A comprehensive review of AI-driven approaches for smart grid stability and reliability

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ABSTRACT

The stability and reliability of smart grids are essential for ensuring efficient and secure electricity delivery, particularly amid the increasing integration of renewable energy sources. This review presents a comprehensive analysis of artificial intelligence (AI)-based methods for real-time grid management, and fault detection. Unlike previous works that focus on isolated grid functions, this study provides a unified framework encompassing energy monitoring and control, optimization, and resilience. Machine learning, deep learning, and reinforcement learning techniques are systematically evaluated across diverse grid tasks, highlighting their strengths, limitations, and implementation challenges. Special attention is given to hybrid models that combine AI with optimization strategies to address issues such as scalability, computational complexity, and adaptability. The paper identifies critical research gaps and offers actionable recommendations to advance AI-driven smart grid operations, promoting more resilient, adaptive, and intelligent power systems.

Abbreviations

ANFIS	Adaptive neuro-fuzzy inference system	GAN	Generative adversarial network
AI	Artificial Intelligence	GPR	Gaussian process regression
ANN	Artificial neural network	GEO	Golden eagle optimization
CNN	Convolutional neural network	KNN	K-nearest neighbors
DBN	Deep belief network	LSTM	Long short-term memory network
DDPG	Deep deterministic policy gradient	MAS	Multi-agent system
DER	Distributed energy resource	MILP	Mixed-integer linear programming
DWT	Discrete wavelet transform	1D-CNN	One dimensional convolutional neural network
DRL	Deep reinforcement learning	OPF	Optimal power flow
DNN	Deep neural networks	RL	Reinforcement learning
DSM	Demand-side management	PCA	Principal component analysis
DT	Decision tree	PSO	Particle swarm optimization
ELM	Extreme learning machine	PV	Photovoltaic
EMD	Empirical mode decomposition	RF	Random forest
DL	Deep learning	REDD	Reference energy disaggregation data set
ML	Machine learning	RNN	Recurrent neural network

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FL	Federated learning	SVM	Support vector machine
FNN	Feedforward neural network	UK-DALE	UK domestic appliance-level electricity
GA	Genetic algorithm	VMD	Variational mode decomposition
DQN	Deep Q network	TD3	Twin delayed DDPG

1. Introduction

The global energy crisis and the growing effects of climate change have heightened the demand for sustainable and efficient energy systems [1]. This has accelerated the efforts toward improving energy efficiency and expanding renewable energy use into power grids. At the heart of this transformation is the smart grid, an enhanced power system driven by advanced information and communication technologies [2]. As illustrated in Fig. 1, the rising volume of scientific publications, particularly in the last decade, reflects a growing focus on enhancing the functionality and efficiency of smart grid technologies. Stability and reliability are crucial for integrating renewable energy and improving system resilience [3].

This review provides a comprehensive, structured analysis of real-

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time grid management and fault detection methods. It proposes a unified framework in energy management and fault diagnostics and classification. For each domain, the framework aligns characteristic time scales with decision levels (device, feeder, system) and compute placement (edge, substation, cloud), and it defines interfaces that allow outputs from fault diagnostics (e.g., calibrated risk scores) to tighten operational constraints in optimal power flow, while operational set points and price signals feedback to adapt detection thresholds and priors. This cross-layer perspective ties algorithm design to deployment realities so that advances in artificial intelligence translate into measurable gains in stability, efficiency, and resilience.

1.1. Contributions and significance

1.1.1. Coverage

To address emerging challenges in smart grid stability and reliability, this study offers a thorough review of literature published between 2015 and 2024 using a systematic review methodology. This ensures coverage of key advancements and trends over the past decade, offering a nuanced view of current developments and challenges in smart grid technologies. The review draws from three main sources: (*i*) academic databases like Scopus, IEEE Xplore, ScienceDirect, Google Scholar, and Springer, accessed via the university library with targeted keywords such as "smart grid", "AI in smart grids", "real-time processing", and "fault detection"; (*ii*) bibliographies of key book chapters and foundational surveys; and (*iii*) a rigorous snowball strategy involving backward and forward citation tracking. This was conducted over five iterative rounds to ensure exhaustive literature coverage. Table 1 summarizes the research protocol used.

In the initial phase, studies were selected based on the presence of at least one keyword combination in the title, abstract, or keywords. Abstracts—and full texts when needed—were then reviewed to confirm relevance. The backward and forward snowball method revealed 22 additional overlooked studies. Expert consultations further identified 11 relevant papers missed initially. This collaborative, systematic approach led to a comprehensive review of 318 papers, capturing key advancements and the growing importance of smart grid technologies in the global energy landscape.

1.1.2. Critical synthesis

As smart grid technology continues to advance, numerous comprehensive reviews have examined its multifaceted operations. Notably, Khan et al. [4] analyzed load forecasting and dynamic pricing in DSM, but focused mainly on residential systems, missing the complexities of

Table 1
Research guidelines and procedures.

Topic	Description
Background	
Rationale for the study	Tackle the significant challenges in modern smart grids by focusing on improving grid stability, boosting energy efficiency, and incorporating RES to address rising energy demands and environmental objectives.
Central research question	How can AI-based methods and cutting-edge technologies be leveraged to enhance grid stability, optimize energy distribution, and ensure the scalability of smart grid systems?
Need for further research	Offer a comprehensive and current review of smart grid technologies, highlight gaps in existing research, and propose areas for future exploration.
Search Strategy	
Search parameters	Title; Abstract; Keywords
Type of publications	Review papers and research articles
Databases searched	IEEE Xplore, Scopus, ScienceDirect, Springer
Snowballing technique	Identify additional relevant articles in academic databases, bibliographies, and through backward/forward snowballing techniques based on all previously selected papers
Selection Criteria	
Time frame	January 2015 to December 2024
Language	Restricted to English
Search terms	TITLE-ABS-KEY (("smart grid" OR "smart grids") AND ("grid stability" OR "voltage stability" OR "frequency stability") AND ("AI" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("fault detection" OR "fault classification" OR "grid fault diagnostics") AND ("real-time management" OR "real-time control" OR "real-time optimization") AND ("renewable energy integration" OR "distributed energy resources" OR "RES integration") AND ("predictive maintenance" OR "anomaly detection" OR "monitoring and control") AND ("energy optimization" OR "load forecasting" OR "demand response")).
Boolean logic	OR between keywords; AND between search fields
Inclusion criteria	Studies focusing on smart grid technologies, specifically addressing grid stability, optimization, and predictive maintenance.
Exclusion criteria	Excludes grey literature such as technical reports, theses, conference papers, book chapters.
Peer-reviewed sources	Academic journal articles
Data Synthesis	Descriptive analysis; Tabulation
Study Constraints	Inherent limitations such as the fast pace of technological changes and the diverse range of smart grid applications.

large-scale DSM. In a different approach, Macedo et al. [5] used ANNs in DSM to classify load curves and improve power management. However, their study focuses on ANN-based simulations, lacking coverage of other
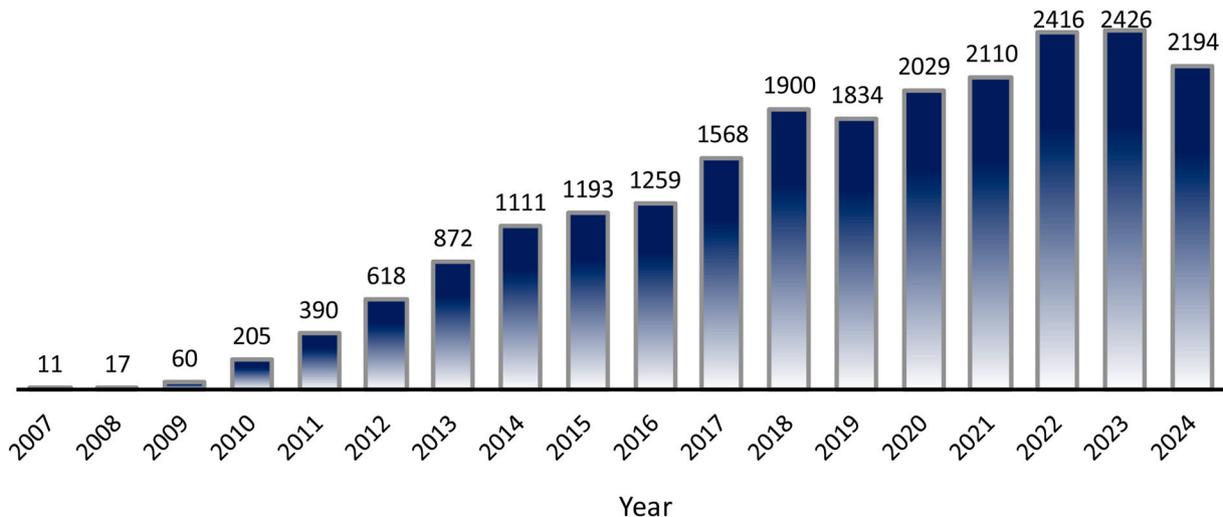

Fig. 1. Studies in the context of smart grid based on Scopus-indexed documents (2007–2024).

ML techniques and their integration into broader grid management. Further contributing to this field, Saini et al. [6] reviewed learning-based models for short-term wind speed forecasting, categorizing them into classical, advanced, and probabilistic ML techniques. However, they did not address integration challenges or complexities related to other renewable energy sources. Table 2 summarizes the existing review papers on various operational aspects of smart grids, highlighting the need for a more comprehensive understanding of the interplay between different technologies and their implications for effective grid management.

Despite the growing volume of literature on smart grid intelligence, existing reviews often focus on isolated components or specific AI methodologies without addressing their holistic integration in real-time grid operations. This review differentiates itself by offering a comprehensive, system-wide analysis of AI applications across five critical dimensions of smart grid stability: real-time energy monitoring, control, optimization, and fault detection. Unlike prior surveys, it directly addresses real-world deployment challenges, such as latency constraints, edge computing, data privacy, model interpretability, and the scalability of AI in high-dimensional, distributed environments. Key contributions of this review include.

- A cross-domain taxonomy of AI techniques (ML, DL, RL, hybrid, and ensemble models) applied to real-time grid functions.
- A focus on real-time responsiveness and deployment feasibility, particularly emphasizing the role of edge AI and communication-aware models.
- A critical synthesis of fault detection methods categorized by fault type and grid architecture, highlighting gaps in high-impedance and multi-fault scenarios.
- A forward-looking agenda covering emerging methods such as FL, multi-agent RL, and graph-based diagnostics, which remain underexplored in existing literature.

1.1.3. Research roadmap

Earlier works have typically advanced energy management (EM) and fault detection (FD) on separate tracks. EM studies refined forecasting, dynamic pricing, dispatch, storage coordination, and demand response—optimizing cost and efficiency within optimal power-flow

formulations—but largely treated protection and diagnostics as exogenous inputs (e.g., the taxonomy in Antonopoulos et al. [22]). FD studies, by contrast, focused on detecting, localizing, and classifying events such as high-impedance, short-circuit, and open-circuit faults, pushing model accuracy and latency yet without a clear path for how diagnostic outputs should alter real-time dispatch or market actions (e.g., the PV-oriented diagnostics survey in Li et al. [23]). This bifurcation yields siloed objectives, duplicated data pipelines, and missed opportunities to trade off risk, cost, and carbon in a closed loop.

The proposed framework bridges these silos by co-designing EM and FD as interoperable layers linked through shared telemetry, common state representations, and explicit interface contracts (see Fig. 2). Concretely, this work organizes AI-based approaches into two top-level branches. The first, Real-time grid management, comprises (*i*) energy monitoring and control (power estimation, dispatch, and control); (*ii*) energy optimization—covering pricing, energy management, and energy storage; and (*iii*) grid stability and aggregation including voltage stability, privacy-preserving data aggregation, and energy disaggregation. The second, fault detection and grid security, spans the principal disturbance classes addressed in this review (e.g., high-impedance, short-circuit, open-circuit, arc, and line faults, PV-specific shading effects). These categories map to characteristic time scales, decision layers (device, feeder, system), and compute placements (edge, substation, cloud). Diagnostic outputs (e.g., calibrated risk scores by fault family) are routed into EM optimizers as hard constraints or risk-weighted costs, while EM set-points and prices feed to adapt detector thresholds and priors. This alignment grounds algorithmic advances in deployment realities and translates AI techniques into measurable gains in stability, efficiency, and resilience.

2. Foundational concepts in AI-based models in smart grids

As illustrated in Fig. 3, the terms AI, ML, and DL are often used interchangeably in various domains, although they represent distinct concepts. AI encompasses the entire field, with ML as a subset and DL as a further specialization within ML [24]. This section provides an overview of different ML and DL, emphasizing their relevance to smart grids, methodologies, and implementation strategies.

Table 2
Comprehensive overview of existing review papers on smart grids.

Ref.	Number	Span	Scope							Features	Description
			Rtp	F	Fd	S	Dr	Ad	O		
[4]	101	up to 2015		✓			✓			1, 2	Reviews mathematical and AI models for DSM in residential energy management
[5]	27	up to 2013					✓			3, 4	Uses digital meter data to optimize power management through load curve classification
[6]	192	up to 2022		✓						1, 5	Reviews 41 ML models for short-term wind forecasting in smart grids
[7]	182	up to 2023		✓			✓			1	Discusses DL's role in improving electricity demand forecasting and demand response
[8]	123	up to 2022				✓				2	Reviews ML techniques for detecting and mitigating cyber threats in smart grids
[9]	350	up to 2019		✓						1, 5	Examines ML and ANN models for wind, solar, and geothermal energy forecasting
[10]	123	up to 2023			✓	✓		✓		1, 3	Focuses on anomaly detection and intrusion prevention in smart grids
[11]	123	up to 2023			✓	✓	✓			1, 2, 3	Explores AI's impact on privacy and security in demand response modeling
[12]	34	2016–2023					✓		✓	2, 3	Reviews traditional and intelligent methods for DSM optimization
[13]	343	up to 2021					✓		✓	1, 2, 5	Discusses computational methods for optimizing demand response strategies
[14]	230	up to 2022		✓						4, 5	Reviews evolution from traditional to ML-based load forecasting methods
[15]	115	up to 2022		✓						1, 2, 3	Highlights ML/DL as more accurate than traditional approaches for forecasting
[16]	122	up to 2022				✓				1, 3	Addresses gaps in DL applications for smart grid cybersecurity
[17]	180	up to 2023				✓				1, 4	Proposes solutions using ML and blockchain for smart grid vulnerabilities
[18]	251	up to 2022		✓			✓			1, 4	Reviews AI and blockchain integration to improve demand response
[19]	246	up to 2020					✓		✓	1, 2, 5	Discusses how DSM optimizes energy use and reduces carbon emissions
[20]	70	up to 2016							✓	1, 5	Reviews methods for handling uncertainties in renewable energy and load demands
[21]	163	up to 2021		✓	✓	✓				2, 3	Explores AI's role in forecasting, grid stability, and security
This study	318	2015–2024	✓		✓				✓	1, 2, 3, 4, 5	Critically analyzes AI-based techniques for improving smart grid stability and reliability through studying real time grid management and grid fault detection

Scope: Real time processing (Rtp); Forecasting (F); Fault detection (Fd); Security (S); Demand response (Dr); Anomaly detection (Ad); Optimization (O); **Features:** Comprehensive coverage (1); Critical analysis (2); Gap identification (3); Real world implementation (4); Sustainability and renewable integration (5).
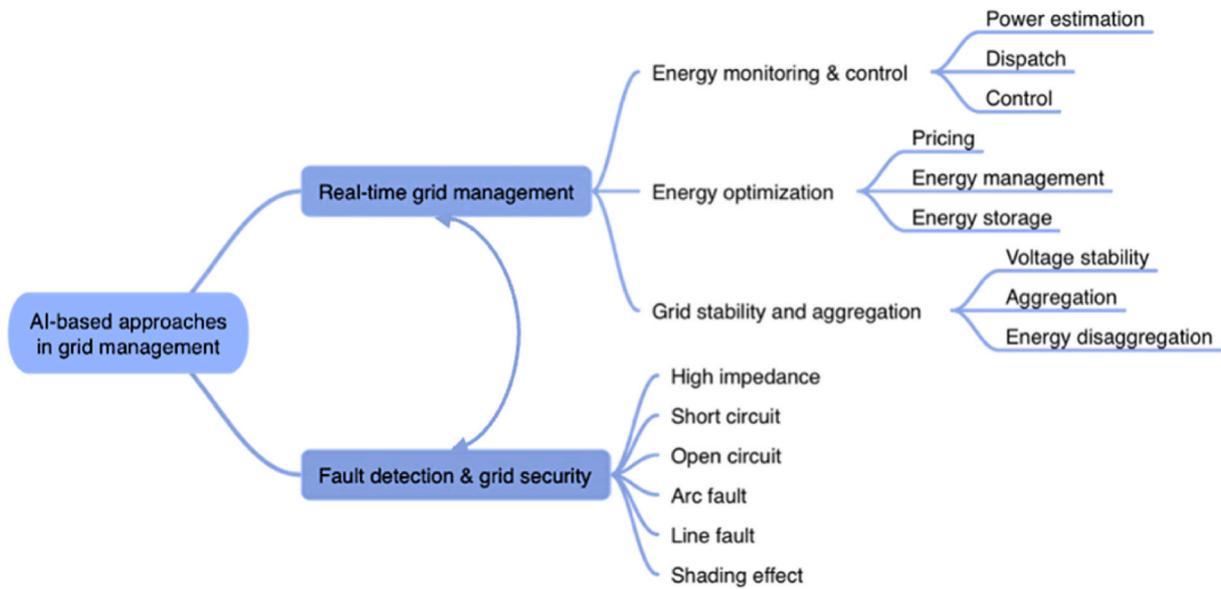
Fig. 2. Classification of cross-cutting approaches for enhancing grid stability and reliability.
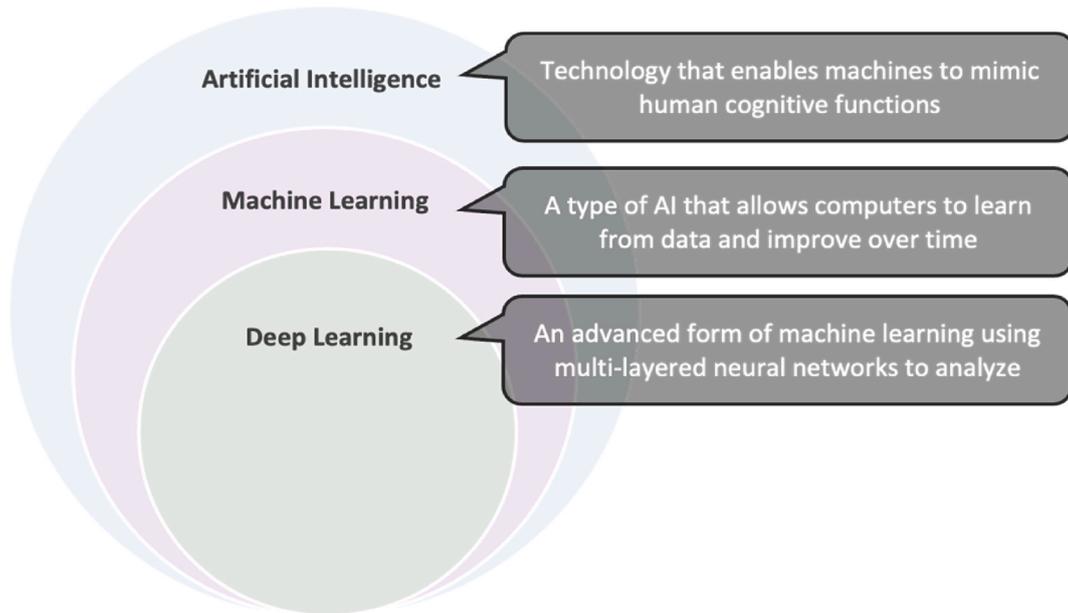

Fig. 3. The hierarchy of Artificial Intelligence, Machine Learning, and Deep Learning.

2.1. Machine learning models

ML models in smart grids are designed to continuously learn and adapt by analyzing vast amounts of data, enabling the grid to detect and respond to emerging patterns without requiring explicit programming. These algorithms play a crucial role in automating the analysis of system events and identifying potential threats, such as cyber-attacks or anomalies in grid operations. As illustrated in Fig. 4, ML techniques include supervised learning, unsupervised learning, semi-supervised learning, and RL [25].

