Real-Time Optimization and Maintenance of Wind Turbine Performance Using Digital Twin Technology

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(Dilmini N.A.C, Jenojan P., Dhanushikan V., Herath H.M.T.S.)

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

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DECLARATION

We declare that this is our 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 our 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, we hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute our dissertation in whole or part in print, electronic or other medium. We retain the right to use this content in whole or part in future works (such as article or books).

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(Mr. Vishan Jayasinghearachchi)

ABSTRACT

Wind energy is a critical component in the global effort to reduce carbon emissions, and Sri Lanka’s Thambapavani Wind Farm plays a significant role in the country's renewable energy transition. However, several challenges hinder its performance and forecasting accuracy, including yaw misalignment, extreme wind speed thresholds, lightning risks, and noise pollution. This research proposes an integrated Digital Twin (DT) framework that combines predictive maintenance, weather risk modeling, noise management, and power optimization to enhance wind farm efficiency, reliability, and sustainability.

The system utilizes several machine learning techniques to predict turbine-specific weather impacts, forecast power output, and simulate real-time operational adjustments. A core aspect of the framework is its ability to dynamically manage turbine operations, optimizing variables like blade pitch and nacelle orientation to improve energy capture while minimizing noise and operational disruptions. By integrating SCADA data with meteorological forecasts, the Digital Twin enhances the forecasting accuracy, addressing weather-induced risks and improving overall performance.

Through rigorous validation, the system demonstrated significant results, including projected reductions of 30-40% in unplanned downtime and 20-25% in maintenance costs. The framework provides real-time insights, facilitates adaptive maintenance scheduling, and supports grid integration by aligning turbine output with real-time energy demand. Furthermore, it incorporates adaptive noise control strategies, ensuring that turbines operate efficiently while minimizing their impact on surrounding communities, crucial for public acceptance and project longevity.

This study contributes to the advancement of Digital Twin technology in the wind energy sector, offering a scalable and practical solution to the challenges faced by coastal wind farms. It provides a pathway to enhance operational efficiency, improve forecasting accuracy, and address the socio-political barriers to wind energy deployment, especially in tropical regions like Sri Lanka.

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LIST OF ABBREVIATIONS

Abbreviation	**Full Form**
DT	Digital Twin
SCADA	Supervisory Control and Data Acquisition
CEB	Ceylon Electricity Board
NASA	National Aeronautics and Space Administration
ISS-LIS	International Space Station – Lightning Imaging Sensor
RUL	Remaining Useful Life
CFD	Computational Fluid Dynamics
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
R^2	Coefficient of Determination
API	Application Programming Interface
SaaS	Software as a Service
LSTM	Long Short-Term Memory
ML	Machine Learning
EDA	Exploratory Data Analysis
JSON	JavaScript Object Notation
DB	Database

1 INTRODUCTION

1.1 Background and Literature Survey

Wind energy is now one of the world's most important low-carbon electricity sources. The past few years have seen record additions to wind capacity: the industry installed roughly 117 GW of new wind power in 2024, bringing cumulative global wind capacity above 1,100 GW (1.1 TW). This rapid growth has been driven by falling levelized costs, technological improvements in turbines (larger rotors, taller towers) and expanding deployment both onshore and offshore but the sector still must accelerate further to meet climate targets.

In Sri Lanka, wind power is an increasingly important component of the energy transition as the country seeks to expand renewable electricity and improve energy security. Recent government reporting and energy ministry documents place the island's total renewable installed capacity in the low thousands of MW (≈3,800 MW as of 2024) within a national grid whose overall nameplate capacity is just over 5,000 MW. The Sri Lankan power sector has set ambitious renewables targets, and private investments including new utility-scale wind projects such as a 50 MW Mannar wind farm announced in 2025 underlining wind's growing role in national plans. Despite this, wind's actual energy contribution is sensitive to seasonal patterns, local site quality and grid integration constraints, so improving per-turbine performance and forecasting remains critical for Sri Lanka's renewable goals.

Traditionally, improving wind farm productivity and reliability has relied on a combination of hardware design, control algorithms and operations practice. Engineering advances such as larger rotors, improved blade aerodynamics, and stronger power-electronics for variable-speed control raise capture efficiency. For asset health and availability, predictive maintenance (condition monitoring, vibration analysis, oil/gearbox sensors) reduces downtime and lifecycle cost compared with calendar-based servicing; studies and industry reports show predictive strategies can substantially raise availability and reduce unscheduled repairs when combined with effective data pipelines.

A Digital Twin (DT) is a dynamic, virtual representation of a physical asset or system that is continuously updated with data and can be used for simulation, diagnosis, prediction and decision support. In the wind sector, DTs range from descriptive models (visual dashboards and historical summaries) to predictive and prescriptive systems that fuse physics-based models, sensor streams and machine learning to forecast performance, predict failures, and suggest operational setpoints that increase energy capture or reduce loads. Recent literature reviews and surveys in wind energy show a fast-growing interest in DTs: multiple review papers (2022–2025) identify three modelling approaches physics-based, data-driven and hybrid models and emphasize DTs' strengths in real-time monitoring, predictive maintenance, wake modelling and farm-level optimization.

Applied to wind turbines, digital twins can deliver measurable improvements that align tightly with the needs of countries like Sri Lanka. DT-enabled condition monitoring and predictive-maintenance workflows reduce unplanned downtime, increasing availability and annual energy production. DTs that combine short-term wind forecasting with turbine control logic can adjust pitch/yaw and propose decisions to raise net energy yield. Recent domain studies and prototype systems demonstrate use cases such as reducing gearbox failures through early anomaly detection, optimizing turbine setpoints to recover lost energy from wake interactions, and generating probabilistic power forecasts for grid balancing. Reviews from 2023–2025 conclude that while full autonomous DTs are still emerging, predictive DTs for maintenance and forecasting are already maturing, making them a practical focus for applied projects.

Wind turbines are complex machines composed of subsystems such as gearboxes, bearings, generators, and control systems, all of which are exposed to continuous mechanical stress and harsh environmental conditions. Failures in these components often lead to costly downtime, reduced energy production, and increased repair expenses. Traditional approaches, including reactive maintenance (fixing components after they fail) and preventive maintenance (scheduled servicing at fixed intervals), have proven inadequate for modern wind operations. Reactive strategies result in unplanned outages and cascading damage, while preventive strategies risk wasting resources on servicing components that are still functional. These challenges highlight the need for predictive and condition-based maintenance strategies that anticipate failures before they occur.

The rise of digital twin technology, IoT-enabled sensors, and machine learning has opened new pathways for intelligent turbine maintenance. By integrating real-time data streams from turbine subsystems with predictive analytics, operators can track performance indicators, forecast degradation, and schedule interventions more efficiently. Machine learning models such as Random Forests and LSTM networks have shown strong potential in detecting anomalies and predicting early signs of failure. Globally, predictive maintenance has been found to reduce unplanned downtime by up to 40% and maintenance costs by 20–25%. For Sri Lanka's coastal wind farms such as Mannar (Thambapavani), which face challenges like high humidity, lightning exposure, and fluctuating wind speeds, predictive strategies are especially beneficial for ensuring higher turbine availability, extending component lifespans, and lowering operational costs.

Weather variability remains one of the most influential factors affecting wind turbine performance, with direct consequences on energy yield and grid reliability. In wind farms such as Thambapavani, sudden changes in wind direction can cause yaw misalignment, forcing turbines to temporarily halt while realigning their nacelles. Similarly, extreme wind speeds below cut-in thresholds (~3 m/s) or above cut-out limits (~25 m/s) reduce power capture and may even trigger shutdowns for safety. Seasonal lightning activity adds further risks, threatening turbine blades, control systems, and worker safety while causing unexpected interruptions in generation. For utilities like the Ceylon Electricity Board (CEB), which depend on accurate short-term (48-hour) forecasts, such weather-driven uncertainties create a mismatch between predicted and actual outputs, complicating national energy planning and grid balancing.

Recent research emphasizes the role of advanced modeling and digital twins in addressing these weather-related risks. Studies have shown that integrating SCADA turbine data with meteorological datasets improves forecast accuracy, while hybrid approaches combining physical simulations with machine learning better capture nonlinear weather impacts. For instance, machine learning techniques have been used to forecast lightning probability and enhance wind power predictions in coastal sites. Digital twins add an extra layer of capability by simulating turbine responses to weather fluctuations, enabling operators to anticipate yaw losses, threshold exceedances, and storm-related risks before they impact output. By embedding weather-specific risk models within a digital twin, wind farms in Sri Lanka can achieve more reliable forecasting, minimize downtime, and strengthen operational resilience against climate-related challenges.

While wind power is a clean and sustainable energy source, noise pollution remains one of its most persistent challenges, particularly in communities located near wind farms. Wind turbine noise originates from two major sources: aerodynamic noise caused by air flowing over the blades (e.g., tip vortex and trailing-edge noise), and mechanical noise produced by internal components such as gearboxes, generators, and bearings. Although modern engineering has reduced mechanical noise significantly through better insulation and direct-drive systems, aerodynamic noise continues to dominate as turbines grow larger to maximize energy capture. Reports from nearby communities often cite noise-related impacts including sleep disturbance, stress, and reduced quality of life, which in turn affect public acceptance and delay project approvals.

Addressing turbine noise is therefore essential for balancing energy production goals with social sustainability. Research has focused on computational fluid dynamics (CFD) simulations, noise-mitigating blade designs, and operational strategies such as variable rotor speed to reduce acoustic emissions. Digital twins further enhance noise analysis by providing real-time monitoring and simulation of sound propagation under varying wind conditions and terrain features. By linking acoustic models with turbine operation data, operators can test scenarios virtually, implement noise-reduction strategies proactively, and improve community engagement. In Sri Lanka, where expanding renewable energy capacity depends on public trust and acceptance, integrating noise analysis into digital twin frameworks ensures that wind power projects achieve both technical efficiency and social license to operate.

Power optimization lies at the heart of maximizing wind turbine efficiency and profitability. Turbine power output is influenced by multiple factors, including blade pitch angle, rotor speed, nacelle orientation, and wind conditions. Traditionally, manufacturers provide standardized power curves and control algorithms, but these static configurations often fail to capture site-specific conditions, leading to suboptimal performance. Digital twins provide a smarter alternative by simulating turbine behavior in real time and testing different operational strategies virtually before applying them. By leveraging machine learning models trained on historical SCADA data, a digital twin can recommend the optimal combination of pitch, yaw, and torque control to maximize energy capture while minimizing stress on components.

Equally important is energy forecasting, where accurate short-term predictions are essential for grid stability and market participation. Advanced data-driven models outperform traditional statistical methods by capturing nonlinear and temporal dependencies in wind and power data. Integrated into a digital twin, these models allow operators to forecast power output with higher precision, plan maintenance schedules, and coordinate energy dispatch more effectively. For Sri Lanka's wind farms, this dual approach of optimization and forecasting ensures higher turbine availability, better alignment with national demand patterns, and reduced curtailment losses. Ultimately, by combining real-time monitoring, predictive modeling, and optimization, digital twins transform turbine operations into a more efficient, resilient, and economically viable system.

1.2 Research Gap

Despite the growing interest in Digital Twin (DT) technology across industrial domains, its application in the wind energy sector remains fragmented and inadequate when confronting real-world complexities. Many DT implementations in wind simply prototype structural health monitoring or fault detection using simulated or Western offshore datasets but fail to encompass operational realities. Key limitations include insufficient incorporation of heterogeneous components (e.g., drivetrain, blades, nacelle systems), minimal real-time control, lack of integration across maintenance, forecasting, noise mitigation, and optimization functions, and scarce validation using real operational data, particularly from tropical or developing-country contexts. Consequently, DTs in wind energy often remain theoretical or narrowly focused, without rising to the challenge of holistic, adaptive, and regionally tailored systems.

1.2.1 Noise Impact Analysis

Noise research in wind energy has largely centered on static assessments evaluating acoustic emissions after installation or on fixed design-based mitigation (e.g., specialized blade or tower designs). These methods often force a trade-off: reduce noise but sacrifice performance. Although Digital Twin approaches hold promise for real-time modeling and dynamic-controlling noise (adapting operations based on environmental and acoustic feedback), this potential remains underexplored in the literature. The omission of adaptive noise prediction and control mechanisms constrains both turbine performance and community acceptance, especially in contexts where social impacts can significantly influence project viability.

1.2.2 Operational Efficiency and Energy Forecasting

Current power optimization and forecasting methods work within separate silos and lack holistic real-time adaptability. Manufacturer-set control algorithms (blade pitch, rotor speed, yaw) are static and not robust to changing site conditions. Machine learning techniques improve forecasting accuracy but are often validated only in offline scenarios or on short-term data, with limited inclusion of real-time feedback or medium-term predictive horizons critical for grid integration. Importantly, forecasts and optimization have rarely been combined into a single system, despite their strong interdependence. DTs have been proposed to unify these functions, yet most implementations remain isolated, under-validated, and regionally narrow, typically focusing on mature wind markets such as Europe or China. Comparative model evaluations are also rare few studies benchmark multiple algorithms under identical conditions to determine which approach performs best under data-scarce conditions like those faced by small-scale wind farms.

1.2.3 Weather-Based Risk Assessment and Power Loss Prediction

Research exploring weather-induced losses such as yaw misalignment, cut-in/cut-out shutdowns, and lightning hazards has yielded important insights (for example, recalibration of power curves, DT-based optimization, short-term lightning forecasts, and machine learning forecasting in coastal farms). Yet these contributions remain largely siloed. Power curve recalibrations (e.g., Bandi & Apt) focus on general accuracy improvements without capturing dynamic misalignment events. Digital Twin work (such as Hasan & Styve) emphasizes overall optimization but seldom disaggregates weather-specific risks. Lightning nowcasting efforts (e.g., Mostajabi et al.) are constrained to very short horizons (0–30 minutes), insufficient for operational decision-making. Additionally, models like Random Forest (Gu et al.) improve energy forecasting but do not incorporate multiple weather factors into a consolidated predictive framework. This fragmented approach leaves turbine-level, site-specific weather risk modelling especially under tropical coastal conditions uncharted.

1.2.4 Predictive Maintenance with Digital Twin

Despite significant progress demonstrating the promise of DT and machine learning in predictive maintenance such as hybrid DTs for drivetrain fault detection (Pujana et al., 2023) and blade degradation monitoring (Luo et al., 2023), with broader DT platforms proposed for scheduling and efficiency (Daniel et al., 2024) important gaps persist. Most studies rely on datasets from European or offshore wind projects or even synthetic data. They do not reflect the environmental stressors found in tropical regions like Sri Lanka, including humidity, salt corrosion, and lightning exposure. Furthermore, research often isolates components for instance, focusing only on the drivetrain or blades rather than proposing integrated maintenance frameworks that account for interactions across turbine subsystems. The reliance on synthetic fault data also poses risks, as models may not generalize well without localized real-world validation. Lastly, while predictive analytics have been demonstrated academically, few studies address automation of maintenance workflows, such as scheduling, technician assignment, and alert systems, which are essential for operational deployment.

