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Machine Learning and Explainable AI Techniques for Smart Grid Stability, Security, and Decentralized Energy Management: A Survey

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Abstract: Smart grids increasingly rely on artificial intelligence to address the variability introduced by renewable energy generation, distributed prosumers, and bidirectional communication in modern power systems. Machine learning (ML), deep learning (DL), and explainable artificial intelligence (XAI) have been applied to various challenges, including rapid stability classification, dynamic security assessment, electricity demand forecasting, and decentralized energy management. These approaches employ diverse algorithms and methodologies, ranging from classical and ensemble learning models to deep neural networks and multi-agent systems. Recent developments also include peer-to-peer (P2P) energy trading, complex-network-based grid resilience analysis, and clustering-based load forecasting. Despite significant progress, several challenges remain, including the heavy reliance on simulated benchmark datasets, limited validation under real-world operating conditions, and the lack of integrated explainability in high-performing predictive models. Differences in datasets, evaluation metrics, and experimental settings further complicate the comparison and generalization of existing approaches. Addressing these limitations requires more diverse datasets, improved model interpretability, stronger cybersecurity measures, and effective integration of grid stability assessment with decentralized energy management and market mechanisms.

Keywords: smart grid stability, machine learning, explainable AI, decentralized energy management, peer-to-peer energy trading, multi-agent systems

I. INTRODUCTION

Power systems today look quite different from the ones the classical control literature was written for. Large-scale integration of renewable energy sources (RES), distributed energy resources (DERs), and bidirectional communication infrastructure – collectively referred to as the smart grid – has turned what used to be a largely predictable, centrally dispatched system into something far more dynamic [3], [9], [21]. Wind and solar output fluctuate over time, while maintaining frequency and voltage within safe limits increasingly requires faster and more localized decision-making [1], [11]. One response to this changing environment is the Decentral Smart Grid Control (DSGC) paradigm, in which individual consumers adjust their demand based on real-time frequency signals rather than relying entirely on instructions from a central operator [22], [25]. However, the effectiveness of such decentralized control depends on the ability to estimate the stability state of the grid quickly and reliably [7], [11], [17].

Machine learning (ML) has increasingly been applied to address this stability-estimation problem. Data-driven classifiers can identify unstable operating conditions within milliseconds [9], [18], while deep learning models have been investigated for transient stability and dynamic security assessment under fault conditions [1], [5]. Machine learning techniques are also being used for electricity-demand forecasting, including prediction of building-level power consumption [2], [8]. In parallel, multi-agent systems have been explored for coordinating distributed energy resources across microgrids and community energy systems without depending entirely on a centralized controller [3], [10], [20]. These developments have increased the need for models that are not only accurate but also understandable to system operators. Consequently, explainable artificial intelligence (XAI) techniques such as SHAP and LIME have gained attention for providing insight into the factors influencing model predictions [2], [6], [12].

Despite these developments, research in this area remains distributed across several closely related but often separately studied topics. Stability prediction, dynamic security assessment, explainable AI, decentralized energy

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management, peer-to-peer energy trading, grid resilience, and load forecasting are frequently investigated using different datasets, evaluation metrics, and methodological assumptions. As a result, it can be difficult to understand how the different approaches relate to one another, which techniques are commonly used for particular problems, and where important research gaps remain. A unified view is therefore useful for understanding the broader role of AI and ML in modern smart-grid stability and energy management.

Recent research on AI and ML-based smart-grid stability, security, and decentralized energy management covers seven major areas: classical and ensemble machine learning for stability prediction, deep-learning-based transient and dynamic security assessment, explainable AI for power systems, multi-agent decentralized energy management, peer-to-peer energy trading, complex-network-based grid resilience, and clustering-based load forecasting. These research directions employ diverse techniques and datasets, with varying levels of predictive performance, computational complexity, and practical applicability. However, several challenges remain, including dependence on simulated benchmark datasets, limited real-world validation, restricted generalization across different datasets, and insufficient integration of explainability into high-performing predictive models.

The key contributions include the classification of recent AI/ML research into a unified seven-category taxonomy, a comparative evaluation of the techniques and experimental settings used across different research areas, and an analysis of major challenges and future research opportunities. The relationship between predictive performance, computational complexity, and interpretability is also examined, particularly in smart-grid stability prediction. Furthermore, important research priorities include developing more diverse datasets, improving real-world validation, integrating explainability into predictive models, strengthening cybersecurity measures, and establishing closer coordination between technical grid-management approaches and energy-market mechanisms.

