

Review

Energy Symbiosis in Isolated Multi-Source Complementary Microgrids: Diesel–Photovoltaic–Energy Storage Coordinated Optimization Scheduling and System Resilience Analysis

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Abstract

The coordinated scheduling of diesel generators, photovoltaic (PV) systems, and energy storage systems (ESS) is essential for improving the reliability and resilience of islanded microgrids in remote and mission-critical applications. This review systematically analyzes diesel–PV–ESSs from an “energy symbiosis” perspective, emphasizing the complementary roles of diesel power security, PV’s clean generation, and ESS’s spatiotemporal energy-shifting capability. A technology–time–performance framework is developed by screening advances over the past decade, revealing that coordinated operation can reduce the Levelized Cost of Energy (LCOE) by 12–18%, maintain voltage deviations within 5% under 30% PV fluctuations, and achieve nonlinear resilience gains. For example, when ESS compensates 120% of diesel start-up delay, the maximum disturbance tolerance time increases by 40%. To quantitatively assess symbiosis–resilience coupling, a dual-indicator framework is proposed, integrating the dynamic coordination degree ($\zeta \geq 0.7$) and the energy complementarity index ($\text{ECI} > 0.75$), supported by ten representative global cases (2010–2024). Advanced methods such as hybrid inertia emulation (200 ms response) and adaptive weight scheduling enhance the minimum time to sustain (MTTS) by over 30% and improve fault recovery rates to 94%. Key gaps are identified in dynamic weight allocation and topology-specific resilience design. To address them, this review introduces a “symbiosis–resilience threshold” co-design paradigm and derives a ζ –resilience coupling equation to guide optimal capacity ratios. Engineering validation confirms a 30% reduction in development cycles and an 8–12% decrease in lifecycle costs. Overall, this review bridges theoretical methodology and engineering practice, providing a roadmap for advancing high-renewable-penetration islanded microgrids.

Keywords: island microgrid; energy symbiosis; collaborative optimization; system resilience; LCOE



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1. Introduction

Island-type microgrids, as independent power supply systems, play an irreplaceable role in critical facilities such as remote islands, border outposts, mobile base stations, and hospitals [1,2]. According to the International Energy Agency (IEA) 2023 report, approximately 789 million people worldwide lack access to the main power grid, with 85% of them residing in remote areas. Island-type microgrids represent the most cost-effective power supply solution for these regions and are critical infrastructure for ensuring basic livelihood and national defense security.

As shown in Figure 1, a microgrid system on a certain island reef uses a diesel–PV–ESS to achieve 99.97% power supply reliability throughout the year, far exceeding the 95.2% achieved by traditional diesel generators. In 2022, a microgrid project at a tertiary hospital also demonstrated that a multi-source complementary system could maintain continuous power supply to critical loads such as the ICU for over 72 h during a typhoon-induced main grid outage, highlighting its strategic value as a “last line of defence”. However, isolated multi-source complementary systems face three core challenges: first, the volatility of renewable energy sources leads to system stability issues [3], such as PV output fluctuations of up to 30% of rated capacity within five minutes in tropical regions, which conflicts with the several-minute start-up time of diesel generators; second, the system’s low inertia characteristics pose frequency control challenges [4], the equivalent inertia of microgrids with over 40% PV penetration decreases by approximately 60%, making it prone to frequency deviations exceeding the ± 0.5 Hz safety limit [5]; third, the requirement for rapid fault isolation creates protection coordination challenges [6], as short-circuit current direction in multi-source systems may reverse within milliseconds, leading to a malfunction rate of up to 23% for traditional overcurrent protection.

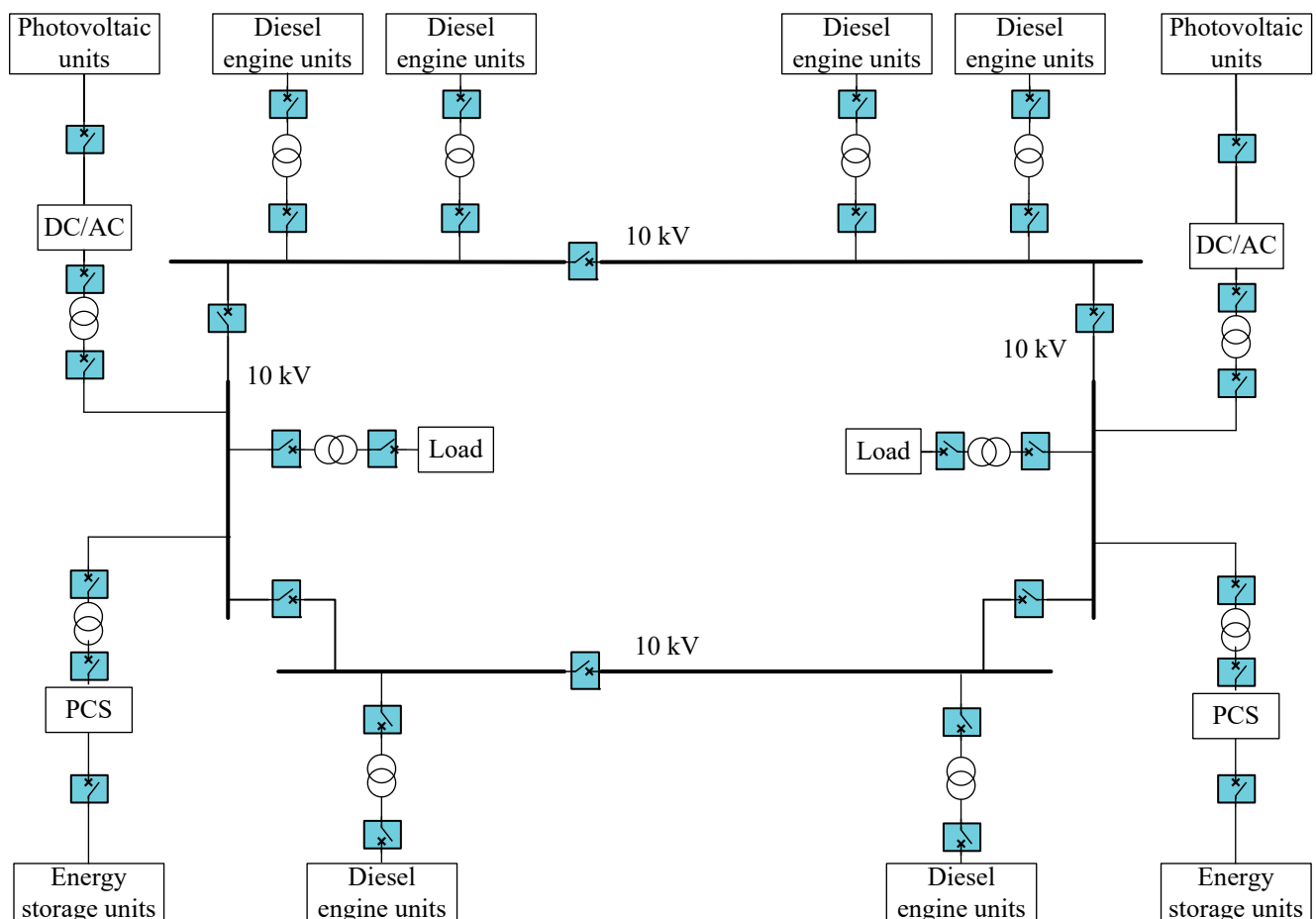


Figure 1. Microgrid system on a certain island reef.

There are still several open issues and areas that warrant further investigation in current domestic and international research. While existing studies have provided valuable insights, some aspects remain insufficiently addressed, particularly in the following areas:

- Limitations of existing review literature. Although recent reviews have advanced the understanding of microgrid coordination, most have primarily focused on binary structures such as PV–storage or wind–diesel systems. Comparatively fewer studies

have examined the more practical three-component diesel–PV–storage systems in engineering applications. In addition, the applicability of current reviews is often limited to grid-connected systems, with relatively less attention paid to islanded scenarios that involve unique challenges such as frequency stability and black-start modes [4]. Methodologically, many studies treat optimization scheduling and resilience assessment separately, leaving the intrinsic connection between them underexplored [5].

- Challenges in three-way synergistic research. Despite significant progress, at least three unresolved issues remain. (1) A universal capacity allocation criterion is lacking. For instance, empirical studies on Hawaii’s microgrid suggest optimal diesel–PV–storage ratios between 1:1.5:0.8 and 1:2.1:2.2, yet no consistent theoretical explanation has been provided for such variations. (2) The universality of synergistic control strategies requires further validation, as comparative analyses (e.g., across 10 isolated microgrids in Africa) indicate that the same control method can lead to $\pm 15\%$ differences in economic outcomes [6]. (3) Current resilience assessment frameworks are often simplified, with metrics such as the System Average Interruption Duration Index (SAIDI) unable to fully capture resilience characteristics across multiple time scales [7].
- Relationship between symbiosis and resilience. Although the concept of energy symbiosis has been introduced, its quantitative link to system resilience is not yet well established. First, no unified indicator system exists for measuring the degree of symbiosis, making cross-study comparisons challenging [8]. Second, the pathways through which symbiosis enhances resilience remain insufficiently clarified. For example, simulation studies suggest that economically optimal scheduling can also reduce frequency deviations by up to 20%, yet the underlying mechanisms are rarely analyzed from a resilience perspective. Finally, the post-fault recovery capacity of synergistic scheduling remains underexplored, limiting its practical application in resilience-oriented design [9].

In terms of technology evolution charting, based on bibliometric methods, a four-stage technology roadmap was constructed, as shown in Figure 2. 1995–2005 was the independent operation stage, with simple parallel connection of various energy sources; 2006–2015 was the primary coordination stage, using rule-based control strategies [8]; 2016–2020 was the intelligent optimization stage, with widespread application of model predictive control (MPC) [9]; 2021 to the present is the symbiotic evolution stage, with the realization of AI-driven adaptive scheduling [10]. The chart also marks nine key technological breakthroughs, such as the commercial application of the Power Conversion System (PCS) bidirectional conversion technology in 2018.

The remainder of this paper is organized as follows. Section 2 explores the mechanisms of energy symbiosis, including the fundamental interactions among diesel, PV, and storage systems, a comparative assessment of collaborative optimization scheduling methods, and the formulation of symbiosis quantification indices. Section 3 presents a comprehensive resilience analysis, covering the definition and assessment framework, the impacts of alternative scheduling strategies, and the balance between resilience and economic performance. Building on this, Section 4 proposes a synergistic design paradigm that integrates symbiosis degree and resilience thresholds, and it validates the framework through a real-world case study of an island hospital microgrid in Southeast Asia. Section 5 discusses core challenges, breakthrough pathways, and a prospective framework for future research. Section 6 discusses solutions to this issue. Finally, Section 7 concludes the paper with a summary of key findings and contributions.

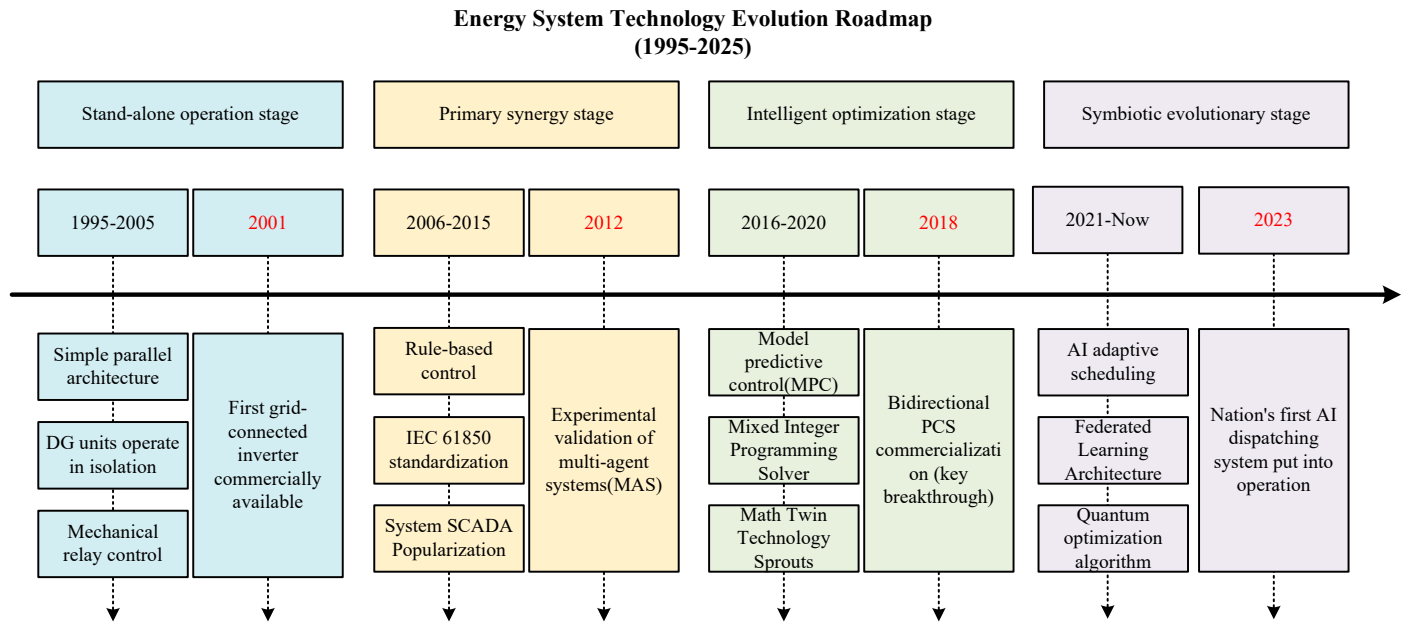


Figure 2. Technology evolution chart.

