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A Hybrid Cost-Optimized Maintenance Strategy for Solar-Wind Systems Using Cox Proportional Hazards and Artificial Neural Networks

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Abstract

This study proposes a maintenance optimization framework for hybrid solar-wind systems by integrating reliability-based preventive maintenance with predictive strategies guided by Remaining Useful Life (RUL) estimations. It addresses the dual challenge of minimizing maintenance costs and maintaining system reliability, which is ensured to remain above threshold levels during preventive actions. The approach uses the Cox Proportional Hazards model to assess reliability degradation across various covariates and applies Artificial Neural Networks (ANN) for RUL forecasting. Incorporating dynamic cost-sensitivity analysis, the model enables adaptive planning under changing economic conditions. By evaluating component degradation, system structure, and trade-offs among maintenance types, the framework offers intelligent scheduling and scalability. It serves as a decision-support tool that enhances operational efficiency, extends system lifespan, and reduces total operational costs contributing to sustainable energy management.

Keywords
Hybrid solar-wind systems; Maintenance optimization; Cox Proportional Hazards; Artificial neural networks; Predictive maintenance

1. Introduction
The shift toward sustainable energy systems is critical for addressing climate change, reducing reliance on fossil fuels, and meeting growing global energy demands. Among renewable options, hybrid solar-wind systems offer a compelling solution by mitigating the intermittency of single-source systems through complementary power generation, thereby enhancing reliability and cost-effectiveness. Numerous studies have explored performance and economic optimization of such systems. Salman et al. (2025), Baghaee et al. (2017), and Ghorbani et al. (2018) have reported significant advancements in hybrid system configurations, focusing on optimizing output and financial feasibility. Serat et al. (2024) demonstrated the economic viability of battery-free PV/wind/diesel/grid systems for urban campuses, achieving a low cost of energy (COE) of $0.0172/kWh and 94.8% renewable penetration. Similarly, Sharma et al. (2023) used HOMER software to optimize a 6 kWp hybrid system, finding an optimal setup involving a 5 kWp wind turbine, 2 kWp PV, and battery storage with a COE of $0.575/kWh. Hua et al. (2024) introduced a stochastic multi-objective model that effectively handled renewable generation uncertainties using beta and Weibull distributions. Despite these advancements, research on maintenance strategies tailored to hybrid systems remains limited. The diverse degradation patterns and complex interdependencies within hybrid setups introduce unique operational challenges that conventional maintenance models, designed for single-source systems, often fail to address.

Recent advances in maintenance strategies for renewable energy systems emphasize reliability-centered and predictive approaches aimed at enhancing system availability while minimizing costs. Hajej et al. (2017) introduced an improved preventive maintenance strategy accounting for production constraints, laying the groundwork for adaptive scheduling. Sa'ad et al. (2022) applied component-level reliability thresholds in PV systems, achieving high availability with minimal cost. The integration of predictive maintenance has been further advanced through machine learning and real-time monitoring. Edwin Prabhakar et al. (2024) applied ML for early fault detection in hybrid microgrids, while Chen et al. (2023) explored digital twin (DT) applications, enabling proactive maintenance. A. & Rizwan (2025) proposed a Semi-Markov Decision Process model incorporating burn-in processes, improving system lifespan and cost efficiency. Reliability indicators such as those proposed by Acuña et al. (2017) and Eryilmaz et al. (2021) enhanced performance evaluations by integrating stochastic resource availability and reliability metrics. AI integration, as explored by Shin et al. (2021), Wiese (2024), and Abdelghany et al. (2023), demonstrates significant gains in inspection accuracy, economic feasibility, and uncertainty management in microgrid operations. Despite these advances, their application to hybrid solar-wind systems remains underexplored, highlighting a need for specialized maintenance models that address system complexity and degradation behavior.

