

Article

Optimal Sizing of a Hybrid Nanogrid System Using Multi-Objective Neural Architecture Search Under Improved Uncertainty and Battery Degradation: A Case Study of Desert Camping in Hafr Al-Batin, Saudi Arabia

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Abstract

Optimal sizing of hybrid renewable energy systems for desert camps is a multi-objective problem that must account for cost, reliability, component degradation, and uncertainty. This paper introduces an improved multi-objective neural architecture search (IMONAS) framework for hybrid nanogrid sizing in the desert environment of Hafr Al-Batin, Saudi Arabia. The framework combines neural optimization, stochastic uncertainty modeling, and explicit battery degradation modeling, a combination not addressed in the reviewed studies for this application. Six test cases are examined by varying uncertainty assumptions, battery degradation, and the annual duration of uncertain operation. For each case, IMONAS provides Pareto-front solutions that specify the photovoltaic, diesel generator, battery autonomy, and inverter choices while minimizing the cost of energy (COE) and the loss of power supply probability (LPSP). IMONAS is compared with the original MONAS and five other multi-objective optimization methods. In addition to visual Pareto-front comparisons, the assessment uses Pareto-dominance indicators, namely the C-metric and an aggregated score derived from pairwise C-metric comparisons across the algorithms and cases. The results provide a validated sizing framework for remote arid-region nanogrids under uncertainty and battery degradation.

Keywords: battery degradation; diesel generator; uncertainty; multi-objective optimization; nanogrid; neural architecture search; solar energy



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1. Introduction

The transition towards sustainable energy systems has kept renewable energy integration at the center of energy research, especially in remote and off-grid locations with abundant resources. The deserts of Saudi Arabia have strong renewable energy potential, but extreme temperatures, dust accumulation, and logistical constraints make energy

system operation difficult. Systems designed for milder environments may therefore fail when deployed in desert regions [1–3]. In Saudi Arabia, the renewable energy ambitions of Vision 2030 coincide with growing demand for desert tourism and recreational camping facilities. This creates a need for optimized, reliable, and cost-effective power systems that can operate under harsh environmental conditions, where conventional systems often struggle [4–6].

Hafr Al-Batin, a city in Saudi Arabia's Eastern Province bordering Kuwait, is known for its winter desert camps. The city receives average horizontal solar irradiation of 5.8 kWh/m²/day, which indicates strong photovoltaic (PV) generation potential. It also experiences temperature variations of approximately 15–45 °C. Grid connectivity, fuel supply, and seasonal camping activities produce substantial load-demand variations [7,8]. In the load profiles used in this study, the average daily demand is 27.06 kWh and 72.63 kWh for the weekdays and weekends, respectively. These conditions require sizing methods that account for uncertainty in resource availability and load behavior while maintaining economic viability and operational reliability. Nanogrids offer a modular way to combine energy resources, but they also require reliable power electronic interfaces for fault-tolerant operations under extreme weather conditions [9].

Several studies have investigated hybrid renewable energy system sizing with meta-heuristic algorithms. This review focuses on works relevant to the Saudi Arabian desert. Boucekara et al. [10] developed an improved decomposition multi-objective evolutionary algorithm (IMOEAD) for Yanbu City. Their approach achieved an energy cost of USD 0.0716–0.1159/kWh while incorporating load uncertainty through Monte Carlo simulations and modeling a 75% battery capacity reduction over the system lifetime [10]. Alotaibi et al. [11] proposed a gradually reduced-particles particle swarm optimization (GRP-PSO) algorithm that reduced convergence time by 58% relative to conventional approaches. They evaluated pumped hydro storage and reported a levelized cost of energy of USD 0.034325/kWh, with a 34.2–41.1% cost reduction compared with battery and green hydrogen storage systems [11]. Eltamaly et al. [12] introduced demand response strategies in smart-grid frameworks and reported a 20.66% reduction in component size with zero loss of expected energy by using dynamic tariffs linked to the battery state of charge.

Despite these advances, most studies still use metaheuristic algorithms. Table 1 summarizes ten studies on hybrid renewable energy systems sizing in Saudi Arabia. As shown in Table 1, only one reviewed study used neural network-based optimization. Hussein Farh et al. (2024) applied a reinforcement learning neural network algorithm (RLNNA), obtaining an annualized system cost of USD 1,219,744 with zero loss of power supply probability and an 86.37% renewable fraction [13]. RLNNA converged faster and produced better solutions than a genetic algorithm (GA) [14], particle swarm optimization (PSO) [15], and self-adaptive differential evolution (DE) [16]. However, one implementation is not enough to establish the suitability of neural architecture search for hybrid microgrid sizing.

The remaining nine studies used metaheuristic approaches, including IMOEAD [10], GRP-PSO [11], PSO variants [12], MOEA/DD [17], NSGA [18], ARO [19], SDO [20], SSO [21], and comparative implementations of OOA, ZOA, and FFO [22]. Related work has also reported multi-objective evolutionary algorithms for renewable system design and sizing [23], including scenario-dominance formulations for hybrid renewable energy systems [24,25]. Advanced power electronic architectures, such as dynamic weighted-selection control for multi-source load management, may further improve neural-optimized systems by supporting flexible resource allocation and fault tolerance [26].

Recent work on multi-objective neural architecture search (MONAS) offers a more adaptive optimization framework. The evolutionary MONAS framework proposed by [27] uses a coevolutionary strategy and a two-stage offspring generation mechanism to address multimodal and many-objective neural architecture search problems. It maintains two interacting populations so that convergence and diversity preservation can be handled separately. This structure helps the algorithm explore multiple Pareto sets and reduce premature convergence. MONAS uses a two-stage search mechanism in which crossover and differential evolution are applied at different phases. It also uses a diversity-aware fitness evaluation mechanism to prioritize well-distributed solutions. This feature is relevant to hybrid energy system design, where several conflicting configurations can be feasible. Despite its performance in neural architecture optimization, MONAS has seen limited use for hybrid renewable energy system sizing under uncertainty, battery degradation, and harsh environmental conditions.

Table 1. Characteristics of included studies on hybrid renewable energy system optimization in Saudi Arabia.

Study	Location	System Components	Optimization Algorithm	Primary Objectives
H. Boucekara et al., 2023 [10]	Yanbu	PV, Wind, Battery, Diesel	IMOEA	COE, LPSP
Majed A. Alotaibi et al., 2021 [11]	Dumah Aljandal	Wind, PV, PHES	GRP-PSO LCE	
A. Eltamaly et al., 2021 [12]	Northern Saudi Arabia	Wind, PV, Battery, Diesel	PSO, BA, SMO	COE, LOLP
H. Boucekara et al., 2021 [8]	Hafr Al-Batin	Solar PV, Battery, Diesel	MOEA/DD	COE, LPSP
Doaa M. Hasanin et al., 2021 [18]	Yanbu	PV, Wind, Diesel, Battery	NSGA	LPSP, COE, RF
Ahmed S. Menesy et al., 2024 [19]	Yanbu	PV, Wind, Diesel, Battery	ARO	COE, LPSP, Excess Energy
F. Alturki et al., 2020 [20]	Northern Saudi Arabia	PV, Wind, Battery, Diesel	SDO	ASC, LPSP, REF
A. Fathy et al., 2020 [21]	Aljouf	PV, Wind, Battery, Diesel, Inverter	SSO	COE, LPSP
Mohammed Alqahtani et al., 2025 [22]	Tabuk	PV, Wind, Biomass, Battery	OOA, ZOA, FFO	NPC, LPSP
Hassan M. Hussein Farh et al., 2024 [13]	Saudi Arabia	Solar PV, Wind, Battery, Diesel	RLNNA	ASC, LPSP, REF

The reviewed literature leaves three gaps that matter for desert camping applications. First, uncertainty modeling remains limited. H. Boucekara et al. used Monte Carlo simulation to quantify load uncertainty [10], whereas other studies relied on deterministic sensitivity analyses with $\pm 20\%$ variations in wind speed and solar irradiance [11,21] or used reliability metrics such as loss of power supply probability as indirect uncertainty proxies [13,22]. This matters because probabilistic uncertainty modeling can shift Pareto fronts and expose reliability–cost trade-offs that deterministic approaches may obscure [10]. Desert environments add correlated uncertainty through solar availability and temperature-induced efficiency changes, while camping loads are also irregular and require stochastic treatment.

Second, only three of the ten reviewed studies explicitly model battery degradation [8,10,11], even though degradation affects long-term cost and reliability. Boucekara et al. [10] modeled depth-of-discharge effects, charge–discharge cycling, and calendar aging, and reported a 75% capacity reduction over the system lifetime. Alotaibi et al. [11] modeled depth-of-discharge relationships, lithium-ion battery state of health ending at 80% capacity, and self-discharge rates of 0.2% per day. Boucekara et al. [8] emphasized temperature effects and recommended battery operation at 25 °C to maintain derating factors. Studies that omit degradation can underestimate replacement costs and bias the design toward battery banks that do not maintain performance over 20–25 year system lifetimes.

Third, the combination of neural architecture search, uncertainty modeling, and battery degradation has not been investigated for Hafr Al-Batin desert camps or similar environments. Boucekara et al. [7,8] provided direct applications to Hafr Al-Batin desert camps, with cost of electricity values ranging from USD 0.1933 to 0.278 /kWh for interconnected microgrid configurations serving daily demands of 30.93–72.46 kWh [8]. However, that work used a multi-objective evolutionary algorithm based on dominance and decomposition (MOEA/DD) rather than neural optimization. The reported 42–50% cost reductions

from microgrid interconnection relative to standalone nanogrids [8] indicate substantial optimization potential, but the approach still relies on deterministic assumptions and simplified degradation representation. Desert-specific factors, including temperature extremes of 15–45 °C, dust effects on PV performance, and seasonal load variation, require an integrated optimization framework that can capture nonlinear environmental relationships.

These gaps motivate the present study: the development and validation of a multi-objective neural architecture search framework with stochastic uncertainty modeling and explicit battery degradation for hybrid nanogrid sizing in Hafr Al-Batin desert camping applications. Unlike conventional metaheuristics based on predefined search heuristics, neural architecture search can learn sizing policies from environmental and operational data and adapt to nonlinear system behavior. The proposed framework uses stochastic scenario generation to represent relationships among solar availability, temperature effects, load variation, and battery degradation. Its degradation model includes calendar aging, cycle aging, and temperature-dependent capacity fade, allowing lifecycle cost and battery sizing to be evaluated over extended desert operation.

A modified and improved version of MONAS has been proposed in this paper to increase the efficacy of the optimization process. The modification is made in the search strategy of the algorithm, rather than in the population initialization or the fitness evaluation functions, which were kept the same as in MONAS. In the original MONAS, GA-based operators are used during the first half of the iterations, while DE-based operators are used during the second half according to a fixed schedule. In contrast, the proposed IMONAS replaces this rigid mechanism with an adaptive selection process in which GA and DE are selected dynamically during the search according to updated probabilities. These probabilities are automatically adjusted based on the survival success of the offspring generated after environmental selection. In this way, IMONAS offers a better search strategy at different stages of the optimization process while maintaining an improved balance between exploration and exploitation.

In light of the above discussion, this research makes three contributions. First, it applies improved multi-objective neural architecture search (IMONAS) to hybrid renewable energy system sizing and extends the neural optimization evidence beyond the single RLNN study reported in [13]. Second, it models load uncertainty and battery degradation together and evaluates their effects through six scenarios [12,18,19]. Third, it provides a sizing framework calibrated for Hafr Al-Batin desert camps, using empirical load profiles, environmental data, and operational constraints that reflect Saudi Arabian desert tourism.

The remainder of this paper is organized as follows. Section 2 presents the system modeling framework, including PV generation, battery storage with degradation, diesel backup, battery bank sizing, and inverter sizing for desert camping applications. Section 3 formulates the multi-objective optimization problem, including the objective functions, constraints, and decision variables. Section 4 describes the Hafr Al-Batin case study, including geographic and climatic data, camping load profiles, component specifications, and converter architecture requirements. Section 5 presents the neural architecture search algorithm and the associated equations. Section 6 reports and discusses the optimization results for the six test cases. Section 7 concludes the paper.

2. Nanogrid System Components

Figure 1 shows the independent hybrid nanogrid considered in this study. The system consists of a PV system, a battery bank, an inverter, and a diesel generator supplying a desert camping tent load. The following subsections describe the sizing models used for these components [28].

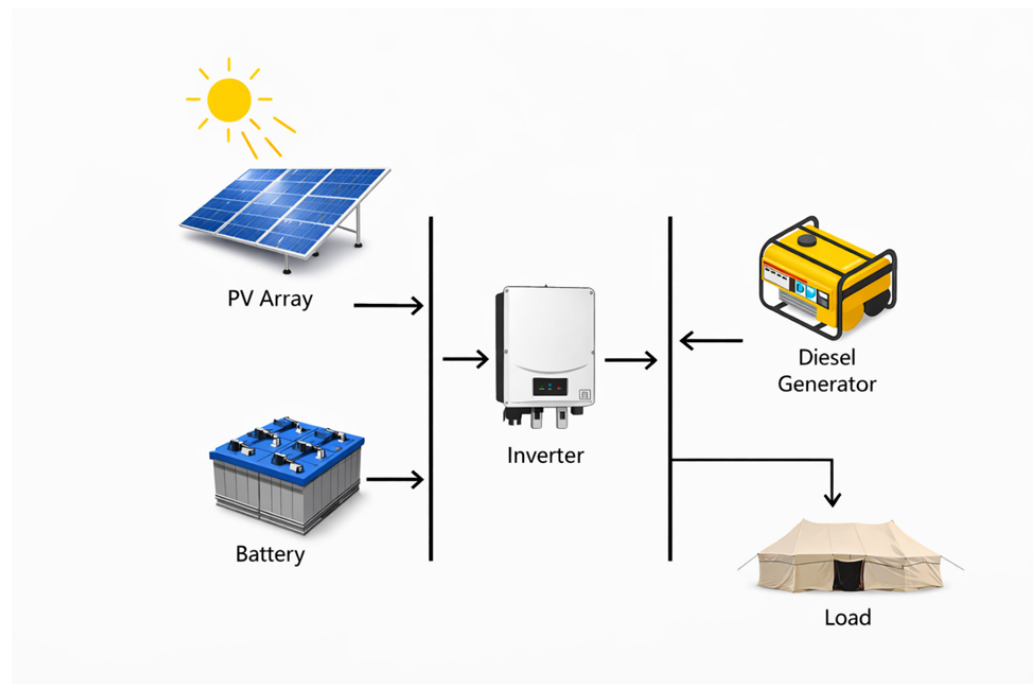


Figure 1. Independent hybrid nanogrid.

2.1. Photovoltaic System

The power output of the PV panel (P_{PV}) is calculated as [29,30]:

$$P_{PV} = P_n \times F / (F_{ref}) [1 + B_k ((T_a + (0.0256 \times F)) - T_{stc})], \quad (1)$$

where P_n denotes the rated PV power at standard test conditions (STCs), F is the solar radiation (W/m^2), F_{ref} is the reference irradiance, set to $1 \text{ kW}/m^2$, B_k is a constant equal to $-3.7 \times 10^{-3} (1/^\circ\text{C})$, and T_a is the ambient temperature. T_{stc} denotes the PV cell temperature under STC (25°C).

2.2. Diesel Generator

A diesel generator is the auxiliary energy source in the hybrid system and reduces the required storage capacity. It also improves supply reliability for remote loads. Because diesel generators operate inefficiently at low loading, they are mainly used during peak demand and battery depletion periods. The sizing procedure must therefore avoid light-load or no-load operation [31]. For the hybrid renewable system, diesel generator output must be estimated accurately. The fuel consumption of the diesel generator $F(t)$ is expressed as [32]:

$$F(t) = aP_{DG}(t) + bP_{DG}^{rated}, \quad (2)$$

where $P_{DG}(t)$ denotes generated power and P_{DG}^{rated} denotes rated power. The equation uses two fuel consumption coefficients, a and b , which are set to 0.246 and 0.08415, respectively, in this study [33]. The total diesel engine efficiency (η_{DE}) is calculated from the thermal brake efficiency of the diesel unit ($\eta_{temp,brake}$) and the generator efficiency ($\eta_{generator}$).

$$\eta_{DE} = \eta_{temp,brake} \times \eta_{generator}, \quad (3)$$

2.3. Battery Bank Sizing

The battery bank capacity and the required number of battery units must be determined for the hybrid renewable energy system. The following parameters directly affect battery sizing [7,34]:

1. Autonomy days (ADs) refer to the number of consecutive days the battery bank can sustain the required load without solar energy input.
2. The maximum usable capacity of the battery, referred to as the depth of discharge (DoD). A common practice is to configure the system to operate within 40–80% of the typical discharge range [35].
3. Ambient temperature directly affects battery capacity and lifetime. Elevated temperatures can increase available capacity while reducing battery life. Batteries are generally recommended to be maintained at 25 °C when the derating factor (K_T) is equal to one.

