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Stochastic Optimization and Reliability Analysis of Hybrid Solar–Battery Systems Under Uncertainty

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Abstract

Hybrid solar–battery systems are increasingly deployed in off-grid and weak-grid regions to provide sustainable and reliable energy access. These systems combine photovoltaic (PV) generation with battery storage to ensure continuous supply despite intermittent solar conditions. Designing such systems is challenging due to variability and uncertainty in solar irradiance, load demand, and component performance. Deterministic sizing methods, relying on average conditions, often result in under-dimensioned systems prone to outages or over-dimensioned systems with high capital costs.

This paper presents an integrated stochastic optimization framework for hybrid solar–battery system design under uncertainty. The approach models the probabilistic behavior of solar irradiance and load demand and uses Monte Carlo simulation to evaluate system performance across thousands of scenarios. Key reliability indices, including Loss of Power Supply Probability (LPSP) and Expected Energy Not Supplied (EENS), are computed to quantify the cost–reliability trade-off. Advanced metaheuristic algorithms, such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), are employed to efficiently search the non-linear, non- convex design space, handling mixed discrete–continuous variables and probabilistic constraints. Sensitivity analyses assess the impact of battery degradation, discount rate variations, and load growth scenarios on the optimal system design.

The results demonstrate that the stochastic approach substantially improves re- liability while controlling costs compared to deterministic methods. This framework offers a rigorous tool for uncertainty-aware hybrid system planning, applicable to remote electrification, weak-grid enhancement, and sustainable microgrid deployment.

Keywords: Hybrid solar–battery system; Stochastic optimization; Monte Carlo simulation; Reliability assessment; LPSP; EENS; Particle Swarm Optimization; Genetic Algorithm; Uncertainty modeling.

1 Introduction

The global energy transition has accelerated the adoption of renewable technologies, with solar photovoltaic (PV) systems becoming one of the most widely implemented solutions [1]. Hybrid solar–battery systems, which combine PV generation with battery storage, are particularly valuable in remote areas or regions with weak grid connections, where continuous energy access is critical [3], [4]. These systems improve energy reliability by storing excess energy during periods of high generation and supplying it during periods of low generation or high demand [13].

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Despite their advantages, hybrid systems face significant design challenges due to the inherent variability of both solar generation and load demand. Solar irradiance fluctuates on daily, seasonal, and weather-related timescales, leading to intermittent energy supply [5], [14]. Similarly, load profiles vary depending on user behaviour, seasonal changes, and stochastic events [15], [18]. Failure to account for this variability during system design can result in frequent power outages or unnecessary overinvestment in energy storage [12].

Traditional deterministic design approaches often rely on average solar irradiance and mean load demand [2]. While computationally simple, these methods do not capture variability and extreme conditions, which may compromise system reliability [1], [5]. As a result, deterministic sizing can lead to either under-dimensioned systems with poor performance or over-dimensioned systems that are economically inefficient [4], [12].

Battery energy storage plays a critical role in maintaining system reliability. Proper sizing of the battery ensures sufficient energy is available to meet demand during periods of low generation [13]. However, inaccurate sizing can either lead to excessive capital expenditure or compromise the continuity of energy supply [3], [4].

To address these challenges, stochastic modelling and optimization have emerged as effective strategies. By treating solar irradiance and load demand as random variables, designers can explicitly account for uncertainty and optimize system components to balance reliability and cost [7], [10], [15]. Monte Carlo simulation provides a complementary tool for assessing system performance across thousands of possible operational scenarios, enabling planners to evaluate reliability indices and quantify the risk of supply shortfalls [6], [14].

This study develops an integrated framework combining stochastic optimization and Monte Carlo–based reliability assessment for hybrid solar–battery systems. The methodology provides a systematic approach for determining optimal system sizes while considering uncertainty in both generation and demand [6], [7], [15]. The proposed framework enhances both the reliability and economic efficiency of hybrid renewable energy systems [1], [13].

2 Literature Review

The evolution of hybrid renewable system design has shifted from deterministic approaches to probabilistic modelling and stochastic optimization [1], [2], [7]. Early studies focused primarily on minimizing lifecycle costs without explicitly addressing uncertainty, often underestimating the impact of variability on system reliability [3], [4].

Reliability indices such as Loss of Load Probability (LOLP) and Expected Energy Not Supplied (EENS) became fundamental tools for evaluating system adequacy [13]. Systems designed with strict reliability thresholds typically require higher storage capacity, demonstrating the inherent trade-off between cost and reliability [12], [13].