2. Analysis of Energy Symbiosis Mechanisms

2.1. The Symbiotic Foundation of Diesel, PV, and Energy Storage

The ternary symbiotic system consisting of diesel generators, PVs and energy storage achieves system-level optimization through complementary characteristics. Diesel generators provide power support, and their dynamic response model is shown as Equation (1) [11].

$$\frac{dP_{diesel}}{dt} = \frac{1}{\tau}(P_{ref} - P_{diesel}) \quad (1)$$

where P_{diesel} represents the actual output power of the diesel generator set (MW); P_{ref} represents the input power of the system (MW), generated by dispatch control; τ represents the response time constant of the diesel generator set (15–30 s), reflecting the inertial delay in power adjustment. Equation (1) describes the dynamic process of the diesel generator set's output power tracking command, characterized by a first-order inertial loop with a response time constant τ of 15–30 s, and also provides system inertia support with an inertial time constant H of approximately 3–5 s.

As a clean energy source, the output fluctuation model of PVs is shown in Equation (2) [12].

$$\Delta P_{PV} = \mu \cdot P_{rated} \cdot e^{-t/\lambda} \quad (2)$$

where ΔP_{PV} represents the fluctuation in PV power output (MW); P_{rated} is the rated capacity of the PV system (MW); μ is a fluctuation amplitude coefficient ranging from 0.2 to 0.4, indicating the proportion of instantaneous power changes caused by factors such as cloud cover; λ represents the fluctuation time constant over 5 to 15 min, reflecting the rate of fluctuation decay, and has characteristics of zero marginal cost and diurnal periodicity. Equation (2) describes the exponential decay-type fluctuations in PV power output caused by weather changes (such as cloud movement). PV power generation has no fuel costs, but its output is uncontrollable and relies on energy storage or diesel generators for balancing.

Energy storage realizes energy transfer in space and time, and the SOC dynamic equation is shown as Equation (3) [13].

$$SOC(t) = SOC_0 + \frac{1}{C} \int_0^t \eta P_{ess}(\tau) d\tau \quad (3)$$

where $SOC(t)$ denotes the SOC of the energy storage system at time t (in percentage); SOC_0 denotes the initial SOC (40–80%); C denotes the rated capacity of the energy storage system (MWh); η denotes the charge/discharge efficiency (92–96%), accounting for energy conversion losses; $P_{ess}(\tau)$ denotes the charge/discharge power of the energy storage system at time τ (MW), with positive values indicating discharge and negative values indicating charging. Equation (3) reflects the dynamic process of energy accumulation in the energy storage system over time, with the integral form embodying the principle of energy conservation.

An often-overlooked yet critical aspect of diesel–PV–ESS microgrid operation is the degradation of battery systems. The cycle life of batteries is strongly dependent on operational parameters such as depth of discharge (DOD), SOC operating window, and charge/discharge rate. Empirical studies have shown that narrowing the SOC range (e.g., 30–70%) can extend the cycle life by more than 40%, albeit at the cost of reduced usable capacity and potentially higher LCOE due to increased oversizing requirements. Conversely, operating under wider SOC ranges (e.g., 20–90%) maximizes instantaneous flexibility but accelerates capacity fade, reducing long-term economic efficiency. Recent modeling approaches integrate semi-empirical battery aging models into microgrid scheduling optimization. For example, rain flow counting-based cycle aging models and equivalent circuit degradation models have been embedded into mixed-integer optimization frameworks, enabling explicit trade-off analysis between short-term performance and long-term asset longevity. When such models are applied, results indicate that limiting daily DOD to below 70% can reduce annualized degradation costs by 15–20%, while maintaining SOC within an optimal mid-range significantly lowers the probability of critical failures in high-reliability applications. In the context of energy symbiosis, incorporating degradation-aware SOC management is essential. SOC constraints should not be static but dynamically adjusted according to operating conditions such as PV fluctuation intensity, diesel generator ramping availability, and load criticality. Coupling degradation models with scheduling optimization allows balancing immediate resilience requirements (e.g., sustaining MTTS during disturbances) against lifecycle costs. This highlights the importance of developing adaptive SOC management strategies that explicitly account for battery health, ensuring system-level resilience does not come at the expense of accelerated ESS degradation.

The typical energy flow in the topology shown in Figure 1 has typical characteristics. The energy storage PCS is connected in parallel with the diesel generator to the AC bus to form a two-way energy flow path, and there are key node constraint expressions as shown in Equation (4) [13].

$$\sum P_{diesel} + P_{PV} + P_{ess} = P_{load} + P_{loss} \quad (4)$$

where P_{PV} represents the real-time output power of PV systems (MW); P_{ess} represents the charging and discharging power of ESS (positive for discharging, negative for charging); P_{load} represents the total power demand of the load (MW); P_{loss} represents system losses (2–5%), including transformer and line losses, etc. The analysis of Equation (4) reveals that the three components complement each other, as shown in Table 1. The system's instantaneous power must satisfy both load demand and losses, reflecting the principle of energy conservation. Energy storage regulates supply–demand balance through bidirectional power flow (P_{ess} can be positive or negative), jointly ensuring stable system operation.

As shown in Table 1, diesel generator sets have the core advantages of rapid power support and inertia response, but they are limited by high fuel costs and carbon emissions. They can provide stability and backup power; PV power is a zero-cost, clean energy source, but it is affected by intermittency and diurnal cycles. It can reduce fuel consumption but relies on energy storage to smooth output; ESS offer millisecond-level response and the ability to transfer energy across time and space, but they have limited capacity and suffer

from lifespan degradation issues. They can smooth out fluctuations and achieve frequency regulation and peak shaving. Through relevant models and constraints, the ternary system can achieve economic efficiency (minimizing diesel consumption), stability (utilizing diesel inertia and energy storage rapid response), and environmental friendliness (maximizing PV penetration rate) [14,15].

Table 1. System-level complementarity comparison [13].

Component	Core Strengths	Limitations	Synergistic Effect
Diesel generator set	Fast power support, inertia response	High fuel costs, carbon emissions	Providing stability, backup power
PV	Zero cost, clean energy	Intermittent, diurnal periodicity	Reducing fuel consumption, relying on energy storage smoothing
Energy storage	Millisecond response, energy space-time transfer	Limited capacity, life decay	Smoothing fluctuations, frequency modulation and peak shaving

The Mutual Aid Factor (MAF) is used as the functional dimension, and its expression is shown as Equation (5).

$$MAF = \frac{\int_{t_0}^{t_f} \min(P_{diesel}(t), \Delta P_{PV}^{fluct}(t)) dt}{\int_{t_0}^{t_f} \Delta P_{PV}^{fluct}(t) dt} \quad (5)$$

where $P_{diesel}(t)$ denotes the actual output of the diesel generator set at time t (MW), $\Delta P_{PV}^{fluct}(t)$ denotes the fluctuation power of PV power at time t (measured value—predicted value) (MW), and t_0, t_f denote the start and end times of the statistical time window (s/h).

The physical significance of the MAF can be explained through the relationship between the numerator and denominator of its formula: the numerator represents the total actual compensation power of the diesel generator set for PV fluctuations, achieved by taking the minimum value between the diesel output and PV fluctuations to avoid over-compensation; the denominator is the sum of the absolute values of the total PV fluctuation power. The ratio between the two quantifies the compensation efficiency of the diesel generator set for PV fluctuations. The range of MAF values has clear engineering guidance significance: when MAF approaches 1, it indicates that the diesel generator set can perfectly compensate for PV fluctuations, achieving an ideal state; when MAF approaches 0, it means that the diesel generator set is not participating in compensation, and PV fluctuations are completely handled by energy storage. In practical applications, the value of MAF directly influences system design and scheduling optimization strategies: if MAF is below 0.6, the compensation capability can be enhanced by increasing the diesel generator set's ramp rate (k_{ramp}) or expanding the energy storage power capacity; simultaneously, in scheduling optimization, the MAF can be maximized by adjusting the parameters of the cooperative control law (k_p, k_i), thereby improving the system's stability and reliability.

The dynamic dimension is described by Symbiosis Entropy (SE), whose expression is shown as Equation (6).

$$\begin{cases} SE = - \sum_{i=1}^N p_i \ln p_i \\ p_i = \frac{E_i}{E_{total}} \end{cases} \quad (6)$$

where E_i denotes the energy contribution of the i -th type of energy (MWh), E_{total} denotes the total energy output of the system (MWh), and p_i denotes the contribution ratio of the i -th type of energy, where $p_i \in [0, 1]$.

The physical significance of symbiotic entropy (SE) is reflected in its entropy value range: when SE approaches 0, it indicates that the system is highly ordered, typically manifested by diesel generators dominating operation ($P_{diesel} \approx 1$); when SE approaches $\ln 3 \approx 1.1$, it reflects that the system is in a completely disordered state, at which point the energy contributions of diesel, PVs, and energy storage are evenly distributed, with poor coordination and dependence on random fluctuations [16]. The optimization objective is to dynamically schedule SE to maintain it within an intermediate range (e.g., 0.3–0.6) to achieve efficient complementarity between PV and diesel power while ensuring that energy storage plays a moderate regulatory role. SE and the MAF have a dynamic relationship: a high MAF (diesel efficiently compensating for PV fluctuations) typically corresponds to a low SE (diesel-dominated operation). Therefore, the relationship between the two must be balanced through the flexible regulation of energy storage, such as maintaining $SE \approx 0.4$ when $MAF > 0.7$, thereby balancing the system's compensation efficiency and coordinated orderliness.

As shown in Table 2, in the optimized operation of the diesel-PV-energy storage system, the MAF and SE serve as key indicators to jointly guide system regulation. The optimization direction of MAF is to improve the compensation efficiency of diesel generators for PV fluctuations, which can be achieved by increasing the ramp rate of diesel generators and the speed of energy storage power response. The optimization goal of SE is to maintain moderate coordination and orderliness of the system, which needs to be achieved by adjusting the energy output ratio (such as implementing output limits on PV). Through the joint analysis and coordinated optimization of MAF and SE, the system can simultaneously achieve dual objectives: on one hand, improving the MAF value ensures rapid compensation for PV fluctuations, thereby enhancing system operational reliability; on the other hand, optimizing the SE value prevents overloading of a single energy source, improving economic efficiency while effectively extending equipment lifespan. This dual-indicator coordinated optimization strategy ensures the system's rapid response capability to fluctuations while maintaining the orderliness and economic efficiency of multi-energy synergy.

Table 2. Joint analysis method of MAF and SE [16].

Indicator	Optimization Direction	Regulatory Measures
MAF	Improving diesel compensation efficiency	Increased diesel ramp rate and energy storage power response speed
SE	Maintain moderate coordination and orderliness	Adjusting the proportion of energy output (such as PV limitation)

2.2. Comparative Analysis of Collaborative Optimization Scheduling Methods

Based on the characteristics of the centralized architecture shown in the typical topology in Figure 1, a comparative analysis of the adaptability of rule-based strategies, MPC, multi-agent systems (MAS), and mixed integer programming was conducted, as shown in Table 3.

In the multi-time-scale scheduling process of the diesel-PV-storage microgrid, different collaborative optimization methods exhibit significant differences in terms of computational complexity, model dependence, and real-time feasibility. The rule-based strategy (Rule-based Strategy) mainly relies on threshold judgment and preset priority allocation, and its single-cycle computational complexity is usually linearly related to the number of rules, $O(R)$. If periodic updates or priority reordering are required, the complexity can rise to $O(R \log R)$. Such methods have the advantages of simple implementation and fast real-time response, but they are less adaptable when dealing with multi-objective conflicts

and nonlinear coupling problems [8]. MPC typically models the scheduling problem as a rolling time-domain quadratic programming (QP), and its computational complexity is related to the prediction time domain length H and the dimension of control variables N in a cubic relationship, $O((H \cdot N)^3)$. If using Riccati decomposition or sparse structure, it can be reduced to $O(H \cdot N_x^3)$, where N_x is the system state dimension. MPC can maintain high robustness under dynamic constraints, but it is highly dependent on the accuracy of the system model and the computational burden increases significantly with the increase in time domain and constraint quantities. MAS and Deep Reinforcement Learning (DRL) methods need to distinguish between training and online reasoning stages: In actual operation, the online decision-making of a single agent only requires one forward propagation, and the complexity is linearly related to the number of network parameters, while in training or cross-agent coordination stages, if consensus iteration and information interaction are involved, the computational and communication overhead grows approximately at $O(I \cdot N)$ rate, where I is the number of iterations and N is the number of agents [19]. In contrast, Mixed-Integer Programming (MIP) belongs to NP-hard problems due to its inclusion of binary decision variables, and its worst-case computational complexity grows exponentially, $O(2^m \cdot \text{poly}(N))$, where m represents the number of binary decision variables. For microgrid capacity planning and long-term optimization problems, as the equipment scale and time resolution increase, the variable quantity linearly expands, leading to a sharp increase in computational burden [20]. Although recent methods such as decomposition, relaxation, and scenario reduction can alleviate the computational pressure to some extent, in large-scale and highly uncertain microgrid scenarios, these methods still face challenges such as long solution time and limited scalability.

Table 3. Comparative analysis of the adaptability assessment of collaborative optimization scheduling methods.

