

Multi-Scenario Pre-Feasibility Analysis of a Hybrid Renewable Energy System for Data-Scarce Regions Using NSGA-II-Based Multi-Objective Optimisation

Prakruti Dave¹, Kaushal B. Patel²

¹Science and Humanities Department, School of Engineering, P P Savani University, Kosamba, Surat, Gujarat, India

²Narmada College of Science and Commerce, Zadeshwar, Bharuch, Gujarat, India

Abstract - Optimal sizing of standalone photovoltaic (PV)–wind turbine–battery hybrid renewable energy systems (HRES) for off-grid communities must balance two conflicting goals, minimum cost and maximum supply reliability, under uncertain renewable resources. This work does not aim at site-specific performance prediction; it develops a reproducible pre-feasibility framework for data-scarce regions, where measured meteorological records do not exist. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is used to characterise how the cost–reliability trade-off behaves across the full spectrum of resource availability. Synthetic stochastic profiles (lognormal solar irradiance, Weibull wind speed with $k = 2.2$, and a double-Gaussian residential load), consistent with published resource distributions, serve as the controlled experimental variable and define four scenarios from highly favourable to a severe stress-test bound. Five decision variables are optimised to minimise Life Cycle Cost (LCC) and a compound Loss of Power Supply Probability (LPSP) reliability index, with TOPSIS as a post-Pareto decision layer. Resource availability dominates achievable reliability: minimum LPSP ranges from 0.00% (High Renewable) to 43.66% (Worst Case), with LCC spanning \$4,660–\$69,740. Multi-run validation confirms consistent convergence (standard deviation of minimum LPSP = 0.001%). Site-specific validation against measured data is identified as future work.

Keywords: hybrid renewable energy system, NSGA-II, multi-objective optimisation, pre-feasibility screening, data-scarce regions

1. INTRODUCTION

Standalone hybrid renewable energy systems (HRES) are a leading option for electrifying remote and off-grid communities in sub-Saharan Africa, South and Southeast Asia and Pacific island regions, where grid infrastructure is absent or unreliable [1], [2], [53]. A PV–wind turbine–battery configuration removes diesel-fuel dependency, lowers life-cycle energy cost and reaches users beyond the economic range of grid extension [3]–[5]. Sizing such a system, i.e. choosing the numbers of PV modules, wind turbines and battery units that serve a target load under stochastic resource variability, is inherently a multi-objective problem [3], [4]. The two principal objectives, minimum Life Cycle Cost (LCC) and maximum supply reliability, quantified by the Loss of Power Supply Probability (LPSP), conflict, because any component that improves reliability raises capital and maintenance expenditure [6]. The Pareto-optimal front of non-dominated cost–reliability trade-offs is therefore the natural solution concept for feasibility studies, in which neither cost budgets nor reliability thresholds are fixed in advance [8], [9]. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [10], with fast non-dominated sorting, crowding-distance diversity preservation and elitist selection, is the dominant algorithm for generating such fronts on mixed integer–continuous problems [13], [14]. Because renewable resources are uncertain, HRES design also relies on probabilistic resource descriptions: clearness-index and lognormal models for solar irradiance [17] and Weibull distributions with shape $k \approx 2$ for wind speed [26].

Classical and single-objective sizing. Graphical and iterative methods are simple but scale poorly to the mixed integer–continuous search spaces of modern HRES [19]–[21]. Metaheuristics made global optimisation tractable: Yang et al. [7] introduced genetic-algorithm (GA) cost minimisation under an LPSP constraint, a single-objective paradigm followed by many studies [16], [22], [23], [29], [40], [57]; a comparison of ten metaheuristics found no algorithm dominant across all instances [24]; and tools such as HOMER [25] offer practitioner accessibility at the expense of Pareto-front generation [3], [4]. *Limitation:* reliability is treated as a post-hoc constraint rather than a co-objective, so a single optimum, not the trade-off, is returned [47].

Multi-objective sizing. Recognition that LCC and LPSP are co-objectives moved the field to multi-objective evolutionary optimisation [6], [9], with NSGA-II prominent owing to well-spread fronts and reliable convergence [13], [14]. Alternatives include SPEA2 [30] and grey-wolf and whale-optimisation variants [28], [31], [32]. NSGA-II produced a more diverse front than MOPSO on a PV–wind–battery–diesel system (hypervolume 0.04350 vs. 0.04336) [43], gravitational-search variants have been benchmarked against both [44], and enhanced NSGA-II formulations now couple sizing with power management [45]. *Limitation:* every benchmark NSGA-II study, including the direct predecessor [11] and the recent comparators [43], [44], relies on site-specific typical-meteorological-year (TMY) data and fixes one Pareto front under one resource condition [47]. Such studies cannot be applied where no measured records exist, which is precisely where pre-feasibility analysis is most needed [52].

Post-Pareto decision-making. Multi-criteria decision-making (MCDM) is an active complement to Pareto generation: Mathaba and Abo-Al-Ez [46] combine MEREC-weighted VIKOR with multi-objective optimisation for off-grid HRES, Ridha et al. [47] apply PROMETHEE-II to a triple-objective configuration problem, and Tomczewski et al. [48] couple NSGA-II with AHP-based selection. TOPSIS [33], [34] and equivalent methods are thus increasingly, though not yet universally, integrated into HRES workflows. *Limitation:* in most Pareto studies the front remains an analytical artefact rather than an implementable design recommendation [46]–[48].

Uncertainty treatment. Deterministic TMY-based optimisation cannot fully capture resource uncertainty [2], [35]. Monte Carlo propagation [36] and scenario-based stochastic programming [37]–[39] have been applied; stochastic treatment is reported to raise the cost of energy appreciably relative to deterministic sizing [49]; and hybrid stochastic–robust, degradation-aware and remote-region frameworks continue to appear [50]–[52], [58]. *Limitation:* these methods estimate the expected performance of a known site; they do not show how the structure of the Pareto front itself responds as the resource regime changes.

The studies above optimised HRES size with NSGA-II or competing metaheuristics under deterministic or stochastic resources, *but* three gaps remain. All benchmark NSGA-II HRES studies depend on measured site data [11], [43], [44], which restricts the framework to locations that already have meteorological records [52]. How the structure of the LCC–LPSP Pareto front (its spatial extent, minimum achievable LPSP and optimal configurations) evolves across a resource-availability spectrum from highly favourable to severely constrained conditions has not been systematically investigated [47], [49]. TOPSIS and equivalent post-selection methods are not yet standard in HRES Pareto pipelines [46]–[48]. Such controlled, regime-wide analysis is rarely reported.

Therefore, in the present investigation, the objective is not to predict performance at any specific location but to develop a reproducible pre-feasibility framework for data-scarce regions. It characterises how the LCC–LPSP Pareto front of a standalone PV–wind–battery HRES behaves across the full spectrum of resource availability and translates the resulting fronts into actionable configurations. A standalone NSGA-II implementation is applied across four synthetic stochastic scenarios (Base Case, Low Solar, High Renewable, Worst Case), built from physically justified distributional models with no reference to any geographic site, and TOPSIS is integrated as a post-Pareto decision layer for each scenario. The use of synthetic profiles is a deliberate methodological choice, not a substitute for measured data: generating resources from controlled distributional parameters makes resource availability an independent experimental variable that can be swept systematically and reproduced exactly, which a study tied to one site’s fixed TMY record cannot achieve. The novelty is threefold: **(i)** treatment of resource availability as a controlled, fully reproducible input through synthetic stochastic profiles, enabling parametric pre-feasibility screening for regions lacking measured records; **(ii)** the first systematic characterisation of how the LCC–LPSP Pareto front evolves across a resource-availability spectrum from highly favourable to severely constrained; and **(iii)** integration of TOPSIS to convert each scenario’s Pareto front into a single implementable configuration. The scope is stated explicitly: (a) the framework targets data-scarce regions without measured records; (b) the synthetic scenarios are the controlled experimental variable, not a reproduction of any site; (c) the study investigates Pareto-front behaviour across resource regimes, not site performance; and (d) site-specific validation against measured data is future work. The framework is therefore a pre-feasibility screening tool whose outputs inform early-stage design exploration rather than final, site-calibrated sizing.