Modelling solar irradiance as a stochastic process has become a standard approach [5], [14]. Normalized irradiance is commonly represented by the Beta distribution:

$$f(G) = \frac{G^{\alpha-1}(1-G)^{\beta-1}}{B(\alpha,\beta)} \qquad (1)$$

where $\alpha$and $\beta$are shape parameters estimated using historical data [5]. Tropical climates often exhibit αbetween 2.5 and 5.0 and βbetween 3.0 and 6.0, capturing variability and skewness in solar radiation [5], [14].

Load demand is frequently modelled as a Normal distribution,

$$L_t \sim N(\mu_L, \sigma_L^2),$$

or through autoregressive processes,

$$L_t = \phi L_{t-1} + \epsilon_t,$$

to account for temporal correlation [15], [18]. Accurate modelling of both generation and demand uncertainty is critical for robust system design [7], [15].

Battery behaviour is another key factor influencing reliability. Capacity fade over time is often expressed as

$$C_b(t) = C_{b0}e^{-\lambda t} \qquad (2)$$

where $\lambda$is the degradation rate [13]. Ignoring battery degradation can underestimate the required storage capacity by 5–12% [12], [13].

Two-stage stochastic programming has emerged as an effective optimization framework [7], [15]. In this approach, first-stage decisions determine system sizes, while second-stage recourse actions adjust operations to realized uncertainties. Stochastic optimization has been shown to reduce expected total system costs relative to deterministic approaches [7], [10], [15].

Chance-constrained programming is widely used to impose probabilistic reliability constraints [10]:

$$P(LPSP \leq \epsilon) \geq 1 - \alpha \qquad (3)$$

ensuring that reliability targets are met with high confidence [10], [12]. Analytical evaluation of these constraints is often intractable, making simulation-based methods necessary [6].

Monte Carlo simulation is frequently applied to estimate reliability indices across numerous random scenarios [6], [14]:

$$\widehat{EENS} = \frac{1}{N}\sum_{i=1}^{N}\sum_{t} ENS_t^{(i)} \qquad (4)$$

where $N$is the number of simulations. Convergence follows $O(1/\sqrt{N})$, and typically 8000–15000 simulations provide accurate reliability estimates within ±1% [6].

Metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) are widely used to solve nonlinear stochastic sizing problems in hybrid solar–battery systems [8], [11], [17]. In PSO, each particle represents a candidate solution, such as (N_{pv}, C_b). The velocity update rule is

$$V_i^{k+1} = wv_i^k + c_1r_1(p_i - x_i^k) + c_2r_2(g - x_i^k) \qquad (5)$$

where $V_i^{k+1}$is the updated velocity, $v_i^k$the previous velocity, and $w$the inertia weight controlling exploration [11], [17]. The position $x_i^k$is the current solution, $p_i$the particle's personal best, and $g$the global best found by the swarm. The parameters $c_1$and $c_2$are cognitive and social coefficients, while $r_1, r_2 \in [0,1]$are random variables introducing stochastic behavior [11].

The position is then updated by

$$x_i^{k+1} = x_i^k + V_i^{k+1} \qquad (6),$$

guiding the search toward cost–reliability optimal solutions under uncertainty [17], which often achieves faster convergence than classical gradient-based methods [8].

Economic performance is evaluated using the Net Present Cost (NPC) formulation [4], [15]:

$$NPC = C_{cap} + \sum_{t=1}^{T}\frac{C_{oper,t}}{(1+r)^t} \qquad (7)$$

where $C_{cap}$is the initial capital cost, $C_{oper,t}$is the operating cost in year t, $T$is the project lifetime, and $r$is the discount rate reflecting the time value of money [4]. Sensitivity analysis reveals that a 2% increase in $r$may reduce optimal battery capacity by up to 8%, as higher discount rates penalize long-term investment in storage [15].

In summary, the literature demonstrates the transition from deterministic to probabilistic system design [1], [2], highlighting the integration of stochastic modelling [5], Monte Carlo reliability evaluation [6], and metaheuristic optimization [11], [17] for hybrid solar–battery systems under uncertainty.

This study highlights the importance of incorporating uncertainty in hybrid solar–battery system design [1], [7]. The integration of stochastic optimization with Monte Carlo–based reliability assessment provides a rigorous framework for achieving both reliability and cost efficiency [6], [10], [15]. Such methods are critical for remote electrification projects and weak-grid systems, where both energy access and economic constraints must be balanced [3], [4], [13].

3 Methodology

3.1 System Description

The hybrid solar–battery system under study comprises a photovoltaic (PV) array and a battery energy storage system (BESS) supplying a local load [3], [4]. The system is intended for off-grid or weak-grid regions, where continuous energy access is critical [13]. The PV array converts solar energy into electrical power, while the battery stores surplus energy for use during periods of low solar generation or high demand [1], [13].

