



Power System Resilience Enhancement Using Intelligent Monitoring and Control Techniques: A State-of-the-Art Review

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Abstract

Power system resilience has emerged as a critical priority in modern electrical grids, driven by increasing frequency of extreme weather events, cyber threats, and the integration of distributed energy resources. This comprehensive review examines state-of-the-art intelligent monitoring and control techniques designed to enhance power system resilience across pre-event, during-event, and post-event phases. The paper systematically analyzes advanced monitoring technologies including phasor measurement units, SCADA systems, IoT sensors, and smart metering infrastructure, alongside intelligent control paradigms encompassing artificial intelligence, machine learning, adaptive control, model predictive control, and distributed multi-agent systems. Through critical evaluation of recent implementations and case studies, this review identifies key integration approaches, performance metrics, and validation methodologies. Significant findings include the achievement of 95.57% cyber-attack detection accuracy using time-frequency convolutional neural networks, reduction of disaster recovery computational time from 2.6 hours to 7.3 seconds through AI-assisted optimization, and 50% reduction in required photovoltaic-battery system capacity through intelligent model predictive control. The review also addresses persistent challenges including cybersecurity vulnerabilities, data integrity concerns, scalability limitations, and the need for physics-informed hybrid approaches. Future research directions emphasize the integration of physical constraints with machine learning, adversarial-robust learning frameworks, and edge-cloud co-design for distributed resilience. This synthesis provides researchers and practitioners with a comprehensive understanding of current capabilities and future pathways for resilience-oriented power system design.

Keywords: Power system resilience, intelligent monitoring, intelligent control, artificial intelligence, machine learning

1. Introduction

Modern power systems face unprecedented challenges from multiple fronts: climate-driven extreme weather events, sophisticated cyber threats, aging infrastructure, and the rapid integration of variable renewable energy sources. Traditional power system design paradigms, which prioritized reliability under normal operating conditions and N-1 contingency scenarios, prove insufficient for addressing the complex, cascading failures characteristic of contemporary disruptions. This reality necessitates a fundamental shift toward resilience-oriented design frameworks that emphasize not only the prevention of failures but also rapid adaptation and recovery capabilities. Power system resilience is conceptualized as the capability to withstand disruptions, adapt operational modes dynamically, and recover essential services with minimum loss to critical loads (Zahraoui et al., 2024). Unlike traditional reliability metrics that focus on steady-state performance, resilience encompasses the entire disruption lifecycle: pre-event preparedness through hardening and forecasting, during-event absorption through islanding and local control, and post-event recovery through reconfiguration and restoration (Yang, 2024). This holistic perspective requires integrated solutions that combine advanced sensing, real-time analytics, and intelligent control.

The convergence of three technological trends has catalyzed significant advances in power system resilience enhancement. First, the proliferation of high-resolution monitoring infrastructure, including phasor measurement units, smart meters, and IoT sensors, provides unprecedented visibility into system dynamics. Second, advances in artificial intelligence and machine learning enable sophisticated pattern recognition, predictive analytics, and autonomous decision-making from massive data streams. Third, distributed computing and edge intelligence architectures support real-time control actions even under communication constraints or cyber attacks. This review synthesizes recent research on intelligent monitoring and control techniques for power system resilience enhancement, with particular emphasis on implementations validated through simulation or field deployment. The scope encompasses monitoring technologies that enable situational awareness and anomaly detection, control algorithms that optimize system response under disruption, and integration frameworks that coordinate these capabilities across hierarchical and distributed architectures. The analysis draws from peer-reviewed literature spanning multiple application domains including transmission systems, distribution networks, microgrids, and building-level energy management systems.

The remainder of this paper is organized as follows. Section 2 establishes theoretical foundations and key concepts in resilience quantification. Section 3 examines intelligent monitoring techniques including PMU-based wide-area monitoring, SCADA systems, IoT sensors, and cyber-attack detection methods. Section 4 analyzes intelligent control paradigms encompassing AI/ML-based control, adaptive control, predictive control, and distributed multi-agent systems. Section 5 discusses integration approaches and system architectures. Section 6 identifies persistent challenges and limitations. Section 7 outlines future research directions, and Section 8 concludes with key takeaways and recommendations.

