

Article

Research on Microgrid Resilience in Highway Service Areas Based on Federated Multi-Agent Deep Reinforcement Learning

Jiyong Li, Zhiliang Cheng *, Yide Peng, Hao Huang and Chen Ye

School of Electrical Engineering, Guangxi University, Nanning 530004, China; jiyong_li@gxu.edu.cn (J.L.); pengyide2000@163.com (Y.P.); 2312392035@st.gxu.edu.cn (H.H.); yc17332402502@163.com (C.Y.)

* Correspondence: 2312392013@st.gxu.edu.cn; Tel.: +86-180-771-09298

Abstract

This paper proposes a Federated Multi-Agent Deep Reinforcement Learning (FMADRL) framework to enhance the resilience of highway service area microgrids against extreme weather events. The method integrates Generative Adversarial Networks with Monte Carlo simulations to generate high-fidelity weather scenarios, enabling privacy-preserving collaborative optimization across distributed microgrids. A multi-objective approach using the Ripple-Spreading Algorithm yields balanced solutions for economic efficiency, reliability, and response speed. Large-scale simulations demonstrate significant improvements: the proposed method achieves an 88.3 score on the comprehensive system resilience metric, reduces the average fault recovery time from 46.6 min to 8.4 min, lowers annual operating costs by 69.3%, equivalent to 536,945.1 USD, and achieves annual carbon emissions reductions of 285 Mg. This approach provides an innovative solution for enhancing the resilience of distributed microgrids during extreme weather events.

Keywords: extreme weather; federated learning; highway service area; microgrid resilience; multi-agent deep reinforcement learning; multi-objective optimization; ripple diffusion algorithm; scenario generation

1. Introduction

Extreme weather events occur frequently worldwide, causing significant harm to socioeconomic systems and personal safety. At the same time, they pose a serious threat to the safe and stable operation of power systems, especially in grids with a high proportion of renewable energy. In recent years, there has been a noticeable trend of increasing occurrences of multiple extreme weather events repeatedly striking specific regions. For example, Texas in the United States experienced large-scale power outages due to hurricanes [1], heatwaves [2], and winter storm [3]; similar multi-hazard events have also occurred in countries such as Australia [4]. The World Meteorological Organization (WMO) has pointed out that the decade from 2015 to 2024 was the warmest on record [5], and the climate crisis continues to intensify. Against this backdrop, extreme events such as severe convective weather not only occur more frequently than traditional disasters like typhoons [6], but are also more difficult to predict, seriously affecting the stability of power supply.

The reliability and robustness of global electrical networks are being impacted by the reciprocal effects of climate change and severe weather events [7]. In response to climate change and to achieve the 2050 net-zero emissions target, the global energy system is undergoing rapid transformation. The International Energy Agency (IEA) predicts that renewable energy must account for more than 60% of global electricity generation by



Academic Editor: Francesco Riganti Fulginei

Received: 18 December 2025

Revised: 12 January 2026

Accepted: 14 January 2026

Published: 19 January 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

2030 [8]; China's distributed photovoltaic (PV) installed capacity already accounts for 42% of the country's total PV installed capacity [9]. However, clean energy generation such as wind and PV is highly dependent on meteorological conditions and is prone to severe power fluctuations under extreme weather conditions [10,11]. At the same time, electricity load may also rise sharply due to extreme temperatures [12], putting the balance between supply and demand in the power system under tremendous pressure. Actual cases show that extreme weather in Texas in 2021 triggered large-scale power outages and severe economic losses [13]; the cold wave in Northwest China in 2023 caused significant deviations in power forecasting [14]. These situations reveal that extreme weather is significantly exacerbating the operational risks and safety pressures of the power system through both the power source side and the load side [15–17].

Therefore, the “normalization” of extreme weather is profoundly changing the development logic of energy transformation. The planning and operation of the power system need to shift comprehensively from solely pursuing the growth of installed capacity to enhancing the “climate resilience” of the system [18]. Microgrid systems are becoming increasingly complex and intelligent, playing a crucial role in enhancing resistance to extreme weather events, promoting energy equity by ensuring reliable power supply to underserved areas, and promoting energy equity [19]. As critical nodes within the transport network, the resilient operation of microgrid systems at highway service areas during extreme weather is vital for ensuring traffic safety and facilitating emergency response [20].

2. Literature Review

Based on previous research that identified key influencing factors through surveys and ISM–MICMAC analysis, Bai et al. [21] constructed a tripartite evolutionary game model involving the government, service area operators, and carbon emission reduction technology providers, focusing on highway service areas. Wang et al. [22] developed a highway typical scenario operation and maintenance energy demand forecasting model.

Supriya, Y. et al. [23] proposed a unified framework based on FL, which uses PSO algorithm to predict and respond to disasters faster. But its diversity, timeliness, and the gap with the real world deployment are questionable. Ma et al. [24] proposed a resilience-oriented design (ROD) technique to protect distribution grids against high-impact but low-probability extreme weather events. However, traditional microgrid dispatch methodologies primarily based on deterministic optimization or simplistic stochastic optimization struggle to effectively address the high uncertainty introduced by extreme weather. Specific limitations include 1. overly simplified forecasting models that fail to capture the complex spatiotemporal evolution of extreme weather; 2. decision-making mechanisms exhibit sluggish response times, failing to meet real-time dispatch requirements; 3. lack of effective multi-area coordination mechanisms; 4. insufficient robustness, with performance deteriorating sharply under uncertain conditions [25–27].

Vardhini et al. [28] proposes a resource-efficient energy management (REEM) framework for a microgrid interconnected with the main power system. To address the issue of significant unpredictability and intermittent nature of renewable energy sources, particularly wind and solar power, Meng et al. [29] introduces a novel optimization model based on online reinforcement learning.

Shen et al. [30] proposed a collaborative hierarchical dispatch optimization model integrating multi-connected microgrids and Active Distribution Networks (ADN), incorporating disaster mitigation with diverse operational strategies. However, this model focuses solely on the day-ahead scheduling level, failing to establish a closed-loop optimization system spanning the ‘day-ahead-intraday-real-time’ multi-timescale framework.

Yin et al. [31] proposed a multi-objective power system scheduling method adaptable to dynamic operating conditions and varying degrees of renewable energy integration. However, this model primarily addresses single-region system optimization, inadequately accounting for transmission capacity constraints, network loss distribution, and congestion management impacts on scheduling strategies within interconnected grids.

Deep Reinforcement Learning (DRL), possessing robust environmental perception and decision-making capabilities, has been extensively applied in power system optimization scheduling [32–34]. Guo et al. [35] proposed a real-time dynamic optimal energy management (OEM) based on Deep Reinforcement Learning algorithms to assist EMS in making optimal scheduling decisions. Domínguez-Barbero et al. [36] effectively addressed nonlinear dynamic challenges using DRL, investigating the performance of the two-delay deep deterministic policy gradient (TD3) for microgrid EMS incorporating nonlinear battery losses. However, single-agent DRL still faces the curse of dimensionality when handling large-scale distributed systems.

Multi-Agent Reinforcement Learning (MARL) offers a novel paradigm for addressing distributed microgrid cooperative optimization problems [37,38]. Qiu et al. [39] proposed a resilience-oriented decentralized coordination framework for NMG and introduced a novel MARL approach to enhance resilience-boosting efficiency. However, insufficient sampling during Shapley value estimation may lead to biased credit allocation. Al-Hameed et al. [40] proposed MARL framework to perform complex joint optimization of resource allocation (NOMA network power, user scheduling) and network stability, but the agent decision itself has computational delay, and its research did not evaluate the impact of decision delay on system performance in the scenario of rapid user movement. Wang et al. [41] focused on the collaborative scheduling of mobile power and maintenance teams in post disaster recovery, and proposed a decentralized hierarchical MARL framework. However, potential multi-objective conflicts such as recovery speed, fairness, and resource consumption are not considered. Gao et al. [42] proposed a Multi-Agent Reinforcement Learning (MARL) method based on attention mechanism, which can learn optimal microgrid strategies without requiring complex system modeling. However, their method may not be able to verify absolute compliance with safety constraints (such as grid fault ride-through capability) under certain boundary conditions. Recent research trends integrate MARL with federated learning [43–45] and transfer learning [46–48].

In extreme weather modeling, conventional approaches primarily rely on historical statistics or simplistic probability distributions [49]. S. Hanif et al. [50] proposed a distribution network modeling and simulation platform capable of estimating aggregate electricity demand under extreme weather conditions. However, this approach neglects equipment performance degradation under extreme temperatures.

Chen et al. [51] utilized copula models to analyze correlations between typhoon-induced flooding and torrential rainfall, integrating these into a comprehensive energy system planning model. Nevertheless, simplified dynamic constraints and failure mechanisms may underestimate actual risks. Wang et al. [52] constructed a hybrid deep learning model combining convolutional neural networks (CNNs) and bidirectional long short-term memory (BiLSTM) networks, yet neglected model parameter updates and physical constraint equations inherent in real meteorological dynamics.

Using XGboost model and rainfall scenario analysis, Zeng et al. [53] simulated three rainfall scenarios—normal, 10-year, and 20-year return periods. However, the three rainfall scenarios designed in this paper are too extensive in time scale and fail to reflect the key characteristics of rainfall process.

Furthermore, the robustness of optimization algorithms is highly dependent on effective parameter tuning. Recent studies have employed advanced design-of-experiment

methods to enhance algorithm reliability. For example, Taguchi-based optimization frameworks have been successfully applied to tune parameters for a range of power system problems, from capacitor placement in distribution networks [54] to hyperparameter configuration for load forecasting models [55]. These methods systematically identify robust parameter settings that minimize performance variance.

3. Aim of the Study

The increasing frequency and intensity of extreme weather events present severe challenges to the resilience of power systems, particularly for distributed microgrid clusters in critical infrastructures like highway service areas. While existing research in Deep Reinforcement Learning (DRL) and Multi-Agent Reinforcement Learning (MARL) has shown promise in microgrid optimization, critical limitations persist when applied to extreme weather scenarios.

This study aims to develop and validate a novel Federated Multi-Agent Deep Reinforcement Learning (FMADRL) framework specifically designed to enhance the resilience of highway service area microgrids. The primary objectives of this work are as follows:

To develop a high-fidelity extreme weather scenario generation model that integrates Generative Adversarial Networks (GANs) with Monte Carlo simulations. This model is designed to efficiently produce a large number of spatiotemporally correlated scenario samples, moving beyond the limitations of traditional methods to accurately reflect the dynamic characteristics of extreme events.

To establish a privacy-preserving, collaborative optimization framework by organically combining federated learning (FL) with MADRL. This framework is intended to enable efficient coordination among distributed microgrids without centralizing sensitive operational data, thereby overcoming the “data silo” issue and enhancing scalability.

To introduce the Ripple-Spreading Algorithm (RSA) into the multi-objective optimization process, aiming to obtain a well-distributed Pareto front that provides robust decision-making options balancing economic efficiency, reliability, and response speed.

The ultimate goal is to demonstrate that the proposed FMADRL framework can significantly improve key resilience metrics, including reducing fault recovery time and operational costs, thereby providing a robust and innovative solution for securing power supply in critical transportation infrastructures under extreme weather conditions. The performance of the proposed method will be rigorously validated against several state-of-the-art algorithms through large-scale simulations.

4. Materials and Methods

4.1. Microgrid System Architecture for Highway Service Areas

The highway service area microgrids constitute a complex energy system, primarily comprising distributed power sources (photovoltaic, wind power), energy storage systems, electric vehicle charging stations, mobile emergency power supplies, and various loads. The system achieves coordinated control of its components through an Energy Management System (EMS). This paper constructs an integrated energy system architecture encompassing five adjacent service area microgrids, three emergency power supply vehicles, and an FMADRL distributed collaborative control center, as illustrated in Figure 1. Due to specific methodological and practical reasons, this study focuses on a cluster consisting of five adjacent service areas. This scale can demonstrate the challenges faced by distributed coordination and uncertainty management, and it is also easy for in-depth algorithm development and verification. Secondly, the service areas are separated by 30 to 50 km, which is a typical configuration in many road networks, making this study of practical significance.

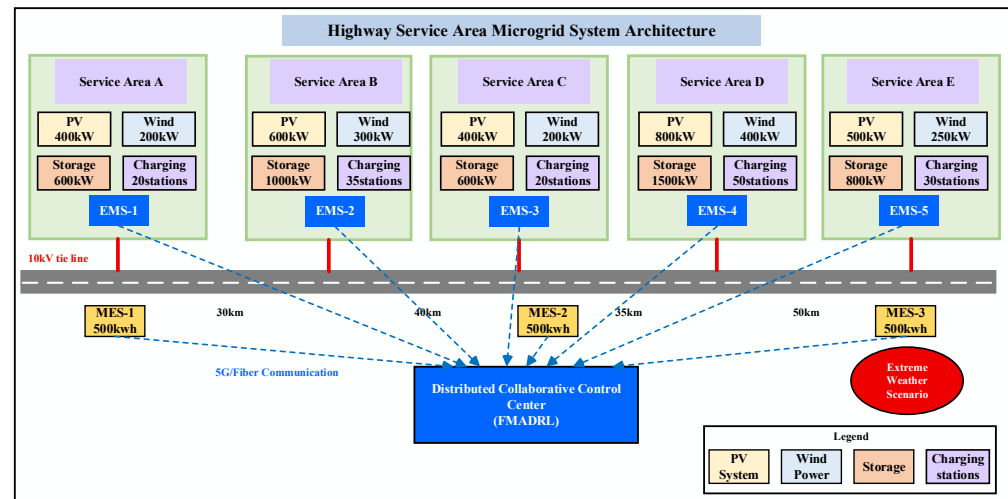


Figure 1. Microgrid system architecture for highway service areas.