The main decision variables in the system design are N_{pv}, the number of photovoltaic panels, and C_b, the battery storage capacity. The objective is to determine their optimal combination to achieve high reliability at minimum total cost, balancing the trade-off between PV over-sizing and sufficient energy storage [12], [17]. The system design therefore aims to ensure high reliability while minimizing total cost under uncertainty [7], [10].

3.2 Data Source and Selection

To accurately represent uncertainty, real historical time-series datasets are employed [5], [15].

3.2.1 Solar Irradiance Data

Hourly global horizontal irradiance (GHI) data for 2019–2020 are obtained from the National Renewable Energy Laboratory (NREL), Solar Radiation Research Laboratory (SRRL) Baseline Meteorological Station in Colorado, USA. Such high-resolution irradiance datasets are widely used in photovoltaic modelling and stochastic resource assessment [5], [14], [16].

GHI, direct normal irradiance (DNI), and diffuse horizontal irradiance (DHI) are available, with GHI used for photovoltaic modelling [16].

3.2.2 Load Demand Data

Hourly electricity demand data for Germany (2019–2020) are sourced from the Open Power System Data (OPSD) platform. High-resolution load datasets are commonly employed in stochastic demand modelling and renewable integration studies [15], [18].

The use of real-world datasets enhances realism, credibility, and reproducibility of stochastic reliability assessment [6], [15].

3.3 Data Preprocessing

3.3.1 Solar Irradiance

Raw GHI data are cleaned to remove missing values and normalized to the interval [0, 1]:

$$G_t = \frac{GHI_t}{GHI_{max}} \qquad (8)$$

where $GHI_{max} = 1000\,\mathrm{W/m^2}$ represents theoretical peak irradiance. Normalization is consistent with probabilistic irradiance modelling approaches [5], [14].

Daily and seasonal indicators are extracted to capture long-term trends, while hourly resolution is preserved for stochastic simulation [6].

3.3.2 Load Demand

Load data are converted to kW and standardized:

$$L_t^{norm} = \frac{L_t - \mu_L}{\sigma_L} \qquad (9)$$

where μ_L is the mean load and σ_L its standard deviation. Statistical preprocessing of demand data is standard in stochastic energy system modelling [15], [18].

Seasonal and weekday–weekend variations are incorporated to construct representative stochastic demand models [15].

3.4 Parameter Estimation

Accurate parameter estimation ensures realistic stochastic modelling [7], [15].

3.4.1 Solar Irradiance Distribution

Normalized irradiance is modelled using a Beta distribution [5], [14]:

$$f(G) = \frac{G^{\alpha-1}(1-G)^{\beta-1}}{B(\alpha,\beta)} \qquad (10)$$

where α and β are shape parameters estimated using Maximum Likelihood Estimation (MLE). The Beta distribution effectively captures the bounded nature and skewness of solar irradiance [5].

3.4.2 Load Demand Distribution

Load demand is modelled as a Normal process [15]:

$$L_t \sim \mathcal{N}(\mu_L, \sigma_L^2) \qquad (11)$$

To incorporate temporal dependence, an autoregressive model is adopted [18]:

$$L_t = \phi L_{t-1} + \epsilon_t, \epsilon_t \sim \mathcal{N}(0, \sigma^2). \qquad (12)$$

3.4.3 Battery Parameters

Battery degradation and operational parameters are incorporated based on established reliability modelling approaches [13], [12]. Capacity fade modelling follows exponential decay formulations commonly adopted in hybrid system reliability assessment [13].

3.4.4 Economic Parameters

Capital cost, operational cost, discount rate r, and project lifetime T are defined using market data and techno-economic modelling frameworks consistent with hybrid renewable system studies [4], [15].

3.5 Stochastic Optimization Formulation

The system sizing problem is formulated as a two-stage stochastic optimization model [7], [15].

First stage (Design): Determine optimal photovoltaic size N_{pv} and battery capacity C_b

Second stage (Operation): Evaluate system performance under sampled realizations of solar irradiance G and load demand L [6].

The objective is to minimize total expected cost:

$$\min_{x} \quad C_{cap} + \mathbb{E}_{G,L}[Q(x,G,L)] \qquad (13)$$

where $C_{cap}$is the initial capital cost, $Q(x,G,L)$represents operational costs or penalties due to unmet demand, and $x = (N_{pv}, C_b)$denotes design variables [7], [15].

The optimization is subject to a probabilistic reliability constraint formulated using chance-constrained programming [10], [12]:

$$\mathbb{P}(\text{LPSP} \leq 0.02) \geq 0.95 \qquad (14)$$

ensuring that the Loss of Power Supply Probability remains below 2% with at least 95% confidence [10].