2. Background and Theoretical Foundations

2.1 Resilience Definition and Conceptual Framework

Power system resilience extends beyond traditional reliability by explicitly addressing high-impact, low-probability events and the system's ability to maintain or rapidly restore critical functions. The resilience framework typically decomposes system response into four distinct phases: preventive actions that reduce vulnerability through infrastructure hardening and predictive analytics; protective actions that absorb initial impacts through rapid detection and isolation; adaptive actions that reconfigure topology and redistribute resources to maintain critical services; and restorative actions that return the system to normal operation (Zahraoui et al., 2024). This phase-based taxonomy provides structure for organizing monitoring and control interventions across the disruption timeline.

2.2 Resilience Quantification Metrics

Quantifying resilience requires metrics that capture both the magnitude of service degradation and the temporal dynamics of recovery. Common approaches include resilience curves that plot service level versus time, with resilience quantified as the integral of service loss over the disruption period. Network-theoretic metrics assess structural vulnerability through node and edge vitality indices, which measure the impact of component removal on network connectivity and power flow capacity. Control-theoretic metrics evaluate closed-loop stability margins under worst-case communication failures or measurement corruption (Lu et al., 2016). Operational metrics focus on practical outcomes such as critical load service duration, time to restoration, and the minimum number of sequential faults required to trigger cascading failure (Ibrahim et al., 2022).

2.3 Cyber-Physical System Considerations

Modern power systems function as cyber-physical systems where physical power flows are monitored and controlled through digital communication networks. This tight coupling introduces new vulnerabilities, as cyber attacks can manipulate measurements, corrupt control signals, or disrupt communication channels. Recent scholarship on integrated governance architectures demonstrates that fragmented compliance, cybersecurity, and risk-management functions can significantly undermine organizational resilience, whereas unified governance alignment and control harmonization improve risk visibility and coordinated response across critical infrastructures (Joseph, 2013). Resilience enhancement must therefore address both physical disruptions and cyber threats through integrated monitoring and control strategies. Bayesian network models have been applied to quantify cyber-physical risk propagation and guide defense resource allocation (Hossain et al., 2020).

3. Intelligent Monitoring Techniques

Intelligent monitoring forms the foundation for resilience-oriented control by providing high-fidelity situational awareness, enabling rapid anomaly detection, and supporting data-driven decision-making. This section examines key monitoring technologies and their applications in resilience enhancement.

3.1 Phasor Measurement Units and Wide-Area Monitoring

Phasor measurement units represent a transformative advancement in power system monitoring, providing synchronized voltage and current phasor measurements at sampling rates up to 120 Hz. This temporal resolution enables detection of transient phenomena and inter-area oscillations that remain invisible to traditional SCADA systems. PMU data supports multiple resilience functions including transient stability assessment, oscillation detection, and cyber-attack identification. Recent research demonstrates the effectiveness of PMU-based monitoring for cyber-resilience. Qiu et al. (2023) developed a Time and Frequency based Convolutional neural Network (TFCN) that processes high-speed synchrophasor measurements to detect false data injection attacks. The TFCN architecture extracts both temporal patterns and frequency-domain signatures from PMU streams, achieving 95.57% detection accuracy on a modified IEEE 39-bus system. Critically, the approach demonstrated faster stability restoration compared to traditional neural network architectures, highlighting the importance of domain-informed feature extraction for real-time resilience applications.

The integration of PMU networks with machine learning enables predictive stability assessment. Sun et al. (2022) proposed a Temporal and Topological Embedding Deep Neural Network (TTEDNN)

that combines graph convolutional networks with temporal convolutional networks to predict transient stability from early-stage PMU measurements. By incorporating grid topology through a grid-informed adjacency matrix, the model achieved superior prediction performance on IEEE 39-bus and 118-bus systems while demonstrating transfer learning capability to more complex scenarios.

3.2 SCADA Systems and Supervisory Control

Supervisory Control and Data Acquisition systems remain the backbone of power system monitoring and control, providing measurements of voltages, currents, power flows, and breaker statuses across transmission and distribution networks. While SCADA systems operate at lower sampling rates than PMUs, their comprehensive coverage and integration with control infrastructure make them essential for resilience applications. The cyber-physical nature of SCADA systems introduces vulnerabilities that must be addressed through intelligent monitoring. Research has focused on risk-based frameworks for defense resource allocation. A recent study developed a risk assessment model that quantifies the propagation of cyber attacks through SCADA networks and their physical consequences, enabling optimization of defense investments across measurement nodes and communication links (IEEE Transactions on Industry Applications, 2024). This approach balances defense costs against potential physical impacts, providing a systematic methodology for hardening critical monitoring infrastructure.