The remaining sections are organized as follows. Section II describes the taxonomy of AI/ML techniques for smart-grid stability and energy management. Section III reviews the existing literature across the seven identified categories. Section IV presents a comparative analysis of the reviewed approaches and discusses the major trends observed. Section V examines the key challenges and potential future research directions. Finally, Section VI presents the conclusion.

II. Taxonomy of AI/ML Techniques for Smart Grid Stability and Energy Management

Reading across the reviewed literature, seven distinct groupings emerge, as summarized in Fig. 1. These groupings reflect both the specific sub-problem being addressed, such as stability classification or energy trading, and the dominant methodological approach, including classical machine learning, deep learning, and agent-based coordination.

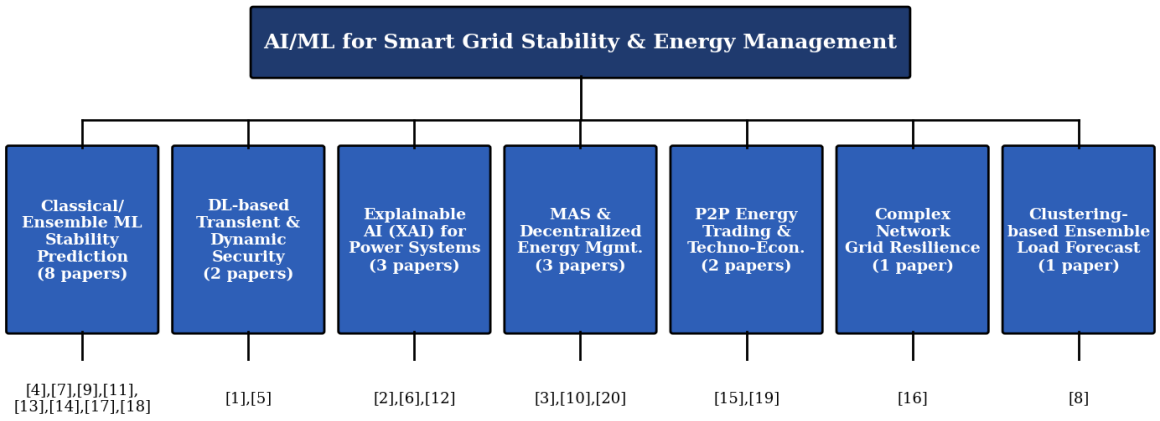


Fig. 1 Proposed taxonomy of AI/ML techniques for smart grid stability and energy management.

A. Classical/Ensemble ML for Stability Prediction

A major research direction treats smart grid stability as a classification problem, typically involving binary classification and, in some cases, multi-class classification. Several studies evaluate classical machine learning techniques using the widely adopted DSGC four-node simulated dataset. Commonly used models include Support Vector Machine (SVM), Random Forest (RF), XGBoost, LightGBM, and Artificial Neural Networks (ANN), either individually or as components of stacked ensemble approaches [4], [7], [9], [11], [13], [14], [17], [18].

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B. DL-based Transient and Dynamic Security Assessment

Another research direction focuses on transient stability under fault disturbances and dynamic security assessment in situations where phasor measurement unit (PMU) data may be incomplete. These studies employ deep learning architectures, particularly attention-based networks and convolutional neural networks (CNNs), together with data-imputation techniques to improve the reliability of security assessment [1], [5].

C. Explainable AI (XAI) for Power Systems

Explainability represents another important research direction, focusing on improving the interpretability of machine learning models used in power-system applications. Techniques such as SHAP, LIME, and ELI5 have been applied to forecasting and other energy-related models. Related studies also examine the adoption of explainable AI within the broader energy domain and identify the challenges associated with interpreting complex predictive models [2], [6], [12].

D. Multi-Agent Systems and Decentralized Energy Management

Multi-agent systems (MAS) have been investigated for coordinating distributed energy resources, controllable loads, and prosumers across microgrids and community energy systems. These approaches are frequently combined with metaheuristic optimization techniques such as Particle Swarm Optimization (PSO), Bat Algorithm (BAT), Differential Evolution (DE), and Harmony Search (HS) to improve energy-management decisions and resource allocation [3], [10], [20].

