High Resilience Integrated Emergency Interconnection And Communication Technology Applicable To Power Systems Under Extreme Climatic Conditions

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Extreme climatic conditions pose significant operational challenges to power systems by increasing fault occurrences, communication failures, voltage instability, and large-scale outages. This study proposes a high-resilience integrated emergency interconnection and communication framework for reliable power system operation during extreme weather events. The proposed system combines Optimal Power Flow (OPF) control with hybrid communication technologies, including satellite, unmanned aerial vehicle (UAV), and Mobile Ad Hoc Network (MANET)-based communication systems. In addition, a hybrid artificial intelligence fault detection model integrating Random Forest (RF) and Support Vector Machine (SVM) with ensemble learning is developed for accurate fault identification. The methodology is implemented on the IEEE 14-Bus System using the Newton–Raphson load flow method. Extreme climatic conditions are modeled through scenario-based simulations, while Monte Carlo simulations are employed to generate synthetic disturbances and faults. Communication performance is evaluated through delay and packet loss analysis within hybrid fiber–IoT communication networks. The framework also incorporates rule-based communication selection, optimization-driven coordination strategies, load shedding optimization, and power balancing mechanisms to maintain system stability during emergencies. Experimental results demonstrate strong resilience and communication performance, achieving a Voltage Deviation Index (VDI) of 0.04281 p.u., Resilience Index (RI) of 0.7241, Recovery Time (RT) of 5.64 hours, and Energy Not Supplied (ENS) of 2.85 MWh. The communication system records latency between 0.005 s and 0.018 s, throughput of 99.34 Mbps, and a Communication Reliability Index (CRI) of 0.9782. The hybrid fault detection model achieves 98.83% accuracy, confirming the effectiveness of the proposed framework for resilient smart grid operations.

Keywords: Power System Resilience, Extreme Climatic Conditions, Optimal Power Flow, Hybrid Communication Networks, AI-Based Fault Detection

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1. Introduction

Power system options are critical to facilitating the economic and social development of modern society, supporting industrial, commercial, and residential electricity needs [1]. Renewable energy sources, and distributed generation and smart grid technologies have increased the operational complexity and dynamic behavior of power systems [2]. The system becomes more susceptible to disturbances because of its complex structure, making it difficult to handle extreme weather events like hurricanes, floods, heatwaves, and storms [3].

Table 1. Comparison with Recent Resilience-Oriented Frameworks

Study	OPF	Hybrid Communication	AI Fault Detection	Integrated Decision Framework
Thirumalai et al. [4]	No	No	No	Partial
Sharifpour et al. [5]	No	No	No	No
Bahramirad et al. [6]	Partial	No	No	No
Almasoudi [7]	No	No	Yes	No
AlHaddad et al. [8]	No	No	Yes	No
Proposed Work	**Yes**	**Yes**	**Yes**	**Yes**

Natural disasters cause severe physical damage to communication networks which include fiber optics, which leads to either delayed control actions or complete control action failures. Recent research has investigated artificial intelligence together with hybrid communication systems, yet there is no existing framework which combines power system control and communication systems and intelligent fault detection for severe weather conditions [9]. This research develops a high-resilience integrated emergency interconnection and communication framework combining power grid control, hybrid communication, and AI-based fault detection for reliable operation during extreme weather. The framework integrates OPF-based control, satellite/UAV/MANET/fiber/IoT-based SCADA communication, and a hybrid RF–SVM fault detection model within a unified simulation platform. Monte Carlo simulation generates weather-driven fault scenarios using the IEEE 14-bus system, enabling comprehensive resilience evaluation. Rule-based communication selection minimizes latency and packet loss, while cloud-based monitoring supports centralized decision-making, load shedding, and power balancing. MATLAB-based validation demonstrates improved communication reliability, faster recovery, reduced Energy Not Supplied, and enhanced fault detection versus conventional approaches.

