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Cost-Effective Maintenance Planning for Reliable Hybrid Solar and Wind Energy Systems

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Abstract. This paper presents a novel maintenance planning model for hybrid solar and wind energy systems, integrating optimized energy production with maintenance scheduling to achieve cost-effective and reliable operations. The study addresses two interconnected challenges: first, optimizing the energy production system by determining the required number of solar photovoltaic (PV) panels and wind turbines to meet fluctuating random load demands, and second, developing a maintenance strategy that minimizes costs while ensuring system reliability. The model utilizes theoretical production data to estimate failure rates for PV and wind turbine systems based on their energy outputs. These failure rates are used to compute the average number of failures across varying maintenance schedules for the hybrid system. The optimization results reveal that the optimal number of preventive maintenance actions is two ($N = 2$) over a 12-period planning horizon, corresponding to an optimal maintenance cost of 2,139,003 NGN, while maintaining system reliability above 90%. Sensitivity analysis demonstrates the model's robustness, showing that an increase in corrective maintenance costs leads to a proportional increase in maintenance frequency, with the model consistently prioritizing subsystems with higher failure rates. These findings highlight the model's potential as a valuable decision-support tool for energy managers, enabling the development of effective maintenance strategies that minimize disruptions to energy production and align with real-world operational patterns.

1 Introduction

The transition to renewable energy sources from fossil fuels has not only been driven by the need to combat climate change and reduce greenhouse gas emissions, but also by growing concerns over the economic and environmental unsustainability of traditional energy systems. Renewable energy systems, particularly solar photovoltaic (PV) and wind turbines, have emerged as key solutions for providing clean and sustainable power. These systems are increasingly being integrated into hybrid renewable energy systems (HRES) to maximize reliability and minimize dependency on conventional energy sources, especially in remote or isolated areas [1].

However, the operation and maintenance (O&M) of these systems pose significant challenges, including component failures, efficiency degradation, and the need to balance maintenance costs with system reliability [2]. In addressing these challenges, maintenance strategies play a vital role in ensuring the reliability, availability, and cost-effectiveness of renewable energy systems. Innovative techniques, such as predictive maintenance using artificial intelligence and machine learning, have been proposed to improve fault detection and minimize downtime [3].

While considerable research has focused on maintenance strategies for individual renewable energy systems, hybrid configurations introduce additional complexities that are not adequately addressed in current literature. These complexities include the integration of diverse component types, varying failure modes, and differing maintenance requirements for solar photovoltaic (PV) and wind subsystems.

Maintenance strategies for PV systems have typically focused on reducing efficiency decline and ensuring compliance with energy supply contracts. Key performance indicators (KPIs) have been developed to guide plant managers in improving reliability and performance [2]. In wind turbines, maintenance strategies often involve addressing mechanical failures, which significantly impact system reliability and operational costs. Hybrid approaches, such as Failure Modes and Effects Analysis (FMEA) combined with the Analytic Hierarchy Process (AHP), have been employed to identify and prioritize failure modes, thereby enhancing reliability and reducing operational costs [4].

Preventive maintenance has gained significant attention in renewable energy systems due to its ability to reduce unplanned downtime and ensure system reliability. In PV systems, a study developed an algorithm to optimize maintenance actions based on reliability thresholds, achieving high system availability at minimal costs [5]. Similarly, in wind turbines, preventive maintenance strategies integrated with forecasted power generation have been proposed to determine the optimal

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number of maintenance actions required to minimize downtime and maximize availability [6].

Despite these advancements, maintenance optimization for hybrid solar and wind systems remains limited in scope. Existing studies often treat PV and wind systems as isolated units, without adequately addressing their interdependence within hybrid configurations. Moreover, current frameworks rarely integrate production optimization with maintenance planning an aspect that is essential for ensuring system reliability under real operating conditions [7].

