

# **Multi-Objective Optimisation of Hybrid Solar-Wind Systems with Integrated Production and Maintenance Planning Using NSGA-II**

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## **Abstract**

This paper presents a multi-objective production–maintenance optimisation framework for a hybrid solar–wind–battery energy system in northern Nigeria. The approach integrates component reliability, system availability, and lifecycle cost into a unified decision-making model, solved using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Production sizing of photovoltaic (PV) panels, wind turbines, and battery storage units, together with preventive maintenance scheduling, is jointly optimised over a 60-month planning horizon. The optimisation problem is formulated as a tri-objective mixed-integer nonlinear program (MINLP), and NSGA-II is employed to generate the full Pareto front in a single run. Three representative Pareto-optimal configurations are reported, demonstrating clear cost–reliability trade-offs: the lowest-cost solution achieved 87.83% reliability at €25.72 million; a balanced configuration improved reliability to 90.21% at €27.68 million; and the highest-reliability solution reached 96.12% at €30.92 million. The optimised maintenance strategies consistently identified the rotor shaft and gearbox as critical components requiring frequent intervention, while higher-reliability scenarios demanded increased storage capacity and more intensive preventive maintenance. The proposed framework offers a practical decision-support tool for designing hybrid renewable energy systems where cost, reliability, and availability must be considered simultaneously.

## **Keywords**

Energy optimisation, Hybrid renewable energy systems, Maintenance scheduling, Power generation and storage, Reliability and maintenance.

## **1. Introduction**

The global energy sector is undergoing a profound shift toward renewable sources, driven by the imperative to combat climate change, lower carbon emissions, and overcome the economic volatility linked to dependence on fossil fuels (Eloranta et al., 2026). Among renewable alternatives, hybrid renewable energy systems (HRES) that combine solar photovoltaic (PV) and wind turbines have emerged as particularly promising solutions for meeting both grid-connected and off-grid electricity demands (Ghanbari et al., 2024). The complementary nature of solar and wind resources offers advantages in smoothing power generation profiles and reducing reliance on single-source variability (Munoz-Pincheira et al., 2025). However, the intermittent and stochastic characteristics of these renewable sources pose significant operational challenges, including power supply fluctuations, demand-supply mismatches, and grid stability concerns (Alqahtani et al., 2024). To overcome these obstacles and ensure continuous power availability, advanced energy management techniques and reliable system configurations are required. As a result, availability and dependability are now crucial performance indicators in the design and operation of HRES (Hosny et al., 2025).

Cutting-edge computational intelligence approaches, including genetic algorithms (GA), particle swarm optimisation (PSO), and mixed-integer linear programming (MILP), have recently been employed to identify the optimal sizing and configuration of hybrid solar-wind systems. Under reliability limitations defined by loss of power supply probability (LPSP), genetic algorithms (GA) have been routinely used to identify optimal component capacities while reducing net present cost (Munoz-Pincheira et al., 2025). Similarly, the Artificial Electric Field Algorithm and Political Optimisation Algorithm have been used in conjunction with conventional techniques in the hybrid PSO-SFLA algorithms, which have demonstrated improved convergence characteristics and solution accuracy for microgrid applications in remote areas (Hosny et al., 2025). Temporal complementarity analysis between wind and solar sources has been incorporated into energy management methods and cost-minimisation techniques beyond sizing optimisation. To find workable solutions, cost-minimisation studies have increasingly incorporated operational constraints, storage system dynamics, and real-time meteorological data. Systems created using these methods have shown the ability to meet up to 98.3% of the total electricity demand while maintaining high reliability indices (Alqahtani et al., 2024).