The battery bank capacity, measured in ampere-hours (Ah), is determined as follows:

$$B_{\text{req}} = \frac{L_d \cdot AD}{DoD \cdot K_T}, \quad (4)$$

where L_d represents the consumed ampere-hours in a single day (Ah/day).

The number of batteries required in parallel (N_p) is determined from the required battery bank capacity (B_{req}) and the capacity of the selected battery unit (B_u):

$$N_p = \frac{B_{\text{req}}}{B_u}, \quad (5)$$

The number of series-connected batteries (N_s) needed to achieve the required voltage is

$$N_s = \frac{V_{\text{sys}}}{V_b}, \quad (6)$$

where V_{sys} and V_b are the DC system voltage and battery voltage, respectively, measured in volts.

The product of N_p and N_s gives the total number of required batteries:

$$N_{\text{tot}} = N_p \cdot N_s, \quad (7)$$

The total battery bank cost (C_{Bank}) is calculated as the product of the unit battery cost (C_u) and the number of batteries:

$$C_{\text{Bank}} = N_{\text{tot}} \cdot C_u, \quad (8)$$

2.4. Inverter Sizing

One inverter can provide the required power supply for a compact hybrid system, while larger systems may require additional inverters. The number of inverters therefore needs to be determined during sizing [36]. For a standalone system, the required number of inverters (N_{inv}) is obtained from the ratio of maximum load power (P_L) to maximum inverter power (P_{inv}).

$$N_{\text{inv}} = \frac{P_L}{P_{\text{inv}}}, \quad (9)$$

For a grid-connected system, the ratio of the maximum hybrid-system output power (P_H) to P_{inv} is used to determine the required number of inverters ($N_{\text{inv}}^{\text{grid}}$), but this case is not addressed in this study.

$$N_{inv}^{grid} = \frac{P_H}{P_{inv}}, \quad (10)$$

2.5. Modeling Uncertainty in Microgrids

Uncertainty should be explicitly considered in optimization-based microgrid studies because several important variables are inherently non-deterministic in practice. These include load demand, renewable generation, electricity prices, generating-unit availability, consumer behavior, and islanding conditions. Since such factors cannot be represented adequately under purely deterministic assumptions, stochastic modeling is commonly used to provide a more realistic description of system behavior [37].

2.5.1. Stochastic and Deterministic Models

In a deterministic model, all input variables are assumed to be known. Therefore, for a given set of inputs, the model produces a unique and repeatable output. Although deterministic models are useful as baseline references, they may not accurately capture the actual operating conditions of microgrids, where several parameters fluctuate randomly over time [38].

In contrast, a stochastic model treats one or more inputs as random variables. Consequently, repeated runs of the model may produce different outputs even when the same general operating conditions are assumed. The collection of these outputs can then be interpreted statistically. Among the most widely used stochastic techniques, Monte Carlo simulation is particularly attractive because it generates multiple random realizations of uncertain inputs and evaluates the system repeatedly under these scenarios [39,40].

In this work, uncertainty is introduced into the load demand profile using a Monte Carlo-based perturbation mechanism [37]. Let the original load profile be denoted by

$$P_{\text{Load}}(t), \quad t = 1, 2, \dots, T, \quad (11)$$

where $P_{\text{Load}}(t)$ is the load demand at time step t , and T is the total number of time samples.

A set of N_u uncertain time instants is selected randomly from the interval $\{1, 2, \dots, T\}$, where N_u denotes the number of uncertainty events introduced into the load profile. Let this random set be represented by

$$\mathcal{T}_u = \{t_1, t_2, \dots, t_{N_u}\}. \quad (12)$$

In addition, let α denote the uncertainty level expressed in decimal form, where $\alpha \in [0, 1]$. For each selected instant $t_k \in \mathcal{T}_u$, a binary random variable b_k is generated such that

$$b_k \in \{0, 1\}. \quad (13)$$

If $b_k = 1$, the load is decreased by a fraction α , whereas if $b_k = 0$, the load is increased by the same fraction. Thus, the perturbed load profile $\tilde{P}_{\text{Load}}(t)$ is defined as

$$\tilde{P}_{\text{Load}}(t_k) = \begin{cases} P_{\text{Load}}(t_k)(1 - \alpha), & \text{if } b_k = 1, \\ P_{\text{Load}}(t_k)(1 + \alpha), & \text{if } b_k = 0. \end{cases} \quad (14)$$

Equivalently, (14) can be written in compact form as

$$\tilde{P}_{\text{Load}}(t_k) = P_{\text{Load}}(t_k)[1 + \alpha(1 - 2b_k)], \quad k = 1, 2, \dots, N_u. \quad (15)$$

For all time instants not selected in $\mathcal{T}_u$, the load remains unchanged, i.e.,

$$\tilde{P}_{\text{Load}}(t) = P_{\text{Load}}(t), \quad t \notin \mathcal{T}_u. \quad (16)$$

Accordingly, the uncertain load profile is obtained by randomly selecting a subset of time samples and perturbing each selected value upward or downward by a prescribed percentage. This procedure is repeated across Monte Carlo runs to generate multiple possible realizations of the load demand. These realizations are then used to assess the effect of load uncertainty on the sizing and performance of the microgrid.

The main advantage of this approach lies in its simplicity and computational efficiency. It enables uncertainty to be incorporated directly into the load model without requiring a more complex forecasting framework or a fully time-correlated stochastic process. Therefore, it provides a practical way to evaluate the robustness of the proposed design under uncertain demand conditions.

2.5.2. Battery Degradation

Battery replacement during the project lifetime is undesirable due to its economic impact and its influence on system operation. Therefore, battery degradation should be explicitly considered in storage sizing studies to obtain more realistic planning results. The main factors affecting battery degradation include the depth of discharge (DoD), the allowable number of charge/discharge cycles, and the calendar lifetime of the battery energy storage system [41].

In [42], a mixed-integer programming (MIP) approach was employed to determine the optimal battery size and DoD for a standalone microgrid. A probabilistic mixed-integer linear programming (MILP) model incorporating battery degradation in the energy-cost minimization problem was presented in [43] for the integration of renewable energy sources and storage systems in fast-charging stations. In [44], an enhanced MILP-based framework considering both service life and capacity degradation was proposed to determine the battery size, DoD, and replacement year.

In this work, battery degradation is modeled through a time-dependent degradation factor that progressively reduces the effective battery capacity over the planning horizon. When degradation is considered, the degradation factor is defined as

$$\gamma(t) = 1 + \frac{0.75 - 1}{7 \times \text{Number_Week} \times 24} t, \quad (17)$$

where t denotes time in hours. According to (17), the battery capacity decreases linearly from its nominal value at the beginning of operation to 75% of its initial value at the end of the considered horizon. When degradation is neglected, the degradation factor is simply taken as

$$\gamma(t) = 1. \quad (18)$$

The degradation factor is directly incorporated into the battery charging and discharging constraints. Accordingly, the maximum admissible charging energy and discharging energy at time step t are changed based on the degradation value.

Therefore, the degradation progressively shrinks the feasible operating range of the battery over time by reducing the effective usable capacity. Consequently, the long-term contribution of the storage system becomes more limited, which leads to a more realistic representation of the battery behavior within the optimization framework. This assumption should be interpreted as a linear degradation to 75% of the initial battery capacity at the end of the horizon, rather than as a generic degradation model. The cycle aging, calendar aging, or temperature-dependent effects are not calculated separately in this modeling

rather it adopts a simplified linear capacity-based representation to capture the long-term impact of battery degradation in a computationally efficient manner.

3. Problem Formulation

3.1. Multi-Objective Optimization Formulation

The nanogrid model and the multi-objective optimization problem are formulated as follows [7,16]:

$$\min_{\mathbf{x}} F(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x})], \quad (19)$$

$$\text{s.t. } h(\mathbf{x}) = 0, \quad (20)$$

$$g(\mathbf{x}) \leq 0. \quad (21)$$

where $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ represent the cost of electricity (COE) and loss of power supply probability (LPSP), respectively. Vector $\mathbf{x}$ contains the design variables. The function $h(\mathbf{x})$ represents the equality constraints, whereas $g(\mathbf{x})$ represents the inequality constraints.

The objective is to find a diverse set of non-dominated solutions (i.e., vectors $\mathbf{x}$) that minimize the objectives while satisfying the constraints.

3.2. Objective Functions

3.2.1. Cost Analysis

The cost-effectiveness of a hybrid renewable energy system can be assessed with several metrics. This study uses COE, which represents the cost per unit of supplied energy. COE is calculated as [45]:

$$COE = CRF \times \frac{NPC_{total}}{\sum_{h=1}^{8760} P_{load}}, \quad (22)$$

The capital recovery factor (CRF) accounts for the interest rate (i) and the system lifetime. The net present cost (NPC_{total}) includes capital investment, maintenance, operating, and replacement costs over the project lifetime. P_{load} is the hourly consumed power. For a PV panel and system lifetime of m , CRF is calculated as

$$CRF = \frac{i(1+i)^m}{(1+i)^m - 1}, \quad (23)$$

3.2.2. Reliability Analysis

Uncertainty must be considered when designing a renewable energy system. If renewable resources are lower than expected, or if technical problems occur, the system may fail to meet demand. The loss of power supply probability (LPSP) measures this condition and is computed as [46]:

$$LPSP = \sum_{t=1}^{8760} \frac{\text{Time}(P_a(t) - P_{load}(t))}{8760} \times 100, \quad (24)$$

where $P_a(t)$ and $P_{load}(t)$ are the available and required power at time t , respectively.

3.3. Design Variables

The number of PV panels (nPV), diesel generators (nDG), and autonomy days (nAD) are design variables because they directly affect system performance. To give the designer/operator more options beyond these usual sizing variables, the developed program also considers commercially available PV panel, battery, and inverter models. The program uses model data as input and selects the component models during optimization. This

allows the designer/operator to choose components based on cost and reliability despite the large number of available market options.

Therefore, the vector of design variables is as follows:

$$\mathbf{x} = [n_{PV}, n_{DG}, n_{AD}, m_{PV}, m_{battery}, m_{inverter}], \quad (25)$$

The variables m_{PV} , $m_{battery}$, and $m_{inverter}$ represent the PV, battery, and inverter models, respectively.

3.4. Constraints

The optimization formulation includes battery capacity constraints, defined as follows:

$$E_{min} \leq E_{Battery}^i \leq E_{max}, \quad (26)$$

$$E_{min} = (1 - DoD) C_{Battery}, \quad (27)$$

where $E_{Battery}^i$ is the stored battery energy at the i th hour. E_{min} and E_{max} are the minimum and maximum battery energy storage capacities, respectively. The formulation also includes the depth of discharge, denoted as DoD, to prevent over-discharge (80% in this work).

4. Case Study and Data Description

The Arabian Peninsula has abundant solar resources, and several Gulf nations have sought to use this resource for power generation [47]. Saudi Arabia, however, still relies heavily on fossil fuels for electricity supply [48]. Previous studies using Saudi Arabian data have examined the techno-economic feasibility of renewable energy integration [49] and sustainability indicators related to economics, environment, technology, energy, and society. Figure 2 shows global horizontal solar irradiation for Saudi Arabia.

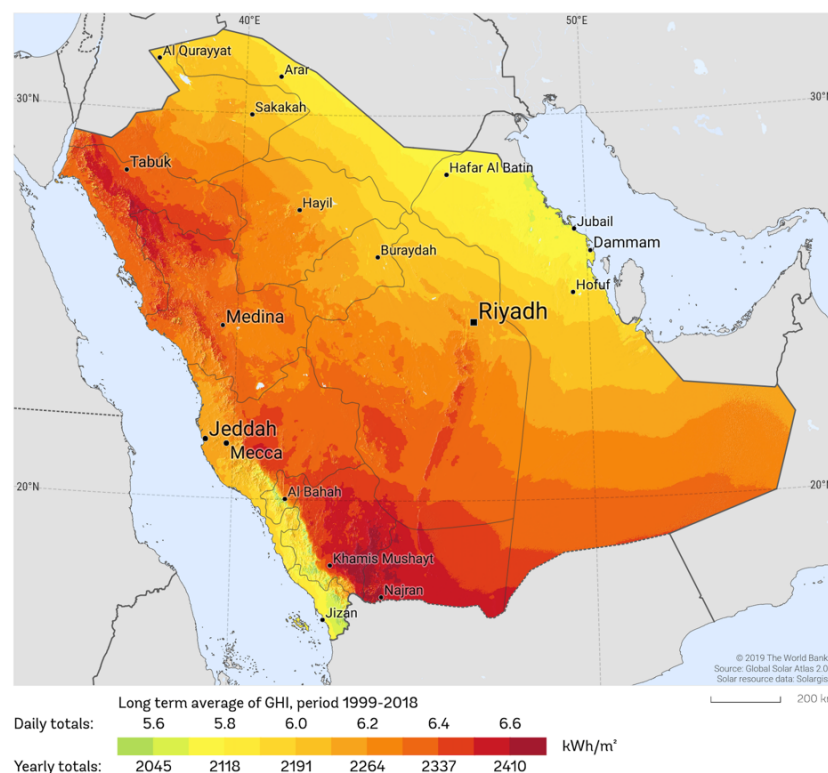


Figure 2. Global horizontal irradiation in Saudi Arabia.

The average daily total horizontal irradiation in Hafr Al-Batin, a city in Saudi Arabia's Eastern Province, is approximately 5.8 kWh/m². The city is known for winter desert camps that are commonly powered by diesel generators, which contribute to local emissions. The hourly solar irradiation for Hafr Al-Batin is shown in Figure 3.

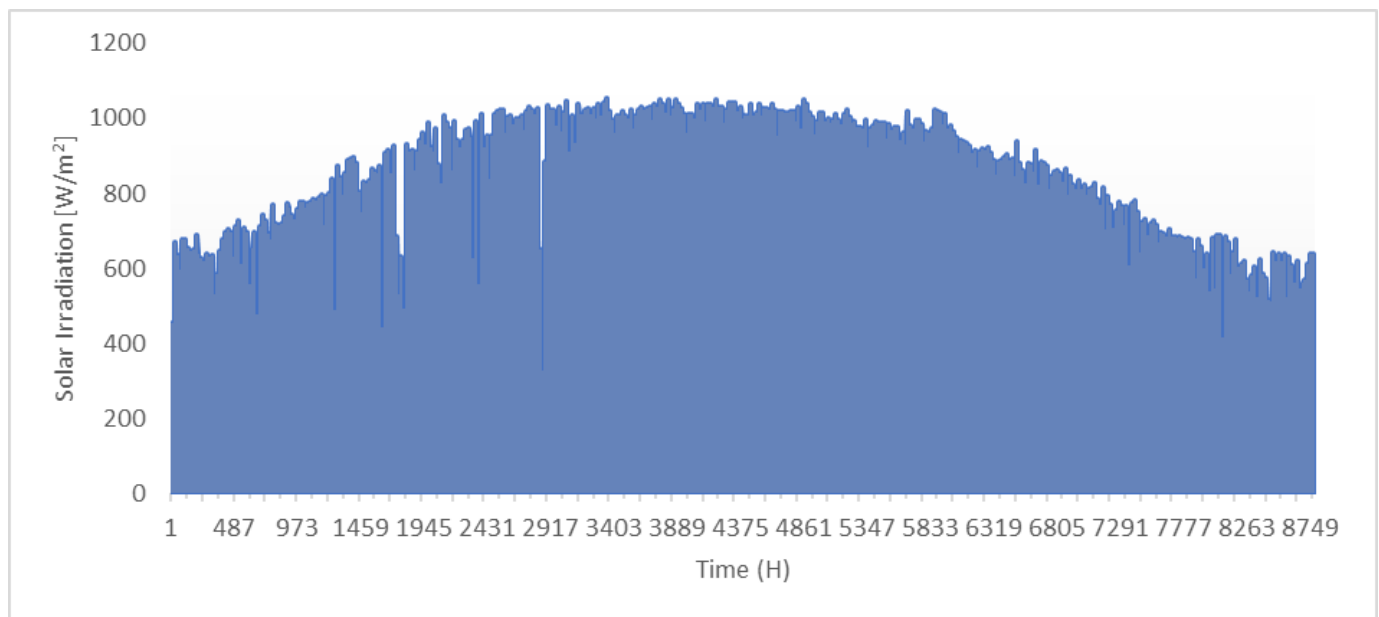


Figure 3. Hourly solar irradiation for Hafr Al-Batin city.