2.1.1. Supervised learning

Supervised learning is essential for predicting outcomes using datasets with defined inputs and outputs. In cases with partial output data, semi-supervised learning leverages both labeled and unlabeled data, improving model accuracy, especially in grid scenarios with incomplete

information. SVM, a supervised learning method, are valuable for fault detection and anomaly identification in smart grids. By identifying an optimal hyperplane, SVM distinguishes faults and anomalies with high precision, crucial for grid stability and failure prevention [24]. Eqs. (1) and (2) represent the SVM objective function, which minimizes error by determining the optimal hyperplane.

$$W(\alpha) = -\sum_{i=1}^{L} \alpha_i + \frac{1}{2} \sum_{i=1}^{L} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j X_i X_j \tag{1}$$

Kernel trick equation minimizing W subject to:

$$\sum_{i=1}^{L} y_i \alpha_i = 0 \quad 0 \le \alpha_i \le C \tag{2}$$

where, α_i represents the Lagrange multiplier, X_i are the support vectors, and y_i and y_j are binary class labels for the training samples i and j,
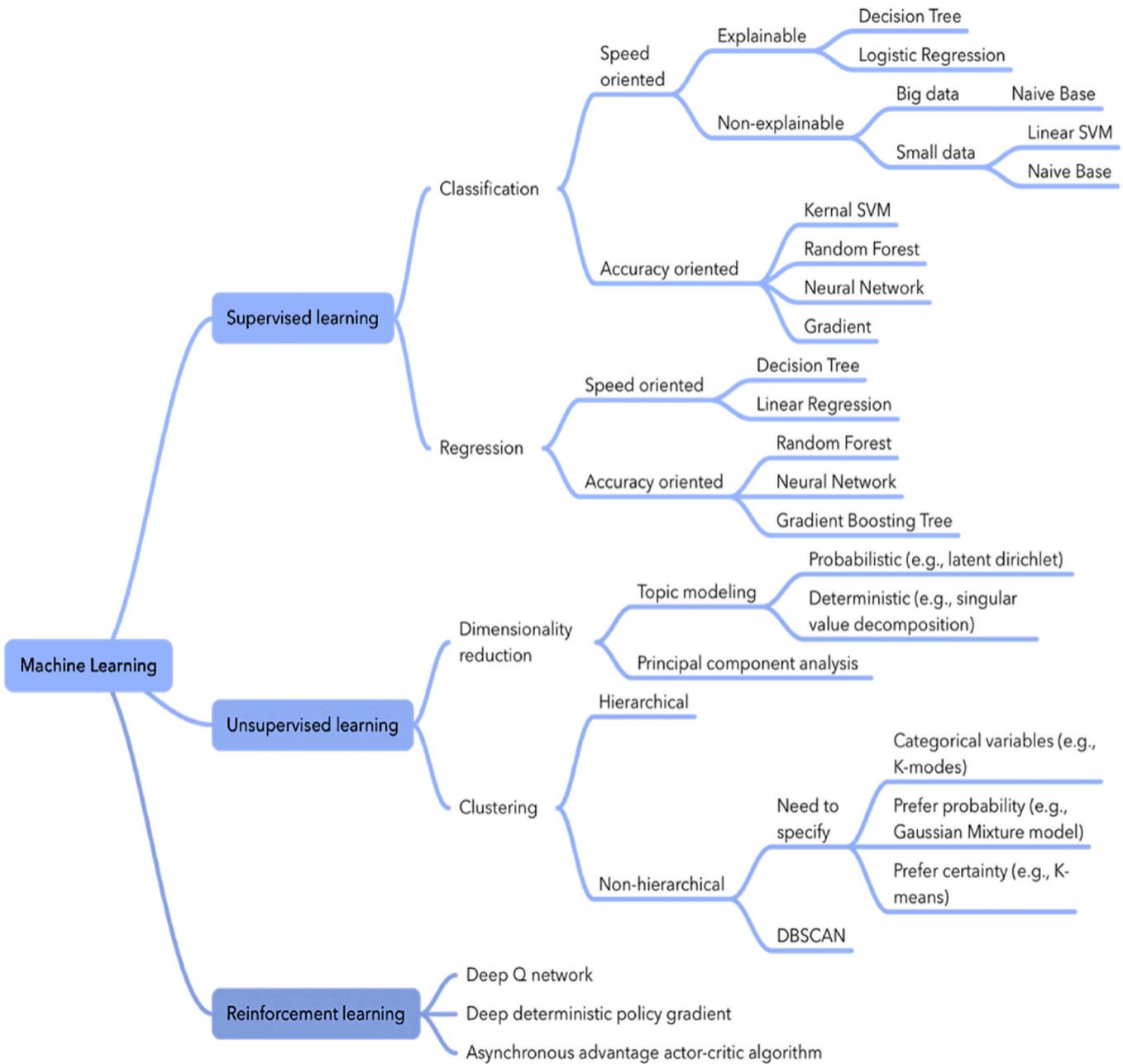
Fig. 4. Machine learning methods and algorithms.

respectively, where $y_i, y_j \in [-1, 1]$.

KNN, a supervised learning method, classifies inputs based on their nearest neighbors, making it ideal for fault classification and energy consumption categorization. The choice of distance metric (e.g., Euclidean, Mahalanobis) and the value of K are key to ensuring accuracy [26].

Naive Bayes is used for data categorization in smart grids, such as predicting demand spikes or security breaches. Despite assuming feature independence, it is efficient and performs well with simple feature relationships [26]. The continuous form, gaussian naive bayes, is represented in Eq. (3).

$$P(x = (v|C_k)) = \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{\frac{-(v-\mu_k)^2}{2\sigma_k^2}}$$ (3)

The probability of class C given an input x can then be calculated as Eq. (4):

$$P(C|x) = \frac{P(x)|(C)}{P(x)}$$ (4)

DT and RF are used for classification in smart grids. While DTs are simple and interpretable, they can overfit, especially with imbalanced data. RF overcomes this by combining multiple DTs, improving accuracy and robustness, making them effective for predicting power outages and identifying cybersecurity threats [26].

2.1.2. Unsupervised learning

Unsupervised learning identifies hidden patterns in data without predefined labels, making it valuable for managing complex smart grids. It supports clustering and dimensionality reduction, improving grid operations, optimizing resources, and detecting anomalies in energy use or system behavior [26]. Dimensionality reduction simplifies large datasets, enhancing processing and computational performance in real-time grid management. PCA, a common method, reduces

dimensions while preserving variance and essential information [26]. Though PCA effectively reduces dimensions, it lacks class label awareness, limiting its use in tasks needing class separation. Linear discriminant analysis addresses this by maximizing class separation through a linear combination of features, improving fault detection and anomaly classification by preserving separability, reducing overfitting, and boosting accuracy [26].

Clustering is another key unsupervised learning application, grouping data by shared traits. K-means clustering partitions data into K clusters by minimizing within-group variance, effectively identifying similar energy usage patterns. It iteratively assigns data points and recalculates centroids to reduce total squared errors. Though efficient for real-time smart grid use, its accuracy depends on initial centroid selection and data scaling. Poor initialization can cause suboptimal clustering, affecting energy management and grid fault classification. Performance varies with methods like Forgy (random centroid selection) and random partitioning (random cluster assignments) [26].

2.1.3. Reinforcement models

RL is a distinctive ML approach that does not rely on a pre-existing dataset, as shown in Fig. 5. Instead, it operates within a Markov decision process, enabling an agent to interact with a dynamic environment in real time [2]. The agent learns through trial and error, guided by reward values and state representations that highlight key aspects of the task. Rewards indicate performance, and methods like Q-learning use the Bellman equation to update state values and identify optimal actions. A well-designed reward function is crucial for the agent's success, as inadequate rewards can hinder learning and performance. The Q-learning is given by Eq. (5):

$$Q(s_t, a_t) + L_r.(r + \gamma.Q(s_{t+1}, a_{t+1})) \qquad (5)$$

where Q represents the Q-value for a specific state-action pair (s_t, a_t). It updates the previous Q-value by incorporating the current reward r received at the next time step $t + 1$ for state s_{t+1} after acting a_{t+1}, along with the anticipated future reward based on the highest Q-value for the next state [2].

2.2. Deep learning models

As shown in Fig. 6, DL techniques encompass supervised learning, unsupervised learning, and transfer learning. Unlike traditional ML models that depend on manual feature extraction, DL utilizes neural networks that emulate human brain function, learning directly from data through multi-layered architectures [7]. These deep networks can uncover complex patterns and abstractions critical for managing intricate systems. Their ability to autonomously learn features and classify data makes them highly effective for handling the large, dynamic datasets generated by smart grids. Furthermore, transfer learning enhances DL's capabilities by enabling models to leverage previously acquired knowledge for new, related tasks, thereby improving the generalizability of grid operations.

ANNs are a core DL consisting of an input layer, multiple hidden layers, and an output layer. Their capacity to process complex data flows and generate precise predictions makes ANNs particularly beneficial in smart grids, where real-time decision-making is essential for tasks like
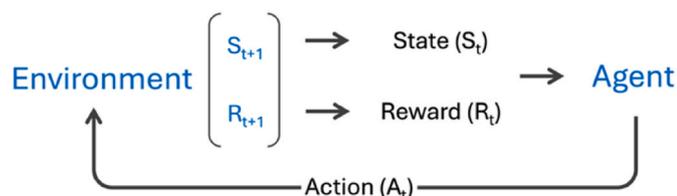
demand forecasting and fault detection [7]. The classification process in ANNs is illustrated by Eq. (6).

$$\sum_{i=1}^{n} (w_i, x_i) + bias \qquad (6)$$

where inputs x_i are multiplied by corresponding weights w_i, and the bias is added before passing through an activation layer as describes as Eq. (7).

$$Output = f(x) = \begin{cases} 1 \ if \ \sum wx + b \geq 0 \\ 0 \ if \ \sum wx + b < 0 \end{cases} \qquad (7)$$

CNNs enhance DL by automatically extracting features through convolutional layers. They improve feature detection in tasks that require spatial hierarchies, such as analyzing sensor data or identifying anomalies in grid monitoring [24]. By utilizing local connections, weight sharing, and pooling layers, CNNs reduce parameters and enhance efficiency with large datasets. Unlike traditional methods that rely on hand-engineered features, CNNs adaptively employ convolutional filters to recognize patterns like energy consumption irregularities. Dilated convolutions extend the receptive field, enabling the model to capture broader contextual information essential for managing grid operations across distributed networks [24].

Autoencoders are used for unsupervised feature extraction, especially in fault detection, due to their effective representation learning, simplicity, and ease of training. Their encoder-decoder structure integrates advanced DL techniques like RNNs and CNNs for complex feature extraction [24]. While linear autoencoders resemble PCA, they provide greater flexibility with nonlinear activation functions, making them more versatile for analyzing complex data [24]. The basic architecture of an autoencoder, mathematically expressed as Eq. (8).

$$h = f(w_e x + b_e) \quad \acute{x} = g(w_d h + b_d) \qquad (8)$$

where, x is the input, $\acute{x}$ is the reconstructed output, and h represents the latent space. The encoder's weights and biases are w_e and b_e, while the decoder's weights and biases are w_d and b_d.

2.3. Hybrid models

Hybrid models are essential for improving the efficiency and accuracy of smart grid systems by integrating various methodologies to minimize uncertainties and optimize performance [27]. Smart grids generate complex data from energy generation, distribution, and consumption, requiring advanced modeling for tasks like demand prediction and anomaly detection. Different types of hybrid models have emerged to address these challenges.

Data-driven hybrid models combine preprocessing techniques, such as wavelet transforms and chaos analysis, with AI models to analyze noisy energy consumption data effectively, enhancing accuracy in demand forecasting and fault detection [27]. Optimization-based hybrid models integrate algorithms like GA and PSO with AI, fine-tuning parameters to optimize predictive performance and reduce overfitting, particularly for load balancing and energy dispatch [27]. Finally, ensemble AI frameworks combine models like CNNs, RNNs, and RL to improve robustness and accuracy, effectively managing scenarios such as renewable energy management and energy storage optimization by processing spatial data and optimizing real-time energy distribution [27].

3. Advanced grid stability and reliability techniques

This section presents a comprehensive overview of the real-time processing techniques employed for grid management, and fault detection. These methods are categorized according to fault types and the models utilized in the management and detection processes.
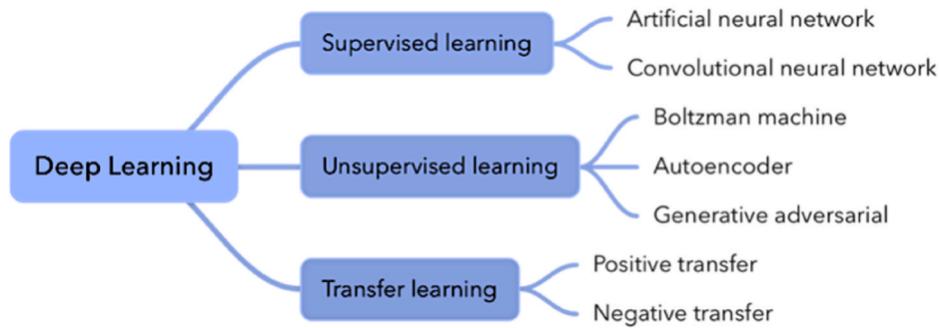

Fig. 5. Reinforcement learning structure.

Table 3
Overview of studies on real time energy monitoring and control.

Ref.	Processing			Solution method						Contribution and limitations
	PE	DI	CO	AI-based			O	DA	H	
				DL	RL	ML				
[28]	✓			✓						ConvLSTM was used for real-time PV-based power flow estimation under noise, achieving high accuracy but sensitive to input noise.
[29]		✓		✓			✓			An expandable DL with optimization improved dispatch/control in smart grids, though real-time scalability remains challenging.
[30]	✓					✓				SVM enabled behavior-aware energy management via distributed learning but struggled with real-time scaling under dynamic loads.
[31]			✓				✓			PSO-based distributed control enhanced smart grid optimization yet lacked robustness to topology changes.
[32]		✓					✓			A consensus-based ADP algorithm enabled fully distributed microgrid dispatch but may face issues under DER variability.
[33]			✓				✓			Optimization with demand prediction improved transit control, though irregular demand reduced forecast accuracy.
[34]	✓								✓	LSTM and deep Q-learning optimized smart traction energy use, but model complexity hinders broad deployment.
[35]		✓					✓			A two-layer model accounted for storage hidden costs in microgrid dispatch but depends on precise cost estimates.
[36]			✓		✓					Multi-armed bandits enabled adaptive real-time smart grid co-evaluation but underperformed with high uncertainty.
[37]	✓							✓		DFT-based measurement detected power transients under off-nominal frequency but struggled with rapid large deviations.
[38]	✓						✓			Distributed optimization improved real-time OPF control in smart grids but required extensive communication infrastructure.
[39]	✓						✓			Stochastic optimization balanced renewable power with flexible loads, though real-time convergence speed was limited.
[40]			✓				✓			Online feedback optimization ensured fair distribution grid management, but adapting to rapid load shifts remained difficult.
[41]	✓					✓				Hierarchical Temporal Memory detected anomalies and predicted data in one pass, with limited accuracy in non-patterned data.
[42]			✓						✓	ML with feature selection and FNN predicted grid stability in real time but required high-quality labeled datasets.
[43]		✓					✓			MILP optimized hybrid energy use in smart microgrids, though high computation time restricted real-time scalability.
[44]			✓				✓			OPF with IoT-enabled demand response improved grid flexibility, but interoperability across devices posed challenges.
[45]			✓				✓			Stochastic optimization balanced prosumer grids in real time but needed continuous state updates and robust forecasting.
[46]			✓	✓	✓					Data acquisition and trajectory optimization improved UAV mission efficiency, though mission diversity limited model generalization.
[47]			✓		✓					A Deep Q-Network enabled autonomous multi-energy control, but training instability in complex states was a key issue.
[48]			✓				✓			Lyapunov-based real-time energy management in smart homes balanced multiple objectives but required precise demand estimation.
[49]			✓						✓	Multi-task LSTM aggregated real-time data for anomaly localization, though dependent on synchronized multi-source inputs.
[50]			✓					✓		Boundary wavelet transform enabled fast overcurrent protection in DG systems, but accuracy dropped under high-frequency noise.
[51]			✓				✓			A hybrid stochastic and MILP-based method improved distribution management efficiency, though complexity limited real-time feasibility.
[52]			✓					✓		Dynamic regression detected short-term load anomalies quickly, but sensitivity to data fluctuations caused false positives.
[53]			✓						✓	Ensemble models with RVFL accurately assessed delayed voltage recovery yet required extensive labeled fault data.
[54]			✓				✓			Volt-var optimization via real-time co-simulation enhanced smart grid voltage control, but standard compliance was complex.
[55]			✓						✓	Multi-agent deep RL coordinated EV and grid operations, but communication delays impacted performance.
[56]			✓						✓	Bayesian graph neural networks and symbolic search optimized real-time pricing, though interpretability and training cost were high.
[57]			✓				✓			Distributed optimization-controlled storage under DC-OPF constraints, but real-time convergence and communication overhead remained concerns.
[58]			✓				✓			Stochastic OPF and Lyapunov optimization improved microgrid energy management, but real-time application required rapid state updates.
[59]		✓							✓	Twin delayed DDPG with clustering enabled real-time energy scheduling yet suffered from complex hyperparameter tuning.
[60]		✓					✓			MILP optimized cryogenic storage dispatch economically, though computation time limited use in real-time market fluctuations.
[61]			✓		✓					Q-learning scheduled home appliances efficiently in real time, but exploration caused suboptimal short-term decisions.
[62]			✓				✓			Mixed-integer programming reduced EV charging peak loads, yet high model complexity hindered real-time responsiveness.
[63]			✓		✓					Off-policy RL managed prosumer demand response flexibly, though required extensive experience replay data.
[64]		✓			✓					Twin delayed DDPG secured risk-aware economic dispatch, but performance degraded in highly uncertain scenarios.
[65]		✓	✓							DNNs controlled integrated microgrid dispatch, but model reject ability and stability required tuning.
[66]			✓					✓		Stationary wavelet transform detected DC grid faults in real time, but localization accuracy was limited under multiple faults.

Table 3 (*continued*)

Ref.	Processing			Solution method						Contribution and limitations
	PE	DI	CO	AI-based			O	DA	H	
				DL	RL	ML				
[67]			✓				✓			A two-stage optimization model improved emergency dispatch for heat-power microgrids, but slow first-stage computation impacted timeliness.
[68]		✓				✓				Imitation learning using grid expert strategies enabled real-time dispatch, though adaptability to unseen grid events was limited.
[69]			✓				✓			A hybrid metaheuristic (arithmetic optimization + PSO + DE) controlled grid-connected PV systems effectively but was computationally intensive.
[70]			✓		✓					Multi-agent deep RL achieved safe decentralized inverter control despite communication delays, though coordination under high latency remained challenging.
[71]			✓				✓			A MAS using GA, PSO, GSA, and ACO optimized multi-microgrid operations, but algorithm tuning was complex and scenario dependent.
[72]			✓						✓	Recursive least squares identified turbine dynamics for sensor less MPPT control, but real-time adaptation to wind variability remained difficult.
[73]	✓						✓			Quadratic programming-based feedback optimization estimated and controlled grid states in real time but relied heavily on accurate initial estimation.
[74]			✓				✓			Online feedback optimization with sensitivity estimation improved adaptive grid control, though robustness under abrupt changes was limited.
[75]			✓			✓				A recurrent high-order neural network controlled DFIG wind turbines during grid disturbances but required retraining for varying fault conditions.
[76]			✓				✓			Two-stage correction-based dispatch improved microgrid economy, but initial forecast inaccuracies limited the effectiveness of final corrections.

PE: Power estimation, DI: Dispatch, CO: Control.

for dispatch under constraints. However, their reliance on centralized models, deterministic assumptions, and slower convergence makes them less suitable for distributed, real-time scenarios. Recent work explores hybrid frameworks that combine AI with constraint-aware solvers (e.g., RL with MILP, DL with OPF), aiming to merge learning flexibility with physical feasibility. Despite progress, several gaps persist: (*i*) power estimation under uncertainty at the edge remains limited; (*ii*) DL and RL models still lack transparency, hindering operational trust; (*iii*) most algorithms are trained offline, restricting adaptability to real-world disturbances; (*iv*) and decentralized, scalable dispatch solutions are underrepresented, despite the growing role of prosumers and distributed resources. Table A1 in Appendix A lists the typical datasets, common metrics, and known limitations in real-time energy monitoring and control.

3.1.2. Real-time energy optimization

Real-time energy optimization enables dynamic pricing, energy management, and storage coordination, as reflected in Table 4. Most studies (>60 %) as shown in Fig. 8 rely on mathematical optimization such as convex, bi-level, or metaheuristic (e.g., PSO, GA) to manage pricing (50 %), energy flow (48 %), and, to a lesser extent, storage (2 %). These methods are computationally efficient but assume static constraints, limiting adaptability in high-variability or adversarial environments.

To address these limits, recent works integrate AI—particularly RL (e.g., Q-learning [79], PPO [92], DDPG [129])—with optimization frameworks. Hybrid models, such as Q-learning with PSO [87] or DRL with dual decomposition [93], improve flexibility but raise concerns over convergence stability, computational cost, and explainability. Multi-agent DRL approaches [106] further enhance distributed control yet suffer from coordination overhead and training complexity. Storage optimization remains underexplored. Techniques like Lyapunov and MILP [101,109,135] provide stability under uncertainty but assume accurate forecasts and ideal system behavior. Emerging hybrid solutions (e.g., stochastic DRL [103]) show promise, yet real-time responsiveness under imperfect data and stochastic pricing remains a key research gap. Unsupervised learning (e.g., clustering [91,97]) aids load segmentation for pricing adaptation but lacks integration with real-time control and dynamic user behavior tracking. Similarly, adversarial RL [102] and imitation learning [122] introduce robustness and generalization potential, but scalability and training reliability are unresolved. Key

research gaps include: (*i*) scalable, explainable RL for non-stationary dynamics; (*ii*) hybrid learning–optimization frameworks with convergence guarantees; (*iii*) real-time, distributed storage control under incomplete information; and (*iv*) integration of forecasting uncertainty into adaptive decision-making.

A practical resolution to the scalability and latency gaps is to cast real-time demand response as a two-stage Stackelberg game where a system-level leader updates prices or operational constraints and many followers (prosumers/aggregators) respond in parallel with best-response load schedules [137]. Follower problems are convexified (e. g., quadratic or linear costs with comfort and device constraints) and solved independently; solutions and sensitivities are then aggregated for a leader update. This structure admits wall-clock compatibility with 5–15-min pricing cycles and sub-minute feeder actions because (*i*) follower solves run in parallel on edge or aggregator nodes and (*ii*) the leader typically converges in a few Newton/gradient steps when warm-started from the previous interval (e.g. Refs. [78,80,83–85]).

Computational overhead is further contained through offline-trained surrogates. Price-elasticity and comfort models (RNN/DRL) are fit on historical traces; at runtime, the leader uses only forward evaluations and small corrective updates rather than full retraining (e.g. Refs. [86, 92]). Network coupling and reliability are enforced with distributed operators—dual decomposition or consensus/ADMM—so each participant solves a local subproblem while exchanging a few dual variables, which limits message size and iteration counts under realistic bandwidth (e.g. Refs. [93,100]).

Price updates can employ smooth Newton-type steps that accelerate convergence without inflating per-step cost [81]; utility- or incentive-based follower objectives handle heterogeneous preferences and devices [84]. For multi-seller/multi-buyer settings, bilevel programming with metaheuristic assistance (e.g., GA variants) scales to large populations while keeping the leader iteration budget bounded (e. g. Refs. [80,85]). Altogether, parallel follower solves, warm-started leader updates, surrogate inference, and distributed feasibility enforcement explain how game-theoretic hybrids deliver low wall-clock times with measurable gains in welfare, peak reduction, and constraint satisfaction in operational DR programs (e.g. Refs. [78,83,93]). Table A2 in Appendix A lists the typical datasets, common metrics, and known limitations in real-time energy optimization.

Table 4
Overview of studies on real time energy optimization.