E. Peer-to-Peer Energy Trading and Techno-Economic Analysis

Peer-to-peer (P2P) energy trading represents a closely related research direction with greater emphasis on market mechanisms and economic performance. Existing approaches investigate mechanisms such as double auctions, Lyapunov-based online energy control, and techno-economic analysis to support energy trading and evaluate the economic benefits of decentralized prosumer communities [15], [19].

F. Complex-Network-based Grid Resilience

Complex-network approaches provide a different perspective by representing the power grid as an interconnected network rather than focusing solely on individual-node prediction. Such approaches investigate structural resilience and reliability using network-based measures, including centrality and vitality metrics, to identify vulnerable components and assess the robustness of power-grid structures [16].

G. Clustering-based Ensemble Load Forecasting

Clustering-based approaches have also been applied to electricity-demand forecasting. One approach uses unsupervised K-Means clustering to identify groups of similar consumption patterns before applying an ensemble machine learning forecasting model. This combination of clustering and ensemble learning improves building-level electric-power-consumption prediction compared with a non-clustered forecasting approach [8].

III. LITERATURE REVIEW

A. Category A: Classical/Ensemble ML for Stability Prediction

Ghosh and Kole [7] were among the first to run a broad head-to-head comparison, benchmarking nine classical classifiers – SVM, Logistic Regression, KNN, Naive Bayes, Decision Tree, Random Forest, SGD, XGBoost, and Gradient Boosting – on the DSGC simulation dataset. XGBoost came out on top (97.5% accuracy, 99.8% AUC-ROC), though the study stopped short of testing on any real-world data. Bayomi et al. [17] reached a similar conclusion with a smaller model set (XGBoost, Random Forest, Neural Network, KNN, SVM), again finding XGBoost strongest at 97.79% accuracy, but were candid about a limitation of their own: the roughly 60,000-instance dataset was, in their words, not large enough, and feature selection still needed to be done properly. Mohsen et al. [11] took a narrower approach, tuning a plain ANN rather than comparing several models, and got to 97.36% test accuracy through careful hyperparameter search – though without any ensemble baseline to check it against. Gunjal et al. [14] ran a comparison of their own (SVM, Logistic Regression, Decision Tree, Bagging, LightGBM) and again landed on a boosting method, LightGBM, as the best performer at 96% accuracy on the same restricted four-node topology.

Later work in this category pushes accuracy a bit further by layering models on top of each other. Ramasamy et al. [9] built a cost-sensitive stacked ensemble – XGBoost, Naive Bayes, Nu-SVM, and Random Forest feeding into an SVM meta-classifier – and reported 98.6% accuracy, though again without any deep-learning comparison. Al-Selwi et al. [4] went further still, pairing a stacked bidirectional LSTM with a purpose-built Adaptive Aquila Optimizer for feature selection and tuning; this pushed accuracy to 99.55%, but at a real cost in model size (67,602 parameters) and with no evidence yet that it holds up on noisier, real-world data. Aliyeva and Abdullayev [13] took a middle path, fusing MLP and XGBoost into a hybrid model that reached a 97.60% F1-score. Interestingly, Kandukuri and Banad [18] found that a carefully tuned SVM (99.9% accuracy) actually beat both LightGBM and a deep feed-forward network on the same

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dataset, and observed that LightGBM seemed to do better with larger datasets while SVM held its own with limited data – a reminder that the "best" model here may simply depend on how much data is available, rather than on any universal ranking.

Taken together, this category makes a fairly clear case that ensemble and boosting methods – XGBoost, LightGBM, stacked ensembles – tend to beat single classifiers. What's less encouraging is that all eight of these studies lean on essentially the same simulated four-node DSGC dataset, which leaves open the question of how well any of this actually generalizes to real, larger-scale grid topologies (see Section V).