3.3 IoT Sensors and Distributed Monitoring

The proliferation of Internet of Things devices enables fine-grained monitoring at the distribution edge, including building-level energy management systems, distributed energy resource controllers, and environmental sensors. IoT-based monitoring supports distributed situational awareness and enables local decision-making that remains functional during communication failures. Liu et al. (2024) surveyed cyber-resiliency enhancement for distributed energy resource-based smart grids, emphasizing the role of edge sensors in intrusion detection and anomaly identification. The distributed nature of IoT monitoring provides redundancy against single points of failure while enabling rapid local response to disturbances. However, the large attack surface introduced by numerous IoT devices necessitates robust security protocols and anomaly detection algorithms.

3.4 Smart Meters and Advanced Metering Infrastructure

Smart meters and Advanced Metering Infrastructure provide bidirectional communication between utilities and customers, enabling monitoring of consumption patterns, voltage quality, and outage detection at the customer level. While smart meter data typically has lower temporal resolution than PMU or SCADA measurements, the comprehensive coverage across distribution networks supports multiple resilience functions. Applications of smart meter data for resilience include outage detection and localization, voltage monitoring for conservation voltage reduction, and demand forecasting for critical load prioritization. The integration of smart meter data with machine learning enables predictive analytics for demand response and load management during disruptions (Zahraoui et al., 2024). Advanced metering infrastructure also supports faster service restoration by providing real-time feedback on restoration progress and identifying remaining outages.

3.5 Comparative Analysis of Monitoring Techniques

Table 1 synthesizes the key characteristics, capabilities, and applications of the intelligent monitoring techniques examined in this section, providing a structured comparison to guide technology selection for specific resilience applications.

Table 1: Comparative Analysis of Intelligent Monitoring Techniques for Power System Resilience

Monitoring Technology	Temporal Resolution	Spatial Coverage	Key Capabilities	Resilience Applications	Advantages	Limitations	Representative Implementations

Phasor Measurement Units (PMUs)	30-120 Hz	Transmission & subtransmission	Synchronized phasor measurements; wide-area visibility; transient detection	Cyber-attack detection; transient stability assessment; oscillation monitoring	High temporal resolution; synchronized measurements; enables real-time analytics	High cost; requires communication infrastructure; cyber vulnerability	Qiu et al. (2023): 95.57% attack detection; Sun et al. (2022): TTEDNN stability prediction
SCADA Systems	2-10 seconds	Transmission & distribution	Supervisory control; topology monitoring; breaker status; power flow measurements	Risk assessment; defense resource allocation; topology reconfiguration	Comprehensive coverage; integrated with control; mature technology	Lower temporal resolution; limited transient visibility; cyber attack surface	IEEE TIA (2024): risk propagation modeling; defense optimization frameworks
IoT Sensors & Edge Devices	Variable (ms to minutes)	Distribution edge & customer premises	Distributed sensing; local intelligence; environmental monitoring; DER telemetry	Edge anomaly detection; local control; distributed situational awareness	Distributed architecture; local autonomy; redundancy; cost-effective	Large attack surface; interoperability challenges; data quality variability	Liu et al. (2024): DER-based grid cyber-resiliency; edge intrusion detection
Smart Meters & AMI	15-60 minutes (typical)	Customer level (comprehensive)	Consumption monitoring; voltage quality; outage detection; bidirectional communication	Outage detection & localization; demand forecasting; critical load identification; restoration verification	Comprehensive customer coverage; enables demand response; supports restoration	Low temporal resolution; limited real-time capability; privacy concerns	Zahraoui et al. (2024): ML-based demand forecasting; critical load scheduling

Note: Temporal resolution and spatial coverage values represent typical implementations and may vary based on specific system configurations. Resilience applications listed are representative examples and not exhaustive.

4. Intelligent Control Techniques

Intelligent control techniques leverage advanced algorithms and real-time data to optimize power system response under disruption. This section examines major control paradigms and their applications in resilience enhancement.