A key component of HRES design is reliability modelling, which offers mathematical frameworks for forecasting component lives and system performance degradation. The Weibull distribution has become the most widely used statistical model for analysing failure patterns in renewable energy system components (Han et al. 2023) due to its versatility in capturing different failure modes through its shape and scale parameters. The Weibull-based techniques have been utilised in (Chermite and Rachid Douiri 2024) with the Tiki Taka hybridised Algorithm to extract parameters from PV models under changing temperature and irradiance conditions. The results demonstrated a remarkable accuracy in parameter estimation. Also, for assessing the lifetime distributions of crucial wind turbine subassemblies, which include generator slip rings and main shafts, where the location parameter significantly affects reliability predictions, a three-parameter Weibull model was developed by (Han et al., 2023). In another study, climate-based degradation models using physics-based methods that account for location-specific environmental factors have been incorporated into inverter reliability assessment (Alavi et al., 2024). The findings illustrate that degradation rates vary significantly across different climate zones and have a significant impact on power electronics lifetime predictions. Other studies have focused on characterising hybrid system architecture using reliability block diagram and failure mode analysis techniques, which allow quantification of overall system reliability through series-parallel component configurations and the systematic identification of critical failure paths (Alqahtani et al., 2024). These modelling frameworks provide essential foundations for developing maintenance strategies that proactively address component degradation before catastrophic failures occur, thereby ensuring sustained system performance throughout operational horizons.

Maintenance optimisation is an essential link between theoretical reliability models and actual operational performance in renewable energy systems. To determine optimal maintenance intervals and component replacement schedules that maximise system availability while accounting for environmental effects on component degradation, scheduled preventive maintenance (PM) strategies have been developed using iterative numerical techniques (Sa'ad et al., 2021a). Through automated component selection within computational frameworks, selective preventive

maintenance algorithms based on reliability thresholds have proven successful in reducing maintenance costs while attaining availability levels exceeding 99.75% (Sa'ad et al., 2022a). The integration of artificial neural network forecasting with systematic preventive maintenance has enabled wind turbine maintenance strategies that consider power generation rates, and automatically select components falling below minimum reliability margins for perfect maintenance through replacement, thereby minimising maintenance downtime and maximising availability (Sa'ad et al., 2022c). These diverse maintenance modelling approaches collectively contribute to enhanced system performance by enabling strategic timing of interventions and resource allocation.

Furthermore, existing reliability and maintenance studies frequently examine PV systems or wind turbines in isolation rather than jointly modelling interdependencies and failure correlations in hybrid configurations (Sa'ad et al., 2021b); (Sa'ad et al., 2022b). The application of evolutionary algorithms to maintenance optimisation problems has been limited, despite their demonstrated effectiveness in other renewable energy system contexts (Han et al., 2023). Additionally, simplified yet accurate hybrid reliability structures that can be efficiently integrated into system-level optimisation frameworks without excessive computational burden have not been adequately developed.

Multi-objective formulations that comprehensively incorporate reliability, cost, and availability as concurrent optimisation objectives are crucial. As they capture the complex trade-offs inherent in realistic system operation. (He et al., 2026) developed a multi-objective optimisation using the NSGA-III algorithm and the TOPSIS decision-making method for an energy storage system. The results demonstrate a round-trip efficiency (RTE) of 51.12 %. In another study, (Eloranta et al., 2026) developed a multi-objective model for a Smart local energy system to balance cost, emissions, and self-sufficiency.

Despite substantial progress in HRES optimisation and maintenance modelling, several critical research gaps persist, limiting the practical applicability of existing approaches. The current literature predominantly treats production optimisation and maintenance planning as separate problems, lacking unified frameworks that simultaneously optimise both within integrated models for hybrid solar-wind systems. Multi-objective formulations that comprehensively incorporate reliability, cost, and availability as concurrent optimisation objectives are crucial to capture the complex trade-offs inherent in realistic system operation.

The present work addresses these gaps by proposing a unified production-maintenance model for hybrid solar-wind systems that employs Weibull-based component reliability modelling and integrates multi-objective optimisation using NSGA-II to simultaneously optimise reliability, cost, and availability. This approach provides a comprehensive framework for sequential optimisation that explicitly accounts for the interdependencies between production forecasting and maintenance scheduling in hybrid renewable energy systems, thereby advancing both theoretical understanding and practical implementation capabilities in this critical domain.

The remaining sections of the paper are as follows: Section 2 formulates the mathematical model; Section 3 presents the results and their analysis; and Section 4 concludes the study (Table 1).