Ref.	Processing			Solution method						Contribution and limitations
	PI	EM	ES	AI-based			O	DA	H	
				DL	RL	ML				
[77]	✓						✓			Real-time pricing is optimized using quantum-behaved PSO to achieve welfare equilibrium among diverse user types, offering fast convergence but requiring careful parameter control.
[78]	✓						✓			A robust decision-making model supports industrial load management under uncertain demand, using scenario-based optimization that ensures reliability but can yield overly cautious solutions.
[79]	✓				✓					Q-learning enables decentralized, adaptive real-time pricing by continuously learning from system states, though it may converge slowly in dynamic environments.
[80]	✓						✓			A bilevel optimization model combines PSO and branch-and-bound to coordinate pricing in multi-energy microgrids, optimizing interactions but increasing computational burden.
[81]	✓						✓			A cosh-based smoothing Newton algorithm solves non-smooth pricing problems with rapid convergence, but it depends heavily on precise derivative information.
[82]	✓						✓			The Levenberg–Marquardt algorithm is used to optimize real-time pricing by leveraging energy complementarity between microgrids and the main grid, though it risks local optima.
[83]	✓						✓			A bi-level optimization approach manages demand response through price and incentives in multi-energy systems, effectively shifting load but complex to solve in real time.
[84]	✓						✓			Real-time pricing is modeled with a logistic utility function and solved using a smoothing Newton method, accurately capturing user response but assuming idealized consumer behavior.
[85]	✓						✓			A distributed GA under a bilevel framework supports real-time pricing for multiseller-multibuyer grids under load uncertainty, offering flexibility at the cost of high computation.
[86]	✓			✓						RNNs are used to predict optimal real-time electricity prices, improving temporal accuracy but requiring extensive training data and model tuning.
[87]	✓				✓					Dual-agent Q-learning is used for real-time energy scheduling of prosumers with elastic loads, enabling adaptive decisions and better flexibility, though requiring high training time and careful reward design.
[88]	✓						✓			A convex optimization-based decentralized model integrates microgrids into the smart grid for real-time energy management, offering scalable and efficient dispatch, but depends on accurate convex approximations.
[89]	✓				✓		✓			Q-learning and DRL are combined to coordinate network reconfiguration and Volt-VAR control, enhancing real-time adaptability, yet challenged by graph complexity and convergence tuning.
[90]	✓						✓			Real-time pricing is optimized using a geometric mean optimization algorithm that incorporates price elasticity and PHEV charging, achieving improved load balance but sensitive to input parameter scaling.
[91]	✓					✓				Unsupervised learning via K-means clustering is applied to ensure fairness in real-time energy pricing, grouping similar load behaviors effectively, though limited in handling outliers or evolving patterns.
[92]	✓						✓			Proximal policy optimization, a DRL technique, manages smart home energy use in real time, improving cost savings and adaptability, but demanding large training data and computation.
[93]	✓						✓	✓		A distributed convex optimization and dual decomposition framework supports real-time demand response in multi-seller, multi-buyer markets, promoting scalability and autonomy, though requiring reliable coordination.
[94]	✓						✓			A hybrid grey wolf and differential evolution algorithm schedules home power under real-time and critical peak pricing, improving efficiency, yet sensitive to algorithm parameter tuning.
[95]	✓						✓			Bacterial foraging optimization is used for managing energy in smart homes and communities under real-time tariffs, offering bio-inspired adaptability but prone to slow convergence in large solution spaces.
[96]	✓								✓	Deep FNNs and deep Q-networks are used to manage real-time microgrid energy, enabling intelligent control under uncertainty but requiring significant offline training and tuning.
[97]	✓					✓				Hierarchical clustering analyzes generalized load patterns under real-time pricing, helping identify consumer behavior trends but limited in capturing temporal dynamics.
[98]	✓								✓	A dynamic optimization and clustering approach determines retail electricity prices based on real-time load profiles, improving responsiveness but dependent on load pattern consistency.
[99]	✓						✓			A simulation-based optimization technique examines vulnerabilities in real-time electricity markets, revealing risks from data integrity attacks but not offering direct mitigation strategies.
[100]	✓						✓			A distributed consensus-based ADMM algorithm coordinates optimal demand response and real-time pricing, enabling decentralized control with scalability, though sensitive to communication delays.
[101]	✓						✓			Convex optimization is used to schedule battery energy storage systems under real-time pricing, optimizing operational costs but assuming accurate forecasts and ideal storage models.
[102]	✓				✓					Robust adversarial DRL models real-time residential demand response with renewable energy, enhancing system robustness but requiring large and diverse training data.
[103]		✓					✓			A combination of stochastic and Lyapunov optimization manages real-time microgrid energy with reduced battery size, ensuring stability and cost efficiency under uncertainty.
[104]			✓				✓			An offline convex optimization approach schedules energy storage for renewable integration in microgrids, minimizing costs but unable to adapt to real-time fluctuations.
[105]		✓					✓			A distributed gradient algorithm enables real-time multi-objective microgrid management within an agent-based bargaining framework, allowing flexibility but requiring extensive inter-agent coordination.
[106]		✓							✓	Multi-agent DRL with value decomposition and binary integer programming optimizes battery swapping operations, offering real-time scheduling but requiring significant computational resources.
[107]	✓							✓		Real-time pricing is derived using distributed data fusion across network nodes, enabling improved accuracy through collaborative sensing, but requires consistent and synchronized data streams.
[108]		✓			✓					DRL is used for residential real-time demand response, dynamically adapting to load changes with improved user comfort, though training overhead is considerable.
[109]		✓					✓			Lyapunov optimization schedules energy in real-time smart grids with renewables, ensuring system stability and queue management, but depends on well-tuned Lyapunov parameters.
[110]		✓					✓			Mixed-integer programming plans smart charging using precomputed real-time schedules, achieving optimized performance but limited by static forecast accuracy.
[111]		✓					✓			A robust distributed control strategy uses Lyapunov optimization to manage energy in smart grids, providing resilience to uncertainties but sensitive to parameter variability.

Table 4 (*continued*)

Ref.	Processing			Solution method						Contribution and limitations
	PI	EM	ES	AI-based			O	DA	H	
				DL	RL	ML				
[112]		✓				✓				Semi-supervised SVM detects real-time anomalies in household energy usage with minimal labeled data, improving detection efficiency but limited in generalizing across diverse home profiles.
[113]	✓						✓			MILP-based optimization manages household operations using bi-directional EV and storage under real-time pricing, increasing flexibility but with scalability concerns in larger systems.
[114]		✓					✓			Hybrid evolutionary algorithms, including GA and PSO variants, schedule loads and manage renewable integration in real time, enhancing adaptability but computationally intensive.
[115]		✓							✓	Battery state-of-charge is forecasted in real-time using LSTM and ARIMA models, increasing microgrid reliability, though requiring frequent retraining for accuracy.
[116]		✓					✓			Quadratic programming optimizes real-time energy storage in grid-connected systems based on market prices, reducing costs but assuming linear cost structures and ideal forecasts.
[117]		✓					✓			A multi-period data-driven control strategy integrates OPF with stochastic optimization to manage storage in virtual power plants, offering flexibility over time but relying on accurate forecasting.
[118]		✓							✓	Multiple neural network architectures—including cascade, Elman, and time-delay models—are compared for real-time performance evaluation of a 5 MW solar PV plant, enhancing modeling precision but requiring extensive training data.
[119]		✓					✓			A modified PSO algorithm manages community energy storage under uncertain real-time prices, increasing energy efficiency while facing parameter sensitivity and convergence trade-offs.
[120]		✓					✓			A net present cost-based optimization method is applied to size and control grid-connected storage under real-time pricing, reducing long-term costs but assuming static economic factors.
[121]		✓					✓			A near-linear complexity scheduling algorithm integrates large-scale EVs into the grid in real time, improving scalability while simplifying certain network constraints.
[122]		✓							✓	A hybrid framework combines GAN-based imitation learning, MILP, PPO, and deep Q-networks to manage real-time hydrogen refueling station energy, enhancing robustness but computationally demanding.
[123]		✓					✓			Real-time optimal scheduling for grid-tied microgrids uses the Honey Badger algorithm and PSO, handling load uncertainties effectively but depending on algorithm parameter tuning.
[124]		✓					✓			Bi-level energy management of multi-nanogrids is optimized in real time using Aquila and improved Aquila optimization with PSO, offering accurate control but increasing model complexity.
[125]		✓							✓	DL-based adaptive dynamic programming manages real-time microgrid control, enabling intelligent response strategies but requiring a well-trained adaptive model.
[126]		✓			✓					A real-time power management system with a memory self-organizing incremental neural network predicts PV output, adapting to changing patterns but limited by initial training quality.
[127]	✓						✓			An anti-predatory PSO algorithm addresses real-time pricing in remote microgrids with emission and stochastic renewable considerations, improving economic dispatch but sensitive to parameter variations.
[128]		✓					✓			A modified PSO method enables real-time energy management in grid-connected microgrids, enhancing convergence and load optimization but requiring parameter fine-tuning.
[129]		✓		✓						Deep deterministic policy gradient is applied to schedule large-scale hydrogen production using off-grid renewable energy, providing real-time control but with high model complexity.
[130]		✓				✓				DWT is used for real-time monitoring and assessment of solar microgrid temperatures, supporting fault detection but limited in predictive energy control.
[131]	✓								✓	A bi-level optimization model enables grid-aware pricing through real-time power tracing, offering dynamic cost allocation but depending on full observability of system states.
[132]		✓					✓	✓		Real-time grid forecasting and control are improved using data cleaning and Lyapunov optimization, addressing missing behind-the-meter information but sensitive to data quality.
[133]		✓					✓			Stochastic optimization supports distributed power management via megawatt trading in real-time electricity markets, encouraging demand-side flexibility with moderate computational needs.
[134]		✓			✓					Double-Q learning handles real-time energy storage arbitrage under uncertain market prices, enabling adaptive decision-making but challenged by training stability.
[135]		✓					✓			A finite-time horizon Lyapunov approach manages energy storage with renewable integration, offering stable control but limited by horizon assumptions and modeling fidelity.
[136]		✓					✓			A multi-objective optimization method coordinates demand response and real-time thermal rating to enhance wind energy utilization, balancing load and generation effectively but increasing model complexity.

PI: Pricing, EM: Energy management, ES: Energy storage.

3.1.3. Real-time grid stability and aggregation

Maintaining grid stability and leveraging aggregated data are central to resilient energy systems. Table 5 reveals a methodological shift toward ML and DL for real-time voltage stability, data aggregation, and energy disaggregation. Voltage stability monitoring now employs ML-based estimators (e.g., ANN [138], LSTM [139]) capable of nonlinear mapping with limited retraining. These models achieve high predictive accuracy (<0.32 % error [139]) but depend on consistent feature relevance and field data quality—posing challenges under grid reconfiguration or noisy telemetry. Multi-objective optimization frameworks (e.g. Ref. [140]) integrate predictive analytics and constraint satisfaction but often lack scalability for real-time deployment due to their computational intensity.

Aggregation techniques, such as binary decomposition with Laplace transforms [141], offer privacy-preserving real-time aggregation of metering data. While effective in securing communication and maintaining low overhead, these methods may degrade with increasing node heterogeneity or asynchronous updates—an unresolved issue in federated energy networks. Energy disaggregation, as explored via deep CNNs with autoregressive models [142], shows strong accuracy on public datasets (e.g., UK Domestic Appliance-Level Electricity, Reference Energy Disaggregation Data Set). However, such models face generalization issues across regions, appliance diversity, and load signatures.

Moreover, their utility in active control loops (e.g., fault isolation or demand-side actuation) remains largely unexplored. The integration of learning models for multi-variable grid stability monitoring and load-level disaggregation signals a move toward fine-grained, edge-aware intelligence. Still, gaps persist in: (i) adaptive model retraining under distribution-level dynamics; (ii) real-time disaggregation with interpretability and fault sensitivity; and (iii) secure, low-latency aggregation in heterogeneous smart grid environments. Future work should explore
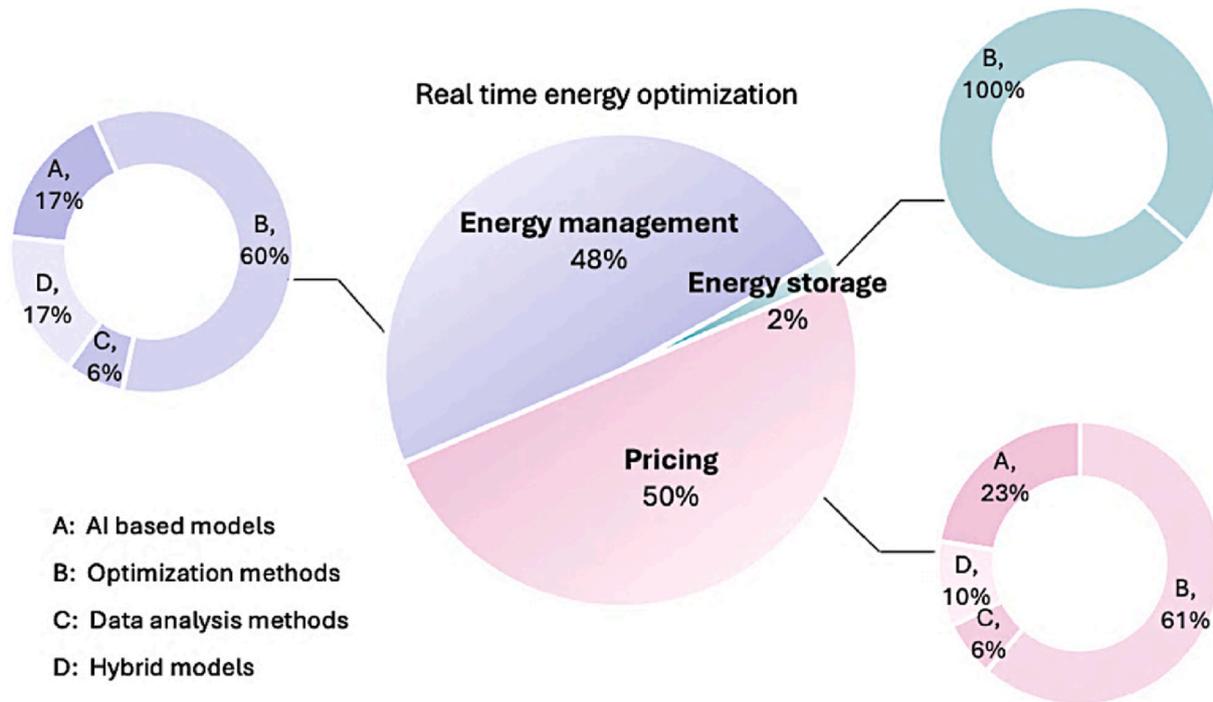
Fig. 8. Distribution of models employed for real time energy optimization.

Table 5
Overview of studies on grid stability and aggregation.

Ref.	Processing			Solution method					Model	Description	Results
	VS	AG	ED	AI			O	DA	H			
				DL	RL	ML						
[140]	✓						✓			Multi objective programming	Hierarchical self-adaptive data-analytics using ensemble-based randomized learning and multi-objective optimization for voltage stability assessment.	High accuracy and speed in voltage stability assessment; outperforms existing methods.
[141]		✓						✓		Laplace multi-dimensional decomposition algorithm, binary decomposition aggregation	Privacy-preserving aggregation via binary decomposition for secure real-time monitoring.	Accurate aggregation with improved privacy and efficiency over previous schemes.
[142]			✓						✓	Multi-channels deep CNN, autoregressive model	Real-time energy disaggregation using multi-channel deep CNN and autoregressive model.	High disaggregation accuracy on UK-DALE and REDD datasets with small model size.
[138]	✓					✓				ANN	Robust neural network voltage estimator with feature selection, trained on field data.	Accurate real-time voltage predictions with minimal retraining every 10–20 days.
[139]	✓								✓	FNN, radial basis function, LSTM, ELM	ANN-based real-time prediction of voltage and frequency using RNNs.	Very low error (<0.32 %) in predicting grid voltage and frequency in real-time tests.

VS: Voltage stability, AG: Aggregation, ED: Energy disaggregation.

graph-based deep models, federated disaggregation, and privacy-preserving optimization techniques for scalable, decentralized grid intelligence. Table A3 in Appendix A lists the typical datasets, common metrics, and known limitations in grid stability and aggregation.

3.2. Fault detection and diagnostics

Fault detection is essential for network reliability and safety but differing in immediacy and methodologies. Real-time fault detection uses advanced monitoring systems and analytics to quickly identify issues like equipment malfunctions, short circuits, and ground faults. By analyzing high-frequency sensor data, operators can take immediate corrective actions to prevent small issues from escalating. Techniques like DBN, cumulative sum methods, neural networks, Kalman filters, and RL enhance the accuracy and speed of real-time detection.

3.2.1. High impedance fault detection and classification

High impedance faults are difficult to detect due to low current signatures easily masked by noise. Table 6 shows that while data-driven techniques, especially ML/DL, offer improvements overrule-based detection, they largely rely on simulated data and remain fragile under real-world noise, topological shifts, or measurement variability. Signal decomposition methods like DWT and VMD remain dominant in preprocessing. Though effective at feature extraction, they are sensitive to parameter tuning, lack scalability, and become computationally prohibitive in large-scale or real-time settings. Kalman filters offer

Table 6

Overview of high impedance fault detection and classification.

Task focus	Energy type	Ref.	Model	Dataset	Limitation
Detection	RES	[143]	DWT, DT	Simulated 5-bus micro-grid using PSCAD	Real-life implementation challenging, not validated with physical data.
		[144]	FNN, DWT	MATLAB/SIMULINK, IEEE 13-node distribution network	Measurement noise impact not fully addressed, limited focus on localization.
	Electrical Power	[145]	Backpropagation neural network	Testing System Data	Limited to specific network scenarios, sensitivity to noise.
		[146]	Adaptive boosting	PSCAD/EMTDC	Adaptability to changes in network topology, accuracy depends on noise handling.
		[147]	Sensitive sparse PCA	Simulated and real-world data	Dependent on measurement settings, noisy environments impact detection.
		[148]	Multi-task logistic low-ranked dirty model	PMU data	Model performance can suffer under extreme noise, needs scenario adaptation.
		[149]	DL	Simulated data	Dependent on high sensor accuracy, complexity in sensor selection and data loss.
		[150]	Semi-supervised learning, probabilistic learning, feature selection	Real-time μ-PMU data, Simulation dataset	Ineffective for strong arc faults, limited by data sampling and signal variability.
		[151]	DNN	Real low-voltage distribution grid in Portugal	Limited by data availability, high fault resistance, generalization issues across grids.
		[152]	CNN, wavelet transform	Simulated high impedance fault waveforms, real noisy measurement data	Complex parameter selection, threshold optimization, noise and harmonics affect performance.
		[153]	CNN	Historical high impedance fault data from multiple distribution networks	Limited high impedance data, performance depends on quality of augmented data.
		[154]	DWT	Simulated in MATLAB/Simulink	Complex feature extraction, risk of overfitting, dependence on statistical feature extraction.
		[155]	VMD	Simulations and field tests	Sensitive to noise, high computational cost, limited for large-scale networks.
		[156]	ANN, DWT	MATLAB/Simulink	Dependence on simulated datasets, noise interference challenges, lack of real-world testing.
		[157]	VMD	Simulation and field tests	Effective only for faults up to 200 Ω, challenges with low resistance faults.
		[158]	DNN, LSTM-RNN, CNN, DBN	Power line fault detection dataset	Limited incipient fault data, augmentation needed for nonstationary signals.
		[159]	Continuous wavelet transform, gaussian smoothing	Simulations and Field Data	Limited high impedance fault data, complexity in μ-PMUs data acquisition.
		[160]	Graph convolutional network	PSCAD/EMTDC simulation data	Affected by ground surfaces, harmonic pollution, flexible network topologies.
		[161]	Transformer with differential architecture search	IEEE 14 bus distribution system, VSB power line fault detection database	Limited adaptability to real-world complex fault conditions.
		[162]	Extend Kalman filter	Simulations in MATLAB and Simulink	Sensitive to noise in fault signals, optimization needed for real-time application.
	Electrical Power, RES	[163]	Optimal transient extracting transform, PSO	Modified IEEE 30 bus radial system with renewables	Complexity in model training, potential overfitting, challenges with multi-load scenarios.
		[164]	SVM, CNN, DWT	Real-time simulations	Adapting to dynamic environments complex, validation under diverse conditions needed.
		[165]	Improved complete ensemble empirical mode decomposition with adaptive noise	Simulated data	High impedance faults present complexity due to nonlinear behavior; challenges in real-world conditions.
Detection and classification	RES	[166]	KNN, SVM	Simulated data set	Lacks comparison between ANN; does not fully explore diverse renewable sources; computational speed not addressed.
		[167]	Radial basis function neural network, SVM, nonlinear autoregressive with external input, DWT	IEEE-5 feeder test bed	Limited to tested microgrid models; performance can vary with different configurations.
	Electrical Power	[168]	Maximal overlap DWT, extreme gradient boosting	IEC-1457 microgrid model, IEEE 13 bus microgrid	Limited to distribution lines with DGs; does not address faults in other configurations.
		[169]	Fuzzy inference system	Simulated test system data	Recalibration needed for different topologies; accuracy can degrade with noisy measurements or changing grid dynamics.
		[170]	Discrete Kalman filter	CIGRE microgrid benchmark on MATLAB/Simulink; dSPACE MicroLab hardware setup	Lack of practical solutions for all high impedance fault scenarios; limited feature analysis.
		[171]	Kalman filter, SVM	Historical data	High computational cost, sensitive to noise, requires large dataset.

denoising but degrade under rapidly varying arc faults.

Traditional ML models (e.g., FNN, SVM) offer basic classification but depend on manual feature engineering and perform poorly in evolving fault scenarios. DL such as CNNs, LSTMs, and hybrids (e.g., DBN + LSTM, CNN + DWT + SVM) show improved fault localization and noise resilience but require significant labeled data and are computationally intensive, limiting real-time deployment, especially at the edge (e.g., μ-PMUs). Table B1 in Appendix B lists the typical datasets, common metrics, and known limitations in high impedance fault detection and classification.