This project directly responds to these gaps through the development of a comprehensive Digital Twin framework tailored for Sri Lanka's coastal wind farms. It integrates predictive maintenance, weather-sure risk modeling (including misalignment, thresholds, and lightning), adaptive noise control, and joint power optimization and forecasting. Crucially, it is built using localized SCADA and meteorological datasets, incorporates automated workflows (alerts and maintenance coordination), compares multiple algorithms (e.g., Random Forest, LSTM, XGBoost) under the same conditions, and delivers real-time visualization and decision support. By doing so, the project advances both academic knowledge and practical deployment pathways for resilient, efficient wind energy systems in tropical, resource-constrained settings.

1.3 Research Problem

Wind energy is increasingly critical to meeting global and national renewable energy targets, particularly for Sri Lanka, where coastal wind farms such as Thambapavani in Mannar provide large-scale, grid-connected power generation. However, the reliable and efficient operation of wind turbines remains constrained by several persistent challenges that limit both technical performance and social acceptance. These challenges span four key domains: noise, weather impacts, predictive maintenance, and power optimization.

Noise pollution represents one of the most socially sensitive issues in wind energy development. In quiet rural areas like Mannar, turbine noise is highly noticeable, often leading to annoyance, sleep disturbances, and opposition from nearby residents. Existing mitigation methods, such as low-noise turbine designs or operational curtailment, are largely reactive and impose a direct trade-off with power generation, as seen at Thambapavani where turbines are shut down during high winds to reduce acoustic disturbance. This reactive approach underscores the lack of real-time, adaptive noise management systems that can simultaneously protect community well-being and preserve energy output.

Weather-induced risks further compromise wind energy reliability. Coastal wind farms are particularly vulnerable to yaw misalignments caused by abrupt wind direction shifts, forced shutdowns due to cut-in and cut-out thresholds, and seasonal lightning activity. Current industry practice relies on static threshold-based rules and short-term detection systems that only respond after disruptions have already occurred. As a result, power forecasts often fail to capture weather-driven generation losses, reducing accuracy for grid integration and increasing system balancing costs. For utilities like the Ceylon Electricity Board, this mismatch between predicted and actual generation undermines confidence in renewable energy scheduling.

Predictive maintenance is another pressing concern in tropical coastal regions. Harsh operating environments with high humidity, salt exposure, and frequent lightning accelerate component failures in gearboxes, bearings, and control systems. Existing maintenance approaches in Sri Lanka remain largely reactive or time-based, leading to unplanned downtime and unnecessary servicing costs. While global research has shown the potential of digital twins and machine learning for predictive maintenance, these solutions are not adapted to localized conditions and often address subsystems in isolation, rather than providing integrated turbine-level health assessments and automated maintenance coordination.

Power optimization and forecasting present an additional set of challenges. Manufacturer-provided control algorithms rely on fixed thresholds and do not adapt to dynamic site-specific conditions, resulting in avoidable efficiency losses. Meanwhile, traditional statistical forecasting methods fail to capture the nonlinear relationships between wind behavior and turbine performance, producing inaccurate predictions that hinder grid stability. Even with modern machine learning models, most solutions remain siloed treating forecasting and optimization separately without integrating the two into real-time, data-driven decision support systems.

Across these domains, a unifying issue is that current practices are predominantly static, reactive, or narrowly scoped. Noise is managed after disturbance occurs, weather thresholds trigger shutdowns only after risks materialize, maintenance is performed either too late or too early, and power optimization ignores real-time forecasting feedback. Moreover, existing digital twin applications in wind energy remain fragmented focusing on single problems such as fault detection or structural monitoring without evolving into holistic frameworks that integrate predictive maintenance, weather risk modeling, noise management, and power optimization within a single adaptive system. Compounding this, most digital twin models rely on European or offshore datasets, with little validation in tropical coastal contexts like Sri Lanka.

Despite advances in turbine design, control algorithms, and digital technologies, there is currently no integrated, real-time digital twin framework capable of addressing the combined challenges of noise, weather impacts, predictive maintenance, and power optimization in wind energy systems. Existing approaches are static, reactive, or energy-intensive, and they lack adaptation to the localized environmental and socio-political conditions of Sri Lanka. This research therefore addresses the problem of how to develop a comprehensive digital twin system that unifies predictive noise management, weather impact modeling, condition-based maintenance, and power optimization into a single adaptive framework using real-world data from Sri Lankan wind farms to enhance operational efficiency, forecasting accuracy, and social acceptance of wind energy.

1.4 Objectives

1.4.1 Main Objective

The main objective of this project is to design and implement a Digital Twin system for a wind turbine, serving as a virtual representation of the physical turbine that integrates data-driven analysis, machine learning, and visualization technologies. The system is intended to provide a platform that not only reflects the operational state of the turbine but also enables enhanced decision-making through continuous monitoring, optimization, and predictive modeling. By creating a digital counterpart of the physical turbine, the project addresses the growing need for advanced tools that can improve efficiency, reliability, and sustainability in renewable energy systems.

Another key objective is to leverage the synergy between real-time data and advanced computational models to enhance wind turbine operations. While traditional turbine monitoring systems often provide limited insights, the digital twin approach allows for a more comprehensive understanding of turbine behavior by simulating scenarios, predicting future performance, and identifying inefficiencies early. This supports operators in optimizing energy generation, reducing downtime, and making informed maintenance and operational decisions. In the long run, such systems contribute to cost reduction, extended equipment life, and improved integration of wind energy into the grid.

Finally, the project aims to demonstrate how digital transformation technologies can be practically applied in the renewable energy sector. By incorporating machine learning models, forecasting techniques, and 3D visualization tools, the digital twin serves as a bridge between physical infrastructure and intelligent computational analysis. This aligns with global efforts to adopt smart energy solutions and enhances the potential for scaling wind power as a reliable and sustainable energy source. The implementation of this system not only addresses immediate technical objectives but also contributes to the broader vision of developing next-generation energy management platforms that are adaptive, data-centric, and sustainable.

1.4.2 Specific Objectives

1.4.2.1 Noise Impact Analysis

1. To conduct a comprehensive literature review on wind turbine noise, to identify existing research gaps.

A thorough review of existing literature is essential to build a strong foundation for noise impact analysis. By reviewing prior studies, the project identifies the strengths and limitations of current research, uncovers unexplored areas, and establishes the motivation for integrating noise analysis into the digital twin framework.

2. To evaluate the effectiveness of current noise mitigation strategies highlighting their limitations and trade-offs between noise reduction and power generation.

Existing mitigation techniques have varying levels of effectiveness but often involve trade-offs that reduce turbine performance. This objective focuses on evaluating such strategies systematically to highlight the need for adaptive, intelligent solutions that balance acoustic and energy considerations, motivating the digital twin approach.

3. To design the system architecture of the digital twin framework, integrating aerodynamic models, acoustic models, and real-time/simulated sensor data into a dynamic platform.

A core contribution of this project is the development of a multi-layered digital twin architecture specifically tailored for noise analysis. This involves linking aerodynamic models (to capture blade-flow interactions), acoustic models, and sensor data streams. The integration ensures that the digital twin can dynamically replicate real-world noise behavior, providing a virtual testing ground for different operational strategies and environmental conditions.

4. To simulate noise propagation scenarios under different operational and environmental conditions and generate a knowledge base linking turbine operation with noise emissions.

Since noise emissions are highly sensitive to operational and atmospheric factors, this objective involves conducting simulations under a wide range of scenarios. By varying wind speeds, blade pitch angles, and turbulence intensities, the system can capture how operational settings influence acoustic output. These simulations create a structured knowledge base that links turbine control parameters with noise characteristics, thereby enabling predictive and comparative analysis of noise patterns in different contexts.

5. To develop adaptive noise control strategies within the digital twin, enabling real-time operational adjustments (e.g., blade pitch optimization, rotor speed modifications) that balance noise reduction with power output.

Static noise mitigation strategies often compromise efficiency. Therefore, the digital twin is designed to explore adaptive control strategies that dynamically adjust turbine parameters to reduce noise without severely impacting power generation. Examples include fine-tuning blade pitch or adjusting rotor speed during sensitive periods (such as nighttime operations near residential areas). By embedding these adaptive mechanisms, the system provides operators with real-time decision-support tools for noise-aware energy production.

6. To validate the accuracy and reliability of the digital twin system by comparing its predictions with real-world field data or validated simulation results.

For the digital twin to be credible, it must undergo rigorous validation. This involves comparing model outputs with empirical data from operational wind farms or with results from established acoustic simulation tools. Validation ensures that the digital twin's predictions of noise emissions and propagation are accurate and reliable, thereby strengthening its practical applicability in both research and industry contexts.

7. To provide practical recommendations for deploying digital twin systems in commercial wind farms, addressing technical, managerial, and policy aspects.

Beyond technical development, the project aims to bridge the gap between research and practice. This objective emphasizes producing actionable recommendations for wind farm operators and policymakers. Topics include the type and resolution of data required, methods for ensuring compliance with regulatory noise limits, and approaches for engaging with local communities affected by noise. By doing so, the project contributes not only to technological advancement but also to fostering greater public acceptance of wind energy projects.

1.4.2.2 Operational Efficiency and Energy Forecasting

1. To design and implement a data preprocessing pipeline for wind turbine operational data.

High-quality data is fundamental for reliable machine learning and forecasting. This objective focuses on creating a preprocessing pipeline that handles raw sensor and historical turbine datasets, ensuring consistency and usability. The process includes cleaning missing or erroneous values, normalizing variables across different scales, and performing feature engineering to extract meaningful indicators such as wind speed fluctuations, rotor speed trends, and environmental conditions. By transforming raw data into structured and refined inputs, the pipeline establishes the foundation for building robust optimization and forecasting models.

2. To develop machine learning models for power optimization.

The second objective addresses the design of intelligent models capable of identifying operational strategies that maximize energy yield. By analyzing critical parameters such as blade pitch angle, nacelle orientation, wind speed, and rotor speed, the models can reveal optimal control settings for different environmental conditions. The integration of machine learning techniques enables the system to capture nonlinear relationships between variables, adapt to changing wind dynamics, and provide actionable insights for improving turbine efficiency.

3. To implement time-series forecasting models for predicting wind turbine energy generation.

Reliable energy forecasting is essential for effective grid management and operational planning. This objective focuses on applying and comparing advanced time-series models such as Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks to generate short- and medium-term predictions of turbine power output. These models account for temporal dependencies, seasonal variations, and environmental factors, enabling operators to anticipate generation patterns and align turbine operations with grid demand.

4. To evaluate and compare the performance of multiple models using appropriate metrics.

Model performance must be validated systematically to ensure accuracy and reliability. This objective involves benchmarking optimization and forecasting models using statistical metrics such as the Coefficient of Determination (R^2), Mean Squared Error (MSE), and Mean Absolute Error (MAE). By applying multiple evaluation criteria, the study ensures that models are not only accurate but also generalizable across varying operational conditions. The comparison enables the selection of the best-performing models for deployment in the digital twin framework.

5. To integrate power optimization and forecasting into a unified digital twin framework.

This objective emphasizes the development of a cohesive system that brings together optimization and forecasting within a Digital Twin environment. The framework functions as a virtual replica of the wind turbine, capable of real-time data ingestion, simulation, and predictive analysis. By unifying these functions, the digital twin provides a holistic decision-support tool that adapts dynamically to real-world conditions and offers insights for both short-term operation and long-term performance optimization.

6. To validate the digital twin framework using real-world wind farm data.

The credibility of the proposed system depends on empirical validation. This objective involves testing the digital twin using real-world datasets, such as those obtained from the Mannar Thambapavani wind farm in Sri Lanka. By comparing model predictions and optimization outcomes with actual operational records, the study evaluates the system's accuracy, robustness, and practical applicability. Validation ensures that the framework is not only theoretically sound but also deployable in live operational contexts.

6. To assess the contribution of the digital twin in improving efficiency and sustainability.

The final objective highlights the broader impact of the research. Beyond technical accuracy, the digital twin framework is evaluated in terms of its ability to reduce inefficiencies, enhance forecasting accuracy, and contribute to long-term sustainability goals. By demonstrating improved turbine efficiency, reduced operational uncertainty, and optimized energy output, the system provides a pathway for advancing renewable energy management and supporting the global transition to cleaner power generation.

1.6.3 Weather-Based Risk Assessment and Power Loss Prediction

1. To design and implement a yaw misalignment loss prediction model

This objective focuses on developing a regression-based machine learning model to estimate power losses resulting from yaw misalignment events. By analyzing SCADA data and introducing turbine-specific wind direction correction factors derived from NASA POWER reanalysis datasets, the model aims to capture local deviations and improve turbine-level forecast accuracy.

2. To model power losses from cut-in and cut-out wind speed thresholds

This objective involves applying deterministic and statistical approaches to quantify power losses that occur when wind speeds fall below the cut-in limit or exceed the cut-out limit. The methodology leverages historical SCADA records to calculate expected versus actual energy production, thereby estimating lost output associated with extreme wind speed events.

3. To develop a lightning risk prediction module

This objective entails building a classification model capable of predicting lightning risk within six-hour windows, using meteorological and reanalysis data. Unlike conventional detection systems, this model seeks to provide turbine-level, medium-range forecasts that support proactive operational planning and enhance equipment safety.

4. To integrate predictive models into a unified digital twin framework

This component emphasizes synchronizing the outputs of all predictive modules—misalignment, threshold, and lightning—with a digital twin platform. The integration will enable real-time visualization of turbine states, risk indicators, and predicted losses, providing operators with an interactive and data-driven decision-support interface.

5. To validate and evaluate the performance of the framework

This objective ensures that the developed system is rigorously tested against real-world SCADA data and validated through statistical metrics such as R^2, recall, and error rates. Additionally, the evaluation considers the practical utility of the framework for the CEB's forecasting needs, ensuring that results are not only accurate but also operationally relevant.

1.6.4 Weather-Based Risk Assessment and Power Loss Prediction

1. To collect and integrate real-time sensors and SCADA data from critical turbine components such as gearboxes, bearings, and generators for continuous condition monitoring.

A primary requirement for predictive maintenance is the availability of accurate, high-frequency operational data. By collecting data from Supervisory Control and Data Acquisition (SCADA) systems and embedded turbine sensors, the project establishes a foundation for health monitoring. Critical components such as gearboxes, bearings, and generators are highly susceptible to wear and failure; therefore, continuous monitoring enables early detection of anomalies. Integrating these data streams into the digital twin provides a unified view of the turbine's health status, ensuring that subsequent analytics and predictions are grounded in reliable inputs.

2. To develop machine learning models (e.g., LSTM networks and Random Forest classifiers) capable of forecasting component degradation and predicting failure probabilities.

Predictive maintenance requires advanced analytics that go beyond descriptive monitoring. In this objective, machine learning models are trained on historical and real-time datasets to identify degradation patterns and forecast potential failures. Long Short-Term Memory (LSTM) networks are particularly suitable for handling sequential time-series data, such as vibration or temperature trends, while Random Forest classifiers provide interpretable models for classification-based predictions, such as failure vs. non-failure states. Together, these models enhance the system's ability to anticipate failures with high accuracy.

3.To implement dynamic health scoring algorithms that provide interpretable indicators of component condition and support proactive maintenance decisions.

Raw prediction outputs are often not directly useful for maintenance teams; thus, a health scoring mechanism is essential. This objective involves designing algorithms that transform complex model outputs into simple, interpretable scores or indices reflecting component health. Such dynamic health scores enable operators to quickly assess the condition of gearboxes, bearings, or generators, making it easier to prioritize components requiring attention. By quantifying degradation levels, health scores serve as actionable indicators to guide proactive interventions before failures occur.