Table 1 Parameter notations

|             |                                           |    |                   |                                              |                |
|-------------|-------------------------------------------|----|-------------------|----------------------------------------------|----------------|
| $N_{pv}$    | Number of PV panels                       | -  | $R_{pv}(t)$       | PV subsystem reliability at time t           | -              |
| $N_{wt}$    | Number of wind turbines                   | -  | $R_{wt}(t)$       | Wind turbine subsystem reliability at time t | -              |
| $N_b$       | Number of battery units                   | -  | $\beta_i$         | Weibull shape parameter for component i      | -              |
| $N_{pm}$    | Number of preventive maintenance actions  | -  | $\eta_i$          | Weibull scale parameter for component i      | months         |
| $P_s(t)$    | Power output per PV panel at period t     | kW | $\lambda_{hs}(t)$ | Hybrid system failure rate at time t         | Failures/month |
| $P_{wt}(t)$ | Power output per wind turbine at period t | kW | A                 | System availability                          | -              |

|             |                                                 |                  |                           |                                                                         |        |
|-------------|-------------------------------------------------|------------------|---------------------------|-------------------------------------------------------------------------|--------|
| $SOC(t)$    | State of charge of battery storage at period t  | -                | $T_{\text{maint}}$        | Total maintenance downtime                                              | months |
| $C_{pv}^c$  | Unit capital cost of a PV panel                 | €                | $\mu_{p_i}$               | Mean preventive maintenance duration for component i                    | months |
| $C_{wt}^c$  | Unit capital cost of a wind turbine             | €                | $M_c$                     | Mean corrective maintenance duration                                    | months |
| $C_{bat}$   | Unit capital cost of a battery storage          | €/kWh            | $m_i(k)$                  | Binary maintenance selection: 1 if component $i$ maintained at period k | -      |
| $C_{pk,pv}$ | Unit operating cost per kWh from the PV panel   | €/kWh            | $\varphi(N)$              | Average Number of failures                                              | -      |
| $C_{pk,wt}$ | Unit operating cost per kWh from a wind turbine | €/kWh            | $H$                       | Planning horizon                                                        | months |
| $C_{s+}$    | Unit cost of energy storage                     | €/kWh            | $\phi$<br>(Service level) | Minimum probability of demand satisfaction                              | -      |
| $C_{s-}$    | Unit cost of energy shortage                    | €/kWh            | $\varphi^{-1}$            | Inverse standard normal CDF                                             | -      |
| $D(t)$      | Mean Load demand at period t                    | kWh              | $R_{th}$                  | Minimum Reliability threshold                                           | -      |
| $V(t)$      | Variance of load demand at period t             | kWh <sup>2</sup> | $R_{pv}(t)$               | PV subsystem reliability at time t                                      | -      |
| $h_{hs}(t)$ | Hybrid system reliability at time t             | -                | $R_{wt}(t)$               | Wind turbine subsystem reliability at time t                            | -      |

## 2. Mathematical Modelling

### 2.1 Production Modelling

This section presents the production modelling for the hybrid system, outlining the production forecast, storage sizing, and the production objective function.

#### 2.1.1 Artificial Neural Network Forecast

Short-term power generation forecasting is implemented using a feedforward Artificial Neural Network (ANN) trained on historical meteorological data from Sumaila, Kano. (11°30'05"N, 8°57'52"E), which serves as an empirical, real-world validation baseline for the geographic and environmental context of Northern Nigeria. The ANN provides period-level forecasts of solar PV output  $P_s(t)$  and wind output  $P_{wt}(t)$ , which serve as the per-unit production inputs in the total production function in equation 2. Here, we used a three-layer feedforward network, with an input layer consisting of three neurons for solar irradiance [W/m<sup>2</sup>], ambient temperature [°C] and wind speed [m/s]. The hidden layer has 9 neurons with ReLU activation, and the output layer has two neurons for  $P_s(t)$  and  $P_{wt}(t)$ .