2. SYSTEM MODELLING

2.1 System configuration and PV model

The HRES is standalone: N_{PV} PV modules, N_{WG} wind turbines and N_{bat} battery units share a common DC bus, and a DC–AC inverter supplies a time-varying residential AC load; no grid connection is present. At each hourly step the net power $P_{net}(t) = P_{PV}(t) + P_{wind}(t) - P_{load}(t)$ charges the battery ($P_{net} > 0$), discharges it ($P_{net} < 0$), or is recorded as a deficit when $P_{net} < 0$ and the battery is at minimum state of charge (SOC) [9], [11]. The AC output of the PV array is

$$P_{PV}(t) = N_{PV} \cdot P_{rated} \cdot \frac{G_{eff}(t)}{G_{STC}} \cdot \eta_{MPPT} \cdot \eta_{inv} \quad (1)$$

with $P_{rated} = 250$ W, $G_{STC} = 1000$ W/m², $\eta_{MPPT} = 0.97$ [41] and $\eta_{inv} = 0.95$ [11], [18]. The effective irradiance on the tilted surface is

$$G_{eff}(t) = G(t) \cdot \max(0, \cos(\beta - \beta_{opt})) \quad (2)$$

where β (decision variable, 0°–90°) is the PV tilt angle and $\beta_{opt} = 30^\circ$ is a mid-latitude representative optimum [18]. Eq. (2) is a simplified screening proxy that penalises tilt deviation symmetrically about β_{opt} ; it does not resolve solar azimuth, zenith or seasonal variation. Consequently, the convergence of tilt towards 30° observed in Section 6.2 is a built-in property of the model rather than a site-derived optimum.

2.2 Wind turbine model

The piecewise power curve of a single turbine is

$$P_{WT}(v_h) = \begin{cases} 0 & v_h < v_{ci} \text{ or } v_h \geq v_{co} \\ P_{rated} \eta_{wg} \frac{v_h^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} & v_{ci} \leq v_h < v_r \\ P_{rated} \eta_{wg} & v_r \leq v_h < v_{co} \end{cases} \quad (3)$$

with $P_{rated} = 1000$ W, $\eta_{wg} = 0.30$, $v_{ci} = 3.0$ m/s, $v_r = 12.0$ m/s and $v_{co} = 25.0$ m/s [11]. A cubic law is used in the partial-load region, consistent with the approximately cubic dependence of available wind power on wind speed. The hub-height wind speed follows the power-law shear correction [9]

$$v_h(t) = v_{ref}(t) \cdot \left(\frac{h}{h_{ref}} \right)^{1/7} \quad (4)$$

with $h_{ref} = 33$ m and shear exponent $\alpha = 1/7$ (neutral stability, open terrain). The total wind power is $P_{wind}(t) = N_{WG} \cdot P_{WT}(v_h(t))$.

2.3 Battery model and reliability index

The battery bank capacity is given by Eq. (5), and the hourly self-discharge rate derives from the daily rate $\sigma = 0.005$ day⁻¹ in Eq. (6):

$$E_{bat} = N_{bat} \cdot V_{bat} \cdot C_{nom} = N_{bat} \times 3,600 \text{ Wh} \quad (5)$$

$$\sigma_h = \frac{\sigma}{24} \quad (6)$$

The SOC evolves during charging ($P_{net} \geq 0$) and discharging ($P_{net} < 0$) as

$$SOC(t+1) = SOC(t) (1 - \sigma_h) + \frac{P_{net}(t) \eta_c \Delta t}{E_{bat}} \quad (7)$$

$$SOC(t+1) = SOC(t) (1 - \sigma_h) + \frac{P_{net}(t) \Delta t}{\eta_d E_{bat}} \quad (8)$$

and is clamped to $[SOC_{min}, SOC_{max}] = [0.20, 1.00]$ at every time step. The hourly energy deficit and the LPSP over the annual horizon (8,760 h) are [7], [27]

$$E_{deficit}(t) = \max(0, |P_{net}(t)| \Delta t - (SOC(t) - SOC_{min}) \eta_d E_{bat}) \quad (9)$$

$$LPSP = \frac{\sum_{t=1}^{8760} E_{deficit}(t)}{\sum_{t=1}^{8760} P_{load}(t) \Delta t} \quad (10)$$

All component parameters are consolidated in Table 1.

Table 1. System component parameters.

Component	Parameters
PV module	$P_{rated} = 250$ W; $\eta_{MPP} = 0.97$; $\eta_{inv} = 0.95$; capital cost $C_{PV} = 300$ USD/unit; maintenance $M_{PV} = 10$ USD/yr
Wind turbine	$P_{rated, WG} = 1,000$ W; $\eta_{wg} = 0.30$; $v_{ci}/v_r/v_{co} = 3.0/12.0/25.0$ m/s; $C_{WG} = 2,000$ USD/unit; $M_{WG} = 80$ USD/yr; tower: $C_{tower} = 45$ USD/m, $M_{tower} = 2$ USD/m/yr
Battery	$C_{nom} = 300$ Ah; $V_{bat} = 12$ V; $C_{bat} = 800$ USD/unit; $\eta_c/\eta_d = 0.90/0.90$; $\sigma = 0.005$ day ⁻¹ ; $M_{bat} = 8$ USD/yr; $SOC_{min}/SOC_{max} = 0.20/1.00$; replacements $n_{rep} = 4$
System	Project lifetime $L = 20$ years; time step $\Delta t = 1$ h; simulation horizon 8,760 h

3. Problem Formulation

3.1 Bi-objective optimisation framework

Objective 1 is the Life Cycle Cost, comprising capital, replacement, and operation and maintenance costs over the 20-year project horizon:

$$f_1 = N_{PV}(C_{PV} + L M_{PV}) + N_{WG}[C_{WG} + h C_{tower} + L(M_{WG} + h M_{tower})] + N_{bat}[C_{bat}(1 + n_{rep}) + L M_{bat}] \quad (11)$$

Objective 2 is a compound reliability–resource-utilisation index that combines LPSP with a component-count penalty:

$$f_2 = LPSP + \lambda (N_{PV} + N_{WG} + N_{bat}), \quad \lambda = 0.002 \quad (12)$$

The compound form, rather than a clean $[LCC, LPSP]$ problem, is adopted because in resource-abundant scenarios many distinct component combinations attain $LPSP \approx 0$; this produces a degenerate cluster of mutually non-dominated solutions that collapses the reliability axis and yields a poorly distributed front. The component-count term acts as a

parsimony tie-breaker that restores diversity by favouring the smallest configuration among reliability-equivalent solutions. The weight $\lambda = 0.002$ is calibrated so that the maximum penalty ($\lambda \times 42 \approx 0.08$) stays small relative to the LPSP range $[0,1]$, preserving LPSP as the dominant reliability driver; reported LPSP values are perturbed by at most this amount. Robustness to λ is confirmed in Section 6.5.

