

Article

Stochastic Optimization Approach for Off-Grid Integrated Energy System Considering Renewable Energy Uncertainty [†]

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Abstract

Off-grid integrated energy systems offer a practical solution for remote regions lacking access to the main power grid; however, their planning and design are challenged by the inherent uncertainty of renewable energy resources. To address this issue, this paper proposes a stochastic optimization framework for off-grid integrated energy systems that explicitly accounts for wind speed and solar irradiance variability. Continuous probability distributions combined with Monte Carlo sampling are employed to generate stochastic scenarios, which are embedded into a bi-objective optimization model minimizing total system cost and pollutant emissions under power balance and device operational constraints. Unlike existing studies that primarily focus on cost–reliability trade-offs, this work introduces the Renewable Energy Penetration Rate (REPR) as a quantitative, planning-oriented indicator and systematically investigates its interactions with economic performance, pollutant emissions, and renewable uncertainty. The REPR is not only used to characterize renewable utilization levels, but also to support investment decision-making and the comparative assessment of Pareto-optimal configurations. A real-world off-grid service area is adopted as a case study. The results show that increasing the REPR leads to a significant reduction in carbon emissions while exhibiting a nonlinear impact on total system cost. Specifically, the proposed framework identifies a Pareto-optimal solution set in which the total system cost varies within 40–92 million ¥, carbon emissions are reduced by 86% compared with diesel-dominated configurations, and the REPR increases from 70% to 96.4% as renewable capacity expands. In addition, the analysis reveals that higher renewable volatility requires a larger stochastic sample size to ensure solution stability. These findings demonstrate that the proposed framework provides a more comprehensive and decision-relevant assessment of off-grid integrated energy systems under renewable uncertainty, thereby offering practical insights for low-carbon and economically viable system planning.

Keywords: off-grid system; optimal planning; uncertainty; Monte Carlo method; penetration rate



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1. Introduction

Incorporating various energy sources, including electricity, heating, and cooling power, an Integrated Energy System (IES) enables the interconversion and coordination among

these sources, thereby enhancing multi-energy interactions [1–3]. As energy demand diversifies across regions and application scenarios [4,5], meeting long-distance electricity supply requirements through grid expansion often entails considerable capital investment in transmission and distribution infrastructures [6,7]. Furthermore, the increasing demand for cleaner energy generation presents grid integration challenges due to the inherent intermittency of renewable energy sources on the supply/generation side. In response to these challenges, off-grid integrated energy systems (off-grid IES) have been increasingly adopted to supply energy in areas without reliable grid access [8,9]. Such systems typically integrate solar photovoltaic (PV) panels, wind turbines (WT), energy storage systems (ES), diesel generators (DG), and other high-efficiency energy conversion technologies. For off-grid IES, both economic viability and environmental performance constitute critical design objectives [10,11], which necessitates the application of advanced system modeling and optimization approaches to reduce investment costs, limit fossil fuel consumption, and lower carbon emissions compared with conventional solutions [12]. Several studies have explored optimization strategies for IES. Ref. [13] developed a model for a hybrid photovoltaic-wind turbine-pumped storage system, optimizing its configuration using a genetic algorithm to minimize the gap between energy demand and generation. Ref. [14] presented an optimization framework for the design and scheduling of a photovoltaic-wind-hydrogen integrated energy system, incorporating the carbon trading mechanism and addressing the uncertainty of renewable energy output. Additionally, ref. [15] applies intelligent methods for unit sizing optimization in two micro-grid systems, balancing air pollution emissions while ensuring electricity and thermal energy supply.

In design optimization, solar and wind power are recognized as significant non-conventional generation options due to their environmental benefits, abundant availability, and location independence. These renewable sources enhance system reliability while reducing overall life cycle costs [16,17]. However, there is significant variability and uncertainty in predicting the renewable energy sources generations and fluctuations in power supply [18], which presents challenges for maintaining supply–demand balance in off-grid IES [19].

To address the volatility and uncertainty of wind and solar power for more effective planning and design, it is necessary to develop mathematical models for their uncertainty characterization before performing optimization calculations. In design optimization studies, uncertainty can be handled through several established approaches, such as stochastic optimization, robust optimization, and interval-based optimization. Robust optimization aims to obtain solutions that remain feasible under parameter perturbations by emphasizing worst-case realizations, which may lead to conservative decision-making outcomes [20–22]. By contrast, interval optimization represents uncertain parameters using bounded intervals and reformulates objectives and constraints accordingly. Owing to the fact that only the upper and lower limits of uncertainties are required, this approach is generally regarded as straightforward to implement [23]. However, when it comes to energy system design, the results are often hard to meet load demands at different time points, and the decision-making scheme, which uses interval representation, is difficult to apply directly in real scenarios [24,25]. Stochastic optimization uses probabilistic model as the mathematical representation of renewable generation, using historical statistical data to obtain the corresponding probability density functions or cumulative distribution functions but often requires extensive data to establish probability density functions [26,27]. In the presence of sufficient historical data, stochastic optimization is found to be more suitable compared to the conservative nature of robust optimization and the lack of precision in uncertainty description typical of interval optimization [28]. Various probability distribution functions including Weibull, chi-square, Lognormal, gamma, and Rayleigh have been suggested to

model wind speed data [29]. The chi-square and Weibull distributions are specific cases of the generalized gamma distribution. Detailed analysis of this probability distribution model is available in an extensive literature review [30]. In the study of renewable energy generation characteristics, Weibull distribution, and beta distribution probability models have been widely used and found to be useful and appropriate for the model of wind speeds and solar irradiance [31–35].

Stochastic optimization typically constructs probabilistic representations of uncertain parameters by exploiting large volumes of historical data and fitting them with continuous probability distributions. To quantify uncertainty effects and reformulate stochastic problems into tractable deterministic equivalents, Monte Carlo simulation is widely adopted for scenario generation in integrated energy systems (IES) [36–38]. For instance, Ref. [39] employs Monte Carlo-based scenario modeling to characterize uncertainties associated with wind power output, load prediction, and random equipment outages. Furthermore, ref. [40] utilized stochastic models to represent the inherent uncertainties in renewable energy sources and load demands, approaching these through probability scenario-based planning. The Monte Carlo method utilizes probability density functions to determine the values of uncertain variables, thus transforming complex uncertain problems into deterministic ones [41]. Therefore, the Monte Carlo method provides a valuable means to analyze stochastic optimization.

In the design optimization of off-grid IES, the primary objectives extend beyond merely reducing operation costs, they also include enhancing overall energy efficiency and optimizing pollutant emissions [42–44]. To guarantee the model's practicality and accuracy, a multi-objective algorithm that considers both carbon emissions and economic costs is frequently utilized to solve the model [45]. Ref. [46] proposed a multi-objective stochastic optimization model to optimize the configuration and operation strategy of an integrated energy system, considering the uncertainties of solar irradiance and building load. Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is used for optimization to achieve optimal energy, economic, and environmental benefits.

Several researches into stochastic optimization for off-grid IES, especially regarding the uncertainties associated with wind speeds and solar irradiance, have been conducted to improve the overall efficiency and reliability of such systems. Ref. [47] introduces an uncertainty-aware planning method by replacing the expected power output with the upper α -quantile derived from historical data and validates the proposed approach through stochastic sampling and Monte Carlo simulation to assess system investment distributions. Ref. [48] develops an integrated planning strategy for energy storage systems aimed at cost reduction, where wind power generation is modeled using a Gaussian probability density function and uncertainties are addressed via scenario-based stochastic programming. Furthermore, ref. [49] presents a stochastic programming model for multi-objective optimization, fitting wind speed with a Weibull distribution and solar radiation with a hybrid beta kernel density estimation. Monte Carlo simulation combined with K-means clustering is applied to generate and reduce multiple scenarios, thereby improving computational efficiency and solution accuracy.

Despite these advances, existing studies predominantly focus on addressing renewable energy uncertainty to improve economic performance or operational feasibility, while the role of renewable energy penetration rate (REPR) is often treated implicitly or evaluated only in a deterministic manner. In particular, there remains a lack of systematic investigation into the coupled relationship among REPR, economic cost, pollutant emissions, and renewable uncertainty within a unified stochastic optimization framework. Moreover, the majority of existing approaches transform stochastic problems into deterministic equivalents without explicitly quantifying the probabilistic nature of renewable energy

penetration and its implications for investment decision-making under uncertainty. Considering these research gaps, this work develops a stochastic optimization framework for an off-grid IES comprising PV panels, wind turbines, diesel engines, energy storage systems, and energy conversion devices, while explicitly accounting for uncertainties in renewable energy generation. The proposed framework simultaneously minimizes economic cost and pollutant emissions and introduces a probabilistic characterization of the renewable energy penetration rate through quantitative uncertainty analysis. Furthermore, from an investment perspective, the economic feasibility of the system is evaluated by systematically examining the relationship between REPR and key economic performance indicators. This paper is an extended and substantially revised version of our earlier conference paper published in the Electrical Artificial Intelligence Conference 2024 [1,50]. Compared with the conference version, the present work provides a more comprehensive methodological formulation, enhanced uncertainty modeling, a more in-depth analysis of the REPR, and expanded numerical experiments, offering a more rigorous and complete presentation of the proposed framework. The main contributions of this study are summarized as follows:

1. We characterize renewable energy using continuous probability distribution functions and employing the Monte Carlo method as a sampling technique for the stochastic optimization.
2. We introduce the Renewable Energy Penetration Rate (REPR) to evaluate the capability of the off-grid system to meet load demands and their corresponding carbon emissions.
3. We consider the inclusion of diesel power as an optimization variable to lower the investment, and the Pareto-optimal set solutions are compared and analyzed.
4. We provide investment recommendations by analyzing the relationship between the system's REPR, various economic indicators, and carbon emissions.
5. We conduct an in-depth analysis of the stochastic optimization method and discussed the correlation between source-side volatility and sample size.

The remainder of this paper is organized as follows: The second section introduces the methodology including model, objective function, constraints, optimization variables, uncertainty, and stochastic optimization method. The third section provides data, simulation results, case analysis, and discussion. Finally, the fourth section constitutes the conclusion.

2. Methodology

2.1. Model

Figure 1 presents the configuration of the proposed off-grid system, in which wind turbines, photovoltaic arrays, and the energy storage system constitute the main power supply components. The electric chiller and electric boiler are responsible for satisfying cooling and heating demands, respectively, whereas diesel generators are employed as auxiliary backup units.

2.1.1. Photovoltaic Panel

The electrical output of the PV panels is calculated as

$$P_{PV}(t) = \begin{cases} \eta_{PV}\eta_{PVS}P_{st}\frac{G(t)}{G_{st}}, & G(t) < G_{st}, \\ \eta_{PV}\eta_{PVS}P_{st}, & G(t) \geq G_{st}. \end{cases} \quad t = 1, 2, \dots, T \quad (1)$$

$$TC_{PV} = Inv_{PV} \quad (2)$$

where $P_{PV}(t)$ is the electrical output of the photovoltaic panels at time t (kW); P_{st} denotes the rated output under standard test conditions (kW); $G(t)$ corresponds to the solar irradiance at time t (kW/m²), while G_{st} is the reference irradiance under standard conditions (kW/m²); η_{PV} and η_{PVS} represent the conversion efficiency of the PV modules and the overall PV system, respectively; TC_{PV} refers to the total cost of the photovoltaic system (¥); and Inv_{PV} indicates its investment cost (¥).