B. Category B: DL-based Transient and Dynamic Security Assessment

Hou et al. [1] proposed a Spatio-Temporal Gated Hybrid Attention Network (ST-GHAN) – building on the self-attention and graph-attention mechanisms originally developed for sequence and graph-structured data [23], [24] – combined with FACTS-device (SVC/STATCOM) control and hierarchical-clustering transfer learning, for transient stability assessment under renewable integration. Tested on the IEEE 39-bus and NPCC 140-bus systems, it delivered a 2–6% accuracy gain over prior methods, though the authors acknowledge that power-electronic converter dynamics are not fully captured by the model. Boronuosi et al. [5] tackled a related but distinct problem – what to do when PMU data goes missing – using a Generative Adversarial Imputation Network (GAIN) ahead of a CNN classifier. The result held up to 99.48% accuracy even with as much as 50% of the data missing, which is a fairly strong result, though it too has only been tested in simulation rather than against real control-center data or under an actual cyberattack scenario.

Advanced deep learning techniques address the limitations of conventional static classifiers used for stability prediction. Attention mechanisms capture spatiotemporal relationships, while Generative Adversarial Networks (GANs) handle missing data to improve the reliability of dynamic security assessment. Although these approaches demonstrate promising performance in simulated environments, their effectiveness under real-world operating conditions remains uncertain due to the limited validation using data from operational power grids.

C. Category C: Explainable AI (XAI) for Power Systems

Machlev et al. [6] put together a broad review of XAI techniques used in energy and power systems, and one finding stands out: SHAP and LIME dominate the field, while deep-learning models – arguably the ones that need explaining the most – are rarely paired with any explainability tool at all. Kuzlu et al. [12] took a more hands-on approach, applying LIME, SHAP, and ELI5 to a Random Forest solar PV forecasting model on the GEFCOM 2014 dataset, and showing quite clearly how each tool trades off computational cost against whether the explanation is local or global in scope. Ramos et al. [2] came at the question from a systematic-review angle, using PRISMA methodology to trace the overlap between short-term electricity-demand forecasting and XAI specifically in buildings, and concluded that studies focused purely on forecasting accuracy still substantially outnumber ones that also try to explain their predictions.

The common thread across all three is not encouraging, but it is at least clear: XAI tools like SHAP and LIME are technically mature at this point, yet they are rarely built into the models that actually get deployed for grid forecasting or stability assessment. That gap is really what makes Category C a cross-cutting concern for Categories A and B, rather than a self-contained sub-field.

D. Category D: Multi-Agent Systems and Decentralized Energy Management

Ghazimirsaeid et al. [3] built a multi-agent EMS (EMS-MAS) for grid-connected green buildings, using metaheuristics – BAT, PSO, DE, HS – to schedule controllable loads under demand-response pricing. A nice feature of their design is that agents can make decentralized decisions without needing to know what strategy their competitors are running. Billah et al. [10] combined MAS control with Particle Swarm Optimization to manage a hybrid microgrid across islanded, transition, and grid-connected modes, and used MATLAB/Simulink to quantify the trade-off between operational cost and carbon footprint under different climatic scenarios. Bhattacharya et al. [20] took the field in a somewhat different direction, introducing a trust-based social-capital factor into MAS-based resource allocation for community energy systems – grounded explicitly in Ostrom's principles for managing shared resources – and showed through ablation studies that adding this trust factor meaningfully cuts blackout frequency.

There's a visible shift here from purely optimization-driven MAS coordination [3], [10] toward something more socially informed [20], though it's worth noting that all three studies are still simulation-based and none has been tried in an actual field deployment.

E. Category E: Peer-to-Peer Energy Trading and Techno-Economic Analysis

Zhu et al. [15] developed a Lyapunov-optimization-based online energy control scheme paired with a double-auction trading mechanism for P2P trading among prosumers. One appealing feature is that participants can bid without knowing the full statistics of the system, and can join or leave the market without adding computational overhead – a practical property that matters a lot if this kind of system is ever going to scale. Jose et al. [19], working from a more economic

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angle, ran a techno-economic analysis of a decentralized residential prosumer consortium and found that a consumer-to-prosumer mix of roughly 70–80% to 20–30% cuts the average payback period by 40%, and that shifting 25–30% of load reduces the payback further, increasing overall system profit by 35% relative to a conventional decentralized model.

Market mechanisms and economic performance are important aspects of decentralized energy systems. However, AI-driven stability assessment (Categories A and B) and market-oriented coordination mechanisms (Categories D and E) are often investigated independently. This separation highlights the need for integrated approaches that combine grid stability assessment with energy trading and resource allocation to improve the reliability and efficiency of smart-grid operations.