3.2 Decision variables and constraints

Five decision variables span the design space: the number of PV modules $N_{PV} \in \{1, \dots, 12\}$, wind turbines $N_{WG} \in \{0, \dots, 6\}$ and battery units $N_{bat} \in \{1, \dots, 24\}$ (integers), the PV tilt angle $\beta \in [0^\circ, 90^\circ]$ and the wind-turbine hub height $h \in [10, 50]$ m (continuous). The SOC constraint $SOC(t) \in [0.20, 1.00]$ is enforced at every time step. No minimum-LPSP constraint is imposed, so that the full Pareto front is recovered.

4. NSGA-II METHODOLOGY

4.1 Algorithm and implementation

NSGA-II [10] is a fast, elitist multi-objective evolutionary algorithm built on three mechanisms: (i) $O(MN^2)$ non-dominated sorting assigns a Pareto rank to every candidate in the combined parent–offspring pool; (ii) crowding distance favours sparsely populated regions of objective space without external archiving; and (iii) elitist selection ensures that non-dominated solutions found earlier are never discarded [13], [14]. These properties suit HRES sizing, whose objective surfaces are non-convex and whose search space mixes integer and continuous variables, conditions under which gradient-based methods are inapplicable [12]. Comparative studies confirm that NSGA-II gives a more diverse front than MOPSO for PV–wind–battery systems (hypervolume 0.04350 vs. 0.04336) [43] and is competitive with gravitational-search variants [44].

The MATLAB implementation uses a population of $N = 60$ and $G = 100$ generations (6,000 function evaluations per scenario), each evaluation being a full 8,760-hour energy-balance simulation. Simulated binary crossover (distribution index $\eta_{SBX} = 15$, probability $p_c = 0.90$) and polynomial mutation ($\eta_{PM} = 20$, $p_m = 0.15$) are applied; integer variables are rounded to the nearest integer after each operator, and the initial state of charge is $SOC(0) = 0.50$. Fixed per-scenario seeds (13i, $i = 0, 1, 2, 3$) guarantee exact reproducibility.

4.2 TOPSIS post-Pareto decision layer

TOPSIS [33], [34] converts each scenario's Pareto front into one implementable configuration. For candidate i and objective j ($j = 1$: LCC, $j = 2$: LPSP), the objective values are min–max normalised on the front's own extremes, $r_{ij} = (f_{ij} - f_j^{\min}) / (f_j^{\max} - f_j^{\min})$, so that the ideal point is (0,0). With weights w_j , the weighted distances to the ideal point (S_i^+) and to the anti-ideal point (S_i^-), and the closeness coefficient, are

$$S_i^+ = \sqrt{\sum_{j=1}^2 w_j^2 r_{ij}^2}, \quad S_i^- = \sqrt{\sum_{j=1}^2 w_j^2 (1 - r_{ij})^2} \quad (13)$$

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (14)$$

and the solution with the highest C_i (the TOPSIS score) is selected. Three selection regimes are examined: (a) equal, unconstrained weights ($w_1 = w_2 = 0.5$); (b) cost-weighted (0.7/0.3) and reliability-weighted (0.3/0.7) preferences; and (c) a deployability constraint, in which TOPSIS is applied only to Pareto points with $LPSP \leq 10\%$.

4.3 Convergence validation and computational cost

Three procedures validate the optimisation: (i) *multi-run statistics*, using five independent seeds (0, 13, 42, 77, 99) per scenario at full parameters and reporting the mean and standard deviation of minimum LPSP, minimum LCC and Pareto-set size; (ii) the *hypervolume indicator* [42], computed at every generation for the 2-D dominated region against the reference point $(1.1 \times LCC_{max}, 1.10)$ (Fig. 5b); and (iii) a λ -sensitivity analysis, $\lambda \in \{0.001, 0.002, 0.005\}$ at reduced parameters ($N = 30$, $G = 50$). Five runs follow common practice in the HRES NSGA-II literature, given the cost of each run and the very low run-to-run variability observed (Section 6.1). All optimisations ran in MATLAB R2024a on an Intel Core i7 workstation with 16 GB RAM; each scenario takes about 2–5 minutes and the entire study (four scenarios, convergence tracking, λ -sensitivity and five-seed validation) about 30–40 minutes, so the framework suits routine pre-feasibility screening on standard hardware.

5. SCENARIO-BASED SYNTHETIC FRAMEWORK

5.1 Synthetic profile generation

All resource and load profiles are generated algorithmically from fixed distributional parameters and per-scenario seeds, so results are exactly reproducible without any measured meteorological dataset [15]. Solar irradiance combines a deterministic seasonal–diurnal envelope with lognormal multiplicative noise [17], where doy is the day of year, h_{day} the hour of day and $\xi_{\text{solar}} \sim \text{Lognormal}(0, \sigma_{\text{solar}})$:

$$G(t) = 850 \left[1 + 0.45 \sin\left(\frac{2\pi(\text{doy} - 80)}{365}\right) \right] \sin\left(\frac{\pi(h_{\text{day}} - 6)}{14}\right) \xi_{\text{solar}} \quad (15)$$

Wind speed superimposes seasonal variation and Weibull-distributed perturbations $W \sim \text{Weibull}(k = 2.2, \lambda = 1)$ [26], with per-scenario wind scale S_{wind} and noise scale σ_{wind} (Table 2):

$$v_{\text{ref}}(t) = \left[5.0 + 1.8 \sin\left(\frac{2\pi \text{doy}}{365} + \pi\right) \right] S_{\text{wind}} + 4 \sigma_{\text{wind}} W \quad (16)$$

The residential load follows a double-Gaussian diurnal profile with morning and evening peaks:

$$P_{\text{load}}(t) = \left[P_{\text{base}} + A_{\text{eve}} e^{-\frac{(h_{\text{day}}-19)^2}{2 \cdot 2^2}} + A_{\text{morn}} e^{-\frac{(h_{\text{day}}-8)^2}{2 \cdot 1.5^2}} \right] \left[1 + 0.12 \sin\left(\frac{2\pi \text{doy}}{365}\right) \right] + \varepsilon \quad (17)$$

with $P_{\text{base}} = 550$ W, $A_{\text{eve}} = 650$ W, $A_{\text{morn}} = 350$ W and Gaussian noise $\varepsilon \sim \mathcal{N}(0, 60^2)$ W, clipped to [350, 2600] W. This gives a mean load of about 0.74 kW and a peak of about 1.5 kW, broadly representative of a small off-grid residence [11]. Fig. 1 shows the first 30 simulated days of each scenario.

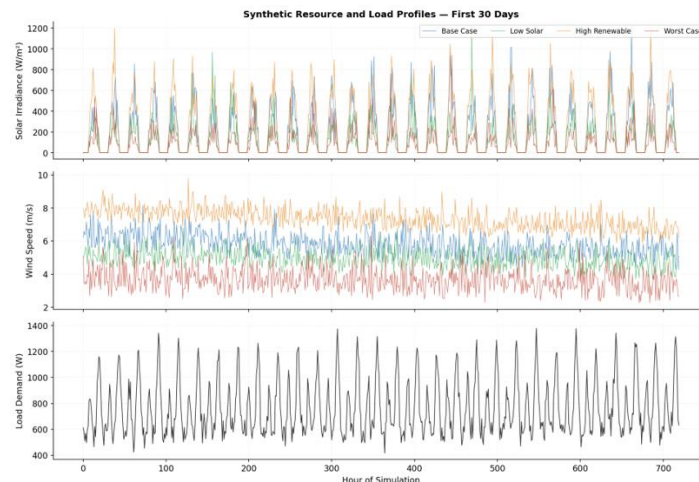


Fig. 1. Synthetic resource and load profiles for all four scenarios (first 30 simulation days).