4.1 Artificial Intelligence and Machine Learning-Based Control

Artificial intelligence and machine learning techniques enable adaptive, data-driven control strategies that can handle the complexity and uncertainty characteristic of disrupted power systems. Applications span fault detection, optimal restoration planning, and real-time voltage control. Yang (2024) developed an AI-assisted disaster response framework for interdependent power distribution systems. The approach introduces an Operational Interdependence Simulator that models cascading failures across coupled infrastructure networks and uses machine learning to prioritize recovery actions. AI agents trained on thousands of offline scenarios compute optimal recovery paths in real-time when given fault locations. Validation on an IEEE 70-node distribution system demonstrated dramatic computational efficiency gains, reducing recovery planning time from 2.6 hours using traditional optimization to 7.3 seconds with the AI-assisted approach, while achieving prediction accuracy with R-values up to 0.97. Cross-domain studies of human–AI collaboration further indicate that increasing automation shifts expert roles toward supervisory refinement and validation of algorithmic outputs, highlighting the importance of human-in-the-loop oversight for safety-critical intelligent systems (Usman, 2017).

For voltage control applications, Du et al. (2022) proposed a physics-informed evolutionary strategy to mitigate fault-induced delayed voltage recovery. The method combines reinforcement learning with a trainable action mask that embeds physical constraints, improving sample efficiency and robustness compared to purely data-driven approaches. Case studies on the IEEE 300-bus system demonstrated superior performance relative to state-of-the-art benchmarks, highlighting the value of integrating domain knowledge with machine learning for safety-critical control applications. Deep learning techniques have also been applied to transient stability assessment, which is critical for maintaining synchronism during and after disturbances. Darbandi et al. (2020) developed a feedforward neural network with conjugate gradient backpropagation for real-time stability prediction on the IEEE 39-bus system, achieving superior accuracy, precision, and true positive rate compared to baseline methods. The real-time assessment capability enables proactive control actions to prevent instability.

4.2 Adaptive Control Strategies

Adaptive control techniques adjust controller parameters in real-time based on system measurements, enabling robust performance under varying operating conditions and uncertainties. This capability is particularly valuable for resilience applications where system characteristics may change dramatically during disruptions. For frequency regulation in low-inertia microgrids with high renewable penetration, adaptive model predictive control has demonstrated significant advantages. Hao et al. (2023) proposed an AMPC method that uses an unscented Kalman filter to estimate and update internal prediction model parameters in real-time. Simulation results on an isolated microgrid with high photovoltaic and wind turbine penetration showed that AMPC outperformed traditional PI controllers in maintaining frequency stability under large disturbances, effectively addressing the challenges posed by reduced system inertia. Adaptive control has also been applied to grid-forming inverters, which are essential for microgrids and future low-inertia grids. Recent research on online recursive least squares impedance estimation enables adaptive tuning of virtual synchronous generator controller gains, ensuring robust operation with specified settling time and damping ratio under varying grid conditions. This adaptive capability enhances resilience by maintaining stability across a wide range of operating scenarios.

4.3 Model Predictive Control and Optimization

Model predictive control formulates control decisions as optimization problems that explicitly account for system dynamics, constraints, and forecast information. This framework is well-suited for resilience applications involving energy storage, renewable generation, and critical load management. Gaikwad et al. (2020, 2021) developed an MPC-based intelligent control system for residential energy management during extended outages. The system optimizes battery charging/discharging and critical load scheduling based on solar generation and demand forecasts, formulated as a mixed-integer linear program. Simulations for a single-family house in Florida during Hurricane Irma demonstrated that the intelligent MPC system could halve the required photovoltaic-battery system capacity compared to non-intelligent baseline controllers while maintaining the same critical load service duration. This result highlights the significant economic benefits of intelligent control for resilience applications. At the distribution system level, Mohan et al. (2022) applied mixed-integer linear programming and fuzzy C-rate control for battery energy storage system scheduling to maximize critical load service time

during outages. The approach was validated on an IEEE 33-bus distribution network and introduced an apparent-power resiliency metric that accounts for both real and reactive power requirements.