The paper is organized as follows: Section 2 reviews the literature on power system resilience, hybrid communication networks, and AI-based fault detection. Section 3 presents the materials and methods, covering the OPF-based control, hybrid communication architecture, RF–SVM fault detection methodology, the IEEE 14-bus test system, and Monte Carlo weather modeling. Section 4 presents the results and discussion, evaluating resilience, communication, and fault detection performance. Section 5 concludes the study and outlines future research directions.

2. Literature review

Recent studies have investigated resilience strategies under extreme weather through distributed energy resources, microgrids, and advanced energy management. Thirumalai et al. [4] developed a prosumer-centric microgrid using renewable energy and electric vehicles for local distribution and storage resilience. Sharifpour et al. [5] introduced hydrogen storage-based protection for backup power during prolonged outages. Bahramirad et al. [6] presented a resilience framework emphasizing coordinated operation across power system components. AI has also been widely adopted for fault detection: Almasoudi [7] developed hybrid ensemble classifiers improving detection accuracy, while AlHaddad et al. [8] applied AI-based outage prediction, improving forecasting; however, integration with power control and recovery mechanisms remains limited. Table 1 compares recent resilience-oriented frameworks with the proposed approach. Existing studies primarily address individual aspects such as power optimization, communication, or AI-based fault detection, with limited integration and coordinated decision-making across these components.

The proposed framework integrates OPF-based power optimization, adaptive hybrid communication, and RF–SVM-based fault detection into a unified resilience-oriented architecture, enabling coordinated power redistribution, communication adaptation, and intelligent fault management.

- Existing studies focus on isolated energy management, renewable integration, or fault detection rather than an integrated power–communication framework [4].
- Lack of hybrid communication systems (satellite, UAV, MANET) to ensure reliability during infrastructure failures caused by extreme weather [5].
- Traditional monitoring systems such as SCADA provide limited responsiveness and situational awareness under dynamic conditions [8].
- AI-based approaches are mostly limited to fault prediction, with minimal integration into control, decision-making, and system recovery mechanisms [6].
- Insufficient use of stochastic weather modeling and realistic simulation environments to evaluate system

performance under extreme climatic scenarios [7].

The framework integrates cloud monitoring, adaptive communication, and weather modeling to improve fault detection, recovery, and system resilience.

3. Materials and methods

This section presents the proposed framework combining power modeling, communication infrastructure, climate simulation, fault detection, and monitoring (Figure 1).

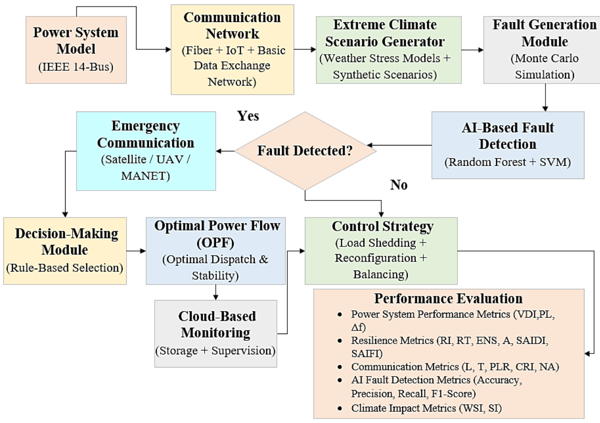

Fig. 1. Integrated Power–Communication Resilience Architecture Under Extreme Climate

Fiber-optic communication provides high-speed and reliable backbone connectivity, while IoT sensors continuously collect real-time operational data from grid components. Their coordinated operation enhances situational awareness, enabling reliable emergency response, adaptive control, and timely decision-making under dynamic operating and environmental conditions. The proposed framework enhances power system resilience and reliability through intelligent fault detection and rapid system recovery under extreme conditions.