5.2 Scenario design and statistical characterisation

Four scenarios span the range from highly favourable to severely constrained resource availability (Table 2). The multipliers do not represent exact climatic classes; they act as a controlled experimental variable, so the absolute calibration of any one scenario is secondary to the systematic variation of relative resource availability. The discrete four-scenario design (one moderate baseline, two single-factor stresses, one compound adverse extreme) is deliberate, in preference to a fine multiplier grid, Monte Carlo ensemble or Latin Hypercube sampling. Those methods estimate the expected outcome for a known site [37]; the present aim is to expose, exactly and reproducibly, how the structure of the Pareto front itself responds to the resource regime, which a compact factorial-style design isolates more transparently than a stochastic ensemble, where front-structure changes would be confounded with sampling noise. Embedding the framework in such an ensemble is a natural extension (Section 7).

Table 2. Synthetic scenario parameters and statistics of the generated series (full 8,760-h horizon; mean load = 739 W in all scenarios). GHI: global horizontal irradiance.

Scenario	Solar scale	σ_{solar}	Wind scale S_{wind}	σ_{wind}	Seed	Mean daytime GHI (W/m ²)	GHI SD (W/m ²)	Annual GHI (kWh/m ² /yr)	Mean wind (m/s)	Wind SD (m/s)
Base Case	1.00	0.35	1.00	0.35	0	542	353	2,772	6.24	1.40
Low Solar	0.55	0.45	0.85	0.30	13	326	259	1,664	5.31	1.19
High Renewable	1.30	0.22	1.40	0.28	26	666	380	3,405	7.99	1.84
Worst Case	0.38	0.55	0.50	0.40	39	236	210	1,208	3.91	0.94

The statistics confirm a monotonic, well-separated gradient of resource availability that preserves the lognormal and Weibull shapes reported in the literature [17], [26]. The constrained scenarios ($\approx 1,664$ and $\approx 1,208$ kWh/m²/yr) fall within ranges of real cloudy temperate and high-latitude sites, and the mean wind speeds (3.9–8.0 m/s) lie within the band typical of inhabited sites. The favourable scenarios deliberately reach the high end: the Base and High Renewable annual GHI (2,772 and 3,405 kWh/m²/yr) sit at or above the sunniest real locations ($\approx 2,600$ –2,900 kWh/m²/yr [55]) and are best read as an upper stress-test bound, not a calibrated site. The scenarios are therefore interpreted by relative resource availability. In the Worst Case, total achievable generation is only $\approx 60\%$ of annual demand (Section 6.2), which bounds its minimum LPSP at $\approx 44\%$.

6. RESULTS AND DISCUSSION

6.1 Pareto-optimal fronts and statistical summary

Fig. 2 shows the NSGA-II Pareto-optimal fronts of the four scenarios, with the TOPSIS selections of Section 6.3 overlaid. Three structural properties hold in every scenario: (i) the fronts are monotonically non-increasing in LCC–LPSP space; (ii) the diminishing-returns curvature is convex, the well-known shape of the HRES cost–reliability trade-off [9]; and (iii) all 60 population members are non-dominated at generation 100, confirming effective constraint handling. The fronts are clearly separated along the LPSP axis: the High Renewable front lies below $LPSP = 10\%$ for the upper-cost half of its solutions, whereas the Worst Case front stays above 43% throughout, a direct consequence of the 62% lower solar scale and 50% lower wind scale relative to the Base Case (Table 2).

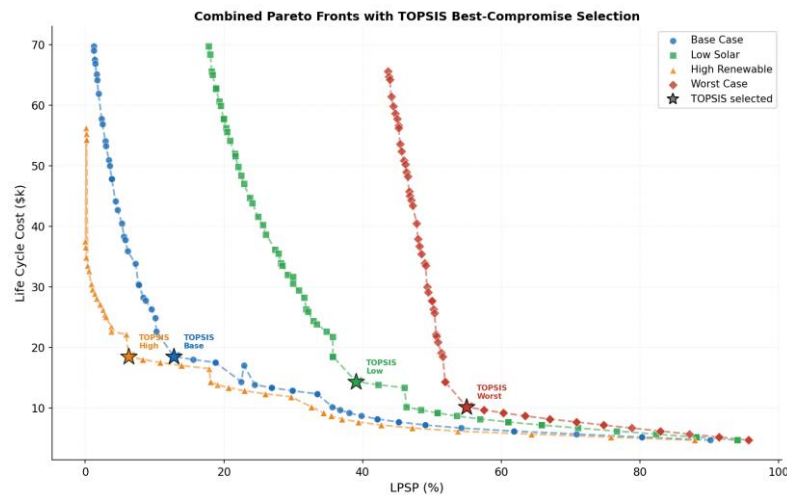


Fig. 2. Combined Pareto fronts of the four scenarios in LCC–LPSP space with the TOPSIS best-compromise selections (stars) overlaid.

Table 3. Statistical summary of the Pareto-optimal fronts (HV: hypervolume).

Scenario	Min LCC (\$)	Max LCC (\$)	Min LPSP (%)	Max LPSP (%)	Points	HV
Base Case	4,660	69,740	1.20	90.14	60	0.0216
Low Solar	4,660	69,740	17.78	94.08	60	0.0317
High Renewable	4,660	56,230	0.00	87.88	60	0.0184
Worst Case	4,660	65,580	43.66	95.71	60	0.0711

Multi-run validation (five seeds) for the Base Case gives mean minimum $LPSP = 1.201\%$ (SD = 0.001%), mean minimum $LCC = \$5,760$ (SD = \$1,356) and a Pareto set of 60 points in all runs. The negligible LPSP spread confirms consistent convergence in the reliability-dominant region of the front, whereas the larger LCC spread arises at the minimum-cost extreme. The high hypervolume of the Worst Case (0.0711) reflects the large dominated area, relative to the reference point, produced by elevated LPSP values across its front; hypervolumes are best compared within rather than across scenarios.

6.2 Optimal configurations and energy balance

Table 4 lists the minimum-LPSP Pareto solution of each scenario together with its annual energy balance against an annual demand of ≈ 6.47 MWh (Fig. 3).

Table 4. Minimum-LPSP configurations and annual energy balance per scenario.

Scenario	N_{PV}	N_{WG}	N_{bat}	β (°)	h (m)	LCC (\$k)	LPSP (%)	PV energy (MWh/yr)	WT energy (MWh/yr)	PV share (%)	Gen./Load (%)
Base Case	12	6	4	29.5	50.0	69.7	1.20	7.66	2.85	72.9	162
Low Solar	12	6	4	30.0	50.0	69.7	17.78	4.60	1.66	73.5	97
High Renewable	12	2	4	31.0	45.3	37.5	0.00	9.41	2.01	82.4	176
Worst Case	12	6	3	30.0	50.0	65.6	43.66	3.34	0.54	86.1	60

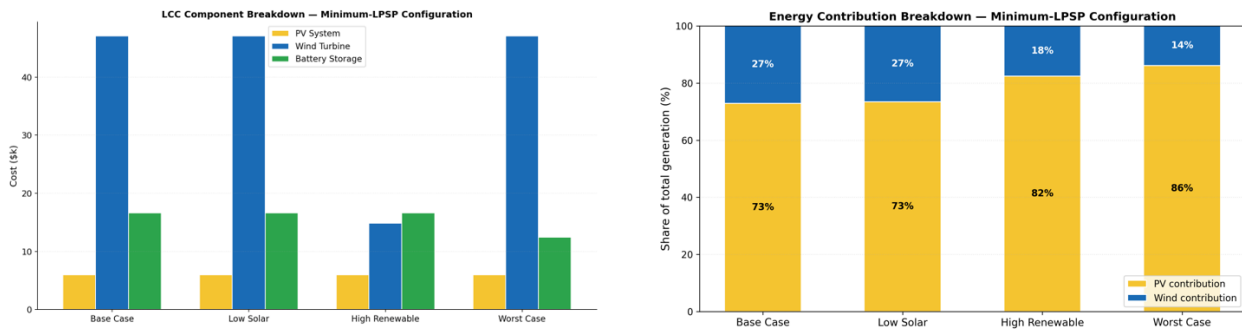


Fig. 3. (a) LCC component breakdown and (b) PV/wind energy contribution for the minimum-LPSP configuration of each scenario.