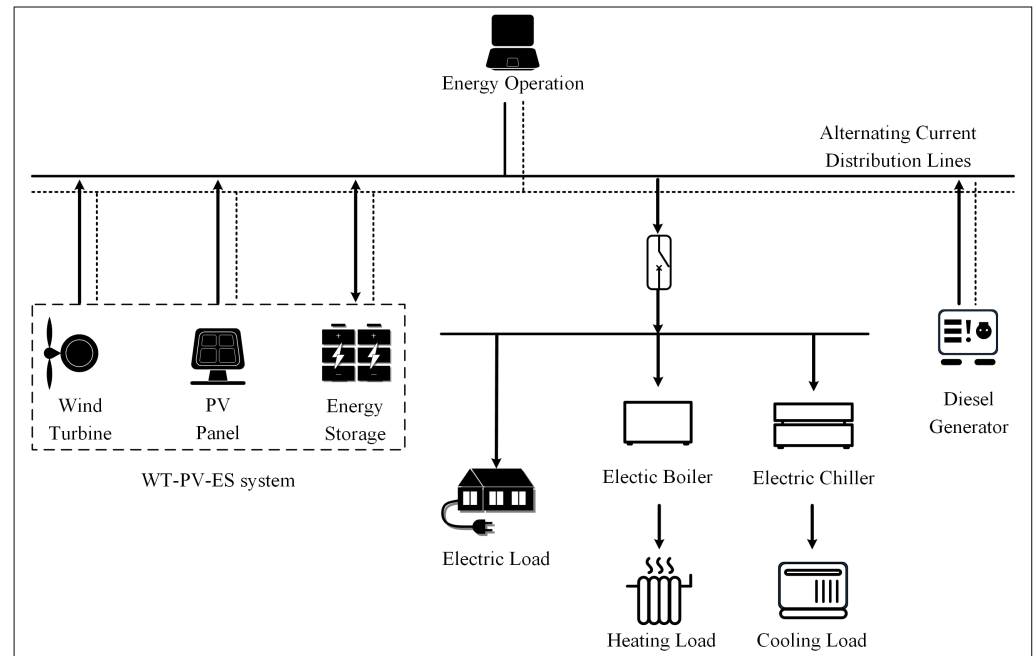


Figure 1. Structure of the off-grid IES.

2.1.2. Wind Turbine

For wind energy conversion, the power output of the wind turbine is modeled as a function of wind speed:

$$P_{WT}(t) = \begin{cases} 0, & 0 \leq v(t) \leq v_{in}, v(t) > v_{out}, \\ \eta_{WT} \frac{v(t)-v_{in}}{v_n-v_{in}} P_n, & v_{in} \leq v(t) \leq v_n, \\ \eta_{WT} P_n, & v_n \leq v(t) \leq v_{out}. \end{cases} \quad t = 1, 2, \dots, T \quad (3)$$

$$TC_{WT} = Inv_{WT} \quad (4)$$

where $P_{WT}(t)$ denotes the power output of the wind turbine at time t (kW); $v(t)$ represents the corresponding wind speed (m/s), with v_{in} , v_{out} , and v_n indicating the cut-in, cut-out, and rated wind speeds, respectively; P_n is the rated power of the wind turbine under standard operating conditions (kW); η_{WT} denotes the energy conversion efficiency of the wind turbine; TC_{WT} represents the total cost associated with the wind turbine (¥); and Inv_{WT} refers to its capital investment (¥).

2.1.3. Diesel Generator

A diesel generator (DG) serves as a reliable alternative source of electricity for various applications. It produces electricity by utilizing diesel fuel, the mathematical model and operation constraints are as follows [51]:

$$\begin{aligned}
fc(t) &= A_{DG}P_{DGN} + B_{DG}P_{DG}(t), \\
TC_{DG} &= p_{fuel} \times fc(t) + Inv_{DG}, \\
CE_{DG} &= \sum_{t=1}^T P_{DG}(t) \times \eta_{DG}, \\
P_{DG}^{\min} &\leq P_{DG}(t) \leq P_{DG}^{\max}, \quad t = 1, 2, \dots, T.
\end{aligned} \tag{5}$$

where $fc(t)$ denotes the fuel consumption of a diesel generator in time t (L); P_{DGN} denotes the nominal power (kW); $P_{DG}(t)$ denotes the output power in time t (kW); A_{DG} represents the fuel intercept (L/kW); B_{DG} represents the fuel slope coefficient (L/kW); p_{fuel} represents the fuel price (¥/L); Inv_{DG} stands for the investment cost of DG (¥); TC_{DG} indicates the total cost of diesel engine (¥); Inv_{DG} indicates the investment of DG (¥); $P_{DG}^{\max}$ denotes the maximum output power limit of the diesel engine; $P_{DG}^{\min}$ denotes the minimum output power limit of the diesel engine; and CE_{DG} represents the carbon emission of DG (kg).

The carbon emission formulation adopted in this study is expressed in a linear form, which is commonly used in planning-level energy system analysis. This representation is intended to capture the dominant contribution of diesel generator operation to system-wide emissions and to facilitate tractable stochastic multi-objective optimization. At the planning stage, carbon emissions mainly serve as an aggregate indicator for evaluating trade-offs among cost, emissions, and renewable energy penetration under uncertainty. While more detailed nonlinear or dynamic emission models may improve short-term operational accuracy, their impact on long-term capacity planning results is expected to be limited.

2.1.4. Energy Storage System

The mathematical model for the electrical energy storage system (ES) is represented based on the state of charge [52]:

$$\begin{aligned}
E_{\text{stored}}(t) &= E_{\text{stored}}(t-1) + (P_{\text{in}}(t)\eta_{\text{charge}} - \frac{P_{\text{out}}(t)}{\eta_{\text{discharge}}})\Delta t, \\
TC_{\text{ES}} &= Inv_{\text{ES}}, \\
E_{\text{max}} &= d_{\text{ES}}, \\
E_{\text{min}} &\leq E_{\text{stored}}(t) \leq E_{\text{max}}, \\
P_{\text{in,min}} &\leq P_{\text{in}}(t) \leq P_{\text{in,max}}, \\
P_{\text{out,min}} &\leq P_{\text{out}}(t) \leq P_{\text{out,max}}, \\
E_{\text{stored}}(0) &= E_{\text{initial}}, \\
E_{\text{stored}}(T) &= E_{\text{final}}, \quad t = 1, 2, \dots, T
\end{aligned} \tag{6}$$

where $P_{\text{in}}(t)$ represents the charging power in time t (kW); $P_{\text{out}}(t)$ represents the discharging power in time t (kW); $E_{\text{stored}}(t)$ represents the state of charge for electrical energy storage in time t (kW); T represents discrete time steps, Δt is the time interval for each step (kW); d_{ES} represents the capacity of ES (kW); E_{max} represents the maximum capacity of electrical energy storage (kWh); E_{min} represents the minimum capacity of electrical energy storage (kWh); η_{charge} represents the charging efficiency; $\eta_{\text{discharge}}$ represents the discharging efficiency; $P_{\text{in,max}}$ and $P_{\text{out,max}}$ represent the maximum limits for charging and discharging power (kW); $P_{\text{in,min}}$ and $P_{\text{out,min}}$ represent the minimum limits for charging and discharging power (kW); E_{initial} and E_{final} represent the initial and final state of charge for electrical energy storage, respectively (kWh); Inv_{ES} stands for the investment cost of ES (¥); TC_{ES} indicates the total cost of ES (¥); and Inv_{ES} indicates the investment of ES (¥).

2.1.5. Carbon Trade Model

In the off-grid system constructed in this study, carbon emissions primarily originate from the diesel generator. Given the power generation demands of clean energy and carbon emission constraints, it is essential to conduct a quantitative analysis of carbon emissions. To address this, this study employs a multi-objective approach that integrates carbon trading costs into the economic cost objective while simultaneously optimizing carbon emissions. This enhances the importance of clean energy optimization and minimizes carbon emissions as much as possible. This study employs a linear model to calculate carbon trading costs. The model straightforwardly multiplies actual carbon emissions by the carbon trading price for analysis:

$$\begin{aligned} TC_{CO_2}^t &= CTP \times CE_p, \\ CE_p &= CE_{DG} \end{aligned} \quad (7)$$

where $TC_{CO_2}^t$ indicates the carbon trading cost within the IES (¥); CTP denotes the carbon price in the market (¥/kg); CE_p represents the total carbon emissions from system devices (kg); and CE_{DG} indicates the carbon emissions from diesel generator (kg).

2.2. Objective Function

The objective of the proposed IES model is to reduce both the total capital investment and the associated carbon trading cost. Accordingly, the overall system cost consists of the initial investment expenditure and the operational cost. Based on these considerations, the multi-objective optimization problem is formulated as follows:

$$\begin{aligned} \text{Min}F_1 &= \frac{TC_{PV} + TC_{WT} + TC_{ES} + TC_{DG}}{(1+r)^{t-1}}, \\ \text{Min}F_2 &= \sum_1^N \frac{TC_{CO_2}^t}{(1+r)^{t-1}} \end{aligned} \quad (8)$$

where N signifies the operation years, and r represents the interest rate.

2.3. Constraints

The constraints considered in this model include system operational limits, installation capacity constraints, and power balance requirements:

1. System operational constraints are characterized through the mathematical formulations of individual system components.
2. Installation constraints are imposed to restrict the installed capacity of each device within allowable limits, which can be expressed as

$$0 \leq d_i \leq d_i^{\max}, \quad \forall i \in M \quad (9)$$

where Inv_i denotes the investment cost of device i ; p_i is the unit price of the device; M represents the set of all device categories; and $d_i^{\max}$ specifies the maximum allowable capacity of device type i .

3. Power balance constraints encompass electrical, thermal, and gas power balances, represented by

$$\begin{aligned} P_{WD}^t + P_{PV}^t + P_{DG}^t + \xi &= L_{ELOAD}^t + P_{EB}^t + P_{EC}^t, \\ H_{EB}^t &= L_{HLOAD}^t, \\ C_{EC}^t &= L_{CLOAD}^t \end{aligned} \quad (10)$$

where P_i^t denotes the output electrical power of each device; H_{EB}^t denotes the output heat power of EB; C_{EC}^t denotes the output cooling power of EC; L_{ELOAD}^t denotes the electrical load; H_{ELOAD}^t denotes the heat load; C_{ELOAD}^t denotes the cooling load; and ϵ denotes the adjustment factor, normally equals 0.

2.4. Optimization Variables Identification

Accordingly, the investment-related decision variables are represented by x , whereas the operational optimization variables are denoted by y , which can be expressed as

$$\begin{aligned} x &= [d_{EB}, d_{EC}, d_{WT}, d_{PV}, d_{ES}], \\ y &= [P_{EBE}^t, P_{ECE}^t, P_{in,t}, P_{out,t}]^T, \\ t &= 1, 2, \dots, T. \end{aligned} \quad (11)$$

where d_i represents the capacity of each device.

The multi-objective process stems from solving multi-objective nonlinear programming, and its general formulation is presented below:

$$\begin{aligned} \text{Min } F(x) &= (f_1(x), f_2(x))^T, \\ \text{subject to } G_i(x) &\leq 0, \quad i = 1, 2, \dots, m, \\ J_i(x) &= 0, \quad i = m + 1, m + 2, \dots, n. \end{aligned} \quad (12)$$

2.5. Uncertainty

2.5.1. Stochastic Optimization

This paper uses stochastic optimization for analyzing stochastic uncertainties. Stochastic distribution prediction offers additional uncertainty information for operating integrated energy power systems. In this study, parameter estimation methods are adopted to characterize uncertainty. The probability distribution types are predefined, and their corresponding parameters are identified through statistical analysis of historical data [33,48]. Based on the estimated distributions, multiple scenarios are generated to transform the stochastic optimization problem into an expected-value formulation for objective function optimization.