Method Type	Representative Algorithm	Computational Complexity	Topological Adaptability	Typical Application Scenarios	Limitations
Rule-based strategy [8]	Priority control	$O(R \log R)$	★★★★☆	Emergency backup control	Unable to handle multiple goal conflicts
MPC [9]	Rolling optimization	$O(H \cdot N^3)$	★★★★★	PV fluctuation mitigation	Requires Accurate system models
MAS [17]	Game theory algorithms	$O(I \cdot N)$	★★☆☆☆	Distributed architecture	Heavy Communication burden
Meta-heuristic algorithm [18]	Particle swarm optimization algorithm (PSO)	$O(I \cdot N)$	★★★★☆	Parameter optimization	Parameter sensitivity
Mixed integer programming [19]	Branch-and-cut	$O(2^m \cdot \text{poly}(N))$	★★★☆☆	Capacity planning	Computational time

In contrast, mathematical programming methods such as linear programming (LP) [21], QP [22], and mixed-integer linear/QP (MILP/MIQP) can provide strict global optimality and repeatability guarantees when the problem can be linearized or convexified. LP and QP models are typically used for economic scheduling and energy allocation optimization with continuous variables, and they have high solution efficiency [23]; while MILP is widely applied in unit commitment, capacity planning, and energy storage scheduling due to its ability to handle both continuous and discrete variables simultaneously. However, the introduction of Boolean variables makes MILP an NP-hard problem, and its worst-case computational complexity grows exponentially. As the system scale and time resolution increase, the solution time will significantly increase. To further enhance the adaptability to randomness and uncertainty, researchers in recent years have proposed extended frameworks such as two-stage stochastic programming, chance-constrained optimization, and robust/distributionally robust optimization. These methods explicitly characterize the uncertainty set of PV output and load prediction errors, achieving probabilistic guarantees for constraints such as frequency, voltage, and state of charge (SOC), thereby enhancing the feasibility and reliability of the scheduling strategy. However, these methods require precise

parameterization of the uncertainty set, and as the number of scenarios or the dimension of the robust set increases, their computational burden significantly rises. Especially in long-term planning and large-scale microgrid systems, they still face challenges in terms of insufficient solution efficiency and scalability [24].

In addition to the deterministic methods based on rules and MPC, meta-heuristic optimization methods have been widely applied in the scheduling optimization of diesel-pv-storage microgrids in recent years [25]. These methods are particularly suitable for complex, nonlinear, and non-convex optimization problems that simultaneously involve discrete decisions and continuous variables. Common representative algorithms include Genetic Algorithm (GA) [26], Multi-objective Non-dominated Sorting Genetic Algorithm (NSGA-II) [27], PSO [28], Differential Evolution (DE) [29], and Simulated Annealing (SA) [30], etc. These methods can globally explore the potential solution domains in high-dimensional, non-convex search spaces and generate approximate Pareto-optimal solution sets among multiple conflicting objectives, maximizing system resilience indicators, and enhancing system symbiosis indicators, thereby achieving a comprehensive trade-off between economy and robustness [31]. However, meta-heuristic algorithms cannot guarantee strict global optimality, and their convergence speed and solution quality are highly sensitive to initial parameter settings and search strategies. Moreover, the computational complexity of these methods is approximately proportional to the product of population size, evolution generations, and the cost of a single fitness evaluation. Generally, these methods can be accelerated through parallel computing and adaptive search mechanisms. In summary, meta-heuristic optimization methods are applicable to day-ahead scheduling and rolling horizon optimization scenarios, and are often used as the outer global search module in hybrid optimization frameworks to provide high-quality initial solutions for mathematical optimization or MPC, thereby balancing the diversity of solutions and the real-time feasibility of system operation [32].

With the continuous increase in the penetration rate of renewable energy and the complexity of the microgrid system structure, a single optimization paradigm has become difficult to achieve a balance among global optimality, real-time feasibility, and robust stability [33]. Therefore, in recent years, the research trend has gradually shifted towards hybrid optimization and distributed coordination frameworks that combine heuristic algorithms with mathematical optimization methods [34]. These methods typically conduct global search through meta-heuristic algorithms to generate candidate solution sets covering multiple objectives, and then combine convex optimization (such as LP/QP or MILP) to refine the continuous variables to ensure the feasibility and robustness of the solutions under operational constraints and system recovery capabilities [35]. Further, by introducing robust or tubular MPC modules into the hybrid framework, the algorithm's real-time adaptability in dynamic uncertainties can be significantly enhanced [36]. This multi-level optimization process achieves a balance between global exploration and local refinement, improving operational economy while also considering system resilience and recovery capabilities [37]. Overall, heuristic algorithms demonstrate good flexibility and global search capabilities when solving nonlinear and multi-objective optimization problems, while mathematical programming methods have theoretical advantages in verifiability and optimality; MPC provides dynamic constraint feasibility, and DRL gives the system the ability to learn autonomously and adapt to the environment [38]. The resulting hybrid and distributed coordination optimization framework is becoming a key technical path for achieving scalability, robustness, and real-time feasibility in microgrids with a high proportion of renewable energy, and is providing new research directions for multi-energy complementarity, island grid recovery, and rolling scheduling scenarios in the future [39].

The diesel generator set acts as a “stabilizer” (inertia time constant $H = 3\text{--}5$ s), and its coordination efficiency with energy storage is quantified using the dynamic coordination coefficient ζ , as shown in Equation (7) [38].

$$\zeta = \frac{\int_{t_0}^{t_f} P_{diesel}(t) P_{ess}(t) dt}{\sqrt{\int_{t_0}^{t_f} P_{diesel}^2(t) dt \cdot \int_{t_0}^{t_f} P_{ess}^2(t) dt}} \quad (7)$$

where $P_{ess}(t)$ denotes the charging and discharging power of the energy storage system at time t (MW), with discharging being positive, typically ranging from -100% to $+100\%$ of the rated capacity; $P_{diesel}(t)$ denotes the output power of the diesel generator set at time t (MW), typically ranging from 20% to 100% of the rated capacity; t_0 and t_f denote the start and end times of the analysis period, typically set to a 24 h cycle.

Research has shown that the numerator term of the dynamic synergy coefficient ζ is calculated by integrating the product of the power of the diesel generator set and the energy storage system, reflecting the degree of synergy between their power changes—when P_{diesel} and P_{ess} have the same sign (simultaneous discharge or charging), it contributes a positive value; when they have opposite signs, it contributes a negative value; while the denominator term, as the geometric mean of the integral of the square of the power, serves to normalize the numerator term, eliminating the influence of the absolute magnitude of the power, enabling ζ to objectively characterize the coordination efficiency of systems of different scales [38].

When the dynamic coordination coefficient ζ reaches 0.7, it has significant engineering significance, indicating that the power change directions of the diesel generator set and the energy storage system are consistent by 70%. This high level of coordination brings multiple benefits: in terms of system stability, it can control frequency deviation within the ideal range of ± 0.35 Hz; in terms of equipment operational efficiency, it can prevent the diesel generator set from operating under low load conditions, improving operational efficiency by 15–20%; In terms of economic efficiency, optimized power allocation can significantly reduce fuel consumption by 8–12% per MWh, effectively enhancing the overall economic efficiency of the system. This quantitative metric provides a crucial basis for evaluating and optimizing the coordinated operation of energy systems [39].

2.3. Symbiosis Quantification Index

Among the symbiosis quantification indicators, the calculation formula for the ECI is shown as Equation (8) [40].

$$ECI = 1 - \frac{\sum_{t=1}^T |P_{diesel}(t) + P_{PV}(t) - P_{load}(t)|}{2 \sum_{t=1}^T P_{load}(t)} \quad (8)$$

where $P_{diesel}(t)$ represents the output power of the diesel generator set at time t (MW); $P_{PV}(t)$ represents the output power of the PV system at time t (MW); $P_{load}(t)$ represents the load demand power at time t (MW); T represents the statistical time range. The numerator of Equation (8) represents the absolute value of the total deviation between the combined output of diesel and PV systems and the load demand, reflecting the degree of supply–demand matching; the denominator of Equation (8) represents twice the total load demand, used for normalization (the maximum possible deviation is 200% of the load, i.e., when both diesel and PV systems have no output); $ECI \rightarrow 1$ indicates perfect complementarity between diesel and PV systems, with supply–demand deviation approaching zero; $ECI \rightarrow 0$ indicates extremely poor complementarity [40].

Capacity allocation Pareto analysis requires the establishment of a three-objective optimization problem, as shown in Equation (9) [41].

$$\min \left[\alpha \cdot C_{cost} + \beta \cdot \frac{1}{R_{reliability}} + \gamma \cdot E_{carbon} \right] \quad (9)$$

where C_{cost} represents the total cost (including diesel fuel, PV/energy storage investment, operation and maintenance, etc.); $R_{reliability}$ denotes system reliability; E_{carbon} denotes carbon emissions (kgCO₂/year); α , β , γ denote weighting coefficients reflecting the priority of economic efficiency, reliability, and environmental friendliness. The physical significance of Pareto optimization lies in the trade-off among multiple objectives: economic efficiency aims to reduce diesel consumption and energy storage capacity; reliability requires minimizing power outage duration, which necessitates increasing reserve capacity; Environmental friendliness seeks to maximize PV penetration and reduce diesel usage. Concurrently, relevant constraints play a crucial role: diesel power constraints prevent inefficient operation (e.g., efficiency drops sharply below the minimum load rate), SOC constraints ensure energy storage lifespan, and PV upper limits reflect natural resource constraints. Furthermore, weighting coefficients (α , β , γ) influence optimization outcomes. If environmental considerations are prioritized ($\gamma \uparrow$), results tend toward larger PV/energy storage configurations; if economic considerations are prioritized ($\alpha \uparrow$), this may reduce energy storage investment and increase diesel peak shaving [41].

Capacity allocation Pareto analysis must comply with relevant constraints, including diesel generator power limitations, energy storage SOC limitations, and PV output limits, as shown in Equation (10) [42].

$$\begin{cases} \text{Diesel unit power limitation : } P_{diesel}^{min} \leq P_{diesel} \leq P_{diesel}^{max} \\ \text{Energy storage SOC limitation : } SOC_{min} \leq SOC \leq SOC_{max} \\ \text{PV output cap : } P_{PV} \leq P_{PV}^{max} \end{cases} \quad (10)$$

where P_{diesel}^{min} and P_{diesel}^{max} represent the minimum and maximum output of the diesel generator set, respectively; SOC_{min} and SOC_{max} represent the minimum and maximum SOC of the energy storage system, respectively; and P_{PV}^{max} represents the instantaneous maximum available power. Operational practice indicates that it is essential to ensure that the diesel engine operates within technically permissible limits (e.g., 30–100% of rated power), prevent overcharging/overdischarging (e.g., SOC ∈ [20%, 90%] to extend battery life [42]), and account for constraints imposed by lighting conditions and installed capacity.

In different typical application scenarios, there are significant differences in the weights of optimization objectives: in island microgrid scenarios, due to significant power outage losses, high reliability weights (β large) may require sacrificing some economic efficiency; in low-carbon park scenarios, environmental protection is prioritized, with high environmental protection weights (γ large), preferring PV + energy storage modes, with diesel used only as a backup. To address the needs of these different scenarios, optimization algorithms (such as NSGA-II) can be used to generate a Pareto front, with decision-makers ultimately selecting the optimal solution based on actual requirements [41,42].

As shown in Table 4, the current performance is quantified using ECI, and then Pareto optimization is used to identify areas for improvement. Together, these two approaches support the collaborative design of diesel-PV-ESS.

From Figure 3, we can see that based on the definition of the symbiotic foundation of diesel-PV-energy storage, the classification of collaborative optimization scheduling methods, and the quantitative indicators of symbiosis, as well as their roles in the energy symbiosis mechanism, we can sort out the logical relationships: the symbiotic founda-

tion of diesel-PV-energy storage is the underlying logical support for the operation of the energy system, such as determining the diesel generator set (base load, inertia, time constant $\tau = 15\text{--}30\text{ s}$), PV (clean energy constrained by fluctuation coefficient $\mu = 0.2\text{--}0.4$), and energy storage (space temporal transfer with efficiency $\eta = 92\text{--}96\%$), providing the “foundational characteristics” (basic equipment properties and complementary logic) for subsequent scheduling and evaluation; The classification of collaborative optimization scheduling methods serves as the “regulatory tools” bridging theory (symbiosis foundation) and practice (system operation). Based on the equipment characteristics within the symbiosis foundation (such as time constant τ and PV fluctuation amplitude μ), various methods such as rule-based strategies, MPC, and MAS are employed to generate operational plans for diesel, PV, and ESS (e.g., diesel generator start-stop sequences and energy storage SOC trajectories); Symbiosis quantification metrics serve as “diagnostic tools” for system performance. By establishing a three-tier evaluation framework, the operational plans generated by scheduling methods are assessed, and quantified results are output to determine whether the plans meet requirements [39–42].

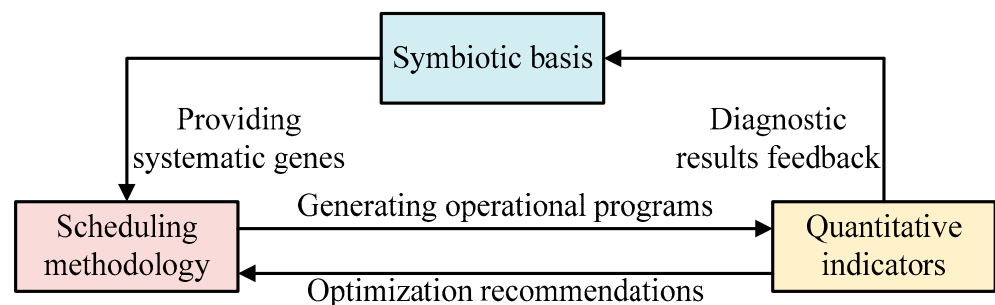


Figure 3. Technology iteration diagram.