The optimised tilt converges to 28° – 31° in all scenarios. Because Eq. (2) fixes the optimum at $\beta_{opt} = 30^\circ$ by construction, this is not an independently determined site-optimal tilt, and β is treated as a fixed-optimum screening parameter rather than a result. More substantively, where $N_{WG} = 6$ and $h = 50$ m, the wind subsystem (turbines plus towers) accounts for $\approx \$47,100$ of the $\$69,740$ LCC (Fig. 3a), making tower height the primary cost driver; High Renewable reaches $LPSP = 0.00\%$ with only two turbines, showing that abundant solar substantially reduces the required wind contribution.

Three behaviours emerge from Table 4 and Fig. 3b. *First*, PV dominates generation in every scenario (73–86%) and its share rises as conditions worsen, because the wind resource degrades faster than solar across the scenario set, a non-obvious result favouring PV-led architectures in the most constrained settings. *Second*, the well-resourced scenarios markedly over-generate (162% and 176% of annual load), so the binding constraint there is temporal mismatch and storage capacity rather than total energy, consistent with the high marginal value of an additional battery seen in the weight sensitivity (Section 6.3). *Third*, the Worst Case generates only 60% of annual demand: the deficit is one of absolute energy, which is why no configuration can reduce its LPSP below $\approx 44\%$ and why this scenario is infeasible under the present component bounds.

6.3 TOPSIS best-compromise selections

Equal-weight TOPSIS ($w_1 = w_2 = 0.5$, Eq. (13) and (14)) was applied to each front; the selections are marked in Fig. 2 and listed in Table 5.

Table 5. TOPSIS best-compromise solutions (equal, unconstrained weights). Hub height is inactive when $N_{WG} = 0$ (values in parentheses).

Scenario	N_{PV}	N_{WG}	N_{bat}	β (°)	h (m)	LCC (\$k)	LPSP (%)	TOPSIS score
Base Case	12	0	3	30.0	(25.0)	18.5	12.76	0.842
Low Solar	12	0	2	30.0	(18.7)	14.3	39.08	0.789
High Renewable	12	0	3	30.0	(30.2)	18.5	6.29	0.819
Worst Case	12	0	1	30.0	(13.5)	10.2	55.02	0.884

In every scenario TOPSIS selects $N_{WG} = 0$, a PV–battery configuration, because at the best-compromise point the marginal cost of the first turbine plus tower ($\approx \$5,700$ at $h = 25$ m) outweighs its normalised reliability gain. Relative to the minimum-LPSP configurations, LCC falls by 73.5% (Base Case), 79.5% (Low Solar), 50.7% (High Renewable) and 84.4% (Worst Case), and the selections lie at the high-curvature knee of each front (Fig. 2), as expected for a distance-to-ideal minimiser [33], [46]. However, the unconstrained selections are acceptable only for the well-resourced scenarios ($LPSP = 12.76\%$ and 6.29%); for Low Solar (39.08%) and Worst Case (55.02%) more than a third to over half of the annual load would be unserved. They illustrate the cost-dominated geometry of equal-weight TOPSIS rather than recommended designs. Table 6 therefore restricts the candidate set to $LPSP \leq 10\%$ before applying TOPSIS.

Table 6. Deployability-constrained TOPSIS best-compromise solutions ($LPSP \leq 10\%$).

Scenario	N_{PV}	N_{WG}	N_{bat}	β (°)	h (m)	LCC (\$k)	LPSP (%)	Feasible points
Base Case	12	3	4	30.8	42.0	44.2	4.35	27 / 60
Low Solar	-	-	-	-	-	-	-	0 / 60 (infeasible)
High Renewable	12	1	4	30.1	39.3	29.6	1.05	23 / 60
Worst Case	-	-	-	-	-	-	-	0 / 60 (infeasible)

Table 6 yields two findings that the unconstrained selection obscures. *First*, in the well-resourced scenarios the deployability constraint reverses the PV-only outcome: the Base Case reintroduces three turbines and a fourth battery to reach $LPSP = 4.35\%$ at \$44.2k (36.6% below its \$69.7k minimum-LPSP design), and High Renewable reaches $LPSP = 1.05\%$ at \$29.6k with a single turbine (21.1% below \$37.5k). Wind capacity is therefore essential, not redundant, once a realistic reliability target is imposed; the apparent optimality of PV-only systems is an artefact of unconstrained equal weighting. *Second*, for the resource-poor scenarios (minimum achievable LPSP of 17.78% and 43.66%) no configuration within the five-variable design space reaches $LPSP \leq 10\%$; these sites are infeasible for the specified load under the present bounds and would require demand-side reduction, expanded component limits or supplementary dispatchable generation. This bifurcation- deployable compromise designs in well-resourced settings versus categorical infeasibility in resource-poor ones- is a more actionable conclusion than the Pareto knee alone.

Weight sensitivity. Table 7 repeats the selection under cost-weighted ($w_{LCC} = 0.7$, $w_{rel} = 0.3$) and reliability-weighted ($w_{LCC} = 0.3$, $w_{rel} = 0.7$) preferences. The response is monotonic and physically sensible: shifting weight toward reliability raises the selected battery (and, for Low Solar, wind) count and lowers LPSP at higher cost, and shifting toward cost does the reverse, so the selection is not an artefact of the equal-weight assumption. Even under maximum reliability weighting, the resource-poor scenarios remain at non-deployable LPSP (31.88% and 51.89%), confirming that their infeasibility is a property of the resource regime, not of the weighting choice.

Table 7. TOPSIS weight sensitivity (LCC \$k / LPSP %).

Scenario	Cost-weighted (0.7/0.3)	Balanced (0.5/0.5)	Reliability-weighted (0.3/0.7)
Base Case	14.3 / 22.51	18.5 / 12.76	22.6 / 10.26
Low Solar	10.2 / 46.33	14.3 / 39.08	26.3 / 31.88
High Renewable	8.7 / 35.49	18.5 / 6.29	18.5 / 6.29
Worst Case	9.2 / 60.28	10.2 / 55.02	14.3 / 51.89

6.4 Cost–reliability trade-off benchmark

Fig. 4 shows the percentage LCC reduction achievable in the Base Case as the tolerated LPSP is relaxed, with the problem of Hossain et al. [11] marked at (8%, 12.12%). The Base Case yields reductions of 11.26% at 2% LPSP, 23.64% at 3% and 56.51% at 8%. Both problems exhibit the same qualitative convex, diminishing-returns curve. This is a sanity check, explicitly not a quantitative validation: the gradient differs by a factor of ≈ 4.6 (56.51% vs. 12.12% at 8% LPSP), so the synthetic Base Case is markedly more cost-elastic than the Auckland case of [11]. The divergence is attributable to the larger five-variable search space and to the synthetic, geographically uncalibrated load and resource profiles, so the absolute cost-reduction figures reported here must not be transferred to a specific site without recalibration. As a second structural reference, Hadj Slama et al. [43] report cost-versus-LPSP gradients for a PV–WT–battery–diesel system that are broadly consistent with cost reductions of tens of percent in the low-LPSP regime for well-resourced standalone systems. Quantitative validation would require reproducing [11] on its own data or calibrating a scenario to a measured TMY dataset (Section 7).