The diagram details the microgrid system layout across five adjacent service areas (A–E), spaced 30–50 km apart and interconnected via 10 kV feeder lines for mutual power support. Each service area configuration comprises (1) photovoltaic (PV) systems (400–800 kW), scaled according to site size and geographical conditions; (2) wind power generation (WT) 200–400 kW, primarily deployed in service areas with abundant wind resources; (3) battery energy storage system (ESS) 600–1500 kWh, utilizing lithium iron phosphate batteries with a cycle life exceeding 6000 cycles; (4) electric vehicle charging station (CS) equipped with 20–50 charging points, including both fast and slow charging.

During extreme weather conditions, the system can deploy three Mobile Emergency Supply (MES) vehicles, each equipped with 500 kWh energy storage capacity and 200 kW power output capability. Under normal operation, each service area prioritizes consumption of locally generated renewable energy, with surplus electricity transmitted via interconnectors to adjacent service areas. During extreme weather, multi-service area coordinated power supply is achieved through interconnectors and MES, ensuring uninterrupted power supply to critical loads.

4.2. Mathematical Model Construction

4.2.1. Objective Function

This paper establishes a three-objective optimization model, comprehensively considering economic efficiency, reliability, and response speed. This multi-objective function will be employed within the subsequent Federated Multi-Agent Deep Reinforcement Learning (FMADRL) framework. It calculates the state-action pair data obtained through agent–environment interaction sampling, serving as the foundational reward signal for training agent policies.

Objective 1: Minimization of Economic Cost

The minimization of economic cost functional expression is as follows:

$$f_1 = \sum_{t=1}^T \left[C_{grid}(t)P_{grid}(t) + \sum_{i \in \mathcal{I}} C_{shed,i}P_{shed,i}(t) + \sum_{j \in \mathcal{J}} C_{deg,j}(t) + C_{MES}P_{MES}(t) \right] \quad (1)$$

where $C_{grid}(t)$ is the grid electricity price at t time (\$), $C_{shed,i}$ represents the load shedding cost for i -th load category (\$), $C_{deg,j}$ indicates the degradation cost of the j -th energy storage device (\$), and C_{MES} signifies the dispatch cost of mobile emergency power supplies (\$).

Objective 2: Minimization of System Risk

The minimization of system risk functional expression is as follows:

$$f_2 = \sum_{s \in \mathcal{S}} \pi_s \sum_{i=1}^N \sum_{t=1}^T V_i(t, s) \cdot P_{fail,i}(t, s) \cdot L_i(t, s) \quad (2)$$

where π_s denotes the probability of scenario s ; $V_i(t, s)$ represents the vulnerability index of equipment i under scenario at time t , $P_{fail,i}(t, s)$ indicates the failure probability, and $L_i(t, s)$ denotes the failure loss.

Objective 3: Minimization of Response Time

The minimization of response time functional expression is as follows:

$$f_3 = \sum_{k=1}^K \left[t_{detect,k} + t_{decision,k} + t_{action,k} + t_{recovery,k} \right] \quad (3)$$

where $t_{detect,k}$ is the detection time for the k -th fault (s), $t_{decision,k}$ is the decision time (s), $t_{action,k}$ is the execution time (s), and $t_{recovery,k}$ is the recovery time (s).

4.2.2. Constraints

(1) Power Balance Constraints

The functional expression is as follows:

$$\sum_{g \in \mathcal{G}} P_g(t) + P_{Grid}(t) + P_{ESS}^{dis}(t) - P_{ESS}^{ch}(t) + P_{MES}(t) = \sum_{l \in \mathcal{L}} P_l(t) + P_{loss}(t), \forall t \quad (4)$$

where $P_g(t)$ is the output power of the g -th distributed power source at time t (kW), including photovoltaic, wind power, etc.; $P_{Grid}(t)$ is the power purchased from the main grid at time t (kW); $P_{ESS}^{dis}(t)$ is the discharge power of the energy storage system at time t (kW); $P_{ESS}^{ch}(t)$ is the charging power of the energy storage system at time t (kW); $P_{MES}(t)$ is the support power from the mobile emergency power supply at time t (kW); $P_l(t)$ is the demand power of the l -th load at time t (kW); $P_{loss}(t)$ is the system network loss power at time t (kW), obtained through power flow calculation; $\mathcal{G}$ is the set of distributed power sources; $\mathcal{L}$ is the set of loads.

(2) Energy Storage System Constraints

State transition equation for the energy storage system:

$$SOC(t+1) = SOC(t) + \frac{\Delta t}{E_{rated}} \left(\eta_{ch} P_{ESS}^{ch}(t) - \frac{P_{ESS}^{dis}(t)}{\eta_{dis}} \right) \quad (5)$$

$SOC(t+1)$ is the state of charge of the energy storage system at time t (%); Δt is the time step (h), taken as 1 hour in this paper; E_{rated} is the rated capacity of the energy storage system (kWh); η_{ch} is the charging efficiency (taken as 0.95); η_{dis} is the discharging efficiency (taken as 0.95).

Energy Storage Power and Capacity Constraints:

$$\begin{cases} 0 \leq P_{ESS}^{ch}(t) \leq P_{ESS,max}^{ch} \\ 0 \leq P_{ESS}^{dis}(t) \leq P_{ESS,max}^{dis} \\ SOC_{min} \leq SOC(t) \leq SOC_{max} \end{cases} \quad (6)$$

where $P_{ESS,max}^{ch}$ represents the maximum allowable charging power (kW); $P_{ESS,max}^{dis}$ denotes the maximum allowable discharging power (kW); SOC_{min} indicates the lower limit of energy storage (%) (set to 20%); SOC_{max} signifies the upper limit of energy storage (%) (set to 90%).

(3) Distributed Generation Constraints

$$0 \leq P_{PV}(t) \leq P_{PV,forecast}(t), 0 \leq P_{WT}(t) \leq P_{WT,forecast}(t) \quad (7)$$

$P_{PV}(t)$ is actual output of the PV system at time t (kW); $P_{PV,forecast}(t)$ is the predicted maximum output of the PV system at time t (kW), generated based on weather data; $P_{WT}(t)$ is actual output of the wind turbine at time t (kW); $P_{WT,forecast}(t)$ is the predicted maximum output of the wind turbine at time t (kW).

(4) Network Power Flow Constraints

The network power flow constraints functional expression is as follows:

$$|P_{tie,j}(t)| \leq P_{tie,max}, V_{min} \leq V_i(t) \leq V_{max} \quad (8)$$

where $|P_{tie,j}(t)|$ represents the transmission power of the j -th interconnection line at time t (kW), with positive and negative signs indicating power direction; $P_{tie,max}$ denotes the maximum allowable transmission power of the interconnection line (kW), determined by line capacity; $V_i(t)$ indicates the voltage magnitude at node i at time t (kV); V_{min} and V_{max} represent the lower and upper limits for safe voltage operation (set at 0.95 p.u. and 1.05 p.u. in this paper).

4.2.3. Resilience Evaluation Metric System

To comprehensively evaluate the resilience of microgrid systems under extreme weather conditions, this paper constructs a six-dimensional resilience assessment indicator system based on reference [56] and references [57], ensuring the objectivity of the evaluation.

(1) Six-Dimensional Resilience Evaluation Indicator System

$$R = \{R_{rob}, R_{rap}, R_{res}, R_{red}, R_{ada}, R_{rec}\} \quad (9)$$

Robustness measures the system's ability to withstand disturbances while maintaining core functions. The robustness functional expression is as follows:

$$R_{rob} = 1 - \frac{\sum_{t \in \text{extreme}} P_{shcd}(t)}{\sum_{t \in \text{extreme}} P_{load}(t)} \quad (10)$$

where R_{rob} is the robustness indicator; values closer to 1 indicate stronger system capability to maintain power supply during extreme events. $P_{shcd}(t)$ represents the system's load shedding power at time t (kW), and $P_{load}(t)$ denotes the system's total load demand power at time t (kW). A lower load shedding rate corresponds to a higher robustness score.

Rapidity measures the system's response and decision-making speed in handling faults. The rapidity functional expression is as follows:

$$R_{rap} = \frac{1}{N_{fault}} \sum_{i=1}^{N_{fault}} e^{-\alpha t_{rapid,i}} \quad (11)$$

where R_{rap} is the rapidity indicator. A value closer to 1 indicates a faster average system recovery speed. N_{fault} is the total number of fault events occurring within the evaluation period. $t_{rapid,i}$ is the recovery time for the i -th fault (min).

Resourcefulness measures the system's capability to mobilize resources and safeguard critical loads during emergency conditions. The resourcefulness functional expression is as follows:

$$R_{res} = \frac{\sum_{r \in R} P_{available,r}}{\sum_{l \in L} P_{critical,l}} \quad (12)$$

where R_{res} is the resourcefulness indicator. A ratio greater than 1 indicates sufficient available resources, with higher values signifying better resourcefulness. r is the index of available emergency resources. R is the set of all available emergency resources in the system (e.g., energy storage, mobile emergency power supplies, backup generators). $P_{available,r}$ is the maximum power that the r -th emergency resource can provide under the current state (kW). l is the index of critical loads. L is the set of all critical loads in the system. $P_{critical,l}$ is the power demand of the l -th critical load (kW).

Redundancy measures the adequacy of a system's reserve capacity. The redundancy functional expression is as follows:

$$R_{red} = \frac{P_{reserve}}{P_{peak}} \quad (13)$$

where R_{red} is the redundancy indicator for system reserve capacity. $P_{reserve}$ is the total reserve capacity of the system (kW). P_{peak} is the historical peak load or design maximum load of the system (kW).

Adaptability measures a system's capability to reconfigure its network and maintain operation under abnormal conditions. The adaptability functional expression is as follows:

$$R_{ada} = \frac{N_{successful \text{ reconfig}}}{N_{total \text{ reconfig}}} \quad (14)$$

where R_{ada} is the adaptability metric, ranging from 0 to 1, where values closer to 1 indicate higher success rates in network reconfiguration. $N_{successful \text{ reconfig}}$ is the number of successful network reconfigurations during the evaluation period. $N_{total \text{ reconfig}}$ is the total number of attempted network reconfigurations during the evaluation period.

Recovery measures the speed and effectiveness of the system's transition from a fault state back to normal operation. The recovery functional expression is as follows:

$$R_{rec} = \frac{1}{T_{total}} \int_{T_{start}}^{T_{recovery}} \frac{P_{served}(t)}{P_{normal}} dt \quad (15)$$

where R_{rec} is the recovery indicator, representing the average power restoration ratio during the recovery period. T_{start} is the start time of the recovery process (min). T_{end} is the end time of the recovery process (min). T_{total} is the total recovery duration (min). $P_{served}(t)$ is the actual load power supplied by the system at time t (kW). P_{normal} is the total load power under normal system conditions (kW).

(2) Data Collection, Processing, and Resilience Composite Score Calculation

After completing simulation tests for the five algorithms (FMADRL, IWOA, HGWO, AHHO, D3PG), raw data for each algorithm across multiple independent runs were collected for the aforementioned six metrics. Due to differing units among metrics, normalization was performed to standardize them within the [0, 1] range for comprehensive comparison. This study employs the minimum–maximum normalization method.

For positive indicators such as robustness and resourcefulness, the normalization formula is

$$S_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (16)$$

For negative indicators, first take their reciprocals to convert them into positive indicators before normalization. In the formula, x_i is the original indicator value, while $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values achieved by all evaluated algorithms on that indicator, respectively. Ultimately, each algorithm receives a standardized score S_i for each indicator.

The comprehensive resilience score employs a weighted aggregation method. The functional expression is as follows:

$$R_{\text{total}} = \sum_{i=1}^6 w_i R_i \quad (17)$$

where R_{total} represents the comprehensive resilience score, which is the final quantified value of the system's overall resilience level. w_i denotes the dimension weight, and R_i indicates the standardized score (0–1) for the i -th resilience dimension.

Dimension weights are determined using the Analytic Hierarchy Process (AHP). Common weight ranges in microgrid resilience research are extracted from references [58], and a judgment matrix is constructed based on algorithm characteristics. A 1–9 scale matrix is defined based on consensus from existing studies regarding the relative importance of dimensions such as robustness and responsiveness.

After calculating the maximum eigenvalue and eigenvector, normalization yields the weight vector $w = [0.20, 0.15, 0.15, 0.15, 0.15, 0.20]$. The consistency ratio (CR) was calculated as 0.05 (<0.1), passing the consistency test.

4.3. Extreme Weather Scenario Generation

This section constructs a high-fidelity extreme weather scenario generation model integrating GAN and Monte Carlo methods. It provides a spatiotemporally correlated uncertainty input set for resilience assessment and optimization, serving as the foundation for quantifying system risks and validating algorithm performance.

4.3.1. CMIP6-Based Long-Term Climate Prediction Ensemble

Radiative forcing (RF) is a key physical metric that quantifies the perturbation of the Earth's energy balance caused by external factors, such as changes in greenhouse gas concentrations, with units of watts per square meter (W/m^2). A positive RF value indicates a net warming effect on the climate system. This study employs the characteristic end-of-century radiative forcing values from four Representative Concentration Pathways (RCPs) under the Shared Socioeconomic Pathways (SSPs) framework—2.6, 4.5, 7.0, and $8.5 \text{ W}/\text{m}^2$ —to construct scenarios representing a spectrum of future climate conditions.

