

Article

Low-Carbon Economic Dispatch of Islanded Microgrids Considering Coordinated Demand Response and Energy Storage via Rotation Quantum Particle Swarm Optimization

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Abstract

To address the high dependence on diesel generation, renewable energy variability, and limited demand-side flexibility of remote islanded microgrids, this study develops a low-carbon economic dispatch framework for an islanded photovoltaic–wind–diesel–battery energy storage system with coordinated demand response. The proposed model minimizes the operating cost, pollutant treatment cost, and load-loss penalty cost while satisfying generation-output, battery state-of-charge, charging and discharging, demand-response, and islanded power-balance constraints. To solve the resulting high-dimensional, nonlinear, and strongly constrained optimization problem, a rotation quantum particle swarm optimization algorithm (RQPSO) is proposed. In contrast to the conventional velocity–position update, RQPSO independently encodes each decision variable using a full-dimensional quantum phase representation and performs the search through a shortest-path rotation-guided phase-updating mechanism. Adaptive angular mutation, elite local refinement, and stagnation-aware restart are further incorporated to balance global exploration, local exploitation, and convergence stability. The algorithm is evaluated using nine 30-dimensional benchmark functions and representative 24 h forecasted load and renewable-generation profiles for Island data. Under the reliability-priority scheduling scheme, RQPSO achieves a total scheduling cost of 69,017.69 CNY, diesel fuel consumption of 6636.20 kg, and estimated CO₂ emissions of 18,332.49 kg. Compared with conventional PSO, these three indicators are reduced by 9.34%, 12.25%, and 12.25%, respectively. RQPSO also reduces the total cost by 6.16–27.36% relative to six comparison algorithms. The results demonstrate that the coordination of demand response and battery storage can improve peak–valley regulation, reduce diesel dependence and emissions, and maintain feasible and economical operation under different renewable-generation conditions.



Academic Editor: Pompodakis Evangelos

Received: 22 June 2026

Revised: 13 July 2026

Accepted: 14 July 2026

Published: 21 July 2026

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Keywords: islanded microgrid; renewable energy; low-carbon economic scheduling; rotation quantum particle swarm optimization; demand response

1. Introduction

Against the background of the global low-carbon energy transition and the growing demand for reliable power supply in remote areas, microgrids have become an important technical solution for enhancing regional energy self-sufficiency and promoting the consumption of renewable energy, owing to their ability to integrate distributed generation, energy storage systems, and flexible load resources. For remote islands, off-grid

communities, and weak-grid regions, conventional power supply systems still largely rely on local controllable sources, such as diesel generators. Although these sources can meet basic load demand to some extent, they are often associated with high fuel transportation costs, insufficient supply security, and considerable pollutant emissions. In recent years, power supply systems on remote islands have gradually shifted from diesel-dominated configurations toward renewable-energy-based hybrid systems with a higher penetration of clean energy [1]. Therefore, improving renewable energy utilization, reducing diesel fuel consumption, and enhancing operational economy while maintaining power supply reliability have become key issues in the optimal operation of islanded microgrids.

Compared with grid-connected microgrids, islanded microgrids cannot rely on the external main grid for power support. Their power balance, frequency stability, and reserve regulation must be maintained jointly by local generation units, energy storage systems, and demand-side resources. Previous studies have developed unified scheduling frameworks for both grid-connected and islanded operating modes, indicating that islanded systems should retain sufficient fuel reserves and battery state of charge to enhance operational resilience under unexpected disturbances [2]. When distributed generators fail, weather conditions change abruptly, or renewable energy output decreases, islanded microgrids are more likely to face load curtailment and power interruption risks. Therefore, improving the energy management and load regulation capabilities of islanded microgrids is of great significance [3]. In addition, photovoltaic and wind power outputs are affected by solar irradiance, ambient temperature, and wind speed, and thus exhibit strong randomness, intermittency, and volatility. For the economic dispatch of islanded microgrids, renewable energy and load uncertainties have been incorporated into day-ahead scheduling models, and the results have shown that such uncertainties significantly affect the economic performance and feasibility of scheduling schemes [4].

Energy storage systems and demand response are important means of improving the operational flexibility of islanded microgrids. By properly scheduling charging and discharging power, energy storage systems can absorb surplus electricity during periods of high renewable generation or low load demand and release electricity during peak load periods or renewable energy shortages, thereby mitigating the impact of power fluctuations on system balance. Studies on remote off-grid microgrids have demonstrated that the rational configuration and coordinated dispatch of energy storage systems can improve renewable energy utilization, reduce operating costs, and enhance power supply resilience under extreme conditions [5]. The combination of hybrid renewable energy systems and energy storage technologies is also considered an effective pathway for achieving low-carbon and reliable power supply in remote areas [6]. In addition to energy storage, demand response can modify user-side electricity consumption behaviour through load curtailment, load shifting, and flexible load regulation, thereby reducing peak demand, improving load profiles, and alleviating supply pressure during peak periods without increasing generation capacity. Probability forecasting, robust optimization, energy storage systems, and hybrid demand response strategies have been introduced into day-ahead microgrid scheduling models to improve operational economy, reliability, and flexibility [7–9]. Moreover, price-based demand response, incentive-based demand response, and flexible load control strategies have been applied to microgrid energy management, showing positive effects on reducing operating costs, improving storage operation, and promoting renewable energy consumption [10,11]. In addition to battery energy storage and demand response, renewable hydrogen has become an important emerging option for improving the long-term flexibility of islanded microgrids [12]. Battery storage is effective for short-term power smoothing and daily peak–valley regulation, whereas hydrogen storage is more suitable for long-duration or seasonal energy shifting. Recent studies have investigated hybrid

hydrogen–battery energy storage systems, renewable power-to-hydrogen systems, and electricity–hydrogen–water integrated systems for remote islands. These studies show that hydrogen-based configurations can reduce diesel dependence, improve renewable energy utilization, and support zero- or low-carbon operation [13]. However, hydrogen systems still face practical barriers, including high investment cost, conversion efficiency loss, electrolyzer degradation, hydrogen storage infrastructure, and operational complexity.

In recent years, low-carbon economic dispatch has become an important research direction in microgrid optimization. Conventional economic dispatch models generally aim to minimize fuel costs, operation and maintenance costs, and electricity purchase and sale costs, which are more suitable for grid-connected microgrids or systems with relatively simple structures. However, for islanded microgrids, scheduling models should also consider load loss penalties and pollutant emissions from diesel generators so as to more accurately reflect system reliability and environmental impacts. Existing studies have introduced integrated demand response, stepped carbon trading mechanisms, carbon capture, energy storage, carbon taxes, and carbon trading policies into multi-energy microgrid and multi-microgrid dispatch models to coordinate operational economy, carbon emission constraints, and energy resource allocation [14–17]. Nevertheless, most existing studies focus on grid-connected or multi-energy interconnected systems, while the coupling relationship among diesel dependence, renewable energy fluctuations, energy storage regulation, demand response, and loss-of-load risk in remote islanded microgrids still requires further investigation. The comparison in Table 1 shows that the existing literature has provided valuable dispatch models for islanded microgrids. Nevertheless, several gaps remain. First, many studies mainly emphasize uncertainty modelling, resilience evaluation, or operation-mode coordination, while the integrated low-carbon economic dispatch of remote islanded microgrids with diesel dependence, pollutant treatment cost, battery regulation, demand response, and load-loss penalty is still insufficiently explored. Second, although several metaheuristic algorithms have been applied to microgrid dispatch, conventional velocity–position-based swarm algorithms may still suffer from premature convergence and insufficient local exploitation when solving high-dimensional constrained scheduling problems. Third, the coordination mechanism between demand response and battery storage in reducing diesel output, improving renewable accommodation, and maintaining islanded power balance requires further quantitative verification.

Table 1. Comparison of representative islanded microgrid dispatch studies.

Study	Configuration	Main Focus	Uncertainty	Solution Method
Hou et al. [18]	Islanded microgrid with renewable generation and load resources	Data-driven two-stage day-ahead economic dispatch	Renewable and load uncertainty	Machine learning-based forecasting + dispatch optimization
Wodicker et al. [19]	PV–diesel–battery microgrid under grid-connected and islanded modes	Unified dispatch for cost and resilience	Islanded resilience, fuel reserve, battery SOC, unserved energy	MPC-based dispatch
Hosseina et al. [20]	Island microgrid with RES, ESS, EV, DR, and compensation devices	Resilience-oriented energy and load management	Resource interruptions, load curtailment, voltage deviation, emissions	Multi-objective Moth Flame Algorithm

In terms of solution methods, microgrid optimal dispatch problems are typically characterized by high dimensionality, strong constraints, non-convexity, and nonlinearity. Traditional mathematical programming methods may require considerable model simplifi-

cation and suffer from increased computational burden when dealing with complex models and numerous constraints. In contrast, metaheuristic algorithms do not require gradient information of the objective function and possess strong global search capability; therefore, they have been widely used in microgrid energy management and economic dispatch problems [21]. Among them, particle swarm optimization has been extensively applied because of its simple structure, few control parameters, and fast convergence speed. However, the conventional velocity–position updating mechanism of particle swarm optimization can easily lead to premature convergence in complex high-dimensional search spaces due to the loss of population diversity. To address this issue, improved particle swarm optimization algorithms and hybrid methods combining chaotic search with particle swarm optimization have been applied to microgrid dispatch problems involving wind power, photovoltaic generation, energy storage, and controllable generation units, thereby enhancing global search and local exploitation capabilities [22,23].