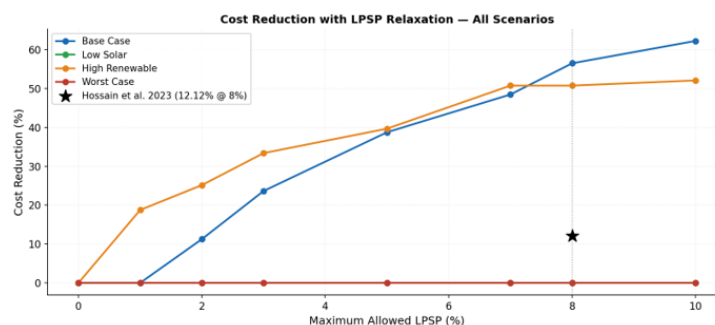


Fig. 4. Percentage LCC reduction versus LPSP tolerance for all scenarios; the star marks the problem of Hossain et al. [11].

6.5 λ -sensitivity and convergence

Fig. 5a shows the Base Case fronts for $\lambda \in \{0.001, 0.002, 0.005\}$ at reduced parameters ($N = 30, G = 50$). The minimum LPSP values are 1.20%, 1.91% and 1.91%, a spread of 0.71 percentage points. The front shape is qualitatively stable; the main effect of increasing λ is a modest upward shift at the minimum-LPSP end, consistent with the penalty on maximum-deployment configurations. The selected $\lambda = 0.002$ therefore preserves diversity in resource-abundant scenarios without materially distorting the reliability-dominant region of the front. Fig. 5b shows that the Base Case hypervolume converges by about generation 60 and remains stable through generation 100, with no further improvement in the final 40 generations. Together with the negligible multi-run LPSP standard deviation (0.001%), this confirms that $N = 60$ and $G = 100$ suffice for this five-dimensional mixed integer–continuous problem, consistent with NSGA-II behaviour on analogous sizing problems [12], [44].

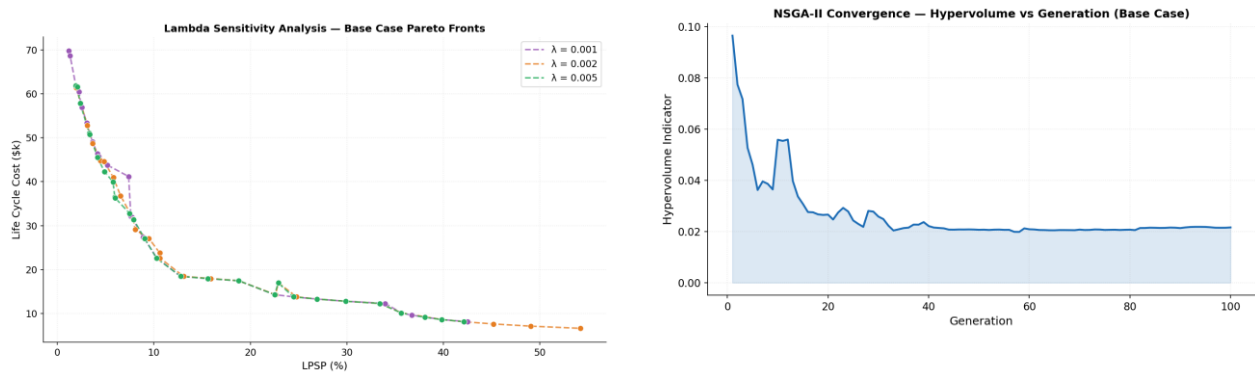


Fig. 5. (a) Base Case Pareto fronts for $\lambda \in \{0.001, 0.002, 0.005\}$; (b) NSGA-II hypervolume versus generation (Base Case).

6.6 Why the synthetic framework matters

The principal contribution of this study is not an optimal design for a particular site but the quantification of how the geometry of the cost–reliability Pareto front changes as resource availability moves from favourable to severely constrained regimes. This insight transfers across data-scarce regions because it depends on relative, not absolute, resource values: PV dominance that strengthens as conditions deteriorate, the shift of the binding constraint from total energy to storage in well-resourced regimes, categorical infeasibility once generation falls below demand, and the rational response of post-Pareto selection to designer preferences are governed by the structure of the resource–reliability relationship, not by the coordinates of any location. A practitioner facing a site with no measured record can therefore position it within the scenario spectrum and read off the expected front behaviour and dominant design driver, which is exactly the function of a pre-feasibility screening tool; absolute sizing remains a later step requiring measured data.

7. Conclusions, Limitations and Future Work

This paper presented an NSGA-II multi-objective framework for sizing a standalone PV–wind turbine–battery HRES across four synthetic stochastic scenarios, with TOPSIS integrated as a post-Pareto decision layer. Four conclusions emerge. (1) Resource availability is the dominant determinant of achievable reliability. Minimum LPSP spans 0.00% (High Renewable) to 43.66% (Worst Case), showing that resource scarcity, not algorithmic limitation, bounds the feasible reliability space. The Base Case minimum-LPSP configuration ($N_{PV} = 12, N_{WG} = 6, N_{bat} = 4, h = 50$ m, LCC = \$69.7k, LPSP = 1.20%) is robust across five independent seeds (SD = 0.001%). (2) Post-Pareto selection is decisive for practical recommendations. Under equal, unconstrained weighting TOPSIS favours PV-only battery configurations ($N_{WG} = 0$) with 51–84% LCC reductions, but these give impractical reliability in resource-poor scenarios (LPSP up to 55%). A deployability constraint ($LPSP \leq 10\%$) reverses this outcome: the Base Case and High Renewable designs reintroduce wind capacity to reach LPSP of 4.35% (\$44.2k) and 1.05% (\$29.6k), whereas Low Solar and Worst Case admit no configuration meeting the threshold within the design bounds. Wind capacity is thus essential once realistic reliability is required, and resource-poor sites are categorically infeasible for the specified load. (3) The synthetic framework works as a reproducible proof-of-concept screening tool. It reproduces the qualitative convex diminishing-returns structure reported for real-data HRES optimisation [11], while the large difference in gradient magnitude shows that it suits early-stage design-space exploration, not site-specific quantitative prediction. (4) The compound reliability index is robust. Minimum LPSP varies by at most 0.71 percentage points across $\lambda \in \{0.001, 0.002, 0.005\}$, so the penalty weight does not materially affect the reliability-dominant region of the front.

Limitations and future work. The framework is a screening tool: (a) validation against measured meteorological data, by reproducing [11] on its own data or calibrating a scenario to a measured TMY dataset, is required before outputs are applied to a specific location; (b) the tilt model of Eq. (2) is a symmetric proxy, so tilt results are not site-optimal and a solar-position model should replace it; (c) the favourable scenarios represent an upper stress-test bound of irradiance; and (d) embedding the framework within a Latin Hypercube or Monte Carlo resource ensemble, and including battery degradation and demand-side or dispatchable options for the infeasible regimes, are natural extensions.