Table 4. Comparison of models and decision impacts in system optimization.

Indicators/Models	Core Variables	Decision Impact
ECI [41]	P_{diesel}, P_{PV}	Assess the complementarity of existing systems and provide guidance on capacity expansion.
Pareto optimization [42]	C_{cost}, R, E	Balancing cost, reliability, and environmental friendliness during the design phase

Figure 4 shows a hierarchical logical flow chart of the energy ko-creation mechanism.

The hierarchical logic flow chart of the energy symbiosis mechanism clearly shows the closed-loop operation process of “symbiosis foundation → dispatching method → quantitative indicators → optimization plan”, corresponding to the three layers of input, processing, and output, promoting continuous optimization of the system. The logic of each layer is as follows: In the hierarchical structure and core module, the input layer contains the “symbiosis foundation” and “dispatching method” [43]. where the symbiosis foundation provides the “genetic makeup” of the energy system at its lowest level, encompassing the characteristics and functional complementary relationships of diesel, PV, and ESS. It outputs “system parameters” to the scheduling methods. The scheduling methods then utilize rule-based strategies, MPC, MAS, and other techniques based on the system parameters from the symbiosis foundation to generate energy operation plans, which are output to the processing layer as “operation data”; The core of the processing layer is the “quantitative indicators”, which receive operational data from the scheduling method, diagnose the plan using a three-tier evaluation system, and output “evaluation results”, while also providing feedback to the scheduling method in the form of “improvement strategies”; The output layer focuses on “optimized schemes”, integrating the evaluation

results and improvement strategies from the quantitative indicators. On one hand, it feeds back “improvement strategies” to the scheduling method to guide adjustments to the operation scheme. On the other hand, it feeds back “updated parameters” to the symbiotic foundation (in extreme cases or for long-term optimization, adjusting equipment selection and functional definitions). Ultimately, it outputs an optimized scheme tailored to system requirements, enabling the energy symbiosis mechanism to iterate continuously. In terms of process logic, the input layer → processing layer is represented as symbiotic foundation → scheduling method → quantitative indicators, forming a “gene → regulation → diagnosis” transmission chain. The parameters of the symbiotic foundation determine the regulatory logic of the scheduling method, and the operational data of the scheduling method serves as the basis for evaluating quantitative indicators. For example, the PV fluctuation coefficient μ influences the optimization objective of MPC, thereby determining the evaluation results of quantitative indicators for “PV smoothing effects”; The processing layer → output layer is represented as quantitative indicators → optimization solutions, forming a closed-loop process of “diagnosis → improvement. [43]” Quantitative indicators identify issues with the solution, output improvement strategies (such as expanding energy storage), drive adjustments to the scheduling method’s operational plan, and even prompt updates to the symbiotic foundation’s parameters. Ultimately, an optimized energy operational plan is output, enabling the system to adapt to demands and continuously upgrade. The core function of the entire process is closed-loop iterative optimization, achieving the “theory (synergistic foundation) → practice (scheduling methods) → verification (quantitative metrics) → optimization (solution iteration)” closed-loop. From minor adjustments to scheduling strategy parameters (e.g., MPC’s α/β weights) to major updates to equipment characteristics in the synergistic foundation, all are dynamically optimized within this process to ensure the energy synergistic system consistently aligns with resilience, economic efficiency, and other requirements, efficiently supporting stable energy operations [44].

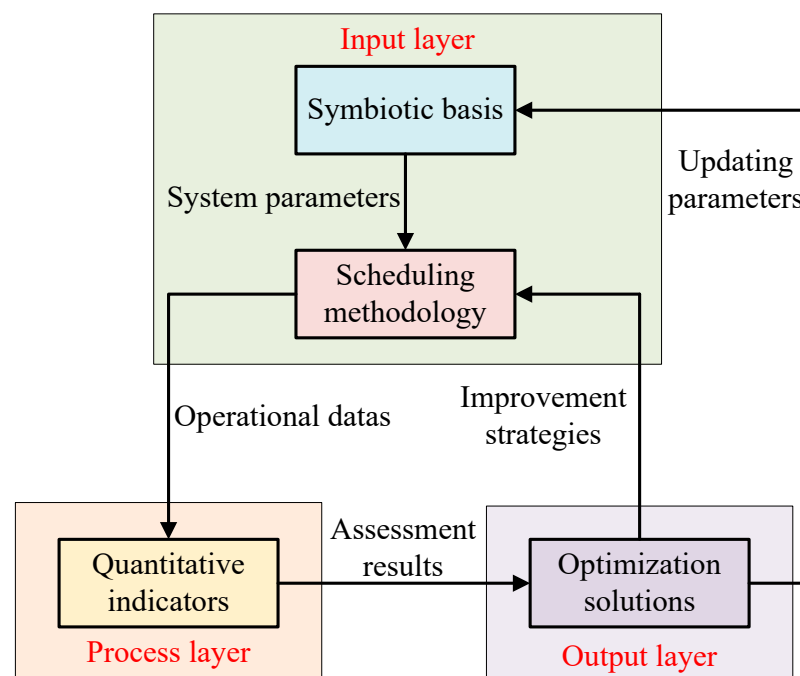


Figure 4. Chart showing the hierarchical logic of the energy symbiosis mechanism.

3. System Resilience Analysis

3.1. Resilience Definition and Assessment Framework

The modeling of resilience requirements mainly focuses on the typical topology shown in Figure 1, covering three aspects: disturbance resistance, self-healing ability, and quantitative indicators. Disturbance resistance includes two aspects: the dynamic equation of diesel generator start-up and the constraint of energy storage support capacity. The dynamic equation of diesel generator start-up is shown as Equation (11) [44,45].

$$t_{start} = t_{detect} + \max\left(\frac{P_{required}}{k_{ramp}}, t_{mech}\right) \quad (11)$$

where t_{start} represents the total time (s) from the occurrence of the fault to the full power output of the diesel generator set; t_{detect} represents the fault detection time (50–100 ms), which depends on the response speed of the protection device; $P_{required}$ denotes the power deficit that the diesel generator set must compensate for (MW); k_{ramp} denotes the power ramp-up rate of the diesel generator set (10–20%/min), e.g., a generator set with a rated power of 1 MW increases by 100–200 kW per minute; t_{mech} denotes the mechanical start-up delay (2–5 min), including physical processes such as lubricant preheating and crankshaft acceleration. It should be noted that the diesel generator set start-up time is determined by both electrical response (power ramp-up) and mechanical inertia, with the maximum value of the two being taken. If an additional 500 kW is required, with $k_{ramp} = 15\%/min$ (i.e., 75 kW/min), the ramp-up time = $500/75 \approx 6.67$ min. If $t_{mech} = 4$ min, the total $t_{start} = 0.1$ s + 6.67 min ≈ 6.67 min [45].

The energy storage support capacity constraint expression is shown as Equation (12) [46].

$$SOC_{crit} = \frac{P_{critical} \cdot t_{start}}{\eta_d C} \quad (12)$$

where SOC_{crit} denotes the critical state of charge, below which the system may fail; $P_{critical}$ denotes the critical load power (MW), such as hospitals and communication equipment; η_d denotes the energy storage discharge efficiency (typically 92–96%); C denotes the total energy storage capacity (MWh). Calculate the minimum SOC requirement for the energy storage system to independently support critical loads within the diesel generator start-up time t_{start} . If the real-time $SOC < SOC_{crit}$, the system enters a high-risk state, requiring the disconnection of non-critical loads or the activation of backup power sources [46]. Let $P_{critical} = 200$ kW, $t_{start} = 6.67$ min (≈ 0.111 h), $C = 1$ MWh, $\eta_d = 0.96$, and the calculation results are shown as Equation (13).

$$SOC_{crit} = \frac{200 \cdot 0.111}{0.96 \times 1000} \approx 2.3\% \quad (13)$$

In actual systems, higher redundancy is set, such as an alarm when $SOC < 10\%$. The expression for self-healing capacity assessment (SOC recovery kinetics) is shown as Equation (14) [47].

$$\frac{dSOC}{dt} = \frac{P_{charge}}{C} - \frac{P_{PV}}{C\eta_c} - \lambda_{load} \quad (14)$$

where P_{charge} represents the external charging power (MW); P_{PV} represents the real-time output of PV power, which must be considered for efficiency during charging; η_c represents the energy storage charging efficiency (typically 92–96%); λ_{load} represents the load fluctuation coefficient (0.05–0.2 p.u./h), reflecting the impact of random load changes on SOC. Equation (14) describes the energy storage SOC recovery rate, which is jointly affected by

charging power, PV output and load fluctuations. When the conditions are met, it is shown as Equation (15). The system then enters a steady state (charging and discharging balance).

$$\frac{dSOC}{dt} = 0 \quad (15)$$

The resilience quantification index system includes MTTS and maximum tolerable PV penetration rate [48]. The expression for MTTS is shown as Equation (16).

$$MTTS = \int_{t_0}^{t_f} I(P_{supply} \geq 0.95P_{load})dt \quad (16)$$

where $I(\cdot)$ denotes the indicator function (equal to 1 when the condition is satisfied, and 0 otherwise); P_{supply} denotes the actual power supply of the system (MW); $0.95P_{load}$ denotes the resilience threshold (allowing a 5% power deficit); t_f denotes the system collapse time (e.g., when the energy storage SOC = 0 or the diesel generator is overloaded), which is the total time the system maintains power supply to 95% or more of the load after a disturbance, directly reflecting its disaster-resilient endurance capability [48].

The expression for the maximum tolerable PV penetration rate ρ_{max} is shown as Equation (17) [49].

$$\rho_{max} = \arg \max_{\rho} \left(\frac{P_{PV}}{P_{PV} + P_{diesel}} \right) \text{ s.t. } f_{deviation} \leq 0.5\text{Hz} \quad (17)$$

where ρ represents the PV penetration rate, i.e., the proportion of PV power in the total power supply; $f_{deviation}$ represents the system frequency deviation (limited to 0.5 Hz to prevent grid disconnection). Equation (17) indicates the maximum PV penetration rate that the system can accommodate while ensuring frequency stability. Empirical data ranging from 65% to 78% suggests that diesel generators must retain 22% to 35% of their capacity for frequency regulation [49]. Values exceeding this range require additional energy storage or fast-response gas turbines.

The resilience assessment framework is summarized in Table 5.

Table 5. Summary of resilience assessment frameworks [47–49].

Capability Dimension	Key Formula	Core Variables	Engineering Significance
Anti-disturbance [45–47]	Diesel starts equation, SOC critical value	t_{start}, SOC_{crit}	Ensure uninterrupted power supply to critical loads after a failure
Self-healing [48]	SOC recovery dynamics [50]	$P_{charge}, \lambda_{load}$	The speed at which the evaluation system recovers from disturbances
Quantitative indicators [49]	MTTS, ρ_{max}	Power supply time, frequency deviation [50]	Guidance on system planning and threshold settings for operation

As shown in Table 5, the system resilience analysis framework establishes a comprehensive evaluation system based on three core dimensions: disturbance resistance, self-healing capability, and quantitative indicators [45–47]. Among these, disturbance resistance is ensured through the diesel generator start-up equation (with the core variable being start-up time t_{start}) and energy storage SOC critical value constraints (with the core variable being SOC_{crit}). Its engineering significance lies in ensuring that critical loads can continue to be powered after a fault occurs, thereby avoiding the risk of power outages; Self-healing capability is based on the SOC recovery dynamics equation, focusing on charging power P_{charge} and load fluctuation coefficient λ_{load} , which are used to evaluate the speed

and efficiency of the system's recovery from disturbances [43,45,48,50]. Minimum time to restore supply (MTTS) and maximum tolerable PV penetration rate (ρ_{max}) are used as quantitative indicators, providing a clear basis for system planning and operation threshold settings through parameters such as power supply time and frequency deviation. In practical applications, this framework can provide guidance for different scenarios: For island microgrids with high MTTS requirements (e.g., exceeding 24 h), large-capacity energy storage must be configured to meet long-term power supply needs; for high PV penetration systems, ρ_{max} can be used to optimize energy storage configuration and diesel generator frequency regulation parameters, achieving a balance between resilience and economic efficiency [49–52].

3.2. Analysis of the Characteristics of Scheduling Strategies' Impact on Resilience

The symbiotic dispatch coordination control law includes two parts: dynamic adjustment of energy storage power and power distribution of diesel generators. The expression for dynamic adjustment of energy storage power is shown as Equation (18) [50].

$$P_{ess} = k_p(P_{PV} - \bar{P}_{PV}) + k_i \int (f - f_{nom})dt \quad (18)$$

where P_{ess} represents the charging and discharging power of the energy storage system, with positive values indicating discharging and negative values indicating charging (MW); P_{PV} represents the real-time output of PV power (MW); $\bar{P}_{PV}$ represents the average predicted PV output (e.g., moving average or previous day's predicted value) (MW); f denotes the actual system frequency (Hz); f_{nom} denotes the rated frequency (50 Hz); k_p denotes the proportional coefficient (0.8–1.2), which adjusts the sensitivity of the PV fluctuation response; a larger k_p results in a more aggressive response but may cause oscillations; k_i denotes the integral coefficient (0.05–0.1), which eliminates frequency steady-state errors; a larger k_i may cause overshoot, while a smaller k_i results in slower regulation. The first term of Equation (18) (proportional control) indicates that when PV output deviates from the predicted value ($(P_{PV} - \bar{P}_{PV}) > 0$), energy storage discharges to compensate for excess power; conversely, it charges. The second term of Equation (18) (integral control) indicates integration of frequency deviation, continuously correcting energy storage output to restore the rated frequency [50].

