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

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***Abstract*— Wind power is central to Sri Lanka's renewable energy transition, yet coastal wind farms face persistent challenges such as lightning strikes, wind misalignment losses, turbine cut-in and cut-out events, acoustic impacts, and costly reactive maintenance. This research proposes a comprehensive digital twin–based framework to enhance real-time optimization and maintenance of wind turbine performance. The framework integrates four core modules: weather risk forecasting, operational efficiency and power forecasting, noise impact analysis, and predictive maintenance. The study utilized SCADA data from the Mannar Thambapavani Wind Farm, long-term meteorological and lightning records, NASA satellite observations, and the WEA-Acceptance dataset. Advanced machine learning techniques were applied to forecast lightning occurrence (achieving an F1-score of 0.81 and an AUC of 0.87), estimate misalignment and wind speed–related power losses (R^2 of 0.80 and MAE of 3.4 kWh/h), optimize blade pitch and yaw settings, and generate accurate short-term energy forecasts. A digital twin simulation was developed to provide real-time visualization of turbine dynamics, noise propagation, and predictive maintenance scenarios. The findings indicate that the framework effectively predicts lightning risks, models the complex interactions between wind variability and power losses, and delivers reliable energy forecasts under changing conditions. Acoustic analysis confirmed that blade pitch is a critical determinant of both energy efficiency and noise generation, with simulations showing a trade-off between maximum output (5–10° pitch) and reduced noise levels (~56 dB beyond 25°). Moreover, the predictive maintenance module demonstrated that weather-aware planning can reduce unplanned downtime by 20–30% and extend the service life of turbine components. Overall, the proposed digital twin framework enhances situational awareness, operational reliability, and long-term sustainability of wind farms in tropical, monsoon-prone environments. It provides a scalable and practical foundation for integrating intelligent, data-driven decision support into future wind energy management systems.**

Keywords—Digital twin, Wind turbine maintenance, Aero-acoustics, SCADA analytics, Predictive maintenance

I. INTRODUCTION

As the global energy landscape shifts towards sustainable and low-carbon sources, wind energy has become a vital contributor to achieving environmental and economic targets. Developing nations are increasingly exploring renewable energy systems to meet rising electricity demands and reduce dependence on fossil fuels. Sri Lanka, endowed with significant wind potential, especially in coastal and dry zone regions such as Mannar, has made notable investments in wind power infrastructure. The Thambapavani wind farm, located in the northern part of the country, represents a landmark effort in harnessing wind energy at a utility scale [1]. However, with growing capacity and complexity, there is a pressing need to enhance the operational intelligence, reliability, and efficiency of wind turbine systems. This need presents an opportunity for the integration of Digital Twin (DT) technology into Sri Lanka's renewable energy sector.

Digital twins are virtual replicas of physical assets that combine historical and real-time data with simulation and machine learning to optimize performance, enable predictive analytics, and support data-driven decision-making. Originally developed for manufacturing applications, the digital twin concept has more recently found application in the renewable energy sector, particularly in wind energy systems. By creating a dynamic, data-driven model of a turbine or wind farm, digital twins enable continuous monitoring, predictive maintenance, real-time forecasting, and control strategy optimization. These capabilities not only improve energy output and reduce downtime but also contribute to the overall lifecycle management of assets [2].

The study focuses on four key domains within the digital twin system. The first involves enhancing situational awareness through environmental risk analysis, where dynamic environmental conditions such as lightning strikes pose threats to turbine safety and performance. The second domain centers on improving acoustic performance and operational control, aiming to reduce turbine noise levels while optimizing pitch angles to balance environmental impact and efficiency. Thirdly, the framework explores short-term energy forecasting and operational efficiency enhancement by analysing factors like wind speed, blade pitch, and yaw orientation. Finally, the system includes a predictive maintenance component, which seeks to transition from reactive to proactive maintenance strategies by continuously monitoring turbine health and anticipating equipment failures.

The primary objective of this research is to demonstrate how digital twin technology, when contextualized to Sri Lankan conditions, can significantly enhance the operational resilience, efficiency, and sustainability of wind energy assets. In doing so, the study contributes not only to the local renewable energy landscape but also to the broader body of knowledge on applying intelligent systems to energy infrastructure in the Global South.