This study employs climate projection data from the Sixth Coupled Model Inter-comparison Project (CMIP6), considering four representative scenarios combining Shared Socioeconomic Pathways (SSPs) with typical concentration pathways: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. Their fundamental characteristics are as follows:

SSP1-2.6: A low forcing scenario under the sustainable development pathway, with RF stabilizing at $2.6 \text{ W}/\text{m}^2$ by 2100, representing a sustainable and low-carbon future.

SSP2-4.5: A medium forcing scenario under the intermediate pathway, with RF stabilizing at $4.5 \text{ W}/\text{m}^2$, representing a continuation of historical trends.

SSP3-7.0: A medium-to-high forcing scenario under regional competition pathways, with RF reaching 7.0 W/m^2 , representing a future characterized by regionalization and uneven development.

SSP5-8.5: High forcing scenario under a fossil fuel-dominated development pathway, with RF at 8.5 W/m^2 , representing a future of high energy consumption and emissions.

4.3.2. Statistical Downscaling Method Combining the Delta Method and Geographically Weighted Regression

To convert coarse-resolution data (approximately 100–300 km) from global climate models into fine-resolution data (target 1–10 km) suitable for highway service area scales, this study employs a statistical downscaling workflow combining the Delta method and geowinning regression. The steps are as follows:

(1) Data Preprocessing:

Download monthly data from the aforementioned CMIP6 models for both the historical period (1961–2014) and future scenario period (2015–2100). Employ the Climate Data Operator (CDO) and Python xarray library to extract, convert units, and resample data, interpolating all data onto a unified latitude–longitude grid.

(2) Delta Increment Calculation:

For each climate model and scenario, compute the change (Delta value) in climate state averages (e.g., monthly mean temperature, monthly total precipitation) during the future period (e.g., 2041–2060) relative to the historical baseline period (1995–2014).

(3) Geographically Weighted Regression Downscaling:

Established geographically weighted regression models for each grid point within the study area. High-resolution observational data (e.g., ERA5-LAND reanalysis data with approximately 0.1° resolution) served as the dependent variable, while CMIP6 historical simulation data acted as the independent variable. This model incorporates a geographically weighted matrix to account for the local influence of geographical factors such as topography, latitude, and distance from the sea on climate variables.

(4) Application of Delta Increments:

The low-resolution Delta increments calculated in Step 2 are applied to the high-resolution observed climate field via the regression relationship established in Step 3, yielding high-resolution climate projections for future periods. This method effectively integrates large-scale climate model signals with local geographic characteristics.

4.3.3. Generative Adversarial Network Architecture

The Generative Adversarial Network comprises a Generator and a Discriminator, employing a deep convolutional network architecture. The Generator maps random noise and conditional vectors into weather sequences, while the Discriminator distinguishes between real weather data and generated data. The following details the network layer parameters and loss calculations.

(1) Generator Network Architecture

The Generator employs a fully convolutional network designed based on the DCGAN framework, with specific layer parameters as follows:

The input layer combines a 100-dimensional random noise vector with a conditional vector (containing season, geographic location, SSP scenarios, etc.) into a joint input of 128 dimensions. The hidden layer consists of five layers of transposed convolutions (deconvolutions). Parameters for each layer are shown in Table 1.

Table 1. Detailed parameters of generator transposed convolution layers.

Layer Number	Input Channels	Output Channels	Convolution Kernel Size	Stride	Padding	Activation Function	Remarks
1 (Input layer)	128	512	4×4	1	0	LeakyReLU	Concatenate of received noise and conditional vector
2	512	256	4×4	2	1	LeakyReLU, BatchNorm	Batch Normalization
3	256	128	4×4	2	1	LeakyReLU, BatchNorm	Batch Normalization
4	128	64	4×4	2	1	LeakyReLU, BatchNorm	Batch Normalization
5 (output layer)	64	4	4×4	2	1	Sigmoid	Output 48×4 weather sequence

(2) Classifier Network Architecture

The discriminator is a convolutional network that takes real or generated weather sequences as input and outputs probability values for authenticity. The input layer is a 48×4 weather sequence matrix processed as multi-channel input (number of channels = 4). The hidden layer consists of 5 convolutional layers, with parameters for each layer shown in Table 2.

Table 2. Detailed parameters of transposed convolution layers in the classifier.

Layer Number	Input Channels	Output Channels	Convolution Kernel Size	Stride	Padding	Activation Function	Remarks
1	4	64	4×4	2	1	LeakyReLU (slope = 0.2), Dropout (0.3)	Receives a 48×4 weather sequence matrix
2	64	128	4×4	2	1	LeakyReLU, BatchNorm	Feature map size halved
3	128	256	4×4	2	1	LeakyReLU, BatchNorm	Stepwise extraction of high-level features
4	256	512	4×4	2	1	LeakyReLU, BatchNorm	Near the bottleneck layer
5	512	1	4×4	1	0	Sigmoid	Outputs a single scalar representing the probability that the input is real data

(3) Loss Function Calculation

The loss function is based on the minimax game formula from the original GAN, but employs an improved objective to avoid gradient saturation issues during early training. Discriminator Loss to maximize the accuracy of distinguishing real data from generated data, the loss function is binary cross-entropy. The functional expression is as follows:

$$\mathcal{L}_D = -\mathbb{E}_{x \sim p_{\text{data}}} [\log D(x)] - \mathbb{E}_{z \sim p_z} [\log(1 - D(G(z)))] \quad (18)$$

where x represents real weather data, z is the noise vector, $D(x)$ is the discriminator output, and $G(z)$ is the generator output. During training, noise is introduced to real data labels (e.g., label smoothing using random values between 0.9 and 1.0), while random values between 0 and 0.1 are applied to generated data to enhance stability. To avoid gradient saturation in $\log(1 - D(G(z)))$ during early training, the generator loss employs an inverted objective function: maximizing the discriminator's misclassification probability for generated data. The functional expression is as follows:

$$\mathcal{L}_G = -\mathbb{E}_{z \sim p_z} [\log D(G(z))] \quad (19)$$

This is equivalent to minimizing binary cross-entropy, where generated data labels are treated as true (labeled as 1).

(4) Training Details

After each discriminator training iteration, the generator is trained once (1:1 alternation). Gradient penalties (WGAN-GP) enforce Lipschitz conditions on the discriminator to enhance convergence stability. All convolutional layers use Xavier initialization, with BatchNorm momentum set to 0.8. Boundary constraints for meteorological elements (e.g., temperature and pressure ranges) are incorporated into the loss function to ensure generated sequences comply with physical laws.

4.3.4. Scenario Generation and Clustering

Using the trained GAN generator combined with Monte Carlo sampling, 1000 candidate extreme weather scenarios were generated. To extract representative patterns from the large number of generated scenarios, the K-means clustering algorithm was applied to group these scenarios into 10 typical scenarios. Key parameters for the clustering process are defined as follows:

(1) Distance Metric

Euclidean distance is employed as the metric for measuring similarity between samples. This distance effectively quantifies the overall divergence among high-dimensional meteorological sequences ($48 \times 4 = 192$ dimensions).

(2) Initialization Method

Initialization employs the K-means++ algorithm to initialize cluster centers, thereby avoiding the local optima issues that may arise from traditional random initialization.

(3) Maximum Iteration Count

The maximum iteration count is set to 300 to ensure the algorithm converges sufficiently.

(4) Convergence Tolerance

The convergence tolerance is set to 1×10^{-4} . Iteration stops when the distance between cluster center movements in two consecutive iterations falls below this value.

4.3.5. Equipment Vulnerability Modeling

Considering the impact of extreme weather on equipment and fault propagation effects, a vulnerability model is established:

$$V_i(t) = V_{\text{base},i} \cdot f(W_i(t)) \cdot \left(1 + \sum_{j \neq i} \rho_{ij} e^{-d_{ij}\lambda_j} V_j(t - \tau_{ij}) \right) \quad (20)$$

where $V_{\text{base},i}$ is the baseline vulnerability of device i (determined by device age, maintenance status, etc.); $f(W_i(t))$ is the weather intensity impact function, implemented using a Sigmoid form; ρ_{ij} is the fault propagation coefficient between devices; d_{ij} is the electrical distance; λ is the spatial attenuation constant; τ_{ij} is the fault propagation delay.

4.3.6. Scenario Generation Model Performance Validation

The proposed GAN–Monte Carlo hybrid approach offers distinct advantages over traditional physics-based scenario generation methods in the context of microgrid resilience assessment. Physics-based models, which rely on solving complex atmospheric dynamics equations, are computationally prohibitive for generating the large number of scenarios (e.g., 1000 in this study) required for robust statistical analysis. More critically, they often

struggle to capture the complex, nonlinear spatiotemporal correlations of extreme weather events at the local scale of highway service areas. The data-driven hybrid model learns directly from high-resolution historical climate data (CMIP6 and ERA5-LAND reanalysis). This enables it to efficiently generate a multitude of plausible scenarios that accurately capture the statistical properties and dynamic evolution characteristics of real extreme events. This capability is crucial for stress-testing the microgrid system against a wide spectrum of potential hazards, thereby providing a more relevant and comprehensive foundation for resilience optimization.

Figure 2 shows the line chart generated by the proposed GAN–Monte Carlo fusion extreme weather scenario model, depicting the evolution of wind speed over 48 h during a typical typhoon passage event. Wind speeds remain steady initially, then begin a sharp increase around hour 15, peaking at approximately 35 m/s by hour 24. Following the intense impact of the typhoon’s core, wind speeds rapidly decline. This curve provides a dynamic and severe extreme weather input scenario for subsequent microgrid resilience assessments.

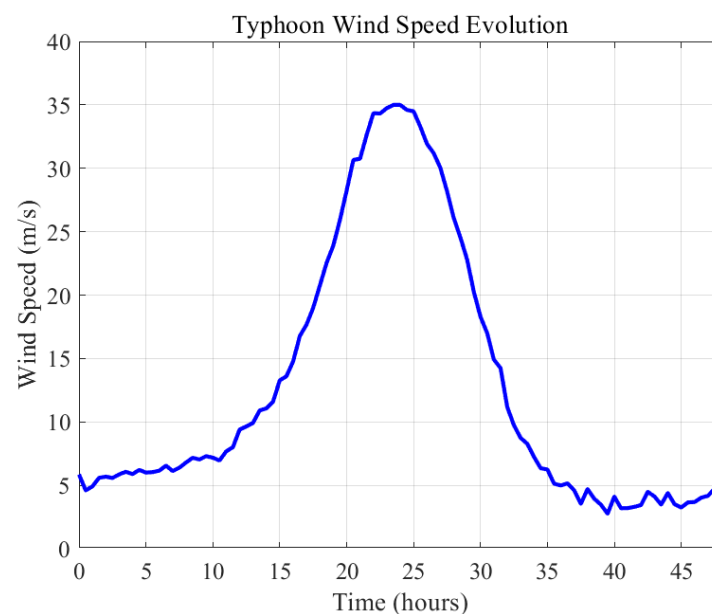


Figure 2. Temporal characteristics of typhoon scenario.

The peak wind speed of 35 m/s (equivalent to a Category 13 typhoon) generated by the model is realistic and aligns with typical extreme weather events. For instance, according to meteorological standards (e.g., China Meteorological Administration), typhoons in coastal regions often exhibit maximum sustained winds of 30–40 m/s.

Figure 3 demonstrates the performance comparison of four clustering algorithms in generating typical weather scenarios, verifying the superiority of K-means. Results clearly show that K-means achieved a contour coefficient as high as 0.93, significantly outperforming Spectral (0.58), Hierarchical (0.52), and DBSCAN (0.45).

This advantage validates the appropriateness of using K-means for clustering massive random scenarios, ensuring the extracted typical scenarios possess the highest intra-class compactness and inter-class separability. This provides high-quality representative samples for subsequent model training.

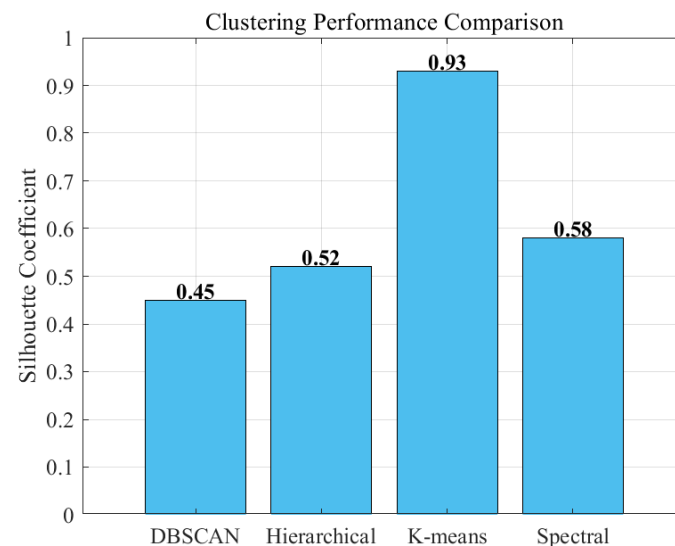


Figure 3. Performance comparison of K-means with different clustering methods.

4.4. Federated Multi-Agent Deep Reinforcement Learning (FMADRL) Framework

This section designs a federated multi-agent distributed collaborative decision-making framework. Serving as the system's intelligent scheduling hub, this framework directly generates real-time optimization strategies for extreme events through interactive learning among multiple agents.