A typical desert camp used for short family stays consists of three living tents, two toilets, one watchman room, and fencing. Table 2 presents the electrical load calculation for a representative camp, and the load details were verified through a visit to a camp in the study area. The average daily energy requirements for weekdays and weekends are 27.06 kWh and 72.63 kWh, respectively. Weekday peak demand is 2.83 kW, whereas weekend peak demand is 4.45 kW. On weekdays, the camp is usually empty between 7:00 a.m. and 4:00 p.m. when residents go to town for work and other daily activities. Figure 4 depicts a typical desert camp, whereas Figures 5 and 6 show the weekday and weekend load profiles, respectively.

Table 2. Appliance load profile for weekday and weekend usage.

Appliance	Load (kW)	Quantity	Hours/Weekday	Hours/Weekend
Toaster	0.16	1	0	1
Ceiling fans	0.45	3	2	13
Cellular Charger	0.026	3	3	4
Laptop computer	0.101	2	2	10
TV Flat screen LCD 46	0.045	2	7	9
Tent light	0.04	12	13	13
Fence lights Type 1	0.04	10	11	11
Fence lights Type 2	0.01	20	10	10
Fence lights Type 3	0.025	10	10	10
Air conditioner	1.129	1	7	10
Refrigerator	0.065	3	16	15
Vacuum Cleaner	0.8	1	1	1



Figure 4. An example of a desert camp tent in Hafr Al-Batin city.

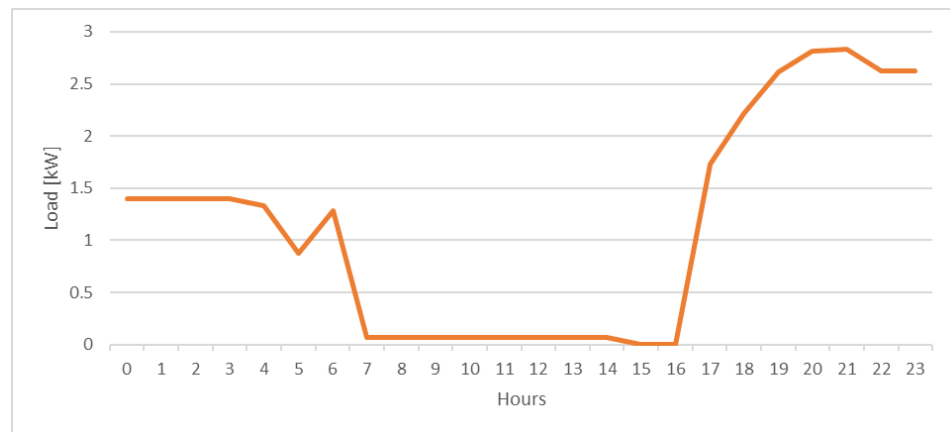


Figure 5. Load profile for a weekday [10].

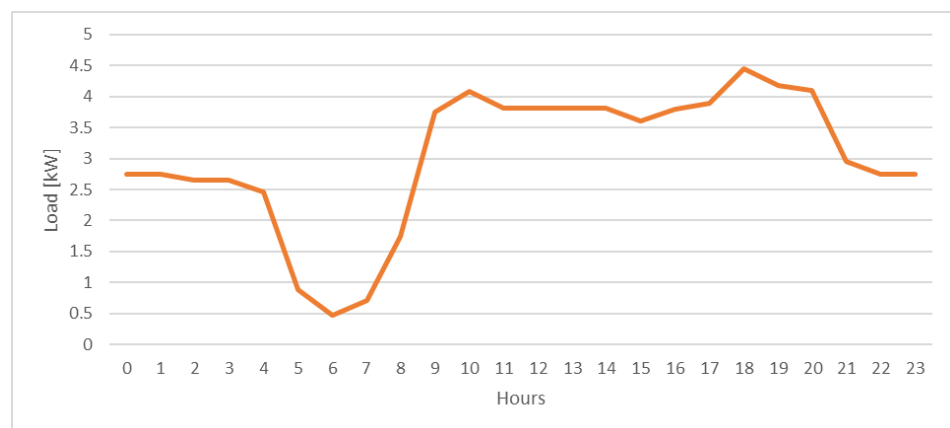


Figure 6. Load profile for a weekend day [10].

5. Problem—Solution Approach

The adopted multi-objective neural architecture search (MONAS) framework is a coevolutionary optimization strategy designed for multi-objective neural architecture search problems (MONASPs) [27]. In this work, the original MONAS is first adopted as the baseline framework, and then an improved version, referred to as IMONAS, is developed to enhance the balance between exploration and exploitation. The algorithms, MONAS and its improved version, are not ANN-based training methods and are not used here to search

for neural network architectures in the conventional deep-learning sense. Rather, they are optimization frameworks inspired by the neural architecture search concept, but they can also be employed as general multi-objective optimization algorithms.

This section summarizes the main principles of the original MONAS framework and then highlights the modifications introduced in IMONAS. The complete details of the original MONAS can be found in [27].

5.1. Multi-Objective Neural Architecture Search (MONAS) Framework

The overall MONAS framework is illustrated in Figure 7. The algorithm starts by randomly initializing two populations: the main population $\mathcal{P}_1$ and the auxiliary population $\mathcal{P}_2$. The main population is evaluated in the objective space using the adopted multi-objective evolutionary algorithm (MOEA), whereas the auxiliary population is guided by a fitness measure that promotes diversity in the decision space. In this work, the fitness assigned to solutions in $\mathcal{P}_2$ is expressed as

$$F_x = C_x + D_x, \quad (28)$$

where C_x denotes the convergence term and D_x denotes the decision-space diversity term.

The convergence term is computed as

$$C_x = \sum_{y \in \mathcal{P}, y \neq x} r(x, y), \quad (29)$$

where

$$r(x, y) = \begin{cases} 1, & \text{if } y \prec x, \\ 0, & \text{otherwise,} \end{cases} \quad (30)$$

and $y \prec x$ means that solution y dominates solution x . The diversity term is defined by

$$D_x = \frac{1}{\text{dist}(x, x') + 2}, \quad (31)$$

where $\text{dist}(x, x')$ is the Euclidean distance between solution x and its k -th nearest neighbor in the decision space.

After evaluation, mating selection is independently carried out for both populations. The mating pool of $\mathcal{P}_1$ is generated according to the selection mechanism of the adopted MOEA, while the mating pool of $\mathcal{P}_2$ is determined by emphasizing decision-space diversity so as to encourage the discovery of multiple equivalent Pareto-optimal sets.

In the original MONAS, offspring generation follows a two-stage mechanism. During the first half of the search process, i.e., when $g < G_{\max}/2$, genetic algorithm (GA)-based variation operators are employed to improve convergence and facilitate broad recombination among solutions. In this stage, offspring are generated using simulated binary crossover (SBX) for real-valued variables and uniform crossover (UC) for binary and integer components, as expressed by

$$(x', y') = \left\{ \text{SBX}(x^{rl}, y^{rl}), \text{UC}(x^{bi}, y^{bi}), \text{UC}(x^{int}, y^{int}) \right\}. \quad (32)$$

During the second half of the search process, differential evolution (DE)-based variation is used to strengthen exploration and capture dependencies among decision variables. For a parent solution p_i and two selected vectors x_i and y_i , the offspring is generated as

$$o_i = p_i + F \cdot (x_i - y_i), \quad (33)$$

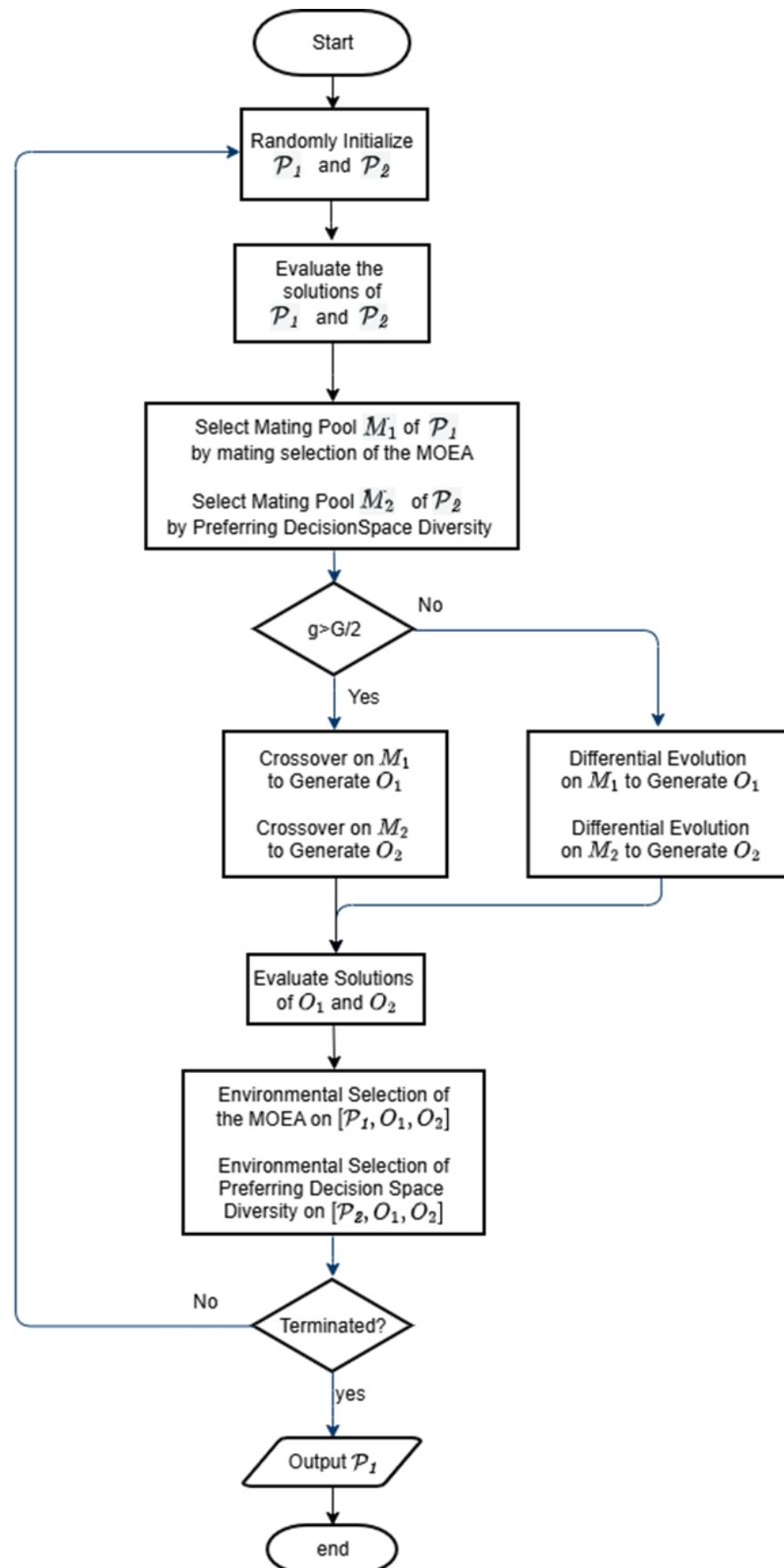


Figure 7. Flowchart of the MONAS framework.

where F is the DE scaling factor. Once the offspring populations are created, environmental selection is performed. The offspring sets generated from $\mathcal{P}_1$ and $\mathcal{P}_2$ are merged with their corresponding parent populations. The next generation of $\mathcal{P}_1$ is selected according to the environmental selection mechanism of the adopted MOEA in the objective space, while the next generation of $\mathcal{P}_2$ is selected using a diversity-oriented strategy in the decision space. Under this strategy, solutions satisfying $F_i \leq 1$ are selected first. If the number of selected solutions exceeds the population size N , truncation is applied by iteratively removing the solution with the smallest diversity contribution:

$$x = \arg \min_{x \in \mathcal{P}_2} D(x). \quad (34)$$

The evolutionary process continues until the stopping condition is satisfied. The final output of the algorithm is obtained from the main population $\mathcal{P}_1$. Therefore, the original MONAS relies on three principal features: (i) a coevolutionary structure that separates convergence and diversity preservation, (ii) a two-stage search process based on GA followed by DE, and (iii) a decision-space diversity maintenance mechanism that supports the identification of multiple equivalent Pareto-optimal solutions.

5.2. Improved MONAS (IMONAS)

Although the original MONAS provides a useful balance between convergence and diversity, its search strategy transition is fixed: GA is always used in the first half of the iterations, while DE is always used in the second half. This rigid schedule may not be optimal for all optimization stages or problem instances. To overcome this limitation, an improved variant, called IMONAS, is proposed in this work.

The overall IMONAS framework is illustrated in Figure 8. The main difference between IMONAS and MONAS is that IMONAS replaces the fixed two-stage search schedule with an adaptive strategy selection mechanism. Instead of forcing the algorithm to use GA during the first half and DE during the second half, IMONAS selects either GA or DE at each iteration according to adaptive probabilities p_{GA} and p_{DE} , with

$$p_{GA} + p_{DE} = 1. \quad (35)$$

At the beginning of the search, both strategies are given equal probability, i.e.,

$$p_{GA} = p_{DE} = 0.5. \quad (36)$$

To evaluate the usefulness of each search strategy, IMONAS monitors the survival of offspring after environmental selection. More specifically, after offspring are generated using either GA or DE, the algorithm counts how many offspring survive into the next generation in both $\mathcal{P}_1$ and $\mathcal{P}_2$. This survival count is used as a measure of the success of the selected strategy. The cumulative success scores of GA and DE are recorded over a learning period.

After every predefined learning window, the average success of each strategy is computed, and the probability of selecting GA is updated according to the relative performance of the two strategies. To avoid abrupt probability fluctuations, a smoothing update is used, and a minimum probability threshold is also enforced so that neither strategy is completely discarded during the search. In this manner, IMONAS maintains the participation of both GA and DE while gradually favoring the more effective one for the current search state.