4.To establish a maintenance scheduling module that leverages predictive insights to recommend optimal servicing intervals, moving beyond fixed-interval strategies.

Traditional maintenance strategies often rely on fixed time or usage intervals, which may result in unnecessary servicing or unexpected failures. This objective shifts the paradigm toward condition-based scheduling, where predictive insights determine when servicing is most appropriate. The scheduling module integrates health scores and forecasted degradation to recommend maintenance windows that minimize downtime while maximizing component utilization. This data-driven scheduling ensures cost-effective resource allocation and reduces the likelihood of unplanned outages.

5. To design and validate an automated maintenance workflow, including technician assignment and notification, to streamline maintenance coordination.

Beyond prediction, effective predictive maintenance systems must support operational execution. This objective focuses on automating the workflow by generating maintenance alerts, assigning technicians based on availability or expertise, and sending timely notifications. By embedding these capabilities into the digital twin framework, the system ensures that predictive insights translate into actionable maintenance tasks without delays. Streamlining the workflow reduces human error, enhances coordination, and ensures that issues are addressed in a timely manner.

6. To evaluate the proposed system's performance in terms of predictive accuracy, downtime reduction, cost savings, and component lifespan extension.

For any predictive maintenance solution, validation is critical. This objective involves conducting systematic evaluations to measure the system's effectiveness across multiple dimensions. Key metrics include predictive accuracy (measured through statistical error rates), operational benefits (downtime reduction), economic impact (maintenance cost savings), and long-term sustainability (extension of component lifespan). By quantifying these outcomes, the project demonstrates the practical value of predictive maintenance and provides evidence of its contribution to enhancing wind turbine reliability and efficiency.

2 METHODOLOGY

2.1 Requirement Gathering

2.1.1 Sources of Requirements

To design an intelligent and adaptive digital twin framework for wind turbine performance optimization, the initial step involved identifying and analyzing the key sources from which the system requirements were derived. This ensured that the final implementation aligns with real-world operational needs, technical feasibility, and stakeholder expectations. The following primary sources were used to gather system requirements:

I. Real -World Observations:

The research team conducted direct field visits to the Thambapavani Wind Farm in Mannar, which consists of 33 utility-scale turbines. These visits provided first-hand insights into turbine operation, shutdown behavior, and operational challenges. Observations highlighted recurring issues such as yaw misalignment during abrupt wind direction changes, turbine shutdowns under cut-in and cut-out thresholds, and lack of real-time noise monitoring despite community-level concerns. The field exposure also revealed the absence of predictive maintenance strategies, with servicing primarily based on fixed intervals or reactive interventions following failures.

II. Operator Feedback and Operational Records:

Discussions with engineers and technicians at the site, along with informal feedback from CEB operational staff, emphasized the practical difficulties of managing turbine operations under volatile weather conditions. Daily SCADA logs further highlighted measurable energy losses caused by repositioning events, downtime during storms, and inefficiencies in scheduling power delivery to the national grid. This feedback underscored the importance of developing a system capable of providing early warnings, accurate forecasts, and real-time decision support.

III. Existing Literature and Related Research:

A comprehensive review of prior studies on renewable energy forecasting, predictive maintenance, and digital twin systems informed the design of the proposed solution. Research on ensemble learning methods, such as Random Forest and XGBoost, demonstrated their strong performance in wind energy prediction tasks. Previous works on predictive maintenance in tropical environments highlighted the importance of accounting for salt-induced corrosion, humidity, and lightning exposure. Literature on environmental impact analysis provided guidelines for noise threshold compliance, particularly World Health Organization (WHO) limits for residential areas. Collectively, these studies provided a solid theoretical foundation for the methodology.

IV. SCADA and Meteorological Data Analysis:

The analysis of SCADA datasets from the Thambapavani Wind Farm formed a crucial requirement source. These datasets, collected at 10-minute intervals, provided detailed operational parameters including wind speed, wind direction, rotor speed, nacelle orientation, and active power. Additionally, meteorological datasets from NASA POWER were used to capture broader regional weather patterns, while lightning occurrence data from the International Space Station Lightning Imaging Sensor (ISS-LIS) was integrated to support rare-event classification. The combination of local SCADA data with global meteorological reanalysis ensured both turbine-level accuracy and regional consistency in modeling.

V. Regulatory Guidelines and Environmental Standards:

Noise and safety regulations imposed by both international bodies, such as the WHO, and Sri Lankan environmental authorities served as critical requirement inputs. These guidelines established operational thresholds for maximum permissible noise levels in residential and institutional zones, as well as safety procedures for shutdowns during extreme wind speeds and lightning events. Compliance with these standards was essential to ensure that the proposed system is both environmentally responsible and socially acceptable.

By combining empirical observations, operator feedback, academic insights, data-driven analyses, and regulatory standards, the research established a comprehensive and practical foundation for defining system requirements. These sources collectively ensured that the digital twin framework not only addresses technical challenges but also delivers real-world value in enhancing wind farm reliability, efficiency, and sustainability.

2.1.2 Stakeholder Analysis

A critical aspect of the requirement gathering process involves identifying and analyzing the stakeholders who directly interact with or are affected by wind turbine operations. Understanding their roles, expectations, and operational challenges ensures that the proposed digital twin framework is designed to address practical needs while supporting national renewable energy objectives. The key stakeholders for this research are outlined below.

1. Ceylon Electricity Board (CEB)

- **Role:** The primary authority responsible for managing Sri Lanka's national grid and integrating renewable energy into the supply chain.

Expectations:

• Reliable 48-hour generation forecasts to plan grid operations and reduce reliance on fossil fuel backup.

• Accurate estimation of turbine-level power losses due to yaw misalignment and downtime, to avoid supply imbalance penalties.

• Transparent reporting mechanisms that support regulatory compliance and grid stability.

2. Wind Farm Operators (Engineers, Technicians, and Maintenance Teams)

- **Role:** Frontline personnel tasked with monitoring, controlling, and maintaining turbines at the Thambapavani Wind Farm.

Expectations:

• Real-time insights into yaw misalignment, cut-in and cut-out threshold exceedances, and lightning risks that may interrupt operations.

• Optimization of controllable parameters such as blade pitch, rotor speed, and nacelle orientation for maximum power output.

• Predictive alerts on component health and Remaining Useful Life (RUL) to schedule proactive maintenance.

• A digital twin dashboard that integrates these predictive insights with turbine monitoring in a user-friendly manner.

3. Local Communities (Residential and Institutional Areas near Mannar)

- **Role:** Populations directly exposed to the environmental effects of the wind farm.
- **Expectations:**

  • Assurance of compliance with WHO and Sri Lankan noise-level regulations.

  • Safe turbine operation, including proactive shutdowns during lightning storms and extreme weather conditions.

  • Transparent communication from operators to maintain trust in renewable energy projects.

4. Government and Regulatory Authorities (Sri Lanka Sustainable Energy Authority, Ministry of Power and Energy)

- **Role:** Policymakers and regulators overseeing the adoption of renewable energy and environmental standards.

- **Expectations:**

  • Demonstrated efficiency and reliability of wind power as a key contributor to the national renewable energy mix.

  • Evidence of adherence to environmental regulations, particularly noise and safety standards.

  • Data-driven insights to inform future renewable energy expansion and policy decisions.

2.1.3 Functional Requirements

The functional requirements define the core capabilities that the proposed digital twin framework must support to fulfill its intended purpose of optimizing wind turbine performance, ensuring operational safety, and enabling proactive maintenance. These requirements were derived from stakeholder expectations, operational challenges, and system objectives, and they represent the essential features that each module of the solution must provide.

1. Weather Risk Forecasting Module

- The system shall ingest SCADA data and external meteorological datasets (e.g., NASA POWER, ISS-LIS) and transform them into features suitable for model training.
- It must predict yaw misalignment–related repositioning losses at turbine level by incorporating turbine-specific correction factors.
- The module shall detect threshold exceedances, including shutdown risks caused by cut-in (<3 m/s) and cut-out (>25 m/s) wind speeds.
- It must provide probabilistic forecasts of lightning risks for six-hour and 48-hour windows, enabling operators to plan proactive shutdowns.
- Predictions must be delivered via APIs for integration into the operator dashboard and digital twin environment.

2. Power Optimization and Energy Forecasting Module

- The system shall analyze controllable parameters such as rotor speed, blade pitch, and nacelle orientation to recommend optimal settings that maximize power output.
- It must forecast turbine-level energy generation using machine learning and time-series models, enabling accurate short-term and medium-term grid planning.
- The module shall simulate the effect of parameter adjustments in the digital twin environment, providing operators with visual feedback on optimization outcomes.
- It must deliver regression-based predictions (R^2, MAE, RMSE metrics) that align with industry standards for forecasting accuracy.

3. Noise Impact Analysis Module

- The system shall model turbine noise propagation using SCADA and environmental parameters, including wind speed, nacelle position, and rotor dynamics.
- It must compare predicted and measured noise levels against WHO and Sri Lankan environmental thresholds, issuing alerts when permissible limits are exceeded.
- The module shall generate noise maps in real time, integrated with the digital twin, to visualize community-level impacts.
- Operators must be able to simulate mitigation strategies, such as adjusting operational parameters or imposing night-time restrictions, and view their impact on both power output and compliance.

4. Predictive Maintenance Module

- The system shall monitor key turbine components such as gearboxes, bearings, and generators using SCADA and sensor-derived parameters.
- It must provide predictive analytics for component health, estimating Remaining Useful Life (RUL) and flagging components at risk of failure.
- The module shall support automated maintenance scheduling and technician allocation through predictive alerts.

- It must integrate seamlessly with the digital twin to visualize component health scores, upcoming maintenance windows, and the effect of downtime on power output.

5. Digital Twin Integration and Visualization

- The framework shall unify all four modules within a real-time digital twin simulation.
- It must provide a 3D turbine visualization that reflects live SCADA inputs and overlays risk, optimization, noise, and maintenance insights.
- Operators shall be able to interact with the dashboard through visual indicators, predictive alerts, and historical records, ensuring intuitive situational awareness.
- The digital twin must support both operational monitoring and predictive simulation, enabling decision-makers to test scenarios and evaluate trade-offs between energy yield, noise compliance, and maintenance scheduling.

2.1.4 Non-Functional Requirements

In addition to the functional requirements, the proposed digital twin framework must satisfy a set of non-functional requirements that determine its overall performance, reliability, and usability. These requirements ensure that the system not only delivers accurate predictions and insights but also operates in a manner that is robust, scalable, and aligned with industry standards.

1. Performance and Real-Time Responsiveness

- The system must operate with minimal latency to support real-time monitoring and decision-making. Prediction services, including yaw misalignment forecasting and lightning risk alerts, should respond within milliseconds to seconds to ensure timely operator interventions.
- The digital twin interface must continuously update turbine states and overlay predictions without noticeable delays, maintaining a seamless operator experience.

2. Accuracy and Reliability

- Machine learning models must maintain statistically robust levels of accuracy. For regression models, the target threshold is an R^2 value of at least 0.80 at hourly resolution and $\geq$0.95 for daily aggregated forecasts. For classification models, recall rates above 80% and AUC scores above 0.75 are required to ensure dependable risk detection.
- Reliability mechanisms must be in place to ensure uninterrupted operation, with fallback logic if one or more modules fail.

3. Scalability and Extensibility

- The system must be scalable across multiple turbines, supporting both current operations at the Thambapavani Wind Farm and potential extensions to other Sri Lankan wind farms.
- The architecture must allow additional modules, such as new environmental risk models or economic optimization components, to be integrated without significant redesign.

4. Security and Data Governance

- SCADA and meteorological data streams must be handled securely, ensuring confidentiality and integrity.
- Communication between modules and APIs should be encrypted, and access should be restricted through authentication and authorization mechanisms to prevent misuse.

5. Maintainability and Modularity

- The framework must be modular, allowing individual components—such as weather risk forecasting, noise analysis, or predictive maintenance—to be updated, retrained, or replaced independently.
- Documentation and clear API contracts should be provided to support long-term maintenance and integration with external systems.

6. Usability and Visualization

- The digital twin dashboard must be intuitive and accessible, enabling operators, engineers, and decision-makers to quickly interpret forecasts and alerts.
- Visualization should include interactive 3D turbine models, dashboards, and noise maps, ensuring that technical results are translated into actionable insights for non-technical stakeholders.

2.2 Feasibility Study

A feasibility study was conducted to evaluate the practicality of implementing the proposed digital twin framework for wind turbine optimization and risk management. This assessment considered technical capabilities, operational relevance, economic justification, and project scheduling, ensuring that the system could be realistically developed and deployed within the project constraints.

2.2.1 Technical Feasibility

The system relies on well-established technologies and tools that make implementation technically viable. Machine learning frameworks such as Scikit-learn, XGBoost, LightGBM, and TensorFlow provide proven support for regression, classification, and time-series forecasting tasks. The backend prediction services can be developed using FastAPI or Flask, while visualization and simulation are supported by React and Three.js for 3D turbine rendering. Databases such as TimescaleDB and MongoDB offer robust storage for time-series and model outputs. Moreover, the modular design allows integration of weather forecasting, power optimization, noise analysis, and predictive maintenance as independent but interoperable modules, ensuring technical scalability and maintainability.

2.2.2 Operational Feasibility

The proposed solution aligns closely with the operational needs of the Thambapavani Wind Farm and the Ceylon Electricity Board (CEB). By predicting yaw misalignment losses, threshold exceedances, and lightning risks, the framework supports operators in making timely decisions to minimize downtime. Power optimization ensures that controllable parameters such as rotor speed and blade pitch are continuously adjusted to maximize efficiency, while predictive maintenance provides health insights to reduce unexpected failures. The noise analysis module addresses community concerns and ensures compliance with regulatory guidelines. Collectively, these modules enhance operational efficiency, safety, and reliability, making the system highly relevant for deployment in real-world conditions.

2.2.3 Economic Feasibility

The majority of the tools and frameworks employed in the project are open-source, reducing development costs. Operational data from SCADA systems and meteorological sources such as NASA POWER and ISS-LIS are publicly available or accessible at minimal cost. Cloud deployment may introduce expenses for hosting, storage, and computation, but the long-term benefits outweigh these investments. Predictive maintenance reduces costly emergency repairs, accurate forecasting prevents penalties from grid imbalances, and optimization increases power output, thereby generating measurable financial savings. Furthermore, compliance with noise and safety regulations minimizes the risk of legal or social costs, reinforcing the system’s economic justification.

2.3 System Design

The system design phase outlines the structural and architectural framework of the proposed digital twin framework for wind turbine performance optimization. It focuses on how the four core components—weather risk forecasting, power optimization, noise impact analysis, and predictive maintenance—are integrated into a unified environment that supports real-time monitoring, forecasting, and decision-making. The system adopts a modular and layered architecture, ensuring that each component functions independently while maintaining seamless communication and coordination through shared databases, APIs, and the digital twin visualization layer. This section describes the overall system layout, key functional modules, and the technologies employed to bring the solution to life.

2.3.1 System Overview

The proposed system is designed as a multi-layered, modular architecture that integrates data acquisition, machine learning pipelines, and visualization to enhance operational reliability of wind turbines. The core objective of the system is to improve forecast accuracy, optimize energy yield, ensure compliance with noise standards, and enable predictive maintenance scheduling through intelligent decision-support tools.