Advanced models like graph convolutional networks and transformers better capture spatio-temporal fault dynamics but remain underexplored in diverse grids and often lack robustness under harmonic pollution or topology reconfiguration. Semi-supervised learning and probabilistic models show early promise with real μ-PMU data but often fail to detect strong arc faults or generalize under varying signal quality. A major limitation across studies is the reliance on synthetic environments (e.g., PSCAD, MATLAB). Real-world datasets are rare, fragmented, and often lack fault diversity. Few models account for mixed-resource grids (conventional + RES) or high-resistance, intermittent arc faults. Critical research gaps include: (i) adaptive models that generalize across fault types and network conditions; (ii) fusion of physics-based and learning models for explainability and robustness; (iii) standardized real-world high impedance faults datasets for benchmarking and (iv) deploying AI on edge devices like μ-PMUs demands a pipeline engineered for sub-cycle inference (≈8–16 ms per frame), tight memory/compute budgets, and high reliability.

Practical steps include: (*i*) Adopt μ-PMU frame rates (≈60–120 fps) as the timing baseline and set per-frame inference to sub-cycle latency, with bounded memory and integer-friendly arithmetic. Field-validated studies demonstrate that real-time neural estimators and detectors can meet such budgets when designed for low-latency input and output timing (I/O) and streaming computation [138,139,172]. (*ii*) Compute minimal rolling features over 1–2 cycles (e.g., voltage/current magnitudes and angles, rate of change, sequence components, and narrow-band energies) to maintain short ring buffers. Streaming wavelet front ends have run in real time on distribution and DC systems, confirming low overhead at the edge [66,138,172]. (*iii*) Prefer 1D depth wise-separable CNNs or tiny GRU/temporal-CNN hybrids fed by the streaming features above. Lightweight CNNs have been applied to grid fault detection with real-time considerations and small memory footprints, including fully convolutional detectors validated on PSCAD/RTDS and practical fault datasets. (*iv*) Start with channel/filter pruning (structure-preserving to keep memory access regular), then post-training 8-bit quantization for CPU/DSP/FPGA targets, and finally knowledge distillation from an accurate teacher to the pruned/quantized student. Edge-oriented grid studies report sustainable deep models at the grid edge and document the latency/energy benefits of compact learners for protection tasks [149].

Practical μ-PMU work underscores the importance of efficient inference under distribution-level noise and rate constraints [150]. (*v*) Attach calibrated anomaly scores or conformal prediction intervals to each decision. On high uncertainty, fall back to conservative actions (e. g., higher trip margins, temporary de-rating) and/or escalate to the control center. Real-time field results in voltage/fault applications illustrate the need for such assurance hooks to sustain accuracy under operating shifts [138,139,172]. (*vi*) Transmit sparse alerts and compact embeddings instead of raw waveforms; push only exception windows and confidence scores. This reduces bandwidth while preserving forensic value, consistent with field-validated μ-PMU/fault-detector deployments that operated across simulated, HIL, and practical datasets [150,172]. (*vii*) Bind the quantized model early to the target edge platform (ARM Cortex-A/R, DSP, or FPGA). Prefer integer kernels and vector intrinsics; on FPGAs, implement fixed-point convolutional/GRU blocks with streaming DMA. Evidence from grid-edge implementations and sustainable deep-learning studies shows that early hardware mapping prevents late regressions in latency and energy (e.g. Refs. [149,173, 174]). (*viii*) Perform periodic, on-device threshold re-tuning and only occasional server-side retraining of the teacher model, followed by over-the-air updates to the student. Keep all on-device updates bounded, unit-tested, and reversible. Deployed neural estimators operating under changing conditions demonstrate that controlled adaptation is essential for long-term reliability.

3.2.2. Short circuit fault detection and classification

Short-circuit faults are frequent and hazardous events in power systems, demanding accurate and immediate detection. Despite their high current signatures, precise localization and classification remain challenging, especially in microgrids or RES-dominated systems. As summarized in Table 7, a broad range of data-driven models have emerged, but most remain limited in generalization, scalability, or real-time feasibility. Signal decomposition techniques like PCA, wavelet PCA, Mallat decomposition, and EMD are effective in feature isolation under noise, especially in PV arrays [175,176,177]. However, these methods often fail under unbalanced conditions or rapid load shifts. Modified decompositions offer enhanced sensitivity but increase computational cost and are rarely tested on real-time datasets.

ML methods such as SVM, KNN, DT, and RFs [179,182,194,195] show robust classification under controlled settings but struggle with non-linear signal dynamics and require manual feature selection. DL, including CNNs, LSTM, autoencoders, and DBNs [178,188,189], are favored for real-time fault detection due to their ability to learn from complex, nonlinear voltage-current patterns. However, they require high-quality data, large training sets, and are computationally intensive, limiting edge deployment. Hybrid and ensemble approaches (e.g., CNN + LSTM [190] or stacking models using ELMs and gradient boosting [198]) offer improved resilience to noise and data variation but face challenges in hyperparameter tuning, overfitting, and operational latency. Contrastive and transfer learning methods [190,201] show promise in low-data scenarios but often fail to generalize across different grid topologies. Another concern is dataset imbalance and the lack of real-world labeled data. Semi-supervised learning and SMOTE-augmented datasets [193] attempt to mitigate this, but accuracy in diverse conditions is rarely validated. Many studies remain confined to simulated or small-scale PV systems, with limited validation under complex network dynamics or high-frequency events [192,200]. Table B2 in Appendix B lists the typical datasets, common metrics, and known limitations in short circuit fault detection and classification.

Critical research gaps remain in the domain of short-circuit fault detection. Most existing models lack real-time processing capability and are not resilient to measurement noise or signal distortion. A significant limitation is their poor generalization across varying grid topologies, weather conditions, and dynamic load profiles. Additionally, the high computational complexity of many DL hinders their deployment on edge devices or in time-critical grid applications. Another key issue is the heavy reliance on simulated datasets, which often fail to capture the variability and unpredictability of real-world fault scenarios. Few approaches are designed to operate effectively in multi-converter-based power systems or adapt to evolving grid configurations, limiting their scalability and robustness in modern energy environments.

3.2.3. Open circuit fault detection and classification

Open circuit faults, commonly occurring in PV systems due to connector degradation or inverter failure, result in abnormal current-voltage profiles, energy loss, and equipment degradation. As shown in Table 8, current detection approaches increasingly rely on ML and neural networks, such as autoencoders [175], ensemble learning [183], and 1D-CNNs [181], which can handle nonlinear patterns in voltage and current. However, these methods often struggle under noisy, dynamic operating conditions, and their performance is highly dependent on high-quality, accurately placed sensors.

Traditional techniques like PCA, kernel density estimation, and Kullback-Leibler divergence [203,204] are efficient for identifying statistical deviations in voltage signals but tend to underperform in the presence of non-Gaussian noise, high-frequency disturbances, or real-world data complexity. Hybrid systems combining filters (e.g., Kalman variants [206,207]) with ML improve adaptability but often suffer from high computational cost and fail to address diverse interference sources in real-time.

Recent models, such as variational autoencoders [205], 3D CNNs [191], and extreme gradient boosting [208], demonstrate better learning of fault characteristics across DC and AC signals. Nevertheless,

Table 7
Overview of short circuit fault detection and classification.

Task focus	Energy type	Ref.	Model	Dataset	Limitation
Detection	RES	[175]	PCA, modified wavelet PCA, fuzzy logic filter	Grid-connected PV system	Performance degrades under noise, limited to small-scale PV systems.
		[178]	Autoencoder neural network	Real operating PV system in Algeria	Limited performance with large datasets due to computation time.
		[179]	SVM, KNN, DT, kernel PCA, robust kernel PCA	Simulated data	Limited to specific fault types and controlled conditions.
		[180]	Multi-linear perceptron, Fourier-multi-linear perceptron	Experimental setup with short-circuit emulation	Limited to specific weather conditions, reliance on accurate PV system model.
		[181]	1D-CNN	Real-time data, MATLAB/Simulink simulations	High dependency on accurate sensor placement, potential for inaccuracies under data uncertainties.
		[182]	RF	Co-simulations in PSIM/MATLAB	Limited fault scenario coverage, incremental learning effectiveness varies.
		[183]	ANFIS	Simulated data in MATLAB Simulink,	Relies on high-resolution PMU data, struggles with missing or low-resolution data.
		[184]	Ensemble Learning	Simulated data for Grid-Connected PV systems	Limited to PV systems, reliance on historical data, not tested in real-time.
		[185]	DT	GCPVS	Computational complexity, missed detection rate, false alarm rate.
		[186]	GPR	Simulated and Real PV Data	Poor performance in abnormal conditions, sensitivity to load variations.
	Electrical Power	[176]	Mallat decomposition algorithm	MATLAB/SIMULINK simulation and physical system tests	Focuses on balanced faults, struggles with unbalanced grids or multiple converters.
		[187]	ANN	Offline digital time-domain simulations in MATLAB/Simulink	Challenges with real-world noise, parameter selection, scalability in high DG penetration.
		[177]	Empirical mode decomposition	Simulated data	Detection limitations under low irradiance and high impedance faults.
		[188]	Wavelet-based DNNs	CERTS microgrid, IEEE 34-bus system	Data distorted by SCADA failures, filtering needed, limited forecasting accuracy.
		[189]	Improved DBN	Online DC fault current data	Requires non-fault disturbances for labeling, relies on adversarial augmentation.
	Electrical Power, RES	[190]	Adversarial-based deep transfer learning, CNN, attention-based bidirectional LSTM	Multi-terminal DC microgrid model	Computationally demanding DL; generalization to real-world data is challenging.
Detection and classification	RES	[191]	PSO	Simulated data	Limited exploration of cycle number effects; insufficient use of data augmentation or transformation.
		[192]	3D CNN	DC and AC signals from PV systems	Limited to low-frequency oscillations; struggles with high-frequency events and noisy data.
		[193]	Semi-supervised learning with self-supervised and adaptive threshold	Real power grid data, benchmark datasets	Imbalanced datasets handled with SMOTE; no real-world dataset; potential high memory and time complexity.
		[194]	LGBM, RF, DT, extreme gradient boosting	Simulated data set	Requires significant computational resources for large-scale systems; performance varies with dataset.
		[195]	SVM, DT, RF, k-NN	Experimental data from PV arrays	Memory constraints limit real-time implementation; generalization restricted by experimental data.
		[196]	Multiclass adaptive neuro-fuzzy classifier	Faulty PVA, healthy PVA	Reliance on local measurements; accuracy can suffer in varied configurations.
	Electrical Power	[197]	CNN, SVM	Modified IEEE123 bus system	Needs noise data for accuracy testing; computational efficiency depends on feature extraction methods.
		[198]	Stacked auto-encoder neural network, multilayer ELM	IEEE 39 bus test system, WAMS data	Fault detection and classification complexity; high computational requirements; dependency on accurate data acquisition.
		[199]	LSTM, FNN, BPA	Phase voltage and current data, zero sequence voltage-current data	High fault detection time; adaptive methods have high computational burden; only inverter-interfaced DGs considered.
		[200]	Logistic regression, adaptive boost	Standard microgrid data, MATLAB/Simulink, Python	Limited original fault data; GAN-generated examples cannot fully match real faults.
		[201]	Contrastive learning with Siamese networks, GANs	Simulated using PSCAD	Generalization issues with different grid topologies; struggles with extreme data anomalies.
		[202]	Deep graph neural network, multi-layer Perceptron	IEEE 13-Bus systems, PSS/E 23-Bus system	Specific detection variable tuning required, computational burden for large datasets.

these approaches are computationally intensive and face challenges in generalization, particularly when deployed in large-scale, heterogeneous PV systems or evolving grid configurations. Models like GPR and ANN-GEO [209,210] further highlight issues with training time, noise sensitivity, and cable joint detection in solar arrays.

Despite notable advancements, key gaps remain. First, most models lack robustness to high-frequency noise and uncertain measurement conditions. Second, they fail to generalize across varying topologies, grid scales, and environmental changes. Third, deep models often exceed the computational limits of edge devices, limiting their real-time

deployment in low-resource settings. Fourth, reliance on simulated or lab-scale data constrains real-world applicability. Finally, limited attention is given to multi-fault detection scenarios or explainable AI techniques, both of which are critical for fault-critical systems. Table B3 in Appendix B lists the typical datasets, common metrics, and known limitations in open circuit fault detection and classification.

3.2.4. Arc fault detection and classification

Arc faults are critical safety threats in electrical and solar systems, potentially causing fires, equipment failure, and grid instability. With

Table 8
Overview of open circuit fault detection and classification.

Task focus	Energy type	Ref.	Model	Dataset	Limitation
Detection	RES	[175]	Autoencoder neural network	Real operating PV system in Algeria	Performance degrades under noise, limited to small-scale PV systems.
		[183]	Ensemble Learning	Simulated data for Grid-Connected PV systems	Relies on high-resolution PMU data, struggles with missing or low-resolution data.
		[181]	1D-CNN	Real-time data, MATLAB/Simulink simulations	High dependency on accurate sensor placement, potential for inaccuracies under data uncertainties.
		[203]	Interval-valued reduced kernel PCA, RF	Emulated data from grid-tied PV systems	Computational complexity due to high-dimensional data; PCA assumptions.
		[182]	ANFIS	Simulated data in MATLAB Simulink,	Limited fault scenario coverage, incremental learning effectiveness varies.
		[204]	PCA, KDE, kullback-leibler divergence	Grid-connected PV system	Struggles with non-Gaussian data, high-frequency noise, environmental variability.
		[205]	variational autoencoders	GPVS	Requires low-band wireless communication, scalability issues at higher voltage levels.
		[178]	SVM, KNN, DT, kernel PCA, reduced kernel PCA	Simulated data	Limited performance with large datasets due to computation time.
		[206]	Unscented Kalman filter, ELM	Simulation and hardware experiments	Does not account for all interference types, detection delay for high-frequency variations.
	Electrical Power	[207]	Extended Kalman filter, RF	Simulation and experimental data	Limited to simulated conditions, real-world variability not fully addressed.
		[208]	Extreme gradient boosting	Real-time capacitance voltage and current data	Challenges in integration with real-world PV systems and scalability.
Detection and classification	RES	[190]	PSO	Simulated data	Computationally demanding DL; generalization to real-world data is challenging.
		[191]	3D CNN	DC and AC signals from PV systems	Limited exploration of cycle number effects; insufficient use of data augmentation or transformation.
		[209]	ANN, GEO	MATLAB simulation data	High training times for some GPR models; non-linearity in PV systems can cause detection issues.
		[194]	SVM, DT, RF, k-NN	Experimental data from PV arrays	Requires significant computational resources for large-scale systems; performance varies with dataset.
		[210]	GPR	Solar cell parameters	Difficulty detecting SAFs due to noise, challenges at cable joints.
	Electrical Power	[198]	LSTM, FNN	Phase voltage and current data, zero sequence voltage-current data	Fault detection and classification complexity; high computational requirements; dependency on accurate data acquisition.

increasing renewable penetration, detecting these faults in noisy, dynamic environments has become essential. Recent research trends as shown in Table 9 emphasize DL—such as denoising autoencoders, GANs, and 3D CNNs ([191,211,212])—which extract arc-specific patterns from both simulated and real PV data. While effective, these models are resource-intensive, require significant preprocessing, and lack real-time applicability on edge devices.

Traditional signal processing methods—like VMD, wavelet transforms, and SVD—are widely applied, often in combination with ML classifiers like SVM and RFs ([214,215,218]). These approaches enhance noise suppression and feature clarity but depend on fine-tuned parameters and show reduced performance under conditions like voltage dips or irradiance variability. Adaptive filters like Kalman and GPR ([209,219]) aim to improve flexibility but face scalability and integration challenges in evolving grids. In industrial contexts, models often rely on deterministic transforms (e.g., fractional Fourier, EMD [216]) to isolate arc signals, but generalization and real-time response remain issues. Ensemble techniques (e.g., RF, adaptive boosting [220, 222]) improve classification across varying scenarios, yet their performance hinges on high-quality, diverse training data.

The review indicates that most contemporary DL approaches are not yet suitable for deployment on edge devices. Many models are sensitive to measurement noise and routine grid reconfigurations. Evidence is further constrained because simulated or laboratory datasets dominate, which limits transfer to operational conditions. Few studies examine temporal attributes such as fault duration or spectral characteristics, and cross-system generalization across feeders, climates, and hardware remains uncommon. In addition, a lack of interpretability hampers operator trusts and, ultimately, field adoption. Progress will require lightweight, noise-robust architectures with clear latency guarantees and interpretable outputs, trained and validated on diverse, real-world datasets gathered across heterogeneous grid contexts. Table B4 in

Appendix B lists the typical datasets, common metrics, and known limitations in arc fault detection and classification.

3.2.5. Line fault detection and classification

Line-to-line and line-to-ground faults are among the most disruptive and hazardous in both conventional and renewable energy systems. Line-to-line faults, caused by direct contact between two conductors, result in severe outages, equipment damage, and safety risks. Detection efforts increasingly rely on ML, with studies employing DTs, RFs, and neural networks such as RNN and LSTM to model temporal dynamics in PV systems ([180,184,223]). These models offer improved fault pattern recognition, but most remain validated only on simulated data and require centralized architectures, limiting adaptability across diverse installations (see Table 10).

In large-scale power systems, high model complexity and computational costs hinder real-time deployment. Transformer-based DL and hybrid ML-optimization techniques (e.g., CNN-PSO) are used to manage high-dimensional data and complex topologies ([173,174]), though generalization under extreme or unseen configurations remains limited. Signal decomposition techniques (e.g., wavelet entropy, DWTs) and fuzzy logic are often applied for noise suppression but rely on high-fidelity, high-speed data inputs ([224,225,226]). Table B5 in Appendix B lists the typical datasets, common metrics, and known limitations in line fault detection and classification.

Similarly, line-to-ground faults—arising from a conductor contacting the ground—pose significant challenges, especially in microgrids and PV systems where intermittent generation and external disturbances complicate detection. Neural networks and SVM are common, with bidirectional LSTM and ensemble methods showing promise in modeling temporal fluctuations ([222,229]). However, the need for accurate zero-sequence measurements and resilience under transient grid behavior remains a limitation. Advanced models like fully

Table 9

Overview of arc fault detection and classification.

Task focus	Energy type	Ref.	Model	Dataset	Limitation
Detection	RES	[211]	Denoising autoencoder, autoencoder, GAN	Synthetic and real-world data, generated using a PV simulator and PV system	High computational complexity, requires denoising and dynamic handling.
		[212]	Vector autoregressive model	Simulation results from PV systems	High complexity in fault handling, extensive resources required for classification.
		[213]	VMD	Experimental data from PV systems	Edge devices computing limitations, resource-intensive computations need optimization.
		[214]	Singular value decomposition denoising, Iterated extended wavelet transform, SVM	Measured experimental data	Fault signal instability, potential for misjudgment, recalculating votes needed.
	Electrical Power	[215]	SVM, PSO, fractional Fourier transform, singular value decomposition	Arc fault experiments with a three-phase motor and inverter load	Requires proper fuzzy rule tuning, detection under low irradiance is challenging.
		[216]	Probabilistic singular value decomposition, empirical mode decomposition, backpropagation neural network	Randomly selected datasets	High computational complexity, requires parallel computing for efficiency.
		[217]	DWT	Simulations and field tests	Dependence on signal-to-noise ratio, threshold determination challenges.
		[218]	SVM, PSO, VMD	Multi-load experimental platform	Sensitivity to disturbances like voltage dip, load change not always considered.
		[219]	Kalman filter, adaptive Kalman filter	Simulation and Control Hardware-in-the-Loop	Complexity in handling large datasets, limitations adapting to grid changes.
		[220]	RF	Arc and fault data sets	Difficulty distinguishing islanding from grid faults, training data quality affects performance.
		[221]	RF, DNN	Experimental data with various load types and positions	High sensitivity to noise; limited robustness in fault classification under uncertainties.
Detection and classification	RES	[209]	GPR	Solar cell parameters	High training times for some GPR models; non-linearity in PV systems can cause detection issues.
		[191]	3D CNN	DC and AC signals from PV systems	Limited exploration of cycle number effects; insufficient use of data augmentation or transformation.
		[222]	Multi-class adaptive boost	MATLAB/Simulink-generated data for various fault conditions	Limited to simulated data, needs further validation on real systems.

convolutional networks, transformer-based DL, and empirical mode decomposition with adaptive noise filtering are deployed to enhance detection robustness in noisy, real-world settings ([225,172,230]). Yet, scalability, noise tolerance, and real-time responsiveness are ongoing issues. Moreover, while some studies integrate field data with simulations ([224,232]), the majority rely on emulated datasets, which limits operational generalization.

Across both fault types, the field trends toward combining data-driven ML models with signal processing techniques for improved accuracy. However, major gaps persist; real-time readiness for edge deployment, adaptability across fault types and network configurations, and interpretability in complex detection tasks. Continued progress hinges on validating lightweight, robust models on heterogeneous real-world datasets across grid types and operating conditions.

3.2.6. Shading effect's fault detection and classification

Shading faults significantly degrade PV system output, causing current mismatch, hot spots, and long-term damage. Although ML techniques such as SVM, RF, and DT ([178,180,194]) are widely applied, they struggle with dynamic irradiance, noise, and nonlinear behaviors due to reliance on labeled, simulation-based data and linear assumptions (see Table 11). DL like 1D-CNNs and CNNs ([181,233]) enhance detection by learning complex patterns but face high computational demands, sensitivity to sensor errors, and limited feasibility on edge devices. Ensemble and hybrid methods (e.g., ANFIS [182], PSO [190]) improve adaptability but remain data-hungry and often overfit simulation-specific scenarios. Kernel methods (e.g., reduced kernel PCA [203], interval- valued PCA [202]) support fault isolation but suffer from high dimensional complexity and reduced robustness in non-Gaussian, noisy signals. Preprocessing with wavelets and exponential moving averages ([234]) helps yet requires substantial memory

and performs inconsistently under fast-changing shading. Table B6 in Appendix B lists the typical datasets, common metrics, and known limitations in shading effect fault detection and classification.

A major gap remains the over-dependence on synthetic or small-scale test data, limiting real-world generalization. Few models adapt online or support explainability for operational trust. Real-time deployment is constrained by inference latency and lack of optimization for embedded systems. While recent ML advances show promise, shading fault detection still lacks scalable, robust, and interpretable models suitable for real-world, real-time PV monitoring. Future work must target lightweight, adaptive learning under noise, limited data, and heterogeneous environmental conditions.