4.4.1. Multi-Agent System Architecture

Each microgrid controller in a service area is modeled as an agent, forming a distributed multi-agent system. The Markov Decision Process (MDP) for agent i is defined as follows:

(1) State Space

The functional expression is as follows:

$$s_i^t = \{s_{\text{local},i}^t, s_{\text{neighbor},i}^t, s_{\text{global}}^t\} \quad (21)$$

where $s_{\text{local},i}^t$ represents local state information, including SOC, load demand, renewable energy output, equipment status, and local weather; $s_{\text{neighbor},i}^t$ denotes shared information from neighboring agents (adjacent service areas), such as neighbor energy storage status, load levels, and interconnection line capacity; s_{global}^t encompasses global information, including electricity price signals, MES location, and system emergency levels.

(2) Action Space

The functional expression is as follows:

$$a_i^t = \{p_{\text{ESS},i}^{\text{ch/dis}}, p_{\text{tie},i}, p_{\text{shed},i}, \text{request}_{\text{MES},i}\} \quad (22)$$

where $p_{\text{ESS},i}^{\text{ch/dis}}$ represents the energy storage charging/discharging power of agent i , (kW). $p_{\text{tie},i}$ represents the interconnection line power exchange value of agent i (kW). $p_{\text{shed},i}$ represents the load shedding amount of agent i (kW). $\text{request}_{\text{MES},i}$ represents the demand level for mobile emergency power of agent i .

(3) Reward Function

$$r_i^t = \alpha_1 r_{\text{econ},i}^t + \alpha_2 r_{\text{rel},i}^t + \alpha_3 r_{\text{envi},i}^t + \alpha_4 r_{\text{coop},i}^t \quad (23)$$

Comprehensively considering economic efficiency, reliability, environmental friendliness, and collaboration, α_1 , α_2 , α_3 , and α_4 represent the corresponding weight coefficients, satisfying the following: $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$.

To scientifically determine weights and avoid subjective bias, this study employs an objective weighting method combining the Analytic Hierarchy Process (AHP) structure with entropy weighting to establish indicator importance:

- Construct hierarchical structure and management. The four dimensions of the reward function (economic efficiency, reliability, environmental friendliness, and collaboration) serve as criteria-level indicators.
- Construct a data-driven judgment matrix. Calculate the intrinsic relationships among indicators based on historical operational data (or simulation data from typical scenarios). Measure the relative importance of each indicator by calculating the conflict (or correlation) between any two indicators. Conflict C_{ij} is quantified using the negative correlation coefficient between indicators i and j or the contradiction quantity derived from indicator values. Ultimately, an objective judgment matrix A is constructed through data-driven correlation analysis.
- Calculate weights and perform consistency check. Calculate the maximum eigenvalue of decision matrix A and its corresponding eigenvector. After normalizing the eigenvector, obtain the initial weights $[\alpha_1, \alpha_2, \alpha_3, \alpha_4]$. Subsequently, conduct a consistency check to ensure the logical validity of the decision matrix (in this study, the consistency ratio $CR < 1$, passing the test).
- Determining final weights. The final weights obtained through the above process are $[0.35, 0.25, 0.15, 0.25]$. This weighting scheme reflects that in enhancing the resilience of microgrids in highway service areas, cost-effective operation and power supply reliability are primary objectives, while environmental sustainability and inter-system coordination serve as crucial supporting goals. Together, these weights form a balanced optimization framework.

4.4.2. DQN Network Architecture

Each agent adopts a Double Deep Q-Network (DQN) architecture. This design decouples the calculation of target Q-values from the action selection process, effectively addressing the overoptimism issue common in traditional DQN Q-value estimation and significantly enhancing training stability.

Q-function updates are based on the Bellman optimality equation using Temporal Difference (TD) learning:

$$Q(s_t, a_t; \theta) \leftarrow Q(s_t, a_t; \theta) + \alpha [r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta)] \quad (24)$$

where $Q(s_t, a_t; \theta)$ is the Q-value estimated by the current network (or online network) parameters θ for executing action a_t in state s_t . $\alpha = 0.001$ is the learning rate controlling the step size of each parameter update. $\gamma = 0.95$ is the discount factor measuring the importance of future rewards relative to immediate rewards. θ is the target network parameter. $\max_{a'} Q(s_{t+1}, a'; \theta^-)$ is the maximum Q-value for the next state s_{t+1} computed using target network parameters θ^- .

4.4.3. Federated Learning Collaboration Mechanism

To protect privacy data across service regions, a federated learning framework is adopted for distributed training. The Federated Average (FedAvg) algorithm proceeds as follows:

(1) Global Model Broadcast

At the start of each training round t , the central server broadcasts the current global model parameters θ_{global}^t to all participating agents (i.e., the five service area microgrid controllers).

(2) Local Model Training

Each agent i receives the global parameters and performs $E = 5$ rounds of local training on its private dataset (stored in its experience replay buffer) to obtain a local model θ_i^{t+1} . The local training objective is to minimize the Temporal Difference error loss function (Equation (25)) using the Adam optimizer with a learning rate of 0.001. Crucially, all raw operational data (e.g., load profiles, generation output) remains locally on the agent's system and is never shared.

Local model training across service areas: after receiving global parameters, each agent i performs E rounds of local training using its local data. The objective is to optimize the parameters of its Deep Q-Network (DQN) to minimize the local loss function based on Temporal Difference error:

$$\min_{\theta_i} \mathcal{L}_i(\theta_i) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{D}_i} \left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_i^-) - Q(s, a; \theta_i) \right)^2 \right] \quad (25)$$

where $\mathcal{D}_i$ is the local experience replay buffer for agent i , and θ_i^- are its target network parameters. Training employs the Adam optimizer with learning rate $\alpha = 0.001$ and momentum parameter $\beta_1 = 0.9$, $\beta_2 = 0.999$ to balance convergence speed and stability. Upon completion, the updated local model parameters θ_i^{t+1} are obtained.

(3) Uploading Model Parameters from Service Areas

To protect data privacy, each agent uploads only the trained local model parameters θ_i^{t+1} to the central server, not any raw operational data.

(4) Central Server Aggregation Update

After collecting all agents' local model parameters, the central server performs federated averaging to generate the next generation of global model parameters.

$$\theta_{\text{global}}^{t+1} = \sum_{i=1}^N \frac{n_i}{n} \theta_i^{t+1} \quad (26)$$

where $n_i = |\mathcal{D}_i|$ represents the effective capacity of agent i 's local experience replay buffer during the current communication round, while $n = \sum_{i=1}^N n_i$ denotes the total buffer capacity across all agents. This weighted averaging ensures agents with larger datasets contribute more significantly to the global model, making the aggregation fairer and more effective.

This iterative process of broadcast, local training, upload, and aggregation continues for a total of 50 communication rounds, allowing the global model to learn from the collective experience of all service areas without centralizing their private data.

4.4.4. Ripple Diffusion Multi-Objective Optimization Algorithm

This paper proposes an efficient multi-objective optimization algorithm for determining the Pareto optimal frontier, providing a set of optimal trade-off solutions for real-time decision-making to guide the optimization direction of collaborative scheduling strategies.

(1) Algorithm Principle

The Ripple-Spreading Algorithm (RSA) simulates the physical process of water droplets creating ripples upon hitting a water surface, demonstrating strong global search capabilities. The core update equation is

$$x_i^{t+1} = x_i^t + r_i^t \cdot \text{rand}() \cdot \frac{x_{\text{best}} - x_i^t}{\|x_{\text{best}} - x_i^t\|} \quad (27)$$

where t denotes the current iteration number. i represents the index of the i -th solution in the population. x_i^t is the position of the i -th solution in the t -th generation. x_i^{t+1} is the position of the newly updated solution. r_i^t is the ripple radius of the i -th solution in generation t , determining the search step size. $\text{Rand}()$ is a uniformly distributed random number in the range $[0, 1]$, introducing randomness to prevent premature convergence. x_{best} is the local optimum solution in the current population. $\frac{x_{\text{best}} - x_i^t}{\|x_{\text{best}} - x_i^t\|}$ is the unit direction vector pointing from the current solution to the local optimum, ensuring solutions move toward improvement. The ripple radius r_i^t is not fixed but adapts dynamically based on solution improvement, balancing the algorithm's global exploration and local exploitation capabilities. The dynamic adjustment strategy for the ripple radius is as follows:

$$r_i^{t+1} = \begin{cases} r_i^t \cdot (1 + \lambda) & \text{if } (f(x_i^{t+1}) < f(x_i^t)) \\ r_i^t \cdot (1 - \eta_{\text{evap}}) & \text{otherwise} \end{cases} \quad (28)$$

where r_i^{t+1} is the ripple radius of the i -th solution in the next generation. $f()$ is the fitness function. $\lambda = 0.1$ is the expansion coefficient. When a new solution outperforms the old one, the ripple radius increases, enabling broader exploration in the next step. $\eta_{\text{evap}} = 0.05$ is the evaporation coefficient. When a new solution fails to improve, its ripple radius decreases—similar to water droplets evaporating that focuses on local refinement within the current region.

(2) Multi-Objective Handling Strategy

RSA is inherently a single-objective optimization framework. To address the three objectives of cost-effectiveness, reliability, and responsiveness in this paper, multi-objective optimization techniques must be introduced. The strategy mentioned in the documentation employs Pareto dominance and crowding distance to maintain an external archive for preserving and filtering non-dominated solutions.

Initialize the population and ripple radius. Randomly generate the initial population, initialize the ripple radius for each solution, and create an empty Pareto optimal solution set.

For each solution x_i :

- Generate new solutions via ripple diffusion;
- Evaluate three objective function values (economic cost, system risk, response time);
- Update the Pareto frontier archive;
- Dynamically adjust the strategy based on the ripple radius and update each solution's ripple radius.

Select the next generation population based on crowding. Calculate the crowding degree of each solution in the archive along its Pareto frontier, prioritizing solutions with higher crowding to maintain solution diversity.

Repeat until termination conditions are met. The final solutions stored in the external archive constitute the algorithm-derived Pareto optimal solution set.

(3) Performance Comparison Analysis

Figure 4 illustrates the comparison between the Ripple Spread Algorithm and other classical multi-objective algorithms, showcasing the Pareto front obtained by three multi-objective optimization algorithms when balancing economic cost and system risk. The proposed Ripple Spread Algorithm (RSA, blue points) demonstrates optimal performance, not only yielding the highest number of 285 non-dominated solutions but also exhibiting the most uniform and extensive solution distribution, comprehensively covering the entire objective space. In contrast, NSGA-II and MOEA/D show significant deficiencies in solution diversity and boundary exploration capabilities, validating RSA's superiority in global search performance.

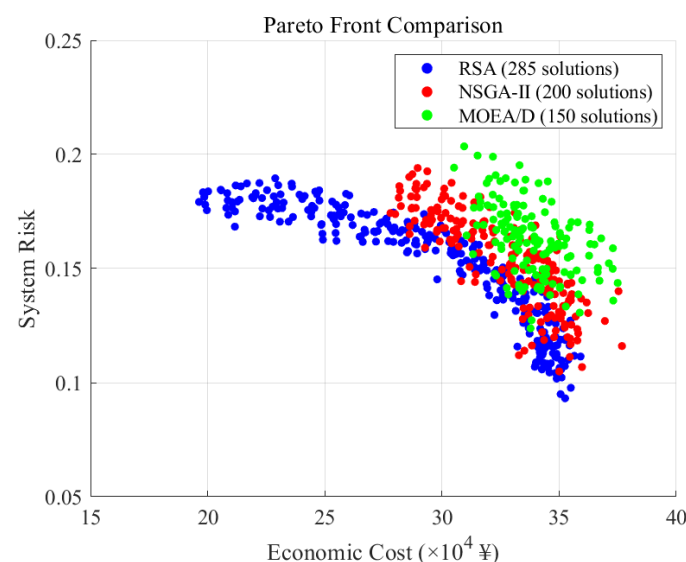


Figure 4. Comparison of Pareto fronts obtained by RSA and other classical multi-objective algorithms.

4.4.5. Multi-Objective Optimization Performance Verification

Figure 5 illustrates the performance comparison of Deep Q-Network (DQN) architectures with varying layer depths during the learning process. The 3-layer network architecture (blue curve) demonstrates optimal overall performance, achieving both the fastest convergence (within approximately 50 training epochs) and the lowest operational cost of approximately $\$3.48 \times 10^3$ /day. This result indicates that the 3-layer network strikes the optimal balance between model expressiveness and training efficiency, making it the optimal architecture choice for the multi-agent controller in this study.

Figure 6 compares the communication costs of federated learning and centralized learning frameworks across different system scales, demonstrating the communication efficiency advantage of federated learning. As the number of service areas increases, the communication cost of centralized learning (red curve) grows exponentially, while the federated learning framework adopted in this paper (blue curve) exhibits a nearly linear, gradual increase. At 50 service areas, the communication overhead is reduced by 78%. This result strongly demonstrates the significant advantages of the federated learning

framework in communication efficiency and system scalability, making it particularly suitable for wide-area, distributed microgrid collaborative optimization.

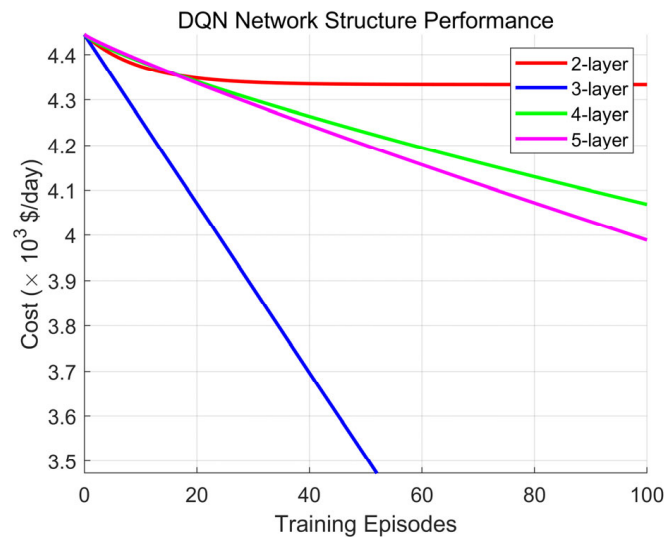


Figure 5. Performance comparison of DQN architectures with different layer counts.