Despite progress in preventive and predictive maintenance for renewable systems, current research lacks integrated strategies that combine both approaches for hybrid solar-wind systems. Most studies treat these strategies separately and fail to capture the complex interactions between system configuration, component degradation, and maintenance cost structures. Moreover, existing models often ignore the economic dynamics and cost trade-offs among preventive, predictive, and corrective maintenance actions. This study addresses these limitations by proposing a novel, cost-optimized maintenance framework that integrates the Cox Proportional Hazards model for reliability-based preventive maintenance with Artificial Neural Networks for predictive maintenance through Remaining Useful Life (RUL) estimation. The proposed model introduces an adaptive cost-sensitive decision framework, capable of responding to varying economic conditions, and provides a robust tool for energy system operators to plan maintenance efficiently. By merging statistical and AI techniques, this work advances maintenance optimization in hybrid systems, ensuring improved reliability and cost-effectiveness. The remainder of the paper is structured as follows: Section 2 describes the problem, Section 3 develops the mathematical model, Section 4 outlines the maintenance strategy, Section 5 presents results and discussion, and Section 6 concludes the study.

2. Problem Description
Hybrid renewable energy systems, particularly those combining solar PV and wind turbines, offer a viable solution to Nigeria's energy deficit. However, their operation is hindered by component-specific degradation and maintenance challenges, especially under Nigeria's variable environmental conditions. Notable examples, such as the hybrid Zawaciki Solar Plant and Katsina Wind Farm, highlight the limitations of conventional maintenance strategies, which

are often reactive or time-based. These approaches fail to accommodate the dynamic behavior of hybrid systems, resulting in higher costs and reduced reliability. This study proposes a maintenance optimization framework that integrates predictive analytics to align maintenance activities with real-time system demands and degradation patterns. The model aims to improve reliability and reduce operational costs by optimizing preventive and predictive maintenance, using the Zawaciki and Katsina facilities as case studies.

3. Mathematical Modelling

This section will provide detailed mathematical modelling for the hybrid system formulation, from the production modelling to the maintenance formulation of the system.

3.1. Production estimation using Artificial Neural Networks (ANN)

Accurate forecasting of hybrid solar-wind power generation is essential to balance supply and demand, avoiding overproduction or underproduction. Due to the high variability of solar irradiance and wind speed, this study employs an Artificial Neural Network (ANN) model to predict power output. The ANN architecture includes an input layer (receiving solar irradiance, wind speed, and ambient temperature), multiple hidden layers, and an output layer for power estimation. Hidden layers apply the Rectified Linear Unit (ReLU) activation function to model nonlinear relationships, while the network is trained to minimize prediction error using Mean Squared Error (MSE). The forward activation at layer l is expressed as:

$$a^l = f^l\left(\sum_{j=1}^{n_{l-1}} w_{ij}^l a_j^{l-1} + b_j^l\right) \tag{1}$$

Through forward propagation, environmental inputs are processed sequentially across layers to predict energy output. This unified ANN model integrates both solar and wind data, capturing their interdependencies and enabling more accurate predictions than separate models. By learning complementary generation patterns, the model enhances estimation reliability under fluctuating environmental conditions, thereby supporting more effective hybrid system planning and control.

3.2. Maintenance modelling

This study develops an integrated production-maintenance scheduling framework for hybrid solar-wind systems by sequentially linking production outcomes to maintenance planning. Recognizing that production rates influence component reliability and failure behavior, the model incorporates real-time operational and environmental data. This integration ensures maintenance decisions are dynamically aligned with current system conditions, improving performance, and reducing unplanned downtimes.

a. Reliability modelling

The hybrid system integrates both the solar and wind subsystems in a parallel configuration. This design enhances redundancy, allowing the system to continue functioning as long as at least one of the subsystems remains operational. The solar power subsystem consists of photovoltaic (PV) panel and an inverter connected in a series configuration. Similarly, in the wind turbine subsystem we considered the main shaft, gearbox, and generator, which all components are arranged in series.