3.2.7. Other fault detection and classification

The research into fault detection and classification across various fault types as shown in Table 12 shows a clear trend toward the integration of both detection and classification within a single framework. While earlier studies focused primarily on detection, more recent research increasingly emphasizes the importance of classification for effective fault management. The methodologies applied range from traditional ML techniques to more advanced DL and hybrid models, reflecting the growing complexity and diversity of fault scenarios in modern electrical systems, particularly in the context of renewable energy. The studies collectively aim to enhance the robustness and reliability of fault detection systems, ensuring better performance and safety in energy distribution networks.

3.2.8. Handling concurrent fault types: architectural and algorithmic changes

Transitioning from single-fault detectors to architectures capable of recognizing concurrent faults (e.g., simultaneous line–ground, arc, and

Table 10
Overview of line-to-line and line to ground fault detection and classification.

Fault type	Task focus	Energy type	Ref.	Model	Dataset	Limitation
Line to line	Detection	RES	[184]	DT	GCPVS	Limited to PV systems, reliance on historical data, not tested in real-time.
			[180]	RF	Co-simulations in PSIM/MATLAB	Limited to specific weather conditions, reliance on accurate PV system model.
			[223]	ANN, multilayer neural network, cascade forward neural network, RNN, bidirectional LSTM	Simulated Data	Central system design required, limited validation on diverse PV panels.
			[224]	Multi-resolution signal decomposition, SVM	Simulation and experimental data	Struggles with non-linear data, assumes linear time-invariant models.
			[225]	Multi-resolution signal decomposition, fuzzy inference system	Simulation and experimental data	Model performance varies in real-world, high-speed data acquisition needed.
			[211]	Vector autoregressive model	Simulation results from PV systems	High computational complexity, requires denoising and dynamic handling.
		Electrical Power	[173]	Transformer-based DL	IEEE 9-bus system	Computational complexity remains high in edge scenarios, PSO cannot generalize.
			[174]	1D-CNN, PSO	Simulated data sets	High computational resources required for real-time implementation; limitations under extreme network configurations.
	Detection and classification	RES	[209]	GPR	Solar cell parameters	High training times for some GPR models; non-linearity in PV systems can cause detection issues.
			[190]	PSO	Simulated data	Computationally demanding DL; generalization to real-world data is challenging.
			[191]	3D CNN	DC and AC signals from PV systems	Limited exploration of cycle number effects; insufficient use of data augmentation or transformation.
		Electrical Power	[226]	Wavelet singular entropy, Fuzzy Logic	Simulated distribution system	Performance degrades with high variability in system parameters; image-based processing adds computational complexity.
			[227]	Self-attention CNN, DWT	Simulated dataset	Does not account for certain real-world faults, network complexities, or scalability with larger systems.
		Electrical Power, RES	[228]	Fuzzy reinforcement encoder adversarial neural network	Simulated smart grid	Computational complexity with EV charging loads and RES fluctuations.
Line to ground	Detection	RES	[222]	ANN, multilayer neural network, cascade forward neural network, RNN, bidirectional LSTM	Simulated Data	Limited to simulated data, needs further validation on real systems.
			[229]	SVM	IEEE 9-bus microgrid	High reliance on accurate zero-sequence waveforms, validation needed in transient conditions.
			[224]	Multi-resolution signal decomposition, fuzzy inference system	Simulation and experimental data	Struggles with non-linear data, assumes linear time-invariant models.
		Electrical Power	[148]	Multi-task logistic low-ranked dirty model	PMU data	Model performance can suffer under extreme noise, needs scenario adaptation.
			[173]	1D-CNN, PSO	Simulated data sets	Computational complexity remains high in edge scenarios, PSO cannot generalize.
			[172]	Fully convolutional network	PSCAD simulation, RTDS simulation, field test, and practical fault data	Sensitive to electronic noise, ripple currents.
			[225]	Transformer-based DL	IEEE 9-bus system	Model performance varies in real-world, high-speed data acquisition needed.
			[230]	Complete ensemble empirical mode decomposition with adaptive noise	Simulation tests and field experiments	Does not address impact of extreme noise or dynamic changes in pre-fault conditions.
	Detection and classification	RES	[209]	GPR	Solar cell parameters	High training times for some GPR models; non-linearity in PV systems can cause detection issues.
		Electrical Power	[231]	FNN	Simulated data from real-time digital simulator and MATLAB/SIMULINK	Dependency on real-time data, computational complexity, offline fault location sensitivity.
			[226]	Self-attention CNN, DWT	Simulated dataset	Performance degrades with high variability in system parameters; image-based processing adds computational complexity.
		Electrical Power, RES	[227]	Fuzzy reinforcement encoder adversarial neural network	Simulated smart grid	Does not account for certain real-world faults, network complexities, or scalability with larger systems.
			[232]	SVM, GPR	7-bus AC microgrid modeled in MATLAB/Simulink and real-time data set	High computational complexity, relies on optimal parameter tuning.

Table 11
Overview of shading effect's fault detection and classification.

Task focus	Energy type	Ref.	Model	Dataset	Limitation
Detection	RES	[178]	SVM, KNN, DT, kernel PCA, reduced kernel PCA	Simulated data	Limited performance with large datasets due to computation time.
		[183]	Ensemble Learning	Simulated data for Grid-Connected PV systems	Relies on high-resolution PMU data, struggles with missing or low-resolution data.
		[180]	RF	Co-simulations in PSIM/ MATLAB	Limited to specific weather conditions, reliance on accurate PV system model.
		[182]	ANFIS	Simulated data in MATLAB Simulink,	Limited fault scenario coverage, incremental learning effectiveness varies.
		[202]	Interval-valued reduced kernel PCA, RF	Emulated data from grid-tied PV systems	Specific detection variable tuning required, computational burden for large datasets.
		[234]	Wavelet-optimized exponentially weighted moving average, PCA	Simulated data from PV systems	Requires large datasets for accuracy, transfer learning reduces complexity but cannot be optimal.
		[233]	CNN	Mendeley solar data, Experimental data	Requires significant computational resources for real-time applications.
		[181]	1D-CNN	Real-time data, MATLAB/ Simulink simulations	High dependency on accurate sensor placement, potential for inaccuracies under data uncertainties.
		[203]	PCA, Kernel density estimator, kullback-leibler divergence	Grid-connected PV system	Computational complexity due to high-dimensional data; PCA assumptions.
		[235]	ANFIS	Grid-connected PV array	Limited by memory constraints, not operational in real-time.
		[204]	Variational autoencoders	GPVS	Struggles with non-Gaussian data, high-frequency noise, environmental variability.
		[236]	Vertices PCA	Grid-connected monocrystalline PV array	Requires parameter tuning in ELM; sensitive to extreme noise beyond tested levels.
Detection and classification	RES	[190]	PSO	Simulated data	Computationally demanding DL; generalization to real-world data is challenging.
		[208]	ANN, GEO	MATLAB simulation data	Challenges in integration with real-world PV systems.
		[194]	SVM, DT, RF, k-NN	Experimental data from PV arrays	Requires significant computational resources for large-scale systems.
		[195]	Multiclass adaptive neuro-fuzzy classifier	Faulty PVA, healthy PVA	Memory constraints limit real-time implementation; generalization restricted by experimental data.

Table 12
Overview of other fault detection and classification.

Fault type	Task focus	Ref.
Phase to ground	Detection	[144,151,177, 237–239]
	Detection and classification	[174,240]
Ground faults	Detection	[211,241]
	Detection and classification	[196]
Pole-to-pole, Pole-to-ground	Detection	[162,242–244]
	Detection and classification	[221]
Transmission line	Detection	[245–247]
	Detection and classification	[248–250]
Phase faults	Detection	
	Detection and classification	[231,251–254]
Others	Detection	[165,255–298]
	Detection and classification	[299–307]

shading events) requires coordinated advances. (*i*) Frame diagnosis as multi-label, multi-instance learning rather than single-label classification and organize outputs hierarchically. Use a physics-informed shared backbone with multiple task-specific heads so the model captures fault co-occurrence while reusing features. Optimize with event-level losses and class-imbalance remedies such as cost-sensitive weighting and hard-example mining to improve performance on rare concurrent faults. (*ii*) Replace purely local one-dimensional filters with graph- and attention-based encoders that jointly process voltages and currents from multiple buses or strings together with the live network topology, allowing the model to recognize what is physically connected when faults overlap. Graph neural networks and transformer variants already show strong performance on transmission and distribution fault transients and real-

time protection, and they extend naturally to multi-label outputs. (*iii*) Use feature extractors that remain stable under noise and mixed phenomena (e.g., symmetrical-component features, wavelet/scattering energies, and harmonic/inter-harmonic signatures) and regularize the network with power-system constraints or physics-informed penalties so that predictions remain feasible even when multiple faults co-occur. (*iv*) At inference time, deploy a lightweight mixture-of-experts or gated architecture that routes segments to specialized detectors (for example, arc, high-impedance, or topology change) and then fuses their calibrated probabilities. Attach well-calibrated uncertainty (prediction intervals or evidential scores) and escalate low-confidence, potentially concurrent cases to conservative protection logic and operator review, accompanied by local explanations. (*v*) Train and validate beyond simulation, since concurrent faults are rare and subject to distribution shift. Stage OPAL-RT or RTDS HIL studies and report end-to-end latency budgets and robustness under realistic disturbances.

4. Insights and future research direction

4.1. Implications and strategic recommendations

The integration of AI into smart grid systems presents not only technical promise but also substantial strategic challenges. As models grow more complex their compatibility with low-power, real-time environments like μ-PMUs becomes strained. Additionally, widespread adoption is limited by the lack of explainability, poor data quality, and sustainability concerns. To operationalize AI at scale, power systems must embrace model compression, human-in-the-loop explainability, self-supervised learning, and carbon-aware optimization. Table 13 summarizes these core challenges and strategic insights in a question–driven format.

Table 13
Strategic questions and AI implications for smart grid stability.

Question	Insight/Strategic implication
How can complex AI models be deployed on low-power edge devices?	Transformer, GNNs, and GAN-based models exceed the processing limits of μ-PMUs and smart meters. To close this gap, lightweight techniques like model pruning, quantization, knowledge distillation, and FL are essential.
Why is explainability critical for AI in smart grid operations?	Most AI models are black boxes, limiting operational trust. Integrating explainable AI (XAI) methods (e.g., SHAP, LIME) and causal inference tools can enable human-in-the-loop fault diagnosis and ensure accountability in critical scenarios.
How can poor data quality be addressed without high labeling cost?	Fault detection suffers from imbalanced, sparse, or noisy data. Adopting active learning, GAN-based data augmentation, and self-supervised learning can reduce dependence on labeled datasets and improve model robustness.
What role does sustainability play in smart grid AI models?	AI models must not only enhance resilience but also minimize energy overhead. Strategies like green AI, eco-RL, and carbon-aware FL align grid operation with global climate goals.
What hinders widespread operational adoption of AI in power systems?	Lack of interpretability, integration complexity, real-time scalability, and data generalization restrict AI deployment. Embedding interpretable, decentralized, and adaptive architectures is vital for scaling across heterogeneous grid topologies.

4.2. Future research agenda: strategic roadmap for AI in smart grids

To address the persistent technical, operational, and environmental gaps identified in current AI applications for smart grids, a structured research agenda must focus on scalable intelligence, data adaptability, and sustainability. The following roadmap as shown in Table 14 outlines key research directions that balance complexity, performance, interpretability, and real-world viability. Each agenda item responds to a pressing challenge and proposes a focused line of inquiry rooted in advanced AI methodologies.

A key avenue for future work is the integration of federated learning

Table 14
Strategic research agenda for AI-driven smart grid systems.

Agenda item	Objective	Key techniques/approaches
FL for grid intelligence	Enable distributed, privacy-preserving model training across substations, DERs, and μ-PMUs.	Federated averaging, split learning, secure aggregation, differential privacy
Cross-modal learning models	Integrate heterogeneous data types for richer grid situational awareness and fault detection.	Multimodal transformers, sensor fusion, attention-based encoders
Zero-shot and few-shot fault diagnosis	Accurately detect rare or novel faults without abundant labeled samples.	Meta-learning, generative models (e.g., GANs, VAEs), contrastive learning
Multi-objective RL	Optimize grid dispatch under competing objectives like stability, cost, and emissions.	Pareto-optimal RL, constrained policy optimization, eco-RL
Graph-based spatio-temporal fault analysis	Detect and localize faults by modeling grid connectivity and time-varying signals.	GNNs, spatio-temporal attention, topology-aware message passing
Lightweight XAI for embedded ai	Provide interpretable decisions on low-power devices without compromising speed or accuracy.	Attention mechanisms, surrogate models, local interpretable models (e.g., SHAP-lite), knowledge distillation for XAI
AI-driven predictive resilience indexing	Forecast and quantify grid health under potential disturbances and dynamic loading.	Ensemble learning, disturbance forecasting, hybrid simulation-learning indexing models

into smart grids, with the central challenge being how to deploy FL across distributed assets while rigorously preserving data privacy. FL can be deployed in smart grids using a cross-silo hierarchy [308]. Feeders, substations, distributed energy resource aggregators, and large prosumers train models on site for tasks such as short-term load and voltage forecasting, anomaly scoring, and inverter control [309]. They transmit only encrypted or privacy-sanitized model updates to a coordinator operated by the utility, which keeps raw meter and phasor measurement unit data on the premises while still producing a global model. In practice, the utility schedules periodic rounds during which each participant runs several local training steps and then uploads model updates through a secure aggregation protocol, so the coordinator sees only the combined result [310]. Client-side gradient clipping and locally applied differential privacy, implemented as small, calibrated noise on updates, reduce the risk of gradient inversion and membership inference while preserving accuracy under an explicit privacy budget. Latency and bandwidth limits can be addressed with communication- and computation-efficient techniques such as sparse or quantized updates and partial model sharing. Utilities can also deploy regional aggregators near substations to perform a first stage of aggregation before forwarding compact summaries upstream, which shortens round times and reduces backhaul traffic. Because data distributions differ across feeders and climates, personalized federated learning allows each participant to fine-tune a small set of local layers or to blend the global model with a client-specific output head, and asynchronous scheduling with selective participation keeps training robust when connectivity is unreliable.

4.3. Sustainability and operational readiness

AI-driven solutions in smart grids must go beyond performance optimization to actively support sustainability, resilience, and real-world applicability. While many models achieve technical success in fault detection, load balancing, or voltage stability, they often neglect their environmental footprint, scalability in operational settings, and robustness under unpredictable conditions. DL demand high computational resources, rarely optimized for energy efficiency—contradicting the clean energy goals they aim to serve. Moreover, most are trained on simulated or small-scale datasets, limiting their performance when deployed in noisy, weather-influenced, or reconfigurable grid environments. To bridge this gap, future models must integrate energy-aware training, scalable learning architectures, and practical constraints like privacy, fairness, and communication loss. Key challenges are.

- Most models lack energy-efficient training, with few leveraging pruning, quantization, or green AI techniques.
- Real-world deployments are limited due to over-reliance on simulated datasets and lack of generalization under noise, weather variability, and topology changes.
- Carbon-aware load scheduling is rarely implemented with real-time emission forecasting or adaptive multi-agent control.
- AI-driven microgrid reconfiguration lacks robustness under disaster conditions (e.g., communication loss or hardware failure).
- EV integration models overlook issues like battery wear, user behavior diversity, and inter-operator coordination.
- Peer-to-peer energy trading models struggle with fairness, trust, and scaling in diverse community settings.
- Sustainability goals are often implicit; models need to explicitly optimize for environmental impact and long-term grid resilience.

4.4. Addressing the simulation-to-reality gap for deployment

A frequent limitation in AI-for-grid studies is exclusive reliance on simulated or lab-bench data, which can understate real-world noise, non-ideal I/O timing, topology changes, and sensor drift. The unified framework therefore incorporates a deployment-oriented pathway and

safeguards that reduce the risk of performance collapse at roll-out.

4.4.1. Validation pathway from simulation to field

Progression should proceed from offline simulation to hardware-in-the-loop (HIL) and, ultimately, to field evaluation. HIL testbeds (e.g., OPAL-RT) expose controllers and learning modules to realistic sampling rates and latency budgets before site trials [69]. Field-level evidence is already available in several domains. For example, multi-architecture ANN evaluation on a 5-MW grid-connected PV plant has demonstrated feasibility under real telemetry and operating variability [118]. In distribution protection, fully convolutional networks for faulty-feeder detection have been validated across PSCAD, RTDS, and practical fault datasets, indicating transfer beyond emulation [172]. More broadly, for protection and automation, transformer-based models and PSO-designed 1D-CNN detectors have been studied on standard test systems with real-time considerations, providing deployment-oriented results [173,174].

4.4.2. Transfer and adaptation on operational data

Generalization to new sites and regimes is improved by transfer learning, semi/self-supervised learning, and domain adaptation on live telemetry. In DC microgrids, transfer learning enables fault detection without prior labeled faults at the target site, improving robustness under operating shifts [190]. Semi-supervised pipelines that combine self-supervised pretraining with adaptive thresholds reduce labeling cost while maintaining accuracy under class imbalance and drift in urban grids [193]. For PV arrays, digital-twin-assisted training and PSO-optimized transformer architectures generate rare or hazardous conditions in silico and then adapt the model to field signals [191].

4.4.3. Physics-aware integration as a feasibility guard

Learning modules are embedded within physics-constrained optimization and control layers so that actions remain admissible with respect to voltage, thermal, and security limits. Cross-layer design for estimation–optimization co-tuning and online feedback optimization on distribution grids provide practical templates for real-time operation under network constraints [73,74]. Within the unified framework, calibrated anomaly scores and fault posteriors enter dispatch either as hard constraints or risk-weighted costs. In the opposite direction, changing set-points, prices, and schedules update detection thresholds and priors. Coupling to grid physics reduces overfitting to simulator artifacts and anchors decisions in feasible operating envelopes.

4.4.4. Robustness, calibration, and drift management

Operational robustness is strengthened through (*i*) noise-aware training with perturbations derived from field data, (*ii*) probability calibration of alarms that feed OPF and protection margins, and (*iii*) drift monitoring with scheduled retuning. Practical monitors include dynamic power benchmarks with CUSUM for distributed PV fleets [257], aerial-imagery inspections integrated with IoT pipelines for condition assessment [255], and electroluminescence-based diagnostics tied to maintenance workflows [258].

4.5. Assurance and interpretability in safety-critical operation

Safety-critical grid functions demand models whose behavior can be inspected, constrained, and trusted at run time. Three complementary design choices could be adopted: (*i*) Regularizing deep models with power-system physics can be used. Add hard constraints and penalty terms that enforce power-flow limits, monotonic demand–price responses, and voltage and frequency bounds. This converts black-box predictors into physics-informed components whose outputs remain feasible by construction and reduces failure modes under distribution shift [311]. (*ii*) Use local feature attribution to show which measurements drove a trip or curtailment, and counterfactuals to indicate the smallest input change that would alter a decision. Log these

explanations alongside actions to support root-cause triage, operator trust, and model governance. (*iii*) Attaching calibrated confidence measures and tight prediction intervals to every prediction can be adopted. Route low-confidence cases to conservative fallbacks—such as temporary de-rating or widened trip margins—or to operator review before committing control actions. This gating maintains reliability under non-stationary conditions and noisy telemetry, consistent with best practice in trustworthy ML for critical infrastructure [312].

4.6. Grid-side scenarios: performance–interpretability trade-offs in power systems

High-capacity learning models often deliver superior accuracy and faster response under non-stationary conditions, yet they can be opaque to operators and harder to certify for worst-case behavior [313]. Classical signal-processing and optimization methods are auditable and physics-transparent, but they may miss atypical events or adapt slowly when conditions shift. The following scenarios show how utilities can strike workable compromises that retain most of the performance gains while keeping decisions traceable.

4.6.1. Transmission and sub-transmission protection

Transformer-based detectors and PSO-designed one-dimensional convolutional relays have reported strong fault detection and location accuracy across diverse transients and operating points, though their internal logic is difficult to audit in live operations [173,174,250]. Interpretable approaches based on wavelet singular entropy and fuzzy logic remain easier to review and certify but require extensive threshold tuning and can underperform for unusual or overlapping faults [226, 227]. A pragmatic compromise keeps a physics-grounded protection core and adds a deep advisory model that proposes trip confidence and location. All actions are gated through protection-coordination checks, and explanations are logged using lightweight attribution consistent with trustworthy AI guidance (e.g. Refs. [311,312]).

4.6.2. Distribution feeder faulty-feeder identification

Fully convolutional networks validated across PSCAD, RTDS, and field data maintain accuracy under noise and moderate topology changes, but operators perceive them as black boxes during incident review [172]. Traditional impedance or rule-based schemes are transparent yet degrade in feeders with significant converter-driven harmonics. A balanced deployment trains physics-guided networks with power-flow and selectivity constraints and exposes calibrated confidence along with counterfactual summaries that indicate which measurements most influenced the decision, improving post-event audit without sacrificing detection latency.

4.6.3. Photovoltaic arc-fault detection at plant scale

Three-dimensional convolutional networks and denoising autoencoders capture weak or intermittent arcs and lower false alarms in large arrays, albeit with substantial compute cost and limited explainability for operators in the control room [191,211]. Spectral thresholding with wavelets or SVD is lightweight and explainable but can be fragile during irradiance ramps or with inverter switching noise [214,217,218]. A two-stage pipeline uses a fast spectral or entropy front-end to gate a deep classifier only on suspicious windows and then constrains alarms by duration, energy, and thermal plausibility before dispatch to maintenance, improving precision while preserving traceability.

4.6.4. High-impedance fault detection on medium-voltage feeders

Edge-oriented convolutional and recurrent detectors and other sustainable deep models increase sensitivity to arcing signatures but raise concerns about on-device validation and explanation, especially when deployed on µ-PMU or relay hardware with tight timing budgets [149, 152]. Frequency-band energy features and related signal methods provide interpretable cues yet struggle with switching events and harmonic

pollution in active networks [143,159,165]. A practical middle ground extracts stable physics-meaningful features such as sequence components and narrow-band energies, feeds a compact neural head, and attaches conformal or calibrated uncertainty. Only high-confidence cases propagate to trip logic, with routine retraining anchored in field telemetry for calibration stability [138,139,312].