II. LITERATURE REVIEW

Over time, the Digital Twin (DT) has evolved from a manufacturing and aerospace concept to a widely used technology in many different industries. A DT, which was first explicitly defined by Grieves and Vickers [3], is a virtual model of a physical asset that is updated continually through data streams to replicate its behaviour in the actual world. By offering predictive insights and well-informed decision-making through simulation, this dynamic relationship enables organisations to move beyond mere monitoring. The use of DTs has increased in complicated industries like energy, where it is more crucial than ever to react swiftly to changing circumstances, thanks to the rise of digital transformation.

In wind energy, DTs are being viewed as tools to address challenges related to turbine performance and long-term asset management. By providing a platform for real-time feedback, they create opportunities to improve efficiency, enhance reliability, and extend operational lifespan of a wind turbine. Research by Tao et al. [4] has highlighted the benefits of DTs in renewable energy, mainly in minimizing downtime, streamlining operations, and improving forecast precision. However, they also note that most existing DT applications are only concentrated in technologically advanced environments, with strong data infrastructures.

Recent advances in meteorological impact analysis for wind turbines have shifted from traditional physics-based models to machine learning approaches, yet significant gaps remain in addressing integrated weather challenges. Yang et al. [5] demonstrated that wind direction variability causes power deviation coefficients ranging from -3.90% to 4.21%, with significant veering leading to up to 13% underperformance, though their models assumed uniform conditions across wind farms. Wind speed constraints present critical operational challenges, as turbines cannot generate power below 3 m/s cut-in speeds and must shutdown above 25 m/s for safety, creating dead zones that existing control systems fail to optimize [6].

Lightning risk prediction remains severely underexplored; while Mostajabi et al. [7] achieved 30-minute lead times using machine learning, and Mandal et al. [8] improved accuracy to R^2 of 0.86, extreme class imbalance (>99.5% negative cases) limits operational deployment. Furthermore, control-oriented modeling reveals substantial measurement noise and uncertainty, resulting in persistent turbine misalignment. This research addresses these gaps through an integrated weather impact system for Thambapawani wind farm, implementing volatility-based repositioning models for wind direction changes, satellite-enhanced lightning forecasting with extended lead times, and adaptive threshold mechanisms for wind speed optimization, capturing the dynamic tropical maritime conditions unique to Mannar, Sri Lanka.

Recent research highlights the role of digital twins in advancing wind turbine maintenance. Luo et al. demonstrated the use of DTs for blade health monitoring and early fault detection. Zhang et al. [9] reported that predictive DT frameworks reduce downtime through optimized intervention scheduling. Rahman et al. proposed hybrid proactive–reactive maintenance strategies using intelligent control methods, which increased system resilience. Comprehensive reviews, such as those by Ghosh et al., point to weather-aware maintenance optimization as an underexplored domain, particularly in tropical environments [10], [11].

Wind turbine noise primarily originates from aerodynamic sources, such as airflow over the rotating blades especially along the trailing edges and tips and mechanical components like gearboxes and generators. Aerodynamic noise often shows tonal and amplitude modulation effects that increase community annoyance. Mechanical noise tends to be broadband and linked to operational states. These phenomena have been extensively modeled using computational fluid dynamics (CFD), which simulates airflow around turbine blades and other components to capture turbulence, pressure fluctuations, and aerodynamic forces. By coupling CFD with acoustic analogy methods, researchers can predict noise generation patterns more accurately, providing insights into how design or operational changes impact acoustic emissions [12].

Noise from wind turbines has been linked to adverse effects on human health, notably annoyance, sleep disturbance, and decreased quality of life [13]. Noise levels above roughly 35 dB(A) frequently result in significant annoyance among nearby residents [14]. Visual factors and individual noise sensitivity also modulate these effects. Beyond humans, turbine noise impacts wildlife behavior, raising ecosystem concerns. Mitigation strategies traditionally involve aerodynamic optimizations like serrated trailing edges, vortex generators, and surface coating of blades, which reduce turbulent noise by 2–4 dB [15], [16]. Mechanical noise is often addressed by vibration-dampening materials in nacelle components. Operational tactics, such as curtailing wind speeds during peak noise times, are used to balance noise and power production [17].