This study addresses these gaps by developing an integrated maintenance planning model for hybrid solar and wind systems. By incorporating production optimization into preventive maintenance scheduling, the proposed framework offers a cost-effective strategy to enhance reliability and operational efficiency in hybrid renewable systems.

The article is organized as follows: Section 2 discusses the mathematical modelling, followed by Section 3, where the maintenance strategy is presented. Section 4 contains the numerical example, results, and discussion. Section 5 concludes the study.

Nomenclature

H Number of production periods
a Weibull shape parameter
c Weibull scale parameter
N_p Number of PV panels
N_w Number of wind turbines
U_k Production rate at period k
N_{pvT} Number of maintenance action for PV
N_{wT} Number of maintenance action for wind turbine
C_{mc} Total cost of maintenance
$C_{pm,s}$ Unit preventive cost for solar
$C_{pm,wt}$ Unit preventive cost for wind turbine
C_{cm} Unit corrective cost for the hybrid system
φ Average number of failures for the hybrid system

2 Mathematical modelling

2.1 Production modelling theoretical

2.1.1 Wind turbine production unit

For an effective management of the wind energy, the production of the wind energy needs to be accurately predicted. Because the prediction of wind energy provides operators to be able to estimate the amount of wind energy generated during each period t for proper management. The Weibull distribution with two parameters is the most commonly model used to describe the probability distribution of wind speed. This is expressed as follows:

$$f(\upsilon) = \frac{a}{c}\left(\frac{\upsilon}{c}\right)^{a-1} exp\left(-\left(\frac{\upsilon}{c}\right)^{a}\right) \tag{1}$$

Following the modelling of wind speed υ in (m/s), a is the shape parameter while c is the scale parameter of Weibull distribution respectively. The average power output of a wind turbine P_{wind} is determined by key operational wind speeds, this including the cut-in υ_{ci}, cut-out υ_{co}, and rated wind speeds υ_r, all of which are based on the turbine's rated power P_r as specified by the manufacturer. The average wind speed of the turbine is represented as:

$$P_{wind}(\upsilon) = \begin{cases} P_r \dfrac{(\upsilon^a - \upsilon_{ci}^a)}{(\upsilon_{ci}^a - \upsilon_r^a)} & for \ \upsilon_{ci} \le \upsilon \le \upsilon_r \\ P_r & for\, \upsilon_r \le \upsilon \le \upsilon_{co} \\ 0 & Otherwise \end{cases}$$

2.1.2 Solar PV production unit

Solar PV panels generate electrical energy in the form of DC. The fundamental factor that drives solar energy production is known as the solar irradiance (*G*) which is received from the sun. Due to its inherent variability, the solar irradiance is treated as a random variable. Due to the variability of the solar photovoltaic (PV) systems, in which it depends on weather conditions for electrical power generation, the irradiance G represented by characterised by beta distribution function with $\alpha \ and \ \beta$ parameters given by:

$$f(G) = \frac{\Gamma(\alpha+\beta)}{(\Gamma\alpha)\Gamma(\beta)} \left(\frac{G}{G_{max}}\right)^{\alpha-1}\left(1-\frac{G}{G_{max}}\right)^{\beta-1}$$

The solar power output of a panel is represented using the following equation:

$$P_S(G,\Delta T) = k_1 \times A_S \times G \times (1 - k_T \Delta T) \tag{2}$$

Where: k_1 is the panel efficiency, A_S is the panel area, G is the measured irradiance in W/m^2, k_T is the temperature coefficient and ΔT is the temperature error. The total Dc power generated by a PV panel can then be expressed as:

$$P(S) = \int_0^{G_{max}} (P_s(G,\Delta T) \times f(G)\,)\, d(G) \tag{3}$$

2.1.3 Production objective function

Within a finite energy production horizon (H), the objective for the production optimization is to minimize the total cost of our system, the total cost of the system includes both the capital and production cost. The decision variables in this optimization are the number of photovoltaic (PV) panels and wind turbines. The horizon is segmented into equal time periods, and the system must meet up with the stochastic load demand at the end of each period. The overall system is governed by the following constraints:

$$minN_p < N_p < maxN_p$$
$$minN_w < N_w < maxN_w$$

The total production cost of the hybrid system is expressed as:

$$C_{pc} = C_{capital} + C_{operational} \tag{4}$$

The capital cost consists of the initial investment in each system component, which includes the installation costs, transportation expenses and assembly costs. In contrast, the operational cost accounts for the production cost, which is influenced by the number of components in operation, as well as the costs associated with the disassembly of components during periods of inactivity.