Quantum-behaved particle swarm optimization introduces quantum-state representation and probabilistic search mechanisms, which can improve search randomness and help particles escape from local optima. Previous studies have shown that hybrid quantum-behaved particle swarm optimization can be used to solve non-convex economic load dispatch problems with multiple fuel types and valve-point effects, demonstrating good performance in alleviating premature convergence and local optima [24]. Enhanced quantum particle swarm optimization has also been applied to combined economic and emission dispatch problems, achieving a balance between early-stage global exploration and later-stage local exploitation [25]. In addition, improved quantum particle swarm optimization algorithms have been applied to microgrid optimal dispatch, providing new solution ideas for complex power scheduling problems. However, when dealing with high-dimensional dispatch variables in islanded microgrids, existing quantum particle swarm optimization algorithms may still suffer from unstable search directions, excessive dependence on penalty functions for constraint handling, and insufficient local exploitation capability in the later search stage.

To address the above issues, this study takes the islanded microgrid on San Cristóbal Island, Ecuador, as the research object and establishes a low-carbon economic dispatch model considering the coordination between demand response and energy storage. The proposed model comprehensively considers photovoltaic generation, wind power, diesel generators, energy storage systems, and flexible loads. The total objective includes system operating cost, pollution treatment cost, and loss-of-load penalty cost. Meanwhile, the model incorporates the power balance constraint under islanded operation, generation output constraints, battery state-of-charge constraints, charging and discharging power constraints, and demand-response constraints. In terms of the solution method, a rotational quantum particle swarm optimization algorithm is proposed. The traditional velocity–position updating mechanism is replaced by quantum phase encoding and rotation gate updating, and quantum NOT-gate perturbation and stagnation-aware reinitialization strategies are introduced to enhance global search capability and population diversity. Finally, simulations are conducted based on a 24 h typical daily scheduling scenario. The proposed algorithm is compared with PSO, GWO [26], BWO [27], and SSA [28], and its effectiveness is verified in terms of total cost, convergence accuracy, and operational stability.

The main contributions of this study are summarized as follows:

- (1) A low-carbon economic dispatch framework is formulated for a practical PV–WT–DE–BESS islanded microgrid with coordinated demand response. Different from studies that mainly focus on system planning, uncertainty forecasting, or resilience evaluation, this study emphasizes the joint scheduling of diesel generation, battery storage, load shedding, and load shifting under an islanded power balance.

- (2) The objective function integrates operating cost, pollutant treatment cost, and load-loss penalty cost, so that economy, environmental impact, and power supply reliability can be evaluated within a unified dispatch model. This formulation is used to quantify how demand response and battery storage reduce diesel dependence and improve renewable energy accommodation.
- (3) Compared with existing quantum-inspired PSO variants, the proposed RQPSO introduces a full-dimensional quantum phase representation, in which each decision variable is independently encoded by a phase angle. This design preserves the search freedom of high-dimensional scheduling variables and avoids dimensional compression. Moreover, a shortest-path rotation-guided updating mechanism is developed to replace the conventional velocity–position model, while adaptive angular mutation, elite local refinement, and stagnation-aware restart are integrated to improve the balance between global exploration, local exploitation, and convergence stability.

2. Microgrid Model

The islanded microgrid studied in this study consists of a photovoltaic (PV) generation system, a wind turbine (WT) generation system, a diesel engine (DE), a battery energy storage system (BESS), and electrical loads. PV and WT systems serve as the main renewable energy generation units, while the DE acts as a controllable supporting power source. The BESS is used to smooth renewable energy fluctuations and participate in peak–valley regulation. Demand response resources improve the operational flexibility of the system through load shedding and load shifting.

2.1. Mathematical Model of PV Arrays

$$P_{PV}(t) = \eta_{PV} S \delta \quad (1)$$

where $P_{PV}(t)$ denotes the power output of the photovoltaic generation system; η_{PV} represents the conversion efficiency of the PV cells; S is the area of the PV panels; and δ denotes the solar irradiance.

The PV model is used as a dispatch-level representation to estimate the available PV power at an hourly resolution. The conversion efficiency is treated as an equivalent efficiency parameter, which can incorporate the average effects of PV cell efficiency, inverter efficiency, and other power conversion losses. Detailed temperature-dependent PV characteristics are not explicitly modelled because the main purpose of the PV model is to provide the available renewable power boundary for the economic dispatch problem rather than to perform device-level photovoltaic performance simulation.

2.2. Mathematical Model of the Wind Turbine

$$P_{WT} = \begin{cases} 0 & v < v_{ci} \text{ or } v \geq v_{co} \\ \frac{P_N(v-v_{ci})}{v_n-v_{ci}} & v_{ci} \leq v \leq v_n \\ P_N & v_n < v < v_{co} \end{cases} \quad (2)$$

where P_{WT} denotes the output power of the wind turbine; P_N represents the rated power of the wind turbine; and v_{ci} , v_n , and v_{co} denote the cut-in wind speed, rated wind speed, and cut-out wind speed, respectively.

The WT model adopts a standard piecewise dispatch-level power curve determined by the cut-in, rated, and cut-out wind speeds. This simplified representation is commonly used in hourly microgrid scheduling because it captures the main operational relationship between wind speed and available wind power. Detailed aerodynamic efficiency curves, pitch-control dynamics, and generator-side losses are not explicitly represented. Their

average effects are assumed to be reflected in the rated power curve and the forecasted wind power profile used in the scheduling case.

2.3. Mathematical Model of the Battery Energy Storage System

$$\text{SOC} = \frac{C_r}{C} \times 100\% \quad (3)$$

$$\text{SOC}(t) = \begin{cases} \text{SOC}(t-1) + \frac{1}{\eta^-} P_{\text{BA}}(t) & P_{\text{BA}} \leq 0 \\ \text{SOC}(t-1) + \eta^+ P_{\text{BA}}(t) & P_{\text{BA}} > 0 \end{cases} \quad (4)$$

where C_r and C denote the remaining energy and rated capacity of the BESS, respectively; $\text{SOC}(t)$ represents the state of charge of the BESS at time t ; $P_{\text{BA}}(t)$ denotes the charging/discharging power of the BESS at time t , where $P_{\text{BA}}(t) \geq 0$ indicates charging and $P_{\text{BA}}(t) < 0$ indicates discharging; and η^+ and η^- represent the charging and discharging efficiencies, respectively.

2.4. Mathematical Model of the Diesel Engine

$$F(t) = aP_{\text{DE}}(t) + bP_{\text{DEN}}(t) \quad (5)$$

where $F(t)$ denotes the fuel consumption; $P_{\text{DE}}(t)$ and $P_{\text{DEN}}(t)$ represent the power output and rated power of the diesel generator at time t ; a and b are the fuel consumption coefficients.

In summary, the mathematical models of the PV array and wind turbine show that their output power is highly dependent on natural conditions, including solar irradiance and wind speed. Consequently, these renewable energy sources exhibit inherent intermittency and variability. To effectively mitigate such fluctuations, a comprehensive energy management strategy is required. Therefore, in microgrid scheduling, renewable generation should be coordinated with other distributed generation units and energy storage devices to smooth power fluctuations and ensure a stable power supply.

3. Optimal Scheduling Model of the Islanded Microgrid

3.1. Modelling Assumptions

To clarify the scope and applicability of the proposed islanded microgrid scheduling model, the following modelling assumptions are adopted in this study:

- (1) Islanded operation assumption. The studied microgrid operates in islanded mode during the whole scheduling horizon. Therefore, there is no power exchange with the external main grid, and the active power balance must be maintained by local PV generation, wind generation, diesel generation, battery energy storage, and demand response resources.
- (2) Scheduling horizon assumption. The scheduling horizon is set to 24 h, and the scheduling interval is 1 h. The model is therefore a day-ahead dispatch model at the hourly time scale, rather than a real-time dynamic control model.
- (3) Renewable generation assumption. PV and wind power are modelled at the dispatch level. The forecasted PV and WT outputs are regarded as the available upper limits of renewable generation in each time interval. Detailed PV temperature dynamics, inverter efficiency variation, turbine aerodynamic characteristics, and pitch-control dynamics are not explicitly modelled. Their average effects are assumed to be reflected in the forecasted renewable generation profiles or equivalent efficiency parameters.
- (4) Diesel generator assumption. The diesel generator is regarded as a controllable supporting power source. Its output is constrained by the minimum and maximum generation limits. Detailed start-up/shut-down processes, minimum on/off time con-