The network is trained using the Levenberg–Marquardt algorithm on a 60-month historical dataset (2018–2023). The data was split into 70% for training, 15% for validation, and 15% for testing. The model achieved a Mean Absolute Percentage Error (MAPE) of 4.2% for solar and 7.3% for wind.

The forecasted results of  $P_s(t)$  and  $P_{wt}(t)$  are used in the total production function equation 2, which enables the propagation of forecast uncertainty into the SOC dynamics and the service-level chance constraint.

#### 2.1.2 Storage modelling

The battery is regarded as the hybrid system's energy storage component. One important consideration is the battery's state of charge  $SOC(t)$  (Li et al., 2012). The battery's current available charge level is represented by the state of charge. The following equation represents the battery's inventory balance:

$$SOC(t) = SOC(t-1) + TP(t) - D(t) \quad (1)$$

Where  $TP(t)$  represents total production, which is given by:

$$TP_{(t)} = N_{wt} * P_{wt,(t)} + N_{pv} * P_{s,(t)} \quad (2)$$

All components of the same type are assumed homogeneous. A service level constraint ensures that stochastic demand is satisfied with probability ( $\emptyset$ ):

$$Prob(SOC_{(t)} \geq 0) \geq \emptyset, \forall \in (1, 2 \dots H) \quad (3)$$

The service-level restriction is converted into its deterministic equivalent to solve the optimisation problem, a step crucial for determining the minimum required energy (assuming normally distributed residual demand). Consequently, storage for each period is expressed as follows to avoid shortages:

$$SOC_{(t)} \geq V_{(t)}\varphi^{-1}(\emptyset) + \bar{D}_{(t)} - SOC_{(t-1)} \quad (4)$$

Where:

$\bar{D}_{(t)}$  is the mean of the random load

$\varphi^{-1}$  is the inverse distribution function of the service level

### 2.1.3 Production sub-objective function

The production optimisation framework's sub-objective is to minimise the cost of hybrid generation. This cost function accounts not only for the operating expenses of energy generation but also for the corresponding capital investments. The model systematically assesses and adjusts the configuration of solar modules, wind turbines, and battery storage units over the uniform time periods that make up the horizon. By doing this, it aims to reduce production costs while accommodating fluctuations in stochastic load demand. The overall production cost is then expressed as follows:

$$C_{production} = C_{capital} + C_{operational} \quad (5)$$

$$C_{capital} = N_{wt} * C_{wt}^c + N_{pv} * C_{pv}^c + N_b * C_{bat} \quad (6)$$

While the operational cost comprises the cost associated with shortages, storage, and running costs expressed as:

$$C_{operational} = C_{running} + C_{storage} + C_{shortage} \quad (7)$$

$$C_{running} = \sum_{t=1}^H (C_{pk,pv} \times N_{pv}(t) * P_s(t)) + \sum_{t=1}^H (C_{pk,wt} \times N_{wt}(t) * P_{wt}(t)) \quad (8)$$

$$C_{storage} = \left( C_s^+ \times \Delta t \times \sum_{t=1}^H (SOC(t) \times 1_{SOC(t)>0}) \right) \quad (9)$$

$$C_{shortage} = \left( C_s^- \times \Delta t \times \sum_{t=1}^H (-SOC(t) \times 1_{SOC(t)<0}) \right) \quad (10)$$

## 2.2 Maintenance Modelling

Here, we present the mathematical modelling for the maintenance planning.

### 2.2.1 Reliability modelling

Solar and wind turbine systems are the two main subsystems of the hybrid under study. These systems comprise various components. The most critical components of each subsystem were considered in this investigation. We considered photovoltaic (PV) panels and an inverter for the PV sub-system, and the rotor shaft, generator, and gearbox for the wind turbine sub-system. These systems were configured as presented in (Figure 1).