4.6.5. Volt/VAR control and feeder reconfiguration

Graph-aware deep reinforcement learning can co-optimize switching and reactive power under changing injections, but the learned policies are difficult to certify for constraint satisfaction and may be brittle under rare contingencies [89]. Online feedback optimization and OPF-based volt-var schemes offer explicit constraints and sensitivity information, though they can be conservative or slower to adapt during fast disturbances [54,73,74]. A resilient architecture maintains OPF or model predictive control as the primary controller and uses deep reinforcement learning to generate warm starts and contingency suggestions. Every proposal is filtered through OPF feasibility, which preserves interpretability and protection margins while recovering much of the performance benefit.

4.6.6. Dynamic pricing and demand response

Reinforcement learning and PPO controllers adapt to non-stationary user behavior and can reduce costs or peaks, although exploration and reward design limit transparency and complicate regulatory approval [79,92]. Bilevel and distributed convex pricing methods, including ADMM-based coordination, provide clear economic interpretations and dual variables but may underperform when preferences drift or data are missing [83,100]. A hybrid Stackelberg formulation runs an explainable leader with smooth Newton-type updates and learned follower surrogates, reporting sensitivities and constraint duals for governance while retaining responsiveness to shifting demand patterns [81,314].

4.6.7. Cyber and false-data-injection detection on SCADA and PMU streams

Deep anomaly detectors improve true-positive rates against stealthy and hybrid attacks but are hard to justify during incident response and may be sensitive to dataset shift [315–317]. CUSUM and residual-based monitors are simple, explainable, and cheap to deploy, yet skilled adversaries can evade them [318]. A layered design places residual tests first and triggers deep inspection only on flagged intervals. State-estimation consistency checks and ranked channel attributions are required before escalation, meeting security needs without sacrificing interpretability for operations and compliance teams [312].

5. Conclusion

This comprehensive evaluate the role of AI in enhancing the stability, and reliability of smart grids. Focusing on real-time energy management, fault detection, optimization, and grid resilience, the study highlighted the growing importance of AI techniques in managing the increasing complexity brought on by the integration of renewable energy sources and the decentralization of power systems. The review demonstrated that AI has significantly advanced the capabilities of smart grids, improving real-time decision-making, and adaptive fault detection. DL and RL have enabled more accurate and scalable control in dynamic environments. The study offered a unified framework and taxonomy of AI techniques, analyzed their application across various fault types, and emphasized the advantages of hybrid methods that combine data-driven intelligence with traditional optimization. Despite these advancements, ongoing challenges persist, including computational complexity, scalability, explainability, and deployment barriers in real-world systems.

CRediT authorship contribution statement

Mehrnaz Ahmadi: Conceptualization, Investigation, Methodology, Data curation, Resources, Formal analysis, Visualization, Validation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. **Hamed Aly:** Conceptualization, Resources, Validation, Writing – review & editing, Project administration, Funding acquisition, Supervision. **Jason Gu:** Resources, Project administration, Funding acquisition, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rser.2025.116424.

Data availability

No data was used for the research described in the article.

References

[1] Ahmadi M, Khashei M. The linear-nonlinear data preprocessing based hybrid (LNDH) models for wind power forecasting. J Model Manag 2023;18(5):1620–34.
[2] Ahmadi M, Aly H. Multi-objective graph-based reinforcement learning for voltage and frequency stability in grid-connected renewable energy systems. In: 2025 international conference on artificial intelligence, computer, data sciences and applications (ACDSA); 2025, August. p. 1–6. IEEE.
[3] Khalid M. Smart grids and renewable energy systems: perspectives and grid integration challenges. Energy Strategy Rev 2024;51:101299.
[4] Khan R, Mahmood A, Safdar A, Khan ZA, Khan NA. Load forecasting, dynamic pricing and DSM in smart grid: a review. Renew Sustain Energy Rev 2016;54:1311–22.
[5] Macedo MNQ, Galo JJM, De Almeida LAL, Lima AC De C. Demand side management using artificial neural networks in a smart grid environment. Renew Sustain Energy Rev 2015;41:128–33.
[6] Saini VK, Kumar R, Al-Sumaiti AS, Sujil A, Heydarian-Forushani E. Learning based short term wind speed forecasting models for smart grid applications: an extensive review and case study. Elec Power Syst Res 2023;222:109502.
[7] Boopathy P, et al. Deep learning for intelligent demand response and smart grids: a comprehensive survey. Comput Sci Rev 2024;51:100617.
[8] Berghout T, Benbouzid M, Muyeen SM. Machine learning for cybersecurity in smart grids: a comprehensive review-based study on methods, solutions, and prospects. Int J Crit Infrastruct Prot 2022;38:100547.
[9] Ahmad T, Zhang H, Yan B. A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. Sustain Cities Soc 2020;55:102052.
[10] Hasan MK, et al. A review on machine learning techniques for secured cyber-physical systems in smart grid networks. Energy Rep 2024;11:1268–90.
[11] Reka SS, et al. Big data analytics and artificial intelligence aspects for privacy and security concerns for demand response modelling in smart grid: a futuristic approach. Heliyon 2024;10(15):e35683.
[12] Akkara S, Selvakumar I. Review on optimization techniques used for smart grid. Meas: Sens 2023;30:100918.
[13] Assad U, et al. Smart grid, demand response and optimization: a critical review of computational methods. Energies 2022;15(6):2003.
[14] Dewangan F, Abdelaziz AY, Biswal M. Load forecasting models in smart grid using smart meter information: a review. Energies 2023;16(3):1404.
[15] Habbak H, et al. Load forecasting techniques and their applications in smart grids. Energies 2023;16(3):1480.
[16] Ruan J, et al. Deep learning for cybersecurity in smart grids: review and perspectives. Energy Convers Econ 2023;4(4):233–51.
[17] Mazhar T, et al. Analysis of cyber security attacks and its solutions for the smart grid using machine learning and blockchain methods. Future Internet 2023;15(2):83.
[18] Khan MA, et al. Artificial intelligence enabled demand response: prospects and challenges in smart grid environment. IEEE Access 2022;11:1477–505.
[19] Sarker E, et al. Progress on the demand side management in smart grid and optimization approaches. Int J Energy Res 2021;45(1):36–64.
[20] Reddy SS, Sandeep V, Jung C. Review of stochastic optimization methods for smart grid. Front Energy 2017;11:197–209.
[21] Omitaomu OA, Niu H. Artificial intelligence techniques in smart grid: a survey. Smart Cities 2021;4(2):548–68.

[22] Antonopoulos I, Robu V, Couraud B, Kirli D, Norbu S, Kiprakis A, Wattam S. Artificial intelligence and machine learning approaches to energy demand-side response: a systematic review. Renew Sustain Energy Rev 2020;130:109899.

[23] Li B, Delpha C, Diallo D, Migan-Dubois A. Application of Artificial Neural networks to photovoltaic fault detection and diagnosis: a review. Renew Sustain Energy Rev 2021;138:110512.

[24] Ahmadi M, Khashei M. A new hybridization filtering-based linear-nonlinear models for time series forecasting. Journal of Engineering Research 2023; (2307–1877):11.

[25] Ahmadi M, Aly H, Khashei M. Enhancing power grid stability with a hybrid framework for wind power forecasting: integrating kalman filtering, deep residual learning, and bidirectional LSTM. Energy 2025:137752.

[26] Ahmadi M, Khashei M, Bakhtiarvand N. Enhancing air quality classification using a novel discrete learning-based multilayer perceptron model (DMLP). Int J Environ Sci Technol 2025;22(5):3051–62.

[27] Ahmadi M, Khashei M. Current status of hybrid structures in wind forecasting. Eng Appl Artif Intell 2021;99:104133.

[28] Senesoulin F, Hongesombut K, Ngamroo I, Dechanupaprittha S. ConvLSTM-based real-time power flow estimation of smart grid with high penetration of uncertain PV considering measurement noise. Comput Electr Eng 2024;115:109108.

[29] Yin L, Gao Q, Zhao L, Wang T. Expandable deep learning for real-time economic generation dispatch and control of three-state energies based future smart grids. Energy 2020;191:116561.

[30] Huang H, Xu H, Cai Y, Khalid RS, Yu H. Distributed machine learning on smart-gateway network toward real-time smart-grid energy management with behavior cognition. ACM Trans Des Autom Electron Syst 2018;23(5):1–26.

[31] Utkarsh K, Trivedi A, Srinivasan D, Reindl T. A consensus-based distributed computational intelligence technique for real-time optimal control in smart distribution grids. IEEE Trans Emerg Top Comput Intell 2016;1(1):51–60.

[32] Xue X, Fang J, Ai X, Cui S, Jiang Y, Yao W, Wen J. A fully distributed ADP algorithm for real-time economic dispatch of microgrid. IEEE Trans Smart Grid 2023;15(1):513–28.

[33] Wang W, Zong F, Yao B. A proactive real-time control strategy based on data-driven transit demand prediction. IEEE Trans Intell Transport Syst 2020;22(4):2404–16.

[34] Ying Y, Tian Z, Wu M, Liu Q, Tricoli P. A real-time energy management strategy of flexible smart traction power supply system based on deep q-learning. IEEE Trans Intell Transport Syst 2024;25(8):8938–48.

[35] Zhang Z, Wang J, Ding T, Wang X. A two-layer model for microgrid real-time dispatch based on energy storage system charging/discharging hidden costs. IEEE Trans Sustain Energy 2016;8(1):33–42.

[36] You M, Zhang X, Zheng G, Jiang J, Sun H. A versatile software defined smart grid testbed: artificial intelligence enhanced real-time co-evaluation of ICT systems and power systems. IEEE Access 2020;8:88651–63.

[37] Ashrafian A, Mirsalim M, Masoum MAS. An adaptive recursive wavelet based algorithm for real-time measurement of power system variables during off-nominal frequency conditions. IEEE Trans Ind Inf 2017;14(3):818–28.

[38] Liu Y, Qu Z, Xin H, Gan D. Distributed real-time optimal power flow control in smart grid. IEEE Trans Power Syst 2016;32(5):3403–14.

[39] Sun S, Dong M, Liang B. Distributed real-time power balancing in renewable-integrated power grids with storage and flexible loads. IEEE Trans Smart Grid 2015;7(5):2337–49.

[40] Zhan S, Morren J, van den Akker W, van der Molen A, Paterakis NG, Slootweg JG. Fairness-incorporated online feedback optimization for real-time distribution grid management. IEEE Trans Smart Grid 2023;15(2):1792–806.

[41] Barua A, Muthirayan D, Khargonekar PP, Faruque MAA. Hierarchical temporal memory-based one-pass learning for real-time anomaly detection and simultaneous data prediction in smart grids. IEEE Trans Dependable Secure Comput 2020;19(3):1770–82.

[42] Darbandi F, Jafari A, Karimipour H, Dehghantanha A, Derakhshan F, Choo KR. Real-time stability assessment in smart cyber-physical grids: a deep learning approach. IET Smart Grid 2020;3(4):454–61.

[43] Saha PK, Chakraborty N, Mondal A, Mondal S. Intelligent real-time utilization of hybrid energy resources for cost optimization in smart microgrids. IEEE Syst J 2024;18(1):186–97.

[44] Estebsari A, Mazzarino PR, Bottaccioli L, Patti E. IoT-enabled real-time management of smart grids with demand response aggregators. IEEE Trans Ind Appl 2021;58(1):102–12.

[45] Pal R, Chelmis C, Frincu M, Prasanna V. MATCH for the prosumer smart grid: the algorithmics of real-time power balance. IEEE Trans Parallel Distr Syst 2016;27(12):3532–46.

[46] Zeng Y, Tang J. MEC-Assisted real-time data acquisition and processing for UAV with general missions. IEEE Trans Veh Technol 2022;72(1):1058–72.

[47] Ye Y, Qiu D, Wu X, Strbac G, Ward J. Model-free real-time autonomous control for a residential multi-energy system using deep reinforcement learning. IEEE Trans Smart Grid 2020;11(4):3068–82.

[48] Chatterjee A, Paul S, Ganguly B. Multi-objective energy management of a smart home in real time environment. IEEE Trans Ind Appl 2022;59(1):138–47.

[49] Ganjkhani M, Gholami A, Giraldo J, Srivastava AK, Parvania M. Multi-source data aggregation and real-time anomaly classification and localization in power distribution systems. IEEE Trans Smart Grid 2023;15(2):2191–202.

[50] Costa FB, Monti A, Paiva SC. Overcurrent protection in distribution systems with distributed generation based on the real-time boundary wavelet transform. IEEE Trans Power Deliv 2015;32(1):462–73.

[51] Paul S, Padhy NP. Real-time advanced energy-efficient management of an active radial distribution network. IEEE Syst J 2021;16(3):3602–12.

[52] Luo J, Hong T, Yue M. Real-time anomaly detection for very short-term load forecasting. J Mod Power Syst Clean Energy 2018;6(2):235–43.

[53] Zhang Y, Xu Y, Dong ZY, Zhang P. Real-time assessment of fault-induced delayed voltage recovery: a probabilistic self-adaptive data-driven method. IEEE Trans Smart Grid 2018;10(3):2485–94.

[54] Manbachi M, Sadu A, Farhangi H, Monti A, Palizban A, Ponci F, Arzanpour S. Real-time co-simulation platform for smart grid volt-VAR optimization using IEC 61850. IEEE Trans Ind Inf 2016;12(4):1392–402.

[55] Bagherinezhad A, Hosseini MM, Parvania M. Real-time coordinated operation of power and autonomous electric ride-hailing systems. IEEE Trans Smart Grid 2023;14(3):2214–25.

[56] Wang J, Gao Y, Li R. Reinforcement learning based bilevel real-time pricing strategy for a smart grid with distributed energy resources. Appl Soft Comput 2024;155:111474.

[57] Xu Y, Hu J, Gu W, Su W, Liu W. Real-time distributed control of battery energy storage systems for security constrained DC-OPF. IEEE Trans Smart Grid 2016;9(3):1580–9.

[58] Shi W, Li N, Chu C-C, Gadh R. Real-time energy management in microgrids. IEEE Trans Smart Grid 2015;8(1):228–38.

[59] Zenginis I, Vardakas J, Koltsaklis NE, Verikoukis C. Real-time energy scheduling applying the twin delayed deep deterministic policy gradient and data clustering. IEEE Syst J 2023;18(1):51–60.

[60] Khani H, Zadeh MRD. Real-time optimal dispatch and economic viability of cryogenic energy storage exploiting arbitrage opportunities in an electricity market. IEEE Trans Smart Grid 2014;6(1):391–401.

[61] Khan M, Seo J, Kim D. Real-time scheduling of operational time for smart home appliances based on reinforcement learning. IEEE Access 2020;8:116520–34.

[62] Zhang G, Tan ST, Wang GG. Real-time smart charging of electric vehicles for demand charge reduction at non-residential sites. IEEE Trans Smart Grid 2017;9(5):4027–37.

[63] Sangoleye F, Jao J, Faris K, Tsiropoulou EE, Papavassiliou S. Reinforcement learning-based demand response management in smart grid systems with prosumers. IEEE Syst J 2023;17(2):1797–807.

[64] Hu J, Ye Y, Tang Y, Strbac G. Towards risk-aware real-time security constrained economic dispatch: a tailored deep reinforcement learning approach. IEEE Trans Power Syst 2023;39(2):3972–86.

[65] Yin L, Zhao L. Rejectable deep differential dynamic programming for real-time integrated generation dispatch and control of micro-grids. Energy 2021;225:120268.

[66] Sabug Jr L, Musa A, Costa F, Monti A. Real-time boundary wavelet transform-based DC fault protection system for MTDC grids. Int J Electr Power Energy Syst 2020;115:105475.

[67] Cui H, Xia W, Yang S, Wang X. Real-time emergency demand response strategy for optimal load dispatch of heat and power micro-grids. Int J Electr Power Energy Syst 2020;121:106127.

[68] Xu S, Zhu J, Li B, Yu L, Zhu X, Jia H, Chung CY, Booth CD, Terzija V. Real-time power system dispatch scheme using grid expert strategy-based imitation learning. Int J Electr Power Energy Syst 2024;161:110148.

[69] Mohapatra B, Sahu BK, Pati S, Ghamry NA, Ghoneim SSM. Application of a novel metaheuristic algorithm based two-fold hysteresis current controller for a grid connected PV system using real time OPAL-RT based simulator. Energy Rep 2023;9:6149–73.

[70] Guo G, Zhang M, Gong Y, Xu Q. Safe multi-agent deep reinforcement learning for real-time decentralized control of inverter based renewable energy resources considering communication delay. Appl Energy 2023;349:121648.

[71] Keshta HE, Ali AA, Saied EM, Bendary FM. Real-time operation of multi-micro-grids using a multi-agent system. Energy 2019;174:576–90.

[72] Thakallapelli A, Ghosh S, Kamalasadan S. Sensorless real-time reduced order model-based adaptive maximum power tracking pitch controller for grid connected wind turbines. Elec Power Syst Res 2021;194:107115.

[73] Picallo M, Liao-McPherson D, Bolognani S, Dörfler F. Cross-layer design for real-time grid operation: estimation, optimization and power flow. Elec Power Syst Res 2022;212:108378.

[74] Picallo M, Ortmann L, Bolognani S, Dörfler F. Adaptive real-time grid operation via online feedback optimization with sensitivity estimation. Elec Power Syst Res 2022;212:108405.

[75] Djilali L, Sanchez EN, Belkheiri M. Real-time neural input–output feedback linearization control of DFIG based wind turbines in presence of grid disturbances. Control Eng Pract 2019;83:151–64.

[76] Sun J, Hu C, Liu L, Zhao B, Liu J, Shi J. Two-stage correction strategy-based real-time dispatch for economic operation of microgrids. Chin J Electr Eng 2022;8(2):42–51.

[77] Lin J, Xiao B, Zhang H, Yang X, Zhao P. A novel multitype-users welfare equilibrium based real-time pricing in smart grid. Future Gener Comput Syst 2020;108:145–60.

[78] Yu M, Lu R, Hong SH. A real-time decision model for industrial load management in a smart grid. Appl Energy 2016;183:1488–97.

[79] Zhang L, Gao Y, Zhu H, Tao L. A distributed real-time pricing strategy based on reinforcement learning approach for smart grid. Expert Syst Appl 2022;191:116285.

[80] Yuan G, Gao Y, Ye B, Huang R. Real-time pricing for smart grid with multi-energy microgrids and uncertain loads: a bilevel programming method. Int J Electr Power Energy Syst 2020;123:106206.

[81] Li Y, Li J, Yu Z, Dong J, Zhou T. A cosh-based smoothing newton algorithm for the real-time pricing problem in smart grid. Int J Electr Power Energy Syst 2022;135:107296.

[82] Qu D, Li J, Yong M. Real-time pricing for smart grid considering energy complementarity of a microgrid interacting with the large grid. Int J Electr Power Energy Syst 2022;141:108217.

[83] Luo Y, Gao Y, Fan D. Real-time demand response strategy base on price and incentive considering multi-energy in smart grid: a bi-level optimization method. Int J Electr Power Energy Syst 2023;153:109354.

[84] Li Y, Li J, He J, Zhang S. The real-time pricing optimization model of smart grid based on the utility function of the logistic function. Energy 2021;224:120172.

[85] Tao L, Gao Y, Zhu H, Liu S. Distributed genetic real-time pricing for multiseller-multibuyer smart grid based on bilevel programming considering random fluctuation of electricity consumption. Comput Ind Eng 2019;135:359–67.

[86] He X, Huang T, Li C, Che H, Dong Z. A recurrent neural network for optimal real-time price in smart grid. Neurocomputing 2015;149:608–12.

[87] Liu D, Cheng P, Cheng J, Liu J, Lu M, Jiang F. Improved reinforcement learning-based real-time energy scheduling for prosumer with elastic loads in smart grid. Knowl Base Syst 2023;280:111004.

[88] Rahim S, Javaid N, Khan RD, Nawaz N, Iqbal M. A convex optimization based decentralized real-time energy management model with the optimal integration of microgrid in smart grid. J Clean Prod 2019;236:117688.

[89] Wang R, Bi X, Bu S. Real-time coordination of dynamic network reconfiguration and volt-VAR control in active distribution network: a graph-aware deep reinforcement learning approach. IEEE Trans Smart Grid 2023;15(3):3288–302.

[90] Li M, Ahad Y. A novel real-time pricing for PHEV, considering price elasticity, and charging control methods of PHEV integrated with smart grids, using GMO algorithm. Eng Sci Technol Int J 2023;47:101538.

[91] Javed HT, Beg MO, Mujtaba H, Majeed H, Asim M. Fairness in real-time energy pricing for smart grid using unsupervised learning. Comput J 2019;62(3):414–29.

[92] Wei G, Chi M, Liu Z-W, Ge M, Li C, Liu X. Deep reinforcement learning for real-time energy management in smart home. IEEE Syst J 2023;17(2):2489–99.

[93] Deng R, Yang Z, Hou F, Chow M-Y, Chen J. Distributed real-time demand response in multiseller–multibuyer smart distribution grid. IEEE Trans Power Syst 2014;30(5):2364–74.

[94] Naz M, et al. Efficient power scheduling in smart homes using hybrid grey wolf differential evolution optimization technique with real time and critical peak pricing schemes. Energies 2018;11(2):384.

[95] Awais M, Javaid N, Aurangzeb K, Haider SI, Khan ZA, Mahmood D. Towards effective and efficient energy management of single home and a smart community exploiting heuristic optimization algorithms with critical peak and real-time pricing tariffs in smart grids. Energies 2018;11(11):3125.

[96] Ji Y, Wang J, Xu J, Fang X, Zhang H. Real-time energy management of a microgrid using deep reinforcement learning. Energies 2019;12(12):2291.

[97] Li J, Lei Y, Huang Q, Qin Z, Chen B. Feature analysis of generalized load patterns considering active load response to real-time pricing. IEEE Access 2019;7:119443–53.

[98] Joseph S, Abdu JE. Real-time retail price determination in smart grid from real-time load profiles. Int Trans Electr Energy Syst 2018;28(3):e2509.

[99] Tan S, Song W-Z, Stewart M, Yang J, Tong L. Online data integrity attacks against real-time electrical market in smart grid. IEEE Trans Smart Grid 2016;9(1):313–22.