4.4 Distributed and Multi-Agent Control

Distributed control architectures enhance resilience by avoiding single points of failure and enabling graceful degradation when communication links fail. Multi-agent systems coordinate local controllers through limited information exchange, supporting both centralized optimization under normal conditions and autonomous local control during disruptions. Ahrens et al. (2021) presented a multi-agent system for power grid resilience enhancement through coordination of smart buildings. The system employs both centralized and decentralized control strategies, using an adaptive evolutionary algorithm to schedule intelligent appliances, battery storage, electric vehicle charging, heat pumps, and combined heat and power plants. Simulation results in extreme load scenarios demonstrated substantial reductions in voltage range deviations, transformer temperatures, and line congestions. Notably, the decentralized strategy showed competitive performance and even surpassed centralized control in reducing congestion-triggered outages when voltage regulation devices were unavailable, demonstrating the resilience benefits of distributed architectures. The concept of networked microgrids extends distributed control to enable coordinated islanding and resynchronization. Mutluri et al. (2024) provided a comprehensive review of networked microgrid architectures, emphasizing distributed controllers, transactive energy frameworks, and blockchain-enabled coordination as pathways to resilient operation. Multi-agent reinforcement learning has been applied to optimize system reliability, load balancing, and generator reactivation in these complex distributed systems.

4.5 Comparative Analysis of Control Techniques

Table 2 provides a comprehensive comparison of the major intelligent control techniques discussed in this section, highlighting their key characteristics, advantages, limitations, and typical applications in power system resilience enhancement.

Table 2: Comparative Analysis of Intelligent Control Techniques for Power System Resilience

Control Technique	Key Characteristics	Primary Advantages	Main Limitations	Typical Applications	Representative Studies
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AI/ML-Based Control	Data-driven learning from historical scenarios; pattern recognition; autonomous decision-making	High adaptivity to complex scenarios; learns optimal strategies from experience; handles nonlinear dynamics effectively	Requires extensive training data; potential poor generalization to unprecedented events; black-box nature limits interpretability	Disaster recovery planning; optimal restoration sequencing; transient stability assessment	Yang (2024): 7.3s recovery planning vs. 2.6h traditional; Du et al. (2022): IEEE 300-bus FIDVR mitigation
Adaptive Control	Real-time parameter adjustment; online system identification; model updating based on measurements	Robust to changing conditions; maintains performance under uncertainty; no offline training required	Requires accurate online estimation; convergence time may limit response speed; stability guarantees needed	Frequency regulation in low-inertia grids; VSG parameter tuning; microgrid control under variable renewables	Hao et al. (2023): AMPC outperforms PI control in low-inertia microgrids
Model Predictive Control	Optimization-based; explicit constraint handling; incorporates forecasts;	Optimal resource utilization; handles multiple objectives; explicit constraint	Computational complexity for MILP; requires accurate models and forecasts;	Battery energy storage scheduling; critical load management; PV-battery optimization	Gaikwad et al. (2020, 2021): 50% reduction in PV-battery capacity; Mohan et al. (2022): IEEE 33-bus

	receding horizon	satisfaction; interpretable decisions	receding horizon tuning	during outages	BESS optimization
Distributed Multi-Agent	Decentralized decision-making; limited communication; local autonomy; graceful degradation	Resilient to communication failures; no single point of failure; scalable architecture; maintains local control	Coordination complexity; potential suboptimality vs. centralized; requires robust local controllers	Smart building coordination; networked microgrids; distribution system voltage control	Ahrens et al. (2021): competitive with centralized control; Mutluri et al. (2024): networked microgrid architectures

Note: Performance metrics and validation results are based on simulation studies and case studies reported in the cited literature. Actual performance may vary depending on specific system characteristics and implementation details.

5. Integration Approaches and Architectures

Effective resilience enhancement requires integration of monitoring and control capabilities through appropriate system architectures. This section examines hierarchical, hybrid, and distributed integration approaches.

5.1 Hierarchical Hybrid Architectures

Hierarchical hybrid architectures combine model-based and data-driven methods in layered frameworks that leverage the strengths of each approach. Model-based methods provide interpretability and formal guarantees, while data-driven methods handle complexity and adapt to changing conditions. A hybrid framework for cyber resilience in frequency control demonstrates this integration strategy (Sirmakesis, thesis). The framework combines observer-based detection with deep learning for attack estimation and mitigation. An autoencoder trained on normal load frequency control states detects cyber attacks by identifying deviations from expected behavior. When attacks are detected, the system switches from the compromised controller to a deep neural network-based estimator that reconstructs healthy control signals from field measurements. This layered approach

maintains load frequency control operation even under sustained cyber attacks, with validation demonstrating robustness against system uncertainties and nonlinearities.