The expression for the power distribution of a diesel generator set is shown as Equation (19) [51].

$$P_{diesel} = \min(P_{ess}^{max} - P_{ess}, P_{diesel}^{rated}) \quad (19)$$

where P_{ess}^{max} represents the maximum dispatchable power of energy storage, i.e., the limit of charging and discharging capacity; P_{diesel}^{rated} represents the rated power of the diesel generator set. Analysis of Equation (19) shows that when energy storage cannot completely compensate for the power gap ($|P_{ess}|$ approaches P_{ess}^{max}), the diesel generator set starts according to the remaining demand, but does not exceed its rated capacity, and the priority logic stipulates that energy storage responds first, with diesel as a backup, reflecting the "symbiotic" characteristic [51].

The summary of the energy storage cooperative control law and diesel power allocation application is presented in Table 6.

Through symbiotic scheduling, the system can achieve dynamic power balancing, rapid energy storage response, and diesel supplementation to fill remaining gaps; frequency stability, integral control to eliminate deviations and prevent grid disconnection; and economic optimization to reduce diesel generator running time and extend energy storage life.

Table 6. Summary of energy storage cooperative control laws and diesel power distribution applications.

Expression	Control Target	Key Variables	Design Inspiration
Energy storage cooperative control law [50]	Smooth out fluctuations + frequency adjustment	$k_p, \bar{P}_{PV}$	Parameters should be selected based on the accuracy of PV predictions.
Diesel power distribution [51]	Ensure continuity of power supply	$p_{ess}^{max}, p_{diesel}^{rated}$	The energy storage capacity must cover the demand during the diesel start-up delay period.

The impact of scheduling strategies on resilience is summarized in Table 7.

Table 7. The impact of scheduling strategies on resilience [52–54].

Strategy Type	Interference Immunity	Self-Healing Ability	Economic Efficiency
Traditional scheduling [52]	Reliance on diesel generators, slow response (minutes)	SOC recovery depends on human intervention	High fuel costs
Symbiotic scheduling [53]	Energy storage with millisecond response + diesel backup	Automatic charging to restore SOC when there is excess PV power [54]	Reduce diesel fuel consumption by 20–40%

Table 7 shows that scheduling strategies have a significant impact on system resilience, with distinct differences among strategies in terms of disturbance resistance, self-healing capability, and economic efficiency. Traditional scheduling strategies rely on diesel generators for disturbance resistance, resulting in slow response times (minutes); In terms of self-healing capability, SOC recovery requires manual intervention; additionally, there is the issue of high fuel costs [52]. In contrast, the symbiotic scheduling strategy combines millisecond-level response from energy storage with diesel backup, enhancing disturbance resistance; in terms of self-healing capability, it can automatically charge and restore SOC during periods of excess PV power; simultaneously, it reduces diesel usage by 20–40%, offering superior economic efficiency. From the perspective of key indicators, under symbiotic scheduling, reduced diesel startup delays and extended energy storage support time improve MTTS; and through coordinated frequency control, higher PV penetration rates are enabled. In terms of engineering considerations for coefficient selection, the proportional coefficient k_p is related to the PV fluctuation standard deviation σ_{PV} , typically $k_p \propto 1/\sigma_{PV}$. If the value is too large, it may cause frequent power reversal in energy storage, accelerating battery aging; The integral coefficient k_i should be selected based on the system's inertia time constant H , generally $k_i \approx 0.1/(2H)$. In summary, the symbiotic dispatch strategy enhances system resilience while balancing economic efficiency, making it the optimal choice. Proper selection of k_p and k_i is critical for system performance [53].

3.3. Balancing the Resilience and Economic Viability of Multi-Source Complementary Microgrids

The resilience–economic trade-off includes a cost model for diesel backup solutions, a full life-cycle cost model for energy storage expansion, and a marginal cost model for PV over-provisioning. The cost model for the diesel backup plan is shown by Equation (20) [54].

$$\Delta C_{diesel} = C_{cap} P_{reserve} + \sum_{t=1}^T C_{fuel} P_{idle}(t) \quad (20)$$

where ΔC_{diesel} represents the total cost increment of the diesel backup plan (\$); C_{cap} represents the unit capacity investment cost of the diesel generator set (\$/kW); Preserve denotes the diesel standby capacity (kW), typically 20–30% of peak load; C_{fuel} denotes the fuel cost (\$/kWh); $P_{idle}(t)$ denotes the no-load operating power of the diesel generator set (20–30% of rated power), used to maintain rapid response capability [54]. The first term of Equation (20) represents the fixed investment cost of standby capacity; the second term of Equation (20) represents the fuel consumption cost of no-load operation (fuel consumption is required even when there is no load). Research shows that the disadvantage of Equation (20) is high fuel costs and high carbon emissions, but it has a fast response speed (seconds).

The full life-cycle cost model for energy storage expansion is shown in Equation (21) [55].

$$C_{ess} = \frac{C_{bat}E}{N_{cycle}} + C_{pcs}P_{rated} \quad (21)$$

where C_{ess} denotes the total cost of the energy storage system over its entire lifecycle (\$); C_{bat} denotes the unit energy cost of the battery (\$/kWh); E denotes the total energy storage capacity (kWh); N_{cycle} denotes the battery cycle life (cycles), which is influenced by the SOC fluctuation amplitude ΔSOC ; C_{pcs} denotes the unit power cost of the PCS (\$/kW); P_{rated} denotes the rated power of the energy storage system (kW) [55].

The marginal cost model for PV over-allocation is shown in Equation (22) [56].

$$\frac{dC_{PV}}{d\rho} = C_{PV}(1 + 0.2\rho) \text{ for } \rho > 0.7 \quad (22)$$

where $\frac{dC_{PV}}{d\rho}$ represents the marginal cost (\$/kW) when the penetration rate of PVs increases; C_{PV} represents the base unit cost of PVs (\$/kW); ρ represents the penetration rate of PVs, and when the penetration rate exceeds 70%, the cost increases nonlinearly, as shown in Equation (23) [57].

$$\rho = \frac{P_{PV}}{P_{PV} + P_{diesel}} \quad (23)$$

Research and practice show that when $\rho > 0.7$, additional investment in curtailment management (such as energy storage and hydrogen production) or grid upgrades is required, resulting in a 10–20% increase in marginal costs at this level of penetration [57]. The cost models for diesel backup solutions, energy storage expansion over the full life cycle, and PV over-capacity marginal costs are summarized in Table 8 [58–60].

Table 8. Summary of the resilience–economic trade-off formula [58–60].

Plan	Core Formula	Design Variable	Optimization Objective
Diesel backup [58] Energy storage expansion [59]	ΔC_{diesel} C_{ess}, N_{cycle}	$P_{reserve}, P_{idle}$ $\Delta SOC, E$	Reduce no-load loss costs Extend cycle life and reduce cost per kilowatt hour
PV over-allocation [60]	$\frac{dC_{PV}}{d\rho}$	ρ , Light rejection ratio	Balancing excess revenue and curtailment losses

As shown in Table 8, the diesel backup solution uses ΔC_{diesel} as its core formula, optimizing Preserve and P_{idle} to reduce no-load loss costs; the energy storage expansion solution focuses on C_{ess} and N_{cycle} , targeting ΔSOC and E to extend cycle life and reduce cost per kilowatt-hour; the PV over-provisioning solution is based on $\frac{dC_{PV}}{d\rho}$, adjusting ρ and curtailment rate to balance over-provisioning benefits with curtailment losses [58]. From an economic perspective, the priority ranking is PV over-provisioning (lowest marginal cost) → energy storage expansion → diesel backup [59]. From a resilience perspective,

when there are high requirements for MTTS, energy storage capacity must increase linearly, with each additional hour of MTTS requiring approximately a 15% increase in C_{ess} [60]. In summary, the appropriate scheme should be selected or combined based on actual resilience requirements and economic considerations.

Table 9 shows the technical logic loop of the three core elements in system resilience analysis. As shown in Table 9, the technical logic of “evaluation—scheduling—economic trade-off” can divide the research on resilience into three interrelated stages [61]. Firstly, in the “definition and evaluation” stage, the mainstream approach provides a unified terminology and measurement framework from the perspective of systems engineering, such as resilience curves, service level-time functions, and multi-stage indicators before, during, and after events (e.g., power restoration time, lost load, etc. [62]), which helps to convert top-level goals (such as MTTR/MTTS, peak shortage ρ_{max}) into quantifiable design inputs, facilitating cross-case comparisons and policy communication. However, the limitation lies in the lack of a completely consistent consensus on the indicator definitions, and static or post-event measurements often fail to reflect the dynamic propagation mechanism of complex interdependencies and cascading failures. Secondly, in the “scheduling strategy” stage, based on the observable quantities formed by indicators and dynamic models, MPC and distributed/coordinated control (including the k_p , k_i parameters in the secondary PI loop) can coordinate generation and energy storage constraints under disturbances and conduct forward-looking rolling optimization. The advantages are that they are both real-time and feasible under constraints, suitable for scenarios with multi-energy coupling and multiple actors [63]. However, they are sensitive to model identification and communication delays, and the cost of parameter tuning and robustness verification is relatively high. In cases of incomplete information on extreme events, the strategies may deteriorate [64]. Finally, in the “economic trade-off” stage, technologies such as REopt and multi-objective evolutionary algorithms are often used to determine the optimal capacity and proportion of energy storage, PV, and diesel, making the “resilience—cost” quantifiable in the long term. The advantage is that they can directly output investment portfolios and strategy costs, but they have a strong prior dependence on scenario assumptions, price paths, and outage probabilities [65]. If resilience constraints or rare extreme scenarios are not explicitly included, the actual resilience of the cost-optimal solution may be overestimated. In summary, the evaluation framework provides the upper-level input of the “goal—indicator” closed loop, the scheduling strategy realizes the parameterization of the coordinated control law at the event scale, and economic optimization strikes a balance between cost and resilience at the planning scale [66]. The coupling of the three can form a “closed-loop design—operation—planning” chain from top-level goals to control parameters and capacity configuration, but further integration is still needed in terms of a unified indicator system, robust scheduling under model uncertainty, and economic assessment for extreme scenarios [67].

Table 9. Technical logic loop of three core elements in system resilience analysis [61–67].

Phase	Key Issue	Dependencies	Decision Output
Definition and assessment [61,62]	How resilient does the system need to be	None (top-level design input)	MTTS, ρ_{max} target value
Scheduling strategy [63]	How to dynamically achieve resilience	Based on indicators and dynamic models	Cooperative control law parameters (k_p , k_i) [64]
Economic trade-offs [65,66]	How much does it cost to achieve resilience	Indicator constraints + strategy costs	Optimal ratio of energy storage/diesel/PV [67]

Figure 5 shows the logical relationship between the three core elements of system resilience analysis.

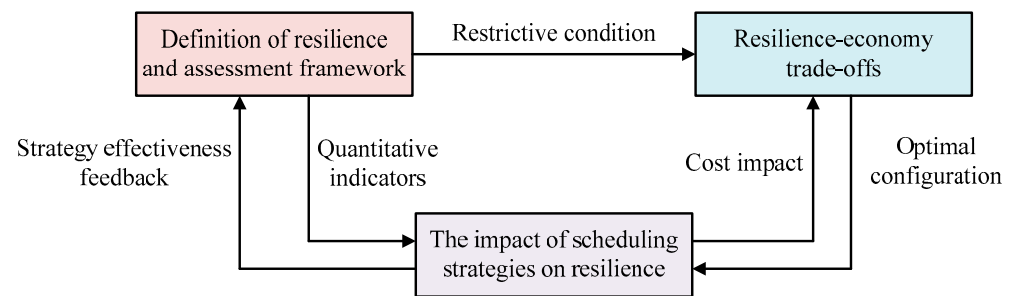


Figure 5. Framework of the Interaction Between Resilience Definition, Scheduling Strategies, and Economy Trade-offs.

Analysis of Figure 5 and Table 9 reveals that the function of the resilience definition and assessment framework is to establish the “rules” (indicators) and “boundaries” (constraints) for resilience analysis [61]. Key indicators include the Minimum Time to Service (MTTS), which must be achieved through scheduling strategies, and the Maximum PV Penetration Rate (ρ_{max}), which is constrained by both scheduling strategies and economic considerations [62]. In the dynamic model, the diesel startup time (t_{start}), and the energy storage SOC critical value (SOC_{crit}) directly influence the design of scheduling strategies, with the output clearly indicating the level of resilience required by the system (e.g., $MTTS > 6$ h) [63]. The impact of scheduling strategies on resilience is primarily achieved through dynamic adjustment of diesel, PV, and energy storage power via control algorithms to meet resilience objectives [64]. Among these, the cooperative control law of symbiotic scheduling can rapidly respond to disturbances (enhancing MTTS), Diesel-energy storage collaboration can optimize the matching of t_{start} and SOC_{crit} [65]. Compared with traditional scheduling, it can verify its improvement effects on MTTS and ρ_{max} , with the output determining “how to achieve resilience” (e.g., energy storage priority response, diesel standby); The resilience–economic trade-off involves optimizing resource allocation under resilience requirements and scheduling strategies [66]. Its cost model compares diesel standby, energy storage expansion, and PV over-provisioning to calculate the incremental costs of different schemes achieving the same resilience (e.g., $MTTS + 10\%$). The Pareto frontier reveals “how much resilience can be purchased for a given cost” (e.g., each additional hour of MTTS from energy storage solutions increases by \$8/MWh), with the output providing the “cost-effective optimal” configuration scheme (e.g., energy storage ratio of 25–35%) [67].