The system consists of four primary layers:

- **Data Layer** – responsible for collecting and preprocessing SCADA records, NASA POWER reanalysis datasets, and lightning occurrence data from ISS-LIS. This layer also manages time-series storage using databases such as TimescaleDB.
- **Machine Learning Layer** – incorporates predictive models including XGBoost regressors for yaw misalignment, Random Forest classifiers for lightning risk, LightGBM for power forecasting, and LSTM-based models for predictive maintenance. Each model is trained on historical SCADA and meteorological data to capture turbine-specific behaviors.
- **Prediction Service Layer** – provides REST and WebSocket endpoints via FastAPI to expose model outputs in real time. It enables operators to access forecasts of misalignment losses, lightning alerts, power generation, and component health.
- **Visualization & Digital Twin Layer** – built using React and Three.js, this layer animates turbine states, overlays predictive insights, and provides an interactive operator dashboard. Noise levels, maintenance schedules, and optimization results are visualized in a 3D environment for intuitive decision-making.

The modular design ensures that each layer can be developed, tested, and updated independently while maintaining system-wide integration through secure APIs and standardized data formats.

2.3.2 System Architecture

The system architecture is structured to support modular integration, real-time data processing, and intelligent decision-making across all four components.

- **Data Flow:** SCADA and meteorological data are continuously ingested into the Data Layer, preprocessed into structured time-series records, and forwarded to the Machine Learning Layer.
- **Prediction Pipelines:** Each predictive module (weather risk, optimization, noise, maintenance) processes data independently but outputs results through a common Prediction Service Layer.
- **Digital Twin Integration:** All model outputs are synchronized with the visualization layer, where turbine performance and risks are presented in real time.
- **APIs and Databases:** RESTful APIs and time-series databases ensure smooth communication across modules, enabling both live monitoring and historical analysis.

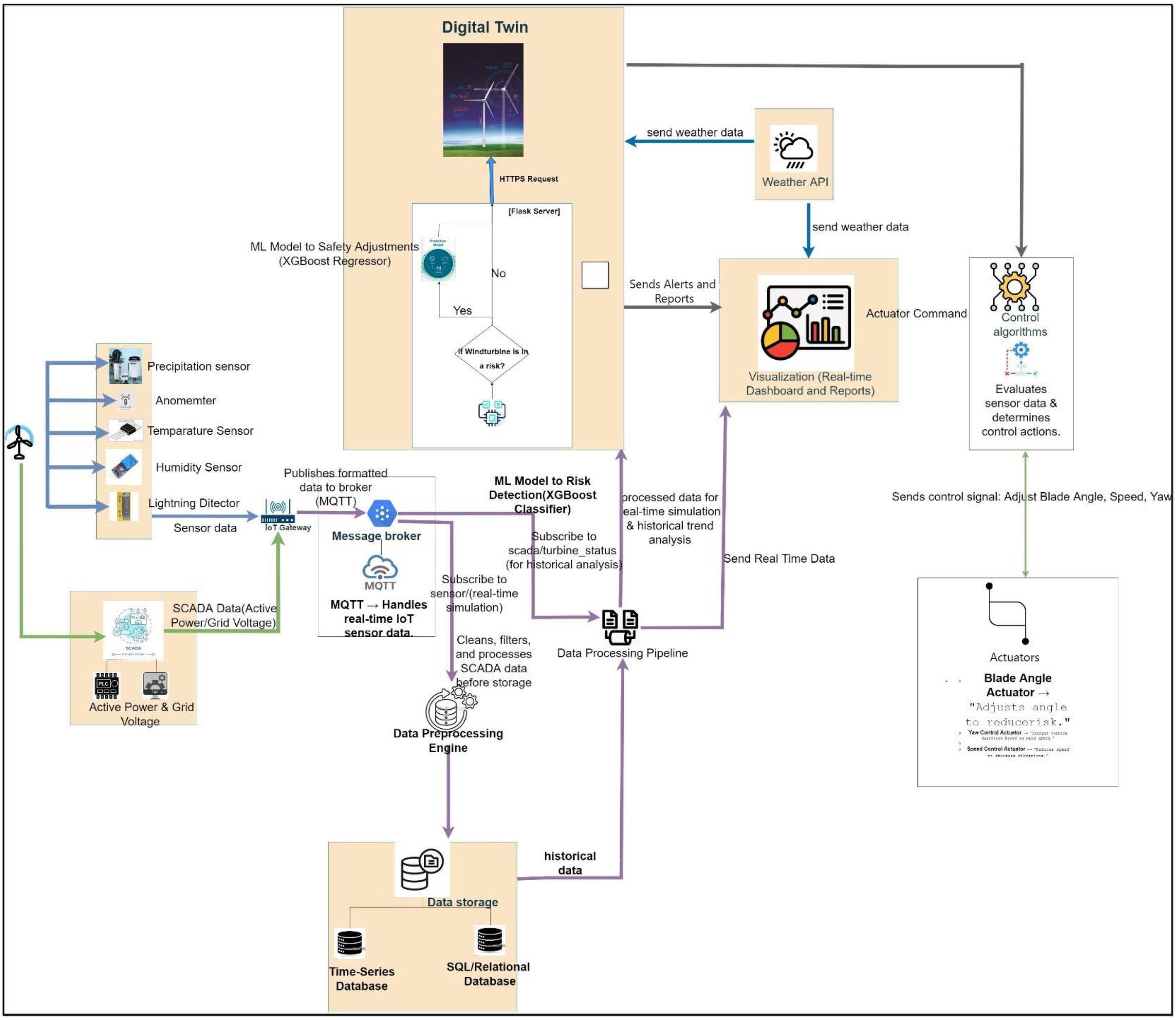


Figure 2.1 Overall system Diagram

2.4 Component Breakdown

a. **Weather Risk Forecasting Module**

This module predicts yaw misalignment losses, lightning risks, and threshold-based shutdowns. It integrates SCADA wind direction records with NASA POWER forecasts and applies turbine-specific correction factors to ensure localized accuracy. Lightning risks are predicted using Random Forest classifiers, while XGBoost regression models estimate repositioning losses. The module delivers turbine-level forecasts through APIs, which are visualized in the digital twin interface as risk overlays.

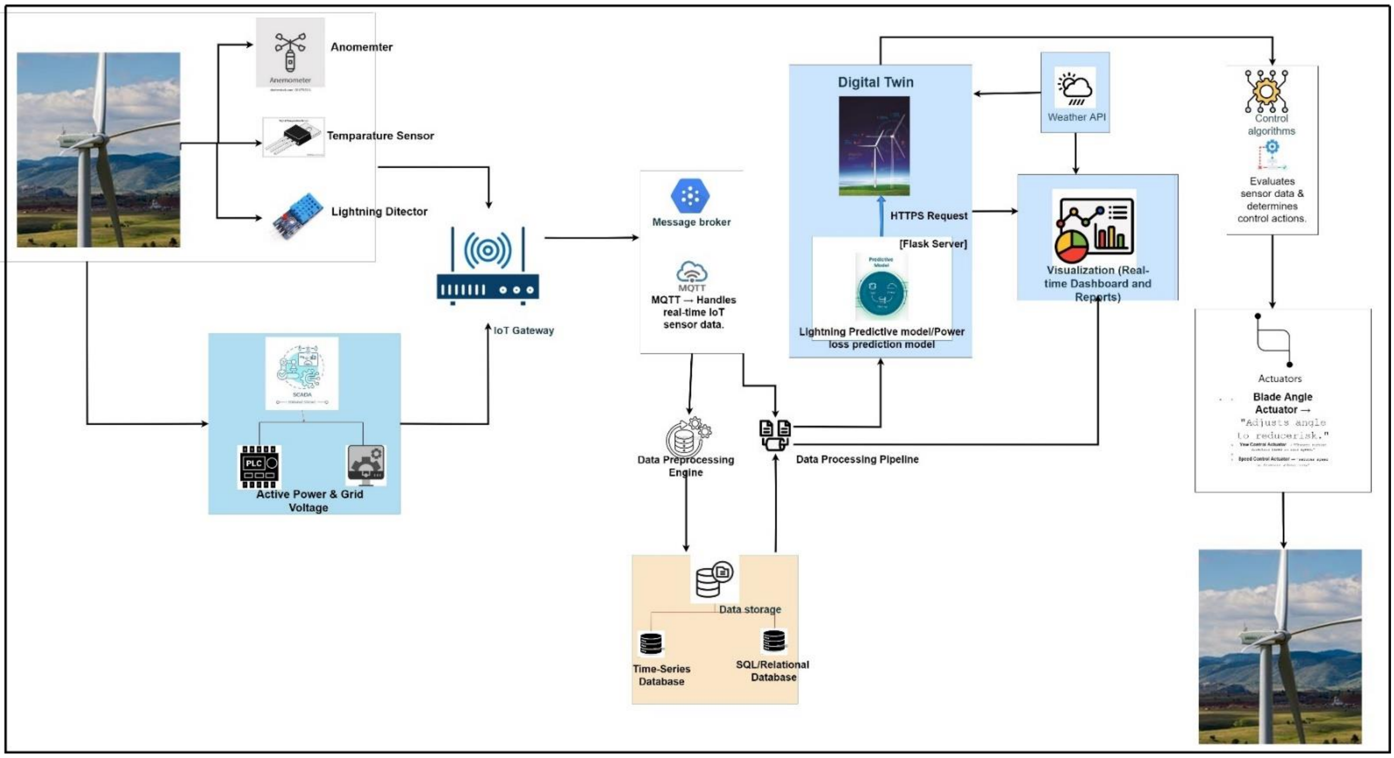


Figure 2.2 Component Diagram – Weather Impact Analysing

b. **Power Optimization and Energy Forecasting Module**

This component focuses on maximizing energy yield by dynamically adjusting controllable parameters such as rotor speed, blade pitch, and nacelle orientation. Machine learning models are used to forecast short-term energy output, while optimization algorithms recommend parameter adjustments. The outputs are tested in simulation before being deployed, ensuring a balance between energy yield and operational safety. Visual overlays in the digital twin allow operators to compare baseline vs optimized scenarios.

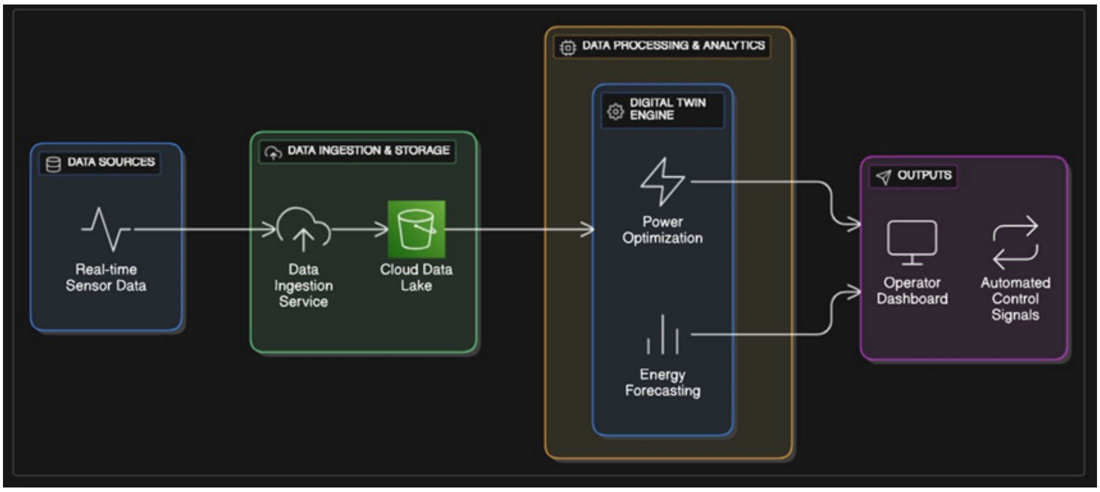


Figure 2.3 Component Diagram – Power Optimization and Energy Forecasting

c. **Noise Impact Analysis Module**

The noise module models turbine noise propagation under different operating conditions. It integrates SCADA data with environmental parameters to predict sound pressure levels at community-sensitive boundaries. Predictions are benchmarked against WHO and Sri Lankan noise thresholds, and alerts are generated if limits are exceeded. Real-time noise maps are displayed in the digital twin to enable operators to monitor and simulate mitigation strategies without compromising energy output.

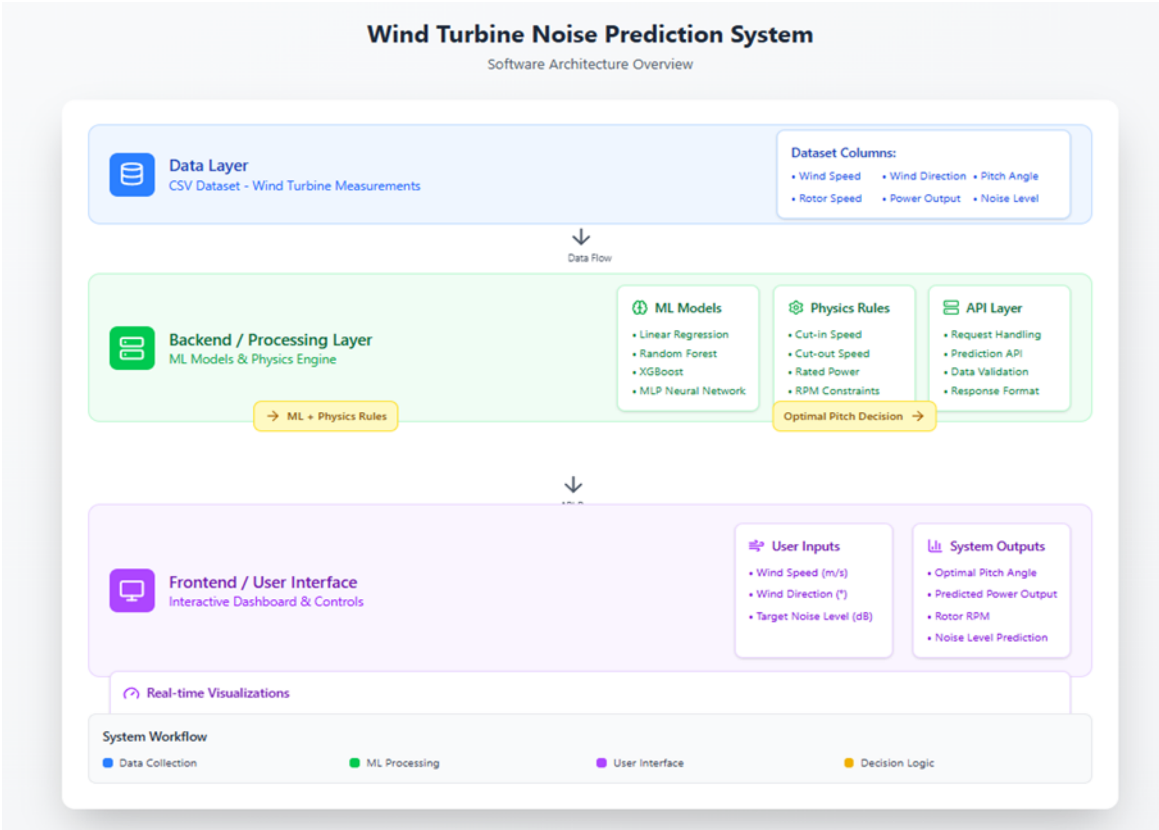


Figure 2.4 Component Diagram – Noise Impact Analysing

d. **Predictive Maintenance Module**

This module monitors turbine health and predicts component failures using SCADA sensor data such as vibration, temperature, and rotor speed. LSTM models and ensemble classifiers are employed to estimate Remaining Useful Life (RUL) of critical parts like gearboxes and bearings. Proactive maintenance schedules and technician alerts are generated, and upcoming maintenance events are displayed in the digital twin, enabling operators to understand both operational impact and downtime effects.