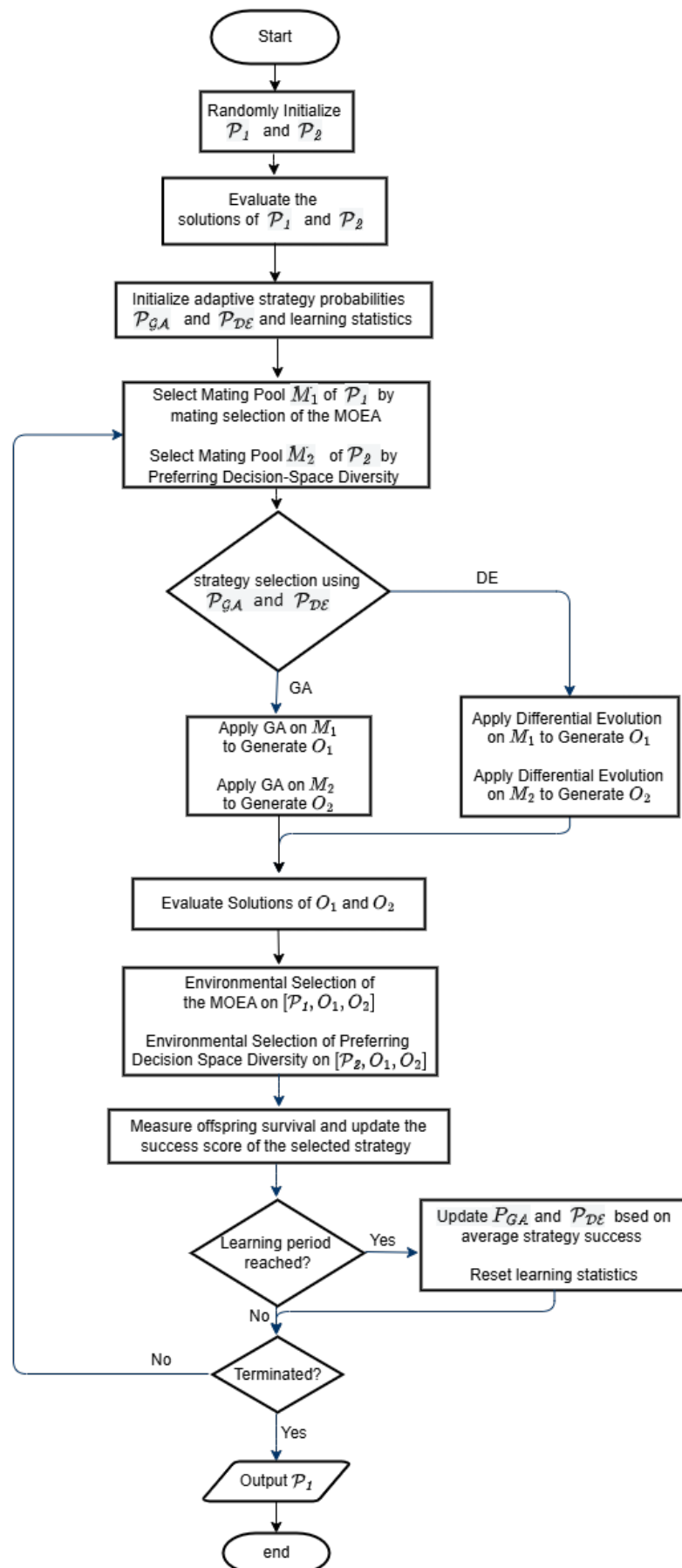


Figure 8. Flowchart of the IMONAS framework.

It should be noted that IMONAS preserves the main coevolutionary structure of MONAS. The two-population architecture, the objective-space and decision-space fitness assignment, and the environmental selection mechanisms remain unchanged. Therefore, the improvement introduced in IMONAS is specifically related to the offspring generation stage, where the search becomes adaptive rather than predetermined.

In summary, the proposed IMONAS improves MONAS by introducing an online learning mechanism for search operator selection. This modification allows the algorithm to dynamically adjust the use of GA and DE according to their observed contribution to population improvement. As a result, IMONAS is expected to provide a better balance between exploration and exploitation, enhance search flexibility, and improve robustness across different optimization cases.

6. Application, Results, and Discussion

This paper investigates the six cases listed in Table 3. The detailed characteristics of the PV panel, battery, and inverter models used in this study are listed in Tables A1–A3 respectively. The proposed IMONAS approach was evaluated against the original MONAS and several comparison algorithms using a population size of 100 particles and 200 iterations. These parameter settings were determined based on preliminary experimental tests. These values were found to provide a good balance between convergence performance, diversity preservation along the Pareto front, and computational efficiency. This is particularly important in the present multi-objective optimization problem, where the objective is not only to approach the Pareto front but also to obtain a well-distributed set of non-dominated solutions. Smaller population sizes or fewer iterations were found to reduce the quality of the Pareto front approximation, whereas larger values increased the computational cost without significant improvement.

Table 3. Summary of the investigated cases.

Case	Description
Case 1	Without uncertainty; without degradation
Case 2	10% load uncertainty for 1000 h/year; without degradation
Case 3	10% load uncertainty for 2000 h/year; without degradation
Case 4	Without uncertainty; with degradation
Case 5	Same uncertainty as Case 2; with degradation
Case 6	Same uncertainty as Case 3; with degradation

Furthermore, to assess the proposed IMONAS algorithm, its performance was compared with the original MONAS and several established multi-objective optimization algorithms: speed constrained multi-objective particle swarm optimization (SMPSO), novel modified particle swarm optimization (NMPSO), multi-objective particle swarm optimization with disturbance operation (MPSOD), multi-objective evolutionary algorithm based on decomposition (MOEAD), and reference vector guided evolutionary algorithm (RVEA). The internal parameters of each algorithm are given in Table 4.

The design variables are bounded as follows:

$$N_{PV} \in [2, 100], \quad (37)$$

$$N_{DG} \in [1, 10], \quad (38)$$

$$AD \in [1, 2], \quad (39)$$

$$PVModel \in [1, 13], \quad (40)$$

$$BatteryModel \in [1, 27], \quad (41)$$

$$InverterModel \in [1, 8]. \quad (42)$$

Table 4. Main internal parameter settings of the compared optimization algorithms.

Algorithm	Parameter	Definition	Value
MONAS	Number of populations	Main and auxiliary populations	2
	Switching point	Transition from GA to DE	$G_{\max}/2$
	Tournament size	Number of candidates in tournament selection	2
	Selection threshold	Environmental selection threshold	1
	GA crossover probability	Probability of crossover	1
	GA crossover index	SBX distribution index	20
	GA mutation factor	Mutation probability factor	1
	GA mutation index	Polynomial mutation index	20
	DE crossover rate	Differential evolution crossover rate	1
	DE scaling factor	Differential evolution scaling factor	0.5
	DE mutation factor	Mutation probability factor after DE	1
	DE mutation index	Polynomial mutation index after DE	20
IMONAS	Number of populations	Main and auxiliary populations	2
	Tournament size	Number of candidates in tournament selection	2
	Selection threshold	Environmental selection threshold	1
	Initial GA probability	Initial probability of selecting GA	0.5
	Initial DE probability	Initial probability of selecting DE	0.5
	GA success score	Accumulated success score of GA	0
	DE success score	Accumulated success score of DE	0
	GA usage count	Number of GA uses in a learning window	0
	DE usage count	Number of DE uses in a learning window	0
	Learning period	Frequency of probability update	10
	Safety constant	Small numerical safety constant	10^{-6}
	Smoothing factor	Smoothing factor in adaptive update	0.8
	Minimum probability	Minimum allowed probability for a strategy	0.1
	GA crossover probability	Probability of crossover	1
	GA crossover index	SBX distribution index	20
	GA mutation factor	Mutation probability factor	1
	GA mutation index	Polynomial mutation index	20
	DE crossover rate	Differential evolution crossover rate	1
	DE scaling factor	Differential evolution scaling factor	0.5
	DE mutation factor	Mutation probability factor after DE	1
	DE mutation index	Polynomial mutation index after DE	20
SMPSO	Tournament size	Number of candidates in tournament selection	2
	Inertia weight	Particle inertia weight	Random in $[0.1, 0.5]$
	Random coefficient 1	First random vector in velocity update	Random in $[0, 1]$
	Random coefficient 2	Second random vector in velocity update	Random in $[0, 1]$
	Acceleration coefficient 1	Cognitive learning coefficient	Random in $[1.5, 2.5]$
	Acceleration coefficient 2	Social learning coefficient	Random in $[1.5, 2.5]$
	Constriction parameter	Constriction-related parameter	$\max(4, C_1 + C_2)$
	Velocity limit	Maximum absolute velocity	$(UB - LB)/2$
	Mutation index	Polynomial mutation distribution index	5
	Mutation probability 1	Probability of activating mutation for a particle	0.15
	Mutation probability 2	Probability of mutating each variable	$1/D$
	Velocity damping factor	Factor applied after boundary violation	0.001
NMPSO	Inertia weight	Particle inertia weight	Random in $[0.1, 0.5]$
	Random coefficient 1	First random vector in velocity update	Random in $[0, 1]$
	Random coefficient 2	Second random vector in velocity update	Random in $[0, 1]$
	Random coefficient 3	Third random vector in velocity update	Random in $[0, 1]$
	Acceleration coefficient 1	Cognitive learning coefficient	Random in $[1.5, 2.5]$
	Acceleration coefficient 2	Social learning coefficient	Random in $[1.5, 2.5]$
	Acceleration coefficient 3	Additional guiding coefficient	Random in $[1.5, 2.5]$
	Personal best	Best position found by each particle	Dominance-based update
	Archive size	Maximum number of stored non-dominated solutions	N
	GA crossover probability	Crossover probability in GAhalf	1
	GA crossover index	SBX distribution index in GAhalf	10
	GA mutation factor	Mutation probability factor in GAhalf	1
	GA mutation index	Polynomial mutation distribution index in GAhalf	10

Table 4. Cont.

Algorithm	Parameter	Definition	Value
NMPSO	Elite guide range	Archive fraction used to guide particles	$\lceil N/10 \rceil$
	Archive recombination range	Archive fraction used in GAhalf	$\lceil N/2 \rceil$
MPSOD	Neighborhood size	Number of neighboring subproblems	$\lceil N/10 \rceil$
	Tournament size	Number of candidates in tournament selection	2
	Neighborhood selection probability	Probability of selecting pbest from neighbors	0.9
	Global selection probability	Probability of selecting pbest from whole population	0.1
	PSO coefficient 1	Cognitive acceleration coefficient	2
	PSO coefficient 2	Social acceleration coefficient	2
	DE crossover rate	Differential evolution crossover rate	0.5
	DE scaling factor	Differential evolution scaling factor	0.5
	Mutation factor	Mutation probability factor	1
	Mutation index	Polynomial mutation distribution index	20
	PSO application probability	Probability of applying PSO update to a variable	0.5
	Random coefficient 1	First random vector in PSO update	Random in $[0, 1]$
	Random coefficient 2	Second random vector in PSO update	Random in $[0, 1]$
	Initial population size	Number of random solutions before classification	2N
MOEA/D	Neighborhood size	Number of neighboring subproblems	$\lceil N/10 \rceil$
	Number of parents	Number of parents used in variation	2
	Crossover probability	Probability of applying SBX crossover	1
	Crossover index	SBX distribution index	20
	Mutation factor	Mutation probability factor	1
	Mutation index	Polynomial mutation distribution index	20
RVEA	PBI penalty parameter	Penalty coefficient in PBI aggregation	5
	Penalty exponent	Controls the rate of change in the APD penalty	2
	Adaptation frequency	Frequency of reference vector adaptation	0.1
	Crossover probability	Probability of applying SBX crossover	1
	Crossover index	SBX distribution index	20
	Mutation factor	Mutation probability factor	1
	Mutation index	Polynomial mutation distribution index	20

Table 3 summarizes the investigated cases. Case 1 is the baseline case without uncertainty or degradation. Case 2 includes 10% load uncertainty for 1000 h/year, while Case 3 applies the same load uncertainty for 2000 h/year. Cases 4–6 correspond to Cases 1–3, respectively, but include battery degradation. The choice of 1000 h/year and 2000 h/year was intended to represent two levels of uncertainty severity, while the 10% deviation was adopted as a bounded fluctuation around the nominal demand profile. This uncertainty representation is a simplified Monte Carlo distribution model chosen for computational efficiency and robustness analysis, rather than a fully correlated probabilistic forecasting model.

6.1. Results and Discussion

For all cases, the objective functions (LPSP and COE) are plotted using identical axis limits. This provides a consistent visual basis for comparing the Pareto fronts (PFs) obtained under different uncertainty and degradation assumptions.

6.1.1. Case 1

Figure 9 shows the solutions obtained for Case 1 using the proposed IMONAS approach. IMONAS identified 69 non-dominated solutions, whose objective vectors form the PF. The plotted solutions lie approximately between (COE = \$0.1819/kWh, LPSP = 0.4299%) and (COE = \$0.3074/kWh, LPSP = 0.3783%). The front spans a clear cost–reliability trade-off instead of concentrating the candidate designs in a narrow region.

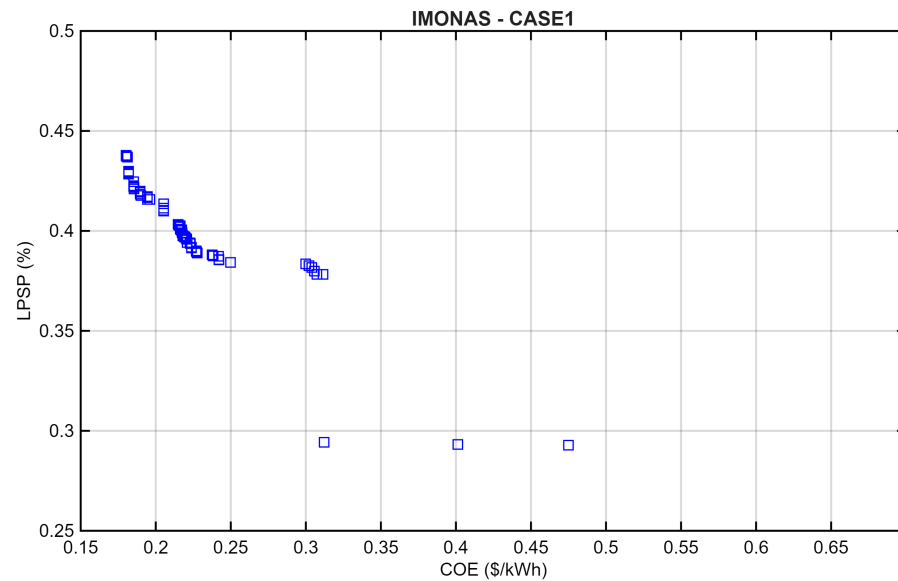


Figure 9. PF obtained for Case 1 using the proposed IMONAS approach.

For convenience, only 20 selected solutions from the obtained PF are reported in Table 5, sorted in ascending order of COE. Solution #1 includes 16 PV panels, one diesel generator, and a battery autonomy of 1.026 days, which is approximately 24 h and 37 min. The selected component models are PV model #1, battery model #16, and inverter model #3. This solution yields $\text{COE} = \text{USD } 0.1819 / \text{kWh}$ and $\text{LPSP} = 0.4299\%$, making it the most economical solution among the listed ones, although with a relatively higher LPSP.

Table 5. Selected solutions from the PF for Case 1 using the proposed IMONAS approach.

Solution	NPV	NDG	AD (Days)	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	16	1	1.026	1	16	3	0.1819	0.4299
2	16	1	1.025	1	16	3	0.1819	0.4290
3	16	1	1.025	1	16	3	0.1819	0.4283
4	18	1	1.000	1	16	3	0.1895	0.4198
5	19	1	1.000	1	16	3	0.1943	0.4168
6	19	1	1.004	1	16	3	0.1945	0.4158
7	19	1	1.023	1	16	2	0.1961	0.4157
8	17	1	1.370	1	16	3	0.2053	0.4104
9	22	1	1.313	1	18	3	0.2164	0.4019
10	23	1	1.315	1	18	3	0.2183	0.3974
11	23	1	1.295	1	18	3	0.2191	0.3971
12	24	1	1.269	1	18	2	0.2231	0.3937
13	25	1	1.314	1	18	3	0.2237	0.3919
14	25	1	1.305	1	18	3	0.2239	0.3915
15	29	1	1.315	1	18	2	0.2384	0.3874
16	32	1	1.314	1	18	2	0.2499	0.3843
17	46	1	1.000	1	18	3	0.2998	0.3835
18	47	1	1.014	1	18	3	0.3020	0.3826
19	48	1	1.009	1	18	3	0.3057	0.3798
20	49	1	1.045	1	18	2	0.3074	0.3783

A second representative design is Solution #8, which uses 17 PV panels, one diesel generator, and an autonomy of about 33 h, with PV model #1, battery model #16, and inverter model #3. This configuration gives $\text{LPSP} = 0.4104\%$ and $\text{COE} = \text{USD } 0.2053 / \text{kWh}$.

Solution #15 consists of 29 PV panels, one diesel generator, and a battery autonomy of approximately 31.5 h, with PV model #1, battery model #18, and inverter model #2. This solution provides $\text{LPSP} = 0.3874\%$ and $\text{COE} = \text{USD } 0.2384 / \text{kWh}$.