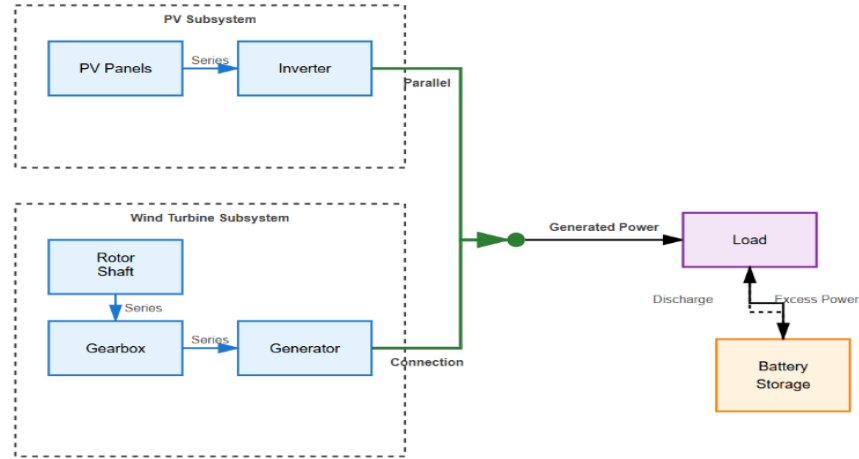


Figure 1. Hybrid Solar-Wind Components Configuration.

$$R_{hs}(t) = 1 - (1 - R_{pv})(1 - R_{wt}) \quad (11)$$

In this study, battery reliability is not explicitly incorporated into the hybrid reliability calculation (Eq. 11). This simplification is adopted for two reasons:

- (i) the battery sub-system reliability is primarily managed through the SOC constraints and the service level constraint (Eq. 4), which indirectly encodes storage availability; and
- (ii) Standardised Weibull failure parameters for lithium-ion battery systems under the specific operating conditions of Kano, Nigeria, are not available in the literature. The reliability model, therefore, focuses on the generation subsystems (PV and wind), while storage adequacy is addressed through a chance-constraint formulation. Incorporating battery reliability modelling is identified as a direction for future work.

Each component's reliability follows a two-parameter Weibull distribution (Ghodrati et al., 2012). This is expressed as:

$$R_i(t) = \exp\left(-\left(\frac{t}{\eta_i}\right)^{\beta_i}\right) \quad (12)$$

### 2.2.2 Availability

Availability is the percentage of time the system is operational and able to meet demand. It is a crucial performance metric in hybrid renewable energy systems. The combined effects of component reliability, failure rate, and maintenance downtime across both subsystems determine the availability of the hybrid solar-wind system. To ensure supply continuity, reduce the risk of blackouts, and limit corrective maintenance interventions, high availability is crucial. In this study, availability is evaluated as:

$$A = \frac{H - T_{\text{maint}}(N_{pm})}{H} \quad (13)$$

The maintenance downtime ( $T_{\text{maintenance}}$ ) includes the Preventive ( $t_{pm}$ ) down time and corrective ( $t_c$ ) Maintenance time. These are the access times for failure evaluation, diagnostic periods, replacement or repair time, or alignment time. This is expressed as:

$$T_{\text{maint}}(N_{pm}) = \underbrace{\sum_{k=1}^{N_{pm}} \sum_{i=1}^{NC} [\mu_{P_i} \times m_i(k)]}_{\text{Total preventive maintenance time}} + \underbrace{\mu_c \times \varphi(N_{pm})}_{\text{Total corrective maintenance time}} \quad (14)$$

### 2.2.3 Maintenance sub-objective function

Over the operating horizon, both planned and unplanned interventions are accounted for in the maintenance cost function. This combines the anticipated cost of corrective maintenance ( $C_n$ ), determined by the average number of

failures, with the overall cost of preventive operations, calculated by multiplying the number of scheduled maintenance activities ( $N_{pm}$ ) by their unit preventive cost ( $C_{pn}$ ). This is expressed as:

$$C_{maint} = C_{pn} * N_{pm} + C_n * \varphi(N_{pm}) \quad (15)$$

Where the average number of failures  $\varphi(N_{pm})$  is given by

$$\varphi(N_{pm}) = \sum_{k=0}^{N_{pm}-1} \left[ \int_{k.T}^{(k+1).T} \lambda_{hs}(t) dt \right] + \int_{N.T}^{H.\Delta t} \lambda_{hs}(t) dt \quad (16)$$