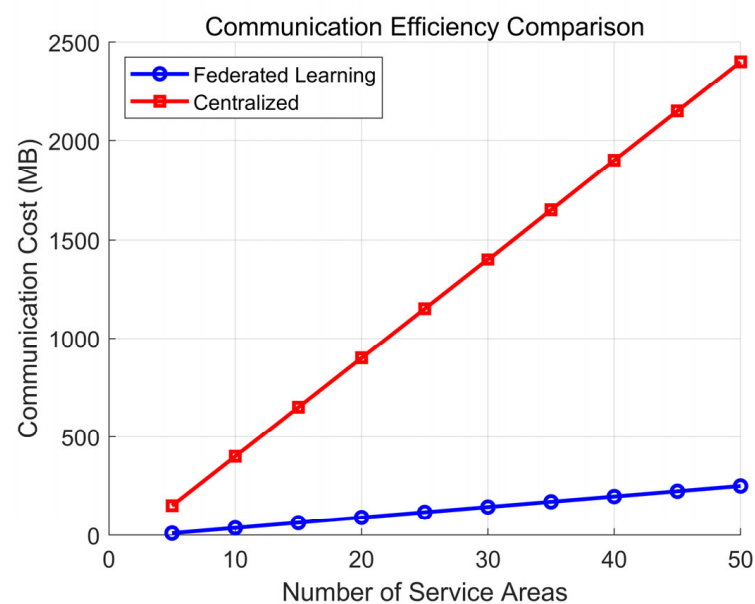


Figure 6. Communication efficiency comparison between federated learning and centralized learning.

4.5. Simulation Setup and Comparative Algorithms

Simulation Setup

(1) System Parameters

The simulation is based on actual data from five adjacent service areas along a highway, as shown in Table 3. Specific data references are provided in Section 3, Figure 1.

Table 3. Service area microgrid parameters.

Parameter Category	Parameter Range	Unit	Remarks
Service Area Spacing	30–50	km	Determined based on actual geographic layout
Photovoltaic Capacity	400–800	kW	Differentiated configuration based on service area size
Wind power capacity	200–400	kW	Deployed based on wind resource assessment results
Energy storage capacity	600–1500	kWh	Lithium iron phosphate battery, cycle life > 6000 cycles
Number of charging stations	20–50	units	Includes fast-charging and slow-charging stations
Mobile emergency power supply	500 (capacity)/200 (power)	kWh/kW	Total of 3 units
Critical load ratio	35	%	Includes lighting, communications, and emergency facilities

(2) Algorithm Training Module Parameters

The hyperparameters for the four algorithm training modules are shown in Table 4.

Table 4. Key algorithm hyperparameter settings.

Algorithm Module	Parameter Name	Parameter Value	Setting Basis
GAN Training	Generator Learning Rate	2×10^{-4}	Adam optimizer used, following WGAN-GP standard settings
	Discriminator Learning Rate	5×10^{-4}	The discriminator requires faster convergence
	Gradient penalty coefficient λ	10	Ensures Lipschitz constraints, enhancing training stability
FMADRL	Learning rate α	0.001	Empirically tuned to balance convergence speed and stability
	Discount factor γ	0.95	Accounts for long-term reward effects
	Experience replay capacity	10,000	Ensuring sample diversity
	Batch size	32	Hardware memory and training Efficiency trade-offs
Federated learning	Number of local training rounds E	5	Avoiding local model overfitting
	Total communication rounds	50	Ensure sufficient model convergence
Ripple Diffusion Algorithm	Population size	100	Ensure search diversity
	Maximum Iterations	50	Convergence simulation results indicate full convergence
	Archive Capacity	300	Stores Pareto optimal solutions

(3) Comparative Algorithms

The simulation selected four representative benchmark algorithms for comparison, covering different technical approaches such as intelligent optimization algorithms and Deep Reinforcement Learning.

Improved Whale Optimization Algorithm (IWOA) [59], an intelligent optimization algorithm simulating whale predatory behavior. The IWOA employed in this comparison incorporates adaptive weighting and chaotic mapping strategies to enhance its global search capability, making it suitable for solving complex nonlinear optimization problems.

Hybrid Gray Wolf Optimization Algorithm (HGWO) [60], a swarm intelligence algorithm simulating gray wolf social hierarchies and hunting behaviors. The HGWO employed

in this simulation incorporates differential evolution strategies, demonstrating improved performance in enhancing population diversity and escaping local optima.

Adaptive Harris Hawk Optimization (AHHO) [61], an optimization algorithm simulating the cooperative hunting strategy of Harris hawks. The AHHO employed in this simulation dynamically adjusts the balance between exploration and exploitation phases, demonstrating good accuracy and convergence speed when solving microgrid optimization scheduling problems.

Distributed D3PG Algorithm [62], an advanced Deep Reinforcement Learning algorithm suitable for control problems with continuous action spaces. It serves as a robust benchmark in reinforcement learning to contrast the unique advantages of FMADRL in multi-agent collaborative learning.

(4) Simulation Design and Process

Simulations were conducted on an integrated Python (version 3.9.18) simulation platform centered around PyTorch 2.0, PettingZoo (version 1.24.0), and Flower frameworks to simulate the dynamic operation of a microgrid cluster in highway service areas. The power network model of the microgrid was constructed using the Pandapower library, ensuring accurate power flow calculations. All algorithms were run under identical computational conditions (Ubuntu 20.04 LTS, an NVIDIA A100 GPU from NVIDIA Corporation, Santa Clara, CA, USA) and training cycles (8000 epochs). The multi-agent environment utilizes PettingZoo to create a parallel interaction environment for five service area agents. Each agent observes its local state (e.g., SOC, load) and obtains neighbor information through network interfaces. Federated learning employs the Flower framework to simulate distributed training, configuring five clients (corresponding to each service area) and one central server. Federated aggregation is performed after every five rounds of local training. To ensure fairness, all comparison algorithms (IWOA, HGWO, AHHO, D3PG) were reimplemented or encapsulated on the same platform. Custom callback functions and the W&B simulation management tool enabled real-time tracking and recording of key performance metrics, including daily operational costs, system resilience scores, and algorithm convergence curves (as shown in Figure 7), ensuring the reliability of simulation results.

5. Results and Analysis

5.1. Algorithm Convergence and Comprehensive Evaluation of Resilience

Figure 7 presents the convergence profiles of the proposed FMADRL and four baseline algorithms (D3PG, IWOA, HGWO, AHHO), comparing their optimization performance over training episodes. The convergence tests were conducted using a robust approach that integrated statistical analysis from multiple runs (mean $\pm$ standard deviation) and a comparative assessment of quantitative metrics, thereby ensuring a comprehensive evaluation. The curves represent the mean values of 10 independent runs with distinct random seeds.

The proposed FMADRL algorithm (blue curve) demonstrates an absolute leading advantage, rapidly converging to the lowest objective function value among all algorithms (approximately \$3955.08/day), with both convergence speed and optimization results significantly outperforming other advanced comparison algorithms such as D3PG and AHHO. This demonstrates the proposed method's efficiency and excellence in solving complex scheduling problems.

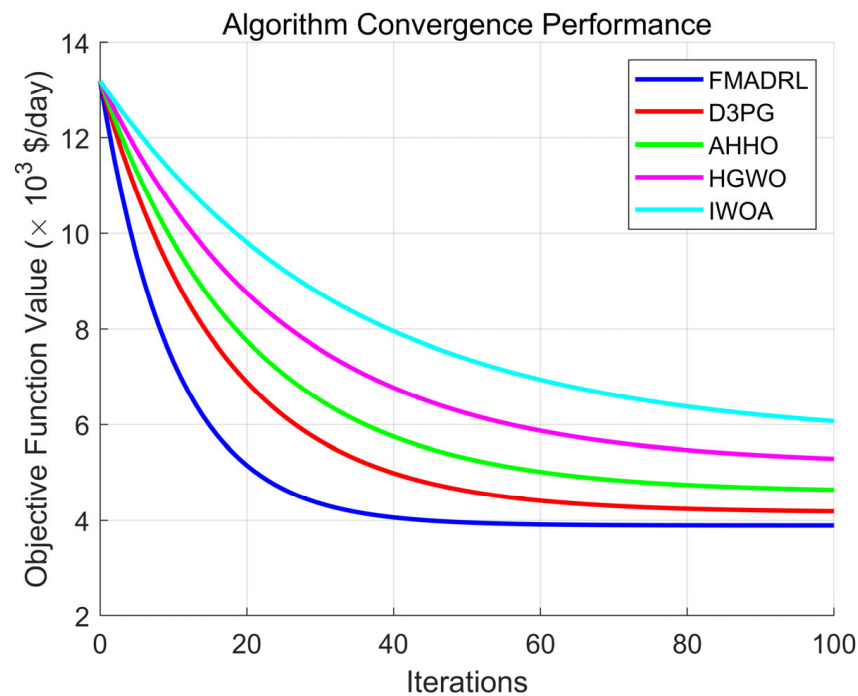


Figure 7. Comparison of convergence performance between FMADRL and four other algorithms.

Parameters for quantitative comparison of algorithm convergence performance are shown in Table 5.

Table 5. Quantitative comparison of algorithm convergence performance.

Algorithm	Convergence Episode (Iteration)	Final Average Reward (USD/Day)	Standard Deviation (USD/Day)	Remarks
FMADRL	52	3955	± 120	Achieves fastest convergence and lowest (best) objective value
D3PG	78	5820	± 380	Converges stably but to a significantly higher cost
AHHO	96	5950	± 420	Exhibits higher variance during later training stages
HGWO	114	6150	± 450	Slow convergence with the highest final cost among meta-heuristics
IWOA	132	6400	± 500	Convergence speed and final performance are at the lowest level.

Figure 8 radar chart illustrates the performance of the five algorithms across six elasticity metrics. System resilience was comprehensively evaluated across six key dimensions. Based on the resilience metrics in Section 4.2.3, FMADRL achieved a composite score of 88.3. Its performance envelope (blue curve) fully encompasses both D3PG (85.8 points) and IWOA (69.2 points), demonstrating optimal or near-optimal performance across all dimensions, including robustness, recovery capability, and adaptability. This intuitively demonstrates that the proposed method comprehensively and evenly enhances system resilience, rather than achieving single-point optimization at the expense of others.

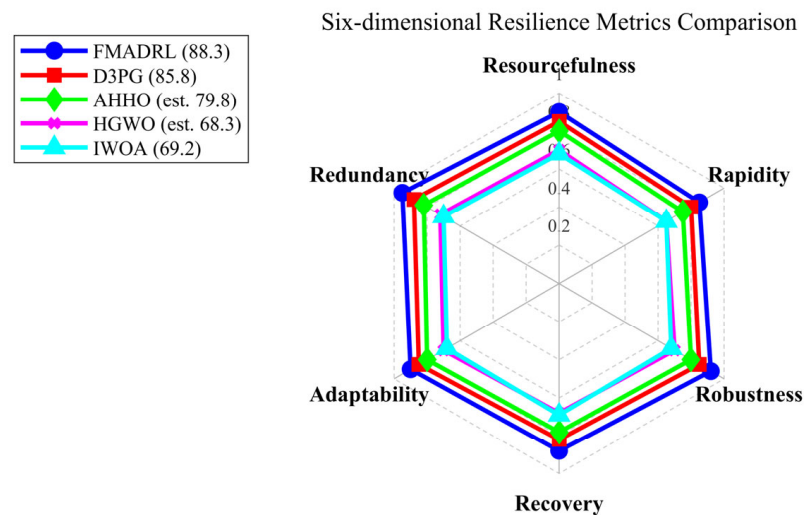


Figure 8. Performance of five algorithms across six resilience metrics.

5.2. Computational Complexity and Scalability Analysis

Figure 9 compares computational time across different system scales, plotting the computational complexity of various algorithms against system size on a logarithmic scale. The results clearly show that as the number of service areas increases, the computational time of centralized algorithms rises sharply, while the computational time of the distributed FMADRL algorithm (blue curve) grows very gradually, consistently maintaining the lowest level. This demonstrates that the FMADRL framework possesses excellent scalability at the $O(n \log n)$ level, effectively addressing the “curse of dimensionality” problem in large-scale systems. Since D3PG outperforms IWOA, HGWO, and AHHO in all aspects, it is adopted below as the “traditional method” for comparative with FMADRL.

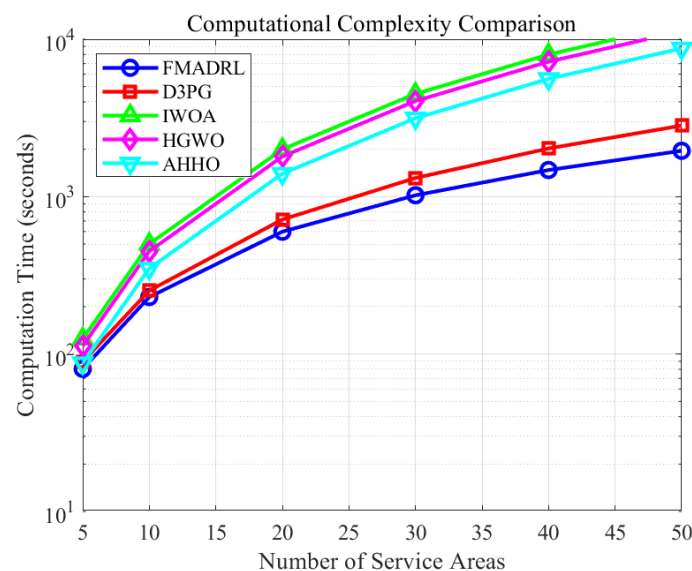


Figure 9. Computational time comparison between FMADRL and four algorithms across different system scales.