To study the REPR of the system by quantifying uncertainty and characterizing the economic viability. The model is processed by following steps:

- Step 1. Probability density functions are used to represent the uncertain renewable energy generation. Then, based on historical statistical data, parameter estimation is proposed to obtain corresponding distribution characteristics.
- Step 2. The stochastic expectation value model is constructed to depict the uncertainty of output as a set of scenarios. Accurate output scenario sets are generated utilizing Monte Carlo simulation for output scenario set generation.
- Step 3. The constraint condition and optimization variables are considered to obtain the off-grid IES stochastic optimization. Finally, the multi-objective algorithm is used to solve the problem.

In practice, historical data are commonly used to characterize the stochastic behavior of renewable energy resources by identifying appropriate probability density functions. Among the available models, the Weibull distribution is widely adopted for wind speed representation, while the beta distribution is frequently used to describe solar irradiance [31–35]. Accordingly, the Weibull and beta distributions are selected in this study to model wind speed and solar irradiance, respectively.

2.5.2. Solar Irradiance Distribution

Solar irradiance $G/G_{\max}$ follows a beta distribution pattern, with a probability density function given by

$$f(x|\alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{(\alpha-1)} (1-x)^{(\beta-1)} \quad (13)$$

where α and β are the two shape parameters of the beta distribution influenced by the average value and standard deviation of the irradiance:

$$\mu = \frac{\alpha}{\alpha + \beta}, \quad \sigma^2 = \frac{\alpha \cdot \beta}{(\alpha + \beta)^2 \cdot (\alpha + \beta + 1)} \quad (14)$$

2.5.3. Wind Speed Distribution

The variation in wind speeds v conforms to the Weibull distribution with a probability density function given by

$$f(x|c, \lambda) = \frac{c}{\lambda} \left(\frac{x}{\lambda} \right)^{(c-1)} e^{-(x/\lambda)^c} \quad (15)$$

where c is the shape parameter, and λ is the scale parameter.

For the wind speed distribution, the shape parameter c governs the overall form of the probability density function. In general, it reflects the relative frequency of extreme wind conditions, with most wind speeds clustering around moderate values. An increase in c shifts the distribution toward higher wind speeds, indicating a reduced occurrence of low wind speeds and an increased likelihood of stronger winds. The scale parameter λ determines the characteristic magnitude of wind speeds. A larger λ corresponds to a wider dispersion of wind speed values and higher characteristic levels, while a smaller λ implies a more concentrated distribution with limited variability. Both parameters are determined by the statistical properties of the measured data, particularly the mean value and standard deviation of the wind speed time series:

$$c = \frac{\sigma}{\lambda}, \quad \lambda = \frac{\mu}{\Gamma(1 + \frac{1}{c})} \quad (16)$$

2.5.4. Distribution Characteristics

To estimate the distribution parameters required for subsequent modeling and analysis, likelihood-based estimation is adopted in this study. Specifically, the irradiance and wind speed datasets obtained after preprocessing are organized into hourly observations over an annual period, denoted as PD_i , where i represents the sample index. Subsequently, the k-means clustering algorithm is applied to the wind speed and solar irradiance data to extract representative typical curves. Based on these clustered datasets, the distribution parameters are identified by minimizing the negative log-likelihood function, which aims to determine the probability distribution that best fits each dataset. The formulation of the negative log-likelihood function is given as follows:

$$\text{MinNL} = - \sum_i \ln(f(PD_i|\alpha_l, \beta_l)), \quad (17)$$

where $\alpha_l, \beta_l \in \Omega$.

In the above equation, $f(PD_i|\alpha_l, \beta_l)$ represents the probability density function of data point PD_i given parameters α_l and β_l .

The negative log-likelihood value, denoted as NL , is obtained by summing the negative natural logarithm of the probability density function evaluated at each data point. Parameter estimation is then formulated as an optimization problem, where the objective is

to minimize the discrepancy between the observed data and the assumed probability distribution. By minimizing NL , the optimal distribution parameters α_l and β_l are identified to achieve the best statistical fit to the data.

2.5.5. Expectation Value Model

In this study, the uncertainty of renewable energy generation is characterized by a set of discrete output scenarios associated with their corresponding occurrence probabilities. Based on this representation, a stochastic expectation framework is established, in which the objective is to minimize the expected value of the formulated multi-objective function:

$$F = E[F_1, F_2] \quad (18)$$

where F represents the objective expectation function, and E represents the expectation.

2.6. Monte Carlo Method

2.6.1. Monte Carlo Multi-Scenario Generation Method

In this study, a static probabilistic scenario-based approach is adopted to characterize the uncertainty of renewable energy generation. This modeling choice is made at the planning level in order to limit computational complexity and ensure tractability when solving the large-scale stochastic optimization problem. Consequently, temporal dependencies and inter-hour correlations of renewable outputs are not explicitly modeled within the current framework. The stochastic expectation value model captures the uncertainty of renewable energy output using a set of scenarios. Generating accurate output scenario sets is crucial and a prerequisite for efficiently solving the model. This paper utilizes Monte Carlo simulation for output scenario set generation. For the uncertainty of wind speeds and solar irradiance, the optimal cost of the proposed expectation value model is a function $f(x, y)$, where x follows a beta distribution, and y follows a Weibull distribution. When $f(x, y)$ comprises two distinct random variables, each following density functions $f_x(x)$ and $f_y(y)$, respectively, we can estimate the expected value $E(f(x, y))$ using the Monte Carlo method. Generating N sets of independent samples $(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)$, where x_i denotes a sample drawn from $f_x(x)$ and y_i from $f_y(y)$, allows us to compute the sample mean estimate:

$$\bar{f} = \frac{1}{N} \sum_{i=1}^N f(x_i, y_i) \quad (19)$$

Next, we calculate the expectation of this estimate, i.e., $E(\bar{f})$. As x and y are independent, we have

$$E(\bar{f}) = \frac{1}{N} \sum_{i=1}^N E(f(x_i, y_i)) \quad (20)$$

Since each sample (x_i, y_i) is independently drawn, we can calculate each expectation separately:

$$E(\bar{f}) = \frac{1}{N} \sum_{i=1}^N \left[\int \int f(x, y) f_x(x) f_y(y) dx dy \right] = E(f) \quad (21)$$

The mean of the sample mean estimate, $\bar{f}$, is equal to the actual mean. To calculate the variance of the sample mean estimate $\text{Var}(\bar{f})$, we perform the following:

$$\text{Var}(\bar{f}) = \text{Var} \left(\frac{1}{N} \sum_{i=1}^N f(x_i, y_i) \right) \quad (22)$$

As x_i and y_i are independent and due to variance properties, we have

$$\text{Var}(\bar{f}) = \frac{1}{N^2} \sum_{i=1}^N \text{Var}(f(x_i, y_i)) \rightarrow 0 \text{ as } N \rightarrow \infty \quad (23)$$

Therefore, as the sample size N approaches infinity, $\text{Var}(\bar{f})$ tends to zero. This implies that as the sample size grows, the variance of the sample mean estimate diminishes, resulting in more stable estimates closer to the true value. Hence, when using the Monte Carlo method to estimate sample means, selecting a sufficiently large N ensures computational accuracy.

2.6.2. Renewable Energy Penetration Rate

For the case in which the generation side consists solely of wind turbines and photovoltaic units, a Monte Carlo-based simulation framework is adopted to obtain the optimal solution. This approach enables a quantitative analysis of the relationship between the Renewable Energy Penetration Rate (REPR) and system cost, thereby supporting investment decision-making under uncertainty. The economic feasibility of the system is further assessed by explicitly incorporating both REPR and renewable generation uncertainty into the analysis. Instead of defining renewable penetration as a deterministic ratio between renewable generation and total load, a probabilistic representation of REPR is introduced. Based on the original load profile, renewable resources are assumed to satisfy the demand with a certain probability. During the sampling process, extreme scenarios characterized by low renewable availability and high load demand can be efficiently identified, in which case diesel generation is dispatched as a backup source. Accordingly, the probabilistic formulation of the renewable energy penetration rate is defined as follows:

$$REPR = P(P_{DG}^t = 0, \xi \leq 0) \quad (24)$$

where P denotes the probability.

Considering a significantly large sample size (N), the law of large numbers is applied, for $\forall \epsilon > 0$:

$$\lim_{N \rightarrow \infty} P\left(\left|\frac{X_1 + X_2 + \dots + X_N}{N} - E(X_i)\right| < \epsilon\right) = 1 \quad (25)$$

Under this formulation, the number of scenarios in which the load is successfully supplied converges to approximately $N \cdot p$. Within the Monte Carlo scenario generation process, the power balance constraint is permitted to be violated in up to $N \cdot (1 - p)$ realizations, thereby enabling a probabilistic representation of supply adequacy. Consequently, the selected sample size plays a critical role in determining the accuracy of the estimated probability that generation satisfies the load. To balance computational efficiency and estimation accuracy, confidence interval analysis is required for determining an appropriate number of samples. Given the multivariate and highly nonlinear nature of the underlying objective function, a non-parametric bootstrap approach is adopted. Specifically, repeated resampling is performed and the corresponding empirical percentiles are used to construct a 95% confidence interval.

First, define the percentile, where for a given probability p , the p percentile of a discrete random variable Y is defined as

$$\text{percentile}(p) = \min\{y \in \mathbb{R} : P(Y \leq y) \geq p\} \quad (26)$$

Using the Bootstrap method to compute the confidence interval for the mean value. Given a data sample $x_1, x_2, \dots, x_n$, where n is the sample size:

- Step 1. Bootstrap Sampling: Randomly draw samples with replacement from the data, with each Bootstrap sample size being n . Repeat this process B times, where B is the number of samples.
- Step 2. Calculate Sample Mean: Compute the sample mean for each Bootstrap sample, denoted as $\bar{x}_1, \bar{x}_2, \dots, \bar{x}_B$.
- Step 3. Calculate Confidence Interval: To compute the 95% confidence interval of the population mean, use the 2.5% percentile and 97.5% percentile of the sample mean. The confidence interval can be represented as

$$(\text{percentile}_{2.5}(\bar{x}), \text{percentile}_{97.5}(\bar{x})) \quad (27)$$

In this context, $\text{percentile}_p(\bar{x})$ represents the p th percentile of the sample mean. The overall workflow of the proposed stochastic optimization methodology is illustrated in Figure 2.

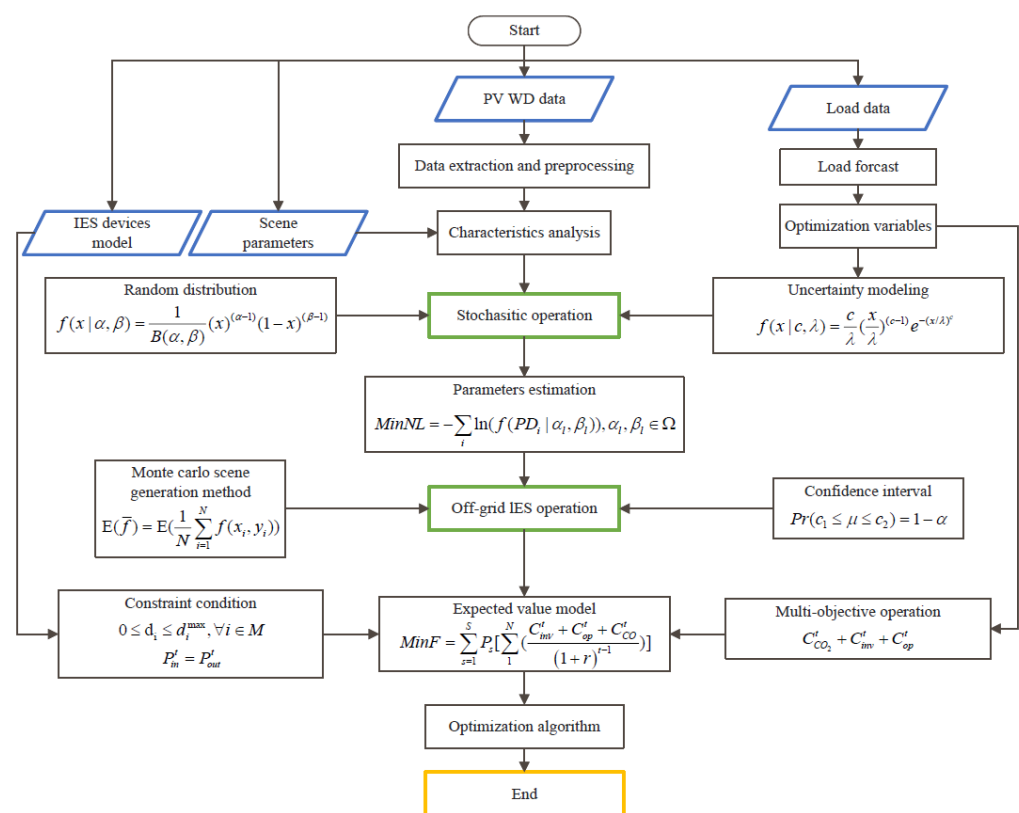


Figure 2. Flow chart of the methodology.