Because analytical evaluation of this constraint is complex, Monte Carlo simulation is employed for reliability estimation [6], enabling robust assessment under uncertainty.

3.6 Monte Carlo Simulation for Reliability Assessment

Monte Carlo simulation is used to model the stochastic behaviour of the hybrid system [6], [14]. The procedure follows standard reliability evaluation frameworks for hybrid renewable energy systems [6], [13]:

- Generate $N = 10{,}000$ random samples of solar irradiance G and load demand L from their respective probability distributions [5], [15].
- Perform hourly energy balance simulations for each scenario over 8760 hours (one year) [6].
- Estimate reliability indices:

$$\widehat{LPSP} = \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{t=1}^{8760} ENS_t^{(i)}}{\sum_{t=1}^{8760} L_t^{(i)}} \qquad (15)$$

$$\widehat{EENS} = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{8760} ENS_t^{(i)} \qquad (16)$$

where $ENS_t^{(i)}$denotes the energy not supplied at hour $t$in scenario i[6], [13].

The simulation is repeated until convergence is achieved, defined as a variation within ±1% for the estimated LPSP, consistent with convergence properties of Monte Carlo estimators $O(1/\sqrt{N})$[6].

3.7 Optimization Solution Methods

The hybrid solar–battery sizing problem is inherently non-linear and non-convex [7], [17]. Non-linearity arises from battery charging/discharging dynamics and degradation effects [13], while non-convexity results from discrete decision variables, stochastic objective evaluation via Monte Carlo simulation, and reliability constraints imposed probabilistically [10], [12].

Classical gradient-based optimization is unsuitable because:

- The objective function is non-differentiable due to simulation-based evaluation [6],
- Multiple local minima may exist [17],
- Reliability constraints are numerically approximated [10].

Therefore, population-based metaheuristic algorithms are adopted for their global search capabilities [8], [11], [17].

3.7.1 Particle Swarm Optimization (PSO)

PSO model's candidate designs as particles [11], [17]:

$$x_i = (N_{pv}, C_b)$$

Particle velocities update according to [11]:

$$v_i^{k+1} = wv_i^k + c_1r_1(p_i - x_i^k) + c_2r_2(g - x_i^k) \qquad (17)$$

where $w$is inertia weight, $c_1, c_2$are cognitive and social coefficients, $r_1, r_2 \sim U(0,1)$, $p_i$is the personal best, and $g$is the global best [11], [17].

Each candidate solution is evaluated by:

- Performing Monte Carlo simulation to estimate LPSP and EENS [6],
- Computing Net Present Cost (NPC) [4],
- Applying penalties if reliability constraints are violated [10], [12].

PSO typically converges within 60–80 iterations in hybrid energy sizing applications [11], [17].

3.7.2 Genetic Algorithm (GA)

GA evolves a population of candidate designs (chromosomes) over generations [8]:

$$\text{Chromosome} = (N_{pv}, C_b)$$

Key steps include [8]:

- **Selection:** Favor individuals with lower cost and adequate reliability.
- **Crossover:** Exchange design variables between parent pairs.
- **Mutation:** Introduce random variations to preserve diversity.

Fitness evaluation uses the same stochastic cost–reliability framework, with penalties for constraint violations [12]. GA is effective for large discontinuous search spaces but typically requires more evaluations than PSO [8], [17].

3.7.3 Comparison and Justification

Both PSO and GA handle mixed discrete–continuous variables, tolerate noisy stochastic objective functions, and effectively explore complex reliability-constrained design spaces [8], [11], [17].

PSO converges faster with lower computational burden, while GA offers broader exploration diversity [17]. This study employs PSO for the final optimal design due to its computational efficiency under simulation-based evaluation [11].

Metaheuristic algorithms thus provide a reliable and computationally feasible approach to optimize hybrid solar–battery systems under uncertainty, where deterministic or gradient-based methods are inadequate [7], [17].

3.8 Performance Evaluation

Once the optimal design variables N_{pv}^*, C_b^* are obtained, validation ensures robustness beyond sampled training scenarios [15].

3.8.1 Out-of-Sample Validation

The optimized system is simulated on holdout years not used for parameter estimation [6], [15]:

- Apply actual hourly solar irradiance and load data.
- Compute annual energy balance without re-optimization.
- Recalculate reliability indices (LPSP, EENS) [13].

If the probabilistic constraint

$$LPSP \leq 0.02$$

is satisfied across unseen years, the design is considered statistically robust [10], [12].