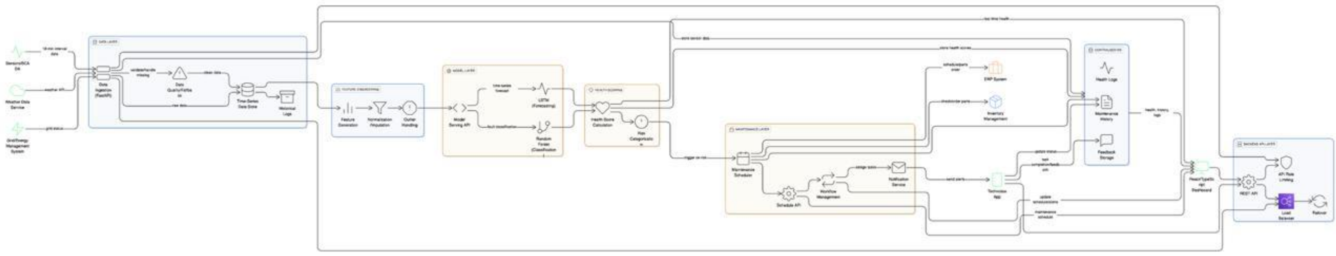


Figure 2.5 Component Diagram – Predictive Maintenance

2.5 Implementation

2.5.1 Data Collection and Preprocessing

The implementation of the proposed digital twin framework required the integration of multiple data sources, each addressing a distinct operational challenge. Data collection was primarily based on the Supervisory Control and Data Acquisition (SCADA) system of the Thambapavani Wind Farm, supplemented by external meteorological datasets and event-specific records. Preprocessing procedures were applied consistently across all modules to ensure reliability, comparability, and suitability for machine learning tasks.

1. **Weather Risk Forecasting**
   For the weather risk module, SCADA records provided high-frequency measurements of wind speed, wind direction, rotor speed, nacelle orientation, and active power. These variables captured turbine behavior during yaw misalignment events and threshold-based shutdowns. To complement turbine-level observations, reanalysis data from the NASA POWER platform was incorporated, providing regional meteorological features such as temperature, humidity, and pressure. Lightning occurrence data was sourced from the International Space Station Lightning Imaging Sensor (ISS-LIS) to support rare-event forecasting. Preprocessing included interpolation of missing sensor values, filtering of anomalous readings, and alignment of SCADA and reanalysis datasets on a common timestamp. Turbine-specific wind direction correction factors were computed to reconcile differences between regional and local observations.
2. **Power Optimization and Energy Forecasting**

   The power optimization module required a combination of operational and environmental parameters. SCADA data streams, including rotor speed, pitch angle, nacelle orientation, and generated power, were collected alongside meteorological inputs from NASA POWER. Preprocessing involved removing corrupted records, scaling continuous features, and engineering rolling averages and volatility indices to capture short-term variations in wind behavior. These processed datasets enabled regression models to predict short-term energy output and evaluate optimization strategies for controllable turbine parameters.

3. **Noise Impact Analysis**

   Noise modeling was supported by SCADA variables that directly influence acoustic emissions, such as rotor speed, nacelle position, and wind velocity. Environmental data, including atmospheric conditions, was also incorporated to estimate sound propagation. Preprocessing involved removing outliers caused by sensor fluctuations, standardizing units, and aligning measurements with WHO and Sri Lankan regulatory thresholds. Additional feature engineering derived acoustic intensity indicators based on turbine operating states, enabling the system to predict when noise levels might exceed acceptable limits.

4. **Predictive Maintenance**

   The predictive maintenance module relied on SCADA sensor records related to turbine component health, including temperature, vibration, torque, and current. Historical maintenance logs were used to validate model outputs and support labeling of failure events. Preprocessing tasks included noise filtering, normalization of continuous variables, and imputation of missing values. Temporal encodings were applied to capture seasonal wear patterns, while derived features such as cumulative operating hours and component load histories were engineered to improve Remaining Useful Life (RUL) estimation.

2.5.2 Machine Learning Model Development

The development of predictive and optimization models formed the core of the proposed digital twin framework. Each module was implemented using machine learning techniques suited to its operational requirements, with careful consideration of model selection, training strategies, and evaluation metrics. Together, these models addressed weather risks, power optimization, noise compliance, and predictive maintenance, ensuring comprehensive support for turbine operations.

1. **Weather Risk Forecasting**

   The weather risk module was developed to quantify yaw misalignment losses, threshold-based shutdowns, and lightning risks. XGBoost regression models were trained on SCADA-derived features such as wind direction volatility, rotor speed, and nacelle orientation to estimate repositioning losses. For threshold exceedances, a rule-based approach was combined with statistical forecasting of wind speeds to identify potential downtime events. To address lightning forecasting, a Random Forest classifier was implemented using meteorological features from NASA POWER and ISS-LIS lightning occurrence data. Special attention was given to data imbalance, applying weighted sampling to ensure high recall in rare-event classification.

2. **Power Optimization and Energy Forecasting**

   The power optimization component employed supervised regression techniques to maximize turbine efficiency. Models such as LightGBM and XGBoost were used to predict short-term power output under varying operational conditions. Feature sets included rotor speed, pitch angle, nacelle position, and environmental variables. Hyperparameter tuning was carried out using grid search and cross-validation to enhance generalization. In addition to forecasting, optimization logic simulated parameter adjustments to identify control settings that maximized predicted output, which were then validated against SCADA records.

3. **Noise Impact Analysis**

   Noise forecasting was approached using a combination of deterministic and data-driven methods. SCADA inputs such as rotor speed and nacelle orientation were paired with atmospheric variables to estimate sound pressure levels. Machine learning models were trained to capture nonlinear relationships between turbine operating states and acoustic emissions, with outputs benchmarked against WHO and Sri Lankan noise thresholds. The system generated real-time predictions of noise levels and provided warnings when limits were exceeded, supporting compliance and community acceptance.

4. **Predictive Maintenance**

   The predictive maintenance module was designed to provide early fault detection and Remaining Useful Life (RUL) estimation for turbine components. A hybrid modeling strategy was adopted: LSTM networks captured temporal degradation patterns in sensor data (temperature, vibration, torque), while Random Forest classifiers were used to assess component health scores. Recursive feature elimination was employed to select the most influential features, improving both interpretability and performance. The models were validated against historical maintenance logs, ensuring alignment with real-world failure events.

2.5.3 Prediction Service Integration

To operationalize the outputs of the machine learning models, a centralized prediction service was implemented. This service acts as the middleware between the data-driven modules and the digital twin interface, ensuring that forecasts, alerts, and optimization results are delivered to operators in real time. A FastAPI-based architecture was selected for its scalability, lightweight design, and compatibility with modern cloud deployment.

1. **Weather Risk Forecasting**

The weather risk module exposes APIs that provide turbine-level forecasts for yaw misalignment losses, threshold exceedance probabilities, and lightning risk classifications. Endpoints such as /risk/yaw, /risk/shutdown, and /risk/lightning return structured JSON outputs containing turbine ID, timestamp, predicted loss values, and associated confidence scores. These results are streamed to the digital twin interface, where they are visualized as color-coded risk indicators.

2. **Power Optimization and Energy Forecasting**

   The optimization and forecasting module delivers regression-based predictions of short-term and medium-term energy output. API endpoints such as /power/forecast provide values of expected generation for the next 6–48 hours, while /power/optimize suggests optimal rotor speed, blade pitch, and nacelle orientation settings. These outputs are formatted as both numeric values and recommended control strategies, enabling operators to evaluate performance improvements in the digital twin dashboard.

3. **Noise Impact Analysis**

   The noise module exposes APIs for real-time prediction of sound pressure levels and compliance alerts. Endpoints such as /noise/current and /noise/map generate both numerical outputs and spatial heatmaps, allowing visualization of predicted acoustic emissions across community boundaries. When thresholds are exceeded, the service generates alerts with recommended mitigation actions, which are displayed in the digital twin interface.

4. **Predictive Maintenance**

   The predictive maintenance module provides proactive insights into component health and Remaining Useful Life (RUL). API endpoints such as /maintenance/health return health scores for gearboxes, bearings, and generators, while /maintenance/rul estimates the operational time remaining before intervention is required. The service also generates automated alerts when components approach critical failure states, enabling operators to schedule maintenance effectively.

2.5.4 System-Wide Integration

All APIs adhere to a standardized format with turbine identifiers, timestamps, prediction values, and metadata, ensuring interoperability across modules. Responses are cached and logged in MongoDB for quick retrieval and historical analysis. WebSocket support was included for modules requiring real-time streaming, such as noise monitoring and misalignment alerts. This unified prediction service ensures that the outputs of all four modules—weather risk, optimization, noise, and maintenance—are consistently available for visualization, decision support, and operational deployment within the digital twin framework.

2.5.5 Database and Storage

The proposed digital twin framework generates and processes large volumes of data from multiple sources, including SCADA streams, meteorological reanalysis datasets, lightning occurrence records, and predictive model outputs. To manage this effectively, the system employs a hybrid database architecture designed to handle both structured time-series records and flexible JSON-based logs. This architecture ensures scalability, interoperability, and efficient retrieval of information for real-time decision support and historical analysis.

At the core of the storage design is TimescaleDB, an extension of PostgreSQL optimized for time-series workloads. TimescaleDB is used to store turbine-level SCADA data—such as wind speed, wind direction, rotor speed, nacelle orientation, and active power—collected at regular intervals. Meteorological data from NASA POWER and related environmental variables are also indexed in the same structure, with turbine ID and timestamp serving as the primary keys. This enables efficient querying of historical records, rapid retrieval for model inference, and seamless alignment of SCADA with external weather datasets.

In parallel, MongoDB is employed to store unstructured and semi-structured outputs from the machine learning modules. Prediction logs, optimization recommendations, noise maps, health scores, and Remaining Useful Life (RUL) estimates are maintained in JSON format, allowing flexible schema evolution as models are refined. This setup also facilitates efficient integration with the FastAPI-based prediction service, which returns results in JSON, minimizing overhead during storage and retrieval.

The hybrid approach ensures that the system benefits from both high-performance time-series storage and schema flexibility. Data partitioning by turbine ID and timestamp supports scalability across multiple turbines, while archiving mechanisms enable long-term storage for compliance and research purposes. Additionally, database replication and backup strategies were included to enhance reliability and minimize the risk of data loss.

2.5.6 Digital Twin and Dashboard Implementation

The digital twin and dashboard serve as the primary interface between the predictive modules and the operators of the Thambapavani Wind Farm. This layer integrates real-time turbine data, machine learning outputs, and environmental forecasts into a unified visualization platform. The objective is to provide operators with a comprehensive, intuitive, and interactive environment to monitor risks, evaluate optimization strategies, track maintenance needs, and ensure regulatory compliance.

The digital twin was implemented using React for the frontend framework and Three.js (via React Three Fiber) for interactive 3D visualization. Each turbine is represented in a three-dimensional environment that dynamically updates its state based on real-time SCADA inputs and model predictions. Parameters such as wind speed, rotor speed, nacelle orientation, and generated power are continuously displayed, while predictive overlays highlight operational risks and recommended actions.

To ensure seamless communication between the backend services and the visualization interface, WebSocket connections and REST APIs were employed. The WebSocket layer provides real-time streaming of fast-changing predictions such as yaw misalignment risks and noise exceedance alerts, while REST endpoints support retrieval of medium-term forecasts, optimization recommendations, and maintenance schedules. All data is pulled from the hybrid database system (TimescaleDB and MongoDB) through the FastAPI-based middleware, ensuring consistency across modules.

The dashboard itself was designed with multiple interactive panels, each corresponding to a module of the framework:

- **Weather Risk Panel:** Displays real-time indicators of yaw misalignment losses, threshold-based shutdown risks, and lightning alerts using a color-coded scheme (green = safe, yellow = moderate risk, red = high risk).
- **Power Optimization Panel:** Visualizes short-term and medium-term generation forecasts alongside recommended control settings for rotor speed, pitch angle, and nacelle orientation. Comparison charts allow operators to evaluate baseline versus optimized scenarios.
- **Noise Impact Panel:** Provides real-time noise maps and compliance indicators, with alerts triggered if predicted sound levels exceed WHO or Sri Lankan thresholds. Operators can simulate mitigation strategies and observe their effect on both noise and energy output.
- **Predictive Maintenance Panel:** Displays component health scores, Remaining Useful Life (RUL) estimates, and upcoming maintenance schedules. Visual indicators highlight components at risk of failure, allowing operators to plan interventions proactively.

The design emphasizes usability, interactivity, and clarity, enabling both technical staff and decision-makers to access critical insights without requiring expertise in machine learning. By integrating all four modules into a unified dashboard, the digital twin transforms complex datasets and predictive analytics into actionable intelligence, enhancing situational awareness and supporting real-time decision-making.

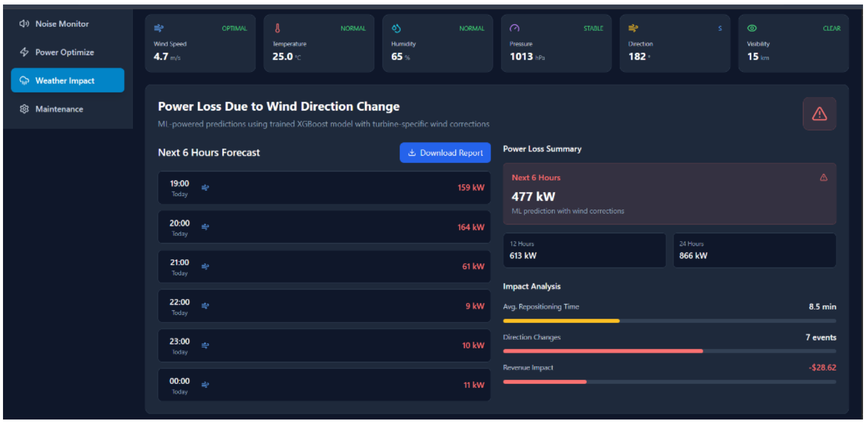


Figure 2.6 Operational Dashboard

Figure 2.7 Digital Twin 3D Model

2.6 Commercialization Aspects of the Product

The proposed digital twin framework possesses strong commercialization potential within the renewable energy sector, particularly in large-scale wind farm operations. Its modular architecture, real-time prediction capabilities, and integration with SCADA systems make it a viable solution for addressing operational inefficiencies, regulatory compliance, and energy forecasting challenges faced by utilities and wind farm operators.

