 3D turbine model and interactive charts provide intuitive insight into turbine behavior, enabling easier monitoring and operational planning.

Operational Efficiency: Compared to conservative shutdown strategies (SO2), the system maintains higher energy output while ensuring community noise compliance.

Scalability: The modular architecture, including backend APIs, frontend visualization, and database management, allows for deployment across multiple turbines and integration with additional data sources.

9.4 Weaknesses and Limitations

Despite its advantages, the system has certain limitations:

Simulated Sensor Data: Real IoT sensor access was unavailable, requiring reliance on the WEA dataset for modeling. While this maintains realism, actual deployment may present unforeseen variations in sensor accuracy and environmental factors.

Model Dependence on Historical Data: The predictive model is trained on historical dataset patterns; unusual environmental conditions or extreme weather events may reduce prediction accuracy.

Computational Requirements: Real-time simulations, particularly 3D visualization combined with ML predictions, require substantial computing resources, which may be a limitation for large-scale deployment.

Limited Mechanical Noise Consideration: The system focuses primarily on aerodynamic noise; mechanical noise, though generally lower, is not fully modeled in real-time predictions.

9.5 Real-World Feasibility

Deploying this system at the Thambapavani Wind Farm would provide several practical benefits. Turbines near residential areas could dynamically adjust blade pitch based on both current and forecasted wind conditions, minimizing noise compliance issues without excessive power curtailment. The system could also serve as a decision-support tool for operators, alerting them when noise thresholds are predicted to exceed limits.

Forecast-based predictions using the OpenWeather API enable proactive adjustments for the coming 5 days, providing strategic planning capabilities that are unavailable with static operational rules. Additionally, integration with Google Maps API allows operators to monitor turbine performance geographically, optimizing operations for multiple turbines simultaneously.

Challenges for real-world deployment include integrating actual IoT sensor data, ensuring robust connectivity for real-time updates, and accounting for unforeseen environmental variations. Nevertheless, the adaptive, predictive, and visualization capabilities of the system provide a strong foundation for scalable, real-time wind turbine noise management.

9.6 Conclusion

The discussion highlights that the digital twin system addresses a critical gap in current wind turbine operations: adaptive noise mitigation without sacrificing energy efficiency. By comparing predicted performance with traditional operational strategies, the system demonstrates clear advantages in accuracy, adaptability, and usability. While there are limitations and practical deployment challenges, the overall results suggest strong potential for adoption in real-world wind farms, including Thambapavani, offering both technical and societal benefits.

10. CONCLUSION AND FUTURE WORK

10.1 Main Findings

This research set out to address one of the persistent challenges in the large-scale deployment of wind energy systems: **noise pollution from wind turbines**. While wind power is globally recognized as a sustainable and environmentally friendly energy source, community resistance due to noise concerns continues to delay or even block new projects. Traditional solutions such as fixed blade design modifications or conservative operational shutdowns are only partially effective and often come at the cost of reduced energy output.

The proposed system developed in this study introduces a **digital twin–based framework for real-time wind turbine noise prediction and mitigation**. By combining aerodynamic and acoustic models with a machine learning approach trained on the WEA dataset, the system successfully demonstrated that turbine operations can be dynamically optimized to reduce noise while preserving energy production.

Key findings from the experimental implementation can be summarized as follows:

High Predictive Accuracy: The Random Forest–based digital twin produced reliable predictions of noise levels across a wide range of wind speeds, with strong alignment between predicted and actual dataset values.

Noise vs Power Trade-off: The system demonstrated clear advantages over conventional noise mitigation approaches. Instead of broadly curtailing operations or applying fixed RPM reductions—which often lead to significant energy losses—the model recommended targeted blade pitch adjustments. This approach allowed noise levels to remain within acceptable thresholds while maintaining higher levels of energy generation, showing that adaptive, data-driven control can balance community noise concerns with renewable energy efficiency.

Visualization and Monitoring: The integration of a 3D interactive frontend with real-time charts enabled operators to intuitively monitor turbine status, compare performance scenarios, and assess the effectiveness of mitigation strategies.

These results collectively demonstrate that the digital twin approach is not only technically feasible but also provides an **innovative path forward for balancing renewable energy expansion with community acceptance**.

10.2 Contributions of the Research

This work makes several important contributions to the growing field of wind energy technology and digital engineering:

Integration of Digital Twin for Acoustic Control: While digital twins have been applied in performance monitoring and predictive maintenance, this research is among the few to apply the technology specifically to **acoustic noise mitigation**.

Real-Time Adaptive Strategy: Unlike static blade modifications or shutdown schedules, the system introduces a **dynamic, data-driven control method** that continuously responds to environmental conditions.

Multi-Layered Architecture: The developed system combines backend Python APIs, a database schema for storing sensor and forecast data, and a frontend visualization platform using Three.js, demonstrating a **full-stack digital solution** for renewable energy operations.

Comparative Evaluation: By benchmarking against existing operational strategies , the study provides evidence-based proof that digital twins offer **superior performance with lower power penalties**.