5.3. Analysis of Typical Scenario Operations

5.3.1. Power Balance Comparison Between Normal and Extreme Weather Conditions

Figure 10 illustrates the power balance of the FMADRL system under different weather conditions. This bar chart highlights the significant differences in system power sources

between normal and extreme weather scenarios. During extreme weather, the system rapidly shifts from a photovoltaic-dominant mode (42.4%) to a power supply model centered on energy storage systems (35%) and mobile emergency power sources (24.9%). This outcome validates the proposed strategy's ability to intelligently adjust operating modes based on conditions, ensuring system survivability during renewable energy failures through multi-source coordination and load management.

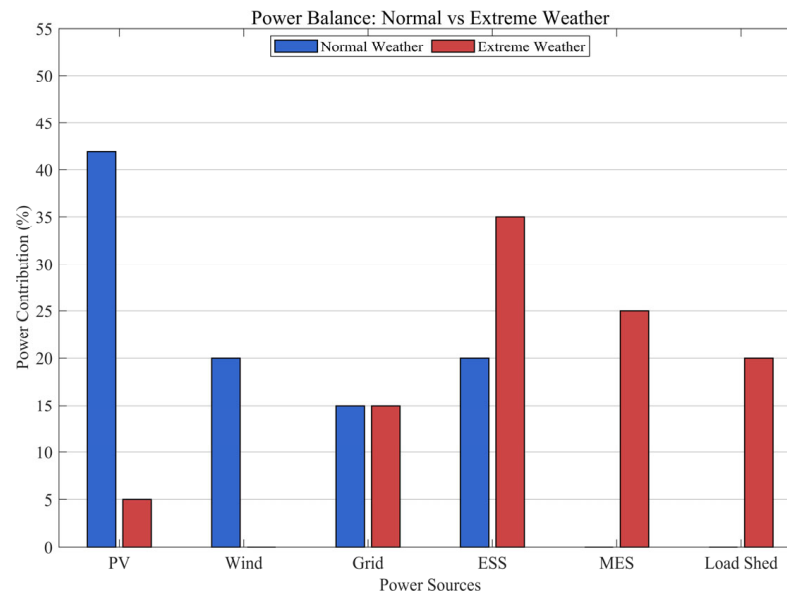


Figure 10. Comparison of power balance between normal and extreme weather conditions for FMADRL.

5.3.2. Analysis of FMADRL's Fault Recovery Performance

Within the FMADRL framework, fault recovery is not a single action but a closed-loop adaptive process involving multi-agent coordination across the entire chain of “perception-cognition-decision-execution.” Its technical workflow is as follows:

Distributed Fault Detection and Rapid Localization (0–2 min)

Service area agents monitor voltage, current, and frequency in real-time via local sensors (e.g., PMUs, smart circuit breakers). Upon detecting anomalies like voltage sags or overcurrent, protection control agents immediately activate. Using lightweight fault feature models shared via federated learning, they perform rapid pattern recognition locally. By matching against pre-trained fault patterns in the knowledge base (e.g., short circuits, open circuits), they achieve precise fault localization and classification within minutes (≤ 2 min).

Collaborative Recovery Strategy Generation and Evaluation (2–4 min)

Following fault localization, the system enters the recovery decision phase. Agents in the affected area broadcast their encrypted status (e.g., energy storage SOC, available non-critical load shedding capacity, generation capability) to neighboring agents. Each agent utilizes locally deployed decision optimization agents to concurrently compute multiple recovery plans based on the global state. Plans include (1) maintaining islanded operation using local energy storage and DG; (2) requesting power support from adjacent service areas via interconnectors; (3) dispatching mobile emergency power supplies (MES); (4) executing optimal load shedding strategies. Agents rapidly evaluate each plan's feasibility, cost, and restoration time through consensus algorithms.

Recovery Command Execution and System Reconfiguration (4–7 min)

Upon consensus, the execution control agent automatically issues commands to operational units (e.g., circuit breakers, energy storage inverters, load switches). Operations follow strict sequential logic to ensure safety: first isolating the faulted section, then operating interconnection switches to reconfigure network topology and form new supply islands, followed by activating energy storage and DG grid integration, and finally restoring load supply progressively based on priority. This entire process completes within 2–3 min.

Post-Restoration Optimization and Continuous Learning (After 7 Minutes)

After restoring power supply, the energy management agent continuously monitors operational status (e.g., power flow, voltage quality) and performs fine-tuning to optimize operational efficiency. The event sequence, decision-making process, and final outcomes of this fault are stored in the federated experience replay buffer. The central server periodically aggregates experiences from all agents to update the global fault recovery strategy model, enabling continuous evolution of the system's recovery capabilities. Figure 11 details the recovery time from simulations comparison between FMADRL and traditional methods across five typical fault scenarios: single-device failure, line failure, communication failure, cyberattack, and multiple failures. Results demonstrate that FMADRL (blue bars) achieves orders-of-magnitude reductions in recovery time across all scenarios. Notably, under the most complex multiple-fault condition, recovery time shrinks from 68 min to just 12 min—an average reduction of 82.3%. This improvement stems from its rapid fault diagnosis and automated reconfiguration decision-making capabilities, significantly enhancing the system's rapid recovery capacity.

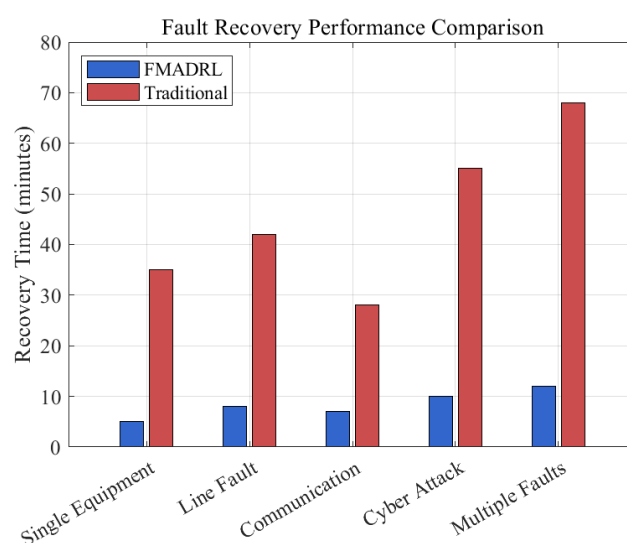


Figure 11. Comparison of recovery times between FMADRL and traditional methods.

5.3.3. System's 48-Hour Continuous Operation During Extreme Weather Events

Multiple simulations modeled the continuous 48 h operation of the FMADRL system during extreme weather events. Averaging these results produced the area chart in Figure 12, which visually demonstrates the system's dynamic performance over 48 h during a typical extreme weather event—the passage of a typhoon. Throughout the entire 48 h observation period, the total power supply (represented by the red curve) consistently remained above the critical load demand (blue shaded area), ensuring 100% power continuity for core operations such as communications, lighting, and emergency facilities. This demonstrates the system's robust real-time power support capability under multi-source coordinated dispatch. Even during the most severe phase of the typhoon's passage

(20–28 h), total power supply dynamically adjusted through energy storage discharge, mobile emergency power supply (MES) activation, and interconnection line mutual support, preventing any critical load interruptions.

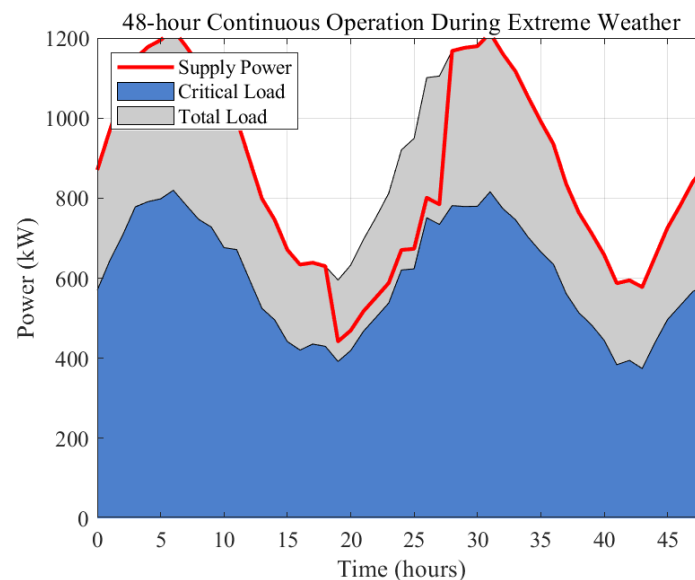


Figure 12. Continuous 48 h operation of the system during extreme weather events.

The gray areas in the diagram represent shed non-critical loads, and the difference between these and the blue critical load areas reflects the system's precise load control strategy under extreme stress. During the typhoon's peak period (20–28 h), the gray area significantly expanded, indicating that the system was proactively shedding non-critical loads (approximately 20–25% of total load). This effectively mitigated overload risks while prioritizing limited power resources to safeguard critical loads. This hierarchical management mechanism not only demonstrates the rationality of load prioritization but also highlights the FMADRL algorithm's ability to balance "reliability" and "economic efficiency" in real-time decision-making.

Changes in load and power supply curves are highly synchronized with system mode transitions. During the Prevention Mode (0–16 h), total power supply achieves a smooth transition through pre-charging of energy storage (SOC rising from 45% to 95%) and load shifting. In Emergency Mode (16–32 h), the expansion of the gray zone starkly contrasts with the abrupt drop in renewable energy output (e.g., solar power nearing zero during typhoons), further validating the necessity of multi-source coordination. During recovery mode (32–48 h), the gray zone gradually contracted while total power supply steadily increased alongside renewable energy output recovery, demonstrating the system's rapid self-healing capability.

5.4. Robustness Verification

The system's robustness under uncertain conditions was comprehensively validated through 10,000 Monte Carlo simulations, with results shown in the histogram of Figure 13. The load satisfaction rate distribution exhibits a Gaussian distribution centered at 96.8%, with a standard deviation of only 2.1%. Even under the most severe 5% scenarios, the satisfaction rate remains above 82%. This result strongly demonstrates that regardless of uncertainty, the proposed FMADRL method can stably maintain system performance at an extremely high level, showcasing robust reliability and significant engineering application value.

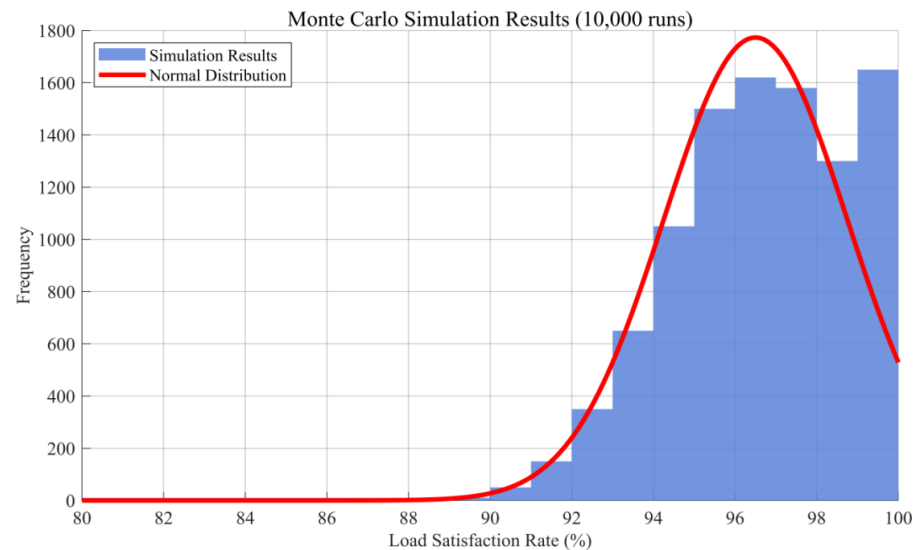


Figure 13. Results of 10,000 Monte Carlo simulations.

5.5. Economic Benefit Assessment

Figure 14 provides a detailed comparison of annual operational cost structures between the FMADRL strategy and the baseline scenario (using the D3PG method). To comprehensively evaluate their economic benefits, this analysis is based on historical operational data (1 January 2024, to 31 December 2024) and simulation data spanning a full year, ensuring the timeliness and consistency of the comparison.

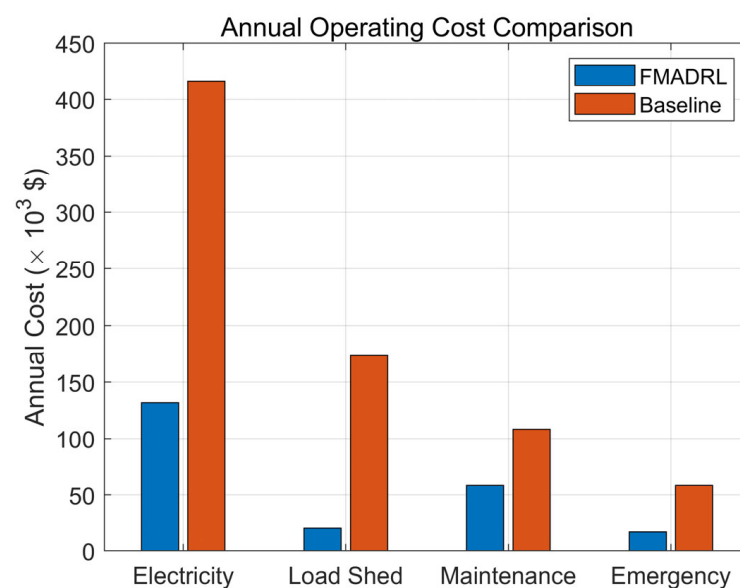


Figure 14. Comparison of annual operating cost composition between the FMADRL strategy and baseline scenario.