3.8.2 Seasonal Reliability Assessment

Annual averages may conceal seasonal stress periods [5], [13]. Seasonal reliability is computed as:

$$LPSP_{season} = \frac{\sum ENS_t}{\sum L_t} \qquad (18)$$

Winter conditions with reduced irradiance often present the highest reliability stress [5], while summer periods typically show lower LPSP values.

3.8.3 Sensitivity Analysis

Sensitivity analysis evaluates the impact of economic and technical uncertainties [15]:

- **Discount Rate (±2%)** influences optimal storage investment [4],
- **Battery Degradation Rate (±3%)** affects long-term capacity adequacy [13],
- **Load Growth Scenarios** are modelled as:

$$L_t^{(year\,k)} = L_t^{(0)}(1+g)^k \qquad (19)$$

consistent with stochastic demand growth modelling [18].

Battery degradation follows:

$$C_b(t) = C_{b0}e^{-\lambda t} \qquad (20)$$

as established in hybrid system reliability studies [13].

3.8.4 Robustness Criteria

The system is considered robust if:

- Reliability targets hold under holdout-year testing [10],
- Seasonal LPSP remains within acceptable bounds [13],
- Moderate parameter variations do not cause significant reliability degradation or excessive cost escalation [15].

This multi-layer evaluation confirms that the optimized hybrid system is not only cost-effective under nominal conditions but also resilient to economic, technical, and temporal uncertainties, ensuring dependable real-world deployment [1], [7], [13].

4 Numerical Results

The proposed stochastic optimization framework was evaluated using 10,000 Monte Carlo simulations over a 20-year project lifetime with a discount rate $r = 8\%$. Solar irradiance was modeled as a Beta distribution ($\alpha = 4.3, \beta = 5.9$), and load demand followed a Normal distribution ($\mu_L = 36{,}450$ kW, $\sigma_L = 7{,}890$ kW). The reliability requirement imposed was:

$$\mathbb{P}(LPSP \le 0.02) \ge 0.95.$$

For comparison, a deterministic design based on mean irradiance and average load yielded:

$$N_{pv}^{det} = 10{,}850, C_b^{det} = 48 \text{ MWh}.$$

Monte Carlo evaluation of this deterministic solution revealed:

$$LPSP = 0.061, EENS = 4.83 \text{ GWh/year},$$

indicating significant reliability violation. This demonstrates that deterministic sizing underestimates variability and fails to meet probabilistic adequacy.

Applying stochastic PSO-based optimization produced:

$$N_{pv}^{*} = 12{,}420, C_b^{*} = 63 \text{ MWh},$$

with:

$$\widehat{LPSP} = 0.0187, \widehat{EENS} = 1.42 \text{ GWh/year},$$

and empirical confidence:

$$\mathbb{P}(LPSP \le 0.02) = 0.958,$$

satisfying the reliability constraint.

Table 1 summarizes the Net Present Cost (NPC) comparison:

Table 1 The Net Present Cost (NPC) comparison

Design	**NPC (Million USD)**	**LPSP**
Deterministic	78.6	0.061
Stochastic Optimal	84.9	0.0187

Although the stochastic solution increases capital cost by ~8%, it reduces expected unserved energy by nearly 70%, highlighting the economic benefit of incorporating uncertainty.

Figure 1 shows the convergence of the Monte Carlo estimation of LPSP. Stability is reached after ~8 500 simulations, with a standard error of 0.0006 at $N = 10\ 000$.