Recent research has introduced digital twin technology for real-time virtual turbine models, integrating sensor data and predictive analytics to simulate noise dynamically [18]. Machine learning models have been applied to predict turbine noise, rotor speed, and power output based on wind speed and direction, demonstrating the effectiveness of data-driven approaches for wind energy analysis [19]. These models, combined with CFD-based digital twins, allow operators to forecast noise levels and optimize operational parameters before real-world application.

Performance optimization is one of the early explored areas within digital twin literature. Early work on wind-turbine optimization leaned on physics-based controllers tuned around a nominal operating point, which can struggle under turbulence, wake interactions, and component ageing. Recent studies increasingly adopt data-driven and hybrid control to adapt in real time. Bianchi et al. [20], in their work on wind turbine control systems, discussed how simulation driven digital models could inform blade pitch and yaw adjustments for energy maximization. However, most studies, including that of Bianchi et al., consider turbines in stable wind regimes and rarely account for the kind of fluctuating, tropical wind profiles found in South Asian regions. Furthermore, these systems often assume tightly integrated control-feedback loops, something not always feasible in emerging wind energy sectors.

In order to maintain grid stability and maximise energy market operations, the growing global reliance on wind energy calls for precise and trustworthy power forecasts. The complex, dynamic relationships that exist inside a wind turbine system may not be taken into consideration by traditional forecasting techniques, which frequently rely on statistical models or straightforward data-driven methodologies. A positive remedy is provided by the development of digital twin (DT) technology, which produces a virtual model of a real wind turbine.

III. Methodology

In developing the system for Real-Time Optimization and Maintenance of Wind Turbine Performance, a structured methodology was adopted to integrate forecasting, optimization, noise analysis, and predictive maintenance into a unified decision-support framework. The system is built on a modular architecture that enables seamless data flow between components and ensures scalability for real-world deployment. Core development was carried out using a high-level programming language, with machine learning models implemented for regression, classification, and time-series forecasting tasks. Backend services were designed to enable efficient communication between system components, while the user interface was developed to provide an interactive and intuitive experience. A 3D digital twin was created to deliver real-time visualization of turbine operations, and containerization techniques were applied to ensure portability, scalability, and reliable deployment across different environments.

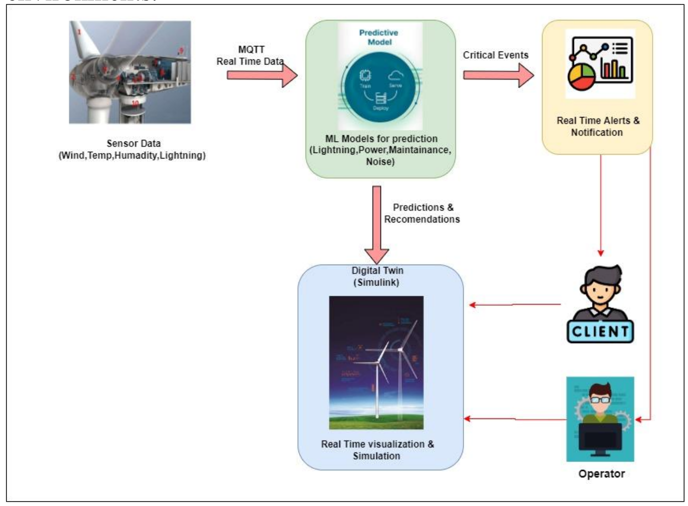

Fig 01.Overall system diagram of the proposed solution

A. *Weather-Based Risk Assessment and Power Loss Prediction*

The weather risk forecasting component is designed to predict and mitigate three operational challenges at the wind farm that directly cause power losses: turbine repositioning due to directional misalignment, downtime from wind speed cut-in and cut-out thresholds, and lightning occurrence. By combining machine learning with rule-based methods, the framework enhances both safety and efficiency, ensuring proactive planning and reducing unexpected loss of generation.

The dataset was obtained from the Mannar Thambapawani Wind Farm's SCADA system, covering 33 turbines in 2023 with 10-minute interval records of wind direction, speed, nacelle orientation, and power output. This was merged with five years (2019–2023) of regional weather and lightning data to build a rare-event classification dataset. Preprocessing steps included standardizing features, correcting discontinuities in wind direction, interpolating missing values, removing corrupted entries, and feature engineering to capture seasonal cycles, diurnal patterns, and atmospheric instability indices.