Ensemble learning improves fault detection robustness by combining Random Forest and SVM classifiers, reducing sensitivity to nonlinear system uncertainties and communication-driven anomalies. This integration enhances classification stability, generalization capability, and reliability in complex smart grid environments. The IEEE 14-bus test system (Figure 2) evaluates power flow, voltage stability, fault propagation, and system recovery under diverse operating conditions. Monte Carlo fault modeling employs repeated random sampling to represent uncertainty in system disturbances. This improves stochastic variability representation and enables statistically reliable resilience evaluation under different fault and environmental conditions in smart grid analysis. The IEEE 14-bus system offers a reliable environment for evaluating the proposed framework under different operating conditions. Probabilistic stochastic weather modeling captures uncertainty and variability in environmental conditions, enabling realistic scenario generation, improved simulation reliability, and comprehensive resilience assessment of smart grid performance under diverse and dynamically changing operational weather conditions.

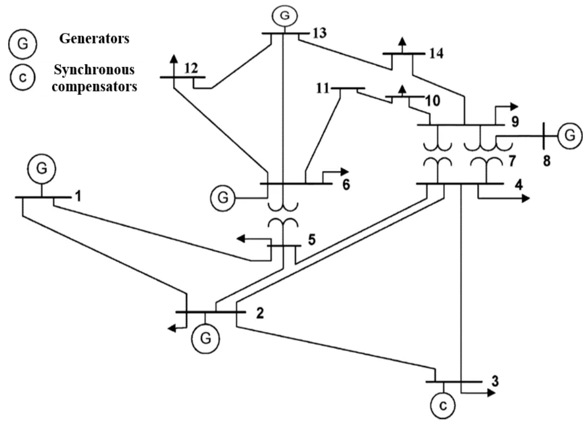

Fig. 2. IEEE 14 bus system

Steady-state load flow uses Newton–Raphson for efficient nonlinear power balance. The Newton–Raphson load flow method was selected for its fast convergence, high numerical accuracy, and computational efficiency, enabling adaptive real-time monitoring through rapid updates of system operating states under changing weather, load, and network operating conditions. SCADA continuously collects voltage, current, and power flow measurements for monitoring. Monte Carlo simulation generates stochastic weather scenarios and random fault occurrences by sampling probability distributions representing normal, moderate, and extreme environmental conditions. This probabilistic approach models uncertainty in weather severity and its impact on grid faults, communication failures, and overall system resilience.

The hybrid communication framework ensures interoperability among satellite, UAV-assisted, MANET, fiber-optic, and IoT-enabled SCADA systems through hierarchical coordination. Data is seamlessly exchanged across edge, relay, and core layers, enabling redundant routing, unified monitoring, and continuous synchronization during dynamic network conditions (figure 3). Communication delay and packet loss are modeled using Eq. (1).

$$P_{loss} = 1 - e^{-\lambda t} \tag{1}$$

where λ s link failure rate and t is time. Stochastic weather events are generated using probabilistic distributions of wind speed, rainfall, and temperature. Monte Carlo sampling models uncertainty through normal, moderate, and extreme weather states, influencing fault occurrence and communication degradation during resilience evaluation. Monte Carlo simulation generates random faults for resilience evaluation; RF–SVM combines decision trees for accurate classification. Nonlinear kernel mapping in SVM transforms overlapping feature spaces into higher-dimensional separable representations, improving classification of communication-assisted fault patterns and enhancing robustness against nonlinear operational variations. The SVM model employs an RBF kernel with box constraint 1 and standardization. A weighted RF–SVM ensemble reduces bias and improves stability.

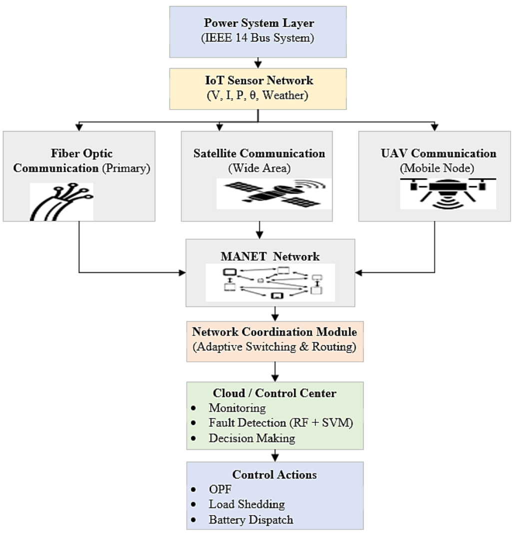

Fig. 3. Hybrid Communication Network Architecture for Resilient Power System

Feature selection uses RF-based importance ranking to select key inputs (V_{dev} , L_{var} , D_{comm} , P_{loss}), normalized and used to train SVM (RBF kernel). Final classification uses validation-based weighted voting, tuned via performance-based weights (w_1, w_2, across four stages: ranking, training, probability output, and weighted fusion.