To clarify the interpretation of the REPR, its relationship with diesel generator utilization, system reliability, and energy contribution is further explained. In the proposed planning framework, REPR is defined as the proportion of load demand supplied by renewable energy sources, including wind power, photovoltaic generation, and energy storage discharge, under stochastic operating scenarios. Since the load is treated as a rigid demand, power balance is always satisfied through the coordinated operation of renewables, energy storage, and the diesel generator. Consequently, the diesel generator is only activated in scenarios where renewable generation and storage are insufficient to meet the load. From this perspective, the statistical distribution of REPR directly reflects the system's dependence on the diesel generator. A higher REPR indicates that a larger share of load demand is met by renewable energy, corresponding to a higher probability of avoiding diesel generator operation, whereas a lower REPR implies more frequent reliance on diesel

generation. In addition, REPR represents the expected energy contribution of renewable sources to the total system supply and exhibits a clear inverse relationship with diesel energy output.

It should be noted that the REPR is not intended to replace conventional instantaneous reliability indices such as LPSP or LOLE, which are primarily designed to capture short-term loss-of-load events. Instead, REPR serves as a planning-oriented probabilistic indicator that characterizes system robustness and dependence on conventional energy sources under renewable uncertainty. Compared with traditional reliability metrics that often rely on time-sequential simulation and additional reliability sub-models, REPR is directly derived from stochastic energy balance results within Monte Carlo scenarios. This allows REPR to be evaluated in a computationally efficient manner without introducing time-dependent state transitions, making it particularly suitable for multi-objective capacity planning and long-term performance assessment. Moreover, REPR provides quantitative insight into renewable energy utilization, diesel generator avoidance, and the overall robustness of off-grid integrated energy systems under uncertainty.

In this study, wind speed and solar irradiance are modeled as stochastic variables using probabilistic distributions and Monte Carlo-based scenario generation, in order to capture the dominant sources of uncertainty at the planning stage of off-grid microgrid systems. The electrical load demand is treated as a deterministic input, as the load profiles are obtained from an actual engineering project provided by the project developer and represent a fixed planning condition for capacity configuration. Consequently, load uncertainty and the statistical correlation between load demand and renewable energy generation are not explicitly considered in the current framework. It is noted that load uncertainty and wind–solar–load correlations can be incorporated using similar probabilistic modeling approaches and the same stochastic optimization framework.

The proposed optimization framework simultaneously addresses economic cost and carbon emission objectives, which necessitates the adoption of a multi-objective optimization algorithm. To obtain reliable and computationally efficient solutions, the non-dominated sorting genetic algorithm II (NSGA-II) is applied. This algorithm organizes candidate solutions based on Pareto dominance while incorporating an elitist strategy to preserve high-quality solutions across generations. Owing to its robust global search capability and inherent parallelism, NSGA-II is well suited for solving complex, nonlinear multi-objective optimization problems.

3. Case Study

3.1. Overview

The Nanshan Service Area is selected as the case study in this work to demonstrate the proposed stochastic optimization framework for off-grid integrated energy systems.

Located in Xinjiang, China, the Nanshan Service Area lies along the S24 expressway in a remote desert region, approximately 120 km away from the nearest public power grid substation, which makes conventional grid connection economically infeasible. Due to the lack of basic infrastructure such as water and electricity, traditional power supply solutions for highway service areas in this region incur excessively high external network investment costs that often exceed operational revenues. In this context, harnessing Xinjiang's abundant wind and solar resources and deploying an integrated, self-sufficient energy system represents a viable solution that supports both reliable energy supply and low-carbon highway transportation development.

The planned service area covers approximately 98 acres and is divided into northern and southern sections on either side of the expressway. The typical energy demand exhibits strong seasonal variability: the annual average electrical load is about 300 kW, while peak

demand reaches approximately 500–560 kW during winter months due to electric heating, with lower load levels observed in summer. Accordingly, the generation mix considered in this study consists of wind turbines, photovoltaic panels, an energy storage system, and a diesel generator as backup supply.

The solar irradiance, wind speed, and load data used in this case study are obtained from on-site measurements and project data provided by the project developer during the planning stage. These datasets form the basis for renewable resource assessment, load characterization, and stochastic scenario generation in the proposed optimization model. The geographical location of Xinjiang and the specific position of the Nanshan Service Area are illustrated in Figure 3, and the main system parameters are summarized in Table 1.



Figure 3. Geographical location of the Nanshan Service Area.

Table 1. Operation Parameters of system.

Parameter	Amount	Parameter	EAmount
G_{st}	210 W/m ²	η_{charge}	0.8
p_{PV}	3.5 ¥/W	$\eta_{discharge}$	0.8
η_{PV}	0.22	$p_{in,max}$	2.5 MW
η_{PVS}	0.85	$p_{out,max}$	2.5 MW
v_{in}	3 m/s	p_{DG}^{max}	500 kW
v_{out}	20 m/s	CTP	0.028 ¥/kg
v_n	12 m/s	p_{fuel}	7 ¥/L
p_{WT}	8 ¥/W	p_{DG}^{max}	500 kW
η_{WT}	0.8	A_{DG}	0.2461 L/kWh
p_{ES}	0.8 ¥/Wh	B_{DG}	0.08145 L/kWh

3.2. Data

3.2.1. Solar Irradiance Analysis

Turpan belongs to a typical continental warm-temperate desert climate zone, characterized by abundant sunshine throughout the year, with annual sunshine hours ranging from 3000 to 3200. The annual average solar radiation is between 583.93 and 629.55 kJ/cm². It boasts a frost-free period of up to 210 days. Figure 4 displays the annual solar radiation intensity data. During summer noon, the sun's altitude is relatively high, resulting in abundant radiant heat. The Turpan Basin experiences long daylight hours in summer, typically with clear weather conditions and weak atmospheric attenuation of solar radiation, contributing to ample illumination. The representative annual total solar irradiance at the station site is 1265 kWh/m². The stability of solar irradiance throughout the year is characterized by the ratio between the minimum and maximum monthly average daily radiation, with minimum values of 2.08 kWh/(m²·d) and maximum is 4.78 kWh/(m²·d), yielding a ratio of 0.43, demonstrating its development and utilization potential.

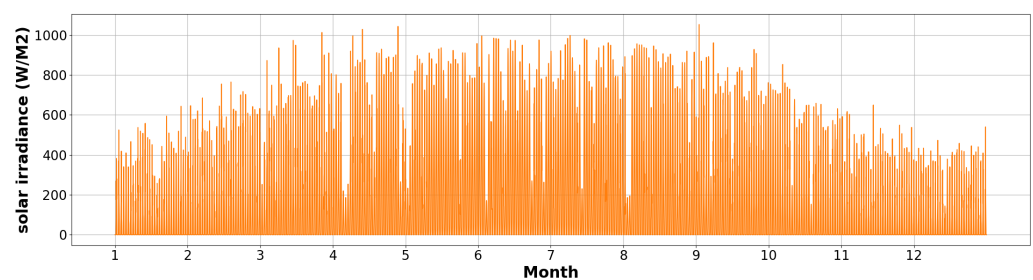


Figure 4. Solar irradiance data throughout the year.

3.2.2. Wind Speeds Analysis

The area's elevation ranges from −35 to 1170 m above sea level, mostly traversing mountainous regions with slopes from 3 to 80 degrees. Figure 5 shows yearly wind speed data. Statistical analysis reveals slight variations in average wind speeds based on Greenwich intermediate-scale data. At heights of 80, 90, 100, and 120 m, average wind speeds are approximately 6.39 m/s, 6.46 m/s, 6.51 m/s, and 6.61 m/s respectively. The prevailing wind direction is NNW, matching the primary wind energy direction. The wind shear index is 0.07. Extrapolating using Windographer software, estimated average wind speeds at 50 m height are about 6.16 m/s. Overall, wind resources are moderate in this area, suggesting low wind speeds.

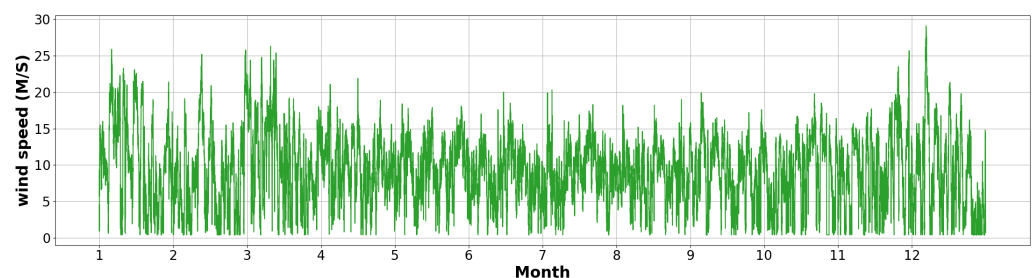


Figure 5. Wind speed data throughout the year.

3.2.3. Load Data

The Nanshan Service Area has a substantial electricity consumption, with an annual usage of 1.578 million kWh, out of which 1.088 million kWh are attributed to electric heating. The total annual electricity consumption amounts to approximately 2.666 million kWh, with an average yearly load of about 300 kW. During the summer months from May to

September, the electricity consumption is lower, averaging around 250 kW. However, in the winter months from November to February of the following year, the consumption significantly increases, with an average load of around 560 kW.

3.3. Results and Discussion

3.3.1. Renewable Energy Fluctuation

The system integrates complementary wind and solar power generation with energy storage systems as auxiliary power sources, while diesel generators serve as emergency backups to ensure power reliability. Considering local wind and solar resources alongside load demands, an off-grid IES is established. To accurately characterize the fluctuation range of renewable energy probability distributions, this study combines the method in Section 2.5 with historical data for in-depth analysis. For solar irradiance, clustering techniques such as the silhouette coefficient and elbow method identify five typical curve types. The preprocessed irradiance data is then classified using the K-means algorithm, followed by a point-by-point 24 h probability distribution fitting for each curve type. This process ultimately yields the probability distribution of solar irradiance intensity based on the beta distribution. Figure 6 illustrates the 95% confidence interval curve, offering valuable insights for enhancing the stability and reliability of renewable energy systems.