REFERENCES

- [1] Y. Sawle, S.C. Gupta, and A.K. Bohre, "Review of Hybrid Renewable Energy Systems with Comparative Analysis of Off-Grid Hybrid System," *Renew. Sustain. Energy Rev.*, vol. 81, pp. 2217–2235, 2018. doi:10.1016/j.rser.2017.06.033
- [2] M.D.A. Al-Falahi, S.D.G. Jayasinghe, and H. Enshaie, "A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system," *Energy Convers. Manag.*, vol. 143, pp. 252–274, 2017. doi:10.1016/j.enconman.2017.04.019
- [3] O. Erdinc and M. Uzunoglu, "Optimum design of hybrid renewable energy systems: Overview of different approaches," *Renew. Sustain. Energy Rev.*, vol. 16, no. 3, pp. 1412–1425, 2012. doi:10.1016/j.rser.2011.11.011
- [4] A. Khare, S. Nema, and P. Baredar, "Solar–wind hybrid renewable energy system: A review," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 23–33, 2016. doi:10.1016/j.rser.2015.12.223
- [5] A. Chauhan and R.P. Saini, "A review on Integrated Renewable Energy System based power generation for stand-alone applications," *Renew. Sustain. Energy Rev.*, vol. 38, pp. 99–120, 2014. doi:10.1016/j.rser.2014.05.079
- [6] M. Fadaee and M.A.M. Radzi, "Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3364–3369, 2012. doi:10.1016/j.rser.2012.02.045
- [7] H. Yang, W. Zhou, L. Lu, and Z. Fang, "Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm," *Sol. Energy*, vol. 82, no. 4, pp. 354–367, 2008. doi:10.1016/j.solener.2007.08.005
- [8] K. Anoune, M. Bouya, A. Astito, and A. Ben Abdellah, "Sizing methods and optimization techniques for PV–wind based hybrid renewable energy system: A review," *Renew. Sustain. Energy Rev.*, vol. 93, pp. 652–673, 2018. doi:10.1016/j.rser.2018.05.032
- [9] D. Abbes, A. Martinez, and G. Champenois, "Life cycle cost, embodied energy and loss of power supply probability for the optimal design of hybrid power systems," *Math. Comput. Simul.*, vol. 98, pp. 46–62, 2014. doi:10.1016/j.matcom.2013.05.004
- [10] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, 2002. doi:10.1109/4235.996017
- [11] M.A. Hossain, H.R. Pota, S. Squartini, F. Zaman, and J.M. Guerrero, "Multi-Objective Hybrid Optimization for Optimal Sizing of a Hybrid Renewable Power System for Home Applications," *Energies*, vol. 16, no. 1, p. 96, 2023. doi:10.3390/en16010096
- [12] M.I. Hlal, V.K. Ramachandramurthy, S. Padmanaban, H.R. Kaboli, A. Pouryekt, and T.S.U.T. Abdullah, "NSGA-II and MOPSO based optimization for sizing of hybrid PV/wind/battery energy storage system," *Int. J. Power Electron. Drive Syst.*, vol. 10, no. 1, pp. 463–478, 2019. doi:10.11591/ijpeds.v10.i1.pp463-478
- [13] K. Deb, *Multi-Objective Optimization using Evolutionary Algorithms*. Chichester, UK: Wiley, 2001.
- [14] C.A.C. Coello Coello, G.B. Lamont, and D.A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*, 2nd ed. New York, NY: Springer, 2007.
- [15] H. Suomalainen, G. Turner, B. Smith, and D. Bhatt, "Simplifications in load and resource modelling: implications for renewable energy system design," *IEEE Trans. Sustain. Energy*, vol. 3, no. 1, pp. 17–24, 2012. doi:10.1109/TSTE.2011.2163392
- [16] A. Maleki and F. Pourfayaz, "Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with LPSP technology by using evolutionary algorithms," *Sol. Energy*, vol. 115, pp. 471–483, 2015. doi:10.1016/j.solener.2015.03.004
- [17] K.T.G. Hollands and R.G. Huget, "A probability density function for the clearness index, with applications," *Sol. Energy*, vol. 30, no. 3, pp. 195–209, 1983. doi:10.1016/0038-092X(83)90149-4
- [18] M.S. Javed, A. Song, and T. Ma, "Techno-economic assessment of a stand-alone hybrid solar-wind-battery system: design and sizing," *Energy*, vol. 176, pp. 704–717, 2019. doi:10.1016/j.energy.2019.03.131
- [19] H. Yang, L. Lu, and W. Zhou, "A novel optimization sizing model for hybrid solar-wind power generation system," *Sol. Energy*, vol. 81, no. 1, pp. 76–84, 2007. doi:10.1016/j.solener.2006.06.010
- [20] B.S. Borowy and Z.M. Salameh, "Methodology for optimally sizing the combination of a battery bank and PV array in a wind/PV hybrid system," *IEEE Trans. Energy Convers.*, vol. 11, no. 2, pp. 367–375, 1996. doi:10.1109/60.507648
- [21] B. Ai, H. Yang, H. Shen, and X. Liao, "Computer-aided design of PV/wind hybrid system," *Renew. Energy*, vol. 28, no. 10, pp. 1491–1512, 2003. doi:10.1016/S0960-1481(03)00011-9
- [22] O. Ekren and B.Y. Ekren, "Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing," *Appl. Energy*, vol. 87, no. 2, pp. 592–598, 2010. doi:10.1016/j.apenergy.2009.05.022
- [23] A. Kaabeche and R. Ibtouen, "Techno-economic optimization of hybrid photovoltaic/wind/diesel/battery generation in a stand-alone power system," *Sol. Energy*, vol. 104, pp. 343–354, 2014. doi:10.1016/j.solener.2014.03.015
- [24] D. Fares, M. Fathi, and S. Mekhilef, "Performance evaluation of metaheuristic techniques for optimal sizing of a stand-alone hybrid PV/wind/battery system," *Appl. Energy*, vol. 305, art. 117823, 2022. doi:10.1016/j.apenergy.2021.117823
- [25] T. Lambert, P. Gilman, and P. Lilienthal, "Micropower system modeling with HOMER," in *Integration of Alternative Sources of Energy*, F.A. Farret and M.G. Simões, Eds. Hoboken, NJ: Wiley, 2006, pp. 379–418. doi:10.1002/0471755621.ch15
- [26] J.V. Seguro and T.W. Lambert, "Modern estimation of the parameters of the Weibull wind speed distribution for wind energy analysis," *J. Wind Eng. Ind. Aerodyn.*, vol. 85, no. 1, pp. 75–84, 2000. doi:10.1016/S0167-6105(99)00122-1
- [27] J.L. Bernal-Agustín and R. Dufo-López, "Simulation and optimization of stand-alone hybrid renewable energy systems," *Renew. Sustain. Energy Rev.*, vol. 13, no. 8, pp. 2111–2118, 2009. doi:10.1016/j.rser.2009.01.010
- [28] S. Mirjalili, S.M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014. doi:10.1016/j.advengsoft.2013.12.007
- [29] T.D. Bhatt et al., "Optimal sizing of standalone PV–wind–battery hybrid system for remote area electrification," *Int. J. Renew. Energy Res.*, vol. 12, no. 1, pp. 330–342, 2022.
- [30] E. Zitzler, M. Laumanns, and L. Thiele, "SPEA2: Improving the Strength Pareto Evolutionary Algorithm," *Tech. Rep. 103*, Computer Engineering and Networks Laboratory, ETH Zürich, 2001.
- [31] D.H. Geleta and M.S. Manshahia, "Grey wolf optimizer for optimal sizing of hybrid wind and solar renewable energy system," *Comput. Intell.*, vol. 38, no. 3, pp. 1133–1162, 2022. doi:10.1111/coin.12349
- [32] S. Mirjalili and A. Lewis, "The Whale Optimization Algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016. doi:10.1016/j.advengsoft.2016.01.008
- [33] C.-L. Hwang and K. Yoon, *Multiple Attribute Decision Making: Methods and Applications*. Berlin, Germany: Springer, 1981.
- [34] M. Velasquez and P.T. Hester, "An analysis of multi-criteria decision making methods," *Int. J. Oper. Res.*, vol. 10, no. 2, pp. 56–66, 2013.
- [35] B.A. Carrasco, A. Lorca, and J. Muñoz, "Scenario-based design of renewable energy systems under resource uncertainty," *Electr. Power Syst. Res.*, vol. 188, art. 106495, 2020. doi:10.1016/j.epsr.2020.106495
- [36] H. Fathy, A. Yousri, and M.A. Elhosseni, "Robust energy management strategy for hybrid renewable microgrids," *Appl. Energy*, vol. 258, art. 114062, 2020. doi:10.1016/j.apenergy.2019.114062
- [37] M. Aien, A. Hajebrahimi, and M. Fotuhi-Firuzabad, "A comprehensive review on uncertainty modeling techniques in power system studies," *Renew. Sustain. Energy Rev.*, vol. 57, pp. 1077–1089, 2016. doi:10.1016/j.rser.2015.12.070
- [38] A.J. Conejo, M. Carrión, and J.M. Morales, *Decision Making Under Uncertainty in Electricity Markets*. New York, NY: Springer, 2010. doi:10.1007/978-1-4419-7421-1
- [39] R. Hemmati and H. Saboori, "Short-term bulk energy storage system scheduling for load leveling in unit commitment: modeling, optimization, and sensitivity analysis," *J. Adv. Res.*, vol. 7, no. 3, pp. 360–372, 2016. doi:10.1016/j.jare.2016.02.004
- [40] L. Xu, X. Ruan, C. Mao, B. Zhang, and Y. Luo, "An improved optimal sizing method for wind-solar-battery hybrid power system," *Energy Convers. Manag.*, vol. 196, pp. 1092–1103, 2019. doi:10.1016/j.enconman.2019.06.072
- [41] H. Rezk and A.M. Eltamaly, "A comprehensive comparison of different MPPT techniques for photovoltaic systems," *Sol. Energy*, vol. 112, pp. 1–11, 2015. doi:10.1016/j.solener.2014.11.010
- [42] E. Zitzler, L. Thiele, M. Laumanns, C.M. Fonseca, and V.G. da Fonseca, "Performance assessment of multiobjective optimizers: An analysis and review," *IEEE Trans. Evol. Comput.*, vol. 7, no. 2, pp. 117–132, 2003. doi:10.1109/TEVC.2003.810758
- [43] A. Hadj Slama, L. Saidi, M. Saidi, and M. Benbouzid, "Metaheuristic Optimization of Hybrid Renewable Energy Systems under Asymmetric Cost-Reliability Objectives: NSGA-II and MOPSO Approaches," *Symmetry*, vol. 17, no. 9, art. 1412, 2025. doi:10.3390/sym17091412
- [44] S.M. Mahmoudi and A. Maleki, "Multi-objective optimization of hybrid energy systems using gravitational search algorithm," *Sci. Rep.*, vol. 15, art. 2550, 2025. doi:10.1038/s41598-025-86476-z
- [45] T. Tezer et al., "Multi-objective optimization of hybrid renewable energy systems with green hydrogen integration and hybrid storage strategies," *Int. J. Hydrogen Energy*, 2025. doi:10.1016/j.ijhydene.2025.03.006
- [46] T.N.D. Mathaba and K. Abo-Al-Ez, "Design of Hybrid Renewable Energy Systems: Integrating Multi-Objective Optimization Into a Multi-Criteria Decision-Making Framework," *Eng. Rep.*, vol. 7, no. 1, art. e13074, 2025. doi:10.1002/eng2.13074
- [47] H.M. Ridha, H. Hizam, S. Mirjalili, M.L. Othman, M.E. Ya'acob, and M. Ahmadipour, "Innovative hybridization of the two-archive and PROMETHEE-II triple-objective and multi-criterion decision making for optimum configuration of the hybrid renewable energy system," *Appl. Energy*, vol. 341, art. 121117, 2023. doi:10.1016/j.apenergy.2023.121117
- [48] A. Tomczewski, S. Mikulski, and J. Szymenderski, "Application of the analytic hierarchy process method to select the final solution for multi-