Backup connectivity via satellite, UAV, and MANET switches automatically to the lowest-cost channel. Adaptive communication channel selection employs dynamic weight adjustment based on real-time latency, packet loss, and link quality metrics. Real-time prioritisation enables optimal switching among satellite, UAV, and MANET links to improve coordination efficiency during disturbances. RF–SVM fault detection triggers OPF-based power reconfiguration for adaptive generator dispatch and voltage control during disturbances. Simultaneously, the communication module selects the optimal satellite/UAV/MANET link for transmitting OPF commands and AI alerts, ensuring coordinated fault detection, power optimization, communication switching, and improved system resilience.

The flexible communication channel selection framework maintains communication continuity by dynamically switching to the most reliable available network during disturbances. This reduces recovery delays, improves coordination among emergency response units, and supports uninterrupted monitoring and control under fluctuating network conditions. The OPF control system serves as an emergency interconnection method, coordinating generator outputs and voltage levels to redistribute power, preventing failures (eq. 2).

$$\min \sum_{i=1}^{n} C_i\left(P_i\right) \tag{2}$$

where, $C_i\left(P_i\right)$ represents the generation cost function and P_i denotes the power generated at node i. The formulation ensures economical operation under constraints. Optimization-driven power redistribution dynamically allocates generation based on network conditions and critical loads, preserving resilience and minimizing cascading failures. OPF-based emergency interconnection coordinates voltage, power balance, and transmission constraints to ensure stable restoration and reliable operation. Essential loads are prioritized while non-critical demand is curtailed, improving voltage stability and power flow reliability during severe disturbances. Centralized cloud-based monitoring enables remote access, real-time data aggregation, and reliable control, satisfying $T_{\mathrm{cloud}} \leq T_{\mathrm{threshold}}$, for timely operation.

Centralized cloud processing aggregates distributed grid data in real time, reducing coordination latency while supporting computational scalability and adaptive control across geographically dispersed smart grid components. The cloud platform securely stores data and coordinates power operations. Load shedding maintains equilibrium, disconnecting non-critical loads by priority weight. The load shedding and power balancing framework is extended to a multi-objective formulation that minimizes economic dispatch cost, manages renewable generation uncertainty, and prioritizes critical loads, enhancing grid resilience by balancing cost, supply variability, and service reliability under dynamic conditions. Combined load shedding and power balancing enable adaptive prioritization of essential loads during extreme conditions. Load shedding and power balancing are implemented through a structured operational sequence involving real-time deficit estimation, priority-based load ranking, and iterative load reduction, followed by post-disturbance recovery to maintain stable system operation. Critical load continuity is ensured during disturbances while non-essential demand is progressively reduced, and system equilibrium is automatically restored once generation and demand balance, strengthening operational resilience. The experimental configuration tests the high-resilience power system framework combining modeling, communication infrastructure, and AI-based fault detection. The training dataset comprises 1200 IEEE 14-bus simulation samples using voltage, communication, and weather features, with stratified data splitting, cross-validation, and hyperparameter optimization (Table 2).

Hyperparameters were optimized using grid search, while the independent test dataset was reserved exclusively for final model performance evaluation (Table 3).

The setup uses a 64-bit system with Intel Core i5-12400, 8 GB RAM, and MATLAB R2024b, using the IEEE 14-bus system as base model (Table 4).