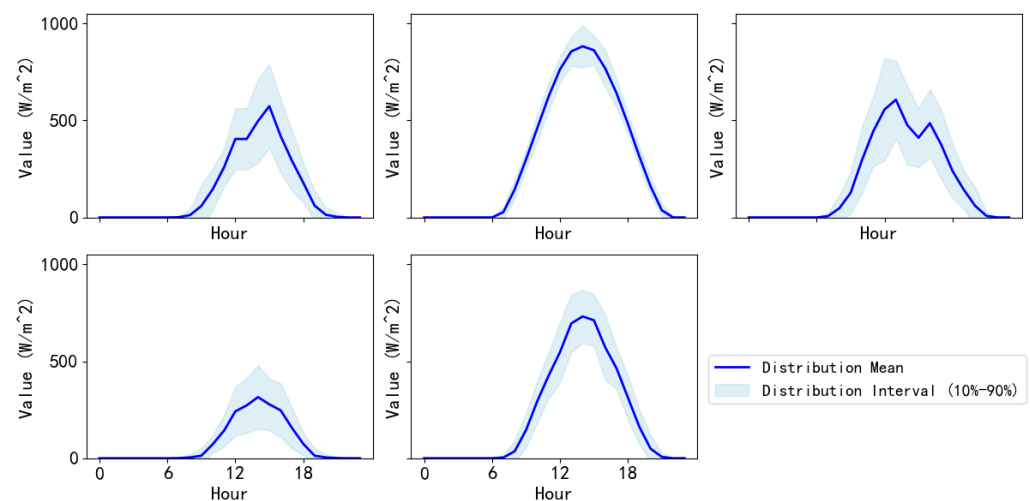


Figure 6. Confidence interval curve of irradiance intensity based on the beta distribution.

Similarly, for wind speed data, clustering analysis is performed to categorize distinct variation patterns. Each wind speed curve type undergoes a 24 h point-by-point probability distribution fitting using the Weibull distribution to capture its probabilistic characteristics. As shown in Figure 7, the resulting 95% confidence interval curve provides crucial data for wind energy resource assessment and system optimization.

Due to the impact of uncertainty processing methods on the capacity fluctuation characteristics of wind turbines and photovoltaic systems under different penetration levels, it is essential to compare the intraday and inter-category variability of wind speed and solar irradiance. By systematically listing the random distribution functions of different curve types, a more comprehensive fluctuation range for wind speed and irradiance can be obtained. This, in turn, serves as a critical basis for analyzing capacity fluctuation characteristics, enabling a deeper understanding of how renewable energy sources behave under varying conditions and improving system planning and stability. Figure 8 shows the random distribution fluctuation of different solar irradiance and wind speed obtained by clustering. Figure 9 shows the fluctuation of renewable energy in a typical day.

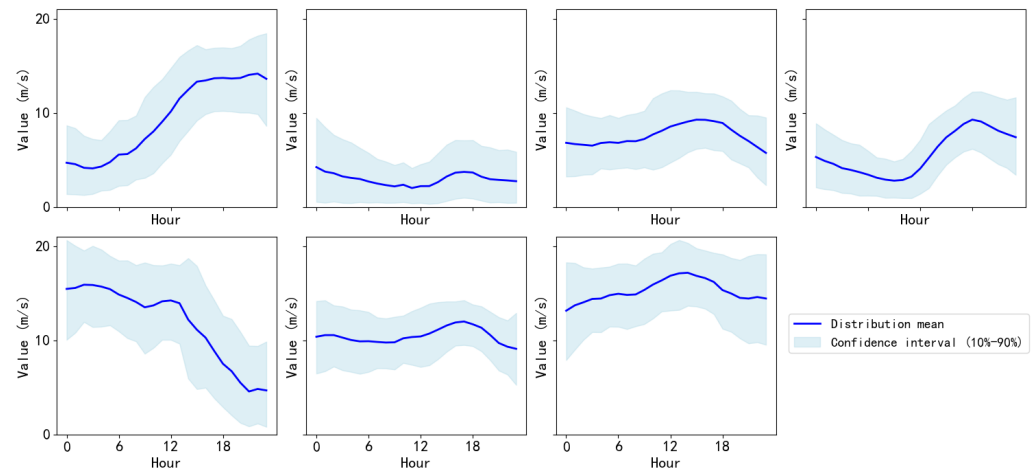


Figure 7. Confidence interval curve of wind speed based on the Weibull distribution.

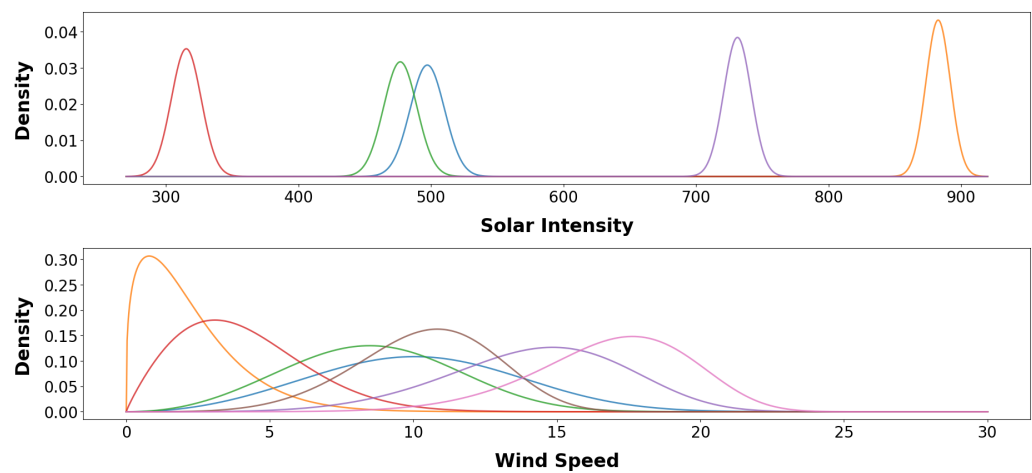


Figure 8. Random distribution fluctuation of renewable energy obtained by clustering.

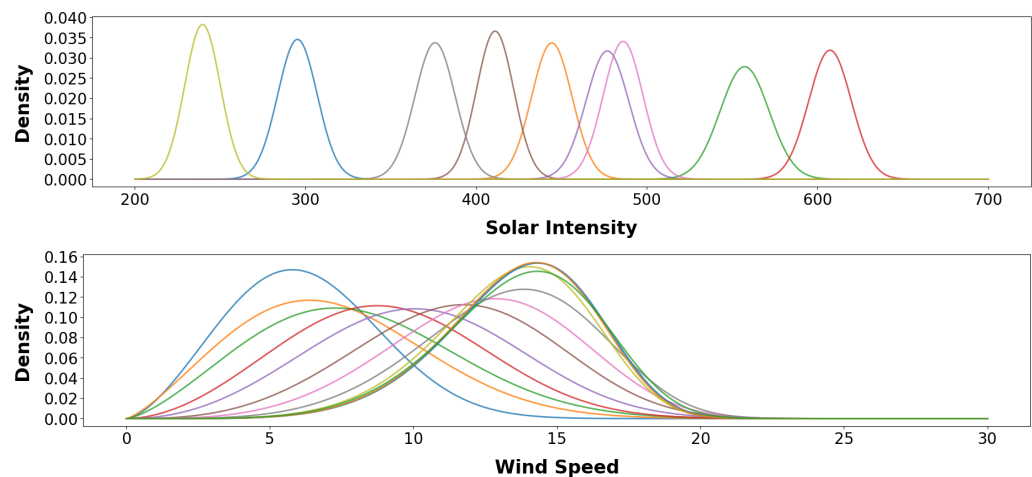


Figure 9. Fluctuation of renewable energy in a typical day.

Furthermore, compared to directly analyzing raw data, the actual power generation characteristics of wind turbines and photovoltaic systems play a more direct and crucial role in capacity planning outcomes. To ensure data comparability across different capacities and eliminate scale differences caused by capacity variations, this study adopts the power-to-capacity ratio as a standardized reference metric. Zero-value data points are excluded to provide a more accurate representation of the actual output characteristics of wind and

solar power systems. As a result, Figure 10 illustrate the beta distribution of the power-to-capacity ratio for photovoltaic panels and wind turbines, offering valuable insights for optimizing capacity allocation.

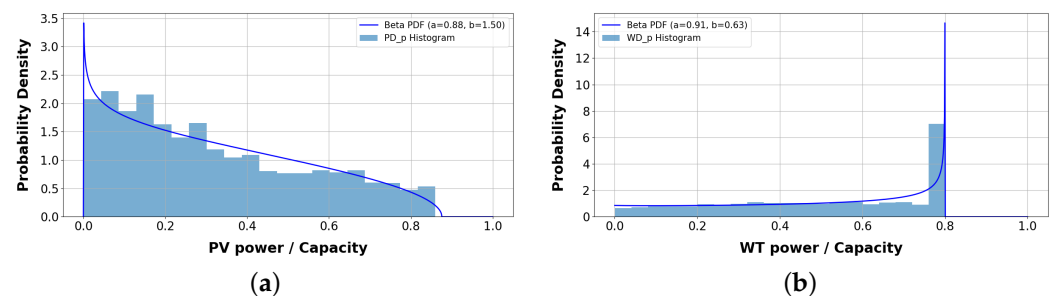


Figure 10. Beta distribution of renewable power normalized by installed capacity. (a) PV power divided by PV panels capacity. (b) WT power divided by WT capacity.

3.3.2. Pareto Set

Figure 11 presents the Pareto solution set obtained from the NSGA-II model. All solutions located on the Pareto frontier are non-dominated, which implies that additional decision-making is required in the system planning stage. In this paper, carbon emissions are converted into carbon trading costs and incorporated into the total cost, based on which an optimal solution is selected from the Pareto set. Within the solution set, the non-dominated front corresponding to the two objectives (carbon emissions and economic cost) covers carbon emission values ranging from 0 to 150 kg/day. The total cost of the wind turbine, photovoltaic, and energy storage system (WT-PV-ES) shows an inverse relationship with carbon emissions. When carbon emissions are minimized, the daily cost reaches 13 thousand RMB, resulting in an annual cost of 4.74 million RMB. Under this operating condition, the diesel generator is not activated throughout the year, and the electric power demand is fully supplied by the WT-PV-ES system. In contrast, the minimum-cost solution corresponds to a carbon emission level of 140 kg/day, for which the daily cost of the WT-PV-ES system is 4 thousand RMB and the annual cost amounts to 1.46 million RMB.

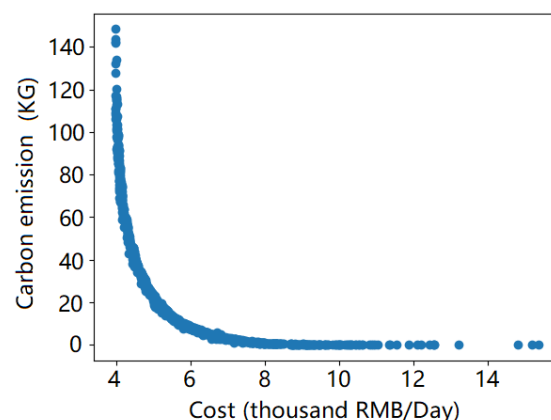


Figure 11. Pareto solution set for the NSGA-II model.