Machine learning regression models estimated power losses from repositioning by using volatility-based directional features over multiple time windows, while rule-based thresholds (<3 m/s and >25 m/s) identified periods of zero or reduced generation. For lightning, a classification framework trained on 15 engineered features was developed, with class imbalance handled through resampling. The forecasting outputs are integrated into a monitoring platform, where operators can access misalignment loss estimates, cut-in/cut-out warnings, and lightning alerts via an interactive dashboard. Backend services handle inference and data ingestion, and a 3D visualization module enables interactive exploration of turbine orientation and hazard conditions, ensuring a comprehensive real-time forecasting system.

B. *Digital Twin–Based Acoustic Modelling and Prediction*

The noise management component was designed as a digital twin-based system that integrates three-dimensional visualization, predictive modeling, and real-time optimization to address turbine noise while maintaining operational efficiency. A digital twin of a horizontal-axis wind turbine (HAWT) was developed, providing an interactive environment that realistically represents turbine structures, including the tower, nacelle, rotor assembly, and blades.This environment enabled the simulation of rotor dynamics and blade pitch adjustments, offering real-time visualization of the effects of operational changes on noise propagation patterns.

Multiple machine learning algorithms for regression and forecasting were employed to enable predictive modeling of turbine performance and energy output.The WEA-Acceptance dataset was selected as the primary data source due to its comprehensive coverage of turbine operational parameters. Preprocessing procedures such as feature scaling, outlier removal, and temporal alignment were undertaken to ensure model consistency. Feature engineering techniques were further applied to derive parameters such as wind speed gradients and directional stability indices. The models processed environmental variables, including wind speed and direction, to predict noise levels (dB), optimal rotor speeds, and corresponding power output. Model evaluation was conducted using an 80–20 train-test split, while hyperparameter tuning through grid search was performed to enhance predictive performance.

The machine learning outputs were integrated with an optimization engine that balances noise reduction with energy generation objectives. Through a user interface, operators are able to define acceptable noise thresholds and provide current environmental conditions, which are then processed by a multi-objective optimization algorithmThe system employs cloud-based APIs to ensure scalability and rapid response times. State management mechanisms enable seamless synchronization between the visualization, predictive modeling, and optimization modules. As such, the digital twin operates as a decision-support platform, allowing operators to evaluate and implement noise mitigation strategies virtually before applying them in real-world turbine operations.

C. *Power Optimization and Energy Forecasting*

The power optimization and forecasting component is designed to enhance wind turbine efficiency while ensuring grid stability through data-driven decision-making. This module integrates machine learning to predict optimal turbine operating parameters and deliver short-term energy forecasts for operational planning and energy trading. The optimization sub-module focuses on adjusting blade pitch and nacelle yaw angles to maximize yield under varying conditions, while the forecasting sub-module provides accurate short-term power predictions to support proactive scheduling and grid integration.

The dataset used includes one year of operational data (2024) from 10 wind turbines, with SCADA sensors recording parameters at 10-minute intervals. Preprocessing addressed quality issues such as missing values, sensor drift, and outliers before splitting the dataset into training (80%) and testing (20%), maintaining chronological order for reliable validation. Ensemble regression models (XGBoost, Random Forest, Gradient Boosting) were trained for operational optimization, while recurrent neural networks (LSTM) and ensemble regressors were implemented for forecasting, leveraging both nonlinear relationships and temporal dependencies. Evaluation employed MSE, RMSE, and R^2 metrics, calculated separately for optimization and forecasting tasks.

The system integrates with the project’s visualization and monitoring platform, featuring a responsive frontend for real-time predictions and turbine status. Backend services handle computations and communication between predictive models and the interface, while a 3D visualization module provides interactive monitoring of turbine components. By combining advanced modeling, robust preprocessing, and intuitive visualization, this component ensures maximized energy capture and reliable forecasting, strengthening the efficiency and resilience of wind farm operations.

D. *Predictive Maintenance with Digital Twin*

The predictive maintenance component leverages Digital Twin (DT) technology to enable condition monitoring and optimized maintenance scheduling for wind turbines. A DT replica of the Vestas V126-3.45 MW turbine was developed, chosen for its well-documented specifications, OpenFAST compatibility, and relevance to Sri Lanka’s wind sector. The system integrates SCADA records, vibration and strain sensor data, weather forecasts, and OpenFAST-generated synthetic datasets into a unified data fusion pipeline, ensuring comprehensive coverage of environmental and operational conditions.