This section defines metrics evaluating power system stability, resilience, communication efficiency, and fault detection performance under extreme conditions. Scenario-based Monte Carlo simulations employ probabilistic weather distributions with defined severity levels and physical impacts on power system components, enabling realistic resilience evaluation under stochastic climatic disturbances, summarized in Table 5.

A consistent mathematical framework is adopted to ensure uniform equation formatting and variable notation throughout all performance metrics. Standardized mathematical expressions are used for the Voltage Deviation Index, Resilience Index, Recovery Time, and Energy Not Supplied, with V_i, V_{ref}, $P(t)$, $P_{\text{ideal}}(t)$, t_{fault}, and t_{recovery} consistently defined.

i) **Voltage Deviation Index (VDI):** The VDI measures the deviation of bus voltages from the nominal reference value is mathematically represented as Eqn. (3),

$$\text{VDI} = \frac{1}{N}\sum_{i=1}^{N} |V_i - V_{\text{ref}}| \tag{3}$$

Where, V_i is the Voltage at bus i, V_{ref} Reference voltage and N is the total number of buses.

ii) **Resilience Index (RI):** Quantifies the system's ability to withstand and recover from disturbances is mathematically represented as Eqn. (4),

$$\text{RI} = \frac{\int_{t_0}^{t_r} P(t)\,dt}{\int_{t_0}^{t_f} P_{\text{ideal}}(t)\,dt} \tag{4}$$

Where, $P(t)$ actual, $P_{\text{ideal}}(t)$ ideal, t_0 start, t_r recovery, and t_f is the End of observation.

iii) **Frequency Deviation (Δf):** Indicates the deviation of system frequency from its nominal value. Frequency stability is evaluated as Eqn. (5),

$$\Delta f = |f_{\text{actual}} - f_{\text{nominal}}| \tag{5}$$

Where, $f_{\text{nominal}} = 50$ Hz and f_{actual} is the Measured system frequency.

iv) **Recovery Time (RT):** Measures the time required for the system to return to a stable state after a fault is mathematically represented as Eqn. (6),

$$\text{RT} = t_{\text{recovery}} - t_{\text{fault}} \tag{6}$$

Where, t_{fault} is the Time of disturbance and t_{recovery} denotes recovery time.

v) **Energy Not Served (ENS):** Represents the total unmet energy demand during outages is mathematically represented as Eqn. (7),

$$\text{ENS} = \sum_{i=1}^{N} \left(P_{\text{demand},i} - P_{\text{served},i}\right) \times t \tag{7}$$

Where, P_{demand} is demand, P_{served} denotes Supplied power and t denotes duration of outage.

4. Results and discussion

This section evaluates framework performance under extreme weather using the IEEE 14-bus system, focusing on resilience and communication. The IEEE 14-bus benchmark was selected for initial validation because it is a standardized and computationally efficient test system. The proposed architecture is scalable, enabling OPF, hybrid communication, and RF–SVM modules to be extended to larger IEEE benchmark systems and practical utility-scale power networks without methodological changes. System achieved 0.04281 p.u VDI, ~0.03 Hz deviation, 98.02% network availability, despite increased latency (Table 6).

Hybrid model achieves 98.88% precision, 98.51% recall, 98.70% F1-score (table 7).

Extreme weather causes 50% generation loss; shedding reaches 9.8% (Figure 4).

Communication degradation from unstable network conditions may reduce routing efficiency through increased latency and packet loss. However, adaptive routing dynamically selects available paths, maintaining coordinated emergency response and reliable system operation during fluctuations. The system achieves RI of 0.7241, RT of 5.64 hours, ENS of 2.85 MWh, 98.02% availability, confirming strong resilience (Table 8).

SAIDI 0.2h, SAIFI 0.066/customer, RI 0.7241, RT 5.64h confirm resilience (Figure 5).