2.2 Maintenance planning modelling

The primary aim of our model is to identify the optimal time frame for performing preventive maintenance (PM) on the hybrid solar and wind energy system. Preventive maintenance refers to scheduled maintenance actions performed at planned intervals to reduce the likelihood of system failure and extend the operational life of components. In this study, we adopt a minimal repair maintenance strategy. However, in cases where unexpected failures occur between scheduled PM intervals, we implement corrective maintenance (CM), which involves restoring the failed component to working condition after a breakdown. Corrective maintenance is typically unplanned, often incurs higher costs, and results in operational downtime.

We have focused on the failure rate caused by equipment degradation due to production operation. This production tends to accelerate the deterioration of the equipment and leads to failure. From the work of Hajej et al. (2011), the failure rate in production is modeled as a function of both the production rate and time. Given the complexity of the hybrid system, which involves varying production rates for both the PV system and the wind turbine, we have developed the output of each component to be treated as a random variable. The instantaneous failure rate at each period k is expressed by the following equation:

$$\Delta\lambda(t, U_k) = f(U_k).\lambda_n(t) \quad t \in [0, \Delta t]$$

From above $\lambda_n(t)$ is the failure rate of an equipment in a nominal operating condition, and production rate U_k. The failure rate is modelled using the Weibull distribution, the failure rate degradation of a machine from [5] can be modelled based on the production rate using the following expression.

$$\begin{aligned}\lambda_x(U_{k,x}, N_{xT}) = \sum_{q=1}^{\frac{H}{T}} \Bigg(\sum_{k=2}^{\frac{T}{\Delta t}} (\frac{T}{\Delta t} - (k-1).(\frac{U_{k,x-1}}{U_{k,xmax}} \\ * \lambda_{n,x}(\Delta t)) \\ + \sum_{k=1}^{\frac{T}{\Delta t}} \left(\int_0^{\Delta t} \frac{U_{kx}}{U_{k,xmax}} * \lambda_{n,x}(t) dt \right) \Bigg) \\ + \sum_{k=\left[\frac{H}{T}\right].\frac{T}{\Delta t}+1}^{\frac{H}{\Delta t}-1} (\left(\frac{H}{\Delta t} - \left[\frac{H}{T}\right].\frac{T}{\Delta t}\right) - (k \\ - \frac{H}{T}.\frac{T}{\Delta t} - 1)(\frac{U_{k,x}}{U_{k,xmax}} * \lambda_{n,x}(\Delta t)) \\ + \sum_{k=\left[\frac{H}{T}\right].\frac{T}{\Delta t}+1}^{\frac{H}{\Delta t}} \left(\int_0^{\Delta t} \frac{U_{k,x}}{U_{k,x}} * \lambda_{n,x}(t) dt \right)\end{aligned} \tag{5}$$

The redundant hybrid system failure rate that composes of the photovoltaic panel and the wind turbine has been modelled by:

$$\begin{aligned}\lambda_{k,hy} = C_{pv}(1 - C_{wt})\lambda_{pv} + C_{wt}(1 - C_{pv})\lambda_{wt} \\ + C_{pv}C_{wt}f(\lambda_{pv}\lambda_{wt})\end{aligned} \tag{6}$$

Where:

$$C_{wt} = \begin{cases} 1 & \text{When the wind turbine is operational} \\ 0 & \text{when the wind turbine is under maintenance} \end{cases}$$

$$C_{pv} = \begin{cases} 1 & \text{when the PV panel is operational} \\ 0 & \text{when the PV panel is under maintenance} \end{cases}$$