Figure 6 shows the system resilience analysis flowchart. The system resilience analysis revolves around the theme of “system resilience analysis” is conducted from three aspects: first, the “resilience definition and assessment framework” is established using formulas such as diesel startup and energy storage SOC threshold values, focusing on disturbance resistance (rapid diesel startup and energy storage support), self-healing (SOC recovery, PV penetration rate threshold), and quantitative indicators (MTTS statistical power supply assurance duration, etc.) to clarify the foundational logic of resilience [68]. Second, it examines the “impact of dispatch strategies”, comparing the effects of traditional dispatch (piecewise function, $MTTS = 4.2$ h) and symbiotic dispatch (cooperative control law, MTTS improved by 61.9% to 6.8 h) on resilience [69]. Finally, using the “resilience–economic trade-off”, the cost formulas for diesel standby and energy storage expansion are combined with Pareto optimality (costs and optimal configuration ratios of different schemes when resilience is improved) to balance demand and investment [70]. The overall approach clearly breaks down the “assessment, improvement, and cost balancing” issues, converting abstract resilience into engineering metrics through formulas and data to guide practical

implementation, serving as an engineering guide for system resilience analysis from theory to practice [71].

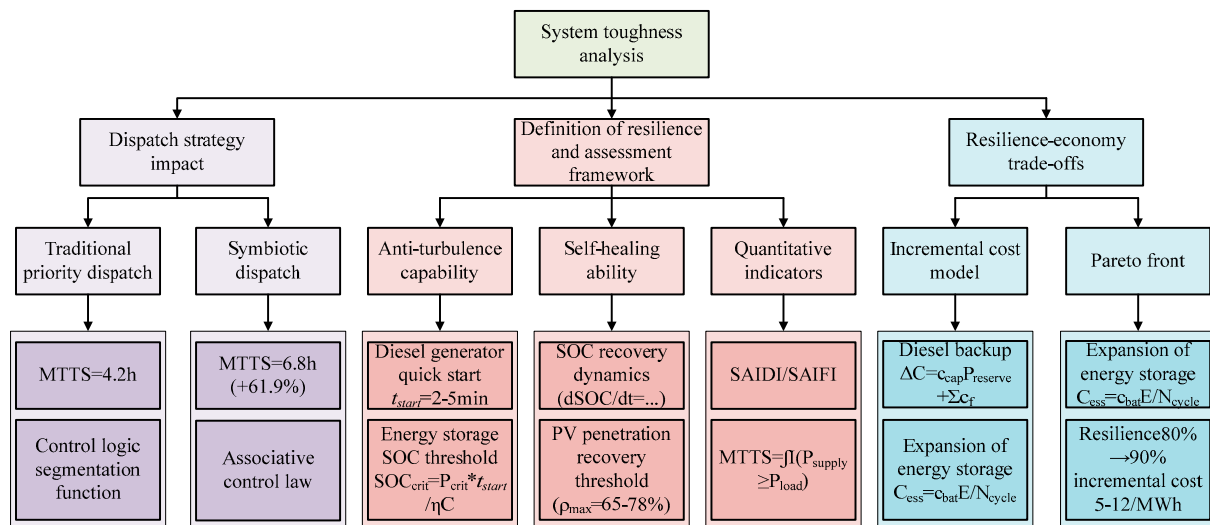


Figure 6. The logical relationship between the three core elements of system resilience analysis.

Figure 7 shows the logical relationship diagram between the energy symbiosis mechanism and the system resilience analysis. The energy symbiosis mechanism, as the core framework and the starting point of the process, provides direction for subsequent links. The system resilience analysis receives its input and analyzes the energy system's ability to respond to disturbances and maintain stability, and is subject to reverse constraints of economic decisions [72]. Economic decisions are made based on the results of system resilience analysis in combination with economic factors, and the two are mutually restrictive. The assessment of symbiosis degree evaluates the effect of energy symbiosis and feeds it back to the energy symbiosis mechanism for optimization and adjustment. The overall logic presents a cycle of “mechanism coordination—analysis support—decision implementation—assessment feedback”, ensuring the dynamic optimization of the energy symbiosis system in terms of resilience, economy, and synergy [73].

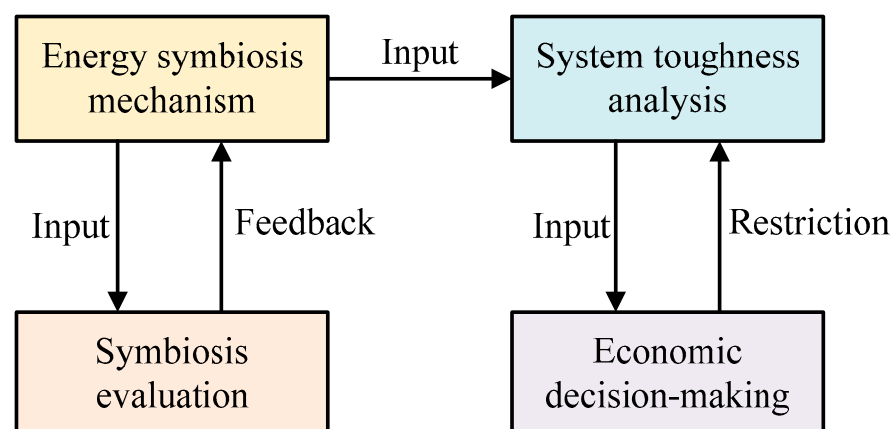


Figure 7. Logical relationship diagram of energy symbiosis mechanisms analysis.

Figure 8 illustrates the logical relationship between the energy symbiosis mechanism and the six core elements of system resilience analysis, divided into left and right modules. In the “system resilience analysis” process on the left side, the definition of resilience serves as the logical starting point to establish standards, which are then transmitted through

demand inputs to define objectives [74]. Scheduling strategies are formulated based on these standards and are constrained by cost considerations resulting from economic trade-offs. Economic trade-offs calculate cost–benefit ratios that impose reverse constraints on strategies [75]. In the right-hand “energy symbiosis mechanism” process, the symbiosis foundation provides the underlying support for scheduling methods. Scheduling methods receive strategy inputs from the left-hand side and combine them with the foundational design scheme [76]. After implementation, they are evaluated and fed back into the symbiosis degree indicators. These indicators measure effectiveness and provide reverse inputs to optimize scheduling methods, forming a closed-loop system. The overall framework is structured around the main threads of “resilient demand → strategy formulation → cost constraints” and “synergy foundation → scheduling implementation → effect evaluation”, linking the two through demand inputs, strategy inputs, and evaluation feedback to achieve cross-module collaboration. This ensures that the energy system dynamically adapts to resilience, economic efficiency, and coordination, enabling scheduling that is both interference-resistant and highly efficient and economical [77].

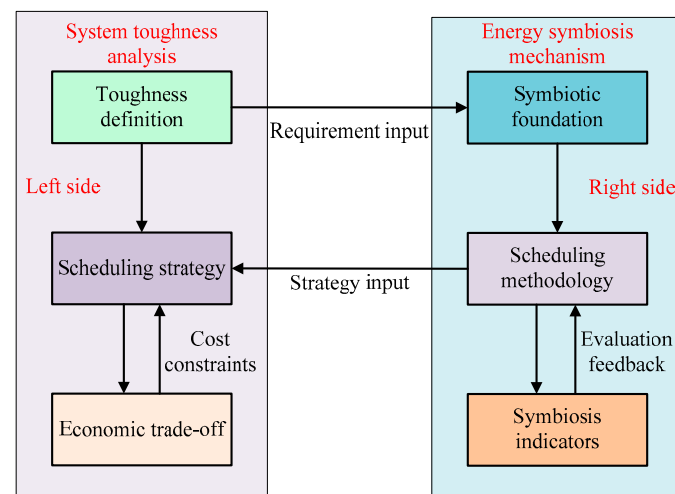


Figure 8. Logical relationship diagram of the six core elements of energy symbiosis mechanisms and system resilience analysis.

Table 10 shows the interaction effects of core parameters. Based on the “three-dimensional” relationship (power balance—dynamic response—energy buffering) in Table 10, it can be observed that: First, the ECI is significantly positively correlated with the resilience index MTTS ($\beta \approx 0.82$). This is consistent with the conclusion that the temporal/spatial complementarity of renewable resources can reduce the net load fluctuation and extend the survivable time of the isolated grid. In the water-solar complementary system, increasing the ECI ($\beta \approx 0.8$) often means a longer survival/support time under the same energy storage scale, thereby enhancing the power supply guarantee level. The advantage lies in improving resilience and economy through resource allocation rather than simply adding energy storage; however, the limitation is that the complementarity is constrained by the seasonality and regional correlation of water inflow and irradiation, with limited extrapolation [78]. Second, the negative correlation between the damping ratio ζ and the frequency deviation Δf ($\beta \approx -0.75$) is in line with the frequency dynamics and primary/droop control mechanism: moderately increasing ζ (e.g., from 0.6 to 0.7) can significantly suppress oscillations and peak overshoot, shorten the settling time, and thereby reduce the Δf after disturbances; however, excessive damping may sacrifice dynamic tracking and potentially introduce steady-state errors, with a strong dependence on parameter tuning and equivalent inertia estimation [79]. Third, the SOC recovery rate is highly positively correlated with the

“fault recovery rate” ($\beta \approx 0.91$), indicating that the charging and discharging strategy of energy storage in the post-disturbance recovery stage (such as SOC envelope/reliability constraints) directly determines the system’s survival time and recovery speed; the advantage is strong operability and ease of integration into optimization scheduling and resilience evaluation (such as MTTs/Survival Time) [80]. However, the disadvantage is sensitivity to battery aging, available capacity, and charging power limits, and a single SOC indicator is insufficient to encompass broader recovery attributes such as black start capability and multi-energy synergy [81]. Overall, the above three types of indicators jointly characterize the entire process of “disturbance resistance—absorption—recovery”: resource-level complementarity improves supply–demand matching and MTTs, control-level damping tuning reduces dynamic over bound risks, and energy storage-level SOC recovery ensures rapid stabilization after faults; in terms of method selection, a multi-objective trade-off should be made considering regional complementarity potential, expected frequency quality, and battery life cost.

Table 10. Core Parameter Interaction Relationship Table.

Evaluation Dimensions	Symbiotic Indicators	Resilience Index	Interaction Coefficient β	Typical Influence Patterns
Power balance [82]	ECI	MTTS	0.82	ECI = 0.8 $\rightarrow$ MTTs = 6h $\pm$ 0.5
Dynamic response [83]	ζ	Frequency deviation Δf	−0.75	ζ 0.6 $\rightarrow$ 0.7, Δf $\downarrow$ 0.15 Hz
Energy buffer [84]	SOC recovery rate	Failure recovery rate	0.91	Rate $\geq$ Recovery rate at 5%/h >90%

Figure 9 illustrates the interaction relationships among core parameters. The diesel generator set’s “inertial support” influence reflects the ζ value indicating resistance to frequency fluctuations, laying the foundation for “disturbance resistance [82]”. PV systems utilize “fluctuation compensation” to address power fluctuations through the ECI, enhancing “disturbance resistance”. ESS improve “self-healing capability” through “SOC management”; “Disturbance resistance” is jointly supported by the ζ value and ECI to address disturbances, while “self-healing capability” relies on SOC management to achieve recovery after a fault [83]. Together, they build the system’s comprehensive resilience to complex operating conditions. Specifically, diesel generators, PV systems, and ESS address inertial support, fluctuation compensation, and state regulation through pathways such as the ζ value, ECI, and SOC management, collaborating to achieve dual-dimensional enhancements in “disturbance resistance + self-healing”, thereby constructing the comprehensive resilience of the energy system [84].

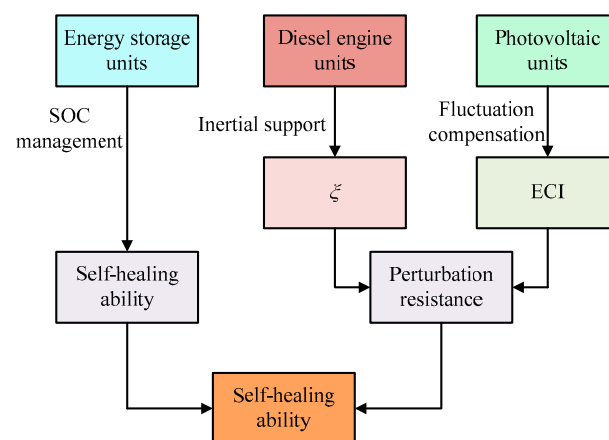


Figure 9. Chart showing the interactive relationships between core parameters.

4. Synergistic Design Paradigm of Symbiosis Degree and Resilience Threshold

4.1. Design Framework for Symbiotic Microgrid Scheduling

High renewable penetration and frequent islanded operation have fundamentally reshaped microgrid scheduling, imposing stricter requirements on dynamic resilience, coordination, and energy complementarity. To address the limitations of conventional fixed-weight optimization and single-inertia designs, this study proposes a symbiotic-resilience threshold co-design framework, which couples index-driven objectives, adaptive weighting mechanisms, and hybrid inertia synthesis. The framework bridges the gap between theoretical optimization and engineering implementation by linking resilience metrics directly to control parameters and hardware configurations [85].