At the high-investment end of the PF, Solution #20 uses 49 PV panels, one diesel generator, battery autonomy of approximately 25 h, PV model #1, battery model #18, and inverter model #2. This configuration achieves the lowest LPSP among the obtained solutions, 0.3783%, but also has the highest COE, USD 0.3074/kWh. The result illustrates the expected trade-off: improved reliability requires a more expensive system configuration.

6.1.2. Case 2

Figure 10 plots the PF obtained for Case 2 using IMONAS. The algorithm generated 56 non-dominated solutions. For clarity, Table 6 lists 20 representative solutions, which capture the cost–reliability trade-off across the front.

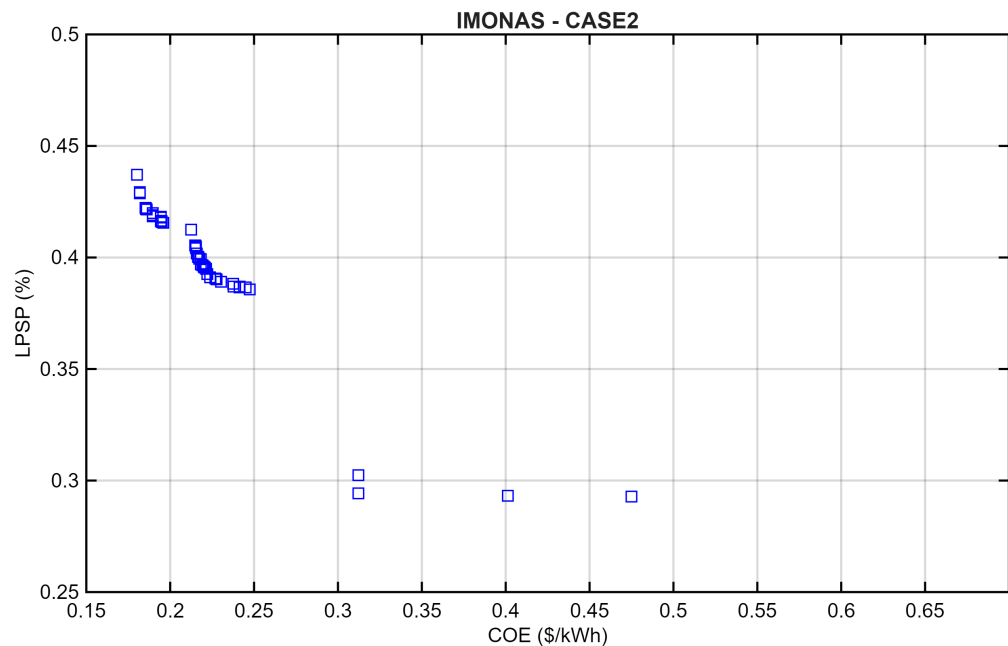


Figure 10. PF obtained for Case 2 using the proposed IMONAS approach.

Table 6. Selected solutions from the PF for Case 2 using the proposed IMONAS approach.

Solution	NPV	NDG	AD	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	16	1	1.025	1	16	3	0.1819	0.4292
2	16	1	1.024	1	16	3	0.1819	0.4291
3	17	1	1.020	1	16	3	0.1854	0.4220
4	17	1	1.018	1	16	2	0.1861	0.4216
5	18	1	1.000	1	16	3	0.1895	0.4200
6	19	1	1.000	1	16	3	0.1943	0.4165
7	19	1	1.000	1	16	3	0.1943	0.4163
8	19	1	1.007	1	16	3	0.1946	0.4163
9	19	1	1.011	1	16	3	0.1948	0.4162
10	21	1	1.306	1	18	3	0.2152	0.4053
11	21	1	1.306	1	18	3	0.2153	0.4052
12	21	1	1.305	1	18	3	0.2153	0.4046
13	22	1	1.307	1	18	3	0.2166	0.4004
14	23	1	1.315	1	18	3	0.2183	0.3992
15	23	1	1.281	1	18	3	0.2199	0.3961
16	24	1	1.316	1	18	3	0.2207	0.3955
17	23	1	1.265	1	18	2	0.2214	0.3950
18	26	1	1.218	1	18	3	0.2304	0.3892
19	29	1	1.319	1	18	3	0.2474	0.3856
20	2	2	1.008	7	18	3	0.3121	0.3023

In this case, Solution #1 includes 16 PV panels, one diesel generator, and battery autonomy of 1.025 days (approximately 24 h and 36 min), with PV model #1, battery model #16, and inverter

model #3. It provides $COE = USD\ 0.1819/kWh$ and $LPSP = 0.4292\%$, making it the least-cost configuration in the reported solution set.

A second representative option is Solution #10, which uses 21 PV panels, one diesel generator, and autonomy of approximately 31.5 h, with PV model #1, battery model #18, and inverter model #3. This solution achieves $LPSP = 0.4053\%$ and $COE = USD\ 0.2152/kWh$.

Solution #18 uses 26 PV panels and one diesel generator, with an autonomy of about 29 h. The selected models are PV model #1, battery model #18, and inverter model #3. This solution yields $COE = USD\ 0.2304/kWh$ and $LPSP = 0.3892\%$.

Solution #20 differs structurally from most other solutions: it includes only two PV panels and two diesel generators, with battery autonomy of roughly 24 h, PV model #7, battery model #18, and inverter model #3. This solution achieves $COE = USD\ 0.3121/kWh$ and a much lower $LPSP = 0.3023\%$.

6.1.3. Case 3

Figure 11 shows the solutions obtained for Case 3. IMONAS generated 74 non-dominated solutions, the largest number among the six cases, giving a wider design space and a richer set of trade-offs. As in the other cases, Table 7 reports 20 representative solutions.

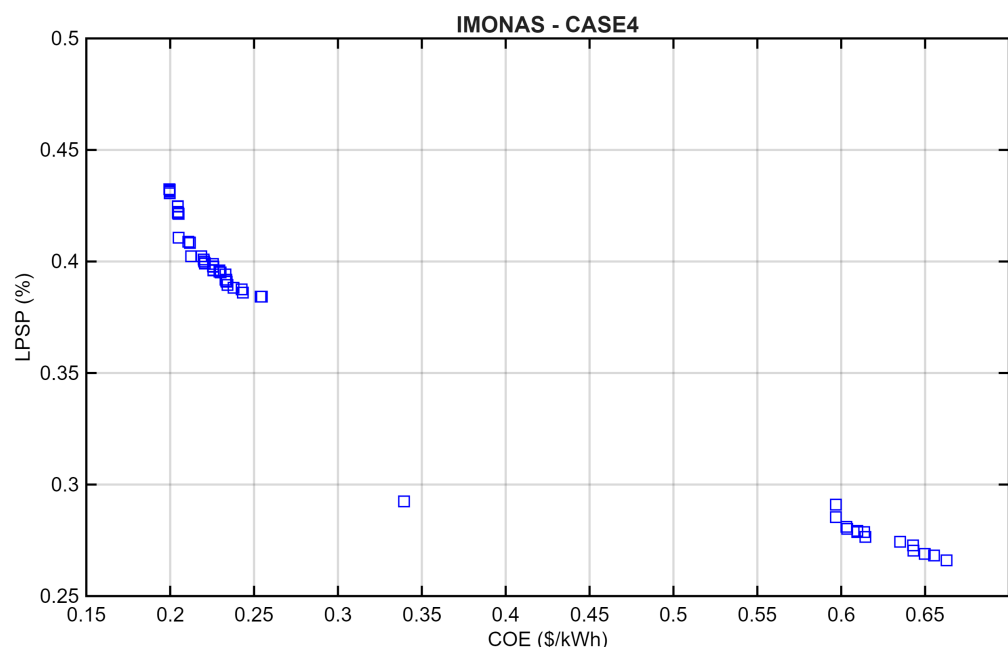


Figure 11. PF obtained for Case 3 using the proposed IMONAS approach.

The first listed configuration, Solution #1, has 16 PV panels, one diesel generator, and battery autonomy of 1.023 days (approximately 24 h and 33 min), using PV model #1, battery model #16, and inverter model #3. Its objectives are $COE = USD\ 0.1819/kWh$ and $LPSP = 0.4291\%$, again representing the lowest-cost solution.

Solution #6 uses 19 PV panels, one diesel generator, and autonomy of about 33 h, with PV model #4, battery model #16, and inverter model #3. This design gives $COE = USD\ 0.2113/kWh$ and $LPSP = 0.4122\%$. Compared with Solution #1, it improves reliability through a different PV model and higher battery autonomy, but at a higher cost.

Solution #15 is a compromise design with 29 PV panels, one diesel generator, PV model #1, battery model #18, inverter model #2, and nanogrid autonomy of around 31 h. It yields $COE = USD\ 0.2384/kWh$ and $LPSP = 0.3876\%$, representing improved reliability at moderate cost.

At the reliability-oriented end of the reported solution set, Solution #20 uses 18 PV panels, 2 diesel generators, and exactly 24 h of autonomy, with PV model #1, battery model #3, and inverter model #3. The corresponding objectives are $COE = USD\ 0.6032/kWh$ and $LPSP = 0.2708\%$. This reduces LPSP substantially, but with a significant increase in system cost and diesel dependence.

Table 7. Selected solutions from the PF for Case 3 using the proposed IMONAS approach.

Solution	NPV	NDG	AD (Days)	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	16	1	1.023	1	16	3	0.1819	0.4291
2	17	1	1.013	1	16	3	0.1854	0.4225
3	17	1	1.020	1	16	3	0.1854	0.4216
4	18	1	1.000	1	16	3	0.1895	0.4200
5	19	1	1.001	1	16	3	0.1943	0.4181
6	19	1	1.385	4	16	3	0.2113	0.4122
7	21	1	1.314	1	18	3	0.2149	0.4093
8	21	1	1.311	1	18	3	0.2150	0.4062
9	22	1	1.308	1	18	3	0.2166	0.4002
10	25	1	1.315	1	18	3	0.2237	0.3954
11	25	1	1.305	1	18	3	0.2239	0.3926
12	25	1	1.312	1	18	2	0.2244	0.3919
13	26	1	1.312	1	18	3	0.2269	0.3908
14	26	1	1.301	1	18	3	0.2271	0.3897
15	29	1	1.289	1	18	2	0.2384	0.3876
16	35	1	1.273	2	18	1	0.2529	0.3848
17	2	2	1.000	1	18	3	0.3121	0.3571
18	2	2	1.000	7	18	3	0.3121	0.3023
19	17	2	1.001	1	3	3	0.5992	0.2729
20	18	2	1.000	1	3	3	0.6032	0.2708

6.1.4. Case 4

Figure 12 shows the PF obtained for Case 4. IMONAS generated 60 non-dominated solutions. The 20 solutions listed in Table 8 show broader variation in battery autonomy and component combinations than in some previous cases.

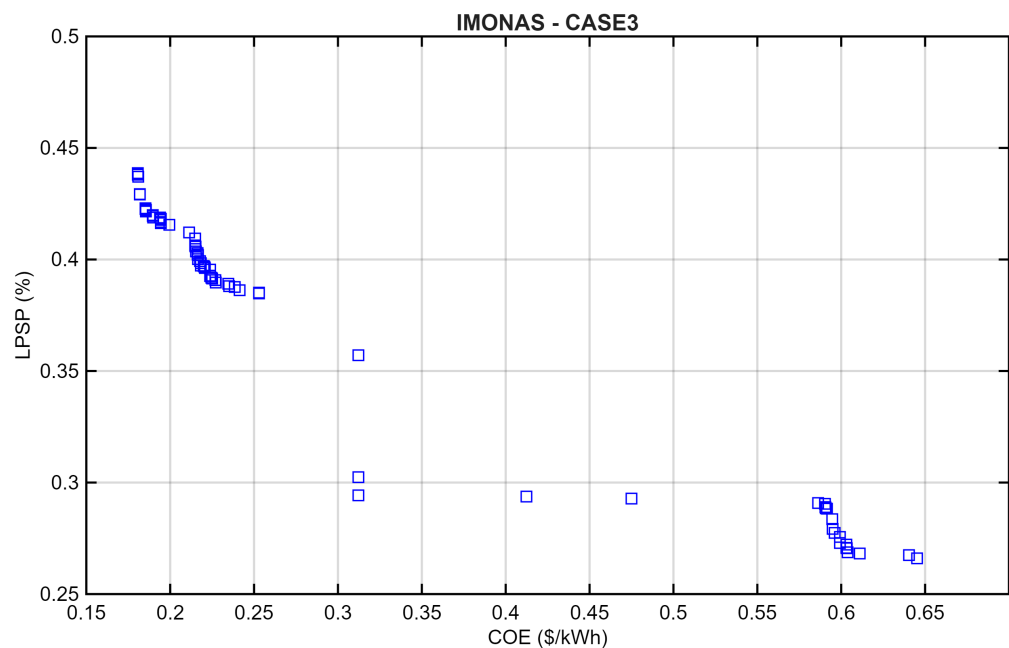
**Figure 12.** PF obtained for Case 4 using the proposed IMONAS approach.

Table 8. Selected solutions from the PF for Case 4 using the proposed IMONAS approach.

Solution	NPV	NDG	AD	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	15	1	1.632	1	16	3	0.1996	0.4322
2	15	1	1.606	1	16	3	0.1998	0.4314
3	16	1	1.637	5	16	3	0.2044	0.4248
4	18	1	1.639	2	16	3	0.2046	0.4220
5	18	1	1.577	1	18	3	0.2109	0.4089
6	18	1	1.570	1	18	2	0.2117	0.4083
7	19	1	1.713	1	18	3	0.2202	0.3999
8	23	1	1.560	1	18	3	0.2256	0.3976
9	23	1	1.573	1	18	3	0.2256	0.3962
10	24	1	1.562	1	18	3	0.2294	0.3959
11	25	1	1.506	1	18	3	0.2329	0.3943
12	25	1	1.514	1	18	3	0.2329	0.3942
13	25	1	1.522	1	18	3	0.2330	0.3919
14	25	1	1.564	1	18	3	0.2335	0.3919
15	25	1	1.568	1	18	2	0.2343	0.3895
16	27	1	1.573	1	18	3	0.2426	0.3874
17	18	2	1.012	2	3	3	0.5968	0.2909
18	19	2	1.009	1	3	3	0.6144	0.2764
19	25	2	1.014	1	3	1	0.6352	0.2744
20	27	2	1.013	1	3	1	0.6428	0.2728

Solution #1 has 15 PV panels, one diesel generator, and a relatively large autonomy of about 39 h, with PV model #1, battery model #16, and inverter model #3. This configuration gives COE = USD 0.1996/kWh and LPSP = 0.4322%.

A second representative design is Solution #5, which includes 18 PV panels, one diesel generator, autonomy of approximately 38 h, PV model #1, battery model #18, and inverter model #3. Its objectives are COE = USD 0.2109/kWh and LPSP = 0.4089%.

Solution #16 comprises 27 PV panels, one diesel generator, autonomy of 1.573 days (around 37 h and 45 min), and models #1, #18, and #3 for PV, battery, and inverter, respectively. This option yields COE = USD 0.2426/kWh and LPSP = 0.3874%, showing that reliability can be improved while maintaining one diesel generator.

At the more reliability-oriented edge of the PF, Solution #20 uses 27 PV panels, two diesel generators, autonomy of almost one day, PV model #1, battery model #3, and inverter model #1. It gives COE = USD 0.6428/kWh and LPSP = 0.2728%. As in the previous cases, lower LPSP is obtained through a substantial cost increase and greater reliance on diesel generation.

6.1.5. Case 5

Figure 13 shows the PF obtained for Case 5. IMONAS produced 47 non-dominated solutions. Although this is fewer than in Cases 1–4, the 20 solutions in Table 9 still include varied PV models, battery models, inverter models, and autonomy levels.

Solution #1 has 18 PV panels, one diesel generator, and an autonomy of approximately one day, with PV model #4, battery model #16, and inverter model #3. This design results in COE = USD 0.1878/kWh and LPSP = 0.4218%, making it the most economical solution in the reported set.