5.2 Wide-Area Monitoring and Graph-Based Resilience Analysis

Wide-area monitoring systems provide comprehensive visibility across large interconnected power systems, enabling coordinated control and resilience assessment. However, the complexity of these systems necessitates scalable analytical frameworks that can identify critical components and assess cascading failure risks. Gautam et al. (2023) developed a transductive graph neural network approach for grid resilience analysis that leverages graph structure and system features to identify critical nodes and links. The method effectively learns resilience metrics based on actual grid operational behavior and demonstrates advantages over traditional simulation-based approaches for cascading outage analysis. The graph-based formulation provides scalability to large-scale power systems through transfer learning, enabling fast resilience assessment that would be computationally prohibitive with conventional methods.

5.3 Distributed Edge-Cloud Architectures

Edge-cloud co-design enables resilient operation by distributing intelligence between centralized cloud resources and local edge controllers. Edge devices perform time-critical monitoring and control functions that must remain operational during communication failures, while cloud resources provide optimization, learning, and coordination services. The multi-agent building control system developed by Ahrens et al. (2021) exemplifies this architecture. Local building controllers continuously monitor grid conditions and can operate autonomously using locally measurable data when communication with the central controller fails. This design provides graceful degradation, maintaining essential grid support functions even under communication disruptions while enabling coordinated optimization when full connectivity is available.

6. Challenges and Limitations

Despite significant progress, several challenges limit the deployment and effectiveness of intelligent monitoring and control for power system resilience.

6.1 Cybersecurity and Data Integrity

The increasing reliance on digital monitoring and control infrastructure expands the attack surface for cyber threats. False data injection attacks can corrupt measurements used for state estimation and control decisions, while label corruption attacks can degrade the training and performance of machine learning models. Wang et al. (2024) demonstrated that false label injection cyber attacks can significantly compromise transient stability assessment accuracy, necessitating multi-module robust methods and human-in-the-loop relabeling workflows to maintain model integrity.

6.2 Scalability and Computational Complexity

Many advanced control algorithms, particularly those based on mixed-integer optimization or deep reinforcement learning, face computational challenges when applied to large-scale systems. While AI-assisted methods have demonstrated dramatic speedups in specific applications, ensuring real-time performance across diverse operating scenarios remains challenging. Transfer learning and physics-informed approaches show promise for improving sample efficiency and generalization, but further research is needed to validate these methods on utility-scale systems.

6.3 Model Uncertainty and Robustness

Purely data-driven control methods may fail in scenarios not well-represented in training data, a critical concern for resilience applications where disruptions often involve unprecedented conditions. The physics-informed evolutionary strategy developed by Du et al. (2022) addresses this challenge by embedding physical constraints through trainable action masks, improving robustness compared to standard reinforcement learning. However, balancing model flexibility with physical consistency remains an active research area.

6.4 Interoperability and Standardization

The integration of diverse monitoring devices, communication protocols, and control platforms requires standardized interfaces and data models. Lack of interoperability can limit the effectiveness of coordinated control strategies and complicate the integration of new technologies. Industry efforts toward standardization, including IEEE 2030 and IEC 61850, provide frameworks for interoperability, but implementation challenges persist.

7. Future Directions and Recommendations

7.1 Physics-Informed Machine Learning

Future research should prioritize the integration of physical constraints and domain knowledge with machine learning algorithms. Physics-informed approaches that embed conservation laws, stability criteria, and operational limits into neural network architectures or training procedures can improve sample efficiency, generalization, and safety. The trainable action mask approach demonstrated by Du et al. (2022) provides one promising direction, while physics-informed neural networks offer alternative frameworks for incorporating differential equation constraints.

7.2 Adversarial-Robust Learning

Developing machine learning models that maintain performance under adversarial attacks is critical for resilience applications. Research directions include adversarial training procedures that expose models to corrupted data during training, robust optimization formulations that minimize worst-case performance, and multi-module architectures that combine diverse detection and estimation methods. Human-in-the-loop workflows that enable expert review and correction of suspicious predictions can provide additional safeguards for safety-critical applications.