At the core of the proposed framework lies a resilience-oriented optimization target that integrates energy complementarity (ECI), dynamic synergy degree (ζ), and maximum PV penetration (ρ_{max}) into a unified metric R_{th} . These indices jointly quantify the system's ability to maintain stable operation under multi-source interactions and external disturbances. The expression of the symbiosis degree-resilience threshold synergy paradigm is shown as Equation (24) [86].

$$\begin{cases} R_{th} = \alpha \cdot ECI + \beta \cdot \zeta + \gamma \cdot \rho_{max} \\ \text{s.t.} \begin{cases} ECI \geq 0.7 \\ \zeta \geq 0.65 \\ \rho_{max} \geq 0.6 \end{cases} \end{cases} \quad (24)$$

where R_{th} denotes the comprehensive resilience threshold; ζ denotes the dynamic synergy degree; and ρ_{max} denotes the maximum PV penetration rate. Energy complementarity (ECI) characterizes temporal anti-correlation among resources, typically obtained via rolling correlation or mutual information [87,88]. The dynamic synergy index ζ reflects phase margin and impedance-matching coordination in voltage and frequency loops [89,90], while ρ_{max} is limited by inertial and ramping capabilities [91,92]. These indicators are physically interpretable and directly related to controller and capacity parameters, although they rely on accurate data assimilation, motivating the integration of digital twin modeling for calibration [93].

This involves two aspects: an innovative dynamic weight distribution mechanism and a breakthrough in hybrid inertial simulation technology. The improved formula for dynamic weight distribution is shown as Equation (25) [94].

$$\alpha(t) = \frac{1 - \sigma_{PV}(t)}{3 - \sigma_{PV}(t) - \sigma_{Load}(t) - \sigma_{SOC}(t)} \quad (25)$$

where $\sigma_{Load}(t)$ represents the load fluctuation coefficient, which reflects the sudden change characteristics of special loads such as hospitals and base stations; $\sigma_{SOC}(t)$ represents the standard deviation of the SOC change rate, which characterizes the degree of energy storage regulation; $\sigma_{PV}(t)$ represents the minute-level fluctuation rate of PV output and is illustrated by Equation (26).

$$\sigma_{PV} = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{P_{PV}(t_i) - \bar{P}_{PV}}{\bar{P}_{PV}} \right)^2} \quad (26)$$

In engineering practice, the dynamic weight allocation mechanism intelligently adjusts energy allocation weights by continuously monitoring the system's operational status: in PV-dominant mode ($\sigma_{PV} > 0.3$), the PV weight coefficient σ_{PV} is automatically reduced

to 0.2–0.3, effectively suppressing the propagation of fluctuations; When entering load-dominant mode ($\sigma_{Load} > 0.25$), the weighting of diesel generators is increased to above 0.5 through the regulatory effect of the formula's denominator, ensuring power support capability; in the balanced mode where parameter fluctuations are minimal ($\sigma < 0.15$), $\alpha \approx 0.33$ a balanced allocation strategy is maintained to achieve optimal synergy among the three energy sources. This adaptive mechanism effectively transforms the scheduling problem into a closed-loop “sense–adapt–reallocate” process, enabling real-time self-regulation without full re-optimization. Nonetheless, overly frequent re-weighting can induce chattering, requiring hysteresis logic or minimum dwell time for stability [95].

To reinforce frequency stability under high renewable penetration, the framework incorporates a hybrid inertia synthesis strategy that emulates additional inertia through energy storage. The mixed inertial simulation technology involves the principle of virtual inertia synthesis, which is expressed as Equation (27) [45].

$$H_{hybrid} = \underbrace{0.7H_{diesel}}_{\text{physical inertia}} + \underbrace{0.3 \frac{E_{ess}}{f_0} \frac{df}{dt}}_{\text{virtual inertia}} r \quad (27)$$

where H_{diesel} denotes the physical inertia of the diesel engine (s); E_{ess} denotes the available energy storage capacity (kWh); f_0 denotes the rated frequency (Hz); and df/dt denotes the rate of change in frequency (Hz/s). This term effectively augments the system's rotational response, achieving frequency support within 200 ms and reducing the nadir depth by up to 60% compared to diesel-only systems [96,97]. An additional protective mechanism limits the rate of change in frequency (ROCOF) to ± 2 Hz/s and reduces k_v to 0.1 when SOC falls below 20%, preventing over-discharge and extending battery life [98]. Consequently, the hybrid inertia model achieves a superior trade-off between dynamic stability and energy asset longevity, outperforming both traditional diesel-governed and purely virtual-inertia systems [99].

Within this framework, multiple control strategies can be hierarchically integrated. Centralized MPC offers accurate constraint handling and short-horizon optimality but suffers from high computational complexity $O((HN)^3)$ [100]. Distributed MPC (DEMPC), often implemented via ADMM iterations, alleviates communication burden and enhances scalability [101–103]. Robust and distributionally robust formulations provide guaranteed feasibility under uncertainty but increase the computational load due to scenario expansion [104,105]. Event-triggered distributed control, in which communication updates are activated by deviations exceeding a threshold, can reduce network traffic by more than 60%, though it requires careful threshold tuning to avoid latency-induced instability [106]. Meanwhile, network reconfiguration and MILP-based topology optimization strengthen N-1 resilience and enhance fault recovery flexibility [107,108]. For global optimization across non-convex decision spaces, hybrid metaheuristic–mathematical programming approaches (e.g., NSGA-II + MILP/QP) provide effective Pareto fronts between economic and resilience objectives [109], albeit with sensitivity to parameter selection and population size.

Figure 10 shows the design flow chart based on the five-stage method.

Engineering implementation follows a five-stage workflow encompassing demand analysis, symbiosis-oriented design, resilience validation, parameter iteration, and final hardware realization. In the first stage, spectral clustering of load profiles and scenario library construction identify resilience requirements such as mean time to survival (MTTS) and frequency deviation limits. The second stage establishes ECI and ζ targets and performs capacity ratio optimization among diesel, ESS, and PV units via Pareto front analysis [110]. The third stage employs digital-twin platforms and Monte Carlo simulations to validate design performance under stochastic disturbances. If resilience targets are not met, the

fourth stage performs adaptive parameter tuning of weight coefficients and network topology reconfiguration based on sensitivity analysis. Finally, the fifth stage outputs engineering parameters including virtual synchronous generator (VSG) control gains, energy storage PCS ratings, and hardware selection lists, verified by HIL or RTDS simulation. This process forms a closed loop of “demand-driven design, validation-driven iteration, and iteration-driven realization”, ensuring consistency between theoretical indices and engineering outcomes.

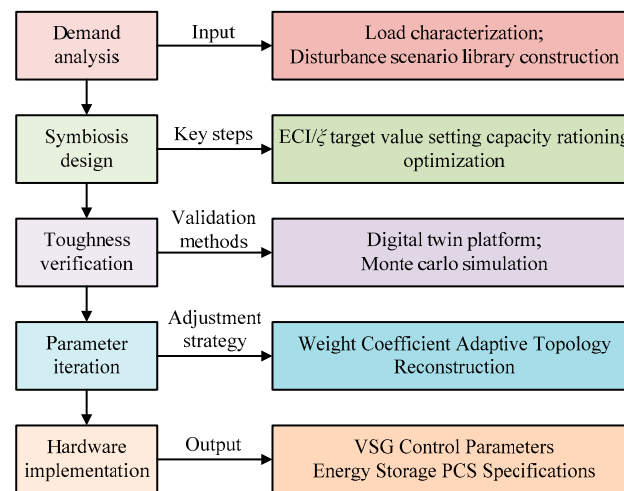


Figure 10. Design process chart based on the five-stage method.

Overall, the proposed framework integrates index-driven objectives, adaptive optimization, and physics-based control into a unified co-design paradigm. Compared to conventional deterministic or single-objective formulations, it dynamically balances resilience, efficiency, and implementability. The inclusion of hybrid inertia synthesis ensures frequency security even in low-inertia scenarios, while adaptive weighting improves robustness to environmental and operational uncertainties. Empirical evidence and simulation results reported in the literature demonstrate that the framework can reduce frequency nadir by up to 60%, shorten fault recovery time by 45%, and extend energy storage lifetime by approximately 25% [111–113]. Hence, the symbiotic-resilience co-design paradigm represents a promising methodological and engineering pathway for achieving resilient, adaptive, and economically efficient islanded microgrids under high renewable penetration.

The design process based on the five-stage method is summarized in Table 11. In the demand analysis stage, spectral clustering can extract “representative days/typical operating conditions” from a large amount of raw load and meteorological data, significantly reducing the dimensionality of subsequent modeling and avoiding the representativeness bias of random sampling [114]. However, it is sensitive to the similarity measure and the selection of the number of clusters. If the load shows strong seasonality or holiday effects, it is still necessary to combine business prior knowledge or digital twin online correction to maintain generalization [115]. In the symbiotic degree design stage, Pareto multi-objective optimization (such as NSGA-II, MOEA/D, etc.) can generate non-dominated solution sets among conflicting objectives such as LCOE, curtailment rate, ENS/MTTS, and be used for capacity ratio decision-making. The advantage is that it is interpretable and can provide a decision frontier [116]. However, when the dimension increases or discrete/continuous variables are mixed, the convergence speed and parameter sensitivity become the main constraints. In recent years, improved NSGA-II, decomposed MOEA/D, and two-stage MCDM can improve efficiency and decision robustness to a certain extent. In the resilience verification stage, real-time digital simulation platforms such as RTDS and PHIL/HIL

can verify the frequency stability and protection logic of VSG/energy storage PCS under extreme disturbances in a closed loop. The advantages are that they are driven by “true time”, can be directly connected to on-site controllers, and can cover dangerous operating conditions [117]. However, their setup costs and professionalism are relatively high, and model granularity, interface stability, and loop delay can affect the extrapolation of conclusions. Therefore, scene equivalence and interface impedance matching methods need to be combined to ensure the credibility of the tests. In the parameter iteration stage, sensitivity analysis can quantify the marginal impact of indicators on parameters (such as weight coefficients, energy storage rated power/energy, VSG inertia/damping), facilitating the formulation of “minimum adjustment to meet standards” adjustment plans. The limitation lies in the linear/local assumption. When there is strong coupling and non-convexity, global or distributionally robust methods and uncertainty propagation analysis should be combined to avoid the risk of “local optimum—global failure”. In the hardware implementation stage, HIL testing is a key “de-risking” step before the controller is put into operation, which can significantly shorten the debugging cycle and improve reliability/resilience. However, it places strict requirements on real-time simulators, power interfaces, and clock synchronization. The best practice is to use RTDS/OPAL-RT as the core, supplemented by grid-side disturbance scripts and synthetic inertia/protection logic case libraries, to form a consistent verification chain from model to prototype [118]. In summary, the process of “spectral clustering—Pareto optimization—RTDS/PHIL—sensitivity analysis—HIL implementation” achieves a unified approach from data-driven representative extraction to multi-objective trade-offs, and then to true-time verification and engineering closed-loop in terms of methodology. The main challenges lie in the robustness of clustering, the time and parameter dependence of evolutionary algorithms, the interface consistency of real-time platforms, and the nonlinear distortion of sensitivity. These need to be continuously improved through the collaboration of digital twins and distributionally robust optimization to enhance the credibility of the entire chain.

Table 11. Summary of the design process based on the five-stage method.

Stage	Input	Output	Tools/Methods
Requirements analysis	Load curve, meteorological data	Resilience indicator requirements (MTTS, etc.)	Spectral clustering algorithm [114]
Symbiosis Design	ECI/ ζ target value	Capacity allocation plan	Pareto optimization [115]
Resilience verification	Topological parameters, control strategies	Fault recovery rate, Δf_{max}	RTDS real-time simulation [116]
Parameter iteration	Performance Evaluation Report	Weighting coefficient adjustment plan	Sensitivity analysis [117]
Hardware implementation	Final design parameters	Equipment Selection List, Control Parameters	HIL test platform [118]

The phased process for designing the resilience and coordination of an energy symbiosis system in an isolated multi-source complementary microgrid follows the sequence of ‘demand → design → verification → iteration → implementation,’ with the logic of each phase as follows:

Step 1: Demand analysis (starting point).

Through ‘load characteristic spectrum analysis’ (analyzing load patterns under different operating conditions) and ‘disturbance scenario library construction (simulating fault, fluctuation, and other disturbance scenarios), the ‘requirements basis is established for subsequent design, clearly defining the challenges the system must address.

Step 2: Symbiosis Design (Core Phase).

Based on the results of the ‘requirements analysis,’ two key steps are conducted:

Step 2.1: Setting ECI/ ζ Target Values. Define Energy Complementarity and Synergy Indicators (ECI) and Resilience Thresholds (ζ) to clarify the system’s optimization direction.

Step 2.2: Capacity Ratio Optimization. Plan the capacity ratios of energy units (e.g., energy storage, power generation equipment) to balance efficiency and resilience within the system.

Step 3: Resilience Validation (Effectiveness Testing).

Two methods are used to verify whether the design meets the requirements:

Method 1: Digital twin platform. Virtual simulation recreates real-world scenarios to test system response.

Method 2: Monte Carlo simulation. Through extensive random simulations, the system's resilience under complex disturbances is statistically analyzed.

Step 4: Parameter Iteration (Optimization Closed Loop).

If verification does not meet requirements, optimization is achieved through strategy adjustments:

Optimization Strategy 1: Adaptive Weighting Coefficients. Dynamically adjust the priority of various metrics in the design (e.g., resilience, economic efficiency).