- criteria optimization of the structure of a hybrid generation system with energy storage,” *Energies*, vol. 17, no. 24, art. 6435, 2024. doi:10.3390/en17246435
- [49] H. Gharoei et al., “Stochastic sizing and energy management of a hybrid energy system using cloud model and improved Walrus optimizer,” *Sci. Rep.*, vol. 15, art. 21205, 2025. doi:10.1038/s41598-025-03212-3
- [50] A.K. Mahmood et al., “Hybrid stochastic and robust optimization of a fuel-cell hybrid system for building electrification using an improved arithmetic optimization algorithm,” *Sci. Rep.*, vol. 15, art. 1779, 2025. doi:10.1038/s41598-025-86074-z
- [51] J.M. Lujano-Rojas et al., “Optimization of size and operation of stand-alone renewable-based systems with diesel and hybrid pumped hydro storage–battery storage considering uncertainties,” *Batteries*, vol. 11, no. 2, art. 70, 2025. doi:10.3390/batteries11020070
- [52] F. Sharifi, M. Najafi, and A. Sheikholeslami, “Optimal allocation and techno-economic assessment of hybrid energy systems considering uncertainty and reliability: a case study in a remote region,” *IET Renew. Power Gener.*, vol. 19, art. e70094, 2025. doi:10.1049/rpg2.70094
- [53] Muhibbuddin, Erdiwansyah, A.Z. Syahir, R. Mamat, and R.E. Sardjono, “A review of optimization strategies for hybrid renewable energy systems toward sustainable clean energy,” *Results Eng.*, vol. 28, art. 104407, 2025. doi:10.1016/j.rineng.2025.104407
- [54] O. Bamişile, D. Cai, H. Adun, M. Dagbasi, C.C. Ukwuoma, Q. Huang, and N. Johnson, “Towards renewables development: Review of optimization techniques for energy storage and hybrid renewable energy systems,” *Heliyon*, vol. 10, no. 17, art. e37482, 2024. doi:10.1016/j.heliyon.2024.e37482
- [55] World Bank Group / ESMAP, *Global Photovoltaic Power Potential by Country*. Washington, DC: World Bank, 2020. [Online]. Available: <https://globalsolaratlas.info/global-pv-potential-study>
- [56] M. Sechilariu, “A Comprehensive Review of Sizing and Energy Management Strategies for Optimal Planning of Microgrids with PV and Other Renewable Integration,” *Appl. Sci.*, vol. 14, no. 22, art. 10479, 2024. doi:10.3390/app142210479
- [57] J. Ahn, “Hybrid Genetic Algorithm-Based Optimal Sizing of a PV–Wind–Diesel–Battery Microgrid: A Case Study for the ICT Center, Ethiopia,” *Mathematics*, vol. 13, no. 6, art. 985, 2025. doi:10.3390/math13060985
- [58] M.S. Javaid et al., “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,” *Sustainability*, vol. 18, no. 12, art. 6292, 2026. doi:10.3390/su18126292