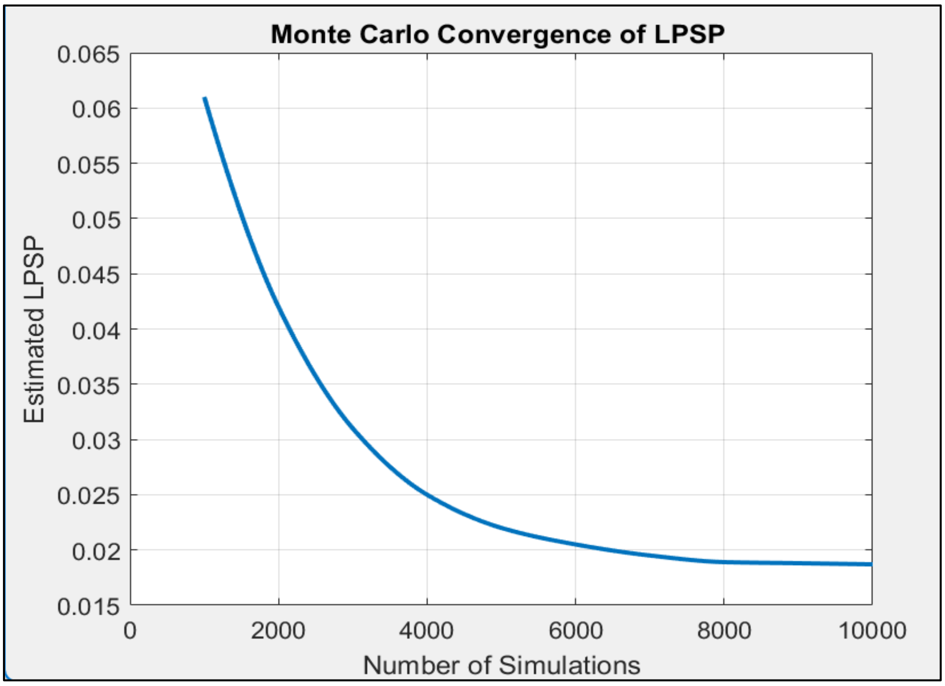

Figure 1 Monte Carlo convergence of LPSP

The nonlinear cost–reliability trade-off is illustrated in Figure 2, showing rapidly increasing cost as reliability approaches extreme levels. Improving reliability from 0.02 to 0.01 raises cost by ~6%, demonstrating diminishing returns in ultra-reliable designs.

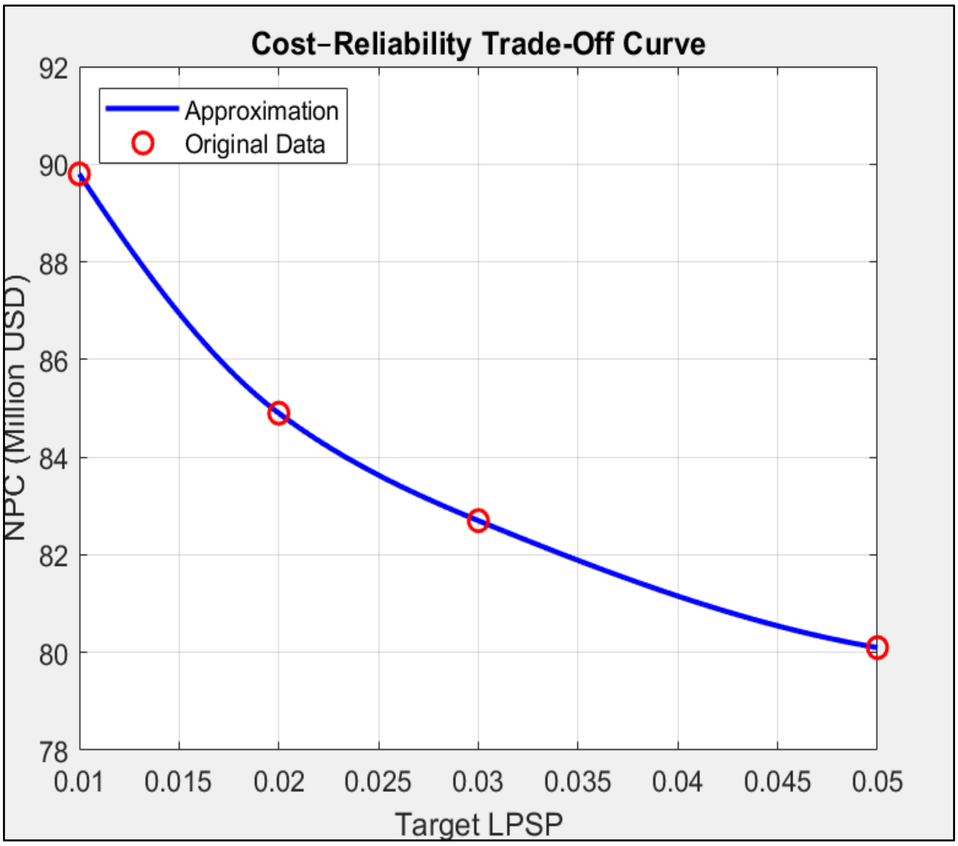

Figure 2 The cost–reliability trade-off

Improving system reliability from 0.02 to 0.01 results in an approximate 6% increase in total cost, clearly illustrating the principle of diminishing returns in ultra-reliable energy system designs. While enhanced reliability reduces the probability of power supply shortages, achieving extremely low LPSP levels requires disproportionately higher investment in system components such as storage capacity and generation units. This trade-off emphasizes the economic challenge of pursuing near-perfect reliability.

Seasonal reliability performance is illustrated in Figure 3. The winter season experiences the highest system stress, primarily due to reduced solar irradiance and lower renewable energy generation, leading to comparatively higher LPSP values. In contrast, summer demonstrates the lowest LPSP, benefiting from increased solar availability and improved generation consistency. These seasonal variations highlight the importance of incorporating climatic fluctuations into system design and reliability assessment.