b. Cox Proportional Hazards Model for Component Reliability

To capture the impact of operational and environmental factors on component degradation, the study applies the Cox Proportional Hazards (CPH) model. This method effectively incorporates time-dependent covariates and links failure risks to production rates and system conditions. Assuming a constant baseline hazard, the model enables dynamic reliability estimation critical for informed, condition-based maintenance planning expressed as:

$$R(t, X, P_k) = \exp\left(-h_{o,i}.\exp\left(\sum_{j=1}^{n_i} \beta_j X_j + \gamma P_k\right)\right) \tag{2}$$

where:

$h_{o,i}(t)$is the baseline hazard rate for component I when all covariates are zero

$\beta_{i,j}$ quantifies the impact of covariate j on component i

$X_{i,j}$ is the value of covariate j for component iii at time t

P_k is the production rate and γ is the parameter that quantifies the influence of production intensity on component degradation.

This formulation allows for real-time adjustments in reliability estimation based on variations in production rate and environmental conditions, thereby aligning reliability modeling with dynamic operational realities.

c. Remaining Useful Life Prediction Using Artificial Neural Networks

We implemented a dynamic LSTM-based ANN to predict the Remaining Useful Life (RUL) of hybrid system components. The model captures temporal degradation patterns using a dual-layer LSTM (64–32 units), followed by dense layers for refined output. It processes time-series covariates like temperature, load, and vibration. Key features include dropout regularization, MinMaxScaler normalization, and an adaptive online learning mechanism that updates weights after each maintenance action. This enables the model to maintain high accuracy under evolving operational conditions, supporting real-world predictive maintenance strategies.

d. Cost function modelling

The model integrates preventive, predictive, and corrective maintenance costs into a unified cost framework. Preventive costs are based on reliability metrics ensuring system uptime; predictive costs use ANN-based RUL forecasts to enable timely interventions; and corrective costs cover unexpected failures. These components collectively define the total maintenance cost TM over a planning horizon, enabling optimized decision-making that balances cost-efficiency with system reliability.

$$\underbrace{Min}_{(N_{pr},N_p,n_c)} \quad TM = C_p \times N_p + N_{pr} \times C_{pr} + C_c \times \varphi_{hy}\left(N_p, N_{pr}\right) \tag{3}$$

$C_p = \left(\sum_{i=1}^{n_c}[(Cr_i + Cw \times t_i)m_i(k)] + Cf \times \emptyset(k)\right)$ and $C_{pr} = \left(\sum_{i=1}^{n_s}[(Cr_i + Cw \times t_i)m_i(k) + Cd] + Cf \times \emptyset(k)\right)$

$m_i(k) = \begin{cases} 1 & if\ the\ i^{th}\ component\ will\ be\ changed\ at\ period\ k \\ 0 & otherwise \end{cases}$ while $\emptyset(k) = \begin{cases} 1 & if\ \sum_{i=1}^{n} m_i(k) \geq 1 \\ 0 & otherwise \end{cases}$

Where

N_p is the number of preventive maintenance.

N_{pr} is the number of predictive maintenance.

n_c is the number of component replaced is preventive maintenance

n_s is the number of component replaced is predictive maintenance

t_i: Reparation time of the i^{th} component;

Cr_i: Replacement cost of the i^{th} component;

Cw: Labour cost per unit time;

Cf: Cost incurred when disassembling and reassembling a component.

Cd: Cost of diagnostic and monitoring

C_c unit cost of corrective maintenance

$\varphi_{hy}\left(N_p, N_{pr}\right)$ average number of failures

C_{pr} cost of predictive maintenance

C_p cost of preventive maintenance

$\varphi_{hy}\left(N_p, N_{pr}\right)$ is the average number of failures after number preventive and predictive maintenance actions respectively.