[100] Nguyen DH, Narikiyo T, Kawanishi M. Optimal demand response and real-time pricing by a sequential distributed consensus-based ADMM approach. IEEE Trans Smart Grid 2017;9(5):4964–74.

[101] Lujano-Rojas JM, Dufo-López R, Bernal-Agustín JL, Catalão JPS. Optimizing daily operation of battery energy storage systems under real-time pricing schemes. IEEE Trans Smart Grid 2016;8(1):316–30.

[102] Reka SS, Venugopal P, Alhelou HHA, Siano P, Golshan MEH. Real time demand response modeling for residential consumers in smart grid considering renewable energy with deep learning approach. IEEE Access 2021;9:56551–62.

[103] Li B, Chen T, Wang X, Giannakis GB. Real-time energy management in microgrids with reduced battery capacity requirements. IEEE Trans Smart Grid 2017;10(2):1928–38.

[104] Rahbar K, Xu J, Zhang R. Real-time energy storage management for renewable integration in microgrid: an off-line optimization approach. IEEE Trans Smart Grid 2014;6(1):124–34.

[105] Dehghanpour K, Nehrir H. Real-time multiobjective microgrid power management using distributed optimization in an agent-based bargaining framework. IEEE Trans Smart Grid 2017;9(6):6318–27.

[106] Liang Y, Ding Z, Zhao T, Lee W-J. Real-time operation management for battery swapping-charging system via multi-agent deep reinforcement learning. IEEE Trans Smart Grid 2022;14(1):559–71.

[107] Izumi S, Azuma S. Real-time pricing by data fusion on networks. IEEE Trans Ind Inf 2017;14(3):1175–85.

[108] Li H, Wan Z, He H. Real-time residential demand response. IEEE Trans Smart Grid 2020;11(5):4144–54.

[109] Albogamy FR, Paracha MYI, Hafeez G, Khan I, Murawwat S, Rukh G, Khan S, Khan MUA. Real-time scheduling for optimal energy optimization in smart grid integrated with renewable energy sources. IEEE Access 2022;10:35498–520.

[110] Frendo O, Gaertner N, Stuckenschmidt H. Real-time smart charging based on precomputed schedules. IEEE Trans Smart Grid 2019;10(6):6921–32.

[111] Xu Y, Yang Z, Gu W, Li M, Deng Z. Robust real-time distributed optimal control based energy management in a smart grid. IEEE Trans Smart Grid 2015;8(4):1568–79.

[112] Wang X, Yang I, Ahn S-H. Sample efficient home power anomaly detection in real time using semi-supervised learning. IEEE Access 2019;7:139712–25.

[113] Erdinc O, Paterakis NG, Mendes TDP, Bakirtzis AG, Catalão JPS. Smart household operation considering bi-directional EV and ESS utilization by real-time pricing-based DR. IEEE Trans Smart Grid 2014;6(3):1281–91.

[114] Albogamy FR, Khan SA, Hafeez G, Murawwat S, Khan S, Haider SI, Basit A, Thoben K-D. Real-time energy management and load scheduling with renewable energy integration in smart grid. Sustainability 2022;14(3):1792.

[115] NaitMalek Y, Najib M, Bakhouya M, Essaaidi M. Embedded real-time battery state-of-charge forecasting in micro-grid systems. Ecol Complex 2021;45:100903.

[116] Owais S, Shohan MJA, Islam MM, Faruque MO. Management of grid connected energy storage systems employing real-time energy price. J Energy Storage 2024;92:112097.

[117] Xiao C, Sutanto D, Muttaqi KM, Zhang M. Multi-period data driven control strategy for real-time management of energy storages in virtual power plants integrated with power grid. Int J Electr Power Energy Syst 2020;118:105747.

[118] Narasimman K, Gopalan V, Bakthavatsalam AK, Elumalai PV, Shajahan MI, Michael JJ. Modelling and real time performance evaluation of a 5 MW grid-connected solar photovoltaic plant using different artificial neural networks. Energy Convers Manag 2023;279:116767.

[119] Hossain MA, Chakrabortty RK, Ryan MJ, Pota HR. Energy management of community energy storage in grid-connected microgrid under uncertain real-time prices. Sustain Cities Soc 2021;66:102658.

[120] Dufo-López R. Optimisation of size and control of grid-connected storage under real time electricity pricing conditions. Appl Energy 2015;140:395–408.

[121] Zheng Y, Shang Y, Shao Z, Jian L. A novel real-time scheduling strategy with near-linear complexity for integrating large-scale electric vehicles into smart grid. Appl Energy 2018;217:1–13.

[122] Huy THB, et al. Robust real-time energy management for a hydrogen refueling station using generative adversarial imitation learning. Appl Energy 2024;373:123847.

[123] Hassaballah EG, Keshta HE, Abdel-Latif KM, Ali AA. A novel strategy for real-time optimal scheduling of grid-tied microgrid considering load management and uncertainties. Energy 2024;299:131419.

[124] Emam AA, Keshta HE, Mosa MA, Ali AA. Bi-level energy management system for optimal real-time operation of grid tied multi-nanogrids. Elec Power Syst Res 2023;214:108957.

[125] Wu N, Wang H. Deep learning adaptive dynamic programming for real time energy management and control strategy of micro-grid. J Clean Prod 2018;204:1169–77.

[126] Kow KW, Wong YW, Rajkumar R, Isa D. An intelligent real-time power management system with active learning prediction engine for PV grid-tied systems. J Clean Prod 2018;205:252–65.

[127] Anand H, Ramasubbu R. A real time pricing strategy for remote micro-grid with economic emission dispatch and stochastic renewable energy sources. Renew Energy 2018;127:779–89.

[128] Hossain MA, Pota HR, Squartini S, Abdou AF. Modified PSO algorithm for real-time energy management in grid-connected microgrids. Renew Energy 2019;136:746–57.

[129] Liang T, Chai L, Cao X, Tan J, Jing Y, Lv L. Real-time optimization of large-scale hydrogen production systems using off-grid renewable energy: scheduling strategy based on deep reinforcement learning. Renew Energy 2024;224:120177.

[130] Saha BC, et al. On-Grid solar microgrid temperature monitoring and assessment in real time. Mater Today Proc 2022;50:5013–20.

[131] Jodeiri-Seyedian S-S, Fakour A, Jalali M, Zare K, Mohammadi-Ivatloo B, Tohidi S. Grid-aware pricing scheme in future distribution systems based on real-time power tracing and bi-level optimization. Sustainable Energy, Grids and Networks 2022;32:100934.

[132] Jalali M, Alizadeh-Mousavi O. Application of real-time distribution grid monitoring for grid forecasting and control considering incomplete information of resources behind-the-meter. IEEE Open Access J Power Energy 2022;9:308–18.

[133] Okawa Y, Namerikawa T. Distributed optimal power management via negawatt trading in real-time electricity market. IEEE Trans Smart Grid 2017;8(6):3009–19.

[134] Yu Y, Cai Z, Huang Y. Energy storage arbitrage in grid-connected micro-grids under real-time market price uncertainty: a double-q learning approach. IEEE Access 2020;8:54456–64.

[135] Li T, Dong M. Real-time energy storage management with renewable integration: finite-time horizon approach. IEEE J Sel Area Commun 2015;33(12):2524–39.

[136] Ali M, Degefa MZ, Humayun M, Safdarian A, Lehtonen M. Increased utilization of wind generation by coordinating the demand response and real-time thermal rating. IEEE Trans Power Syst 2015;31(5):3737–46.

[137] Palaniyappan B, Vinopraba T. Dynamic pricing for load shifting: reducing electric vehicle charging impacts on the grid through machine learning-based demand response. Sustain Cities Soc 2024;103:105256.

[138] Pertl M, Douglass PJ, Heussen K, Kok K. Validation of a robust neural real-time voltage estimator for active distribution grids on field data. Elec Power Syst Res 2018;154:182–92.

[139] Chettibi N, Pavan AM, Mellit A, Forsyth AJ, Todd R. Real-time prediction of grid voltage and frequency using artificial neural networks: an experimental validation. Sustainable Energy, Grids and Networks 2021;27:100502.

[140] Zhang Y, Xu Y, Dong ZY, Zhang R. A hierarchical self-adaptive data-analytics method for real-time power system short-term voltage stability assessment. IEEE Trans Ind Inf 2018;15(1):74–84.

[141] Yang X, Ren X, Lin J, Yu W. On binary decomposition based privacy-preserving aggregation schemes in real-time monitoring systems. IEEE Trans Parallel Distr Syst 2016;27(10):2967–83.

[142] Deng L, Pang C, Zeng X, Zhang J, Huang C. Real-time energy disaggregation algorithm based on multi-channels DCNN and autoregressive model. IEEE Access 2022;10:110835–48.

[143] Biswal T, Parida SK. A novel high impedance fault detection in the micro-grid system by the summation of accumulated difference of residual voltage method and fault event classification using discrete wavelet transforms and a decision tree approach. Elec Power Syst Res 2022;209:108042.

[144] Shafiullah Md, AlShumayri KA, Shafiul Alam Md. Machine learning tools for active distribution grid fault diagnosis. Adv Eng Software 2022;173:103279.

[145] Guo MF, et al. An incremental high impedance fault detection method under non-stationary environments in distribution networks. Int J Electr Power Energy Syst 2024;156:109705.

[146] Li B, Liao K, Yang J, He Z. A data-driven fault detection scheme for DC distribution networks based on the adaptive boosting technique. Appl Energy 2024;374:123949.

[147] Cui L, Liu Y, Wang L, Chen J, Zhang X. High-impedance fault detection method based on sparse data divergence discrimination in distribution networks. Elec Power Syst Res 2023;223:109514.

[148] Gilanifar M, Cordova J, Wang H, Stifter M, Ozguven EE, Strasser TI, Arghandeh R. Multi-task logistic low-ranked dirty model for fault detection in power distribution system. IEEE Trans Smart Grid 2019;11(1):786–96.

[149] Sirojan T, Lu S, Phung BT, Zhang D, Ambikairajah E. Sustainable deep learning at grid edge for real-time high impedance fault detection. IEEE Trans Sustainable Comput 2018;7(2):346–57.

[150] Cui Q, Weng Y. Enhance high impedance fault detection and location accuracy via μ-PMUs. IEEE Trans Smart Grid 2019;11(1):797–809.

[151] Sapountzoglou N, Lago J, De Schutter B, Raison B. A generalizable and sensor-independent deep learning method for fault detection and location in low-voltage distribution grids. Appl Energy 2020;276:115299.

[152] Wang S, Dehghanian P. On the use of artificial intelligence for high impedance fault detection and electrical safety. IEEE Trans Ind Appl 2020;56(6):7208–16.

[153] Zhang, et al. A transfer learning-based high impedance fault detection method under a cloud-edge collaboration framework. IEEE Access 2020;8:165099–110.

[154] Hamatwi E, Imoru O, Kanime MM, Kanelombe HSA. Comparative analysis of high impedance fault detection techniques on distribution networks. IEEE Access 2023;11:25817–34.

[155] Wang X, Gao J, Wei X, Guo L, Song G, Wang P. Faulty feeder detection under high impedance faults for resonant grounding distribution systems. IEEE Trans Smart Grid 2022;14(3):1880–95.

[156] Pourfaraj A, Iman-Eini H, Bazyar S, Ahmadi S, Asadi E, Langwasser M, Liserre M. A fault detection Algorithm based on artificial neural network threshold selection in multi-terminal DC grids. IEEE Trans Power Deliv 2023;38(4):2510–20.

[157] Wei X, Wang X, Gao J, Wang B, Yang D. High impedance fault detection based on arc changing tendency and nonlinear least squares for active distribution networks. IEEE Trans Ind Inf 2024;20(6):8572–84.

[158] Sun L, Muguira L, Jiménez J, Lázaro J, Yong W. High performance platform to detect faults in the smart grid by artificial intelligence inference. IEEE Trans Smart Grid 2023;15(1):504–12.

[159] Bai H, Gao JH, Li W, Wang K, Guo MF. Detection of high-impedance fault in distribution networks using frequency-band energy curve. IEEE Sens J 2023;24(1):427–36.

[160] Pandey A, Mohanty SR. Graph convolutional network based fault detection and identification for low-voltage DC microgrid. Journal of Modern Power Systems and Clean Energy 2022;11(3):917–26.

[161] Thomas JB, Shihabudheen KV. Neural architecture search algorithm to optimize deep transformer model for fault detection in electrical power distribution systems. Eng Appl Artif Intell 2023;120:105890.

[162] Larik NA, Li MS, Wu QH. Enhanced fault detection and localization strategy for high-speed protection in medium-voltage DC distribution networks using extended kalman filtering algorithm. IEEE Access 2024;12:30329–44.

[163] Prasad CD, Biswal M, Mishra M, Guerrero JM, Malik OP. Optimal threshold-based high impedance arc fault detection approach for renewable penetrated distribution system. IEEE Syst J 2022;17(2):2971–81.

[164] Arévalo P, Cano A, Benavides D, Jurado F. Fault analysis in clustered microgrids utilizing SVM-CNN and differential protection. Appl Soft Comput 2024;164:112031.

[165] Pandey AK, Kishor N, Mohanty SR, Samuel P. A reliable fault detection algorithm for distribution network with DG resources. Elec Power Syst Res 2023;223:109548.

[166] Guillen D, Olveres J, Torres-García V, Escalante-Ramírez B. Hermite transform based algorithm for detection and classification of high impedance faults. IEEE Access 2022;10:79962–73.

[167] Cano A, Arévalo P, Benavides D, Jurado F. Integrating discrete wavelet transform with neural networks and machine learning for fault detection in microgrids. Int J Electr Power Energy Syst 2024;155:109616.

[168] Patnaik B, Mishra M, Bansal RC, Jena RK. MODWT-XGBoost based smart energy solution for fault detection and classification in a smart microgrid. Appl Energy 2021;285:116457.

[169] Chaitanya BK, Yadav A. An intelligent fault detection and classification scheme for distribution lines integrated with distributed generators. Comput Electr Eng 2018;69:28–40.

[170] Mumtaz F, Imran K, Rehman H, Qureshi HA. Hardware supported fault detection and localization method for AC microgrids using mathematical morphology with state observer algorithm. IEEE Access 2024;12:12446–57.

[171] Cui Q, El-Arroudi K, Weng Y. A feature selection method for high impedance fault detection. IEEE Trans Power Deliv 2019;34(3):1203–15.

[172] Yuan J, Jiao Z. Faulty feeder detection based on fully convolutional network and fault trust degree estimation in distribution networks. Int J Electr Power Energy Syst 2022;141:108264.

[173] Yoon D-H, Yoon J. Development of a real-time fault detection method for electric power system via transformer-based deep learning model. Int J Electr Power Energy Syst 2024;159:110069.

[174] Mitra S, Mukhopadhyay R, Chattopadhyay P. PSO driven designing of robust and computation efficient 1D-CNN architecture for transmission line fault detection. Expert Syst Appl 2022;210:118178.

[175] Ammiche M, Kouadri A, Halabi LM, Guichi A, Mekhilef S. Fault detection in a grid-connected photovoltaic system using adaptive thresholding method. Sol Energy 2018;174:762–9.

[176] Guo MF, Yang N-C, You L-X. Wavelet-transform based early detection method for short-circuit faults in power distribution networks. Int J Electr Power Energy Syst 2018;99:706–21.

[177] Sarangi S, Biswal C, Sahu BK, Samanta IS, Rout PK. Fault detection technique using time-varying filter-EMD and differential-CUSUM for LVDC microgrid system. Elec Power Syst Res 2023;219:109254.

[178] Seghiour A, Ait Abbas H, Chouder A, Rabhi A. Deep learning method based on autoencoder neural network applied to faults detection and diagnosis of photovoltaic system. Simulat Model Pract Theor 2023;123:102704.

[179] Dhibi K, Mansouri M, Bouzrara K, Nounou H, Nounou M. An enhanced ensemble learning-based fault detection and diagnosis for grid-connected PV systems. IEEE Access 2021;9:155622–33.

[180] Rebouças Filho PP, Nascimento NMM, Sousa IR, Medeiros CMS, de Albuquerque VHC. A reliable approach for detection of incipient faults of short-circuits in induction generators using machine learning. Comput Electr Eng 2018;71:440–51.

[181] Aljafari B, Satpathy PR, Thanikanti SB, Nwulu N. Supervised classification and fault detection in grid-connected PV systems using 1D-CNN: Simulation and real-time validation. Energy Rep 2024;12:2156–78.

[182] Amiri AF, Oudira H, Chouder A, Kichou S. Faults detection and diagnosis of PV systems based on machine learning approach using random forest classifier. Energy Convers Manag 2024;301:118076.

[183] Mansouri MM, Hadjeri S, Brahami M. New method of detection, identification, and elimination of photovoltaic system faults in real time based on the adaptive Neuro-fuzzy system. IEEE J Photovoltaics 2021;11(3):797–805.

[184] Dhibi K, Mansouri M, Abodayeh K, Bouzrara K, Nounou H, Nounou M. Interval-valued reduced ensemble learning based fault detection and diagnosis techniques for uncertain grid-connected PV systems. IEEE Access 2022;10:47673–86.

[185] Benkercha R, Moulahoum S. Fault detection and diagnosis based on C4.5 decision tree algorithm for grid connected PV system. Sol Energy 2018;173:610–34.

[186] Fazai R, Abodayeh K, Mansouri M, Trabelsi M, Nounou H, Nounou M, Georghiou GE. Machine learning-based statistical testing hypothesis for fault detection in photovoltaic systems. Sol Energy 2019;190:405–13.

[187] Baghaee HR, Mirsalim M, Gharehpetian GB, Talebi HA. OC/OL protection of droop-controlled and directly voltage-controlled microgrids using TMF/ANN-based fault detection and discrimination. IEEE J Emerging and Selected Topics in Power Electronics 2019;9(3):3254–65.

[188] James JQ, Hou Y, Lam AY, Li VO. Intelligent fault detection scheme for microgrids with wavelet-based deep neural networks. IEEE Trans Smart Grid 2017;10(2):1694–703.

[189] Liu Y, Mao M, Zheng Y, Chang L. DC short-circuit fault detection for MMC-HVDC-grid based on improved DBN and DC fault current statistical features. CPSS Transactions on Power Electronics and Applications 2023;8(2):148–60.

[190] Wang T, Zhang C, Hao Z, Monti A, Ponci F. Data-driven fault detection and isolation in DC microgrids without prior fault data: a transfer learning approach. Appl Energy 2023;336:120708.

[191] Hong Y-Y, Pula RA. Diagnosis of photovoltaic faults using digital twin and PSO-optimized shifted window transformer. Appl Soft Comput 2024;150:111109.

[192] Hong Y-Y, Pula RA. Detection and classification of faults in photovoltaic arrays using a 3D convolutional neural network. Energy 2022;246:123391.

[193] Zhang J, Cheng L, Yang Z, Xiao Q, Khan S, Liang R, Wu X, Guo Y. An enhanced semi-supervised learning method with self-supervised and adaptive threshold for fault detection and classification in urban power grids. Energy and AI 2024;17:100377.

[194] Bhattacharya D, Nigam MK. Energy efficient fault detection and classification using hyperparameter-tuned machine learning classifiers with sensors. Measurement: Sensors 2023;30:100908.

[195] Saiprakash C, Joga SRK, Mohapatra A, Nayak B. Improved fault detection and classification in PV arrays using Stockwell transform and data mining techniques. Results Eng 2024:102808.

[196] Belaout A, Krim F, Mellit A, Talbi B, Arabi A. Multiclass adaptive neuro-fuzzy classifier and feature selection techniques for photovoltaic array fault detection and classification. Renew Energy 2018;127:548–58.

[197] Kurup AR, Summers A, Bidram A, Reno MJ, Martínez-Ramón M. Ensemble models for circuit topology estimation, fault detection and classification in distribution systems. Sustainable Energy, Grids and Networks 2023;34:101017.

[198] Harish A, Asok P, Jayan MV. A comparative evaluation of stacked auto-encoder neural network and multi-layer extreme learning machine for detection and classification of faults in transmission lines using WAMS data. Energy and AI 2023;14:100301.

[199] Roy B, Adhikari S, Datta S, Devi KJ, Devi AD, Alsaif F, Alsulamy S, Ustun TS. Deep learning based relay for online fault detection, classification, and fault location in a grid-connected microgrid. IEEE Access 2023;11:62674–96.

[200] Baloch S, Muhammad MS. An intelligent data mining-based fault detection and classification strategy for microgrid. IEEE Access 2021;9:22470–9.

[201] Fornás JG, Jaraba EH, Llombart Estopiñan A, Saldana J. Detection and classification of fault types in distribution lines by applying contrastive learning to GAN encoded time-series of pulse reflectometry signals. IEEE Access 2022;10: 110521–36.

[202] Ukwuoma CC, Cai D, Bamisile O, Chukwuebuka EJ, Favour E, Emmanuel GSA, Caroline A, Abdi SF. Power transmission system's fault location, detection, and classification: pay close attention to transmission nodes. Int J Electr Power Energy Syst 2024;156:109771.

[203] Dhibi K, et al. A hybrid fault detection and diagnosis of grid-tied pv systems: enhanced random forest classifier using data reduction and interval-valued representation. IEEE Access 2021;9:64267–77.

[204] Bakdi A, Bounoua W, Guichi A, Mekhilef S. Real-time fault detection in PV systems under MPPT using PMU and high-frequency multi-sensor data through online PCA-KDE-based multivariate KL divergence. Int J Electr Power Energy Syst 2021;125:106457.

[205] Harrou F, Dairi A, Taghezouit B, Khaldi B, Sun Y. Automatic fault detection in grid-connected photovoltaic systems via variational autoencoder-based monitoring. Energy Convers Manag 2024;314:118665.

[206] He S, Tian W, Zhu R, Zhang Y, Mao S. Electrical signature analysis for open-circuit faults detection of inverter with various disturbances in distribution grid. IEEE Trans Ind Inf 2022;19(7):8351–61.

[207] Ji X, Liu D, Xiong P, He S. Multiple open-switch faults detection for grid connected inverter. Sustain Energy Technol Assessments 2022;54:102765.

[208] Hu X, Jia H, Zhang Y, Deng Y. An open-circuit faults diagnosis method for MMC based on extreme gradient boosting. IEEE Trans Ind Electron 2022;70(6): 6239–49.