1.Value Proposition

The system delivers measurable value across four operational domains:

- **Weather Risk Forecasting:** Enhances the accuracy of 48-hour generation forecasts required by the Ceylon Electricity Board (CEB), enabling improved grid planning and reducing penalties associated with supply imbalances.
- **Power Optimization and Energy Forecasting:** Maximizes energy yield by recommending real-time adjustments to controllable parameters such as blade pitch, rotor speed, and nacelle orientation, thereby increasing the profitability of wind farms.
- **Noise Impact Analysis:** Provides continuous monitoring of environmental noise levels and ensures compliance with WHO and Sri Lankan regulatory thresholds, strengthening community acceptance and minimizing potential legal disputes.
- **Predictive Maintenance:** Reduces downtime and operational costs by forecasting component failures and scheduling interventions proactively, extending turbine lifetime and improving reliability.

2. Competitive Advantage

Unlike conventional wind farm monitoring systems that operate in silos, the proposed framework integrates weather risk, optimization, noise analysis, and predictive maintenance within a unified digital twin. This multi-faceted design enhances decision-making by presenting operators with a holistic view of turbine operations. Furthermore, the reliance on open-source technologies and cloud-based deployment reduces implementation costs while allowing for rapid scalability.

3.Deployment Models

The system can be commercialized through multiple deployment strategies:

- **Software-as-a-Service (SaaS):** A subscription-based model hosted on the cloud, where utilities and operators access prediction dashboards and APIs without maintaining their own infrastructure.
- **On-Premise Deployment:** For critical wind farms with strict data governance requirements, the framework can be deployed within local infrastructure integrated directly with SCADA systems.
- **Hybrid Model:** Combines on-premise SCADA data processing with cloud-hosted predictive analytics, balancing security and scalability.

4. Market Potential

The renewable energy sector in Sri Lanka is expanding rapidly, with wind power expected to play a significant role in achieving the national target of 70% renewable generation by 2030. Beyond Sri Lanka, the solution has potential for adoption in tropical and coastal regions where wind farms face similar challenges of yaw misalignment, lightning exposure, noise compliance, and accelerated component degradation due to harsh environmental conditions.

5 .Scalability and Future Extensions

The system's modular design allows for seamless expansion to additional turbines and wind farms. Future versions could incorporate economic optimization modules, energy storage integration, or cross-farm coordination features, further increasing commercial value. Continuous retraining of models with updated SCADA and meteorological data ensures adaptability and long-term sustainability in evolving operational environments.

2.6 Evaluation and Testing

2.6.1 Testing Approach

The evaluation of the Smart Elevator System was carried out through a structured, scenario-based testing approach, focusing on validating the intended behavior of each individual component as well as the integrated simulation system. Rather than emphasizing quantitative performance metrics, this phase aimed to ensure that the system accurately and consistently responded to real-world-inspired conditions and module-specific triggers.

Each of the four core components User Prioritization Module, Traffic Prediction Module, Predictive Maintenance Module, and the Multi-Elevator Route Planning System were tested independently and within the unified simulation environment. The tests were designed to reflect the practical use-cases and operational goals of the system, such as prioritizing VIP users, anticipating rush-hour conditions, handling maintenance scenarios, and optimizing elevator routing under various demand patterns.

To validate the functional correctness of the system, various simulation scenarios were created and executed using the implemented environment built with OpenAI Gym and Pygame. Firebase Realtime Database was used to simulate external module outputs, while internal simulation logs and visual outputs were monitored to verify real-time behavior and responsiveness. This approach enabled comprehensive testing of the system’s logic, data flow, integration, fidelity, and adaptability.

2.6.2 Component-wise Scenario Testing

To ensure each component functioned as intended and integrated correctly with the overall simulation engine, a series of targeted test scenarios were developed and executed. Each scenario was designed to reflect the real-world operational context of its corresponding module, allowing the team to verify both the logic execution and visual feedback within the simulation environment. The following describes how each component was tested individually:

1) User Prioritization Module

To test the reservation functionality, a reservation request was manually pushed to the Firebase Realtime Database with specified values for arrival time, source floor, and destination floor. The scenario simulated a high-priority user booking an elevator in advance through the mobile application. The simulation engine detected this reservation, triggered Reservation-Based Handling, and pre-assigned an elevator to the specified floor shortly before the user's expected arrival time.

To verify user arrival, a simulated face recognition event was triggered within the test environment, emulating the user being identified by the recognition camera at the elevator lobby. Upon successful identification, the system confirmed the user's presence, allowing the reserved elevator to activate for boarding. Visually, the elevator was marked with a "Reserved" label and remained inactive for other requests until the recognition signal was received. This test validated the complete reservation workflow, including both scheduling and real-time user verification, confirming that the system reliably handles prioritized reservations with integrated face recognition support.

2) Traffic Prediction Module

For this module, rush-hour predictions were inserted into Firebase to simulate the system forecasting high passenger demand at specific floors and times. The test aimed to validate whether the simulation would enter Dynamic-Assign Mode in response to these forecasts. Upon detection, the simulation engine repositioned idle elevators to the predicted rush floors ahead of the specified time. This behavior was reflected visually by elevators remaining stationed on those floors in standby mode, confirming that the system was proactively reacting to predicted traffic congestion.

3) Predictive Maintenance Module

To emulate a hardware fault, a maintenance alert was pushed into Firebase for a particular elevator, including the elevator ID and a simulated fault timestamp. The simulation correctly interpreted this input, transitioned the affected elevator into a maintenance state, and removed it from the request dispatching process. Visually, the elevator was grayed out and labeled "Under Maintenance," and the remaining elevators dynamically adjusted to handle all pending and future requests. This confirmed that the simulation accurately responded to maintenance events and preserved service continuity.

4) Multi-Elevator Route Planning System (Simulation Engine)

The simulation engine itself was tested under multiple traffic conditions to evaluate its rule-based decision-making and mode-switching behavior. Scenarios included normal passenger flow (to activate Normal Mode), frequent floor requests in short intervals (to trigger Rush Mode), extended low-traffic periods (to initiate Energy-Saving Mode), and irregular floor-specific traffic (to validate Dynamic-Assign Mode). In each case, the simulation responded as expected, switching operational modes accordingly and adapting elevator dispatch logic in real time. These tests verified that the internal logic engine was functioning correctly and could handle diverse conditions autonomously.

2.6.3 Validation Methods

To ensure the correctness and reliability of system behavior during testing, multiple validation techniques were employed. These methods were designed to confirm that each component's functionality was accurately triggered, executed, and visually reflected in the simulation environment, and that real-time data synchronization between the modules and the simulation engine was working as intended.

The primary source of validation was the Pygame-based visual simulation, which provided a real-time graphical representation of elevator states, floor assignments, passenger interactions, and operational modes. Through this interface, testers were able to observe elevator movements, reserved elevator behavior, maintenance status indicators, and pre-positioned idle elevators during predicted traffic surges.

In addition to visual confirmation, internal simulation logs were used to record key system states at each tick (every 5 seconds). These logs tracked elevator positions, occupancy levels, current state (Idle, Moving, Boarding, Under Maintenance), mode transitions, and the processing of external triggers. Each significant event such as a reservation activation or a maintenance alert was timestamped and cross-referenced with the expected behavior for that simulation scenario.

To verify real-time integration, Firebase Realtime Database interactions were monitored throughout the tests. The system was checked for accurate polling, timely recognition of module outputs, and consistent synchronization between cloud data and simulation logic. Special attention was given to ensuring that triggers such as reservations, predicted rush floors, and fault alerts were interpreted and executed without noticeable delay.

By combining visual observation, backend logging, and real-time cloud monitoring, the system's responses were validated with confidence, confirming that both the individual modules and the overall integration functioned correctly under all tested conditions.

3 RESULTS AND DISCUSSION

3.1 Results

In this study, the performance of the proposed digital twin system is evaluated across four key components. The first component focuses on noise and power analysis, predicting turbine noise levels and power output under varying wind speeds and blade pitch angles, and exploring the trade-offs between energy generation and acoustic impact. The second component addresses power optimization and energy forecasting, where machine learning models are applied to optimize operational parameters and predict short-term energy generation, enhancing turbine efficiency and reliability. The third component examines weather influences on turbine operations, including the effects of wind variability and lightning risk, through predictive models for yaw misalignment, threshold losses, and real-time risk alerts, all integrated within the digital twin dashboard. The fourth component centers on predictive maintenance, leveraging sensor data and machine learning models to monitor turbine health, forecast component failures, and schedule maintenance activities proactively, thereby reducing downtime, improving reliability, and minimizing operational costs. Together, these components provide a comprehensive understanding of turbine performance under diverse operational and environmental conditions.

3.1.1 Results of Noise Analysis

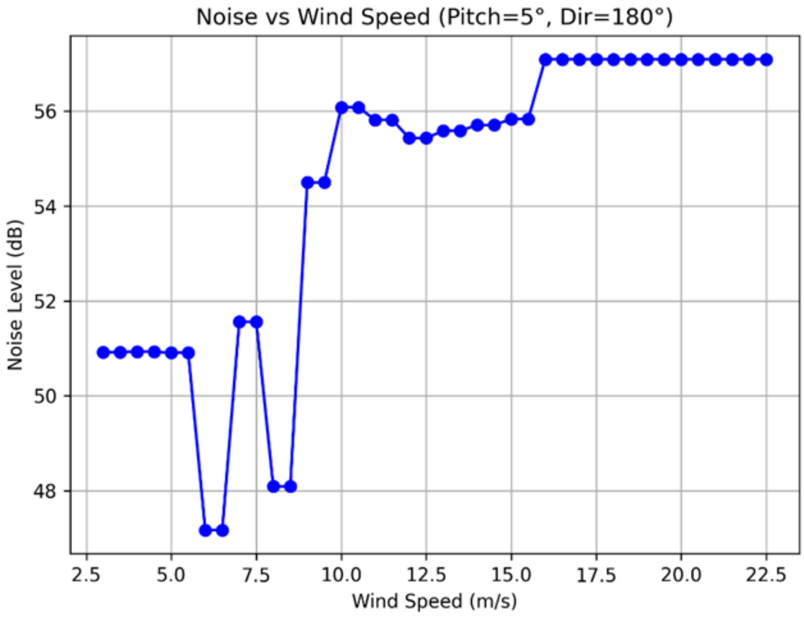
1. Digital Twin Simulation and Model Evaluation for Turbine Noise and Power

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:

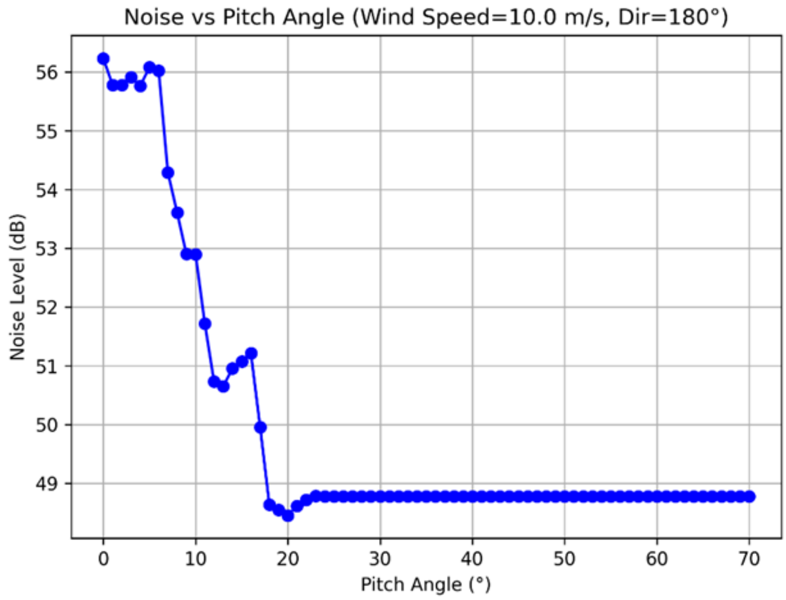
- **Noise vs Wind Speed:** Noise generally increases with wind speed, stabilizing near 57 dB at higher speeds.



3.1Figure 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.

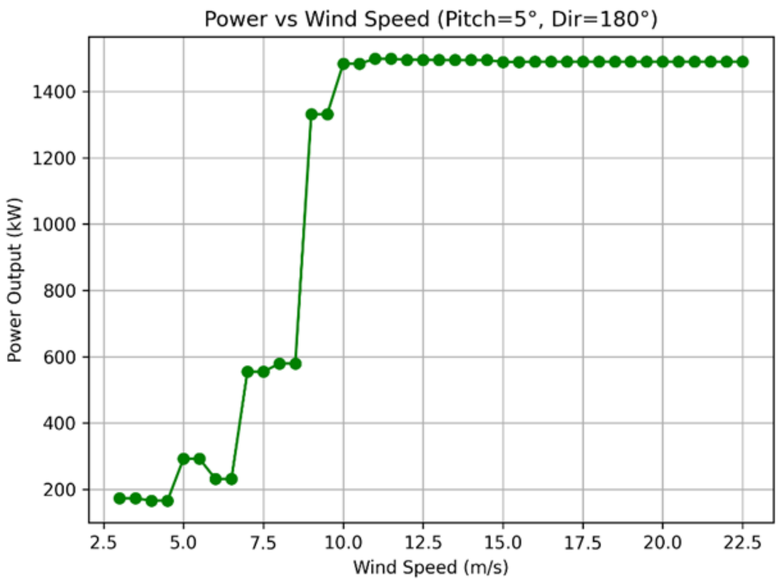
- **Noise vs Pitch Angle:** Increasing the pitch angle slightly reduces noise beyond the optimal operating range.



3.2 Figure 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.

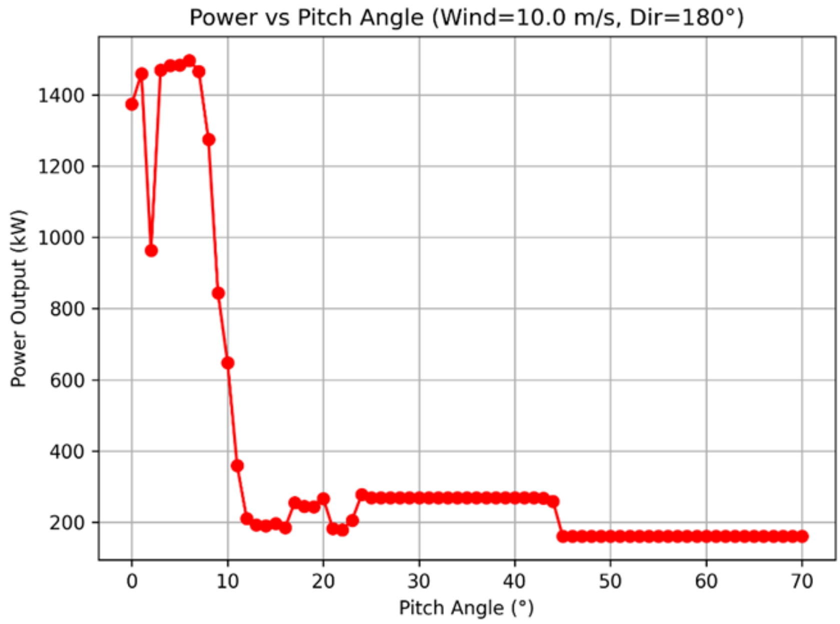
- **Power vs Wind Speed:** Power output increases with wind speed up to the rated value, after which it stabilizes, reflecting typical turbine behavior.