Table 2. Dataset Characteristics and Model Training Protocol

Item	Description
Dataset source	IEEE 14-Bus system under normal and extreme weather simulations
samples	1200 (660 normal, 540 fault)
Train/Validation/Test split	Stratified 70% / 15% / 15%
Feature engineering	Voltage, communication, weather
Cross-validation	Stratified 5-fold cross-validation
Hyperparameter optimization	Grid search

Table 3. Hyperparameter Configuration of the Hybrid RF–SVM Model

Model	Configuration
RF	100 trees, maximum splits = 10
SVM	RBF kernel, box constraint = 1, kernel scale = Auto
Ensemble	RF:SVM weight = 0.5:0.5

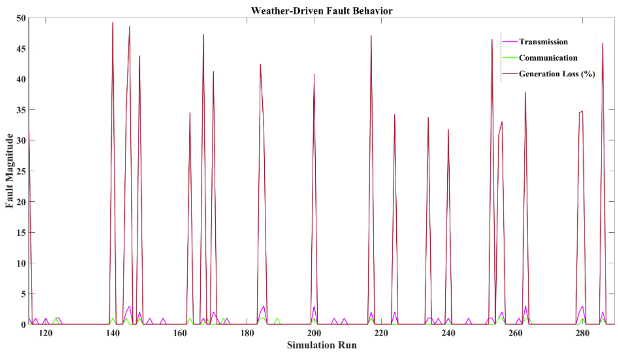

Fig. 4. Weather-Driven Fault Behavior Analysis

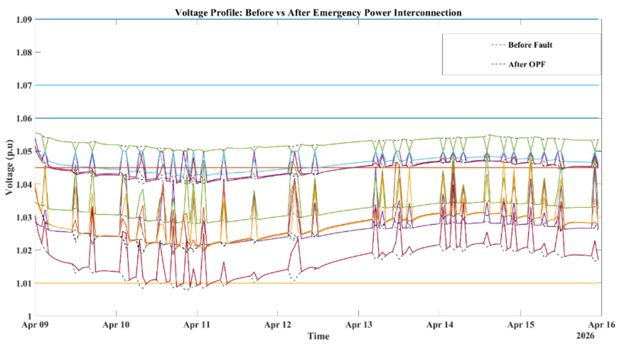

Fig. 5. Voltage Recovery Performance Before and After OPF Control

Stochastic weather simulations validate resilience under normal and extreme conditions.

Table 9 presents time-series validation of cloud-based monitoring, demonstrating centralized coordination through communication latency, packet loss, command success, recovery time, and resilience metrics during prolonged emergency conditions. Communication latency increased under severe weather due to adaptive switching among satellite, UAV, and MANET links. Although jitter, bandwidth utilization, and routing overhead were not explicitly measured, latency and packet loss analysis confirms reliable communication performance during emergency operation.

Table 10 compares the proposed framework with SCADA, standalone OPF, satellite communication, and individual machine learning models, demonstrating improved communication reliability, fault detection performance, and resilience. The proposed framework is assessed against recent studies. Tian et al. [10] used UAV/mobile power systems without unified power-communication optimization; the proposed model achieves RI of 0.7241 and ENS of 2.85 MWh. Hijazi et al. [11] enhanced IoT security without direct power system connection; the proposed framework achieves 0.9782 reliability. Suresh et al. [12] lacked climate modeling, while the proposed model achieved 98.83% accuracy.

Table 11 compares the proposed framework with traditional SCADA systems, standalone fault detection approaches, and existing resilience-oriented smart grid frameworks, highlighting its integrated communication, AI-assisted fault detection, and resilience capabilities. Scenario-based evaluation assesses communication reliability, fault detection accuracy, and power system stability under extreme weather conditions (Table 12).