$$\lambda_{hs}(t) = \frac{-\frac{dR_{hs}(t)}{dt}}{R_{hs}(t)} \quad (17)$$

## 2.3 Sequential Integration

The development of sequential integration in our approach ensures that maintenance decisions are dynamically aligned with predicted production to meet demand, rather than treating energy production and maintenance as independent processes. The system can prioritise component interventions during periods of low generation by linking preventive maintenance scheduling to our load and demand-based energy estimates. This will provide us with a model that maximises availability while minimising operational disturbances. The hybrid renewable energy system will develop significantly with this integrated framework, thereby improving maintenance and energy management efficiency.

## 2.4 Multi-Objective Problem Formulation

### 2.4.1 Problem Convexity and Algorithm

The optimisation model, formulated through the objectives defined in Equations (9)–(11), is categorised as a Mixed-Integer Nonlinear Programming (MINLP) problem. Its inherent non-convexity stems from several factors:

1. Discrete Decision Space: The primary decision variables number of PV panels  $N_{pv}$ , wind turbines  $N_{wt}$ , battery units  $N_b$ , and maintenance interventions  $N_{pm}$  are restricted to the integer domain  $Z^+$ . which is non-convex by definition since it cannot contain convex combinations of its elements. But the maintenance selection variables  $m_i(k) \in \{0,1\}$  introduce an additional combinatorial layer: for NC components and  $N_{pm}$  maintenance intervals, the maintenance subspace alone contains  $2^{NC*N_{pm}}$  possible schedules. This renders exhaustive enumeration and branch-and-bound methods computationally intractable. Gradient-based optimisers are additionally inapplicable as they require a connected, differentiable feasible region.

2. Discontinuous Objective Function: The production cost objective  $f_1$  incorporates indicator functions  $1\{SOC(t) > 0\}$  and  $1\{SOC(t) < 0\}$  in the storage and shortage cost terms. These indicator functions introduce discontinuities in the cost surface at  $SOC(t) = 0$ . All gradient-based and interior-point methods, such as Interior Point Optimiser (IPOPT) or Solving Constraint Integer Programs (SCIP), require at a minimum Lipschitz continuity of the objective; discontinuous objectives render these solvers formally inapplicable.

Considering the multi-objective problem, a classical weighted-sum scalarization is an option, which converts the tri-objective problem into a single-objective MINLP:

$$\min_x w_1 f_1(x) + w_2 f_2(x) + w_3 f_3(x) \quad (18)$$

$$w_1 + w_2 + w_3, \quad w_i \geq 0 \quad (19)$$

solvable by open-source MINLP solvers such as SCIP or Bonmin. However, this approach has two fundamental limitations in the present context: (i) it can only recover Pareto-optimal points on the convex hull of the true Pareto front and systematically fails to identify solutions in non-convex regions of the objective space; and (ii) it requires the weight vector ( $w_1, w_2, w_3$ ) to be specified a priori, introducing subjective bias and necessitating repeated re-runs to approximate the full trade-off surface. Furthermore, exact deterministic MINLP solvers require continuous, differentiable surfaces; the presence of binary scheduling choices  $m_i(k) \in \{0,1\}$  earlier stated creates a massive combinatorial search space of  $2^{NC*N_{pm}}$ , while the indicator functions  $1\{SOC(t) > 0\}$  and  $1\{SOC(t) < 0\}$  introduce

severe surface discontinuities that render traditional gradient-based or branch-and-bound solvers computationally intractable.

NSGA-II, by contrast, generates a well-distributed approximation of the complete Pareto front in a single run using non-dominated sorting and crowding distance preservation (Deb et al., 2002), without requiring any a priori articulation of preferences. This property is particularly valuable in the present application, where the relative importance of cost, reliability, and availability is system- and context-dependent, and decision-makers require the full trade-off landscape before committing to a configuration.