3.3.3. Renewable Energy Penetration Rate Analysis

Considering the inherent uncertainty associated with wind speed and solar irradiance, it is impractical to depend exclusively on an electrical energy storage system to satisfy load demand. In particular, under extreme operating conditions such as periods with no wind, no solar radiation, and increased heating loads during winter, sole reliance on the energy storage system would lead to prohibitively high system costs. Consequently,

diesel generators are incorporated into the optimization framework as a supplementary power source. The simulation results indicate that, for a load with an average demand of 300 kW and a peak demand of 500 kW, supplying 100% of the load solely through renewable resources requires a substantially increased capacity of the WT–PV–ES system. Figure 12 illustrates the relationship between system costs and the REPR. As shown in the figure, the total system cost initially decreases and then increases as REPR rises. The lowest system cost is observed at approximately 60% REPR, indicating the most economically optimal configuration. However, when REPR further increases to 90% or higher, the system cost rises significantly. This is primarily because achieving a higher REPR requires additional wind, solar, and energy storage capacity to ensure reliability under low-wind, low-solar, and high-load conditions, leading to increased investment and operational costs. Furthermore, this study compares the results obtained using an uncertainty-based approach with those from deterministic optimization methods, specifically the economically and environmentally optimal solutions. The economically optimal configuration in the deterministic approach roughly corresponds to the optimized result at an uncertainty-based REPR of 70%. Meanwhile, the uncertainty-based optimization yields a more cost-effective solution at a 60% REPR, demonstrating an approximate 11% improvement in economic performance by modeling the variability of wind and solar resources rather than relying on fixed periodic data. In contrast, the deterministic environmentally optimal configuration corresponds to an uncertainty-based REPR of 96.4%, indicating that the deterministic carbon emission-optimal solution lacks reliability due to its failure to account for wind and solar fluctuations.

The optimized overall system scheme of the project is shown in Table 2. The capacity variation trends of wind turbines, photovoltaics, and energy storage systems with respect to REPR exhibit notable differences. When REPR is below 100%, the capacities of all three components increase in a relatively linear manner. However, under the 100% REPR constraint, the capacities of photovoltaics and energy storage systems increase significantly, while wind turbines are entirely eliminated in the optimal configuration. The primary reason for this phenomenon lies in the differences in power characteristics between photovoltaics and wind turbines. Although photovoltaics generally have a higher average power output than wind turbines, their power fluctuations are significantly greater. When the energy storage capacity is limited, wind turbines and photovoltaics must operate in coordination to maintain power balance and mitigate fluctuations. However, the 100% REPR constraint imposes extremely high requirements on energy storage capacity, enabling the system to effectively smooth out photovoltaic power fluctuations. Consequently, under these conditions, photovoltaics demonstrate superior economic performance and efficiency, leading to their dominance in the optimal configuration while wind turbines are excluded. In addition to capacity variations, the table also illustrates the impact of REPR on carbon emissions. As the REPR increases, carbon emissions (CE) exhibit a decreasing trend, indicating the system's enhanced capability to reduce emissions through increased renewable energy integration. When REPR is 30%, the carbon emissions remain relatively high at 1472.3 t/year. However, as REPR rises to 50%, carbon emissions drop significantly to 969.3 t/year, demonstrating the effectiveness of incorporating more renewable energy sources. Beyond this point, the reduction in carbon emissions continues but at a slower rate. Notably, when REPR reaches 100%, carbon emissions are minimized to 21.7 t/year, showcasing the near-complete decarbonization of the system. The steep decline in carbon emissions as REPR approaches 100% highlights the critical role of energy storage and optimized renewable energy configurations in achieving a low-carbon energy system.

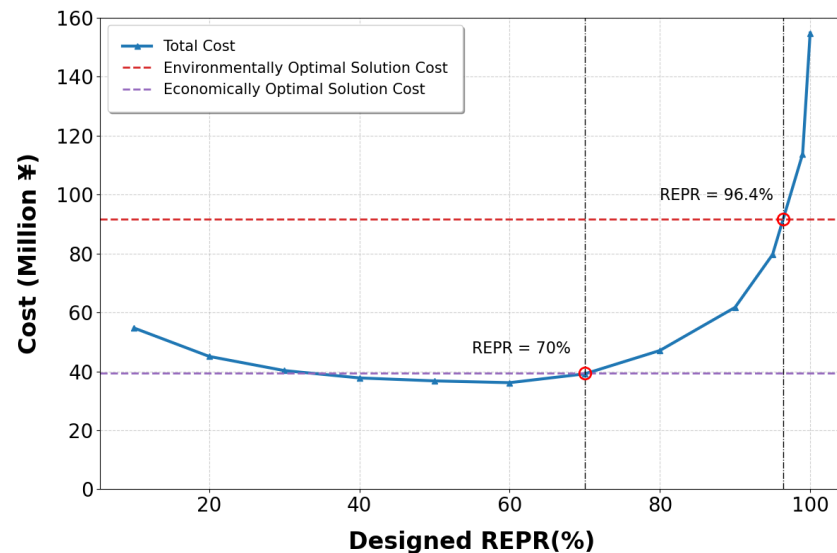


Figure 12. Relationship between REPR and total cost.

Table 2. Capacity and carbon emission for different REPR.

REPR (%)	PV (MW)	WT (MW)	ES (MWh)	CE (t/Year)
30	0.002	0.718	0.486	1472.3
40	0.006	0.867	0.754	1246.7
50	0.019	1.259	0.971	969.3
60	0.117	1.532	1.846	718.4
70	0.346	1.956	2.999	486.4
80	0.748	2.733	3.697	298.1
90	0.957	3.918	5.644	151.1
95	0.929	4.979	8.893	66.4
99	2.196	4.993	20.376	59.2
100	3.628	0.951	49.342	21.7

Since the calculation of REPR is based on a constructed scenario set, it is necessary to validate the results using raw data, i.e., the full-year 8760 h wind, solar, and load data. As shown in Figure 13, the horizontal axis represents the designed penetration rate, which refers to the REPR calculation method proposed in this study. By applying the optimized capacity configuration to the actual 8760 h data for verification, the resulting actual energy balance corresponds to the actual penetration rate on the vertical axis. It can be observed that the calculated designed penetration rate exhibits some redundancy. This is because the complexity of the constructed scenario set is higher than that of the actual data, leading to an elevated penetration rate standard. This redundancy, to some extent, enhances system reliability while also indicating that the proposed method does not require an additional 20% equipment capacity reserve in practical applications, thereby reducing costs.

In order to further verify the reliability implications of the proposed REPR-based planning results from a conventional reliability perspective, additional reliability indices, namely the Loss of Power Supply Probability (LPSP) and the Loss of Load Expectation (LOLE), are evaluated based on the full-year 8760 h wind, solar, and load data. Unlike REPR, which serves as a planning-oriented probabilistic indicator, LPSP and LOLE are computed as post-optimization validation metrics to assess the system's ability to continuously satisfy load demand under actual chronological operating conditions. Based on the additional reliability evaluation, Table 3 presents the relationships between the Renewable Energy Penetration Rate (REPR) and the conventional reliability indices LPSP and LOLE, respectively. As REPR increases, both LPSP and LOLE exhibit a clear decreasing

trend, indicating a progressively lower probability and frequency of load supply shortfalls. This behavior is consistent with the physical interpretation of REPR, as higher renewable penetration—supported by increased renewable generation and energy storage capacity—reduces the system’s reliance on diesel generation and enhances its ability to meet load demand under uncertain operating conditions. The observed monotonic relationship between REPR and the two reliability indices confirms that REPR effectively captures the reliability implications of capacity planning decisions at the system level. Therefore, although REPR is not designed to replace time-sequential reliability metrics, its strong consistency with LPSP and LOLE demonstrates that it can serve as a reliable and computationally efficient planning-oriented indicator for assessing system robustness and renewable utilization in off-grid integrated energy systems.

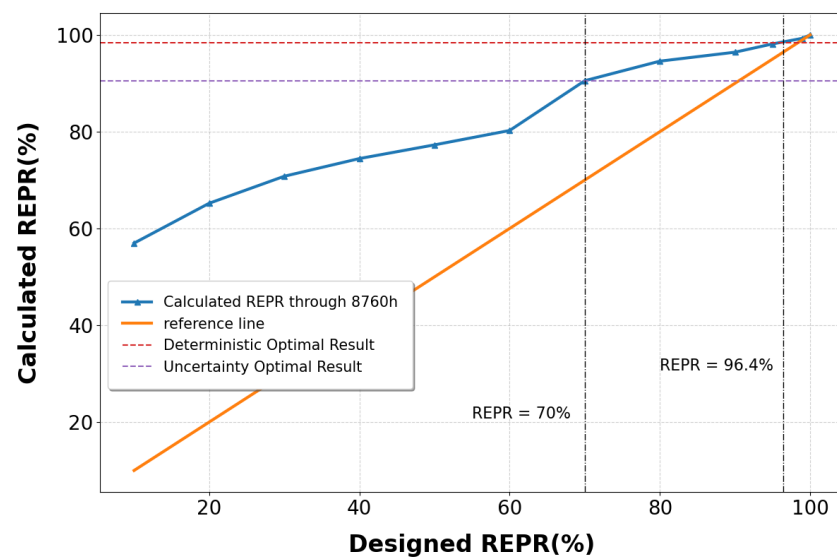


Figure 13. Relationship between design REPR and actual REPR.

Table 3. Reliability indices under different REPR levels.

REPR (%)	LPSP (-)	LOLE (h/Year)
30	0.3637	3186
40	0.2909	2548
50	0.2048	1794
60	0.1389	1217
70	0.0872	764
80	0.0589	516
90	0.0314	275
95	0.0128	112
99	0.0039	34
100	0.0011	10

Based on the trend of the cost curve, relying solely on a WT-PV-ES system to meet the full load demand without diesel generators would lead to a sharp cost increase. Therefore, a trade-off between environmental benefits and economic costs must be considered in system optimization to determine an appropriate REPR. The study results further indicate that for the given load demand (an average of 300 kW and a peak of 500 kW), a fully renewable-based system would require significantly higher capacity and incur substantial costs. Consequently, the optimization incorporates diesel generators as a supplementary energy source to minimize overall system costs.

As shown in Figure 14a, when the total cost is broken down, it can be observed that at low REPR levels, the primary cost component is diesel generation, while at high REPR levels, the main cost comes from wind, solar, and energy storage systems. This cost distribution leads to the characteristic U-shaped cost curve.

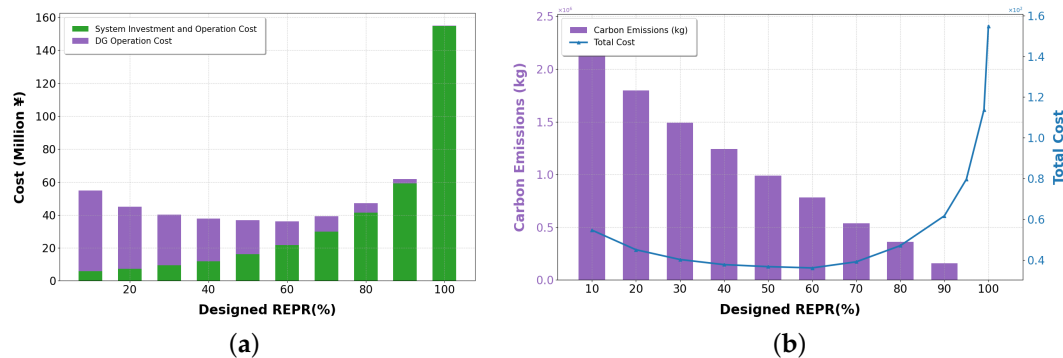


Figure 14. Relationship between renewable energy penetration and system performance. (a) Relationship between REPR and DG cost. (b) Relationship between REPR and carbon emission.

As illustrated in Figure 14b, as REPR increases, the system's reliance on diesel generators gradually decreases, resulting in a significant reduction in carbon emissions. However, once REPR exceeds 60%, despite the environmental benefits, the investment and operational costs of the system begin to rise sharply. This increase becomes particularly pronounced when REPR approaches 100%, where costs surge to extremely high levels. The primary reason for this is the need for additional wind, solar, and energy storage capacity to ensure system reliability under extreme conditions of low wind, low solar availability, and high load demand. Therefore, in practical optimization, relying solely on renewable energy is not feasible. A moderate integration of diesel generators not only enhances system reliability but also significantly reduces overall costs. Balancing economic feasibility and environmental benefits, this study identifies an optimal REPR of approximately 60%, which minimizes system costs while effectively controlling carbon emissions. These findings provide valuable insights for the optimization and design of renewable-based microgrid systems.