- straints, and transient dynamics are not considered because the focus of this study is hourly economic dispatch rather than unit commitment or dynamic stability analysis.
- (5) Battery energy storage assumption. The BESS is used for peak shaving, valley filling, and renewable energy smoothing. The charging and discharging efficiencies are assumed to be constant during the scheduling horizon. The SOC is constrained within the prescribed lower and upper limits. Detailed battery ageing, thermal dynamics, and degradation mechanisms are not explicitly modelled; their effects are represented by the equivalent storage operation and maintenance cost.
 - (6) Demand response assumption. Demand response consists of curtailable load and shiftable load. The maximum load curtailment and load shifting ratios are predefined. Shiftable load must satisfy the energy conservation constraint over the scheduling horizon. The compensation coefficients for load curtailment and load shifting are assumed to be fixed.
 - (7) Power balance assumption. Only the active power balance is considered in the proposed scheduling model. AC power flow, voltage regulation, reactive power compensation, and frequency dynamics are not explicitly included. This assumption is adopted because the purpose of this study is to evaluate the low-carbon economic dispatch performance at the system scheduling level.
 - (8) Cost modelling assumption. The objective function includes operating cost, pollutant treatment cost, and load-loss penalty cost. Renewable curtailment cost, battery degradation cost, and real-time communication cost are not independently formulated in the base objective function because the required penalty coefficients or physical degradation parameters are not available in the case data.
 - (9) Algorithm comparison assumption. All optimization algorithms are evaluated under the same system parameters, renewable generation profiles, load data, decision-variable boundaries, and constraint-handling strategy. Therefore, the comparison focuses on the search capability, convergence stability, and scheduling performance of different algorithms under identical input conditions.

3.2. Objective Function

The optimal scheduling model of the microgrid established in this study aims to minimize the comprehensive scheduling cost of the microgrid system. The cost components mainly include the system operating cost and the pollutant treatment cost. The operating cost consists of the fuel cost of the diesel generator and the maintenance costs of distributed generation units. The pollutant treatment cost accounts for the treatment of CO₂, SO₂, and NO_x emissions. The scheduling horizon is set to 24 h, with a scheduling interval of 1 h.

3.2.1. Operating Cost

C_1 represents the daily fuel cost of the diesel generator during microgrid operation:

$$C_1 = \sum_{t=1}^{24} y c_i p_i(t) \quad (6)$$

where y denotes the fuel price in CNY; c_i is the fuel consumption coefficient of the i -th controllable generation unit; and $p_i(t)$ represents the output power of the i -th controllable generation unit at time t .

C_2 represents the maintenance cost of distributed generation units:

$$C_2 = \sum_{t=1}^{24} r_i p_i(t) \quad (7)$$

where r_i denotes the maintenance coefficient of the i -th distributed generation unit.

Therefore, the total operating cost of the microgrid is expressed as

$$f_1 = C_1 + C_2 \quad (8)$$

3.2.2. Pollutant Gas Treatment Cost

To reduce the environmental pollution caused by controllable generation units, the microgrid adopts treatment measures for pollutant gas emissions. The corresponding pollutant gas treatment cost is expressed as

$$f_2 = \sum_{t=1}^{24} \sum_{j=1}^m \alpha_j y_{ij} p_i(t) \quad (9)$$

where α_j denotes the unit treatment cost of pollutant gas j ; y_{ij} represents the emission coefficient of pollutant gas j for the i -th controllable generation unit; and m is the number of pollutant gas types.

3.2.3. Load-Loss Penalty Cost

$$f_3 = \varepsilon P_{\text{loss}}(t) \quad (10)$$

where ε denotes the load-loss penalty coefficient; $P_{\text{loss}}(t)$ represents the amount of lost load at time t , which can also reflect the power supply reliability of the microgrid.

3.2.4. Total Operating Cost

Combining Sections 3.2.1–3.2.3, the total operating cost can be expressed as

$$f_{\text{min}} = f_1 + f_2 + f_3 \quad (11)$$

3.3. Constraints

3.3.1. Output Constraints of Generation Units

The active power output constraints of distributed generation units, including PV, WT, and DE, are expressed as

$$P_{i,\text{min}} \leq P_i(t) \leq P_{i,\text{max}} \quad (12)$$

where $P_{i,\text{min}}$ and $P_{i,\text{max}}$ denote the minimum and maximum output power of the i -th generation unit.

For PV and WT units, the upper output limits are determined by the forecasted available renewable power at each time interval. Therefore, the scheduled PV and WT outputs cannot exceed the available renewable generation. If the scheduled renewable output is lower than the available output, the difference can be regarded as unused renewable energy. In this study, such unused renewable energy is not penalized by an independent curtailment cost term; instead, the scheduling model encourages renewable utilization by reducing diesel generation, pollutant treatment cost, and load-loss risk through the coordinated operation of BESS and demand response.

3.3.2. Charging and Discharging Constraints of the Battery Energy Storage System

The charging and discharging constraints of the battery energy storage system are given as

$$\begin{cases} S_{\text{BTmin}} \leq S_{\text{BT}}(t) \leq S_{\text{BTmax}} \\ P_{\text{BTmin}} \leq P_{\text{BT}}(t) \leq P_{\text{BTmax}} \end{cases} \quad (13)$$

where S_{BTmin} and S_{BTmax} are the lower and upper limits of the battery capacity; P_{BTmin} and P_{BTmax} denote the minimum and maximum output power of the battery, respectively.

3.3.3. Demand Response Constraints

The actual load after demand response is expressed as

$$P_{L,t}^{DR} = P_{L,t} - P_{cut,t} + P_{shift,t} \quad (14)$$

where $P_{L,t}$ denotes the original load; $P_{cut,t}$ represents the curtailable load; and $P_{shift,t}$ denotes the shiftable load. A positive value of $P_{cut,t}$ indicates that load is shifted into the current period, whereas a negative value indicates that load is shifted out of the current period.

The load shedding constraint is expressed as

$$0 \leq P_{cut,t} \leq \lambda_{cut} P_{L,t} \quad (15)$$

The load shifting constraint is expressed as

$$-\lambda_{shift} P_{L,t} \leq P_{shift,t} \leq \lambda_{shift} P_{L,t} \quad (16)$$

The load shifting conservation constraint is given by

$$\sum_{t=1}^T P_{shift,t} = 0 \quad (17)$$

The lost-load constraint is expressed as

$$0 \leq P_{loss,t} \leq \lambda_{loss} P_{L,t} \quad (18)$$

where λ_{cut} , λ_{shift} , and λ_{loss} denote the maximum load-shedding ratio, maximum load-shifting ratio, and maximum allowable lost-load ratio, respectively.

4. Improved Particle Swarm Optimization Algorithm

4.1. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is a stochastic optimization method based on swarm intelligence. Each particle (i) in the swarm is characterized by its position and velocity in an (N)-dimensional search space, which are denoted as $X_i = (x_{i1}, x_{i2}, \dots, x_{iN})$ and $V_i = (v_{i1}, v_{i2}, \dots, v_{iN})$, respectively. PSO searches for the optimal solution by balancing the individual experience of each particle, represented by its personal historical best position $L_i = (l_{i1}, l_{i2}, \dots, l_{iN})$, and the collective experience of the swarm, represented by the global historical best position $L_g = (L_{g1}, L_{g2}, \dots, L_{gN})$. For a swarm containing M particles, the update equations of the particles are given as follows:

$$v_{ij}^{k+1} \leftarrow \omega^k v_{ij}^k + \eta_1 r_{1j} (l_{ij}^k - x_{ij}^k) + \eta_2 r_{2j} (l_{gj}^k - x_{ij}^k) \quad (19)$$

$$x_{ij}^{k+1} \leftarrow x_{ij}^k + v_{ij}^{k+1}, (i = 1, 2, \dots, M; j = 1, 2, \dots, N) \quad (20)$$

where k denotes the k -th iteration; $x_{ij} \in [x_{\min}, x_{\max}]$ and $v_{ij} \in [v_{\min}, v_{\max}]$ represent the position and velocity of the i -th particle in the j -th dimension, respectively; ω^k is the inertia weight; η_1 and η_2 are the cognitive and social acceleration coefficients, respectively; and r_{1j} and r_{2j} are random numbers uniformly distributed in the interval $[0, 1]$. The parameters η_1 and η_2 determine the tendency of particles to move toward the personal best position and the global best position, respectively. The inertia weight ω^k reflects the trade-off between exploration, namely global search, and exploitation, namely local search. In general, ω^k gradually decreases with the number of iterations, so as to enhance the exploitation capability and improve convergence efficiency when the swarm progressively approaches the optimal solution. PSO has strong exploration capability in the initial stage; however, when approaching the optimal solution, it may converge prematurely due to insufficient population diversity.

4.2. Rotation Quantum Particle Swarm Optimization Algorithm

The improved Full-Dimensional Rotation Quantum Particle Swarm Optimization algorithm, abbreviated as RQPSO, is a quantum-inspired swarm intelligence algorithm for high-dimensional continuous constrained optimization problems. Compared with conventional particle swarm optimization, RQPSO does not update particles through the traditional velocity-position mechanism. Instead, each decision variable is represented by an independent quantum phase angle, and the search process is performed in the phase space through rotation-guided updating.