And

$$f(\lambda_{pv}\lambda_{wt}) = \frac{\lambda_{pv} * \lambda_{wt}}{\lambda_{pv} + \lambda_{wt}}$$

The hybrid failure rates of the system are being computed for every period, and then the average number of failures of the hybrid system is then computed using equation 7. The overall maintenance strategy for hybrid system which composes of the solar and wind components will be implemented at varying intervals to minimize operational disruptions and reduce system downtime. The average number of failures for the hybrid system is expressed as:

$$\varphi_{hy}(\mathrm{N}) = \sum_{k=0}^{N-1} \left[\int_{k.T}^{(k+1).T} \lambda_{k,hy}(t)\, dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{k,hy}(t)\, dt \tag{7}$$

As a result, our maintenance problem is modeled by considering the impact of machine deterioration due to production operation on the system, the total cost of maintenance C_{TM} is given by:

$$C_{TM}(U_{k,hy}, N_{hyT}) = C_{pm,hy} * N + C_{Cm,hy} * \varphi_{hy}(\mathrm{N}) \tag{8}$$

Where:

$C_{pm,hy}$ and $C_{Cm,hy}$ are the preventive corrective maintenance costs respectively.

3 Maintenance strategy policy

This study addresses two closely related sub-problems. First, we solve the production problem by computing the optimal number of components required in both the PV system and wind turbines to satisfy the random load during each period. After solving the production optimization problem, the resulting production plan for the wind turbine and PV panel is integrated into the maintenance strategy. Integrating production into maintenance strategy aids in determining the optimal maintenance schedule.

Our maintenance strategy explicitly incorporates both preventive and corrective maintenance:

- Preventive Maintenance (PM): Regularly scheduled interventions to service or replace components before they fail, based on their degradation levels. PM is less costly and helps in maintaining system reliability by avoiding unplanned downtimes.
- Corrective Maintenance (CM): Maintenance actions taken in response to an actual failure. CM is costlier due to emergency repairs and associated downtime and should therefore be minimized through effective PM planning.

The goal of our maintenance planning model is to develop an optimal maintenance plan for the hybrid system at minimized costs, considering both $C_{pm,hy}$ (preventive maintenance cost) and $C_{cm,hy}$ (corrective maintenance cost). The objective is to identify the optimal number of preventive maintenance actions N* for the hybrid system over a planning horizon. A perfect maintenance plan helps managers in making effective decisions by proactively managing system reliability.

The model computes the average number of failures from the failure rate of the systems. The failure rate of the photovoltaic (PV) system is calculated based on the energy production of the PV panels, and similarly, the failure rate of the wind turbine is derived from its production output. The model then computes the average number of failures for the hybrid system using different combinations of failure rates for the solar and wind turbine at different periods.

Subsequently, the maintenance cost is computed for those combinations, considering both the PV system and wind turbine, each with distinct maintenance intervals. The model optimizes the maintenance planning by exploring different combinations of PM intervals for the PV and wind turbine systems until an optimal plan is identified that minimizes the overall maintenance cost.

The model evaluates the maintenance period for the solar PV system based on λ_{pv}, and for the wind system based on λ_{wt}, and appropriately schedules maintenance actions for each based on their respective deterioration rates. By staggering PM intervals between the two subsystems (PV and wind), the model avoids simultaneous outages, thus ensuring consistent energy supply to meet random demand at all every period.

In summary, the effects of each maintenance type are as follows:

- PM reduces long-term cost and enhances reliability but requires upfront planning.
- CM addresses unforeseen failures but leads to higher costs and potential service interruptions. By balancing both, the model prioritizes preventive actions while accommodating necessary corrective responses to sustain hybrid system performance.

The algorithm for the maintenance strategy is illustrated in Figure 1.