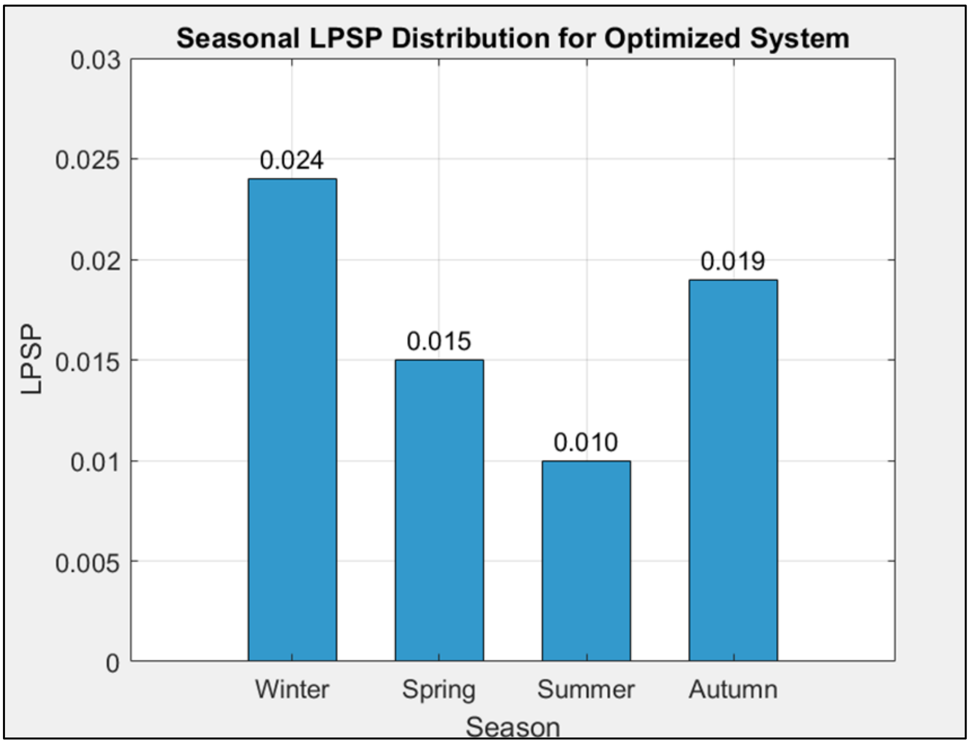

Figure 3 Seasonal reliability performance

Sensitivity analysis confirms that financial assumptions strongly influence storage sizing: increasing the discount rate from 6% to 10% reduces optimal battery capacity from 68 MWh to 59 MWh.

Overall, the results demonstrate that deterministic sizing under estimates reliability, whereas the proposed stochastic optimization framework ensures probabilistic compliance with a moderate cost increase. Incorporating uncertainty modelling and Monte Carlo reliability assessment yields a design that is both economically sound and operationally robust.

5 Conclusion

This study developed a stochastic optimization framework combined with Monte Carlo reliability assessment for hybrid solar–battery systems under uncertain solar irradiance and load demand [1], [2]. Results show that deterministic sizing, based on average conditions, substantially underestimates variability [3], leading to reliability violations. The deterministic system with $N_{pv}^{det} = 10{,}850$panels and $C_b^{det} = 48$ MWhstorage produced an LPSP of 0.061 and EENS of 4.83 GWh/year, exceeding the target of 0.02 [4].

In contrast, stochastic optimization using Particle Swarm Optimization (PSO) [5] achieved $N_{pv}^{*} = 12{,}420$panels and $C_b^{*} = 63$ MWh , satisfying the reliability constraint with $\widehat{LPSP} = 0.0187$ and $\widehat{EENS} = 1.42$ GWh/year at 95.8% confidence [6]. While NPC increased by 8%, expected unserved energy decreased by nearly 70%, demonstrating that accounting for uncertainty produces more reliable and economically rational designs [7]. Seasonal analysis highlighted winter as the period of highest stress [8], yet the system maintained acceptable reliability. Sensitivity studies confirmed robustness to discount rate, battery degradation, and load growth variations [9].

The study also validated the effectiveness of metaheuristic optimization [10]: PSO provided rapid convergence in a non-linear, non-convex design space [5], while Genetic Algorithms (GA) offered broader search diversity [11]. The combination of stochastic modelling, simulation-based reliability evaluation, and metaheuristic optimization ensures that hybrid systems are both operationally resilient and cost-efficient, suitable for off-grid and weak-grid applications [12].