The core idea is to establish a one-to-one mapping between quantum phase angles and decision variables. This full-dimensional encoding avoids the loss of search freedom caused by low-dimensional quantum compression. At the same time, adaptive rotation, random angular perturbation, elite local refinement, and stagnation-aware restart are introduced to improve global exploration, local exploitation, and convergence stability.

4.2.1. Full-Dimensional Quantum Phase Encoding

In RQPSO, each particle is encoded by a full-dimensional phase vector rather than a direct position vector. For the i -th particle, the phase vector is defined as

$$\theta_i = [\theta_{i,1}, \theta_{i,2}, \dots, \theta_{i,D}] \quad (21)$$

$$\theta_{i,j} \in [0, 2\pi] \quad (22)$$

Each phase angle corresponds to one decision variable. The decoding from phase space to decision space is given by

$$x_{i,j} = l_j + (u_j - l_j) \frac{\sin(\theta_{i,j}) + 1}{2} \quad (23)$$

Therefore, the decoded variable always lies within the feasible boundary:

$$x_{i,j} \in [l_j, u_j] \quad (24)$$

This mapping has two advantages. First, it naturally transforms any phase angle into a feasible variable value. Second, it preserves the dimensional independence of decision variables, making the method more suitable for high-dimensional search spaces.

4.2.2. Rotation-Guided Phase Updating Mechanism

The search direction in RQPSO is determined by the angular distance between the current phase, the personal best phase, and the global best phase. To ensure that the particle rotates along the shortest angular path, the angular difference is defined as

$$\Delta(a, b) = \text{mod}(a - b + \pi, 2\pi) - \pi \quad (25)$$

For the i -th particle and the j -th dimension, the angular distances toward the personal best and global best are expressed as

$$\Delta_{i,j}^p = \Delta(\theta_{i,j}^{pbest}, \theta_{i,j}^t) \quad (26)$$

$$\Delta_{i,j}^g = \Delta(\theta_j^{gbest}, \theta_{i,j}^t) \quad (27)$$

Let the normalized iteration progress be

$$\tau = \frac{t}{T_{max}} \quad (28)$$

where t is the current iteration and T_{max} is the maximum number of iterations. The cognitive and social attraction coefficients are adjusted adaptively as

$$c_1(t) = c_1^{start} - (c_1^{start} - c_1^{end})\tau \quad (29)$$

$$c_2(t) = c_2^{start} + (c_2^{end} - c_2^{start})\tau \quad (30)$$

The rotation step size is controlled by a decreasing rotation scale:

$$\alpha(t) = \pi(1 - \tau) + 0.05\pi \quad (31)$$

The phase increment is calculated as

$$\delta\theta_{ij}^t = \frac{\alpha(t)}{\pi} [c_1(t)r_1\Delta_{ij}^p + c_2(t)r_2\Delta_{ij}^s] + \sigma(t)\varepsilon \quad (32)$$

where r_1 and r_2 are random numbers in $[0, 1]$, ε is a standard normally distributed random variable, and $\sigma(t)$ is a decreasing noise intensity.

The phase angle is then updated as

$$\theta_{ij}^{t+1} = \text{mod}(\theta_{ij}^t + \delta\theta_{ij}^t, 2\pi) \quad (33)$$

This mechanism enables the algorithm to conduct large-step exploration in the early stage and small-step exploitation in the later stage.

4.2.3. Adaptive Angular Mutation

To prevent premature convergence and maintain population diversity, RQPSO introduces an adaptive angular mutation probability:

$$p_m(t) = p_m^{start} - (p_m^{start} - p_m^{end})\tau \quad (34)$$

At each iteration, if a particle satisfies the mutation condition, a subset of dimensions is randomly selected:

$$\mathcal{M}_i \subseteq \{1, 2, \dots, D\} \quad (35)$$

For each selected dimension $j \in \mathcal{M}_i$, the phase angle is perturbed by

$$\theta_{ij}^{t+1} = \text{mod}(\theta_{ij}^{t+1} + \pi(2r_j - 1), 2\pi) \quad (36)$$

where r_j is a random number in $[0, 1]$. The mutation probability is large in the early stage and small in the later stage. Thus, the algorithm emphasizes diversity at the beginning and convergence accuracy near the end.

4.2.4. Greedy Selection and Best Solution Updating

After phase updating and decoding, the new position of the particle is obtained as

$$\mathbf{x}_{i,new} = \text{Decode}(\boldsymbol{\theta}_i^{t+1}) \quad (37)$$

The new fitness value is calculated as

$$F_{i,new} = f(\mathbf{x}_{i,new}) \quad (38)$$

A greedy selection strategy is adopted. If the new solution is better than the current solution, the current solution is replaced:

$$\mathbf{x}_i^{t+1} = \begin{cases} \mathbf{x}_{i,new}, & F_{i,new} < F_i^t \\ \mathbf{x}_i^t, & F_{i,new} \geq F_i^t \end{cases} \quad (39)$$

The personal best solution is updated according to

$$\mathbf{x}_i^{pbest} = \begin{cases} \mathbf{x}_{i,new}, & F_{i,new} < F_i^{pbest} \\ \mathbf{x}_i^{pbest}, & F_{i,new} \geq F_i^{pbest} \end{cases} \quad (40)$$

The global best solution is updated by

$$\mathbf{x}^{gbest} = \arg \min_i f(\mathbf{x}_i^{pbest}) \quad (41)$$

This strategy ensures that the best historical information is retained during the search process.

4.2.5. Elite Local Refinement

To improve the local exploitation capability, RQPSO performs local refinement around the global best solution. A local candidate solution is generated as

$$\mathbf{x}_{loc} = \mathbf{x}^{gbest} + \eta(t)(\mathbf{u} - \mathbf{l}) \odot \boldsymbol{\xi} \quad (42)$$

where $\mathbf{u}$ and $\mathbf{l}$ are the upper and lower boundary vectors, $\odot$ denotes element-wise multiplication, $\boldsymbol{\xi}$ is a standard normally distributed random vector, and $\eta(t)$ is a decreasing local search coefficient:

$$\eta(t) = \eta_0(1 - \tau) \quad (43)$$

If the local candidate solution has a better objective value than the current global best solution, it replaces the global best solution. This refinement helps improve convergence accuracy without changing the main swarm search structure.

4.2.6. Stagnation-Aware Restart Mechanism

When the global best solution does not improve for several consecutive iterations, the population may have fallen into a local optimum. RQPSO detects stagnation according to

$$\left| F^{gbest}(t) - F^{gbest}(t-1) \right| < \varepsilon \quad (44)$$

If this condition holds for S consecutive iterations, the worst ρN particles are reinitialized:

$$\boldsymbol{\theta}_i^{new} = 2\pi \mathbf{r}_i \quad (45)$$

where N is the population size, ρ is the restart ratio, and $\mathbf{r}_i$ is a random vector in $[0, 1]^D$. The elite particles are retained, while inferior particles are replaced by new random particles. This mechanism restores population diversity while preserving useful search information.

4.2.7. Algorithm Workflow

The flowchart of RQPSO is shown in Figure 1, and the detailed procedure is described as follows:

- (1) Set the population size, maximum number of iterations, phase angle range, rotation budget, perturbation probability, and the boundaries of each decision variable. Initialize the high-dimensional scheduling vector by encoding the diesel generator output, charging/discharging power of the energy storage system, load shedding amount, load shifting amount, and lost load amount as particles according to the 24 h time sequence.

- (2) Randomly initialize the quantum phase angles of each particle. The scheduling variables are then obtained through the inherent feasible mapping, and the comprehensive cost fitness is calculated according to the constraint-handling strategy.
- (3) Update the personal best and global best solutions. Then, update the phase angles according to the rotation-gate mechanism and perform a quantum NOT-gate perturbation.
- (4) If the global best solution does not improve within the preset number of generations, perform stagnation-aware reinitialization on the inferior particles.
- (5) Determine whether the maximum number of iterations has been reached. If not, return to Step (3); otherwise, output the global optimal scheduling scheme.
- (6) Use the global best solution as the initial value for local refinement to obtain the final scheduling result.