F. Category F: Complex-Network-based Grid Resilience

Moradi Amani and Jalili [16] reviewed and compared several complex-network vitality and centrality metrics for assessing grid resilience, and their side-by-side comparison turned up a useful, fairly specific result: net-ability is the better metric for spotting vulnerable transmission links, while entropic degree is better at flagging vulnerable buses. The harder problem they flag, though, is that purely topological models struggle to capture the grid's actual dynamics, while models that do capture dynamics – the cyber-physical, agent-based ones – tend not to scale. No single approach in the literature they surveyed does both at once.

G. Category G: Clustering-based Ensemble Load Forecasting

Sim et al. [8] combined K-Means clustering – validated with the Elbow, Silhouette, Calinski-Harabasz, and Dunn indices, which is a fairly thorough validation process in itself – with a CatBoost+LightGBM ensemble to forecast building-level electric-power consumption. Clustering first paid off noticeably: MAE dropped by 55.6% and RMSE by 59.3% compared to a non-clustered baseline. The catch is that the study looked at just one Korean apartment complex, and the dataset lacked building-physics attributes such as wall thickness or occupancy that might otherwise help explain some of the remaining error.

IV. Comparative Analysis

Table I lays out the technique, dataset, reported performance, computational complexity, and main limitation of the reviewed studies. Looking across the comparative results, three patterns stand out.

The first is that, within Category A, reported accuracies sit in a surprisingly tight band – roughly 96% to 99.9% – despite wildly different model complexities. A single tuned SVM [18] or a plain ANN [11] performs about as well as, or in some cases better than, a considerably more elaborate stacked BiLSTM with metaheuristic optimization [4] (Fig. 2). That's a bit of a warning sign: it suggests the DSGC benchmark may already be close to saturated for this kind of classification task, and that added model complexity needs to earn its keep through robustness or generalization rather than through marginal accuracy gains that may not mean much on a dataset this constrained.

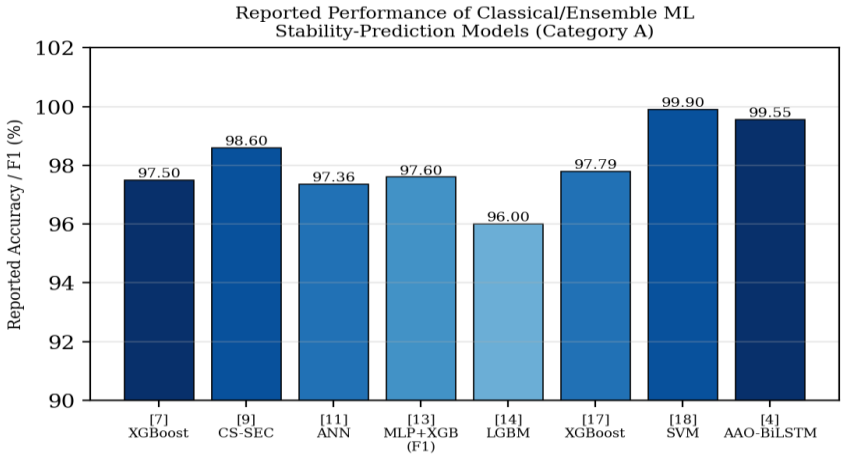


Fig. 2 Reported accuracy/F1 of Category A (classical/ensemble ML) stability-prediction models. Complexity increases toward the right (SVM/ANN → boosting → stacked ensembles), yet accuracy gains beyond ~97% are marginal.

Second, the datasets themselves are not very diverse. Several studies ([1], [4], [5], [7], [9], [11], [13], [14], [17], [18]) rely entirely on simulated benchmarks – mostly the four-node DSGC dataset or the IEEE 39-/118-/140-bus test systems – and only Sim et al. [8] work with real consumption data from an actual deployed site. That's a meaningful limitation on how far the field's conclusions can really be trusted to hold outside simulation, particularly in Category A.

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Third, there's a fairly consistent trade-off between accuracy and interpretability across categories. The highest-accuracy models – stacked ensembles, GAIN+CNN, ST-GHAN – also tend to be the least interpretable and the most computationally demanding, while the XAI-focused papers [2], [6], [12] deliberately give up some predictive sophistication in exchange for transparency. Not one paper in our review manages to combine top-tier accuracy, low complexity, and built-in explainability at the same time, which suggests this three-way trade-off is still an open design problem rather than something the field has already worked out (see Section V).