Solution #5 uses 23 PV panels, one diesel generator, and an autonomy of about 40 h, with PV model #10, battery model #18, and inverter model #2. It gives COE = USD 0.2283/kWh and LPSP = 0.3995%. The longer autonomy and PV subsystem change improve reliability, though at a higher system cost.

At the high-cost end, Solution #20 uses 27 PV panels, one diesel generator, and autonomy of around 40 h, with PV model #1, battery model #1, and inverter model #2. It produces COE = USD 0.2984/kWh and LPSP = 0.3833%, one of the best reliability levels in the reported set.

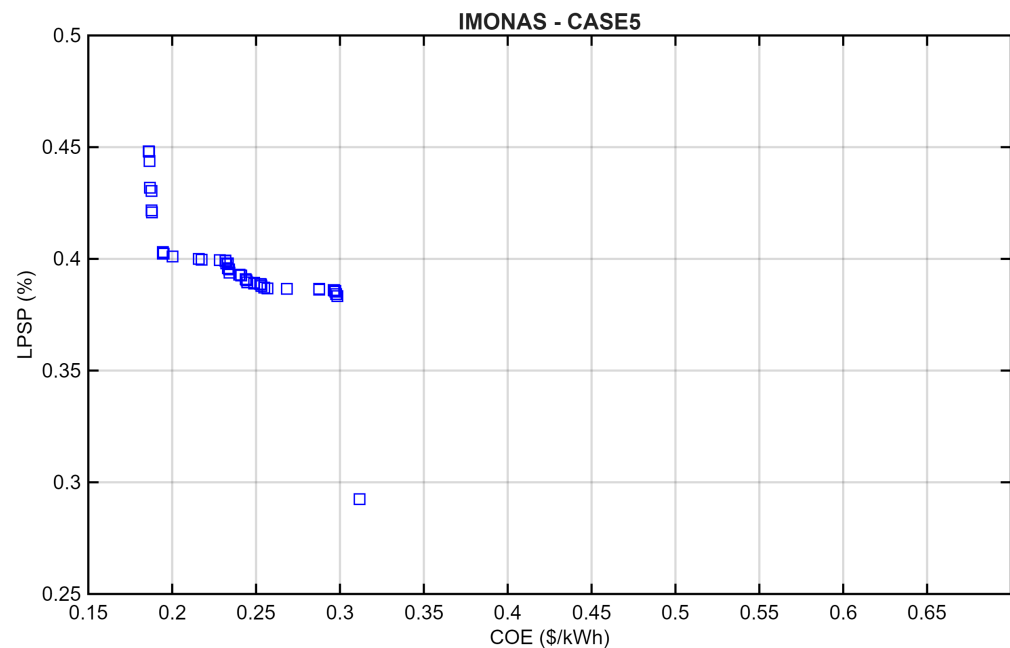


Figure 13. PF obtained for Case 5 using the proposed IMONAS approach.

Table 9. Selected solutions from the PF for Case 5 using the proposed IMONAS approach.

Solution	NPV	NDG	AD	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	18	1	1.024	4	16	3	0.1878	0.4218
2	18	1	1.022	4	16	3	0.1878	0.4209
3	20	1	1.005	5	16	3	0.2002	0.4010
4	22	1	1.083	9	16	4	0.2158	0.4000
5	23	1	1.648	10	18	2	0.2283	0.3995
6	22	1	1.564	8	18	3	0.2322	0.3981
7	27	1	1.533	9	18	3	0.2331	0.3980
8	27	1	1.551	9	18	3	0.2331	0.3976
9	28	1	1.555	10	18	3	0.2340	0.3953
10	30	1	1.547	9	18	3	0.2439	0.3909
11	30	1	1.569	9	18	3	0.2442	0.3905
12	32	1	1.566	10	18	3	0.2488	0.3893
13	32	1	1.572	10	18	3	0.2489	0.3889
14	33	1	1.540	10	18	3	0.2524	0.3887
15	34	1	1.553	10	18	3	0.2569	0.3867
16	27	1	1.629	8	18	3	0.2683	0.3867
17	25	1	1.612	1	1	2	0.2876	0.3866
18	27	1	1.578	1	1	2	0.2962	0.3861
19	27	1	1.630	1	1	2	0.2977	0.3843
20	27	1	1.650	1	1	2	0.2984	0.3833

6.1.6. Case 6

Figure 14 shows the PF obtained for Case 6. IMONAS generated 47 non-dominated solutions, the same number as in Case 5. The PF remains well distributed and provides multiple design options. Table 10 reports 20 selected solutions, although the full PF contains more solutions.

Solution #1 consists of 16 PV panels, one diesel generator, and battery autonomy of approximately 24 h, with PV model #1, battery model #16, and inverter model #3. This design gives COE = USD 0.1826/kWh and LPSP = 0.4242%.

Solution #10 uses 19 PV panels, one diesel generator, and autonomy of 1.000 day, with PV model #1, battery model #16, and inverter model #3. It yields COE = USD 0.1947/kWh and LPSP = 0.3957%.

Solution #14 comprises 28 PV panels, one diesel generator, and autonomy of about 37 h, with PV model #4, battery model #18, and inverter model #3. This solution results in COE =

USD 0.2412/kWh and LPSP = 0.3915%, illustrating the effect of increasing PV penetration and changing component models.

Solution #20 includes 27 PV panels, one diesel generator, and autonomy of around 39 h, with PV model #1, battery model #1, and inverter model #1. It achieves COE = USD 0.3012/kWh and LPSP = 0.3840%. Case 6 therefore follows the same trade-off pattern: reliability improves as the system becomes more expensive and usually larger in renewable and storage capacity.

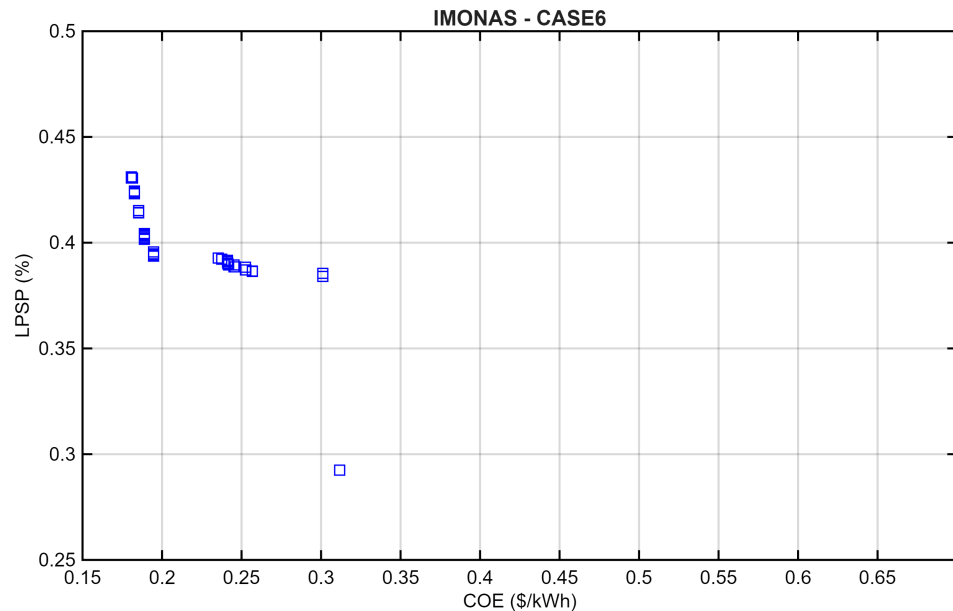


Figure 14. PF obtained for Case 6 using the proposed IMONAS approach.

Table 10. Selected solutions from the PF for Case 6 using the proposed IMONAS approach.

Solution	NPV	NDG	AD	PV Model	Battery Model	Inverter Model	COE (USD/kWh)	LPSP (%)
1	16	1	1.026	1	16	3	0.1826	0.4242
2	17	1	1.026	1	16	3	0.1853	0.4143
3	17	1	1.026	1	16	3	0.1853	0.4141
4	18	1	1.014	1	16	3	0.1889	0.4042
5	18	1	1.014	1	16	3	0.1889	0.4038
6	18	1	1.014	1	16	3	0.1889	0.4037
7	18	1	1.014	1	16	3	0.1889	0.4031
8	18	1	1.013	1	16	3	0.1889	0.4030
9	18	1	1.006	1	16	3	0.1889	0.4016
10	19	1	1.000	1	16	3	0.1947	0.3957
11	19	1	1.000	1	16	3	0.1947	0.3948
12	19	1	1.004	1	16	3	0.1947	0.3941
13	25	1	1.562	5	18	3	0.2353	0.3928
14	28	1	1.538	4	18	3	0.2412	0.3915
15	28	1	1.540	4	18	3	0.2412	0.3910
16	28	1	1.551	4	18	3	0.2414	0.3900
17	29	1	1.540	4	18	3	0.2452	0.3894
18	29	1	1.540	4	18	3	0.2452	0.3886
19	28	1	1.637	4	18	3	0.2524	0.3885
20	27	1	1.631	1	1	1	0.3012	0.3840

Across Cases 1–6, IMONAS yields diverse and well-distributed PFs with feasible nanogrid design alternatives for designers and operators. Lower-COE solutions generally use fewer PV panels and simpler component configurations, but they have higher LPSP values. More reliable configurations usually require more PV panels, longer battery autonomy, and, in some cases, a second diesel generator, which increases COE. The numbers of non-dominated solutions are 69, 56, 74, 60, 47,

and 47 for Cases 1–6, respectively, indicating that IMONAS maintains a broad decision space across the investigated conditions.

6.2. Effect of Uncertainty and Battery Degradation on the PF

Figures 15–17 compare the effects of uncertainty and battery degradation on the optimal nanogrid design. Uncertainty is inherent in microgrid operation because renewable generation, load demand, and other operating conditions vary over time. Battery degradation must also be included because storage capacity gradually decreases, affecting both reliability and cost. Stochastic uncertainty modeling and explicit degradation modeling therefore provide a more realistic basis for nanogrid planning.

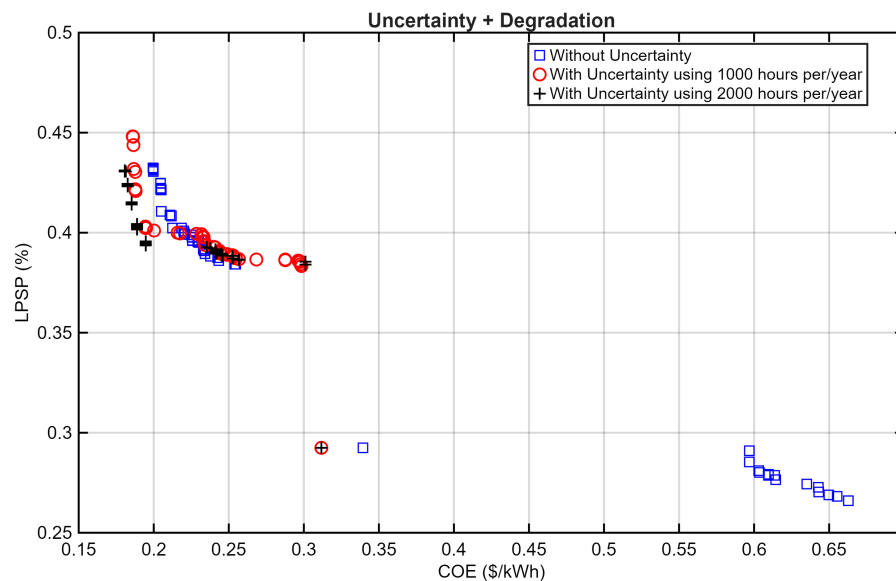


Figure 15. Comparison between the PFs obtained for Cases 1, 2, and 3 using the proposed IMONAS approach.

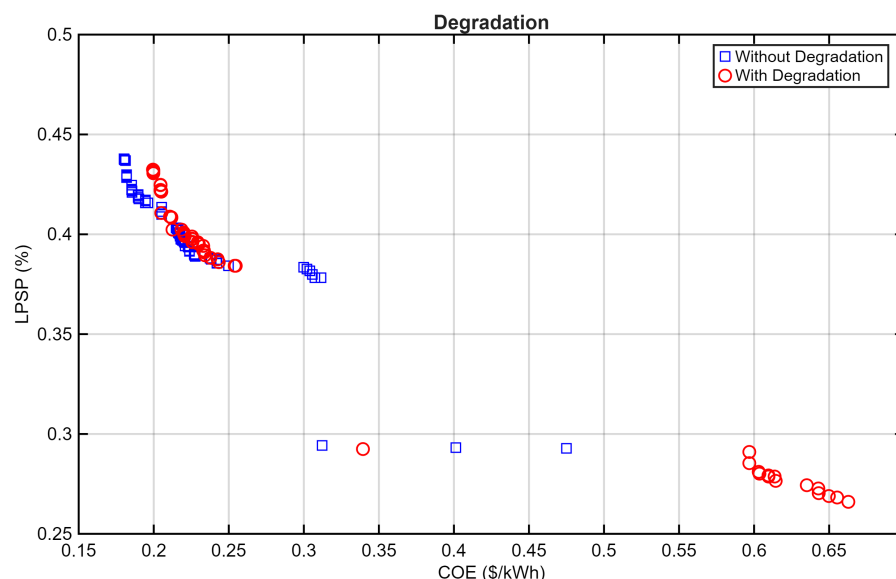


Figure 16. Comparison between the PFs obtained for Cases 1 and 4 using the proposed IMONAS approach.

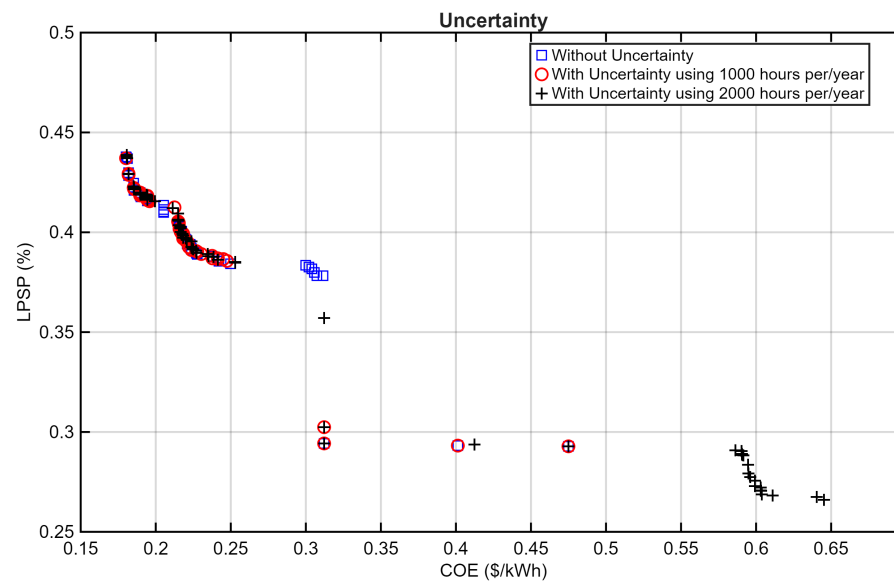


Figure 17. Comparison between the PFs obtained for Cases 4, 5, and 6 using the proposed IMONAS approach.

6.2.1. Effect of Uncertainty

Figure 15 compares the PFs obtained for Case 1, Case 2, and Case 3, which correspond to the following conditions:

- Without uncertainty;
- With uncertainty using 1000 h/year;
- With uncertainty using 2000 h/year.

The PF shifts when uncertainty is incorporated. The deterministic case provides the most optimistic solutions because the uncertain variable is assumed to follow known and fixed conditions. Under this assumption, the optimizer can use the available resource more aggressively, giving lower-cost configurations for a given reliability level.

Once uncertainty is introduced, the PF moves away from the deterministic front, particularly in the low-LPSP region. Maintaining the same reliability under uncertain operation requires more conservative and more expensive system designs. In practical terms, the system needs additional support through larger PV capacity, more storage, or stronger reliance on dispatchable sources such as the diesel generator. As a result, COE increases when uncertainty is considered.