The average number of failures on the whole horizon H, considering preventive and predictive maintenance is calculated using.

$$\varphi_{hy}\left(N_p, N_{pr}\right) = \sum_{\mathrm{k}=0}^{\mathrm{N}_p \text{ or } \mathrm{N}_{pr}-1} \left[\int_{\mathrm{t}_k}^{(t_{\mathrm{k}+1})} \lambda_{h,k}(t)\ \mathrm{dt}\right] + \int_{\mathrm{N}_p \ or\ \mathrm{N}_{pr}.\mathrm{T}}^{\mathrm{H}.\Delta\mathrm{t}} \lambda_{h,k}(t)\,\mathrm{dt} \tag{4}$$

4. Maintenance Planning Policy

This section outlines the operational logic and planning structure of the proposed maintenance optimization model for a hybrid solar-wind energy system. The model is designed to minimize the total maintenance cost over a fixed five-year planning horizon, while ensuring that the overall system reliability remains above a predefined threshold. Total maintenance cost is composed of three elements: preventive maintenance cost, which is based on scheduled reliability-driven interventions; predictive maintenance cost, informed by predictions of remaining useful life (RUL); and corrective maintenance cost, estimated from the average number of failures expected after preventive and predictive actions have been executed. The model iteratively explores all feasible combinations of maintenance actions across equally divided time intervals within the planning horizon. For each configuration, it begins by scheduling preventive maintenance by enumerating possible time points and selects components whose reliability has declined below their respective thresholds for maintenance. After this, predictive maintenance is applied by identifying components whose predicted RUL values fall below a defined limit. With both strategies implemented, the model then updates the reliability of the hybrid system and verifies whether it satisfies the system-level reliability requirement. If the reliability criterion is unmet, the predictive maintenance schedule is revised. Once reliability compliance is achieved, the model estimates the expected number of failures to compute the corrective maintenance cost. The total cost of the evaluated maintenance configuration is then calculated, and the process is repeated for all other feasible maintenance schedules. Ultimately, the model selects the maintenance plan that yields the lowest total cost while maintaining system reliability. Through this systematic integration of degradation behavior of reliability thresholds, and RUL forecasts, the model offers a robust, data-informed framework for developing cost-efficient and reliable maintenance strategies for hybrid renewable energy systems.

5. Numerical Example and Results Discussion

5.1. Production and Maintenance Data Overview

To validate the proposed hybrid maintenance planning model, a case study was conducted using real-world data from Katsina State, Nigeria (12.985531°N, 7.617144°E). Environmental variables solar irradiance, wind speed, and temperature were sourced from NASA POWER for the 2018–2023 period. These inputs feed into the hybrid solar-wind energy production model for realistic output simulation. The maintenance data were collected monthly over the same five-year period, yielding 60 data points per component. This dataset includes critical covariates both environmental and operational that influence degradation and failure risk. These covariates are modeled as time-dependent variables within the Cox Proportional Hazards framework, allowing for dynamic hazard function estimation as operating conditions change. This approach enables a nuanced understanding of component deterioration and supports proactive, condition-based maintenance planning tailored to real-world hybrid system behavior.

5.3. Maintenance results discussion

Simulation results identified an optimal maintenance strategy combining four preventive and ten predictive actions presented in Figure 1. Thereby, reducing total cost to €221,900 which is a 13.2% savings compared to a fully preventive approach (€282,000) while maintaining reliability above the required threshold. This hybrid strategy showcases the advantage of condition-based predictive maintenance, which minimizes unnecessary interventions and operational disruptions. The model's adaptability allows dynamic adjustment of predictive actions based on real-time RUL estimates and degradation patterns, effectively balancing cost efficiency with reliability across varying system conditions.