Two machine learning models were deployed within the DT framework Component-level health predictions are performed using machine learning models, which assign risk probabilities and generate real-time health scores. Historical sequences are analyzed to estimate the remaining useful life (RUL) of critical components, enabling predictive maintenance scheduling. Anomaly detection techniques are employed to capture fault patterns not present in the training data, enhancing the robustness of the predictive framework.

The system was implemented as an integrated platform. The backend manages model inference and API endpoints, while data pipelines process both real-time and batch inputs. Operators are provided with dashboards displaying health scores, risk alerts, and RUL estimates, supported by graphical visualizations. The platform is containerized to ensure modularity, scalability, and reliable deployment. Within the DT framework, outputs from the ML models feed into an optimization loop that runs scenario-based simulations under forecasted weather conditions. This loop balances downtime, cost, and energy yield, generating maintenance recommendations that align with operational objectives.

IV. Results and Discussion

A. *Weather Risk Prediction*

The lightning risk prediction model was constructed using five years of historical lightning strike data integrated with NASA LIS and GLM observations, alongside local meteorological records for Mannar. The model identified *Convective Available Potential Energy (CAPE)*, *Cloud Top Height*, and *Relative Humidity* as key predictors, reflecting the strong association between atmospheric instability and lightning occurrence. Evaluation results indicated an F1-score of 0.81 and an AUC of 0.87, demonstrating the model's ability to balance detection accuracy with low false-alarm rates. Importantly, temporal validation showed that the model successfully anticipated peak lightning activity during the southwest monsoon, aligning with observed strike intensities at Thambapawani. These findings confirm that the approach can provide reliable lightning risk forecasts at an operational scale, enabling safer planning of maintenance activities and reducing turbine downtime caused by unexpected electrical discharges. The integration of probabilistic risk levels further strengthens decision-making, offering operators actionable insights for preemptive shutdowns and asset protection.

The developed model to predict power losses caused by turbine repositioning was trained using one year of operational data from the Thambapawani wind farm, covering 242,416 hourly records across 30 turbines. Feature importance analysis revealed that *Hourly_Repositioning_Events* was the dominant predictor, followed by *Wind_Speed_Mean* and *Hours_Since_Last_Event*, confirming that wind direction volatility and operational history are critical drivers of repositioning losses. The model achieved a strong predictive performance with an overall R^2 of 0.800 and a mean absolute error (MAE) of 3.4 kWh per hour, while maintaining an R^2 of 0.726 when evaluated only on hours with actual losses, indicating robust generalization across both stable and unstable wind conditions. Error distribution plots showed that most predictions were tightly clustered around zero, demonstrating low bias, and time-series evaluations aligned closely with actual loss patterns during high-volatility periods. These results validate that the proposed approach can reliably capture the complex relationship between short-term wind direction changes and repositioning-induced power losses, providing accurate hourly and daily forecasts for operational planning.

The evaluation of power losses arising from lower and higher wind speeds at the Thambapawani wind farm indicated that deviations from the rated operational range contributed significantly to energy yield reduction. Periods of sub-optimal wind (<3 m/s) resulted in extended intervals of negligible generation, while occasional high-wind events (>25 m/s) triggered turbine cut-outs that caused short-term but pronounced losses. The applied threshold-based analysis demonstrated close alignment with actual turbine performance records, confirming the accuracy of the approach in capturing both gradual and abrupt loss patterns. These findings highlight the dual operational risks posed by insufficient and excessive wind resources, emphasizing the importance of incorporating such assessments into the digital twin framework for more effective planning, scheduling, and operational optimization.