The optimization results indicate that REPR directly determines carbon emissions, fundamentally because the capacity of wind, solar, and storage systems indirectly influences the final outcome through optimization. Among these factors, the impact of storage capacity on carbon emissions is the most significant. As shown in Figure 15, carbon emissions exhibit high sensitivity to changes in storage capacity, following an exponentially decreasing trend—as storage capacity increases, carbon emissions drop substantially. Although variations in storage capacity stem from the collective fluctuations of wind, solar, and storage capacities under different REPR settings, the strong sensitivity of carbon emissions to storage capacity suggests that its impact can be analyzed independently. This highlights the critical role of energy storage in reducing carbon emissions and underscores the necessity of optimizing storage capacity in the design of renewable-based microgrids to achieve a balance between environmental and economic benefits.

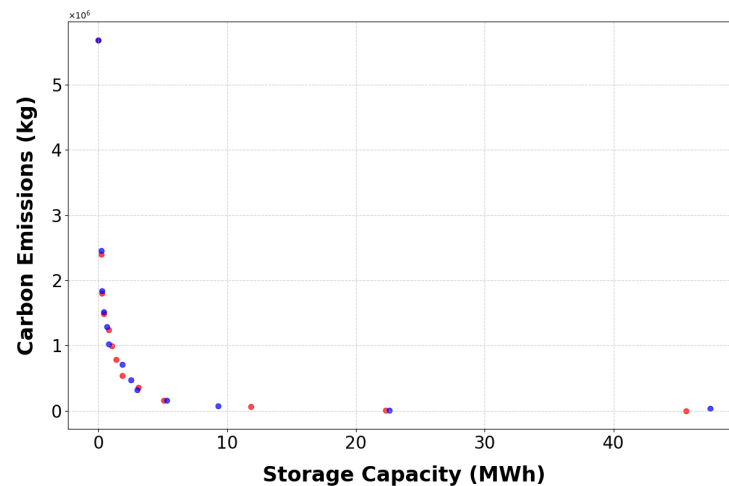


Figure 15. Relationship between the capacity of storage and carbon emission.

3.3.4. Power Balance

The equipment configuration obtained through stochastic optimization calculation using NSGA-II in off-grid IES scenarios can meet the load demand at the rate of different REPRs. Figure 16 illustrates the hourly balance calculation under the REPR at 90% throughout the year. Figures 17–19 represent a typical daily hourly balance chart. It is evident that during transitional seasons, there is ample sunlight but lower wind speeds, while in winter, sunlight is scarce with higher wind speeds. Optimized equipment configurations require larger capacities for PV panels and wind turbines. The substantial capacity of electrical energy storage is crucial for peak shaving and load leveling. The flexibility of electrical energy storage balance the power generation with the reliability of diesel generation to satisfy load demands. In the graph, it can be observed that during winter, there are insufficient wind and solar resources, necessitating the activation of diesel generation to maintain energy balance. Meanwhile, during transitional seasons, wind and solar resources are sufficient. It should be noted that the current uncertainty modeling framework does not explicitly capture joint extreme conditions characterized by simultaneously high energy demand and low solar radiation. As a result, under a limited number of critical operating scenarios, this simplification may lead to deviations in the evaluation of system performance and reliability. Nevertheless, the adopted framework remains suitable for system-level planning analysis under typical operating conditions.

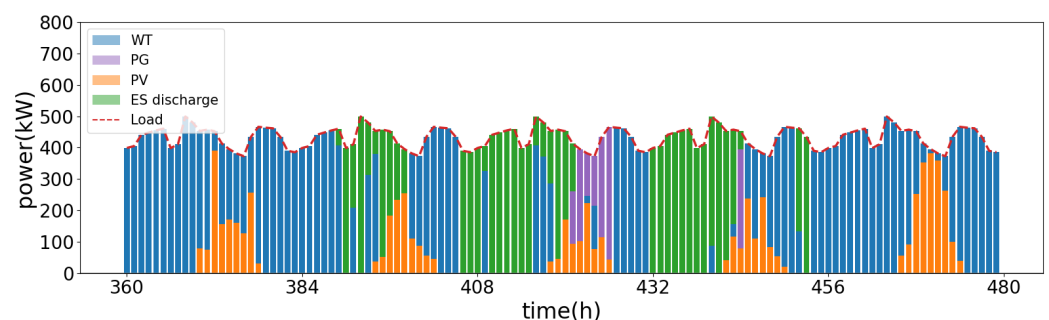


Figure 16. Power balance throughout the year.

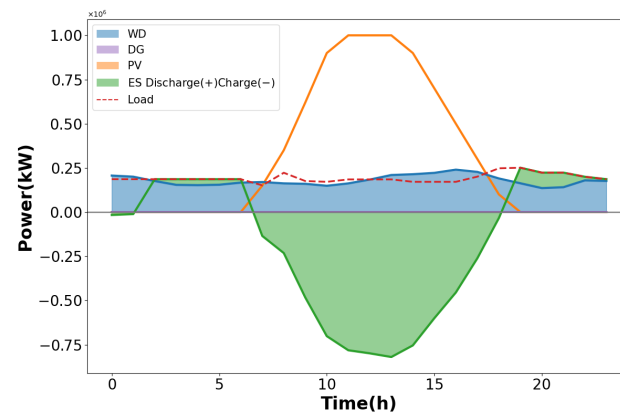


Figure 17. A typical daily hourly balance in April.

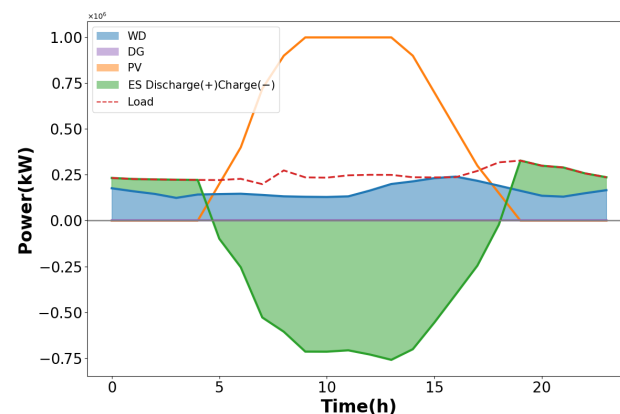


Figure 18. A typical daily hourly balance in July.

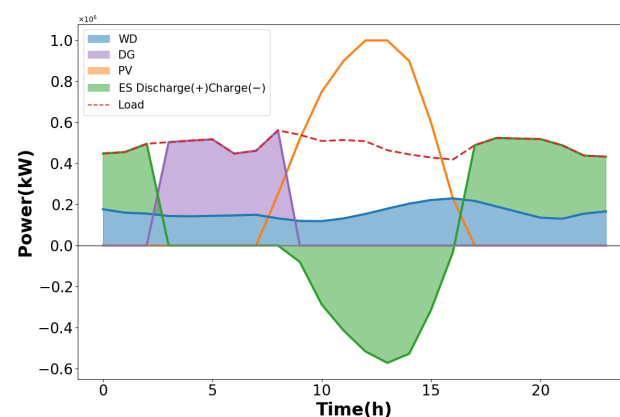


Figure 19. A typical daily hourly balance in January.

3.3.5. Investment Decision Recommendation

This section outlines the economic outcomes of the off-grid IES analysis for different REPRs. Figure 20a shows the variation in the payback period for different REPRs and corresponding investment capacities of the system. According to the graph, if the system is invested in at a capacity corresponding to a 40% REPR, the payback period is only 8 years. With an investment in capacity corresponding to an 80% REPR, the payback period extends to 11 years. However, if the REPR rises to 95% or above, the system is unable to recover the investment costs within its operation lifespan. Figure 20b represents the relationship between the Net Present Value (NPV) and system REPR. As is shown in the chart, the NPV is negative when REPR is above 80%. Figure 21 illustrates. The chart illustrates the Levelized Cost of Electricity (LCOE) values of the system at different REPR, ranging from

40% to 100%. Here, we assume an interest rate of 5% and an asset's useful lifetime of 20 years.

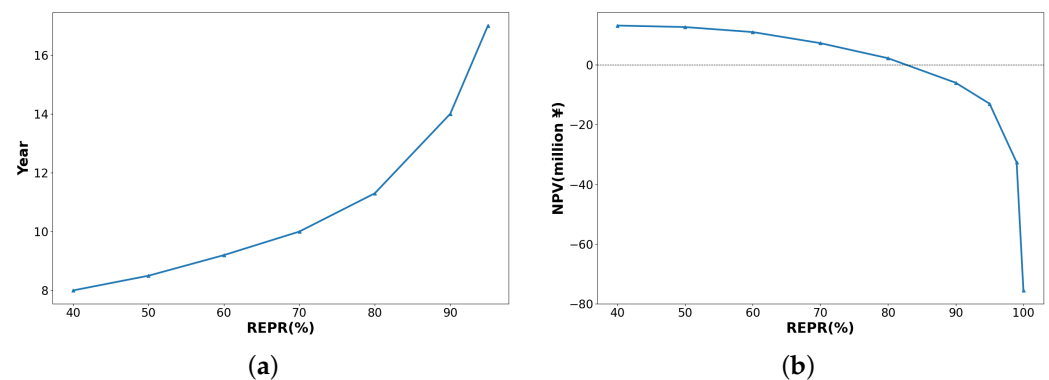


Figure 20. Relationship analysis between investment performance and renewable penetration. (a) Relationship between PP and REPR. (b) Relationship between NPV and REPR.

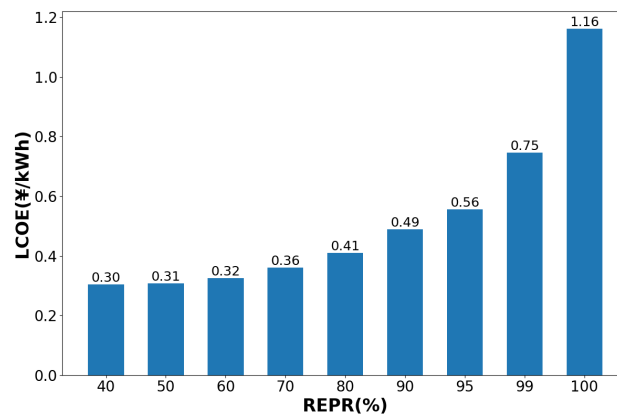


Figure 21. Relationship between LCOE and REPR.

Figure 22a reflects the annual NPV of the system under different levels of system REPRs over the operation years. The chart displays how the system's NPV fluctuates over the years of operation with different REPRs ranging from 50% to 90%. Please note that due to poor economic performance, NPV values remain negative at lower or higher REPR. It can be observed from the graph that for a system with an 80% REPR, the project's NPV turns positive in the 18th year. If the REPR drops to 50%, the project's NPV becomes positive in the 12th year. Figure 22b illustrates the relationship between the NPV of the system and the discount rate under different levels of system REPR. The chart illustrates the variation in NPV values of the system at different REPR, ranging from 50% to 90%, over 20 years. According to the graph, the Internal Rate of Return (IRR) for a system with a 50% REPR is 9.8% over the 20-year operation period, while for a system with an 80% REPR, the IRR is 4.6%. Should the REPR decrease to 40% or below, the NPV of the proposed system will turn negative at discount rates from 0% to 20%. This suggests that achieving a positive NPV under these conditions would necessitate a negative IRR, which is unfeasible.