TABLE I COMPARATIVE ANALYSIS OF THE REVIEWED STUDIES: TECHNIQUE, DATASET, PERFORMANCE, COMPLEXITY, AND KEY LIMITATION

Ref.	Cat.	Technique	Dataset	Reported Perf.	Complexity/Cost	Key Limitation
[1]	B	ST-GHAN + FACTS control + transfer learning	IEEE 39-bus, NPCC 140-bus (sim.)	+2–6% acc. vs. baselines	High (attention + transfer learning)	Converter dynamics not fully modeled
[2]	C	PRISMA systematic review	Scopus-indexed papers	N/A (qualitative)	Low (review only)	Single-database (Scopus) coverage only
[3]	D	MAS-EMS + BAT/PSO/DE/HS	Simulated green-building microgrid	Improved DR profitability (qual.)	Medium-high (MAS + metaheuristic)	Complexity grows with grid size
[4]	A	Stacked BiLSTM + Adaptive Aquila Optimizer	DSGC (4-node, sim.)	99.55% Acc./Prec./Rec./F1	High (67,602 params)	Untested on noisy real-world data
[5]	B	GAIN (imputation) + CNN	IEEE 39-bus, 118-bus (sim.)	Up to 99.48% accuracy	Medium-high (GAN + CNN)	No real control-center validation
[6]	C	Narrative review of XAI methods	N/A (review)	N/A (qualitative)	Low (review only)	No new empirical validation
[7]	A	9 classifiers, best: XGBoost	DSGC (4-node, sim.)	97.5% Acc., 99.8% AUC-ROC	Medium (ensemble boosting)	No real-world / hardware validation
[8]	G	K-Means clustering + CatBoost/LightGBM ensemble	Korean apartment complex (real)	55.6% MAE, 59.3% RMSE reduction	Medium (clustering + ensemble)	Single-site; no building-physics data
[9]	A	Cost-sensitive stacked ensemble (XGB, NB, Nu-SVM, RF + SVM meta)	DSGC (4-node, sim.)	98.6% accuracy	Medium-high (2-level stacking)	No deep-learning comparison
[10]	D	MAS + PSO across operating modes	MATLAB/Simulink hybrid microgrid	Cost $43–62 (mode-dependent)	Medium (MAS + PSO)	Simulation only; single microgrid config.
[11]	A	Tuned ANN	DSGC (4-node, sim.)	97.36% test accuracy	Low-medium (single ANN)	No ensemble/DL benchmark comparison
[12]	C	LIME, SHAP, ELI5 on Random Forest	GEFCOM 2014 (solar PV)	Qualitative XAI comparison	Low-medium (RF + post-hoc XAI)	Single model/dataset evaluated
[13]	A	Hybrid MLP + XGBoost	DSGC (4-node, sim.)	97.60% F1-score	Medium (hybrid ensemble)	No real-time or real-world data
[14]	A	SVM, LR, DT, Bagging, LightGBM (best: LGBM)	DSGC (4-node, sim.)	96% accuracy (LGBM)	Low-medium (gradient boosting)	No optimization applied to improve results

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Ref.	Cat.	Technique	Dataset	Reported Perf.	Complexity/Cost	Key Limitation
[15]	E	Lyapunov optimization + double auction	Simulated P2P prosumer community	Cost savings (simulation)	Medium (online optimization)	Numerical simulation only
[16]	F	Complex-network centrality/vitality metrics	Benchmark + real grid networks	Qualitative vulnerability ranking	Low-medium (graph metrics)	No unified topology+dynamics model
[17]	A	XGBoost, RF, NN, KNN, SVM (best: XGBoost)	DSGC (~60k instances, sim.)	97.79% Acc., 96.7% AUC	Medium (ensemble boosting)	Dataset not large; needs feature selection
[18]	A	SVM, LightGBM, Deep NN (best: SVM)	DSGC (4-node, sim.)	99.9% accuracy (SVM)	Low (SVM) – Medium (DNN)	No LightGBM+SVM hybrid tested
[19]	E	Techno-economic P2P consortium analysis	Simulated residential consortium	40% shorter payback, 35% profit gain	Medium (scenario-based economic model)	Sensitive to assumed load/gen. profiles
[20]	D	MAS + Ostrom trust-based allocation	Synthetic community energy data	Reduced blackout frequency	Medium (MAS + trust modeling)	Synthetic data; preliminary framework