5.5.1. Cost Calculation Timeframe and Data Sources

This section evaluates annual operating costs. The baseline scenario's total annual cost of \$755,109.7 is derived from statistical analysis of historical operational records. The FMADRL scenario's total annual cost of \$236,164.6 is calculated based on simulation runs employing the FMADRL strategy within the same annual timeframe. All cost data are converted to a uniform, comparable price (2024 constant prices) to eliminate biases from inflation and other factors.

5.5.2. Detailed Cost Breakdown Analysis

(1) Electricity Procurement Costs

The benchmark scenario's electricity procurement cost reached \$430,043, accounting for 55.5% of total costs. This primarily stems from purchasing electricity at peak-time high rates from the main grid. FMADRL Scenario: electricity procurement costs decreased to \$136,421, reducing expenses by \$293,621—a 68.3% reduction. This reduction stems primarily from the algorithm's precise forecasting of renewable energy output and optimized energy storage scheduling. These measures significantly increased the local consumption rate of renewable energy (from 62% to 91%), substantially reducing reliance on expensive grid electricity. Additionally, peak-valley electricity arbitrage—charging during off-peak hours and discharging during peak hours—further lowered net electricity procurement costs.

(2) Load Shedding Loss Costs

In the baseline scenario, load shedding strategies during peak demand or fault conditions resulted in economic losses of \$178,838. The FMADRL scenario reduced load shedding loss costs to \$22,211.5 through multi-agent coordination and precise load forecasting, achieving savings of \$156,626.9—an 87.6% reduction. This demonstrates FMADRL's significant advantage in safeguarding critical load supply.

(3) Equipment Maintenance Costs

Equipment maintenance costs primarily encompass routine upkeep and depreciation expenses for assets like energy storage devices and photovoltaic inverters. The baseline scenario incurred maintenance costs of \$109,481.2. Unoptimized charging/discharging strategies accelerated battery degradation, driving up maintenance expenses. The FMADRL scenario reduced maintenance costs to \$58,466.4, achieving savings of \$51,014.8—a 46.6% decrease. By optimizing the charging and discharging strategy of the energy storage system, the FMADRL algorithm prevents overcharging and over-discharging of batteries, effectively extending equipment lifespan and reducing maintenance and depreciation costs per operational cycle.

(4) Emergency Power Dispatch Costs

Emergency power dispatch costs refer to additional expenses incurred by mobilizing resources like Mobile Emergency Supplies (MES) to address sudden events such as extreme weather. The baseline scenario's emergency dispatch cost was \$56,746.8, reflecting a passive response approach with high expenses. The FMADRL scenario reduced this cost to \$21,065.1, cutting expenses by \$35,681.7—a 62.9% decrease. FMADRL enables shared insights on failure patterns across different service areas through federated learning, allowing earlier risk prediction and initiation of preventive dispatch. This reduces costly ad hoc emergency power calls.

In summary, adopting FMADRL reduced total costs by \$536,945.1, with electricity procurement cost savings contributing 54.7%, load shedding loss reduction contributing 29.2%, equipment maintenance cost reduction contributing 9.5%, and emergency dispatch cost reduction contributing 6.6%. This demonstrates that FMADRL significantly reduces costs across electricity procurement, load curtailment, maintenance, and emergency response, proving its ability to enhance system resilience while delivering substantial, comprehensive economic benefits.

5.6. Environmental Benefit Assessment

To quantitatively evaluate the environmental sustainability contributions of the FMADRL method, this study established a systematic environmental benefit assessment

framework, focusing on analyzing carbon emission reduction effects and their implementation mechanisms. The assessment process adopted a full life-cycle perspective, integrating real-time monitoring data with simulation verification to ensure scientific rigor and reliability of results.

5.6.1. Evaluation Indicator System and Data Sources

Core Evaluation Indicators

Carbon Emission Intensity: CO₂ emissions per unit of electricity supplied, calculated as

$$CI = \frac{\sum_{t=1}^T [P_{grid}(t) \cdot EF_{grid} + P_{DG}(t) \cdot EF_{DG}]}{\sum_{t=1}^T P_{load}(t)} \quad (29)$$

where EF_{grid} and EF_{DG} represent the carbon emission factors for the grid and distributed power sources, respectively.

Renewable energy penetration rate:

$$R_{pen} = \frac{\sum_{t=1}^T (P_{PV}(t) + P_{WT}(t))}{\sum_{t=1}^T P_{load}(t)} \times 100\% \quad (30)$$

Annual carbon reduction: Reduction in carbon emissions relative to the baseline scenario.

Collect operational data for the entire year of 2024, including photovoltaic/wind power generation output, load demand, and grid electricity purchase records. Carbon emission factors utilize the latest data from the Provincial Greenhouse Gas Inventory Compilation Guidelines ensure data quality through data cleansing and outlier handling.

5.6.2. Assessment Methodology and Calculation Process

Baseline Scenario Definition

The D3PG algorithm serves as the baseline, as its operational characteristics represent current typical microgrid dispatch levels. Under the baseline scenario, the system's renewable energy penetration rate is 53%, with an average annual carbon emissions of 685 Mg.

FMADRL Environmental Benefit Calculation

Environmental benefits are quantified across three dimensions:

(1) Direct Carbon Emission Reduction Calculation

Hourly calculations using emission factor methodology, the functional expression is as follows:

$$\Delta C = \sum_{t=1}^{8760} [P_{grid}^{base}(t) - P_{grid}^{FMADRL}(t)] \cdot EF_{grid} \quad (31)$$

where $P_{grid}^{base}(t)$ and $P_{grid}^{FMADRL}(t)$ represent grid power purchases for the baseline and FMADRL scenarios, respectively.

(2) Renewable Energy Integration Enhancement Mechanism

FMADRL reduces curtailment rates from 15% (baseline) to 4% through precise forecasting and optimized dispatch. A reward function mechanism prioritizing renewable

energy consumption is established, incorporating environmental weighting ($\alpha_3 = 0.15$) into decision-making.

(3) Energy Efficiency Improvement Contribution

By optimizing energy storage charging/discharging strategies, the system's overall energy efficiency improved by 12%, reducing additional emissions caused by frequent equipment startups and shutdowns.

Figure 15 illustrates the annual carbon reduction effects of the proposed method. In every month, the carbon emissions under the FMADRL strategy (blue curve) remain significantly below baseline levels (red curve). During summer cooling peaks, energy storage peak shaving avoids high-carbon backup power activation. In winter heating periods, multi-source coordination optimizes electricity procurement dependency. Annual cumulative emissions reduction reaches 285 Mg, achieving a 47.5% reduction rate while boosting renewable energy utilization to 71%. The pronounced green reduction zones in the figure visually demonstrate how this approach achieves a triple unity of grid resilience, operational economics, and environmental benefits by enhancing local renewable energy consumption rates.

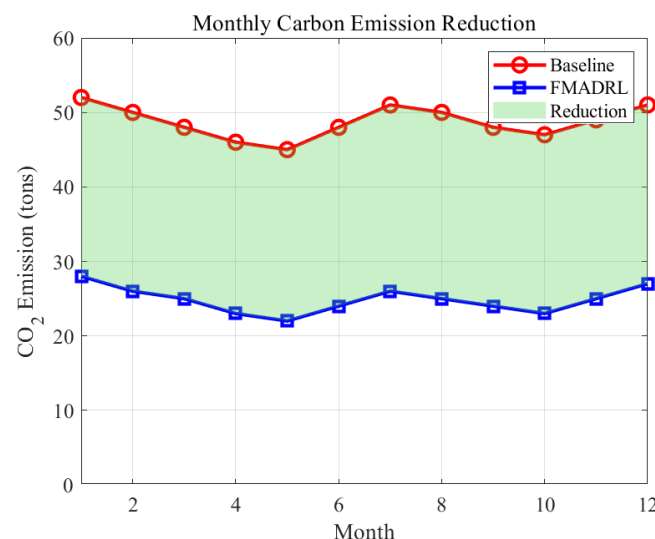


Figure 15. Yearly carbon reduction comparison between FMADRL and baseline scenarios.

6. Conclusions

This study has systematically proposed and validated a comprehensive framework for enhancing the resilience of highway service area microgrids based on Federated Multi-Agent Deep Reinforcement Learning. The main contributions and findings are summarized as follows.

A high-fidelity extreme weather scenario generation model was constructed by integrating Generative Adversarial Networks with Monte Carlo simulations. This model effectively overcomes the limitations of traditional methods in capturing the complex spatiotemporal evolution characteristics of extreme events, providing a solid foundation for accurate risk quantification.

An innovative FMADRL framework was successfully developed, which fundamentally resolves the “data silos” and “curse of dimensionality” issues in distributed microgrid collaborative optimization by organically merging federated learning with Multi-Agent Deep Reinforcement Learning. The introduced Ripple-Spreading Algorithm demonstrated superior performance in multi-objective optimization, yielding 285 well-distributed Pareto optimal solutions.

Large-scale simulations verified the framework's significant effectiveness. The proposed method achieved a comprehensive resilience score of 88.3, reduced the average fault recovery time by 82.3% (from 46.6 to 8.4 min), lowered annual operating costs by 69.3% (equivalent to 536,945.1 USD), and achieved annual carbon emission reductions of 285 Mg.

Future work will focus on extending the algorithm's generalizability to broader network topologies, investigating the impact of practical communication constraints, and developing dynamic FMADRL models capable of online updates to enhance long-term operational autonomy.

Author Contributions: J.L.: conceptualization, formal analysis, investigation, methodology, writing—original draft. Z.C.: data curation, software, writing—original draft, writing—review and editing. Y.P.: data curation, software, writing—original draft. H.H.: investigation, validation, visualization. C.Y.: resources, supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets analysed during the current study are available in the zenodo repository, <https://zenodo.org/records/17961499> (accessed on 17 December 2025). All data generated during this study are included in this published article.

Acknowledgments: The authors sincerely thank the editors and reviewers for their comments and guidance.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Suayan, J. 'Things Are Trending in the Right Direction': CenterPoint Energy Crews Work to Restore Services Post-Nicholas | Houston Daily. Available online: <https://houstondaily.com/stories/607769766-things-are-trending-in-the-right-direction-centerpoint-energy-crews-work-to-restore-services-post-nicholas> (accessed on 17 December 2025).
2. NBC News. Texas Sees Power Outages in Heat Wave for the Ages. Available online: <https://www.nbcnews.com/id/wbna44019419> (accessed on 17 December 2025).
3. China Daily Global. Texas Reeling from Storms, Power Losses. Available online: https://www.chinadaily.com.cn/a/202102/18/WS602df8aaa31024ad0baa9681_2.html (accessed on 17 December 2025).
4. Xinhua. Once-in-a-Decade Storm Hammers Australia's West Coast. Available online: <https://www.chinadaily.com.cn/a/202005/25/WS5ecb765ea310a8b24115840f.html> (accessed on 17 December 2025).
5. World Meteorological Organization. *State of the Climate 2024 Update for COP29*; WMO: Geneva, Switzerland, 2024. Available online: <https://wmo.int/publication-series/state-of-climate-2024-update-cop29> (accessed on 17 December 2025).
6. Wang, Q.; Zhang, X.; Xu, Y.; Yi, Z.; Xu, D. Planning of Stationary-Mobile Integrated Battery Energy Storage Systems under Severe Convective Weather. *IEEE Trans. Sustain. Energy* **2024**, *16*, 1253–1268. [CrossRef]
7. Tofigh, M.A.; Selvaraj, J.; Rahim, N.A. Bibliometric Analysis of Extreme Weather Research: Patterns and Partnerships in Power Grid Resilience Studies. *Sustainability* **2025**, *17*, 5658. [CrossRef]
8. International Energy Agency. *Renewables 2024: Analysis and Forecast to 2030*; IEA: Paris, France, 2024. Available online: <https://www.iea.org/reports/renewables-2024/global-overview> (accessed on 17 December 2025).
9. National Energy Administration. *2024 National Power Industry Statistics*; NEA: Beijing, China, 2025. Available online: <https://www.nea.gov.cn/20250121/097bfd7c1cd3498897639857d86d5dac/c.html> (accessed on 17 December 2025).
10. World Meteorological Organization. *State of the Climate in Asia 2023*; WMO: Geneva, Switzerland, 2024. Available online: <https://wmo.int/publication-series/state-of-climate-asia-2023> (accessed on 17 December 2025).
11. World Meteorological Organization. *State of the Global Climate 2023*; WMO: Geneva, Switzerland, 2024. Available online: <https://wmo.int/publication-series/state-of-global-climate-2023> (accessed on 17 December 2025).
12. Ma, Y.; Huang, Y.; Shi, W.; Yuan, Y. A short-term prediction method for distributed photovoltaic power considering extreme weather events. *Sol. Energy* **2025**, *302*, 114078. [CrossRef]