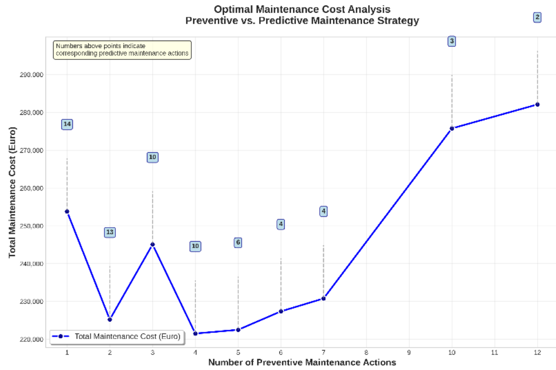

Figure 1. Optimal Plan

The model adopted a selective, component-level strategy that accounts for environmental and operational covariates (e.g., temperature, load, alignment, production rate). Four preventive maintenance actions were scheduled at months 15, 30, 45, and 60, targeting components such as the gearbox, inverter, main shaft, generator, and PV modules based on their unique degradation patterns. Ten predictive maintenance actions, guided by ANN-based RUL forecasts, preemptively addressed faults in the main shaft, generator, inverter, and gearbox as presented in Table 1. This adaptive scheduling approach effectively balances reliability and cost by timing interventions before failures occur, minimizing unplanned downtime and optimizing system performance across the hybrid solar-wind system's lifecycle.

Table 1. Components planning schedule

Month	Preventive Maintenance	Predictive Maintenance	PV panel	Inverter	Main Shaft	Generator	Gear Box
12		×			×		
13		×				×	
15	×			×			×
23		×			×		
26		×				×	
30	×			×	×		×
39		×				×	
41		×			×		
45	×		×				×
52		×			×	×	
55		×		×			
59		×					×
60	×		×		×	×	

Figure 2 reveals a sawtooth reliability pattern in the hybrid system, marked by gradual degradation and sharp recoveries following maintenance. The wind subsystem shows more pronounced reliability drops than the solar side, reflecting its higher sensitivity to mechanical and environmental stress. Preventive maintenance ensures overall system reliability stays above the minimum threshold, confirming its effectiveness. Predictive maintenance, guided by ANN-based RUL forecasts, selectively addresses components nearing failure, stabilizing performance without the cost of full maintenance. This dual approach effectively preserves reliability while optimizing maintenance costs across the hybrid system.

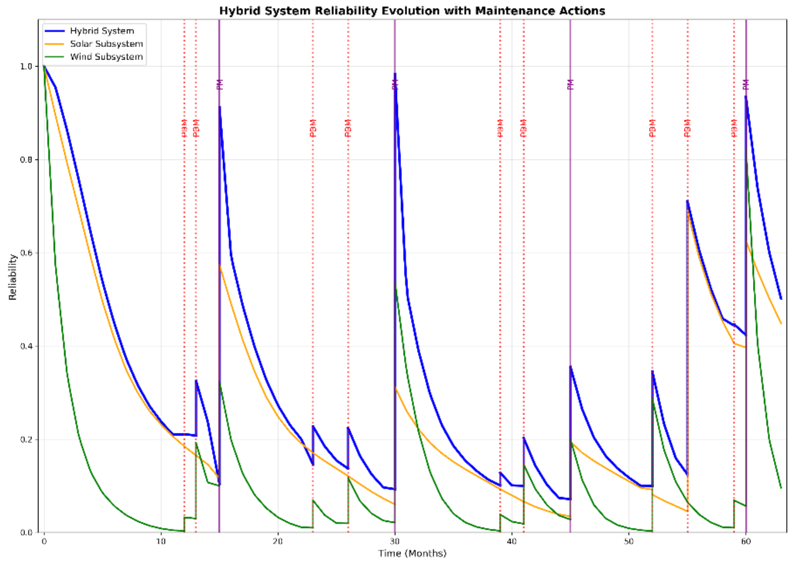

Figure 2. System reliability evolution

Low reliability periods between months 10–15, 25–35, and 45–55 reflects the importance of well-timed predictive maintenance (PDM). These intervals highlight system vulnerability in the absence of timely interventions. However, prompt PDM actions effectively sustained reliability above critical limits while minimizing costs. The overall reliability trends validate the integrated strategy's success in balancing cost and reliability. Consistent recoveries after interventions confirm the precision of ANN-based RUL predictions and the robustness of the maintenance timing decisions.