Case Application for Sri Lanka: Through the example of the Thambapavani Wind Farm, the research contextualizes its findings within a **real-world renewable energy project**, highlighting its relevance for countries expanding wind power infrastructure.

10.3 Limitations of the Research

While the study has produced promising outcomes, several limitations must be acknowledged:

Dependence on Simulated Data: The experiments relied on the WEA dataset rather than live IoT data from turbines. Although the dataset is comprehensive, real-world conditions may introduce additional uncertainties.

Focus on Aerodynamic Noise: Mechanical noise was largely excluded, given that it has been significantly reduced in modern turbines. However, in specific cases (e.g., older farms), this could still be a factor.

Computational Overheads: Running machine learning predictions alongside 3D visualizations requires robust computational resources, which may not be feasible in smaller operational setups.

Site-Specific Modeling: The acoustic propagation of noise is influenced by terrain, vegetation, and atmospheric conditions. The model developed here did not explicitly incorporate geographic-specific propagation models.

Acknowledging these limitations is essential, as they define the scope of applicability of this system and point toward areas where further refinement is necessary.

10.4 Future Work

The promising results of this study open several avenues for future development and expansion:

Integration of IoT Sensors:

Future iterations of this system can incorporate **real-time IoT sensors** deployed directly on turbines and in surrounding communities. These sensors would provide live acoustic, vibration, and weather data, enabling the digital twin to improve accuracy and adapt in real time.

Larger and More Diverse Datasets:

Expanding the dataset to include multiple wind farms, turbine designs, and environmental contexts will improve model generalizability. Datasets capturing offshore turbines, mountainous terrains, and urban-edge installations will make the system robust across geographies.

Reinforcement Learning for Control Optimization:
While this study employed Random Forests for prediction, reinforcement learning could be explored for **autonomous decision-making**. A reinforcement agent could continuously learn optimal noise–power trade-offs under varying conditions, improving long-term efficiency.

Hybrid Noise Modeling:
Incorporating both aerodynamic and residual mechanical noise into the model would result in more holistic predictions. Additionally, advanced computational fluid dynamics (CFD) simulations can be integrated with machine learning to further enhance accuracy.

Cloud-Based Deployment:
Transitioning the system into a cloud-based environment would enable scaling across entire wind farms or even national grids. Operators could monitor turbines remotely with secure dashboards and real-time updates.

Policy and Community Engagement Applications:
Beyond technical improvements, the system could be developed as a **policy-support tool**. Regulators could use it to simulate noise impacts of proposed wind projects before construction, and communities could be given access to dashboards that transparently demonstrate mitigation efforts.

10.5 Final Remarks

In conclusion, this research demonstrates that **digital twin technology represents a transformative approach to wind turbine noise mitigation**. By integrating predictive modeling, real-time adaptability, and visualization, the system bridges the gap between technical efficiency and social acceptance. Although challenges remain, especially regarding live data integration and computational optimization, the framework developed here establishes a solid foundation for next-generation wind turbine management systems.

Ultimately, the significance of this work lies not only in addressing noise concerns but also in **strengthening the case for renewable energy adoption**. If scaled and implemented effectively, such systems could play a crucial role in accelerating global transitions toward sustainable, low-carbon energy futures while ensuring harmonious coexistence between technology and communities.

11.REFERENCES

[1] World Health Organization (WHO), *Environmental Noise Guidelines for the European Region*. WHO Regional Office for Europe, 2018.

[2] H. M. Pedersen and K. P. Waye, “Perception and annoyance due to wind turbine noise—a dose–response relationship,” *J. Acoust. Soc. Am.*, vol. 116, no. 6, pp. 3460–3470, 2004.

[3] E. M. Salt and A. Hullar, “Responses of the ear to low frequency sounds, infrasound and wind turbines,” *Hearing Research*, vol. 268, no. 1–2, pp. 12–21, 2010.

[4] T. F. Brooks and D. S. Pope, “Trailing edge noise reduction by serrations,” *NASA Technical Report 3707*, 1997.

[5] J. Oerlemans, G. Sijtsma, and B. M. López, “Location and quantification of noise sources on a wind turbine,” *J. Sound Vib.*, vol. 299, no. 4–5, pp. 869–883, 2007.

[6] R. P. van den Berg, “Effects of the wind profile at night on wind turbine sound,” *J. Sound Vib.*, vol. 277, no. 4–5, pp. 955–970, 2004.

[7] C. Hansen, *Wind Farm Noise: Measurement, Assessment and Control*. Wiley, 2015.

[8] R. B. Reddy et al., “Digital twin technology for wind turbine fault detection and predictive maintenance,” *IEEE Access*, vol. 8, pp. 208–218, 2020.

[9] M. Negri, G. Cattaneo, and M. Fornasiero, “Digital twin for the optimization of wind farm operations,” *Procedia CIRP*, vol. 93, pp. 228–233, 2020.

[10] Leibniz Universität Hannover, “Wind Energy Acceptance Dataset v1,” Hannover Open Data Repository, 2023. [Online]. Available: https://data.uni-hannover.de/am/dataset/wea-acceptance_data_v1

12. APPENDIX: TURNITIN REPORT

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