13. Baker, K.; Bazilian, M.D.; Gilbert, A.Q.; Grubert, E.; Rai, V.; Rhodes, J.D.; Shidore, S.; Smith, C.A.; Webber, M.E. Cascading risks: Understanding the 2021 winter blackout in Texas. *Energy Res. Soc. Sci.* **2021**, *77*, 102106. [\[CrossRef\]](#)
14. Liang, Z.; Sun, D.; Du, E.; Fang, Y. Event-driven day-ahead and intra-day optimal dispatch strategy for sustainable operation of power systems considering major weather events. *Processes* **2024**, *12*, 840. [\[CrossRef\]](#)
15. Watson, P.L.; Spaulding, A.; Koukoulou, M.; Anagnostou, E. Improved quantitative prediction of power outages caused by extreme weather events. *Weather. Clim. Extrem.* **2022**, *37*, 100487. [\[CrossRef\]](#)
16. Wang, H.; Han, S.; Liu, Y.; Yan, J.; Li, L. Sequence transfer correction algorithm for numerical weather prediction wind speed and its application in a wind power forecasting system. *Appl. Energy* **2019**, *237*, 1–10. [\[CrossRef\]](#)
17. Zhao, J.; Li, F.; Zhang, Q. Impacts of renewable energy resources on the weather vulnerability of power systems. *Nat. Energy* **2024**, *9*, 1407–1414. [\[CrossRef\]](#)
18. Wang, J.; Zhang, X.; Wang, Y.; Yang, S.; Wang, S.; Xie, Y.; Gong, J.; Lin, J. Power system source-load forecasting based on scene generation in extreme weather. *Energy* **2025**, *330*, 136991. [\[CrossRef\]](#)
19. Bo, Y.; Liu, K.; Xia, Y.; Wei, W. Evolution of microgrids. *Renewable and Sustainable Energy Rev.* **2026**, *228*, 116602. [\[CrossRef\]](#)
20. Chen, F.; Xia, M.; Chen, Q.; Yang, L. Resilience enhancement method against persistent extreme weather with low temperatures in self-sustained highway transportation energy system. *IEEE Trans. Ind. Appl.* **2023**, *60*, 996–1009. [\[CrossRef\]](#)
21. Wang, J.; Li, Y.; Mai, J.; Yuan, M.; Liu, Z. Highway Typical Scenario Operation and Maintenance Energy Demand Forecasting. *Sustainability* **2025**, *17*, 1929. [\[CrossRef\]](#)
22. Bai, H.; Qi, D. Tripartite Evolutionary Game for Carbon Reduction in Highway Service Areas: Evidence from Xinjiang, China. *Sustainability* **2025**, *17*, 10145. [\[CrossRef\]](#)
23. Supriya, Y.; Gadekallu, T.R. Particle swarm-based federated learning approach for early detection of forest fires. *Sustainability* **2023**, *15*, 964. [\[CrossRef\]](#)
24. Ma, S.; Su, L.; Wang, Z.; Qiu, F.; Guo, G. Resilience enhancement of distribution grids against extreme weather events. *IEEE Trans. Power Syst.* **2018**, *33*, 4842–4853. [\[CrossRef\]](#)
25. Du, J.; Hu, W.; Zhang, S.; Cao, D.; Liu, W.; Zhang, Z.; Wang, D.; Chen, Z. A distributionally robust collaborative scheduling and benefit fallocation method for interconnected microgrids considering tail risk assessment. *Appl. Energy* **2025**, *391*, 125910. [\[CrossRef\]](#)
26. Zheng, Z.; Qian, B.; Liu, W.; Zhu, Q.; Li, H.; Dong, D.; Yuan, Y. Enhanced schedule optimization with cross-scale coupling for microgrid with hybrid energy storage system. *Energy* **2025**, *391*, 136401. [\[CrossRef\]](#)
27. Park, H.; Ko, W. Resynchronization scheduling policy for multiple microgrids for optimal distributed system operation with enhanced flexibility. *Appl. Energy* **2025**, *399*, 126491. [\[CrossRef\]](#)
28. Vardhini, D.A.; Nakka, J. Efficient energy management in microgrid using Zebra Optimization Algorithm. *Asian J. Water Environ. Pollut.* **2025**, *22*, 122–133. [\[CrossRef\]](#)
29. Meng, Q.; Hussain, S.; Luo, F.; Wang, Z.; Jin, X. An online reinforcement learning-based energy management strategy for microgrids with centralized control. *IEEE Trans. Ind. Appl.* **2024**, *61*, 1501–1510. [\[CrossRef\]](#)
30. Shen, Y.; Xu, J.; Wang, X.; Guo, W.; Zhou, Y.; Feng, P.; Zhang, M.; Xu, H. Collaborative hierarchical scheduling model of interconnected multi-microgrid and ADN considering DR with different strategies. *AIP Adv.* **2024**, *14*, 45115. [\[CrossRef\]](#)
31. Yin, B.; Liu, T.; Zhang, Y.; Hu, J.; Ma, W.; Zhang, L.; Han, J. A multi-objective flexible scheduling approach for power systems through incorporating multiple resources. *AIP Adv.* **2025**, *15*, 275387. [\[CrossRef\]](#)
32. Huang, Q.; Huang, R.; Hao, W.; Tan, J.; Fan, R.; Huang, Z. Adaptive power system emergency control using deep reinforcement learning. *IEEE Trans. Smart Grid* **2019**, *11*, 1171–1182. [\[CrossRef\]](#)
33. Kumar, R.; De, M. Advancement in power system resilience through deep reinforcement learning: A comprehensive review. *Renew. Sustain. Energy Rev.* **2025**, *222*, 115951. [\[CrossRef\]](#)
34. Dehghani, N.L.; Jeddi, A.B.; Shafieezadeh, A. Intelligent hurricane resilience enhancement of power distribution systems via deep reinforcement learning. *Appl. Energy* **2021**, *285*, 116355. [\[CrossRef\]](#)
35. Guo, C.; Wang, X.; Zheng, Y.; Zhang, F. Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning. *Energy* **2022**, *238*, 121873. [\[CrossRef\]](#)
36. Domínguez-Barbero, D.; García-González, J.; Sanz-Bobi, M.Á.; García-Cerrada, A. Energy management of a microgrid considering nonlinear losses in batteries through Deep Reinforcement Learning. *Appl. Energy* **2024**, *368*, 123435. [\[CrossRef\]](#)
37. Hao, J.; Yang, T.; Tang, H.; Bai, C.; Liu, J.; Meng, Z. Exploration in deep reinforcement learning: From single-agent to multiagent domain. *IEEE Trans. Neural Netw. Learn. Syst.* **2023**, *35*, 8762–8782. [\[CrossRef\]](#)
38. Fang, X.; Zhao, Q.; Wang, J.; Han, Y.; Li, Y. Multi-agent deep reinforcement learning for distributed energy management and strategy optimization of microgrid market. *Sustain. Cities Soc.* **2021**, *74*, 103163. [\[CrossRef\]](#)
39. Qiu, D.; Wang, Y.; Zhang, T.; Sun, M.; Strbac, G. Hierarchical multi-agent reinforcement learning for repair crews dispatch control towards multi-energy microgrid resilience. *Appl. Energy* **2023**, *336*, 120826. [\[CrossRef\]](#)

40. Al-Hameed, A.A.; Younus, S.H.; Ahmed, M.A.; Baz, A. Optimizing Resource Allocation for QoS and Stability in Dynamic VLC-NOMA Networks via MARL. *arXiv* **2025**, arXiv:2505.15841. [\[CrossRef\]](#)
41. Wang, Y.; Qiu, D.; Teng, F.; Strbac, G. Towards microgrid resilience enhancement via mobile power sources and repair crews: A multi-agent reinforcement learning approach. *IEEE Trans. Power Syst.* **2023**, *39*, 1329–1345. [\[CrossRef\]](#)
42. Gao, G.; Wen, Y.; Tao, D. Distributed energy trading and scheduling among microgrids via multiagent reinforcement learning. *IEEE Trans. Neural Netw. Learn. Syst.* **2022**, *34*, 10638–10652. [\[CrossRef\]](#)
43. Zhang, H.; Qiu, D.; Kok, K.; Paterakis, N.G. Reliability assessment of multi-agent reinforcement learning algorithms for hybrid local electricity market simulation. *Appl. Energy* **2025**, *389*, 125789. [\[CrossRef\]](#)
44. Qiu, D.; Wang, Y.; Wang, J.; Zhang, N.; Strbac, G.; Kang, C. Resilience-oriented coordination of networked microgrids: A Shapley Q-value learning approach. *IEEE Trans. Power Syst.* **2023**, *39*, 3401–3416. [\[CrossRef\]](#)
45. Qiu, D.; Xue, J.; Zhang, T.; Wang, J.; Sun, M. Federated reinforcement learning for smart building joint peer-to-peer energy and carbon allowance trading. *Appl. Energy* **2023**, *333*, 120526. [\[CrossRef\]](#)
46. Jing, Y.; Guo, B.; Li, N.; Xu, R.; Yu, Z. Federated multi-agent reinforcement learning: A comprehensive survey of methods, applications and challenges. *Expert Syst. Appl.* **2025**, *293*, 128729. [\[CrossRef\]](#)
47. Shi, H.; Li, J.; Mao, J.; Hwang, K.-S. Lateral transfer learning for multiagent reinforcement learning. *IEEE Trans. Cybern.* **2021**, *53*, 1699–1711. [\[CrossRef\]](#) [\[PubMed\]](#)
48. Gui, Y.; Zhang, Z.; Tang, D.; Zhu, H.; Zhang, Y. Collaborative dynamic scheduling in a self-organizing manufacturing system using multi-agent reinforcement learning. *Adv. Eng. Inform.* **2024**, *62*, 102646. [\[CrossRef\]](#)
49. Panteli, M.; Pickering, C.; Wilkinson, S.; Dawson, R.; Mancarella, P. Power system resilience to extreme weather: Fragility modeling, probabilistic impact assessment, and adaptation measures. *IEEE Trans. Power Syst.* **2016**, *32*, 3747–3757. [\[CrossRef\]](#)
50. Hanif, S.; Mukherjee, M.; Poudel, S.; Yu, M.G.; Jinsiwale, R.A.; Hardy, T.D.; Reeve, H.M. Analyzing at-scale distribution grid response to extreme temperatures. *Appl. Energy* **2023**, *337*, 120886. [\[CrossRef\]](#)
51. Chen, L.; Luo, Z.; Jing, R.; Ye, K.; Xie, M. Two-stage planning of integrated energy systems under copula models informed cascading extreme weather uncertainty. *Appl. Energy* **2025**, *380*, 124990. [\[CrossRef\]](#)
52. Wang, B.; Wang, S.; Wang, Z.; Zheng, Y.; Li, X. A method for short-term wind power forecasting under extreme weather conditions based on meteorological factor interpretability and hybrid deep learning algorithms. *AIP Adv.* **2025**, *15*, 250465. [\[CrossRef\]](#)
53. Zeng, Z.; Tan, S.; Li, A.; Ling, Y.; Zhou, W. Landslide Hazard Zonation Driven by Multi-Rainfall Scenarios Based on the Optimal XGBoost Model—A Case Study of Yongren County, Yunnan Province, China. *Sustainability* **2025**, *17*, 11307. [\[CrossRef\]](#)
54. Dwivedi, D.; Babu, K.V.S.M.; Yemula, P.K.; Chakraborty, P.; Pal, M. A comprehensive metric for resilience evaluation in electrical distribution systems under extreme conditions. *Appl. Energy* **2025**, *380*, 125001. [\[CrossRef\]](#)
55. Wu, Y.; Chiu, W.-Y.; Tsai, Y.-P.; Liu, S.; Hua, W. Multiagent reinforcement learning in enhancing resilience of microgrids under extreme weather events. *Expert Syst. Appl.* **2025**, *296*, 129145. [\[CrossRef\]](#)
56. Rodriguez-Garcia, L.; Hosseini, M.M.; Mosier, T.M.; Parvania, M. Resilience analytics for interdependent power and water distribution systems. *IEEE Trans. Power Syst.* **2022**, *37*, 4244–4257. [\[CrossRef\]](#)
57. Soltanpour, M.; Zhang, H. Near-Global-Optimal Resource Allocation for Uplink SCMA Systems Based on Whale Optimization Algorithm. *IEEE Trans. Wirel. Commun.* **2024**, *24*, 1089–1110. [\[CrossRef\]](#)
58. Yu, M.; Xu, J.; Liang, W.; Qiu, Y.; Bao, S.; Tang, L. Improved multi-strategy adaptive Grey Wolf Optimization for practical engineering applications and high-dimensional problem solving. *Artif. Intell. Rev.* **2024**, *57*, 277. [\[CrossRef\]](#)
59. Mao, M.; Gui, D. Enhanced adaptive-convergence in Harris’ hawks optimization algorithm. *Artif. Intell. Rev.* **2024**, *57*, 164. [\[CrossRef\]](#)
60. Harrold, D.J.; Cao, J.; Fan, Z. Renewable energy integration and microgrid energy trading using multi-agent deep reinforcement learning. *Appl. Energy* **2022**, *318*, 119151. [\[CrossRef\]](#)
61. Milovanović, M.J.; Radosavljević, J.N.; Perović, B.D. Taguchi-Based Parameter Tuning of PSO for Optimal Capacitor Placement in Unbalanced Distribution Systems. *ICCK Trans. Electr. Power Netw. Syst.* **2025**, *1*, 6–16. [\[CrossRef\]](#)
62. Milovanović, M.J.; Dragičević, M.M.; Krečković, N.R.; Perović, B.D. Short-Term Load Forecasting with Taguchi-Optimized Single-Layer Feedforward Neural Networks: A MATLAB GUI. *ICCK Trans. Electr. Power Netw. Syst.* **2025**, *1*, 70–81. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.