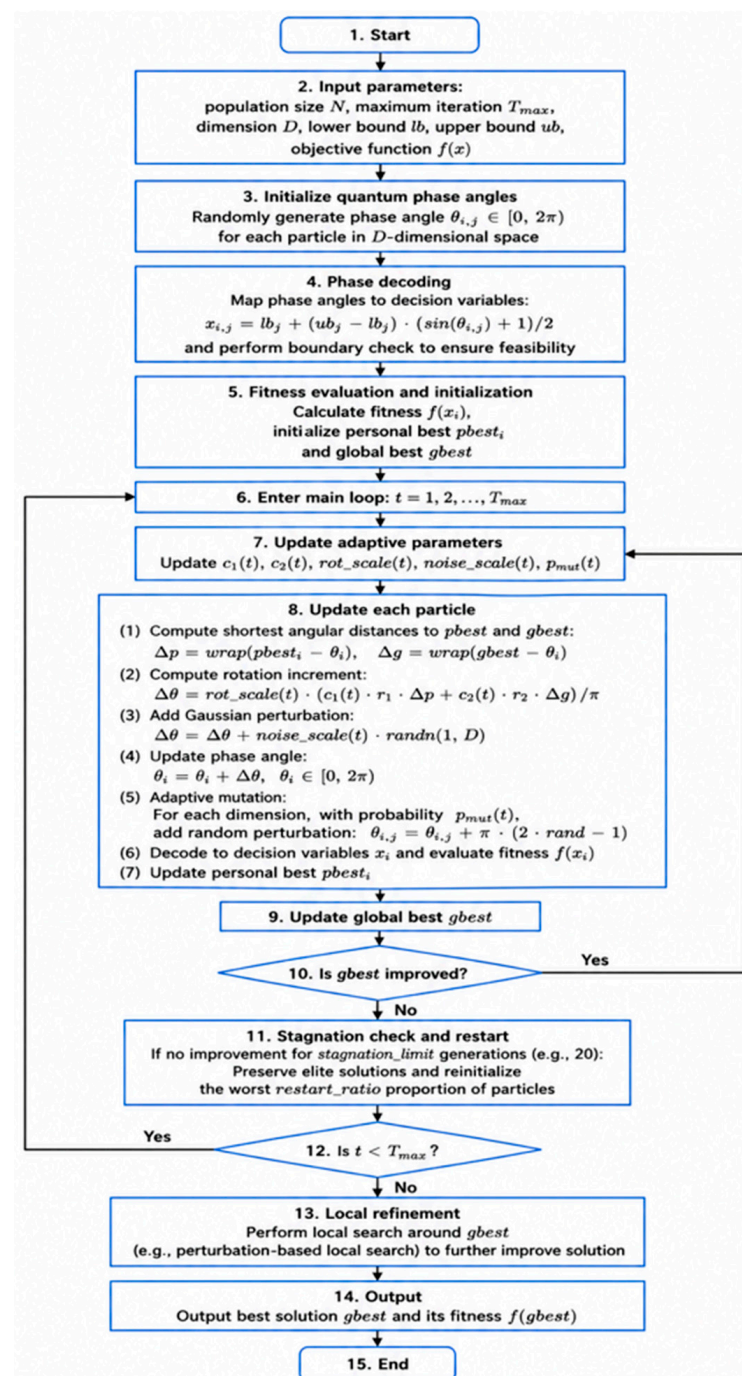


Figure 1. Flow chart of the RQPSO algorithm.

5. Algorithm Performance Test

5.1. Test Functions

To verify the optimization performance and stability of the improved optimization algorithm, five algorithms, namely RQPSO, PSO, GWO, BWO, and SSA, are tested and compared in this study. Nine standard benchmark functions with 30 dimensions are selected [29] to comprehensively evaluate the performance of the five algorithms on different test functions. The selected test functions are listed in Table 2.

Table 2. Parameters of the benchmark functions.

Function	Expression	Dimension	Search Range	Optimum
F1	$f_1(\mathbf{x}) = \sum_{i=1}^n x_i^2$	30	$[-100, 100]$	0
F2	$f_2(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	30	$[-10, 10]$	0
F3	$f_3(x) = \sum_{i=1}^n \left(\sum_{j=1}^i x_j \right)^2$	30	$[-100, 100]$	0
F4	$f_4(x) = \max_i \{ x_i , 1 \leq i \leq n \}$	30	$[-100, 100]$	0
F5	$f_5(\mathbf{x}) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right]$	30	$[-30, 30]$	0
F6	$f_6(x) = \sum_{i=1}^n ([x_i + 0.5])^2$	30	$[-100, 100]$	0
F7	$f_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0, 1)$	30	$[-1.28, 1.28]$	0
F8	$f_8(\mathbf{x}) = \sum_{i=1}^n [x_i^2 - 10\cos(2\pi x_i) + 10]$	30	$[-5.12, 5.12]$	0
F9	$f_9(\mathbf{x}) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^n x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^n \cos(2\pi x_i)\right) + 20 + e$	30	$[-32, 30]$	0

5.2. Analysis of Benchmark Function Results

To evaluate the convergence performance of each algorithm, each benchmark function was independently run 30 times. The population size was set to 30, and the maximum number of iterations was set to 500. The median and interquartile range (IQR) were adopted as the main statistical indicators. The median reflects the typical convergence accuracy of the algorithm and is insensitive to outliers, whereas the IQR describes the dispersion degree of the middle 50% of the results and is used to evaluate algorithm stability.

As shown in Table 2, for the unimodal benchmark functions F1–F4, the median values obtained by RQPSO all reach 0, and the corresponding IQR values are also 0. This indicates that the proposed algorithm can stably converge to the theoretical optimum in continuous differentiable or approximately unimodal search spaces. In contrast, PSO still exhibits relatively large residual errors on F1–F4, while the median values of BWO and SSA are considerably larger, indicating that these algorithms are prone to insufficient convergence or falling into non-optimal regions in high-dimensional search spaces. GWO also achieves high accuracy on F1 and F2; however, its results still contain errors of a certain order of magnitude. By comparison, RQPSO performs better in terms of both convergence accuracy and stability.

For the F5 benchmark function, RQPSO obtains a median value of 2.87×10^1 and an IQR of 3.33×10^{-3} , while GWO obtains a median value of 2.76×10^1 and an IQR of 9.11×10^{-1} . It can be observed that the median value of GWO is slightly lower than that of RQPSO on this function, indicating that GWO has a slight advantage in typical optimization accuracy for F5. However, from the perspective of stability, the IQR of RQPSO is significantly smaller than that of GWO, suggesting that RQPSO produces smaller fluctuations over 30 independent runs and has stronger repeatability. This result indicates that RQPSO does not achieve the absolute best median value on all benchmark functions, but it shows a clear advantage in stability.

For the F6 benchmark function, both RQPSO and GWO achieve median and IQR values of 0, indicating that both algorithms can stably converge to the theoretical optimum. In contrast, PSO, BWO, and SSA still exhibit relatively large errors, suggesting insufficient search accuracy on this type of high-dimensional function. For the F7 function, RQPSO obtains a median value of -3.55×10^0 and an IQR of 3.87×10^{-1} , outperforming the corresponding results of PSO, GWO, BWO, and SSA. This demonstrates that RQPSO can maintain good robustness in benchmark environments involving noise or stochastic perturbations.

For the multimodal benchmark functions F8 and F9, the median values obtained by RQPSO are 0 and 8.88×10^{-16} , respectively, and the IQR values are both 0. This indicates that RQPSO can effectively overcome the interference of local extrema and stably approach the global optimum across multiple runs. In contrast, PSO, BWO, and SSA still show obvious residual errors on F8 and F9, indicating insufficient global exploration capability. Although GWO achieves a small error on F9, its accuracy remains lower than that of RQPSO.

Overall, the results in Table 3 show that RQPSO achieves the best or near-best median results on most of the nine benchmark functions, especially demonstrating high convergence accuracy on F1–F4, F6, F8, and F9. Meanwhile, the IQR values of RQPSO are 0 or close to 0 for most functions, indicating that the results of independent repeated runs are highly concentrated and that the algorithm has strong stability and robustness. Although the median value of RQPSO on F5 is slightly higher than that of GWO, its IQR is significantly smaller, demonstrating that the proposed algorithm achieves a favourable balance between accuracy and stability. In general, RQPSO outperforms the comparison algorithms on both high-dimensional unimodal and multimodal functions, verifying its feasibility and effectiveness for the subsequent optimal scheduling of islanded microgrids.

Table 3. Test results of different algorithms.