V. Challenges and Future Directions

A major challenge in the reviewed literature is the limited real-world validation of AI/ML-based smart-grid models. Most studies in Categories A, B, D, and E rely on simulation environments, such as the four-node DSGC dataset or MATLAB/Simulink models, rather than testing their approaches on actual field-deployed grids [4], [7], [10], [17]. Although simulation provides a controlled environment for evaluating model performance, it may not fully capture the noise, uncertainty, communication delays, and operational variability present in real power systems. Future research should therefore focus on establishing closer collaboration with utilities and testing these models using real PMU streams and deployed microgrid pilots to evaluate their robustness under practical operating conditions.

Another important challenge is the homogeneity of datasets used for stability prediction. Several studies rely on the same four-node DSGC benchmark [4], [7], [9], [11], [13], [14], [17], [18], which raises the possibility that some reported performance improvements may be influenced by the characteristics of a specific benchmark rather than reflecting general methodological improvements. This limitation makes it difficult to determine how well the models would perform across different grid topologies and operating conditions. Future work should therefore develop larger and more diverse multi-scale grid-stability datasets that represent different network topologies, operating conditions, and realistic levels of renewable-energy penetration.

Insufficient integration of explainability is another significant challenge. In the reviewed literature, XAI is largely treated as a separate research direction [2], [6], [12], rather than being integrated directly into high-performing stability and security assessment models [1], [4], [5]. While post-hoc techniques can provide useful explanations, they may not fully address the interpretability requirements of complex grid-management applications. Future research should investigate models that incorporate interpretability by design, including attention-based architectures whose learned attention patterns can be visualized and examined by system operators.

Cybersecurity and adversarial robustness also require greater attention. The reviewed dynamic security and stability models generally do not evaluate their resilience against adversarial manipulation or cyberattack-induced data corruption. Boronuosi et al. [5] identify this issue as an area for future investigation rather than addressing it directly in their proposed approach. Future research could therefore extend GAIN/CNN-based and attention-based architectures with adversarial training, anomaly detection, and anomaly-aware data-imputation mechanisms to improve resilience against corrupted or manipulated measurements.

Another challenge is the fragmentation between technical grid-management research and market-layer research. Stability and security prediction in Categories A and B and market or coordination mechanisms in Categories D and E have largely been investigated as separate problems. The reviewed approaches do not integrate both layers into a single pipeline that simultaneously considers grid stability and market or allocation decisions. Future research could therefore investigate stability-aware AI models coupled with multi-agent trading and resource-allocation mechanisms, allowing market decisions to account for real-time grid stability constraints.

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Finally, scalability remains a challenge for topology-aware and dynamics-aware approaches. Moradi Amani and Jalili [16] highlight that purely topological complex-network models can scale effectively but may not capture the dynamic behavior of power systems, whereas dynamics-aware cyber-physical and multi-agent models [3], [10], [20] can represent such behavior but may face scalability limitations. Future research could explore hybrid graph-neural-network approaches that combine information about network topology with learned dynamic behavior, with the aim of achieving both scalability and improved representation of grid dynamics.

VI. Conclusion

This survey brought together recent research on AI/ML techniques for smart grid stability, security, and decentralized energy management, and organized the literature into a structured framework covering seven major research directions. The resulting taxonomy spans classical and ensemble-based stability prediction, deep-learning-based dynamic security assessment, explainable AI, multi-agent decentralized management, peer-to-peer energy trading, complex-network-based resilience analysis, and clustering-based load forecasting. Across these research directions, several important patterns emerged. Ensemble and boosting methods generally achieve strong stability-prediction performance on widely used DSGC benchmarks, while dataset diversity, real-world validation, integrated explainability, cybersecurity, and coordination between technical and market-layer research remain important challenges. These gaps highlight several opportunities for future work, including the development of AI-driven grid-stability models that are not only accurate but also interpretable, robust to adversarial conditions, scalable to diverse network topologies, and validated using realistic power-system data and practical deployment environments.

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