Between the two uncertain cases, the front for 2000 h/year generally extends further toward higher COE values than the front for 1000 h/year, especially for the most reliable solutions. A longer uncertain operating period therefore imposes a stronger design burden: the optimizer must invest more to preserve supply adequacy. Figure 15 shows that increasing uncertainty reduces the optimism of the deterministic design and makes the reliability–cost trade-off more expensive.

The uncertain cases remain relatively close to the deterministic case in the higher-LPSP region, but the differences become more pronounced as the design moves toward lower LPSP values. Highly reliable configurations are more sensitive to operating uncertainty, so small reductions in predictability may require significant extra investment when the target is to keep power shortages very low.

6.2.2. Effect of Uncertainty and Battery Degradation

Figures 15–17 show that uncertainty and battery degradation both affect the nanogrid PF. The baseline case without uncertainty or degradation gives the most optimistic solutions, with lower COE values for comparable LPSP levels. When uncertainty is introduced, the PF shifts toward more conservative designs, especially in the low-LPSP region, and the 2000 h/year case is generally more penalizing than the 1000 h/year case.

Figure 16 shows that battery degradation also deteriorates the PF. When degradation is considered, the same reliability level can no longer be achieved at the same cost as in the case without degradation. Battery aging reduces effective storage capability over time, forcing the optimizer to

choose more expensive and robust configurations. The effect is visible over a broad portion of the front, so degradation influences both cost-oriented and reliability-oriented solutions.

When uncertainty and degradation are considered simultaneously, as shown in Figure 17, the PF shifts further toward higher COE values. Ignoring these effects can therefore produce overly optimistic designs, whereas including both effects gives a more realistic basis for nanogrid planning.

6.3. Performance Comparison

To assess the effectiveness of the proposed IMONAS algorithm, its performance was compared with the original MONAS and several well-established multi-objective optimization algorithms, namely SMPSO, NMPSO, MPSOD, MOEA/D, and RVEA. The Pareto-front (PF) solutions obtained by the competing algorithms are shown in Figures 18–23. These graphical comparisons are further supported by quantitative performance indicators, including the C-metric, generational distance (GD), inverted generational distance (IGD), hypervolume (HV), and spacing.

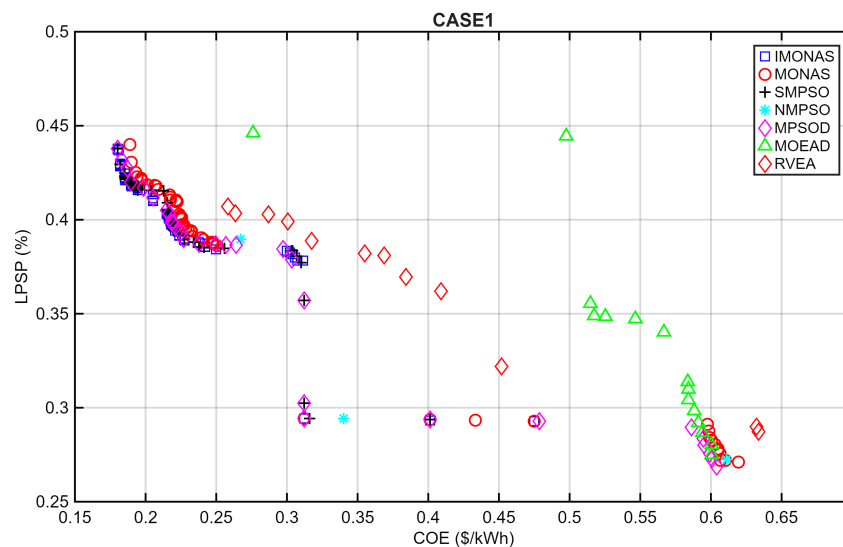


Figure 18. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMPSO, MPSOD, MOEA/D, and RVEA for Case 1.

Statistical C-Metric Analysis over 25 Independent Runs

Since all the compared algorithms are stochastic in nature, each algorithm was independently executed 25 times for each case using different random initializations. For each run, the pairwise C-metric values were calculated between the PF generated by IMONAS and the PFs generated by the competing algorithms. Let A and B denote two approximated PFs. The C-metric is defined as

$$C(A, B) = \frac{|\{b \in B \mid \exists a \in A : a \preceq b\}|}{|B|}, \quad (43)$$

where $|B|$ is the number of solutions in set B , and $a \preceq b$ means that solution a dominates, or is equal to, solution b . Therefore, $C(A, B)$ measures the proportion of solutions in B that are dominated by at least one solution in A . A value of $C(A, B) = 1$ indicates that all solutions in B are dominated by or equal to solutions in A , whereas $C(A, B) = 0$ indicates that none of the solutions in B is dominated by A .

In the revised analysis, the C-metric values were first computed for all 25 runs, and then the mean values were used to quantify the average dominance relationship between IMONAS and each competing algorithm. In addition, the Wilcoxon signed-rank test was applied to the run-by-run C-metric results in order to assess whether the superiority of IMONAS over each competing method was statistically significant. The resulting mean pairwise C-metric values and corresponding p -values are summarized in Table 11.

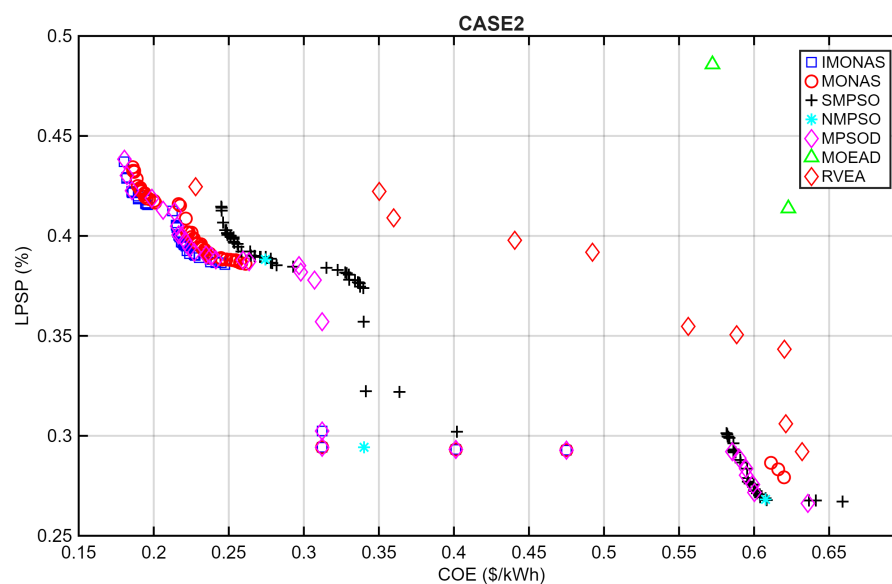


Figure 19. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMPSO, MPSOD, MOEAD, and RVEA for Case 2.

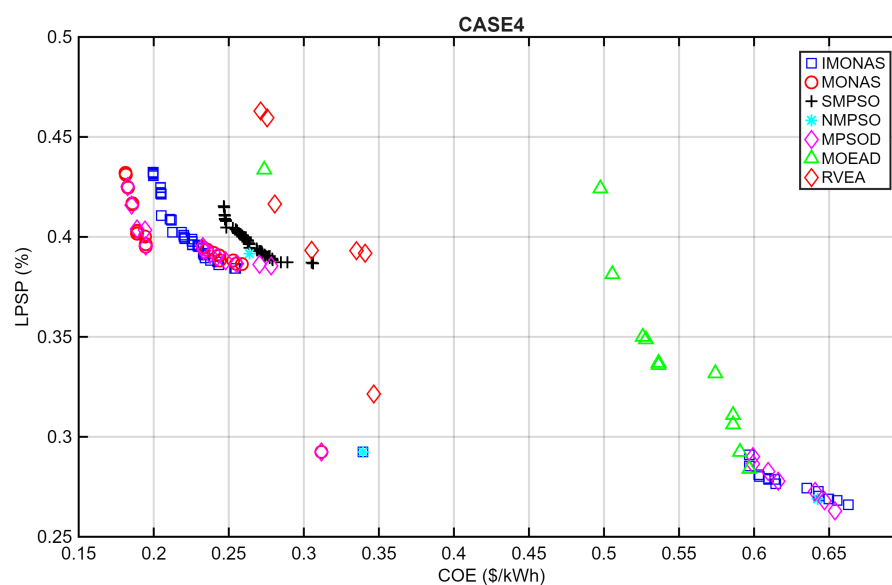


Figure 20. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMPSO, MPSOD, MOEAD, and RVEA for Case 4.

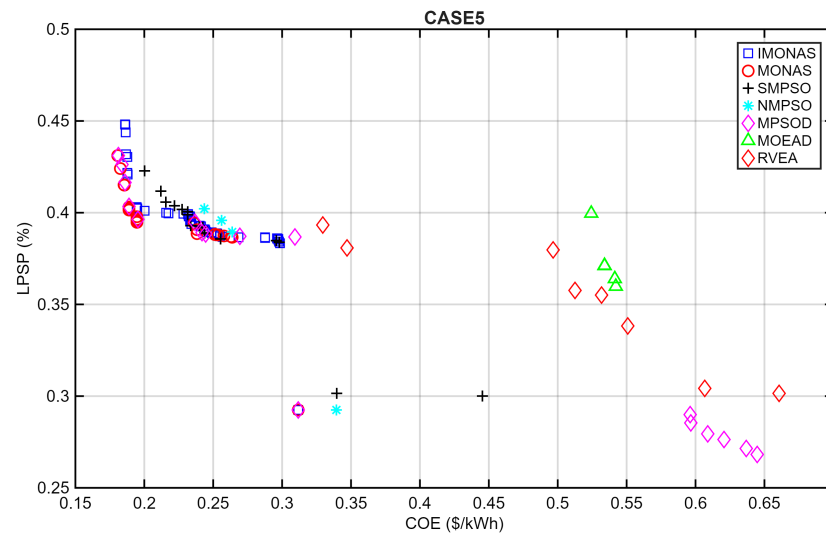


Figure 21. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMP SO, MPSOD, MOEAD, and RVEA for Case 5.

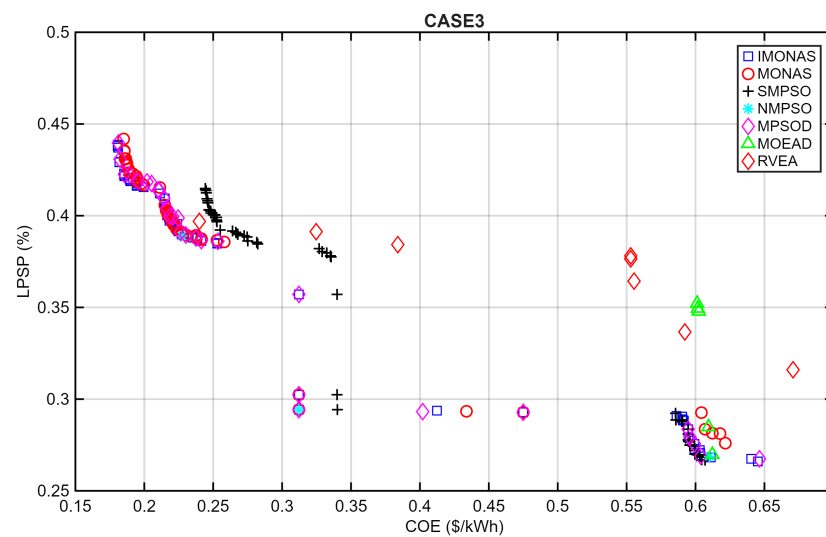


Figure 22. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMP SO, MPSOD, MOEAD, and RVEA for Case 3.

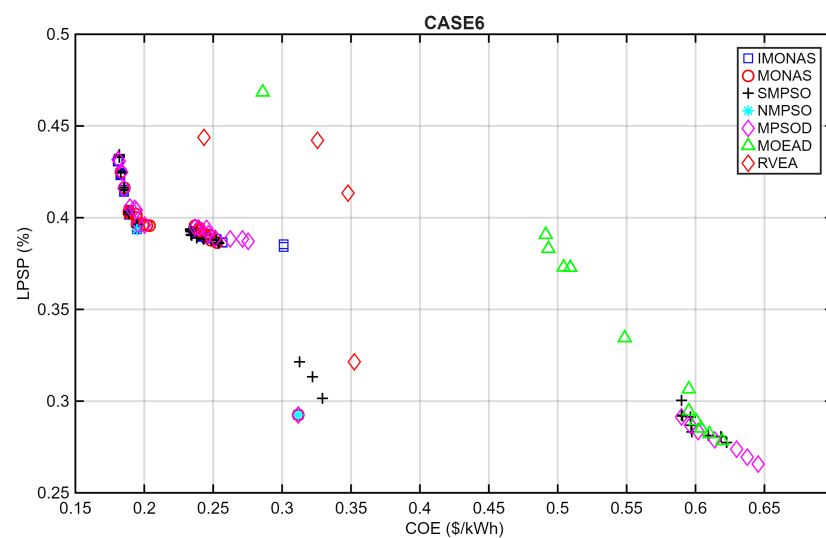


Figure 23. Comparison of the PFs obtained by IMONAS, MONAS, SMPSO, NMP SO, MPSOD, MOEAD, and RVEA for Case 6.

Table 11. Mean pairwise C-metric values over 25 independent runs and corresponding Wilcoxon signed-rank p -values for IMONAS versus the competing algorithms.

Case	Algorithm 1	Algorithm 2	Mean $C(A_1, A_2)$	Mean $C(A_2, A_1)$	p -Value
Case 1	IMONAS	MONAS	0.6331	0.1437	6.02×10^{-4}
Case 1	IMONAS	SMP SO	0.6155	0.1427	3.62×10^{-5}
Case 1	IMONAS	NMP SO	0.3973	0.0838	2.31×10^{-3}
Case 1	IMONAS	MPSOD	0.4557	0.2267	9.42×10^{-3}
Case 1	IMONAS	MOEAD	0.8197	0.0321	1.17×10^{-5}
Case 1	IMONAS	RVEA	0.9776	0.0018	1.83×10^{-6}
Case 2	IMONAS	MONAS	0.6235	0.1675	1.08×10^{-3}
Case 2	IMONAS	SMP SO	0.6187	0.1810	1.08×10^{-3}
Case 2	IMONAS	NMP SO	0.5636	0.0674	1.18×10^{-4}
Case 2	IMONAS	MPSOD	0.4689	0.2956	8.27×10^{-2}
Case 2	IMONAS	MOEAD	0.8656	0.0298	8.74×10^{-6}
Case 2	IMONAS	RVEA	0.9900	0.0000	8.94×10^{-7}
Case 3	IMONAS	MONAS	0.6313	0.1659	2.16×10^{-4}
Case 3	IMONAS	SMP SO	0.6391	0.1213	2.86×10^{-5}
Case 3	IMONAS	NMP SO	0.5183	0.0273	6.12×10^{-5}
Case 3	IMONAS	MPSOD	0.4789	0.2152	4.22×10^{-2}
Case 3	IMONAS	MOEAD	0.8629	0.0076	7.99×10^{-6}
Case 3	IMONAS	RVEA	0.9606	0.0133	3.04×10^{-6}
Case 4	IMONAS	MONAS	0.5723	0.2937	3.70×10^{-2}
Case 4	IMONAS	SMP SO	0.6751	0.0960	1.74×10^{-4}
Case 4	IMONAS	NMP SO	0.7167	0.0402	4.31×10^{-5}
Case 4	IMONAS	MPSOD	0.4628	0.2163	1.19×10^{-2}
Case 4	IMONAS	MOEAD	0.7908	0.0000	1.16×10^{-5}
Case 4	IMONAS	RVEA	0.9722	0.0120	2.44×10^{-6}
Case 5	IMONAS	MONAS	0.7760	0.1259	1.56×10^{-4}
Case 5	IMONAS	SMP SO	0.7711	0.0608	1.38×10^{-5}
Case 5	IMONAS	NMP SO	0.6839	0.0450	6.84×10^{-5}
Case 5	IMONAS	MPSOD	0.5815	0.0391	1.56×10^{-5}
Case 5	IMONAS	MOEAD	0.8535	0.0024	9.38×10^{-6}
Case 5	IMONAS	RVEA	0.9883	0.0000	1.31×10^{-6}
Case 6	IMONAS	MONAS	0.6917	0.2269	4.92×10^{-3}
Case 6	IMONAS	SMP SO	0.6546	0.1235	4.93×10^{-4}
Case 6	IMONAS	NMP SO	0.7846	0.0761	4.19×10^{-5}
Case 6	IMONAS	MPSOD	0.4722	0.2039	8.75×10^{-2}
Case 6	IMONAS	MOEAD	0.8031	0.0057	1.20×10^{-5}
Case 6	IMONAS	RVEA	0.9572	0.0087	1.83×10^{-6}

Table 11 shows that IMONAS consistently achieves substantially higher mean $C(A_1, A_2)$ values than the reverse mean $C(A_2, A_1)$ values against most competing algorithms across all six cases. This indicates that, on average over 25 independent runs, the PF generated by IMONAS dominates a significantly larger portion of the PFs generated by the competing methods than vice versa. The superiority of IMONAS is especially pronounced against MOEA/D and RVEA in all cases, with very large dominance margins and very small p -values. The Wilcoxon signed-rank test further confirms that these differences are statistically significant in nearly all comparisons. The only cases where the statistical significance is weaker are the comparisons with MPSOD in Cases 2 and 6, where the corresponding p -values are slightly above 0.05, indicating that MPSOD remains the closest competitor to IMONAS in those scenarios.