Test Function	Index	RQPSO	PSO	GWO	BWO	SSA
F1	median values	0.00×10^0	8.25×10^2	4.83×10^{-13}	6.59×10^4	3.35×10^4
	IQR	0.00×10^0	4.82×10^2	1.63×10^{-12}	1.12×10^4	1.45×10^4
F2	median values	0.00×10^0	1.73×10^1	3.38×10^{-8}	2.26×10^9	1.32×10^6
	IQR	0.00×10^0	5.93×10^0	3.31×10^{-8}	4.32×10^{10}	1.18×10^8
F3	median values	0.00×10^0	6.01×10^3	1.52×10^1	9.68×10^4	5.19×10^4
	IQR	0.00×10^0	7.00×10^3	3.77×10^1	2.96×10^4	1.52×10^4
F4	median values	0.00×10^0	1.50×10^1	5.95×10^{-2}	8.86×10^1	7.64×10^1
	IQR	0.00×10^0	5.94×10^0	7.30×10^{-2}	3.83×10^0	9.74×10^0
F5	median values	2.87×10^1	5.97×10^4	2.76×10^1	1.69×10^8	7.81×10^7
	IQR	3.33×10^{-3}	4.97×10^4	9.11×10^{-1}	1.46×10^8	6.77×10^7
F6	median values	0.00×10^0	1.04×10^3	0.00×10^0	6.59×10^4	3.40×10^4
	IQR	0.00×10^0	5.03×10^2	0.00×10^0	1.12×10^4	1.33×10^4
F7	median values	-3.55×10^0	-2.13×10^0	-2.94×10^0	-1.03×10^0	9.50×10^1
	IQR	3.87×10^{-1}	7.81×10^{-1}	5.33×10^{-1}	8.18×10^{-1}	2.72×10^1
F8	median values	0.00×10^0	1.26×10^2	3.41×10^1	3.28×10^2	3.91×10^2
	IQR	0.00×10^0	2.22×10^1	2.02×10^1	5.41×10^1	2.45×10^1
F9	median values	8.88×10^{-16}	8.05×10^0	1.30×10^{-7}	1.99×10^1	2.01×10^1
	IQR	0.00×10^0	2.07×10^0	1.49×10^{-7}	3.17×10^{-2}	5.76×10^{-1}

5.3. Parameter Sensitivity Analysis

The sensitivity results in Table 4 show that excessively small mutation probabilities weaken the diversity-maintenance ability of RQPSO, increasing the risk of premature convergence. Conversely, excessively large mutation probabilities introduce excessive randomness and slow down convergence. A moderate mutation probability provides a better trade-off between exploration and exploitation. Similarly, a small stagnation threshold may trigger frequent restarts and disturb convergence, whereas a large threshold delays the escape from local optima. Therefore, the selected parameter values are adopted because they achieve relatively low mean cost, small standard deviation, and stable convergence behaviour.

Table 4. Test results of different parameter.

Parameter	Value	Cost/CNY
Mutation probability1 Stagnation threshold1	0.05 100	72,682.53
Mutation probability2 Stagnation threshold2	0.10 150	69,017.69
Mutation probability3 Stagnation threshold3	0.15 200	73,114.04

6. Case Study and Verification

6.1. Basic Data of the Islanded Microgrid

Since clean energy output is characterized by volatility, the forecast data of photovoltaic generation, wind power generation, and microgrid load on a typical day of San Cristóbal Island are selected for simulation analysis to design a more reasonable microgrid scheduling scheme. The scheduling horizon is set to ($T = 24$) h, and the forecasted load, PV output, and wind power output are shown in Figure 2.

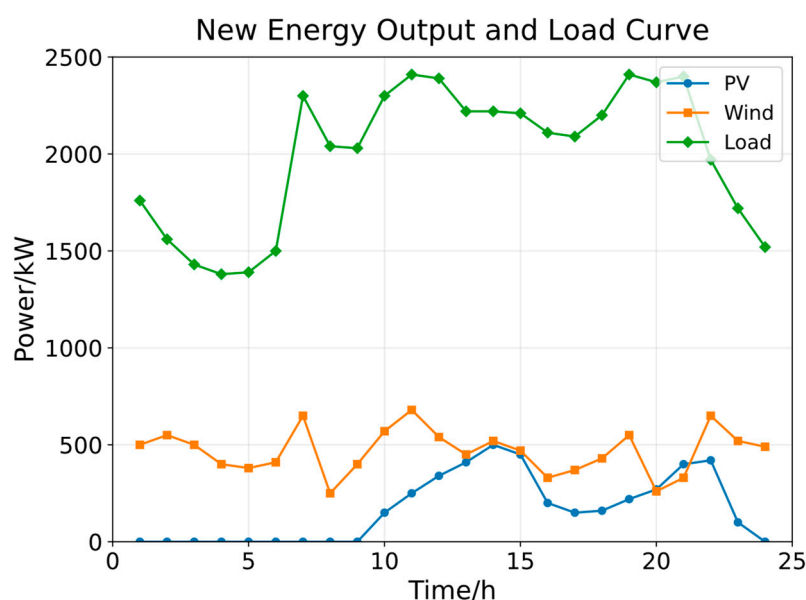


Figure 2. Waveform diagram of load and wind-solar output prediction.

The maximum capacity of the battery is set to 2000 kWh. The specific battery parameters are listed in Table 5, the parameters of distributed generation units are given in Table 6, and the pollutant treatment costs are presented in Table 7.

Table 5. Parameters of the energy storage device.

Parameter	Numerical Value
Maximum state of charge (%)	95
Minimum state of charge (%)	20
Initial state of charge (%)	50
Rated capacity (kWh)	2000
Operation and maintenance unit price (CNY/kWh)	0.026
Charging and discharging efficiency (%)	98
Rated power (kW)	500

Table 6. Distributed power supply parameters.

Parameter	DE	WT	PV
Upper limit of power (kw)	1600	800	500
Lower power limit (kw)	50	0	0
Operation and maintenance costs (CNY/kWh)	0.142	0.0224	0.0096

Table 7. Pollutant treatment costs.

Gas Type	Treatment Cost (CNY/kg)	Pollutant Treatment Coefficient (kg/kWh)
CO ₂	0.21	0.65
SO ₂	14.85	0.0005
NO _x	62.53	0.01

6.2. Simulation Results and Analysis

6.2.1. Scenario Analysis Under Renewable Energy Certainty

In this study, the population size of the algorithms is set to 100, and the maximum number of iterations is set to 500. A mean adaptive method is used to assign weights to the three objective functions, namely the operating cost, environmental protection cost, and load-loss penalty cost, whose weights are denoted as ω_1 , ω_2 , and ω_3 , respectively. The initial weights are all set to 0.33 to achieve a balanced consideration of the three objectives. However, in practical applications, different scenarios may place different emphases on microgrid operation. Therefore, the weights are appropriately adjusted on this basis. The three specific weight configuration schemes are listed in Table 8.

Table 8. Weight coefficient.

Scheme	ω_1	ω_2	ω_3
Scheme I	0.34	0.33	0.33
Scheme II	0.4	0.3	0.3
Scheme III	0.3	0.3	0.4

As shown in Table 9, different schemes lead to different comprehensive costs. In Scheme I, the weight coefficients are allocated in a relatively balanced manner, and its comprehensive cost is higher than that of Scheme II, but it provides higher reliability. In Scheme II, a smaller weight coefficient is assigned to the load-loss penalty cost of the microgrid, resulting in lower reliability and poorer electricity consumption experience. In Scheme III, a larger weight coefficient is assigned to the load-loss penalty cost. Although its

comprehensive cost is slightly higher than that of Scheme I and Scheme II, it achieves the lowest load-loss penalty cost and the highest reliability. Considering the high requirement for power supply reliability in islanded microgrids, Scheme III is selected in the subsequent analysis as the reliability-priority scenario for algorithm comparison.

Table 9. Different weight scheduling results.

Cost	Scheme I	Scheme II	Scheme III
Operating cost (CNY)	42,289.29	40,248.12	44,250.83
Environmental cost (CNY)	19,997.40	18,948.19	21,271.55
Punishment cost (CNY)	5585.84	7954.50	3495.31
Comprehensive cost (CNY)	67,872.53	67,150.81	69,017.69

In this study, a demand response strategy based on load shedding and load shifting is established. The compensation for load shedding is set to 0.6 CNY/kWh, while the compensation for load shifting is set to 0.2 CNY/kWh. Figure 3 shows the amounts of load shedding and load shifting. It can be observed that, based on the proposed demand response strategy, the islanded microgrid achieves a significant peak-shaving and valley-filling effect. Load shifting is mainly used for valley filling during 03:00–06:00 and 22:00–24:00, and for peak shaving during 20:00–21:00, effectively alleviating the supply–demand imbalance during morning and evening peak periods. However, during 07:00–13:00, 16:00–17:00, and 19:00–20:00, the microgrid still faces relatively large power shortages. Therefore, load shedding becomes a necessary measure to maintain system power balance during these periods.

Figure 4 is used to verify the optimization effect of demand response participation in the optimal scheduling of the islanded microgrid. The actual load curve of the microgrid exhibits a relatively significant peak–valley regulation characteristic. Different from the sharp fluctuations of the original load, the optimized load curve reaches a peak of approximately 2400 kW during the morning peak period from 10:00 to 12:00, while the peak during the evening peak period from 18:00 to 20:00 is suppressed to approximately 2300 kW. In addition, the load rapidly decreases to below 1900 kW after 20:00. This indicates that, during the evening peak period, a large amount of flexible load is shifted to the low-load period from 22:00 to 24:00 through economic incentives. As a result, the maximum peak–valley difference in the system is effectively reduced, and the power supply pressure during extreme periods is alleviated.

The discharging of the energy storage system is mainly concentrated in the morning peak period from 08:00 to 12:00 and the evening peak period from 18:00 to 20:00. During the morning peak, when photovoltaic output has not yet fully increased, the energy storage system assists the diesel generator in maintaining high-load operation. During the evening peak, when photovoltaic generation gradually exits the power supply system, energy storage discharging significantly reduces the power supply burden on the diesel generator. The charging of the energy storage system is mainly concentrated in the low-load period in the early morning from 02:00 to 04:00 and the period with strong photovoltaic output in the afternoon from 14:00 to 16:00. This strategy not only absorbs surplus electricity during low-price or low-load periods, but also avoids possible photovoltaic curtailment at noon, thereby improving the overall economy of the system and the utilization efficiency of renewable energy.