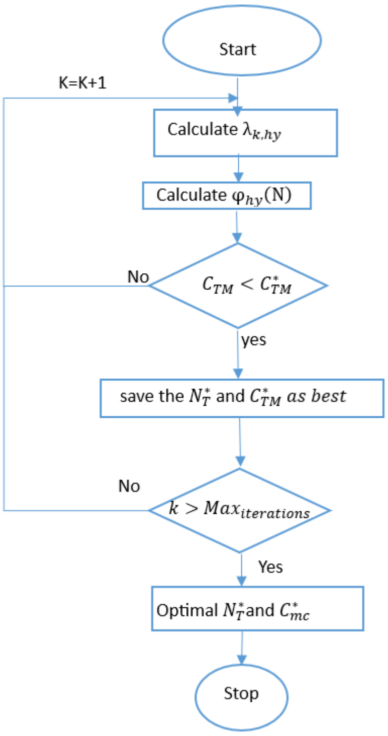

Fig. 1. Maintenance planning algorithm

4 Numerical example and results discussions

4.1 Productions results

In this study, used the solar irradiance, wind speed and temperature of Kumbotso area Kano Nigeria for the NSIA power plant and katsina 11°53′17″N 8°30′10″E. The input data was used the production model. The model objective function is optimizing a hybrid energy system consisting of wind turbines, battery storage, and photovoltaic (PV) panels at minimal, to satisfy unpredictable demand, we aimed to assess how effectively model could compute enough operating units. This unit sufficient to satisfy the random demand, avoid shortages and losses all at minimal cost. The production results are presented in table 1.

Table 1. Optimized production results

Period	Number of PV panels	Number of wind turbines	Power produced by PV's (kW)	Power produced by WT's (kW)
1	126	8	10958	35167
2	137	7	12094	31138
3	133	7	11231	26965
4	123	8	11957	28523
5	122	7	11549	24841
6	102	6	8179	23891
7	119	7	8910	26282
8	126	7	9883	20591
9	113	5	9452	16975
10	136	7	11981	19630
11	136	8	11794	21329
12	121	7	9897	29171

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4.2 Maintenance planning results

The model was successfully simulated, and the results of the maintenance planning are presented in this section. The performance of the maintenance optimization model was evaluated using the theoretical production inputs, providing significant insights into the model's capabilities and the system's maintenance response. The results demonstrate the model's robust adaptability in managing different production profiles while maintaining its primary objective of minimizing total maintenance costs. The model identified the optimal number of maintenance actions N*= 2, with an optimal cost of NGN 2,139,003, as presented in Figure 2.

Further analysis of the maintenance model, shown in Figure 3, highlights the model's capability to address system-specific degradation dynamics. Both renewable energy components solar PV and wind turbine exhibit monotonically increasing failure rates from period 1 to 5, suggesting a shared operational stress effect, despite their different technologies.

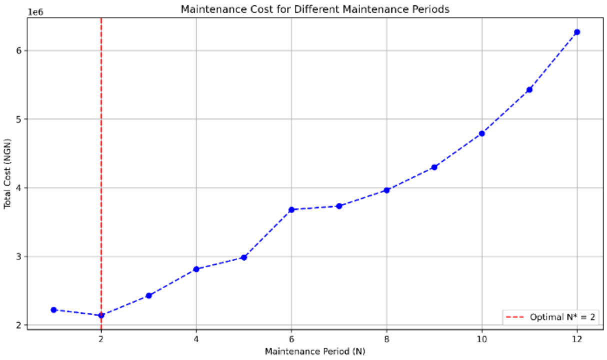

Fig. 2. Cost analysis for Optimal N*

The physical and technical rationale for selecting the maintenance intervals at periods 6 and 12 is driven by observed threshold-based degradation behaviour. Notably, the solar PV component demonstrates an accelerated deterioration rate starting after period 3, surpassing the wind turbine's failure rate by period 5. At this point, the solar PV system reaches a critical failure rate threshold of approximately 0.112, indicating heightened risk of failure. This threshold serves as a trigger for preventive maintenance, prompting the model to schedule its first intervention at period 6. This aligns with the system's preventive maintenance policy that prioritizes intervention on the component with the highest degradation level, ensuring the system is returned to an "as-good-as-new" condition for optimal reliability.