[209] Ganesh RJ, Muralidharan S. Fault causes and its detection in standalone PV system using ANN and GEO technique. ISA (Instrum Soc Am) Trans 2024;152: 358–70.

[210] Javaid A, Shafi I, Khalil IU, Ahmad S, Safran M, Alfarhood S, Ashraf I. Enhancing photovoltaic systems using gaussian process regression for parameter identification and fault detection. Energy Rep 2024;11:4485–99.

[211] Park H-P, Kwon G-Y, Lee C-K, Chang SJ. AI-enhanced time–frequency domain reflectometry for robust series arc fault detection in DC grids. Measurement 2024; 238:115188.

[212] Chen L, Li S, Wang X. Quickest fault detection in photovoltaic systems. IEEE Trans Smart Grid 2016;9(3):1835–47.

[213] Liu S, et al. Application of the variational mode decomposition-based time and time–frequency domain analysis on series DC arc fault detection of photovoltaic arrays. IEEE Access 2019;7:126177–90.

[214] Gao W, Wai R-J. Series arc fault detection of grid-connected PV system via SVD denoising and IEWT-TWSVM. IEEE J Photovoltaics 2021;11(6):1493–510.

[215] Gao H, Wang Z, Tang A, Han C, Guo F, Li B. Research on series arc fault detection and phase selection feature extraction method. IEEE Trans Instrum Meas 2021;70: 1–8.

[216] Shen Y-L, Xu Z. Fast detection of weak arc faults based on progressive singular-value-decomposition and empirical analyses. IEEE Access 2022;10:130586–601.

[217] Wei M, et al. High impedance arc fault detection based on the harmonic randomness and waveform distortion in the distribution system. IEEE Trans Power Deliv 2019;35(2):837–50.

[218] Guo F, Gao H, Wang Z, You J, Tang A, Zhang Y. Detection and line selection of series arc fault in multi-load circuit. IEEE Trans Plasma Sci 2019;47(11):5089–98.

[219] Gajula K, Herrera L. Detection and localization of series arc faults in DC microgrids using kalman filter. IEEE Journal of Emerging and Selected Topics in Power Electronics 2020;9(3):2589–96.

[220] Dai W, Zhou X, Sun Z, Miao Q, Zhai G. Series AC arc fault detection method based on L2/L1 norm and classification algorithm. IEEE Sens J 2024;24(10):16661–72.

[221] Jiang J, Li W, Wen Z, Bie Y, Schwarz H, Zhang C. Series arc fault detection based on random forest and deep neural network. IEEE Sens J 2021;21(15):17171–9.

[222] Dash PK, Pattnaik SR, Nvdv Prasad E, Bisoi R. Detection and classification of DC and feeder faults in DC microgrid using new morphological operators with multi class AdaBoost algorithm. Appl Energy 2023;340:121013.

[223] Hajji M, Yahyaoui Z, Mansouri M, Nounou H, Nounou M. Fault detection and diagnosis in grid-connected PV systems under irradiance variations. Energy Rep 2023;9:4005–17.

[224] Yi Z, Etemadi AH. Line-to-line fault detection for photovoltaic arrays based on multiresolution signal decomposition and two-stage support vector machine. IEEE Trans Ind Electron 2017;64(11):8546–56.

[225] Yi Z, Etemadi AH. Fault detection for photovoltaic systems based on multi-resolution signal decomposition and fuzzy inference systems. IEEE Trans Smart Grid 2016;8(3):1274–83.

[226] Dehghani M, Khooban MH, Niknam T. Fast fault detection and classification based on a combination of wavelet singular entropy theory and fuzzy logic in distribution lines in the presence of distributed generations. Int J Electr Power Energy Syst 2016;78:455–62.

[227] Fahim SR, Sarker Y, Sarker SK, Sheikh MRI, Das SK. Self attention convolutional neural network with time series imaging based feature extraction for transmission line fault detection and classification. Elec Power Syst Res 2020;187:106437.

[228] Chen T, Liu C. Soft computing based smart grid fault detection using computerised data analysis with fuzzy machine learning model. Sustainable Computing: Informatics and Systems 2024;41:100945.

[229] Aiswarya R, Nair DS, Rajeev T, Vinod V. A novel SVM based adaptive scheme for accurate fault identification in microgrid. Elec Power Syst Res 2023;221:109439.

[230] Wang X, Gao J, Wei X, Zeng Z, Wei Y, Kheshti M. Single line to ground fault detection in a non-effectively grounded distribution network. IEEE Trans Power Deliv 2018;33(6):3173–86.

[231] Shafiullah M, Abido MA. S-transform based FNN approach for distribution grids fault detection and classification. IEEE Access 2018;6:8080–8.

[232] Srivastava A, Parida SK. A robust fault detection and location prediction module using support vector machine and Gaussian process regression for AC microgrid. IEEE Trans Ind Appl 2021;58(1):930–9.

[233] Salameh T, Björk R, Abdelkareem MA, Olabi AG. Detecting the faults of solar photovoltaic module due to the temperature and shading effect by convolutional neural network. International Journal of Thermofluids 2024;22:100643.

[234] Mansouri M, Al-Khazraji A, Hajji M, Harkat MF, Nounou H, Nounou M. Wavelet optimized EWMA for fault detection and application to photovoltaic systems. Sol Energy 2018;167:125–36.

[235] Abbas M, Zhang D. A smart fault detection approach for PV modules using Adaptive Neuro-fuzzy inference framework. Energy Rep 2021;7:2962–75.

[236] Rouani L, Harkat MF, Kouadri A, Mekhilef S. Shading fault detection in a grid-connected PV system using vertices principal component analysis. Renew Energy 2021;164:1527–39.

[237] Ahmadipour M, Murtadha Othman M, Alrifaey M, Bo R, Ang CK. Classification of faults in grid-connected photovoltaic system based on wavelet packet transform and an equilibrium optimization algorithm-extreme learning machine. Measurement 2022;197:111338.

[238] Wu H, Wang J, Nan D, Cui Q, Ouyang J. Transmission line fault cause identification method based on transient waveform image and MCNN-LSTM. Measurement 2023;220:113422.

[239] Pirani M, Hosseinzadeh M, Taylor JA, Sinopoli B. Optimal active fault detection in inverter-based grids. IEEE Trans Control Syst Technol 2022;31(3):1411–7.

[240] Alrifaey M, Lim WH, Ang CK, Natarajan E, Solihin MI, Mohamed Juhari MR, Tiang SS. Hybrid deep learning model for fault detection and classification of grid-connected photovoltaic system. IEEE Access 2022;10:13852–69.

[241] Ajith MA, Shereef RM. Islanding and fault detection of inverter based distributed generations using wavelet packet transform and ensemble. Elec Power Syst Res 2024;231:110356.

[242] Sharma NK, Samantaray SR, Bhende CN. VMD-Enabled current-based fast fault detection scheme for DC microgrid. IEEE Syst J 2021;16(1):933–44.

[243] Saleh KA, Hooshyar A, El-Saadany EF. Hybrid passive-overcurrent relay for detection of faults in low-voltage DC grids. IEEE Trans Smart Grid 2015;8(3): 1129–38.

[244] Liu H, Han H, Zheng X, Sun Y, Su M, Ling T, Liu X. Fuzzy granulation interval-based fault diagnosis method for ring-type DC microgrid. IEEE Trans Smart Grid 2024;15(4):3402–17.

[245] Hu H, Lu H, Shi R, Fan X, Deng Z. A novel fault diagnosis method for key transmission sections based on Nadam-optimized GRU neural network. Elec Power Syst Res 2024;233:110522.

[246] Yildiz T, Abur A. Convolutional neural Network-assisted fault detection and location using few PMUs. Elec Power Syst Res 2024;235:110705.

[247] de Alencar GT, Caneloi dos Santos R, Neves A. A fault recognition method for transmission systems based on independent component analysis and convolutional neural networks. Elec Power Syst Res 2024;229:110105.

[248] Harish A, Prince A, Jayan MV. Fault detection and classification for wide area backup protection of power transmission lines using weighted extreme learning machine. IEEE Access 2022;10:82407–17.

[249] Alhanaf AS, Farsadi M, Balik HH. Fault detection and classification in ring power system with DG penetration using hybrid CNN-LSTM. IEEE Access 2024;12: 59953–75.

[250] Tong H, Qiu RC, Zhang D, Yang H, Ding Q, Shi X. Detection and classification of transmission line transient faults based on graph convolutional neural network. CSEE Journal of Power and Energy Systems 2021;7(3):456–71.

[251] Basher BG, Ghanem A, Abulanwar S, Hassan MK, Rizk MEM. Fault classification and localization in microgrids: leveraging discrete wavelet transform and multi-machine learning techniques considering single point measurements. Elec Power Syst Res 2024;231:110362.

[252] Biswas S, Nayak PK, Panigrahi BK, Pradhan G. An intelligent fault detection and classification technique based on variational mode decomposition-CNN for transmission lines installed with UPFC and wind farm. Elec Power Syst Res 2023; 223:109526.

[253] Islam Siddique MN, Shafiullah M, Mekhilef S, Pota H, Abido MA. Fault classification and location of a PMU-equipped active distribution network using deep convolution neural network (CNN). Elec Power Syst Res 2024;229:110178.

[254] Hong Y-Y, Cabatac MTAM. Fault detection, classification, and location by static switch in microgrids using wavelet transform and Taguchi-based artificial neural network. IEEE Syst J 2019;14(2):2725–35.

[255] Ramírez IS, García Márquez FP, Parra Chaparro J. Convolutional neural networks and internet of things for fault detection by aerial monitoring of photovoltaic solar plants. Measurement 2024;234:114861.

[256] Mirshekali H, Keshavarz A, Dashti R, Hafezi S, Shaker HR. Deep learning-based fault location framework in power distribution grids employing convolutional neural network based on capsule network. Elec Power Syst Res 2023;223:109529.

[257] Meng B, Loonen RCGM, Hensen JLM. Leveraging dynamic power benchmarks and CUSUM charts for enhanced fault detection in distributed PV systems. Energy Convers Manag 2024;314:118692.

[258] Ozturk E, Ogliari E, Sakwa M, Dolara A, Blasuttigh N, Pavan AM. Photovoltaic modules fault detection, power output, and parameter estimation: a deep learning approach based on electroluminescence images. Energy Convers Manag 2024; 319:118866.

[259] Deng F, et al. Research on edge intelligent recognition method oriented to transmission line insulator fault detection. Int J Electr Power Energy Syst 2022; 139:108054.

[260] Zhang X, Guo Z, Zheng Y, Liu J, Yan P, Zheng L. Power grid fault diagnosis using polar PMU data plots. Int J Electr Power Energy Syst 2022;141:108148.

[261] Dhimish M, Holmes V, Mehrdadi B, Dales M. Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection. Renew Energy 2018;117: 257–74.

[262] Qiao L, Zhang Y, Wang Q. Fault detection in wind turbine generators using a meta-learning-based convolutional neural network. Mech Syst Signal Process 2023;200:110528.

[263] Liu J, Duan Z, Liu H. A grid fault diagnosis framework based on adaptive integrated decomposition and cross-modal attention fusion. Neural Netw 2024: 106400.

[264] de Lima Munguba CF, et al. Fault detection framework in wind turbine pitch systems using machine learning: development, validation, and results. Eng Appl Artif Intell 2024;138:109307.

[265] Ruiz-Moreno S, Gallego AJ, Sanchez AJ, Camacho EF. A Cascade neural network methodology for fault detection and diagnosis in solar thermal plants. Renew Energy 2023;211:76–86.

[266] Qian X, Sun T, Zhang Y, Wang B, Awad Gendeel MA. Wind turbine fault detection based on spatial-temporal feature and neighbor operation state. Renew Energy 2023;219:119419.

[267] Belhadi A, Djenouri Y, Srivastava G, Jolfaei A, Lin JC-W. Privacy reinforcement learning for faults detection in the smart grid. Ad Hoc Netw 2021;119:102541.

[268] Stefenon SF, Seman LO, Klaar ACR, Ovejero RG, Leithardt VRQ. Hypertuned-YOLO for interpretable distribution power grid fault location based on EigenCAM. Ain Shams Eng J 2024;15(6):102722.

[269] Dutta S, Sahu SK, Roy M, Dutta S. A data driven fault detection approach with an ensemble classifier based smart meter in modern distribution system. Sustainable Energy, Grids and Networks 2023;34:101012.

[270] Hu W, Jiao Q, Liu H, Wang K, Jiang Z, Wu J, Cong F, Hao G. A transferable diagnosis method with incipient fault detection for a digital twin of wind turbine. Digital Engineering 2024;1:100001.

[271] Wang T, Yin L. Dual-module multi-head spatiotemporal joint network with SACGA for wind turbines fault detection. Energy 2024;308:132906.

[272] Safari A, Sabahi M, Oshnoei A. ResFaultyMan: an intelligent fault detection predictive model in power electronics systems using unsupervised learning isolation forest. Heliyon 2024;10(15):e35243.

[273] Zheng Y, Wang C, Huang C, Li K, Yang J, Xie N, Liu B, Zhang Y. Hierarchical spatial–temporal autocorrelation graph neural network for online wind turbine pitch system fault detection. Neurocomputing 2024;586:127574.

[274] Liu X, Lin Y, Jiang H, Miao X, Chen J. Slippage fault diagnosis of dampers for transmission lines based on faster R-CNN and distance constraint. Elec Power Syst Res 2021;199:107449.

[275] Elmasry W, Wadi M. Edla-efds: a novel ensemble deep learning approach for electrical fault detection systems. Elec Power Syst Res 2022;207:107834.

[276] Srivastava A, Parida SK. Data driven approach for fault detection and Gaussian process regression based location prognosis in smart AC microgrid. Elec Power Syst Res 2022;208:107889.

[277] Lei X, Sui Z. Intelligent fault detection of high voltage line based on the faster R-CNN. Measurement 2019;138:379–85.

[278] Chen L, Xu G, Zhang Q, Zhang X. Learning deep representation of imbalanced SCADA data for fault detection of wind turbines. Measurement 2019;139:370–9.

[279] Allal Z, Noura HN, Vernier F, Salman O, Chahine K. Wind turbine fault detection and identification using a two-tier machine learning framework. Intelligent Systems with Applications 2024;22:200372.

[280] Gao J, Yuan H, Yang A, Rong M, Dai R, Peng Z, Wang X. A fault detection method based on successive variational mode decomposition for the energy absorption branch of modular DC circuit breakers. IEEE Trans Power Deliv 2023;38(5): 3688–700.

[281] Guo Z, Liu M, Wang Y, Qin H. A new fault diagnosis classifier for rolling bearing united multi-scale permutation entropy optimize VMD and cuckoo search SVM. IEEE Access 2020;8:153610–29.

[282] Tong R, et al. A novel ellipsoidal semisupervised extreme learning machine algorithm and its application in wind turbine blade icing fault detection. IEEE Trans Instrum Meas 2022;71:1–16.

[283] Pa M, Uddin MN, Rezaei N. An adaptive neuro-fuzzy model-based algorithm for fault detection in PV systems. IEEE Trans Ind Appl 2023;60(1):1919–27.

[284] Fan C, Xiahou K, Wang L, Wu QH. Data-driven fault detection of multiple open-circuit faults for mmc systems based on long short-term memory networks. CSEE J Power Energy Syst 2024;10(4):1563–74.

[285] Li Q, Zhu Y, Ding J, Li W, Sun W, Ding L. Deep reinforcement learning based resource allocation for cloud edge collaboration fault detection in smart grid. CSEE J Power and Energy Systems 2022;8(4):1001–12.

[286] Taksana R, Janjamraj N, Romphochai S, Bhumkittipich K, Mithulananthan N. Design of Power Transformer Fault Detection of SCADA Alarm Using Fault Tree Analysis, Smooth Holtz–Winters, and L-BFGS for Smart Utility Control Centers. IEEE Access; 2024.

[287] Yang N-C, Sen A. Fast fault detection using optimal intrinsic modes and energy deviation index in distribution systems. IEEE Access 2021;9:139842–51.

[288] Alqudah M, Pavlovski M, Dokic T, Kezunovic M, Hu Y, Obradovic Z. Fault detection utilizing convolution neural network on timeseries synchrophasor data from phasor measurement units. IEEE Trans Power Syst 2021;37(5):3434–42.

[289] Ntalampiras S. Fault diagnosis for smart grids in pragmatic conditions. IEEE Trans Smart Grid 2016;9(3):1964–71.

[290] Li Q, Luo H, Cheng H, Deng Y, Sun W, Li W, Liu Z. Incipient fault detection in power distribution system: a time–frequency embedded deep-learning-based approach. IEEE Trans Instrum Meas 2023;72:1–14.

[291] Zhang X, Zhang Y, Liu J, Zhang C, Xue X, Zhang H, Zhang W. InsuDet: a fault detection method for insulators of overhead transmission lines using convolutional neural networks. IEEE Trans Instrum Meas 2021;70:1–12.

[292] Hassani H, Razavi-Far R, Saif M, Zarei J, Blaabjerg F. Intelligent decision support and fusion models for fault detection and location in power grids. IEEE Transactions on Emerging Topics in Computational Intelligence 2021;6(3): 530–43.

[293] Lin Z, et al. One-class classifier based fault detection in distribution systems with varying penetration levels of distributed energy resources. IEEE Access 2020;8: 130023–35.

[294] Jiang H, Dai X, Gao DW, Zhang JJ, Zhang Y, Muljadi E. Spatial-temporal synchrophasor data characterization and analytics in smart grid fault detection, identification, and impact causal analysis. IEEE Trans Smart Grid 2016;7(5): 2525–36.

[295] Baghaee HR, Mlakić D, Nikolovski S, Dragicević T. Support vector machine-based islanding and grid fault detection in active distribution networks. IEEE J Emerging and Selected Topics in Power Electronics 2019;8(3):2385–403.

[296] Sung Y, Yoon G, Bae J-H, Chae S. TL–LED arc net: transfer learning method for low-energy series DC arc-fault detection in Photovoltaic systems. IEEE Access 2022;10:100725–35.

[297] Mumtaz F, Khan TS, Alqahtani M, Sher HA, Aljumah AS, Almutairi SZ. Ultra high-speed fault diagnosis scheme for DC distribution systems based on discrete median filter and mathematical morphology. IEEE Access 2024;12:45796–810.

[298] Wang Y, Ma X, Qian P. Wind turbine fault detection and identification through PCA-based optimal variable selection. IEEE Trans Sustainable Energy 2018;9(4): 1627–35.

[299] Biju GM, Pillai GN. Hyperparameter optimization of long short term memory models for interpretable electrical fault classification. IEEE Access 2023;11: 123688–704.

[300] Imani A, Moravej Z, Pazoki M. A novel time-domain method for fault detection and classification in VSC-HVDC transmission lines. Int J Electr Power Energy Syst 2022;140:108056.

[301] Dhibi K, Fezai R, Mansouri M, Trabelsi M, Kouadri A, Bouzara K, Nounou H, Nounou M. Reduced kernel random forest technique for fault detection and classification in grid-tied PV systems. IEEE J Photovoltaics 2020;10(6):1864–71.

[302] Pandey AK, Kishor N, Mohanty SR, Samuel P. Intelligent fault detection and classification for an unbalanced network with inverter-based DG units. IEEE Trans Ind Inf 2024;20(5):7325–34.

[303] Zhao M, Barati M. A real-time fault localization in power distribution grid for wildfire detection through deep convolutional neural networks. IEEE Trans Ind Appl 2021;57(4):4316–26.

[304] Goni MOF, et al. Fast and accurate fault detection and classification in transmission lines using extreme learning machine. e-Prime-Advances in electrical engineering, electronics and energy, vol. 3; 2023, 100107.

[305] Roy S, Debnath S. A wavelet based PSD approach for fault detection and classification in grid connected inverter interfaced microgrid. Measurement 2024; 226:114079.

[306] Cao H, Zhang H, Gu C, Zhou Y, He X. Fault detection and classification in solar based distribution systems in the presence of deep learning and social spider method. Sol Energy 2023;262:111868.

[307] Rafi MR, Hu F, Li S, Song A, Zhang X, O'Neill Z. Deep weighted fusion Learning (DWFL)-based multi-sensor fusion model for accurate building occupancy detection. Energy and AI 2024;17:100379.

[308] Khashei M, Ahmadi M, Chahkoutahi F. A mean weighted squared error-based neural classifier for intelligent pattern recognition in smart grids. Int J Electr Power Energy Syst 2025;170:110972.

[309] Qin D, Liu G, Li Z, Guan W, Zhao S, Wang Y. Federated deep contrastive learning for mid-term natural gas demand forecasting. Appl Energy 2023;347:121503.

[310] Hagström F, Garg V, Oliveira F. Employing federated learning for training autonomous HVAC systems. Energy Build 2025:115761.

[311] Raissi M, Perdikaris P, Karniadakis GE. Physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J Comput Phys 2019;378:686–707.

[312] Arrieta AB, Díaz-Rodríguez N, Del Ser J, Bennetot A, Tabik S, Barbado A, Herrera F. Explainable Artificial Intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fusion 2020;58:82–115.

[313] Li Q, Lin T, Yu Q, Du H, Li J, Fu X. Review of deep reinforcement learning and its application in modern renewable power system control. Energies 2023;16(10): 4143.

[314] Yu M, Hong SH. Supply–demand balancing for power management in smart grid: a stackelberg game approach. Applied energy 2016;164:702–10.

[315] He Y, Mendis GJ, Wei J. Real-time detection of false data injection attacks in smart grid: a deep learning-based intelligent mechanism. IEEE Trans Smart Grid 2017;8(5):2505–16.

[316] Abdulaal MJ, Ibrahem MI, Mahmoud MMEA, Khalid J, Aljohani AJ, Milyani AH, Abusorrah AM. Real-time detection of false readings in smart grid AMI using deep and ensemble learning. IEEE Access 2022;10:47541–56.

[317] Kurt MN, Yılmaz Y, Wang X. Real-time detection of hybrid and stealthy cyber-attacks in smart grid. IEEE Trans Inf Forensics Secur 2018;14(2):498–513.

[318] Huang Y, Tang J, Cheng Y, Li H, Campbell KA, Han Z. Real-time detection of false data injection in smart grid networks: an adaptive CUSUM method and analysis. IEEE Syst J 2014;10(2):532–43.