7.3 Scalable Resilience Quantification

Extending resilience quantification methods to large-scale networked systems requires computationally efficient algorithms and appropriate abstractions. Graph neural networks offer a promising direction, enabling learning-based resilience assessment that scales to large networks while capturing topological structure. The transductive GNN approach demonstrated by Gautam et al. (2023) provides fast cascading analysis and critical component identification, with transfer learning enabling application to diverse system configurations. Future research should explore integration of these learning-based methods with physics-based simulation to provide both computational efficiency and physical interpretability.

7.4 Edge Intelligence and Distributed Resilience

Future power systems will require increased edge intelligence to maintain critical functions during communication disruptions. Research should focus on co-design of edge detection algorithms and local fallback controllers, distributed learning frameworks that enable model training across edge devices while preserving privacy, and coordination protocols that enable seamless transitions between centralized and distributed operation modes.

7.5 Economics-Aware Defense Allocation

Resilience enhancement involves tradeoffs between investment costs and risk reduction. Future research should develop integrated frameworks that combine physical impact assessment with economic analysis to guide defense resource allocation. Multi-objective optimization formulations can balance competing objectives such as minimizing defense costs, maximizing critical load service, and ensuring equitable resilience across diverse communities.

8. Conclusion

This comprehensive review has examined state-of-the-art intelligent monitoring and control techniques for power system resilience enhancement, synthesizing recent advances across monitoring technologies, control algorithms, and integration architectures. Key findings demonstrate the significant potential of these approaches: PMU-based cyber-attack detection achieving 95.57% accuracy, AI-assisted disaster response reducing recovery planning time by three orders of magnitude, and intelligent model predictive control halving required energy storage capacity for residential resilience. The analysis reveals that effective resilience enhancement requires integrated solutions that combine high-fidelity monitoring with adaptive, intelligent control across hierarchical and distributed architectures. Phasor measurement units, SCADA systems, IoT sensors, and smart meters provide complementary monitoring capabilities that enable situational awareness across multiple temporal and spatial scales. Artificial intelligence, adaptive control, model predictive control, and distributed multi-agent systems offer diverse control paradigms suited to different resilience challenges and system characteristics. However, significant challenges remain. Cybersecurity vulnerabilities threaten the integrity of monitoring data and control signals, requiring robust detection and mitigation strategies. Scalability and computational complexity limit the application of advanced algorithms to large-scale systems. Model uncertainty and the potential for poor generalization in unprecedented scenarios necessitate physics-informed approaches that balance flexibility with physical consistency. Interoperability challenges complicate the integration of diverse technologies and platforms.

Future research directions emphasize the integration of physical knowledge with machine learning, development of adversarial-robust algorithms, scalable resilience quantification methods, edge intelligence architectures, and economics-aware defense allocation frameworks. These advances will be essential for realizing the full potential of intelligent monitoring and control to enhance power

system resilience in an era of increasing disruptions and complexity. The transition toward resilience-oriented power system design represents a fundamental shift in engineering philosophy, moving beyond traditional reliability paradigms to embrace adaptive, learning-enabled systems capable of withstanding, adapting to, and recovering from diverse disruptions. The techniques reviewed in this paper provide a foundation for this transition, offering researchers and practitioners a comprehensive understanding of current capabilities and future pathways for creating more resilient electrical infrastructure.

References

- Ahrens, M., Kern, F., Schmeck, H., & Leibfried, T. (2021). Strategies for an adaptive control system to improve power grid resilience with smart buildings. *Energies*, *14*(15), 4472. <https://doi.org/10.3390/EN14154472>
- Darbandi, F. S., Tajer, A., & Schneider, K. P. (2020). Real-time stability assessment in smart cyber-physical grids: A deep learning approach. *IET Smart Grid*, *3*(4), 454-463. <https://doi.org/10.1049/IET-STG.2019.0191>
- Du, W., Lasseter, R. H., & Khalsa, A. S. (2022). Physics-informed evolutionary strategy based control for mitigating delayed voltage recovery. *IEEE Transactions on Power Systems*, *37*(3), 2309-2321. <https://doi.org/10.1109/tpwrs.2021.3132328>
- Gaikwad, A., Bhat, S., Jain, N., Khandelwal, A., & Ramakumar, R. (2020). Smart home energy management system for power system resiliency. *2020 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, 1-5.
- Gaikwad, A., Jain, N., Bhat, S., & Khandelwal, A. (2021). Increasing energy resiliency to hurricanes with battery and rooftop solar through intelligent control. *2021 IEEE Green Technologies Conference (GreenTech)*, 456-461.
- Gautam, M., Benidris, M., & Suryanarayanan, S. (2023). A transductive graph neural network learning for grid resilience analysis. *2023 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm)*, 1-6. <https://doi.org/10.1109/smartgridcomm57358.2023.10333912>