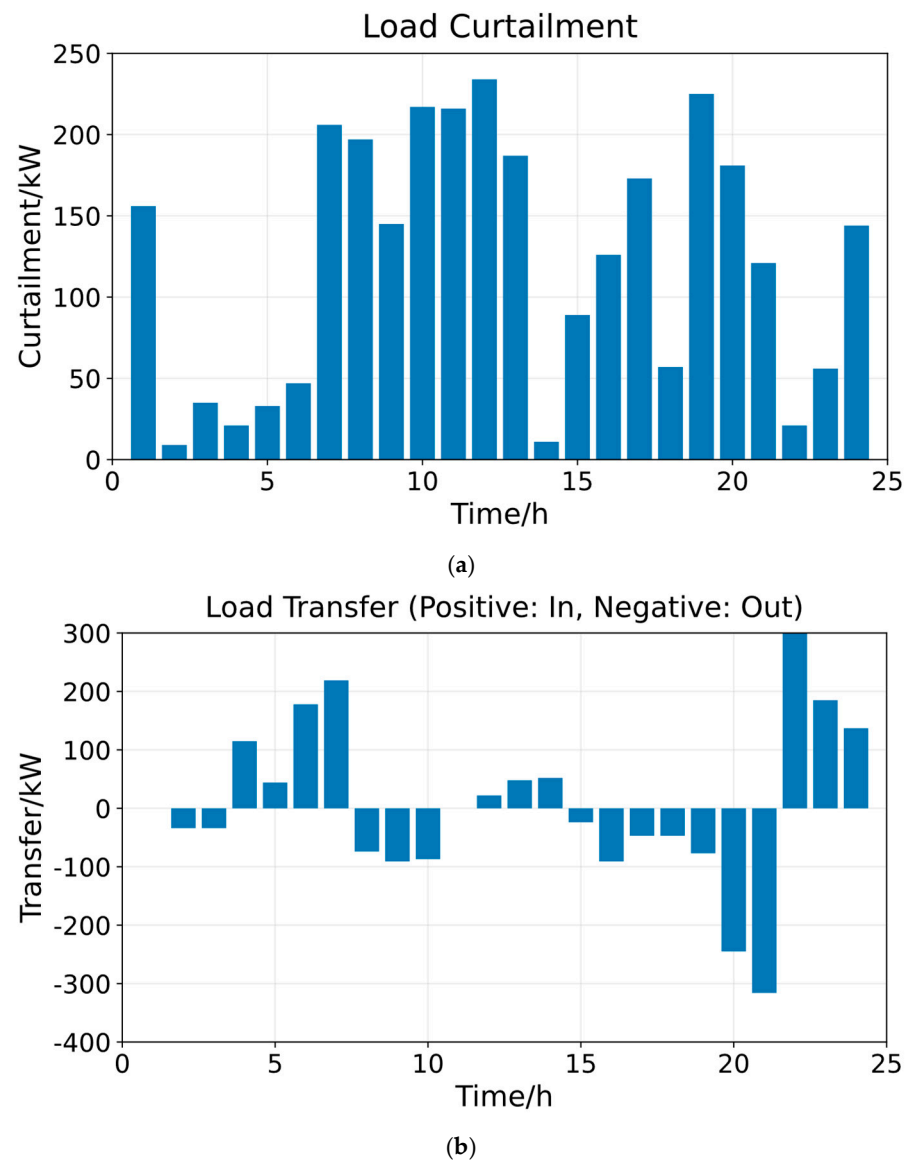


Figure 3. (a) Load reduction and (b) transfer diagram.

6.2.2. Scenario Analysis Under Renewable Energy Uncertainty

To further evaluate the practical applicability of the proposed scheduling method under renewable energy uncertainty, two additional renewable generation scenarios were constructed based on the original 24 h scheduling case. The base scenario uses the original photovoltaic and wind power forecast data. In the low-renewable scenario, both photovoltaic and wind power outputs are reduced to 80% of their original values. In the high-renewable scenario, both photovoltaic and wind power outputs are increased to 120% of their original values. The load profile remains unchanged in all three scenarios, so that the influence of renewable generation fluctuation on the scheduling cost can be directly observed.

The scheduling results are shown in Table 10. In the base scenario, the total scheduling cost is 69,017.70 CNY. When the renewable generation decreases by 20%, the total cost increases to 75,935.99 CNY, representing an increase of approximately 10.02% compared with the base scenario. This is because the reduction in photovoltaic and wind power output increases the dependence of the islanded microgrid on diesel generation and demand-side regulation, leading to higher fuel consumption, operation cost, and environmental treatment cost.

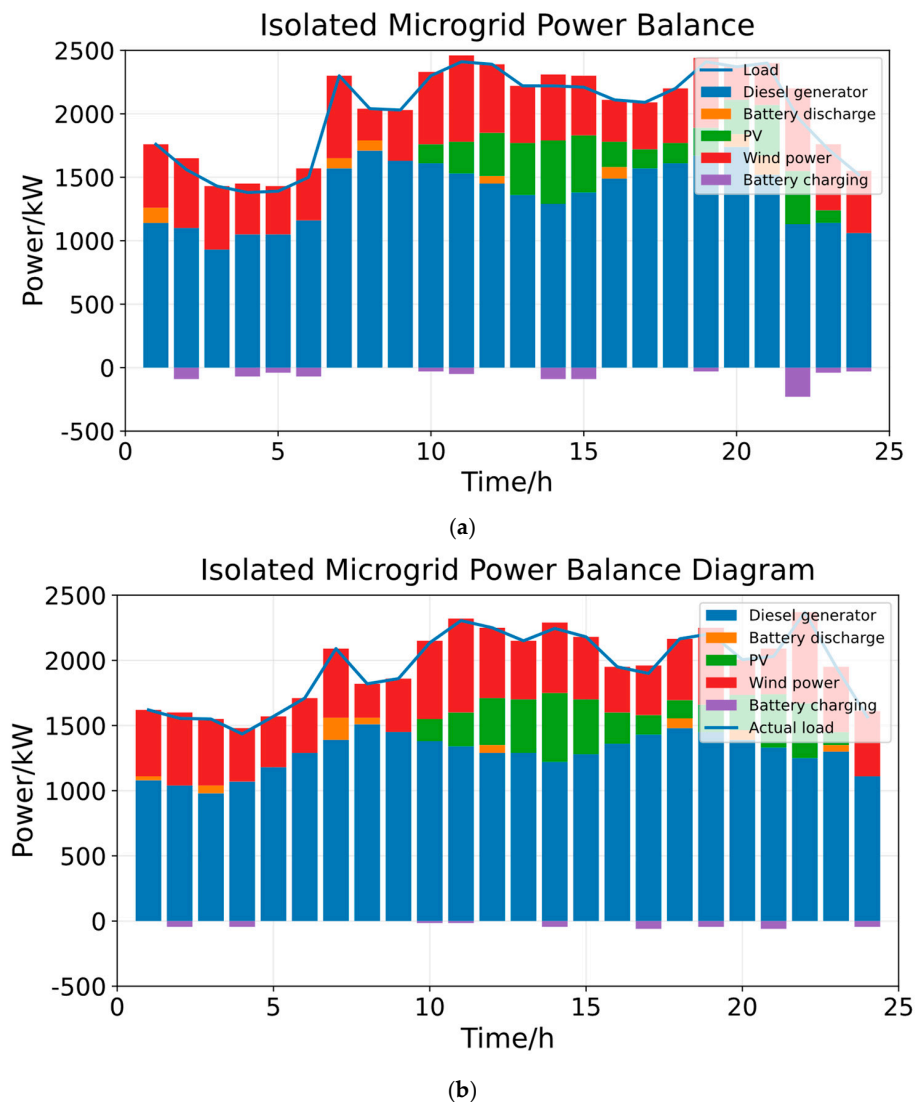


Figure 4. Power balance diagram ((a) no demand response; (b) using demand response).

Table 10. Scheduling cost under different renewable energy scenarios.

Scenario	Total Cost (CNY)
Low renewable	75,935.99
High renewable	62,099.29
Base	69,017.69

In contrast, when the renewable generation increases by 20%, the total scheduling cost decreases to 62,099.29 CNY, which is approximately 10.02% lower than that of the base scenario. This result indicates that higher renewable energy availability can reduce the output of diesel generators and improve the economic performance of the islanded microgrid. Meanwhile, the battery energy storage system can absorb part of the additional renewable generation and release electricity during high-load periods, which further improves the coordination between renewable generation and load demand.

Overall, the scenario analysis demonstrates that renewable energy uncertainty has a significant influence on the low-carbon economic dispatch of islanded microgrids. The proposed RQPSO-based scheduling method can effectively respond to different renewable generation levels and provide feasible scheduling schemes under both renewable shortage

and renewable surplus conditions. Therefore, the additional scenario results improve the practical relevance of the proposed method.