Communication reliability and fault detection varied across climatic conditions, with optimal performance during heatwaves and reduced performance under flooding and ice storms. Despite severe disturbances, the proposed framework maintained adaptive operation, stable system performance, and consistent resilience across diverse extreme weather scenarios. The improved performance is achieved through the coordinated integration of OPF-based power optimization, hybrid satellite/UAV/MANET communication, and RF–SVM fault detection, which collectively reduce voltage deviation, improve latency and throughput, increase the resilience index, and enhance fault

Table 4. System Configuration Details

Parameter	Specification
System	64-bit, x64; Intel Core i5-12400 (2.50 GHz); 8 GB RAM (3200 MT/s); 466 GB Storage; Intel UHD Graphics 730
Software	MATLAB R2024b
Test System	IEEE 14-Bus System; 100 MVA Base Power; 14 Buses; 5 Generators; 20 Branches
Data Dimensions	Bus: 14×13; Generator: 5×21; Branch: 20×13; Generator Cost: 5×7

Table 5. Weather Scenario Modeling Parameters Used for Monte Carlo Simulation

Weather Variable	Distribution (Parameters)	Normal	Moderate	Extreme	Physical Impact
Wind speed	Weibull ($k = 2.0$, $\lambda = 8.5$)	< 8	8–18	> 18	Line outages
Rainfall	Gamma ($\alpha = 2.1$, $\beta = 9.0$)	< 10	10–35	> 35	Flooding
Temperature	Truncated Normal ($\mu = 32$, $\sigma = 7$)	20–35	35–42	> 42	Generator derating
Lightning	Poisson ($\lambda = 0.35/0.90$)	Low	Moderate	High	Line faults
Flood depth	Lognormal ($\mu = -1.2$, $\sigma = 0.55$)	< 0.2	0.2–0.5	> 0.5	Substation flooding

Table 6. Communication System Performance Metrics

Communication Type	Latency (s)	PLR	NA
Satellite	0.005–0.009	0.5%–1.0%	High
UAV	0.008–0.014	1.0%–2.0%	Moderate
MANET	0.010–0.020	1.5%–2.5%	Adaptive
Overall System	—	0.5%–2.5%	**98.02% (Average)**

Table 7. Performance Comparison for Fault Detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	FPR	FNR
Random Forest	97.917	97.952	97.407	97.679	0.016667	0.025926
SVM	99.000	99.071	98.704	98.887	0.007576	0.012963
Hybrid Model	98.833	98.885	98.519	98.701	0.009091	0.014815

Table 8. Resilience Performance Metrics

Metric	Value
RI	0.7241
RT	5.64 hours
ENS	2.85 MWh
System Availability (A)	98.02%
SAIDI	0.2 hours (12 min)
SAIFI	0.066 interruptions

Table 9. Time-Series Validation of Cloud-Based Emergency Monitoring and Control

Validation Metric	Value	Unit
Peak cloud latency	17.6	ms
Average cloud latency	10.57	ms
Maximum packet loss ratio	2.00	%
Maximum load shedding	9.8	%
Minimum command success	96.2	%
Recovery time (RT)	5.64	h
Energy Not Served (ENS)	2.85	MWh
Resilience Index (RI)	0.7241	—

detection accuracy.

Table 13 compares the proposed RF–SVM framework with recent CNN, Vision Transformer, and LSTM models. The proposed framework achieves comparable performance while integrating OPF, hybrid communication, and climate-driven resilience evaluation The ablation study demonstrates the contribution of each RF–SVM component under identical severe weather conditions, confirming that feature selection and ensemble learning collectively improve fault detection performance and model robustness (Table 14).

The framework maintains stability under extreme weather with 0.04281 p.u VDI, RI 0.7241, RT 5.64h, and 98.83% fault detection accuracy.

5. Conclusion and future work

The research introduced an integrated emergency interconnection and communication framework to improve power system resilience under severe weather conditions. The proposed framework combines OPF-based control, hybrid satellite–UAV–MANET communication, and a hybrid RF–SVM fault detection model with ensemble learning. The IEEE 14-Bus System was used to develop a simulation environment incorporating Monte Carlo-based climate scenarios and fault generation under diverse weather conditions. Results demonstrate improved power system stability, communication reliability, and fault detection performance during extreme climatic disturbances. The OPF-based control strategy effectively regulates voltage and maintains frequency stability, reducing the likelihood of cascading failures. The hybrid communication architecture ensures reliable data transmission through adaptive communication selection across multiple network layers, while the RF–SVM model accurately identifies faults under varying environmental conditions. System evaluation confirms rapid recovery following disturbances, supporting resilient operation during emergency conditions. Adaptive communication selection, intelligent fault detection, and OPF-based optimization enable coordinated operation between power and communication infrastructures, enhancing operational reliability and recovery capability. The integrated framework provides a scalable and unified solution for resilient smart grid operation by combining power system control, hybrid communication, and intelligent fault detection, making it suitable for maintaining secure and reliable electricity services during severe environmental disturbances.