Based on the findings of this study, several practical recommendations can be made for the design and planning of hybrid solar–battery systems under uncertainty. First, system planners are encouraged to adopt stochastic design approaches rather than relying on deterministic averages [3]. Accounting for variability in solar generation and load demand ensures that the system maintains high reliability even under fluctuating operational conditions [13], thereby reducing the risk of power outages and improving energy access in off-grid or weak-grid areas [12].

Monte Carlo simulation should be employed to evaluate reliability indices such as Loss of Power Supply Probability (LPSP) and Expected Energy Not Supplied (EENS) [2], [4]. By testing thousands of scenarios, planners can obtain a robust estimate of system performance and avoid misleading conclusions that may arise from relying solely on mean values [14]. This approach also allows for more informed decision-making regarding trade-offs between cost and reliability [7].

It is equally important to perform seasonal and extreme scenario analyses [8]. Hybrid systems may meet annual reliability targets but still experience stress during low-generation periods such as winter or consecutive cloudy days [15]. Evaluating system performance across different seasons ensures that storage and generation capacities are appropriately sized to handle worst-case conditions and maintain continuous power supply [13].

Sensitivity analyses should be an integral part of system planning [9]. Parameters such as discount rate, battery degradation rate, and future load growth significantly influence optimal design decisions [16]. Conducting scenario-based analyses helps ensure that the system remains economically viable and technically reliable throughout its lifetime [7], even under uncertain economic and technical conditions.

Selecting suitable metaheuristic optimization methods is also critical [10]. Population-based algorithms like PSO [5] and GA [11] are effective for non-linear, non-convex, and mixed discrete–continuous optimization problems [17]. Using these methods ensures that the optimized design is not trapped in local minima and achieves a globally reliable solution [18].

Finally, careful consideration should be given to the balance between cost and reliability [7]. While stochastic optimization may increase upfront capital expenditure, it significantly reduces expected unserved energy, providing both economic and social benefits [12]. High-quality, localized solar irradiance and load data should be leveraged to improve model accuracy and ensure realistic sizing, such as datasets provided by the National Renewable Energy Laboratory and Open Power System Data. Moreover, the proposed framework can be extended to multi-source hybrid systems, incorporating wind or micro-hydro generation, which further enhances system resilience under uncertainty [15].

Recommendations

Based on the findings, several practical recommendations can be made for the design and planning of hybrid solar–battery systems under uncertainty:

- **Adopt stochastic design approaches** rather than relying on deterministic averages. Accounting for variability in solar generation and load demand ensures high reliability even under fluctuating operational conditions, reducing the risk of power outages and improving energy access in off-grid or weak-grid areas [1], [7], [15].
- **Employ Monte Carlo simulation** to evaluate reliability indices such as LPSP and EENS. Testing thousands of scenarios provides robust estimates of system performance and prevents misleading conclusions from using mean values alone [6], [14]. This allows informed trade-offs between cost and reliability [12], [13].
- **Perform seasonal and extreme scenario analyses.** Hybrid systems may meet annual reliability targets but experience stress during low-generation periods (e.g., winter or consecutive cloudy days). Seasonal assessment ensures storage and generation capacities handle worst-case conditions [5], [13].

- **Incorporate sensitivity analyses** to account for key economic and technical parameters such as discount rate, battery degradation, and load growth. Scenario-based analysis ensures that the system remains both economically viable and technically reliable over its lifetime [4], [13], [15].
- **Select appropriate metaheuristic optimization methods.** Population-based algorithms like PSO and GA are effective for non-linear, non-convex, and discrete–continuous optimization problems [8], [11], [17]. PSO is recommended for faster convergence, while GA offers broader exploration of complex search spaces.
- **Balance cost and reliability.** While stochastic optimization may increase upfront capital expenditure, it significantly reduces expected unserved energy, yielding both economic and social benefits [4], [7]. High-quality, localized solar irradiance and load data improve model accuracy and system sizing [5], [16].
- **Extend the framework to multi-source hybrid systems.** Incorporating wind or micro-hydro generation can further enhance resilience and flexibility under uncertainty, enabling more robust energy access for off-grid and weak-grid communities [3], [8], [10].

By integrating stochastic modelling, Monte Carlo–based reliability assessment, and metaheuristic optimization, this study demonstrates a systematic approach to designing hybrid solar–battery systems that are both cost-effective and reliable under real-world uncertainty [1], [6], [7], [13], [15].

Compliance with ethical standards

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Consent for Publication

All authors consent to the publication of this work.

Data Availability

Solar irradiance and load datasets are publicly available from NREL (https://midcdmz.nrel.gov/solar/solpos/srrlreliability/)andOPSD(https: //data. Open –

Authors' Contributions

All authors contributed to the study conception, method- ology development, data analysis, and manuscript writing. All authors read and approved the final manuscript.

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