After the maintenance action on the solar PV system at period 6, its failure rate resets to zero. Meanwhile, the wind turbine component continues to degrade. A second distinct degradation trajectory emerges, with the wind turbine experiencing a significantly higher failure rate (about 0.192) by period 12, compared to the solar PV system (0.103). The maintenance model identifies this period as a second critical intervention point, based on the steep increase in failure rate and risk of operational interruption. Hence, the second maintenance action is optimally scheduled at period 12, specifically targeting the wind turbine.

This scheduling reflects the model's ability to adaptively respond to asymmetric wear patterns in hybrid systems where each sub-system's degradation is governed by unique operational and environmental stressors. These differences necessitate component-specific maintenance intervals rather than a unified maintenance window for both technologies.

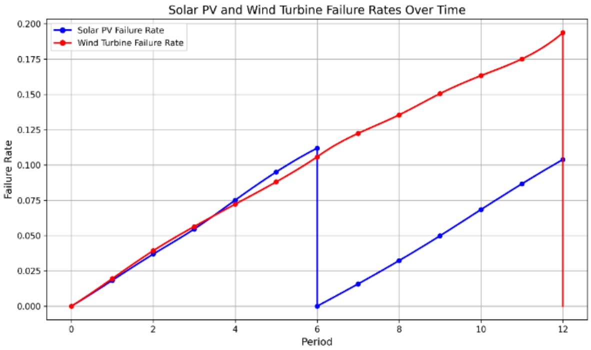

Fig. 3. Optimal Planning of Maintenance Strategy

From the component contribution plot in Figure 4, we observe how the solar PV and wind turbine contribute to the hybrid system's failure rate over the 12-period planning horizon. During periods 1–5, both components degrade in parallel, contributing nearly equally. However, post-maintenance shifts in contribution reflects the selective repair policy: at period 6, the solar PV's failure rate drops to zero, making the wind turbine the sole contributor. By period 12, after the wind turbine is maintained, this pattern reverses.

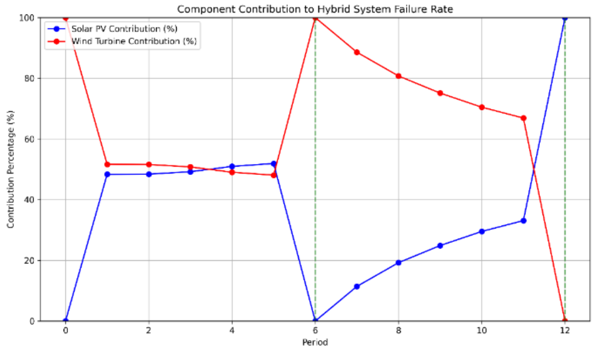

Fig.4. Component's contribution to hybrid failure rate

The oscillating nature of component-level failure contributions further supports the use of staggered, degradation-triggered maintenance scheduling, rather than fixed intervals. This strategy ensures that interventions are both cost-effective and reliability oriented.

Figure 5 shows the reliability-cost trade-off curve. The convex shape confirms the presence of diminishing returns in maintenance frequency**.** The optimal maintenance frequency of N*= 2 balances cost and reliability, achieving over 90% system reliability while maintaining minimal maintenance expenditure. This result corresponds with maintenance actions taken at periods 6 and 12 rationalized not arbitrarily but based on observable system wear thresholds and risk escalation patterns.