Optimization Strategy 2: Topological Structure Reconfiguration. Modify system hardware/connection methods (e.g., energy storage layout, equipment networking) to enhance synergy.

Step 5: Hardware Implementation (Implementation Output).

After iterative optimization, output actual engineering parameters:

Engineering Parameter 1: VSG controller parameters (control configuration of the virtual synchronous generator)

Engineering Parameter 2: Energy storage PCS specifications (capacity and performance metrics of the energy storage converter)

Overall, Logic: Following a closed-loop process of “demand-driven design, validation-driven iteration, and iteration-driven implementation,” this approach ensures the resilience and coordination of the energy system under complex operating conditions, ultimately delivering engineering-ready device parameters from theoretical design to hardware implementation.

4.2. Case Study: Island Hospital Microgrid in Southeast Asia

To validate the practical applicability of the proposed symbiosis–resilience framework, a real-world case from a tertiary hospital microgrid in Southeast Asia is analyzed. The system comprises a 2.5 MW diesel cluster, a 3.0 MWp PV array, and a 1.5 MWh lithium-ion battery ESS, supplying critical medical loads such as ICU and surgical theaters. During Typhoon Tanmei (2024) [119], the island grid was disconnected from the mainland for 72 h. Two scenarios were compared: (i) diesel-only backup operation, and (ii) diesel–PV–ESS symbiotic scheduling. Results are summarized in Table 12.

Quantitative assessment confirmed that under symbiotic operation, the ECI averaged 0.78 and the dynamic coordination coefficient (ζ) remained within 0.71–0.76, both exceeding the recommended thresholds ($\text{ECI} > 0.75$, $\zeta \geq 0.7$). This ensured coordinated balancing between diesel inertia, PV generation, and ESS fast response. From an economic perspective, diesel–PV–ESS symbiosis saved 5600 L of fuel over the 72 h outage, translating into a 14% reduction in LCOE. Environmentally, this equates to approximately 15 tons of avoided CO₂ emissions. Importantly, the extended MTTs (76 h vs. 48 h) demonstrated the resilience advantage of the framework, ensuring uninterrupted supply to critical hospital loads despite prolonged isolation [119]. This case study validates the proposed symbiosis framework as both practically feasible and economically advantageous. It demonstrates that the dual-indicator approach (ECI, ζ) provides actionable guidance in real-world settings, bridging theoretical design and field-level resilience requirements.

Table 12. Microgrid Case Study Results [119].

Indicator	Diesel-Only Backup	Diesel–PV–ESS Symbiosis	Improvement
MTTS	48 h	76 h	+ 58%
Fault recovery rate	79%	92%	+13%
Voltage deviation	$\pm 6.5\%$	$\pm 4.0\%$	−38%
Frequency deviation	± 0.55 Hz	± 0.30 Hz	−45%
Diesel runtime share	100%	65%	−35%
Fuel consumption (3 days)	20,000 L	14,400 L	−28%
Equivalent LCOE	0.168 USD/kWh	0.144 USD/kWh	−14%
CO ₂ emissions	baseline	−18% reduction	—

5. Challenges and Future Directions

5.1. Core Challenges

Isolated multi-source complementary microgrids still face critical technical bottlenecks that hinder their reliable operation under high renewable penetration. A key challenge lies in the temporal mismatch between diesel and PV dynamics. Diesel generators require 2–5 min to start and have ramping rates limited to 10–20% per minute, while PV output can fluctuate by up to 30% within seconds due to cloud movement. This disparity leads to a three- to five-fold increase in the probability of frequency deviations beyond the ± 0.5 Hz safety threshold when PV penetration exceeds 60%. In addition, most diesel units must operate above a 40% minimum load rate to avoid efficiency losses and mechanical issues, which restricts their flexibility during high PV output periods and results in unnecessary curtailment of renewable energy [120].

Another major issue concerns the subjectivity of multi-objective weight allocation in current scheduling methods. Most frameworks rely on fixed weight coefficients to balance economy, reliability, and sustainability, yet a $\pm 10\%$ adjustment in these ratios can produce up to 18% variation in overall scheduling costs. This sensitivity highlights the lack of adaptive and data-driven approaches to weight allocation, which limits the fairness and robustness of optimization outcomes. Similarly, the SOC–lifetime coupling of batteries has not been accurately captured in most existing models. While empirical studies show that expanding the DOD window from 70% to 90% can shorten cycle life by more than 35%, such nonlinear degradation effects are rarely incorporated into optimization, leading to an incomplete understanding of long-term trade-offs between operational performance and asset longevity [121].

Finally, the spatiotemporal propagation of PV forecast errors remains insufficiently considered. One-hour-ahead forecasts often show 15–25% error rates with non-Gaussian heavy-tailed distributions. These errors not only affect single-period dispatch but also propagate across multiple sites and time horizons, compounding uncertainty in reserve allocation. Neglecting such correlated error dynamics forces operators to adopt conservative scheduling strategies, which in practice causes 10–15% losses in energy utilization efficiency. Addressing these limitations requires targeted advances in fast-response hybrid inertia design, adaptive and data-driven optimization methods, degradation-aware ESS scheduling, and robust uncertainty modeling to enhance both resilience and economic efficiency of islanded microgrids [122].

5.2. Breakthrough Path

In response to the above challenges, this study discusses potential solutions from three dimensions.

At the hardware level, the hybrid inertia simulation technology of diesel generator–energy storage can effectively bridge the dynamic response gap [123]. By embedding the virtual synchronous generator (VSG) control algorithm in the energy storage converter, the equivalent system inertia can be increased by 50–80%. In addition, applying diesel engine pre-lubrication and cylinder temperature maintenance technology reduces cold start time to less than 30 s, which has been shown to decrease frequency deviation by up to 42%.

At the algorithm level, particular attention is given to the refinement of weight allocation strategies. Traditional fixed weights often rely on subjective expert judgment, which limits adaptability. To overcome this, an adaptive weight adjustment mechanism based on DRL demonstrates promising potential [124]. For example, the Double-Delay Deep Deterministic Policy Gradient algorithm can dynamically learn the mapping between system state and scheduling objectives, enabling real-time optimization of weight coefficients with a fine adjustment granularity of 0.05. A field microgrid case on an island reported a 12% reduction in operational costs when applying this data-driven approach. These results highlight that adaptive and data-driven weighting not only reduce subjectivity but also improve robustness and decision quality under uncertainty.

At the architectural level, introducing hydrogen as a fourth energy carrier significantly expands the operational boundaries of microgrids [125,126]. By coupling proton exchange membrane electrolyzers (efficiency ~65%) with fuel cells (efficiency ~55%), the system can absorb more than 150% of surplus PV generation while providing up to 72 h of long-duration storage. The main challenge remains economic: current investment costs of \$800/kW must be reduced below \$300/kW to achieve commercial viability. Preliminary techno-economic analyses indicate that this target may be attainable within 5–8 years through scaled-up manufacturing and catalyst innovations.

Together, these hardware, algorithmic, and architectural innovations illustrate a forward-looking roadmap for enhancing resilience and sustainability. In particular, the integration of adaptive, data-driven weight allocation aligns with future research priorities by addressing subjectivity and strengthening optimization-based scheduling.

5.3. Proposed Framework for Future Research

Based on the above analysis, this thesis constructs a “symbiotic-resilience” collaborative design framework, which includes four key stages: (1) Demand quantification stage: spectral clustering algorithms are used to analyze load characteristics, and a test library containing various disturbance scenarios, such as extreme weather and equipment failures, is generated based on Monte Carlo simulation; (2) Structural Configuration Stage: Implementing a “sandwich” energy architecture: a rapid response layer (energy storage, $\tau < 100$ ms), an inertial support layer (diesel generator + VSG), and a renewable energy layer (PV + hydrogen energy), with power decoupling achieved between layers via a DC bus; (3) Intelligent decision-making stage: a hierarchical reinforcement learning architecture is implemented, with the lower layer using an LSTM-based predictive controller for second-level regulation, and the upper layer using multi-agent reinforcement learning (MARL) to achieve hour-level optimization scheduling; (4) Validation and evaluation stage: A digital twin platform is established, integrating device-level high-precision models (e.g., diesel engine Mean Effective Pressure model) and system-level reliability assessment algorithms. The innovative value of this framework lies in using the symbiosis index ($ECI \geq 0.75$) as a design constraint rather than a post-evaluation metric. Simulations indicate that this approach can improve system performance by 25–40% while reducing lifecycle costs by 8–12%.

6. Discussion

This study highlights the critical role of coordinated scheduling among diesel generators, PV systems, and ESS in enhancing the reliability and resilience of islanded microgrids. From an energy symbiosis perspective, several key insights emerge. First, the integration of diesel's security function, PV's clean generation, and ESS's spatiotemporal flexibility can jointly reduce operational costs and improve resilience. Quantitative evidence shows that coordinated operation reduces LCOE by 12–18%, limits voltage deviations to within 5% under 30% PV fluctuation, and extends disturbance tolerance by up to 40% when ESS compensates diesel start-up delays. These findings validate the effectiveness of coupling energy complementarity with resilience-oriented design.

Nevertheless, important challenges remain. Dynamic weight allocation in multi-objective scheduling often relies on static or subjective settings, which may compromise adaptability under variable conditions. Existing methods also lack topology-specific resilience design, as many frameworks are developed under idealized assumptions that may not hold in diverse real-world architectures. Furthermore, current degradation modeling of batteries is often simplified, overlooking the trade-offs between SOC management and long-term ESS longevity. Similarly, most resilience indices focus on either operational or topological aspects, while the proposed ζ -ECI framework suggests that resilience is inherently multidimensional and dynamically coupled with symbiosis.

To address these gaps, several solutions are outlined. At the algorithmic level, adaptive and data-driven methods such as reinforcement learning and uncertainty-aware optimization can provide real-time, context-sensitive weight allocation, thereby reducing subjectivity and improving robustness. At the system design level, the introduction of hybrid inertia emulation and dynamic SOC windows can simultaneously improve short-term frequency stability and long-term asset health. At the architectural level, extending the system boundary to include hydrogen as an additional energy carrier may provide new pathways for long-duration storage and resilience enhancement. Finally, the proposed symbiosis–resilience threshold paradigm and the ζ -resilience coupling equation offer promising theoretical tools to guide optimal capacity ratios and system planning.

Looking forward, future research should focus on integrating uncertainty modeling of PV and load, degradation-aware ESS scheduling, and resilience-oriented performance evaluation into a unified optimization framework. Multi-case engineering validation remains essential to bridge theory and practice, ensuring that advanced methodologies are tested across diverse geographic, climatic, and application contexts. By systematically addressing these challenges, the coordinated diesel–PV–ESS microgrid paradigm can evolve into a robust, scalable, and economically viable solution for remote and mission-critical power systems.

7. Conclusions

This study systematically investigates the cooperative operation mechanisms of islanded multi-source complementary microgrids, focusing on the synergistic integration of diesel generators, PV arrays, and ESS. By analyzing multiple engineering cases and conducting quantitative evaluations, several key conclusions can be drawn.

First, the energy symbiosis mechanism significantly enhances system economics. Optimized coordination among diesel, PV, and ESS reduces the LCOE by 12–18%. This improvement is primarily attributed to a 23–35% reduction in diesel generator runtime, an increase in PV penetration up to 65%, and more than 40% enhancement in energy utilization through storage arbitrage. Notably, when the dynamic synergy index (ζ) exceeds 0.7, the system enters a high-efficiency operating regime, achieving stable generation costs of 0.12–0.15 USD/kWh.

Second, collaborative scheduling strategies substantially strengthen system resilience. The combination of MPC and adaptive weight adjustment yields remarkable improvements: the minimum time to supply is extended by over 30%, fault recovery rate increases from 82% to 94%, and maximum tolerable PV penetration rises by 8 percentage points. These enhancements are largely enabled by intelligent SOC management and rapid diesel generator response, with ESS contributing 65–75% in emergency frequency support.

Third, engineering-oriented recommendations are proposed. For ESS configuration, capacity should cover the diesel startup delay, typically requiring 20–30% of rated diesel power, while PCS ratings must ensure adequate flexibility. For PV integration, high-resolution hybrid forecasting (physical modeling + machine learning) is essential to maintain prediction errors below 12% and trigger storage reserves when deviations exceed 15%. For system optimization, a three-tier design is suggested: (1) optimal capacity ratio of diesel: PV: ESS within 1:1.2–1.8:0.5–1.0; (2) Pareto front-based trade-offs between LCOE and SAIDI; (3) dynamic parameter constraints such as diesel minimum load $\leq 40\%$, ESS SOC within 30–70%, and inverter overload margin $\geq 10\%$.

Finally, future research directions include (i) the integration of hydrogen as a fourth energy carrier, (ii) the development of DRL-based multi-timescale scheduling strategies, and (iii) resilience enhancement under extreme weather scenarios.

Overall, the proposed “symbiosis–resilience” framework provides a systematic solution for the design, retrofit, and operation of islanded microgrids. It offers practical guidance for advancing the reliable and economical application of renewable energy in remote and critical infrastructures.

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Nomenclature

PV	PV
ESS	Energy Storage Systems
LCOE	Levelized Cost of Energy
ζ	Integrating the Dynamic Coordination Degree
ECI	Energy Complementarity Index
IEA	International Energy Agency
PCS	Power Conversion System
DOD	Depth of Discharge
SOC	State of Charge
MAF	Mutual Aid Factor
SE	Symbiotic Entropy
MPC	Model Predictive Control

MAS	Multi-agent Systems
DRL	Deep Reinforcement Learning
VSG	Virtual Synchronous Generator

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