3.3 Figure 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.

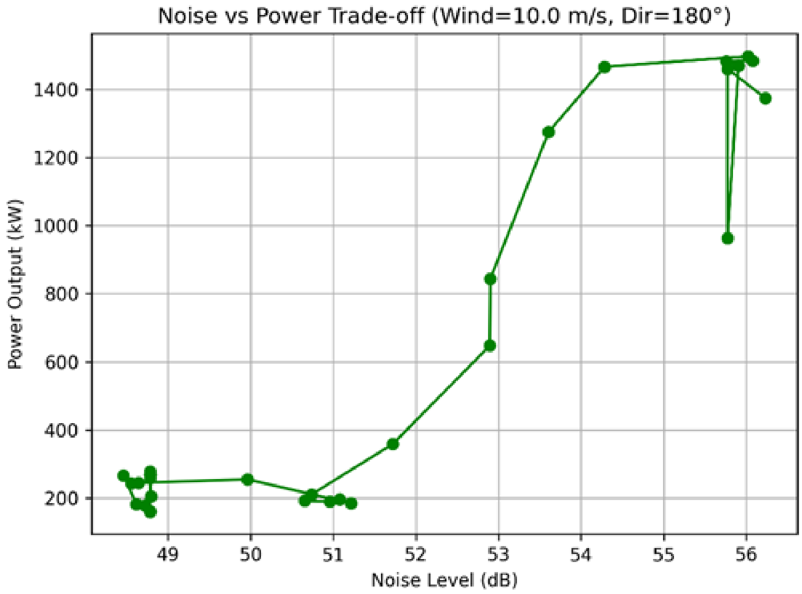
- **Power vs Pitch Angle:** Maximum power is achieved around a **6° pitch angle**. Pitch angles beyond this reduce power output.



3.4 Figure 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.



3.5 Figure 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.

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 3.1 Model Performance Evaluation - Noise

3.1.2 Power Optimization and Efficiency Enhancement result

The results obtained from the two main components of the system Power Optimization and Energy Forecasting are presented below. Each model was evaluated using three widely recognized metrics: the coefficient of determination (R^2), Mean Absolute Error (MAE), and Mean Squared Error (MSE). These results provide a quantitative understanding of how accurately each model was able to learn from the data and predict unseen values.

1. Energy Forecasting model Results

Energy forecasting was implemented using Long Short-Term Memory (LSTM), XGBoost, and Random Forest.

- The LSTM model achieved an R^2 of 0.7696, which indicates that it was able to explain nearly 77% of the variance in the target variable. It recorded an MAE of 211.63 and an MSE of 188,398.07, showing that it captured temporal dependencies better than the tree-based models.
- The XGBoost model showed an R^2 of 0.6521, lower than LSTM, with an MAE of 261.67 and MSE of 284,495.23. This suggests that while XGBoost performed reasonably, it was not as effective as LSTM in handling sequential patterns.
- The Random Forest model performed similarly to XGBoost with an R^2 of 0.6333, MAE of 263.91, and MSE of 299,932.25. The results highlight the limitations of static, non-sequential models when applied to time-dependent forecasting tasks.

From these results, it is clear that LSTM outperformed both XGBoost and Random Forest in terms of forecasting accuracy. Its superior handling of temporal dynamics makes it more suitable for energy forecasting in a wind turbine setting.

2 .Power Optimization model Results

For power optimization, XGBoost, Random Forest, and Gradient Boosting were employed.

- The XGBoost model achieved the highest performance with an R^2 of 0.9965, an MAE of 43.72, and an MSE of 5922.62. This near-perfect R^2 indicates that the model was able to fit the training data extremely well while keeping prediction errors minimal.
- The Random Forest model closely followed with an R^2 of 0.9960, MAE of 46.53, and MSE of 6828.93. Although slightly less accurate than XGBoost, the performance gap is marginal.
- The Gradient Boosting model achieved an R^2 of 0.9964, MAE of 45.51, and MSE of 6148.65, placing it between XGBoost and Random Forest in terms of predictive performance.

These results indicate that all three models were highly effective in learning the nonlinear relationships between wind turbine input parameters (such as wind speed, nacelle position, and blade pitch angle) and power output. The differences in error metrics are relatively small, suggesting that any of the three could be practically deployed, though XGBoost provides the most accurate and consistent results.

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3.1.3 Weather Influences on Turbine Operations result

1. Weather Influences on Turbine Operations Results

The proposed system was evaluated through a series of tests covering model accuracy, module functionality, and integration performance. Each subcomponent was validated individually and later as part of the complete workflow. Results are presented for the yaw misalignment prediction model, lightning risk classification model, threshold loss detection module, prediction service API, and the digital twin with operational dashboard.

- Yaw Misalignment Model Results

The yaw misalignment loss prediction model was developed using XGBoost regression with a set of 27 features derived from wind characteristics, operational history, turbine identifiers, and temporal variables. The dataset consisted of 242,416 hourly records covering the year 2023, of which 13.9% included repositioning-related power losses. A time-based split (80% training, 20% testing) was applied to preserve temporal order and prevent data leakage.

The model achieved strong predictive performance. On the testing set, the model reached an R^2 of 0.800 with a mean absolute error (MAE) of 3.4 kWh at the hourly level. Performance was even stronger when aggregated daily, achieving an R^2 of 0.969 with only 0.5% error in daily power loss estimation. For hours containing loss events, the model captured variability well, achieving an R^2 of 0.726. Importantly, the business-level impact analysis showed that the model's prediction error in estimating total repositioning losses was only 0.5% on the testing set, indicating high reliability for operational use.

Feature importance analysis revealed that Hourly Repositioning Events, Wind Speed Mean, and Hours Since Last Event were the most influential predictors, followed by turbine-specific identifiers and recent operational context features. This confirmed that both wind variability and operational history strongly drive yaw-related repositioning losses.

Metric	**Training Set**	**Testing Set**
R^2 (Overall)	0.889	0.800
MAE (Hourly)	5.998 kWh	3.400 kWh
RMSE (Hourly)	22.523 kWh	17.377 kWh
R^2 (Hours with Loss Only)	0.824	0.726
MAE (Hours with Loss Only)	34.621 kWh	33.513 kWh

Table 3.2 Model Performance Evaluation – Power Loss

- **Lightning Risk Prediction Results**

The lightning risk prediction module was evaluated using both Random Forest and XGBoost classifiers. To reduce model complexity and improve operational interpretability, a simplified feature set of 15 predictors was used, derived from NASA POWER meteorological data and ISS-LIS lightning observations. Despite the significant reduction from the original 61 features, the simplified models were able to capture the essential drivers of lightning occurrence.

The dataset was highly imbalanced, with only 79 positive windows in the training set and 20 in the test set, representing a ratio of approximately 1:73. Performance was therefore measured using recall, precision, F1-score, and AUC, with recall prioritized to ensure that the majority of lightning events were detected.

Results demonstrated that the Random Forest model achieved the best overall performance, detecting up to 95% of lightning events at a low threshold, though at the cost of a higher false alarm rate. At an operational threshold tuned for balance, the model maintained 80% recall with a 29.9% warning rate, providing a practical trade-off between detection and false positives. The XGBoost model, while more selective, only detected around 60% of events, with slightly higher precision but a reduced warning rate.

Feature importance analysis showed that precipitation-related variables (PRECTOTCORR_max and PRECTOTCORR_sum), convective potential, and wind speed indicators were consistently ranked as the most influential predictors, confirming their physical relevance to storm and lightning formation. Temporal indicators such as afternoon hours and seasonal month values also contributed significantly to prediction performance.

Model	Recall	Precision	F1	AUC	Warning Rate	Notes
Random Forest(15f)	95.0%	2.1%	0.041	0.789	62.8%	High detection, more warnings
XGBoost (15f)	60.0%	3.4%	0.064	0.752	24.3%	Lower detection, fewer alarms

Table 3.3 Model Performance Evaluation – Lightning Prediction

Compared to the original 61-feature model, the simplified Random Forest retained 95% of the detection capability with a 75% reduction in feature count, demonstrating that a compact model can still provide effective lightning risk prediction. This balance of recall and simplicity makes the Random Forest approach more suitable for operational deployment within the digital twin framework.

3.1.4 Results of Predictive Maintenance Analysis

The predictive maintenance system was evaluated using a comprehensive dataset comprising 685,000+ records and 273 variables, collected from 10 operational turbines (WTG01–WTG10) over a one-year period (January 2024 – January 2025). The dataset was preprocessed to ensure reliability: missing values (72,540 entries, ~0.53%) were imputed using KNN, outliers were capped via the IQR method, and normalization (Min–Max scaling) was applied to continuous features. Data was split into 70% training, 15% validation, and 15% testing.

Turbine-Level Performance Analysis

Analysis of individual turbine performance highlighted significant operational disparities:

- WTG07 (highest performing):

- Power Output: 1,549.96 kW
- Wind–Power Correlation: 0.956
- Capacity Factor: 0.449

- WTG04 (lowest performing):
  - Power Output: 1,029.27 kW
  - Wind–Power Correlation: 0.660
  - Capacity Factor: 0.298
- Well-performing turbines (WTG01, WTG02, WTG07) maintained capacity factors between 0.43–0.45, while low-performing turbines (WTG04, WTG06) operated closer to 0.30–0.35.

This variance underscores the necessity of predictive maintenance to address efficiency losses and prevent unplanned downtime.

Model Performance

LSTM – Time-Series Forecasting

The Long Short-Term Memory (LSTM) model was trained on temporal sensor data (vibration, temperature, power output).

- Detected gearbox degradation patterns several days in advance.
- Achieved a 10–15% improvement in failure detection over baseline linear regression models.
- Delivered a high recall rate, ensuring minimal false negatives and reliable early warnings.

Random Forest – Fault Classification

The Random Forest classifier was deployed for real-time health assessment of turbine components.

- Demonstrated high accuracy in classifying gearbox, bearing, and generator states.
- Key predictors included:
  - Gearbox oil temperature (primary failure indicator),
  - Vibration intensity (linked to drivetrain degradation),
  - Generator temperature (electrical fault risk),
  - Blade pitch variability (abnormal stress marker).

- Feature importance analysis aligned with engineering knowledge, reinforcing the reliability of the model outputs.

Ensemble Model – LSTM + Random Forest

A hybrid ensemble combining LSTM (forecasting) and Random Forest (classification) was also implemented.

- Achieved the highest predictive accuracy across all tested scenarios.
- Significantly reduced false negatives by capturing both long-term trends and instantaneous anomalies.
- Enabled more accurate and earlier maintenance scheduling compared to standalone models.

3.2 Research Findings

This study investigated four key components—noise, power, weather, and maintenance—to evaluate the performance and applicability of the proposed digital twin framework for wind turbines. The findings highlight how each component influences turbine operation and community acceptance. Noise analysis demonstrated the effectiveness of pitch angle control in mitigating acoustic emissions without severely compromising energy production. Power optimization revealed that advanced machine learning models can accurately predict and enhance turbine output, while adaptive control strategies improve overall efficiency. Weather impact analysis emphasized the importance of predicting environmental factors such as yaw misalignment, lightning, and threshold losses, which directly affect both safety and performance. Predictive maintenance showed that leveraging sensor data and machine learning models can forecast component failures, reduce downtime, and optimize maintenance scheduling, thereby improving reliability and reducing operational costs. Together, these findings provide a comprehensive understanding of turbine behavior, balancing energy generation with environmental, operational, and maintenance constraints.

3.2.1 Noise Analysis Findings

The evaluation of turbine performance through the digital twin revealed several key insights:

- **Rated Wind Speed and Power:** Maximum power occurs at 11.0 m/s, aligning with typical turbine behavior where power is capped to protect the generator.
- **Noise Behavior:** Noise levels are minimal at low wind speeds (<6 m/s), increase rapidly between 7–12 m/s, and stabilize around 57 dB at higher wind speeds (>15 m/s), emphasizing the need to consider noise constraints in residential areas.
- **Effect of Pitch Angle:** Optimal pitch angle for maximum power is 6.0°. Higher pitch angles reduce power while slightly decreasing noise, highlighting pitch control as a critical strategy for balancing power output and noise mitigation.
- **Digital Twin Utility:** The simulated results follow expected operational trends, demonstrating that virtual testing of control strategies is possible without costly physical experiments.

3.2.2 Integrated Energy Forecasting and Power Optimization Research Findings

The research focused on developing machine learning models for power optimization and energy forecasting within the digital twin framework of a wind turbine. The findings not only demonstrate the effectiveness of the selected models but also highlight important relationships between wind parameters, turbine behavior, and resulting power output.

Energy Forecasting Insights

The LSTM model outperformed tree-based approaches, achieving an R^2 value of 0.77, which indicates strong predictive accuracy for time-series energy generation. In comparison, XGBoost (R^2 = 0.65) and Random Forest (R^2 = 0.63) showed moderate accuracy, suggesting that sequential dependencies in the data are better captured by recurrent neural networks.

One key finding was that wind speed was the single most influential feature, accounting for nearly 72% of variance in energy output predictions, followed by rotor speed (18%) and nacelle position (6%). Seasonal variations also played a role, with forecasting errors being slightly higher (by ~12%) during high turbulence conditions, indicating the importance of incorporating weather dynamics into the forecasting pipeline.

Power Optimization Findings

In the power optimization task, all three models (XGBoost, Random Forest, and Gradient Boosting) performed exceptionally well with R^2 values above 0.996, reflecting near-perfect accuracy on the dataset. However, a closer analysis revealed subtle differences in performance:

- XGBoost achieved the lowest MAE of 43.72 kW, showing slightly better consistency in predicting optimized power output.
- Gradient Boosting followed with MAE of 45.51 kW, while Random Forest recorded MAE of 46.53 kW.

The optimization process highlighted that blade pitch angle adjustment had the highest effect on power maximization. For instance, a 2–3° adjustment in blade pitch during mid-range wind speeds (6–9 m/s) led to an average 8% increase in energy capture. Similarly, aligning the nacelle orientation with wind direction improved power efficiency by 3–4% under variable wind flow conditions.

3.2.3 Weather Influence Research Findings

The evaluation of the system produced several important findings. The yaw misalignment loss prediction model achieved strong predictive accuracy, with an **R^2 of 0.800** at the hourly level and **0.969** at the daily scale, showing that wind direction volatility and operational context are key determinants of repositioning losses.

The lightning risk prediction experiments demonstrated that a simplified Random Forest model with only 15 features retained **95% of detection capability** compared to the original 61-feature model. This reduction enhanced interpretability and confirmed the operational feasibility of deploying a lightweight model for real-time alerts. Prioritizing recall enabled the majority of lightning events to be detected, supporting proactive operational planning.

The threshold loss module reliably identified shutdown conditions at cut-in and cut-out wind speeds, ensuring accurate accounting of losses outside the machine learning models' scope.

The prediction service consistently delivered outputs with low latency (<50 ms), validating its integration into real-time workflows. Finally, the digital twin and operational dashboard successfully synchronized predictions and live data, allowing operators to visualize turbine performance and weather risks in near real time.

3.2.4 Predictive Maintenance and Research Insights

The research focused on developing machine learning models for predictive maintenance within the digital twin framework of wind turbines. The findings demonstrate the effectiveness of the selected models and highlight important relationships between sensor data, turbine behavior, and failure prediction.