The future research will concentrate on two main objectives which involve integrating renewable energy sources into existing systems while creating improved fault detection capabilities through deep learning and advanced deep learning models and developing secure communication methods to enhance cybersecurity. The framework enables power system expansion through its capability to extend beyond boundaries and its capacity for hardware-based validation testing.

Declaration

Data availability

The data used in this study are generated through simulations based on the IEEE 14-Bus system and synthetic datasets created using Monte Carlo methods. The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Funding statement

This research received no external funding.

Author Contribution

Anjiang Liu conceptualized the study, supervised the research, and contributed to methodology development. Shuqing Hao and Yue Li conducted data analysis and simulation experiments. Yu Miao contributed to system modeling and validation. Hongyu Zuo assisted in implementa-

Table 10. Performance Comparison with Conventional Baseline Methods

Method	Communication Reliability (%)	Fault Detection Accuracy (%)	Resilience Index (RI)
Conventional SCADA-based System	91.80	Not Applicable	0.581
Standalone OPF Method	94.50	Not Applicable	0.648
Satellite-based Communication	95.90	Not Applicable	0.683
RF Model	Not Applicable	97.92	Not Applicable
SVM Model	Not Applicable	99.00	Not Applicable
Proposed Framework	**98.02**	**98.83**	**0.7241**

Table 11. Comparative Analysis with Existing Smart Grid Frameworks

Framework	Hybrid Communication	AI Fault Detection	Integrated Resilience Framework
Traditional SCADA System	No	Rule-based	No
Standalone Fault Detection	No	Yes	No
Existing Resilience-Oriented Frameworks	Partial	Partial	Partial
Proposed Framework	**Yes**	**Yes (RF–SVM)**	**Yes**

Table 12. Scenario-Based Performance Comparison

Scenario	Comm. Reliability (%)	Fault Detection (%)	Power Stability (%)
Base	66.14	64.29	72.82
Hurricane	69.84	71.43	68.63
Heatwave	74.50	78.57	59.06
Flooding	61.09	42.86	74.20
Ice Storm	70.37	71.43	45.87

Table 13. Comparison of the Proposed RF–SVM Model with Recent Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
CNN (PSO-CNN) [13]	93.36	94.00	95.00	95.00
Vision Transformer (ViT) [14]	97.88	98.23	97.88	97.86
LSTM [15]	98.11	98.00	97.00	98.00
RF	97.917	97.952	97.407	97.679
SVM	99.000	99.071	98.704	98.887
Proposed RF–SVM	**98.833**	**98.885**	**98.519**	**98.701**

Table 14. Ablation Study of the Proposed RF–SVM Fault Detection Framework

ID	Ablation variant	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	FPR	FNR
A0	Raw features + RF only	97.31	97.42	96.85	97.13	0.0212	0.0315
A1	RF with feature selection	97.917	97.952	97.407	97.679	0.016667	0.025926
A2	SVM only	98.62	98.71	98.15	98.43	0.0106	0.0185
A3	SVM using RF-selected features	99	99.071	98.704	98.887	0.007576	0.012963
A4	Proposed RF–SVM ensemble	98.833	98.885	98.519	98.701	0.009091	0.014815

tion and result interpretation. All authors contributed to writing, reviewing, and approving the final manuscript.

Ethical approval

This study does not involve human participants or animals; therefore, ethical approval is not required.

Consent to participate

Not applicable.

Consent to publication

All authors have reviewed and approved the manuscript for publication.

Competing interests

The authors declare that they have no competing interests.

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