#### 2.4.2 Formal Problem Statement

Models that focus solely on cost-oriented formulations are insufficient, as improvements in economic performance often reduce operational availability or system dependability. Conversely, increasing availability or reliability usually requires greater redundancy or higher maintenance intensity, which raises lifetime costs. Therefore, multiple conflicting performance metrics must be optimised simultaneously for a hybrid renewable energy system. Three primary goals frame the optimisation problem in this work; together, they constitute the performance criteria for the hybrid solar-wind system. The decision variable vector is given by:

$$x = (N_{pv}, N_{wt}, N_b, N_{pm}, m) \quad (20)$$

While our tri-objective minimisation is:

$$\min_x F(x) = \{f_1(x), f_2(x), f_3(x)\} \quad (21)$$

Where:

$$f_1 = C_{production} + C_{maint} \quad (22)$$

$$f_2 = 1 - R_{hs}(t; x) \quad (23)$$

$$f_3 = 1 - A(x) \quad (24)$$

These are subject to:

$$\begin{aligned} SOC_{min} \leq SOC(t) \leq SOC_{max} \quad \forall t \in \{1, \dots, H\} \\ N_{wt} * P_{wt}(t) + N_{pv} * P_{pv}(t) \geq P_L(t) \\ R_{hs}(t) \geq R_{th} \\ Prob(SOC(t) \geq 0) \geq \emptyset \\ N_{pv} \in \{N_{pv}^{min}, N_{pv}^{max}\} \\ N_{wt} \in \{N_{wt}^{min}, N_{wt}^{max}\} \\ N_b \in \{N_b^{min}, N_b^{max}\} \\ m_i(k) \in \{0,1\} \end{aligned}$$

A solution  $x^*$  is Pareto-optimal, if no feasible solution  $x$  satisfies  $f_j(x) \leq f_j(x^*)$  for all  $j \in \{1,2,3\}$  with strict inequality for at least one  $j$ . The objective of the algorithm is to identify the Pareto front  $\mathcal{P}^* = \{x^* | x^* \text{ is Pareto-optimal}\}$ , from which decision-makers select preferred configurations according to operational priorities.

The study uses the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) to solve the tri-multi-objective problem. New candidate solutions are generated at each generation through selection, crossover, and mutation, and then evaluated using the objective functions. After merging the parent and offspring populations, the non-dominated ranking procedure is used to re-sort them. For the next iteration, only the best solutions, those that belong to the best fronts and exhibit good diversity, are retained. The outcome is a well-distributed Pareto front that captures the key trade-offs between the hybrid system's overall cost, availability, and reliability. These solutions serve as the basis for selecting an operational strategy aligned with the system's specific priorities.

### 3. Results and Discussion

The metrological data for Sumaila, Kano (11°30'05"N, 8°57'52"E) are used in the optimisation framework, which considers a 60-month planning horizon. The NSGA-II algorithm was configured with a population size of 200 individuals, sufficient to ensure adequate coverage of the three-dimensional Pareto front for a tri-objective problem of this complexity. A generation limit of 400 was adopted as the termination criterion, providing sufficient iterations for convergence across the mixed-integer decision space. The crossover probability of 0.9 follows the canonical recommendation of (Deb et al., 2002) for NSGA-II applied to nonlinear problems, ensuring aggressive yet controlled

exploration of the feasible region. The mutation probability of 0.25 guarantees, on average, one variable perturbation per individual per generation, balancing exploration and exploitation. Infeasible solutions were handled via a feasibility tournament, ensuring that solutions violating the SOC bounds, power balance, or reliability threshold are always ranked below feasible candidates during selection.

The NSGA-II algorithm generated three representative Pareto-optimal configurations, each reflecting different trade-offs among cost, reliability, and availability. The optimised maintenance schedules for these configurations are presented in Table 2.