6.2.3. Results of Different Comparison Algorithms

As can be observed from the convergence curves in Figure 5, RQPSO not only achieves the lowest final fitness value, but also reaches a stable convergence state within fewer iterations. This indicates that RQPSO can effectively enhance the global search capability and population diversity of the algorithm, thereby reducing the risk of falling into local optima. Therefore, when solving the low-carbon economic scheduling problem of islanded microgrids, RQPSO exhibits both high convergence accuracy and favourable economic performance.

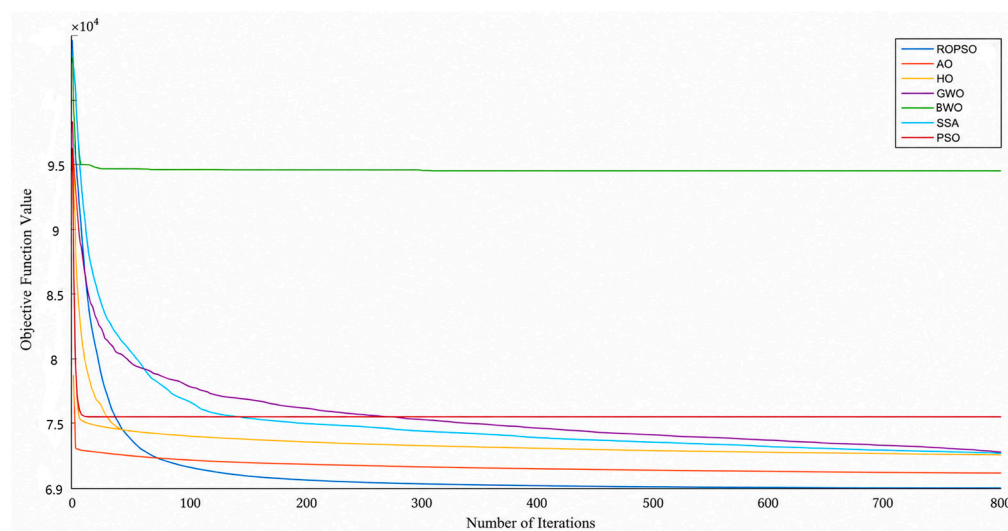


Figure 5. Convergence iteration diagram of each algorithm.

As shown in Table 11, RQPSO yielded the lowest total scheduling cost of 69,017.69 CNY. Compared with GWO, BWO, SSA, PSO, AO, and HO, RQPSO reduced the total cost by approximately 7.92%, 27.36%, 7.69%, 9.34%, 6.16%, and 7.68%, respectively. These results indicate that RQPSO consistently identified more economical scheduling solutions under the same system parameters and constraint-handling strategy.

Table 11. Comparison of the total cost of different algorithms.

Algorithm	Total Cost (CNY)	Diesel Fuel Consumption (kg)	CO ₂ Reduction (kg)
GWO	74,952.32	7362.23	20,388.15
BWO	95,010.61	8523.96	23,547.42
SSA	74,769.46	7631.08	21,081.34
PSO	76,128.71	7562.48	20,891.84
AO	73,546.18	7498.85	20,715.56
HO	74,759.82	7499.27	20,716.72
RQPSO	69,017.69	6636.20	18,332.49

In order to further verify whether the performance improvement is statistically significant in the scheduling, based on 30 independent runs, the Wilcoxon signed rank test was performed at the significance level of 0.05. The null hypothesis is that there is no significant difference between RQPSO and the comparison algorithms. The results in Table 12 of the Wilcoxon signed rank test showed that RQPSO was significantly better than GWO, BWO, SSA, PSO, AO, and HO at a significant level of 0.05.

Table 12. Wilcoxon signed-rank test results between RQPSO and comparison algorithms. The differences were calculated as the final cost of RQPSO minus that of the comparison algorithm. Therefore, a larger W^- indicates that RQPSO obtains lower costs, whereas a larger W^+ indicates that the comparison algorithm obtains lower costs.

Algorithm	<i>p</i> -Value	W+	W−	Z-Value
GWO	1.825×10^{-6}	0	465	−4.771855
BWO	1.825×10^{-6}	0	465	−4.771855
SSA	1.825×10^{-6}	0	465	−4.771855
PSO	2.02×10^{-6}	1	464	−4.751286
AO	1.825×10^{-6}	0	465	−4.771855
HO	1.825×10^{-6}	0	465	−4.771855

7. Conclusions

This study developed a low-carbon economic dispatch framework for an islanded microgrid integrating photovoltaic generation, wind power, diesel generation, battery energy storage, and demand response. The proposed model minimizes the system operating cost, pollutant-emission treatment cost, and loss-of-load penalty cost while satisfying the operational constraints of the generation units, BESS, demand-response resources, and islanded power balance. To solve the resulting high-dimensional, nonlinear, and strongly constrained optimization problem, a rotation quantum particle swarm optimization algorithm was developed. Based on the benchmark-function tests and the case study of San Cristóbal Island, the following conclusions can be drawn.

- (1) The proposed RQPSO improves the search mechanism of conventional PSO by replacing the traditional velocity–position update with full-dimensional quantum phase encoding and rotation-guided phase updating. Each scheduling variable is independently represented in the phase space, thereby preserving the search freedom of the high-dimensional decision vector. Adaptive angular perturbation, elite local refinement, and stagnation-aware reinitialization are further incorporated to maintain population diversity and improve later-stage exploitation. The results obtained from nine benchmark functions show that RQPSO achieved the best or near-best median performance on most of the tested functions and generally produced smaller interquartile ranges than the comparison algorithms. These results demonstrate that RQPSO provides a favourable balance between convergence accuracy and run-to-run stability, although it does not necessarily dominate every comparison algorithm on every individual function.
- (2) The scheduling results demonstrate that coordinated demand response and BESS operation can effectively improve the flexibility of the islanded microgrid. Flexible loads are shifted from high-net-load periods to periods with lower net demand or greater renewable-energy availability, while voluntary load curtailment is activated when load shifting alone is insufficient to relieve the supply pressure. Meanwhile, the BESS charges during low-net-load or high-renewable periods and discharges during high-demand periods. This coordinated operation smooths the net-load profile, reduces the burden on diesel generation, and improves the utilization of available renewable energy.
- (3) In the San Cristóbal Island case study, RQPSO obtained the lowest scheduling cost among the tested algorithms under the same system parameters, decision-variable boundaries, and constraint-handling strategy. Its advantage can be interpreted from both algorithmic and engineering perspectives. From the algorithmic perspective, the full-dimensional phase representation and rotation-guided search mechanism enable RQPSO to maintain population diversity while progressively refining promising so-

lutions. From the engineering perspective, the improved search capability enables the algorithm to identify more economical coordination among diesel generation, renewable generation, BESS operation, load shifting, load curtailment, and involuntary load loss. Consequently, the operating cost, pollutant-emission treatment cost, and loss-of-load penalty can be better balanced within the unified dispatch framework. Therefore, the benefit of RQPSO is reflected not only in its numerical optimization performance but also in the quality of the scheduling solutions obtained under the tested islanded-microgrid conditions.

Several limitations should nevertheless be acknowledged. First, renewable-energy curtailment and battery degradation are not formulated as independent cost terms in the current objective function. In addition, variations in renewable generation are evaluated using representative deterministic scenarios rather than a complete stochastic or robust optimization framework. Future work should therefore incorporate explicit renewable-curtailment costs, battery degradation models, forecast-error scenarios, and uncertainty-aware rolling-horizon dispatch strategies.

Second, the PV and WT models used in this study are dispatch-level representations designed for hourly scheduling analysis. Detailed physical characteristics, including temperature-dependent PV output, inverter-efficiency variation, nonlinear wind-turbine power curves, equipment degradation, and short-term dynamic responses, are not explicitly considered. More detailed renewable-generation and storage models should be introduced in future studies to improve the physical fidelity of the scheduling framework.

Finally, the present study focuses on active-power scheduling over a 24 h horizon. Network-level factors such as AC power flow, voltage regulation, reactive-power support, frequency dynamics, communication delays, and real-time control are outside the current scope. Future research may extend the proposed framework to multi-timescale rolling optimization and real-time energy-management applications and validate its effectiveness using hardware-in-the-loop or practical microgrid platforms.

Author Contributions: Methodology, G.Z.; software, W.Y.; validation, G.Z., W.Y., and F.L.; formal analysis, W.J.; writing—original draft preparation, G.Z. and W.Y.; writing—review and editing, H.Z. and L.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the International Science and Technology Cooperation Project of the Hubei Provincial Department of Science and Technology (2024EHA029).

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding authors.

Conflicts of Interest: Authors Guanting Zhu, Weimin Yu and Wei Jian were employed by the company Changjiang International Engineering Co., Ltd. Author Huawei Zhu was employed by the company China Three Gorges Corporation Basin Hub Operation Management Center. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PV	Photovoltaic
WT	Wind Turbine
DE	Diesel Engine
BESS	Battery Energy Storage System
DR	Demand Response

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