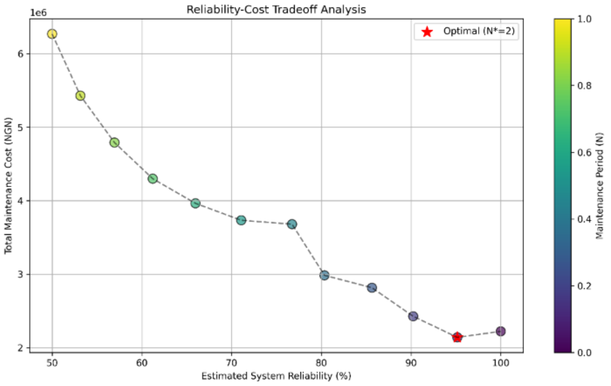

Fig. 5. Reliability-Cost trade off

4.2.1 Sensitivity analysis

In this section, we present a sensitivity analysis to evaluate the impact of variations in the unit preventive maintenance costs and unit corrective cost on the optimal number of maintenance actions on the hybrid system. To do this, we gradually increase the cost difference between corrective and preventive maintenance by adjusting the corrective maintenance cost from NGN 150,000 to NGN 200,000, NGN 300,000, and NGN 400,000, while keeping the preventive maintenance cost fixed at NGN 100,000. The results of this analysis are presented in Table 2.

Table 2. Maintenance action for different corrective cost

	$C_{Cm,hy}$	N_T^*	T	2T	3T	4T	Total Cost (NGN)
Model	200000	2	PV	WT	-	-	2561660
	300000	3	PV	WT	PV	-	3923321
	400000	3	PV	WT	PV	-	4451398

This result highlights the model's ability to identify and prioritize critical maintenance periods even under varying cost constraints. The model ensures efficient resource allocation on the most impactful time frame for maintenance action, while ensuring the overall maintenance strategy remains effective. The model's illustrates adaptability to cost variations and its capacity to maintain system reliability under different scenarios.

5 Conclusion

This study presents a comprehensive maintenance planning model for hybrid solar and wind systems by integrating optimized production outputs into a cost-minimizing maintenance framework that enhances system reliability. The proposed model determines the optimal number of preventive maintenance actions to be two (2), strategically scheduled based on the specific failure rates of the PV and wind subsystems.

A sensitivity analysis demonstrated the model's adaptability to varying preventive and corrective maintenance costs. When corrective maintenance costs increased, the model correspondingly increased the frequency of preventive actions while still targeting the most critical periods. Maintenance scheduling at different intervals for each subsystem minimized system downtime and ensured uninterrupted energy supply, making the model a reliable decision-support tool for energy managers. Overall, the framework contributes significantly to the operational efficiency and sustainability of hybrid renewable energy systems. This was achieved by scheduling maintenance actions based on the sub-system specific failure rates. The maintenance actions for the PV and wind systems were scheduled in separate periods, which minimized the risk of system outages and ensured the continuous satisfaction of energy demand. This approach will provide energy managers with a reliable decision-support tool for effective maintenance planning. The proposed maintenance model offers a practical framework for enhancing the reliability and cost efficiency of hybrid solar and wind energy systems, contributing to the broader goals of sustainable energy management.

However, the study has several limitations. First, the model assumes perfect maintenance (i.e., "as good as new") after each intervention, which may not always be realistic in real-world conditions where partial repairs or degradation residues occur. Second, the simulation is based on theoretical production inputs and does not incorporate real-time operational data or uncertainties in weather conditions, component aging behaviour, or sensor inaccuracies. Third, the interactions between environmental stressors (such as dust, humidity, or temperature cycles) and equipment degradation are not explicitly modelled.

Future research should focus on incorporating stochastic environmental and operational variables to improve the realism of the degradation and failure rate estimations. Additionally, future work could integrate condition-based monitoring data and real-time fault diagnostics to transition the model towards predictive maintenance. Exploring the use of other hazard models, such as the proportional intensity or accelerated failure time models, could also provide comparative insights. Finally, applying the model to empirical field data from deployed hybrid systems would help validate its effectiveness and refine its applicability to diverse geographic and operational settings.

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