- Hao, J., Wang, Y., & Sun, M. (2023). Adaptive model predictive control based frequency regulation for low-inertia microgrid. *2023 5th International Conference on Power and Energy Technology (ICPET)*, 485-490. <https://doi.org/10.1109/icpet59380.2023.10367501>
- Hossain, M. S., Hasan, K. N., & Griffiths, M. (2020). Modeling and assessing cyber resilience of smart grid using Bayesian network-based approach: A system of systems problem. *Journal of Computational Design and Engineering*, 7(3), 352-366. <https://doi.org/10.1093/JCDE/QWAA029>
- Ibrahim, M. S., Dong, W., & Yang, Q. (2022). Resiliency assessment of power systems using deep reinforcement learning. *Computational Intelligence and Neuroscience*, 2022, 2017366. <https://doi.org/10.1155/2022/2017366>
- Joseph, C. (2013). From fragmented compliance to integrated governance: A conceptual framework for unifying risk, security, and regulatory controls. *Scholars Journal of Engineering and Technology*, 1(4), 238–250.
- Liu, Y., Ning, P., & Reiter, M. K. (2024). Enhancing cyber-resiliency of DER-based smart grid: A survey. *IEEE Transactions on Smart Grid*, 15(3), 3087-3103. <https://doi.org/10.1109/tsg.2024.3373008>
- Mohan, V., & Bhende, C. N. (2022). Intelligent control of battery storage for resiliency enhancement of distribution system. *IEEE Systems Journal*, 16(2), 2879-2890. <https://doi.org/10.1109/jsyst.2021.3083757>
- Mutluri, S. K., & Saxena, A. (2024). A comprehensive overview and future perspectives of networked microgrids for emerging power systems. *Smart Grids and Sustainable Energy*, 9(1), 18. <https://doi.org/10.1007/s40866-024-00218-0>
- Qiu, Y., Zhou, H., Gu, W., Xu, Y., Zhao, B., & Lu, S. (2023). Rapid monitoring and defense approach for resilience improvement of grid cyber security. *2023 IEEE Industry Applications Society Annual Meeting (IAS)*, 1-8. <https://doi.org/10.1109/ias54024.2023.10406496>
- Sun, M., Konstantelos, I., & Strbac, G. (2022). Fast transient stability prediction using grid-informed temporal and topological embedding deep neural network. *arXiv preprint arXiv:2201.09245*. <https://doi.org/10.48550/arxiv.2201.09245>

Usman, H. F. (2017). Evaluating the impact of AI-assisted composing on creative decision-making in episodic visual effects. *Scholars Journal of Arts, Humanities and Social Sciences*, 5(12), 1968–1973. <https://doi.org/10.36347/sjahss.2017.v05i12.031>

Wang, Y., Zhang, Y., & Liu, Y. (2024). A multi-module robust method for transient stability assessment against false label injection cyberattacks. *arXiv preprint arXiv:2406.06744*. <https://doi.org/10.48550/arxiv.2406.06744>

Yang, S. (2024). Resilience enhancement for interdependent power systems by AI-assisted disaster response. *Applied and Computational Engineering*, 95, 164-170. <https://doi.org/10.54254/2755-2721/95/20241640>

Zahraoui, Y., Alhamrouni, I., Mekhilef, S., Basir Khan, M. R., Seyedmahmoudian, M., Stojcevski, A., & Horan, B. (2024). AI applications to enhance resilience in power systems and microgrids—A review. *Sustainability*, 16(12), 4959. <https://doi.org/10.3390/su16124959>