Table 2 Maintenance schedules

| Model | Config. 1                        | Config. 2                            | Config.3                           |
|-------|----------------------------------|--------------------------------------|------------------------------------|
| T     | Rotor shaft<br>Generator         | Rotor shaft<br>Generator             | Rotor shaft<br>Gearbox             |
| 2T    | Inverter<br>Generator<br>Gearbox | Inverter<br>Rotor shaft<br>Generator | Inverter<br>Rotor shaft<br>Gearbox |
| 3T    | PV panel<br>Gearbox              | Rotor shaft<br>Gearbox               | Rotor shaft<br>Gearbox             |
| 4T    | Rotor shaft<br>Generator         | Inverter<br>Rotor shaft<br>Gearbox   | Inverter<br>Rotor shaft<br>Gearbox |
| 5T    |                                  | PV panel<br>Gearbox                  | Generator<br>Gearbox               |
| 6T    |                                  |                                      | PV panel<br>Generator<br>Gearbox   |

The three solutions illustrate a progression along the Pareto front. The lowest-cost configuration favours moderate reliability, whereas higher-reliability solutions require greater storage capacity and more frequent preventive maintenance. Configuration 1 is the most economical, whereas Configuration 2 balances investment and reliability improvement. Configuration 3 achieves the highest reliability through expanded battery capacity, additional wind turbines, and a more intensive maintenance schedule. These trends confirm the interdependence among redundancy, storage, maintenance frequency, and system performance. By maintaining uniform diversity along the multi-objective trade-off surface, the algorithm successfully maps non-linear compromises that single-objective or scalarised exact solvers cannot effectively isolate without exhaustive parameter tuning. Table 3 summarises the optimal sizing and maintenance parameters obtained.

Table 3 Optimal Plan

| Model                 | Config. 1     | Config. 2     | Config. 3    |
|-----------------------|---------------|---------------|--------------|
| No. PV panels         | 635           | 684           | 602          |
| No. Wind turbines     | 12            | 12            | 14           |
| Battery Capacity(kWh) | 1444.5        | 1606.5        | 2322.0       |
| No. PM                | 4             | 5             | 6            |
| Cost (€)              | 25,723,711.64 | 27,677,179.64 | 30,916,162.4 |
| Reliability (%)       | 87.83         | 90.21         | 96.12        |

Across all cases, the rotor shaft and gearbox consistently rank as the most frequently serviced components, reflecting their high failure propensity in wind turbine systems. The inverter also recurs across several periods, underscoring its critical role in continuous power conversion. The increase in preventive actions from Configuration 1 to Configuration 3 aligns with the corresponding rise in reliability requirements. These schedules demonstrate that the optimisation method systematically prioritises maintenance for components with the greatest impact on system availability.

The cost–reliability frontier exhibits non-linear behaviour. Moving from the economical solution (Configuration 1) to the balanced case (Configuration 2) yields moderate reliability gains at a modest cost increase. In contrast, the high-reliability configuration (Configuration 3) requires a disproportionately higher investment, driven primarily by larger battery capacity and more frequent preventive maintenance. This behaviour aligns with multi-objective optimisation in hybrid energy systems, where the marginal cost of reliability steepens at higher performance levels.

All three configurations demonstrate feasible operational performance in northern Nigeria. Configuration 2 emerges as a strong compromise, offering meaningful reliability improvements without excessive cost escalation. Maintenance patterns confirm well-targeted interventions, with an emphasis on wind-turbine mechanical components. The results highlight the value of integrating production sizing with maintenance planning: both significantly improve reliability and availability.

#### **4. Conclusion**

This study presented a multi-objective production–maintenance optimisation framework for a hybrid solar–wind system using NSGA-II. The model jointly optimises cost, reliability, and availability, yielding a set of Pareto-optimal configurations that provide decision-makers with flexible deployment options. The results show that higher reliability levels require coordinated increases in storage capacity, maintenance frequency, and subsystem redundancy. The optimised maintenance schedules consistently prioritise the mechanical components of wind turbines, underscoring their critical role in overall system dependability.

The approach demonstrates practical applicability to hybrid systems in resource-constrained environments, such as northern Nigeria. Future work will incorporate explicit battery reliability modelling using Weibull failure statistics, compare the solution quality and computational convergence of NSGA-II with weighted-sum scalarisation solved using MINLP solvers (e.g., SCIP, Ipopt), and alternative metaheuristics (e.g., NSGA-III, PSO), and validate the framework against actual industrial field deployment data while and model long-term degradation and uncertainty.

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