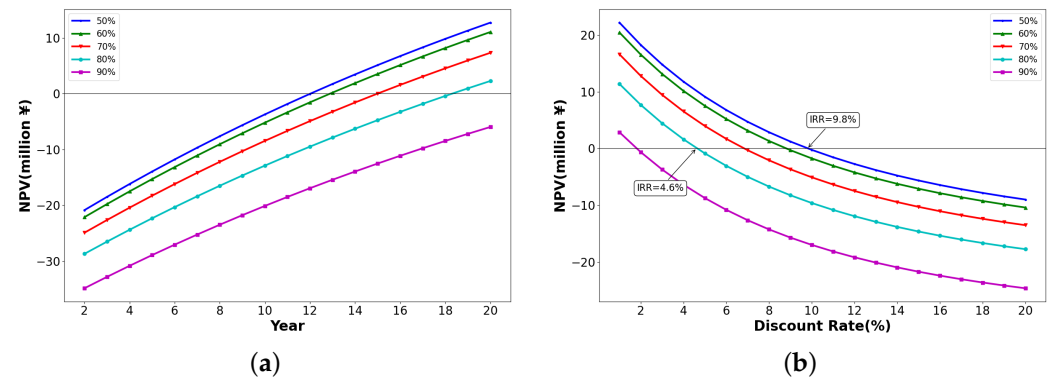


Figure 22. Comparison of system NPV performance. (a) Annual NPV of the system over 20 years. (b) NPV under different discount rates.

3.3.6. Discussion

The method proposed in this paper effectively addresses the mathematical programming problem in off-grid systems with wind and solar uncertainty. However, due to the hyperparameters related to the sampling method, different sample sizes can result in variations in the optimal capacity, even when using the same scenario pool. This implies that the choice of sample size is closely tied to the planning and design requirements.

Figure 23 illustrates the relationship between Monte Carlo sample size and the convergence behavior of the stochastic optimization results. As the sample size increases, the variability among repeated optimization runs is progressively reduced. In particular, when the sample size reaches approximately 2500, the dispersion of the obtained solutions becomes notably smaller, with the optimal solution error constrained within 0.1, indicating a substantial improvement in convergence stability. Although further increasing the sample size to 10,000 or more leads to additional convergence and marginal error reduction, the rate of improvement becomes increasingly limited.

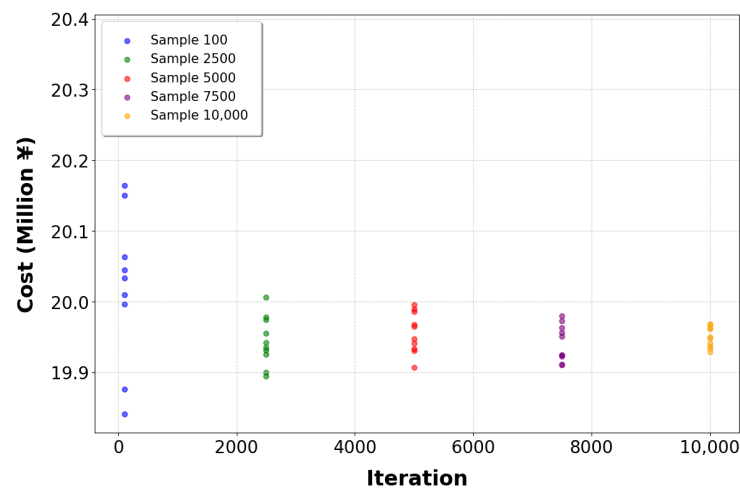


Figure 23. Relationship between sample size and optimization convergence.

From a statistical perspective, for a sample size of 2500, the resulting 95% confidence interval of the proposed probabilistic metric exhibits a width of approximately 5%, indicating that the estimation accuracy has reached a practically acceptable level for planning-oriented analysis. As the sample size increases to 5000 and 10,000, the corresponding confidence interval widths further decrease to approximately 3.7% and 2.9%, respectively. While this trend confirms that larger sample sizes improve estimation precision, the magnitude of improvement beyond 2500 samples becomes progressively smaller. According to the

convergence characteristics of Monte Carlo sampling, these marginal accuracy gains are achieved at the cost of a substantially increased computational burden. Therefore, within the considered planning framework, a sample size on the order of 10^3 provides a reasonable trade-off between computational efficiency and estimation accuracy for evaluating the probability that renewable generation can satisfy load demand.

Based on the above conclusions, an analysis is conducted on the impact of different sample sizes on the total cost of optimized configuration results. Figure 24 illustrates the optimal system planning costs corresponding to different REPR values under varying sample sizes. For REPR values ranging from 10% to 99%, the optimization error exhibits oscillatory behavior as the sample size increases, eventually converging when the sample size exceeds 10,000. In contrast, under the constraint of 100% REPR, the computed results increase monotonically with the sample size, gradually approaching the convergence value, and achieving precise results at extremely large sample sizes. This indicates that optimization calculations under high penetration levels require a trade-off between accuracy and computational efficiency. Given the results obtained for various sample sizes, the monotonicity of the sequence can be leveraged to estimate the convergence value by computing its limit, significantly reducing computational resource consumption. Moreover, this also suggests that when employing a moderate sample size, further refinement of the results under the 100% REPR constraint is necessary.

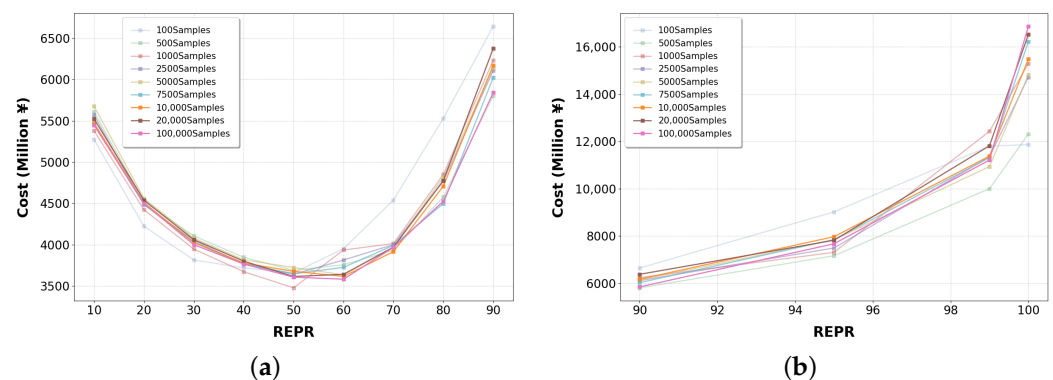


Figure 24. Relationship between REPR and optimal cost in different sample sizes. (a) REPR from 10% to 90%. (b) REPR from 90% to 100%.

Furthermore, the influence of different sample sizes on the optimal capacity of wind turbines, photovoltaic systems, and energy storage devices is examined. Figure 25 presents the optimal capacities of wind turbines, photovoltaic systems, and energy storage devices corresponding to different REPR values under varying sample sizes. Compared to the fluctuation patterns of cost, the variations in the optimized capacities of different components under varying sample sizes exhibit distinct trends. Specifically, for REPR values between 90% and 99%, the fluctuation in optimal capacity is higher than that observed for REPR values below 90%. Under the 100% REPR constraint, the capacity fluctuations become even more pronounced. This phenomenon can be attributed to the increasing sensitivity of the Monte Carlo method to sample size as REPR increases. To estimate the convergence value, it is first necessary to assess the capacity convergence behavior as the sample size increases. It can be observed that for high REPR values, the capacities of wind turbines and energy storage systems tend to converge when the sample size reaches 10,000, whereas the capacity of photovoltaics still exhibits fluctuations. This suggests that the additional cost observed in Figure 24b under high REPR and large sample sizes is primarily driven by the expansion of the photovoltaic system capacity.

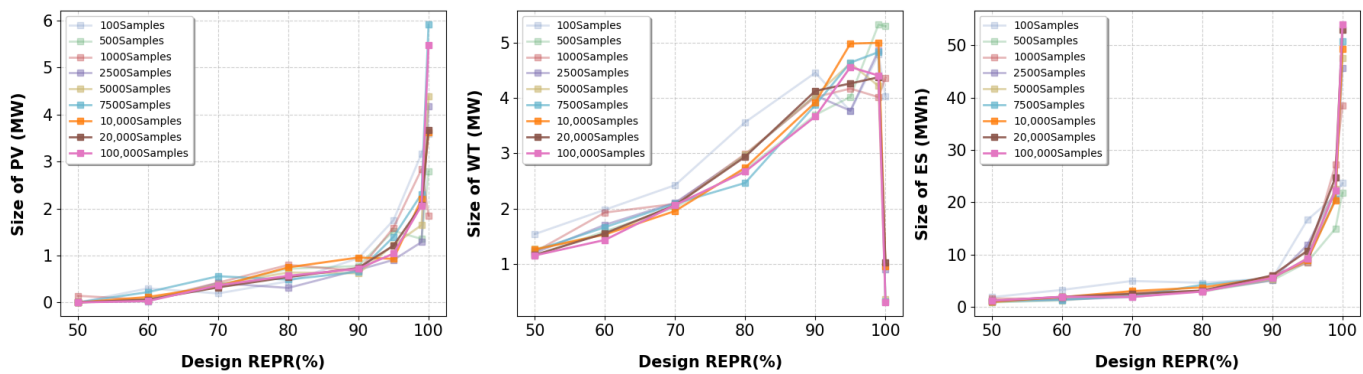


Figure 25. Relationship between REPR and capacity in different sample size.

4. Conclusions

Research on stochastic optimization for off-grid IES, particularly focusing on uncertainties related to wind speeds and solar irradiance, has been conducted considering the general efficiency and reliability of these systems. However, comprehensive studies on the Renewable Energy Penetration Rate (REPR) in off-grid IES under uncertainty remain scarce. In response, this paper presents a method for quantifying REPR using stochastic optimization and the sampling technique.

To validate the model's viability and efficacy, simulations are conducted using the Nanshan Service Area. Investment recommendations are provided by describing the relation between the system's REPR and various economic indicators. When REPR rises to 90% or above, the investment cost is relatively high and the system is unable to recover the investment costs within its operation lifespan. When REPR ranges from 50% to 90%, with the continuous decrease in the REPR, the economic benefits of the system are increasing. However, the increasing share of diesel power generation indicates higher carbon emissions, requiring investors to make decisions. If the system is invested in at a capacity corresponding to a 40% to 50% REPR, the payback period is only 8 years, which is optimal in terms of economy. Results demonstrate that the proposed model enhances the system's economic benefits by quantifying the REPR of the system.

In summary, this study primarily proposes a stochastic optimization framework for an off-grid IES, together with system-level reliability assessment and operational performance evaluation under renewable uncertainty. Nevertheless, several aspects remain beyond the scope of the current work. Specifically, the proposed framework does not explicitly consider load uncertainty, correlations among stochastic wind and solar resources, or the joint extreme operating conditions characterized by high energy demand coinciding with low renewable generation. In addition, the costs associated with diesel generator start–stop cycles are not modeled in detail. Therefore, future research will focus on extending the proposed stochastic optimization approach by incorporating correlated and conditional uncertainty modeling, time-series dependence and inter-temporal correlations of renewable energy generation and load demand, as well as a more detailed representation of diesel generator operational characteristics. In particular, sequential Monte Carlo simulation and time-dependent stochastic modeling will be investigated to enable a more comprehensive representation of system dynamics and chronological operational behavior, thereby further enhancing the robustness and applicability of the planning framework.

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Abbreviations

The following abbreviations are used in this manuscript:

IES	Integrated Energy System
WT	Wind turbines
PV	Photovoltaic
EB	Electric boiler
EC	Electric chiller
ES	Energy storage
DG	Diesel engine
REPR	Renewable energy penetration rate

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