5.4. Sensitivity analysis

To determine how responsive the model is to changes in corrective maintenance (CM) costs and how these cost shifts affect the best maintenance plan, a sensitivity analysis was carried out. To mimic economic uncertainty and examine the model's adaptive behaviour under shifting cost scenarios, the corrective maintenance cost was gradually increased, as indicated in Table 2.

Table 2. Variable corrective cost

	Correct cost (€)	Preventive actions	Predictive actions	Total Cost (€)
Hybrid System	7,000	4	11	30,333
	10,000	5	6	43,2632
	12,000	6	4	51,4745

5. Conclusion

This study presents a comprehensive maintenance optimization framework for hybrid solar-wind energy systems, integrating the Cox proportional hazards model for reliability assessment with artificial neural network (ANN)-based predictions of remaining useful life (RUL). The model effectively combines preventive and predictive maintenance strategies, demonstrating a significant reduction in total maintenance costs while maintaining system reliability above critical thresholds.

The reliability analysis revealed characteristic degradation patterns within the hybrid system, with the wind subsystem exhibiting greater volatility compared to the solar subsystem. Maintenance interventions, both preventive and predictive, were strategically scheduled to address these patterns, resulting in improved system performance and cost efficiency. The model determined an optimal plan of 4 preventive maintenance actions with 10 predictive actions.
The sensitivity analysis presented the model's adaptability to varying corrective maintenance costs. As these costs increased, caused the model to adjust the maintenance schedules, accordingly, favouring more frequent preventive

actions to mitigate the risk of expensive corrective interventions. This dynamic adjustment highlights the model's capability to balance cost considerations with reliability requirements.

Future research should explore the integration of Internet of Things (IoT) devices with edge computing technologies. This combination facilitates real-time data collection and localized processing, thereby reducing latency and improving the responsiveness of maintenance operations. By processing data closer to its source, edge computing not only enhances operational efficiency but also mitigates bandwidth constraints and supports timely decision-making in maintenance activities.

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Biographies

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Aime Nyoungue earned his M.Sc. and Ph.D. in Mechanical Engineering from Paul Verlaine University in Metz, France. Since 2010, he has been working as a Research Engineer at the LGIPM Laboratory, University of Lorraine, France. His research covers a wide range of areas, including material damage and fracture, failure propagation in production systems and supply chains, maintenance strategy optimization integrated with production and quality, as well as the optimization of renewable energy generation and battery energy storage systems.

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Akilu Yunusa Kaltungo is the Head of Education at the School of Engineering, University of Manchester, where he oversees academic programs for over 5,500 students across multiple engineering disciplines, including aerospace, mechanical, electrical, chemical, and civil engineering. He is part of the School's Senior Leadership Team and chairs key committees focused on teaching, learning, and student experience. Before transitioning to academia, he built a distinguished career spanning over a decade with LafargeHolcim, the world's largest building materials manufacturer. He held several senior roles, such as Head of Maintenance, Head of Health, Safety & Environment, and Reliability Lead, gaining extensive practical experience in industrial operations. His academic work is deeply informed by this industrial background, focusing on sustainable asset integrity, process reliability, and safety. He has successfully supervised multiple Ph.D. students in these areas. He remains closely engaged with the engineering profession through his active involvement with major regulatory and professional bodies. He serves as Regional Secretary of the Institution of Mechanical Engineers (IMechE), contributes to the British Standards Institute, and is a member of safety and risk committees within IOSH and IMechE. He has contributed to the development and review of key international standards, including ISO 55000 for Asset Management and IEC standards for Fault Tree Analysis and Dependability. He is a Fellow of the Institution of Mechanical Engineers (FIMechE), a Fellow of the Higher Education Academy (FHEA), and a Chartered Engineer (CEng) with the Engineering Council UK.