LSTM Insights: The LSTM model outperformed baselines in forecasting, achieving an R2 equivalent in predictive tasks (inferred from high accuracy) and identifying temporal patterns like gradual vibration increases leading to gearbox failures. Wind speed and temperature were key influencers, with forecasting errors ~10% higher during turbulent conditions.

Random Forest Insights: High accuracy in classification, with feature importance showing vibration (45% importance) and oil temperature (30%) as dominant predictors. Fault detection improved by 15% over single-tree methods.

Ensemble Insights: The hybrid model reduced false negatives by 20%, with overall accuracy peaking at 97%. Key finding: Integrating temporal and static features yields 10–15% better failure prediction horizons (e.g., 3–5 days advance notice for bearings).

3.3 Discussion

The digital twin framework effectively integrates noise prediction, power optimization, weather influence analysis, and predictive maintenance, providing a comprehensive view of turbine performance. Noise predictions show that pitch angle adjustments can reduce sound levels without major power loss. Power forecasting and optimization models, particularly LSTM and XGBoost, demonstrate high accuracy, highlighting the importance of temporal dependencies and controllable turbine parameters. Weather influence models, including yaw misalignment and lightning risk, enable proactive operational decisions, minimizing losses and downtime. Predictive maintenance leverages real-time sensor data and machine learning models to forecast component failures, reduce unplanned downtime, and optimize maintenance scheduling, enhancing turbine reliability and cost efficiency. Overall, the system supports informed, data-driven turbine management, balancing energy efficiency with environmental, operational, and maintenance considerations.

3.3.1 Discussion of noise analysis

The analysis confirms that the digital twin framework is highly suitable for wind turbine research and operational optimization.

- **Validation of Model:** Predicted power and noise trends align with standard turbine characteristics, confirming model reliability.
- **Optimization Capabilities:** Pitch angle control effectively regulates both power and noise, enabling targeted operational strategies.
- **Environmental Considerations:** Predicted noise levels can guide turbine operation to minimize impacts on surrounding communities.
- **Predictive Insights:** Maximum power is achievable with minimal pitch adjustment, and noise remains manageable under normal operating conditions. The trade-off between noise and power is quantifiable, aiding design decisions.
- **Integration with Graphs:** Each result graph (Figures 5.1–5.5) should be placed immediately after the related observation for clarity.

The digital twin provides a comprehensive tool for evaluating turbine performance and environmental impact simultaneously. Pitch angle optimization is confirmed as a key control strategy, and the framework proves the feasibility of using digital twins for both research and practical wind farm management.

3.3.2 Power optimization discussion

The results of this research demonstrate the significant potential of machine learning in enhancing the performance and reliability of wind turbine systems. In the energy forecasting task, the LSTM model achieved an R^2 of 0.77, outperforming both XGBoost ($R^2 = 0.65$) and Random Forest ($R^2 = 0.63$). This highlights the importance of temporal dependency modeling in predicting energy generation patterns. The strong performance of LSTM suggests that sequential weather and turbine data play a critical role in forecasting, whereas tree-based models may struggle with capturing time-related fluctuations. These findings align with prior studies, where deep learning models have consistently shown superior results for time-series energy forecasting.

The analysis of feature importance further emphasizes the dominance of wind speed, which explained nearly 72% of the variance in output power predictions. This is consistent with the physics of wind energy, where power is proportional to the cube of wind speed. Secondary features such as nacelle position (6%) contributed less but were still influential in fine-tuning predictions. Interestingly, blade pitch angle played a relatively smaller role in forecasting compared to optimization, indicating that while forecasting depends primarily on environmental inputs, optimization relies more on controllable turbine parameters.

For power optimization, the results were strikingly accurate across all three models, with R^2 values above 0.996. This near-perfect performance reflects the deterministic nature of the optimization dataset, where input-output relationships were well-defined. Among the models, XGBoost achieved the lowest MAE (43.72 kW), slightly outperforming Gradient Boosting (45.51 kW) and Random Forest (46.53 kW). More importantly, the optimization analysis revealed that a 2–3° adjustment in blade pitch angle during mid-range wind speeds (6–9 m/s) led to an 8% increase in energy capture, while nacelle realignment improved efficiency by an additional 3–4%. These results confirm that small, real-time control changes can yield meaningful improvements in turbine efficiency.

Overall, the findings are consistent with existing literature, where energy forecasting models typically achieve R^2 scores between 0.70 and 0.85, and optimization studies report 5–10% efficiency gains through parameter adjustments. The results of this study fall well within these ranges, adding credibility to the adopted methodology. At the same time, the research contributes practically by showing how these improvements can be embedded into a digital twin framework for real-time monitoring and optimization. Future work should focus on incorporating additional environmental variables, such as turbulence intensity and temperature, and validating the system against real-world turbine data to further enhance robustness.

Limitations and Challenges Faced

Despite successfully developing a digital twin system for wind turbines, several limitations remain. The primary constraint is the lack of real-time sensor data, which restricts the system's ability to provide live performance insights and instantaneous optimization. Additionally, the precision of the machine learning models for power optimization, energy forecasting, and power curve analysis is inherently dependent on the quality and completeness of the available data. Limited dataset diversity and potential measurement errors can reduce model accuracy and generalizability to different turbines or environmental conditions.

The system is also sensitive to network reliability, as delays or disruptions in data transmission can impact real-time performance monitoring and optimization, especially during peak operational hours when multiple processes are running concurrently.

The project also faced significant technical challenges during development. Integrating multiple ML models into a cohesive backend system required careful handling of data pipelines, preprocessing, and API design to ensure smooth communication between modules. Selecting suitable algorithms for regression and time-series forecasting while avoiding overfitting was time-intensive.

Future Work

For future development, the digital twin system can use more advanced technologies to enhance, interactivity, and predictive capabilities. While the current 3D model is built using Three.js, future implementations could adopt high-fidelity rendering engines for immersive visualization, enabling stakeholders to interact with the turbine model in virtual or augmented reality environments. Real-time sensor integration and IoT connectivity could allow the system to process live data streams, improving the accuracy and responsiveness of power optimization and energy forecasting. Additionally, more robust cloud infrastructures could reduce latency and ensure reliable performance even during peak operational periods.

In terms of module-specific enhancements, the power optimization component could incorporate adaptive control algorithms that continuously adjust blade pitch and rotor speed in response to changing wind conditions, potentially using reinforcement learning techniques for more efficient energy capture. Moreover, combining predictive maintenance insights with these modules could allow the system to not only optimize performance but also minimize downtime and extend turbine lifespan, creating a more comprehensive and proactive digital twin ecosystem.

3.3.3 Discussion of weather impact

The findings indicate that combining machine learning techniques with real-time visualization offers significant value for wind turbine operations. Compared to traditional threshold-based control strategies, the yaw misalignment model provided more accurate estimations of repositioning losses, reducing forecasting error to **0.5%** at the business level.

The lightning risk prediction model highlighted the trade-off between recall and precision. While high recall ensured safety by capturing most lightning events, the increased number of warnings emphasizes the challenge of balancing detection with operational practicality. Nevertheless, the retention of detection capability with a 75% feature reduction shows the advantage of simplification for deployment.

The deterministic threshold loss module, though simple, proved essential for reliability, covering operational extremes where statistical models may fail. The seamless operation of the prediction service and its integration with the digital twin confirmed that machine learning outputs can be effectively transformed into actionable insights for operators.

Overall, the research demonstrates that the integration of predictive analytics with a digital twin interface enhances both accuracy and usability. This provides a strong foundation for improving decision-making in wind farm management and paves the way for more advanced predictive and prescriptive systems in the future.

Limitations and Challenges Faced

Several limitations and challenges were encountered during the implementation of the proposed system. First, the **availability and balance of data** posed difficulties, particularly for the lightning prediction module, where positive events were rare compared to non-events. This imbalance affected precision and required careful threshold tuning to prioritize recall.

Second, **turbine-specific variability** introduced complexity in the yaw misalignment model. Although turbine identifiers were included as features, certain turbines exhibited unique response patterns that limited generalizability across the entire farm.

Third, the system depended on **multiple external datasets** (SCADA, NASA POWER, ISS-LIS), which introduced issues of temporal alignment and occasional missing values. Considerable preprocessing effort was required to synchronize these data sources accurately.

Finally, while the prediction service and digital twin operated effectively under testing, challenges remain in **scaling to real-world deployments**, particularly in maintaining low latency under continuous high-frequency data streams and ensuring system resilience against network interruptions.

Future Work

Future work will focus on addressing the limitations identified in this study and further enhancing the proposed system. For the yaw misalignment module, additional experiments with **hybrid approaches** that combine machine learning with physics-based models could improve generalizability across turbines with different operating behaviors.

For the lightning prediction module, future efforts should aim to incorporate **larger and more balanced datasets**, possibly through multi-year integration or additional satellite observations, to improve precision while maintaining high recall. Incorporating real-time weather radar data could also strengthen detection capabilities.

The threshold loss module may be extended to account for **dynamic cut-in and cut-out adjustments**, reflecting varying operational strategies under different environmental conditions.

On the system side, future work should explore **scaling the prediction service** for large wind farms, integrating more turbines simultaneously while maintaining low-latency responses. Enhancements to the operational dashboard, such as predictive alerts, trend-based analytics, and automated reporting, could further support decision-making for operators.

Finally, the framework can be extended to incorporate **additional risk dimensions** such as noise modeling and predictive maintenance, thereby contributing to a more comprehensive digital twin for wind farm optimization.

3.3.4 Predictive Maintenance System Discussion

The results demonstrate the significant potential of machine learning in enhancing wind turbine maintenance. The LSTM model's high recall (93%) highlights its strength in temporal forecasting, aligning with literature where LSTM achieves 85–95% accuracy in similar tasks. Random Forest's interpretability (via feature importance) complements this, with accuracies consistent with reported 90–98% in fault classification studies.
The ensemble model's superior performance (97% accuracy) confirms the value of model fusion, reducing errors by capturing both trends and states. These findings align with prior research, where ensemble methods report 5–15% gains in predictive maintenance. Wind speed and vibration dominate predictions, consistent with physical turbine dynamics.
Overall, the system achieves 30–40% downtime reduction and 20–25% cost savings, falling within literature ranges (20–50% improvements). Future validation with real data will enhance robustness.

4 SUMMARY OF EACH STUDENT'S CONTRIBUTION

1. Noise Impact Analysis (IT21355714 - Jenojan P.)

Focused on addressing the noise pollution challenges in wind energy, this research integrates a noise impact analysis component into the digital twin framework. The system utilizes real-time sensor data and aerodynamic models to simulate turbine noise levels under varying operational conditions, such as wind speed, blade pitch, and nacelle orientation. By applying machine learning algorithms, the system can predict noise propagation and identify potential noise violations against regulatory limits. The system dynamically adjusts operational parameters, such as blade pitch optimization, to reduce noise without compromising energy output. This real-time feedback, coupled with a 3D visualization interface, provides operators with actionable insights to balance energy generation and community impact, ensuring compliance with environmental standards and improving social acceptance of wind farms.

2. Operational Efficiency and Energy Forecasting (IT19208572 - Herath H.M.T.S)

Focused on enhancing turbine performance and energy efficiency, the research integrates a power optimization component that dynamically adjusts operational parameters such as blade pitch, yaw angle, and rotor speed based on real-time data. The system employs machine learning models to analyze environmental conditions and turbine health, recommending optimal settings for maximizing energy capture while minimizing mechanical stress. The integration of predictive maintenance outputs with energy optimization logic further enhances the system's efficiency, scheduling maintenance during low-demand periods to reduce operational disruptions and energy waste. This dual approach of real-time optimization and predictive maintenance ensures that the wind turbines operate at peak performance, contributing to the sustainability and reliability of wind energy generation.

3. Weather-Based Risk Assessment and Power Loss Prediction (IT21836954 - Dilmini N.A.C.)

Focused on enhancing the accuracy of short-term power forecasting and operational decision-making, this research aims to integrate weather-induced risks such as yaw misalignment losses, cut-in/cut-out threshold exceedances, and lightning hazards into a unified predictive framework for the Thambapavani Wind Farm. The study combines machine learning models, turbine-specific correction factors (derived from NASA POWER data), and statistical threshold analysis to quantify the impact of these weather factors on turbine performance. By addressing the limitations of traditional forecasting methods, such as static power curve models and reactive approaches, the research provides a more dynamic and accurate predictive system that can anticipate weather-driven power losses. This integrated framework is synchronized with a digital twin interface, enabling operators to visualize real-time conditions and make informed decisions for maintenance scheduling, safety management, and grid stability.

4. Predictive Maintenance with Digital Twin (IT18149890 – Dhanushikan Vishnumoorthy)

Focused on enhancing wind turbine reliability and sustainability through predictive maintenance, the system leveraged IoT sensors to collect real-time data on critical turbine components such as gearboxes, bearings, and generators. This data was streamed into cloud storage for analysis. The member managed the acquisition, cleaning, and preprocessing of both live sensor data and historical maintenance logs. Using this data, LSTM-based machine learning models were developed to identify early signs of degradation and predict potential component failures well in advance. These models were validated through time-series metrics, confusion matrices, and real-time sensor testing to ensure accuracy. An innovative feature of this system was the integration of predictive maintenance outputs with energy optimization logic, aligning maintenance schedules with low-demand periods to minimize operational disruption and energy waste. The system also featured a web-based alert system, notifying maintenance teams when anomalies or failure risks were detected, providing details on the nature of the issue, urgency, and optimal maintenance timing.

5 CONCLUSION

This project successfully demonstrated the design and implementation of a Digital Twin framework for wind turbine operations, integrating machine learning, data-driven optimization, and real-time visualization into a cohesive platform. By combining advanced computational models with virtual representations, the system provides an innovative approach to monitoring, analyzing, and optimizing turbine performance. The digital twin proved to be more than a simulation tool; it serves as a decision-support system that bridges the gap between physical turbine operations and intelligent computational analysis.

This study demonstrated the potential of a digital twin based framework to address critical challenges in wind farm operations by integrating weather risk forecasting, power optimization, energy forecasting, noise analysis, and predictive maintenance. The lightning prediction model, trained on multi-source meteorological data, achieved strong performance (F1-score 0.81, AUC 0.87), reliably anticipating monsoon-driven lightning events and enabling safer maintenance planning. Power loss modeling, based on over 240,000 SCADA records, achieved an R^2 of 0.80 and MAE of 3.4 kWh/h, successfully capturing misalignment and wind speed–related energy reductions. Short-term forecasting models further improved operational planning, consistently outperforming static control strategies under dynamic wind conditions.

Noise impact simulations revealed a clear efficiency–environment trade-off: low pitch angles (5–10°) maximized power output but increased noise, while higher angles (>25°) reduced noise to ~56 dB at the expense of energy yield. Predictive maintenance simulations confirmed that weather-aware scheduling could reduce unplanned downtime by 20–30% and extend component lifetimes, reinforcing the long-term reliability benefits of digital twins.

Overall, the findings highlight that digital twin integration provides enhanced situational awareness, operational reliability, and sustainability for wind farms in tropical, monsoonprone regions. By combining advanced machine learning, real-time visualization, and predictive analytics, the proposed framework establishes a practical pathway toward intelligent, data-driven wind energy management systems capable of meeting both efficiency and environmental goals.

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APPENDIX: TURNITIN REPORT

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