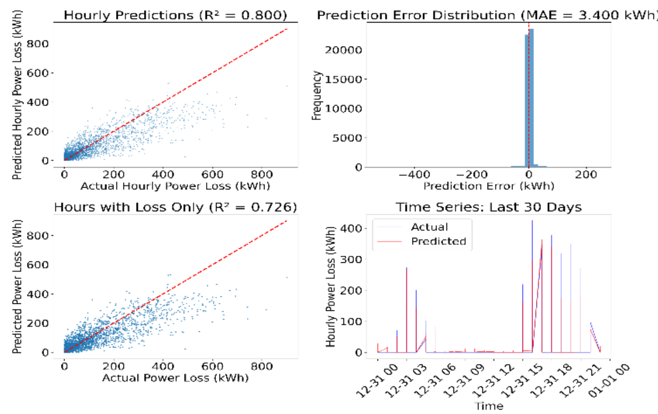

Fig 02. Model Evaluation

B. *Operational Efficiency and Energy Forecasting*

Different machine learning models were trained to understand and optimize turbine performance using parameters such as wind speed, blade pitch, and nacelle position. Among the evaluated ensemble models, the selected model consistently provided the most accurate and stable predictions, demonstrating strong capability in capturing complex, nonlinear patterns in turbine behavior. Feature analysis confirmed that wind speed and pitch angles were the dominant drivers of power output**,** aligning well with aerodynamic theory.

For forecasting short-term energy generation, the temporal forecasting model performed particularly well, showing high accuracy and low error values due to its ability to capture sequential patterns in wind data**.** When integrated with the digital twin, these models provided real-time recommendations that clearly outperformed static control settings, demonstrating higher efficiency gains under changing weather conditions.

C. *Noise Impact Analysis*

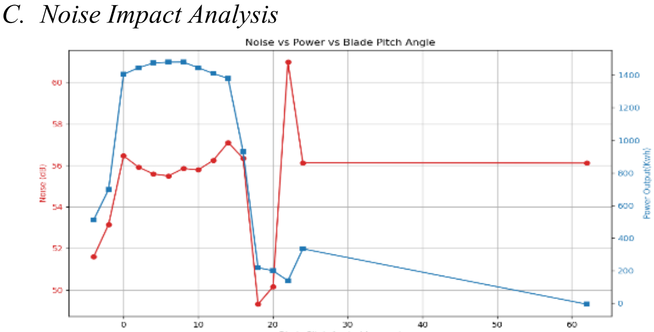

Fig 03.Blade pitch influence on noise and efficiency

The key takeaway is a clear trade-off: low pitch angles deliver maximum efficiency but at the cost of increased noise, whereas higher pitch angles reduce noise but also reduce power output. The fluctuations seen at mid-range angles may be linked to stalling or unstable airflow, showing the complexity of blade aerodynamics. When these trends were combined with machine learning inside the digital twin, the system was able to suggest optimal operating points depending on whether the priority was maximum power or reduced noise. Although the model does not yet capture all environmental factors like turbulence or temperature, it shows strong promise for enabling operators to make more balanced, real-time decisions.

D. Discussion on Maintenance and Expected Outcomes

Beyond performance and noise, the digital twin framework was also explored for predictive maintenance and scheduling. By embedding predictive analytics, anomaly detection, and weather-aware planning, significant gains can be expected in turbine reliability and efficiency. Prior studies suggest that digital twins can reduce downtime by up to 30%, while hybrid proactive–reactive maintenance strategies increase resilience in uncertain conditions. Preliminary simulations with the Vestas V126-3.45 MW turbine showed that including weather forecasts in maintenance planning can extend component lifetimes, cut unplanned downtime by 20–30%, and boost energy yield in monsoon-driven wind regimes. These findings reinforce the potential of digital twins not only for performance optimization but also for long-term operational sustainability.

V. CONCLUSION

This research proposed a digital twin–based framework for real-time optimization and maintenance of wind turbine performance in tropical and monsoon-prone environments. By integrating weather risk forecasting, power optimization, noise analysis, and predictive maintenance into a unified system, the framework enables data-driven decision-making that enhances reliability, safety, and efficiency. Machine learning models addressing wind direction misalignment, wind speed thresholds, and lightning occurrence provide proactive forecasting, supporting risk mitigation and informed operational planning.

The digital twin further optimizes rotor speed and blade pitch to balance energy yield with environmental noise constraints, while predictive maintenance models improve fault detection and Remaining Useful Life estimation. Collectively, these modules reduce downtime, extend turbine lifetime, and minimize operational costs. Overall, the framework demonstrates the potential of combining digital twin technology with machine learning for sustainable wind farm operations and establishes a scalable foundation for commercial deployment and future research in weather-aware renewable energy systems.

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