Because the C-metric is directional, a single pairwise value is not sufficient to establish a complete ranking among all algorithms. Therefore, for each case, an aggregated case-wise C-score was computed as

$$\text{CaseScore}_i = \sum_{\substack{j=1 \\ j \neq i}}^{n_{\text{alg}}} [C(A_i, A_j) - C(A_j, A_i)], \quad (44)$$

where A_i denotes the PF produced by the i th algorithm and n_{alg} is the total number of competing algorithms. This score reflects the net dominance strength of algorithm i against all other algorithms in the same case. A positive value indicates that the algorithm dominates the others more frequently than it is dominated by them, whereas a negative value indicates weaker dominance performance.

Table 12 confirms that IMONAS achieves the highest case-wise C-score in all six cases, which demonstrates the strongest overall dominance behavior among the compared algorithms. MPSOD and MONAS are the closest competitors, particularly in Cases 2, 3, 4, and 6, but they remain consistently below IMONAS. By contrast, MOEA/D and RVEA obtain strongly negative scores in all cases, which indicates weak dominance performance. These results are fully consistent with the visual PF comparisons shown in Figures 18–23.

Table 12. Case-wise aggregated C-scores of the competing algorithms based on the mean pairwise C-metric values over 25 independent runs.

Case	IMONAS	MONAS	SMPSO	NMPSO	MPSOD	MOEAD	RVEA
Case 1	3.2683	1.0652	0.6763	0.8628	2.7125	−4.3895	−4.1956
Case 2	3.3890	1.3017	0.7883	0.1075	3.0447	−4.6649	−3.9664
Case 3	3.5405	1.5636	0.7692	−0.0440	2.9127	−4.7263	−4.0157
Case 4	3.5317	2.7622	0.1210	−0.6395	2.7991	−4.3918	−4.1828
Case 5	4.3812	2.0200	0.2367	−0.1471	2.2955	−4.7295	−4.0569
Case 6	3.7187	2.0953	1.0955	−0.8789	2.7379	−4.4495	−4.3191

The overall NetCScore is then obtained by averaging the case-wise C-scores over the six cases. However, because no single metric can fully characterize the quality of an approximated PF, additional performance indicators were also considered, namely GD, IGD, HV, and spacing. GD measures the average distance from the obtained PF to the reference PF and thus evaluates convergence. IGD measures the average distance from the reference PF to the obtained PF and therefore reflects both convergence and coverage. HV quantifies the volume of the objective space dominated by the obtained PF with respect to a predefined reference point and hence jointly reflects convergence and diversity. The spacing metric evaluates the uniformity of solution distribution along the PF. Since GD, IGD, and spacing are minimization-oriented indicators, lower values are preferred, whereas for HV and NetCScore, higher values are preferred.

For each metric, the algorithms were ranked case by case and run by run, and the average rank was then computed over all cases and runs. The final average rank was calculated as the arithmetic mean of the average ranks obtained for NetCScore, GD, IGD, HV, and spacing. Thus, the headings of Table 13 are interpreted as follows: NetCScore denotes the overall average case-wise C-score, AvgRank_Cscore is the average rank based on the case-wise C-score, AvgRank_GD is the average rank based on GD, AvgRank_IGD is the average rank based on IGD, AvgRank_HV is the average rank based on HV, AvgRank_Spacing is the average rank based on spacing, and FinalAvgRank is the mean of these five average ranks. A lower final average rank indicates better overall performance.

Table 13. Final overall ranking of the compared algorithms based on NetCScore, GD, IGD, HV, and spacing over 25 independent runs.

Algorithm	NetCScore	AvgRank_Cscore	AvgRank_GD	AvgRank_IGD	AvgRank_HV	AvgRank_Spacing	FinalAvgRank
IMONAS	3.6382	1.6067	1.7333	2.6133	2.2267	2.5000	2.1360
MPSOD	2.7504	2.4267	2.5267	1.4133	1.3667	4.0400	2.3547
MONAS	1.8013	3.0533	3.0867	3.6933	3.1000	3.5133	3.2893
SMPSO	0.6145	3.8400	4.0067	2.9667	3.6800	2.0267	3.3040
NMPSO	−0.1232	4.1200	3.6867	5.4600	4.7133	5.7133	4.7387
RVEA	−4.1227	6.3933	6.1800	5.3267	6.0067	5.0867	5.7987
MOEAD	−4.5586	6.5600	6.7800	6.5267	6.9067	5.1200	6.3787

Table 13 clearly shows that IMONAS achieves the best overall performance among all compared algorithms, with the lowest final average rank of 2.1360. In addition to having the highest NetCScore, IMONAS also obtains the best or near-best average ranks in GD, HV, and spacing,

while remaining highly competitive in IGD. MPSOD ranks second overall and represents the closest competitor to IMONAS, mainly due to its strong performance in IGD and HV. MONAS ranks third, followed by SMPSO, while NMP SO, RVEA, and MOEA/D show weaker overall performance. These results demonstrate that IMONAS provides the best overall compromise between dominance strength, convergence toward the reference front, coverage, and distribution quality across the six considered cases.

Furthermore, Figure 18 compares the PFs obtained for Case 1. The IMONAS PF occupies a competitive region of the objective space and provides a favorable compromise between low COE and low LPSP. Its front is well distributed and covers much of the desirable trade-off region, indicating good convergence and diversity. MPSOD and SMPSO also produce competitive solutions in parts of the front, whereas MOEAD and RVEA remain farther from the best trade-off region.

Figure 19 presents the comparison for Case 2. IMONAS extends further toward the desirable lower-left region of the objective plane while maintaining diversity. MONAS also performs reasonably well, but its front is generally less competitive than that of IMONAS. The remaining algorithms, especially MOEAD and RVEA, produce less favorable fronts, consistent with their lower dominance scores in the quantitative analysis.

Figure 22 shows the PF comparison for Case 3. IMONAS provides one of the strongest approximations to the trade-off surface, with a broad and well-distributed set of non-dominated solutions. MPSOD is also competitive in this case, but IMONAS remains more balanced overall. MONAS shows acceptable performance, whereas NMP SO and SMPSO are less consistent. MOEAD and RVEA remain weaker, especially in the low-COE/low-LPSP region.

Figure 20 corresponds to Case 4 and shows a narrower gap between IMONAS, MONAS, and MPSOD. IMONAS still generates a strong PF with good spread and competitive convergence, but several algorithms produce reasonable fronts. Case 4 is therefore more challenging, and IMONAS remains among the leading methods rather than clearly dominating all competitors.

Figure 21 illustrates the results for Case 5. MONAS and MPSOD are particularly competitive, consistent with the high case scores reported later. IMONAS still yields a well-formed PF with acceptable diversity and strong solutions in important parts of the search space. Although IMONAS is not the sole leading method in this case, it remains competitive. MOEAD and RVEA again show the weakest performance.

Figure 23 presents the PF comparison for Case 6. IMONAS regains a clearer advantage, generating a diverse PF close to the best attainable trade-off region. SMPSO also provides some competitive solutions, but the IMONAS front is more comprehensive and better distributed. MONAS performs moderately, while MOEAD and RVEA show limited competitiveness.

Taken together, Figures 18–23 show that IMONAS produces high-quality PFs across the six cases. In most scenarios, it balances convergence toward the best trade-off region with diversity along the front. MONAS and MPSOD are competitive in several cases and occasionally outperform IMONAS in isolated scenarios, but IMONAS has the most stable overall behavior.

7. Conclusions

This study developed and applied an improved multi-objective neural architecture search (IMONAS) framework to optimize a hybrid renewable nanogrid system for desert camping applications in Hafr Al-Batin, Saudi Arabia. The proposed approach integrates neural-based optimization with uncertainty modeling and explicit battery degradation modeling, addressing limitations in the reviewed sizing studies. The originality of the article lies in both the algorithmic improvement to IMONAS by the dynamic selection capability of the operators and its application to a more realistic and comprehensive planning model.

The results show that IMONAS can generate well-distributed Pareto fronts under multiple operating scenarios while balancing cost and reliability objectives. Across the six test cases, the framework identified configurations of PV units, diesel generators, battery autonomy, and inverters that trade off the cost of energy (COE) and loss of power supply probability (LPSP). The results also show that uncertainty and battery degradation affect system design, supporting their inclusion in planning studies for harsh environments.

Comparison with the original MONAS and five other multi-objective optimization techniques indicates that IMONAS has the strongest overall performance across the investigated cases. The visual

PF comparisons and C-metric assessment show improved convergence and diversity in most cases, although MONAS and MPSOD remain competitive under some operating conditions. The framework supports design decisions for hybrid energy systems in remote desert areas by incorporating uncertainty and degradation effects into the sizing process. Future work may extend the framework to real-time adaptive control and include additional renewable resources and demand-side management strategies.

The proposed strategy of nano-grid model optimization can be practically implemented in any other part of the world for islanded loads, with necessary scaling of the parameters. Anyway, the policy of connecting such off-grid loads with the national grid can also be investigated. Battery replacement strategy, selection of the PV panel, its proper maintenance, optimal load management strategy, etc., practical aspects should be considered before any real-life implementation.

There are some limitations of the presented research that can be further investigated and implemented in future work. Real-world experimental validation, more detailed degradation modeling, use of temperature-dependent electrochemical battery models, limited calculation of environmental indicators, inclusion of the latest models of PV, battery, and generators, analysis of the uncertainty models for solar energy, calculation and analysis of the sustainability indicators, etc., are the major aspects to be looked at.

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Appendix A

Table A1. PV panel models and information [35].

Model No.	Name	Y_{PV} (W)	Efficiency	α_P	T_c NOCT ($^{\circ}\text{C}$)	Cost (USD)	Cost (USD/W)
Model #1	Kyocera Solar (KC200)	200.00	0.20	−0.46	47.00	800.00	4.00
Model #2	BP Solar (SX 170B)	170.00	0.17	−0.46	47.00	728.97	4.29
Model #3	Evergreen (Spruce ES−170)	170.00	0.17	−0.46	47.00	731.00	4.30
Model #4	Evergreen (Spruce ES−180)	180.00	0.18	−0.46	47.00	774.00	4.30
Model #5	Evergreen (Spruce ES−190)	190.00	0.19	−0.46	47.00	817.00	4.30
Model #6	Solar World (SW−165)	165.00	0.17	−0.46	47.00	709.97	4.30
Model #7	Mitsubishi (PV−MF155EB3)	155.00	0.16	−0.46	47.00	669.97	4.32
Model #8	Sharp (ND−208U1)	208.00	0.21	−0.46	47.00	898.56	4.32
Model #9	Sharp (NE−170U1)	170.00	0.17	−0.46	47.00	739.50	4.35
Model #10	Mitsubishi (PV−MF165EB4)	165.00	0.17	−0.46	47.00	719.97	4.36
Model #11	Sunwize (SW 150)	150.00	0.15	−0.46	47.00	668.31	4.46
Model #12	Kyocera (KC175GT)	175.00	0.18	−0.46	47.00	799.00	4.57
Model #13	Kyocera (KC175GT)	175.00	0.18	−0.46	47.00	799.00	4.57

Table A2. Battery models and information [35].

Model No.	Name	Efficiency	Capacity (Ah)	Voltage (V)	Cost (USD)	Lifetime (Yrs)	Weight (lbs)
Model #1	MK 8L16	0.85	370.00	6.00	288.77	12.00	113.00
Model #2	Surrette 12-CS-11PS	0.85	357.00	12.00	1118.96	12.00	272.00
Model #3	Surrette 2KS33PS	0.85	1765.00	2.00	874.90	12.00	208.00
Model #4	Surrette 4-CS-17PS	0.85	546.00	4.00	604.23	12.00	128.00
Model #5	Surrette 4-KS-21PS	0.85	1104.00	4.00	1110.44	12.00	267.00
Model #6	Surrette 4-KS-25PS	0.85	1350.00	4.00	1386.85	12.00	315.00
Model #7	Surrette 6-CS-17PS	0.85	546.00	6.00	906.31	12.00	221.00
Model #8	Surrette 6-CS-21PS	0.85	683.00	6.00	1075.01	12.00	271.00
Model #9	Surrette 6-CS-25PS	0.85	820.00	6.00	1241.37	12.00	318.00
Model #10	Surrette 8-CS-17PS	0.85	546.00	8.00	1256.21	12.00	294.00
Model #11	Surrette 8-CS-25PS	0.85	820.00	8.00	1654.76	12.00	424.00
Model #12	Surrette S-460	0.85	350.00	6.00	324.93	12.00	117.00
Model #13	Surrette S-530	0.85	400.00	6.00	370.65	12.00	127.00
Model #14	Trojan L16H	0.85	420.00	6.00	357.00	12.00	121.00
Model #15	Trojan T-105	0.85	225.00	6.00	138.00	12.00	62.00
Model #16	US Battery US185	0.85	195.00	12.00	216.58	12.00	111.00
Model #17	US Battery US2200	0.85	225.00	6.00	127.99	12.00	63.00
Model #18	US Battery US250	0.85	250.00	6.00	126.35	12.00	72.00
Model #19	Surrette S-460	0.85	350.00	6.00	357.36	12.00	117.00
Model #20	Surrette S-530 6V	0.85	400.00	6.00	406.09	12.00	127.00
Model #21	Surrette 4-CS-17PS	0.85	546.00	4.00	770.45	12.00	128.00
Model #22	Surrette 4-KS-21PS	0.85	1104.00	4.00	1206.00	12.00	267.00
Model #23	Surrette 4-KS-25PS	0.85	1350.00	4.00	1508.83	12.00	315.00
Model #24	Surrette 6-CS-17PS	0.85	546.00	6.00	932.31	12.00	221.00
Model #25	Surrette 6-CS-21PS	0.85	683.00	6.00	1164.00	12.00	271.00
Model #26	Surrette 6-CS-25PS	0.85	820.00	6.00	1349.45	12.00	318.00
Model #27	Surrette 8-CS-17PS	0.85	820.00	8.00	1795.71	12.00	424.00

Table A3. Inverter models and specifications [35].

Model No.	Inverter Manufacturer (Model)	Price (USD)	Power (W)	DC Input Voltage (VDC)	AC Output Voltage (VAC)	Nominal Freq. (Hz)	Efficiency
Model #1	Xantrex (XW6048)	3597.75	6000	48	120	60	0.92
Model #2	Xantrex (XW4548)	2878.20	4500	48	120	60	0.92
Model #3	Xantrex (SW5548)	2735.85	5500	48	120	60	0.92
Model #4	Xantrex (SW4048)	2178.96	4000	48	120	60	0.92
Model #5	Outback (GTFX3048)	1760.00	3000	48	120	60	0.92
Model #6	Outback (GVFX3648)	1913.00	3600	48	120	60	0.92
Model #7	Sunny Island (SI4248U)	4228.00	4200	48	120	60	0.92
Model #8	Sunny Island (SI5048U)	6535.00	5000	48	120	60	0.92

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