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ARTIFICIAL INTELLIGENCE IN POWER SYSTEMS: A COMPREHENSIVE REVIEW OF OPERATIONAL ENHANCEMENTS AND EMERGING CHALLENGES

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Abstract- Modern power systems are becoming increasingly complex due to high penetrations of variable renewables, evolving electricity markets, and rising expectations for reliability and resilience. Traditional, model-driven methods struggle to keep pace with this dynamic, data-rich environment. This review examines how Artificial Intelligence (AI) and Machine Learning (ML) are being applied across four core domains of grid operations: (1) forecasting of load and renewable generation with models such as LSTMs and Transformers; (2) fault detection and predictive maintenance for assets like transformers and lines; (3) security and stability control, including anomaly detection, cyber-threat mitigation, and voltage stability assessment; and (4) optimization and control for markets, demand response, and optimal power flow. We compare supervised, unsupervised, and reinforcement learning approaches, noting their data needs, effectiveness, and deployment practicality. Key barriers—data quality, interpretability, computational cost, and AI-driven cyber risks are assessed, and emerging directions such as federated learning and physics-informed neural networks are highlighted as paths toward more transparent, robust, and trustworthy AI-enabled power systems.
Keywords: Artificial Intelligence, Machine Learning, Power Systems, Smart Grid.

1. INTRODUCTION

The global energy system is undergoing a rapid transition toward decarbonization, electrification, and digitalization. Large-scale integration of distributed and intermittent resources especially solar PV and wind—adds variability and uncertainty to generation. At the same time, smart grids enable two-way flows of power and information, with consumers increasingly acting as prosumers through rooftop PV, storage, electric vehicles, and flexible demand. These trends increase the dimensionality and volatility of grid operations, raising the stakes for reliability, resilience, and cybersecurity.

Conventional power-system analysis relies on physics-based models (e.g., power flow, stability, and state estimation) and numerical optimization. While proven and essential, these methods can be difficult to calibrate in real time and may not scale gracefully with heterogeneous data from smart meters, PMUs, and IoT devices. Artificial Intelligence (AI) and Machine Learning (ML) offer a complementary toolkit: they uncover patterns in large datasets, adapt as conditions change, and enable fast predictions for forecasting, anomaly detection, and control [1].

This paper reviews how AI/ML is reshaping power-system operations across four domains: (i) load and renewable forecasting, (ii) asset health monitoring and predictive maintenance, (iii) security and stability (including cyber-physical threats), and (iv) optimization and control for markets and operation (e.g., demand response and optimal power flow). For each, we map techniques supervised, unsupervised, and reinforcement learning to tasks, discuss data and deployment requirements, and identify strengths and weaknesses. We also address cross-cutting challenges such as data quality and governance, model interpretability (the "black-box" problem), computational demands, and AI-introduced attack surfaces. Finally, we outline promising directions—federated learning for privacy-preserving collaboration and physics-informed neural networks that embed domain knowledge to guide the development of transparent, robust, and trustworthy AI-driven grids.

2. LITERATURE REVIEW: THE AI REVOLUTION IN CONTEXT

The idea of applying Artificial Intelligence (AI) to power systems is not new. As early as the 1980s and 1990s, researchers experimented with expert systems and the first-generation neural networks for applications such as fault detection and load forecasting [2]. However, progress was slow due to two major limitations: insufficient computational resources and the scarcity of large, reliable datasets.

In recent years, three major developments have transformed this landscape and triggered a new wave of AI adoption in power engineering.

2.1 The Data Boom

The large-scale deployment of smart meters, phasor measurement units (PMUs), and advanced SCADA systems has produced enormous volumes of high-resolution data. These datasets capture grid conditions, consumption behavior, and equipment performance in ways that were not possible before.

2.2 Advances in Computing

The rise of high-performance computing (HPC), parallel processing, and cloud platforms now allows researchers and utilities to train and deploy complex deep learning models that once required prohibitive resources.

2.3 Algorithmic Breakthroughs

Modern methods such as deep neural networks, recurrent neural networks (RNNs), and reinforcement learning (RL) have introduced the sophistication needed to capture nonlinear grid dynamics, learn from sequential data, and support adaptive decision-making.

Together, these advancements have shifted AI from being a promising research concept into a practical and strategic tool for utilities and grid operators. Today, AI is not just an experimental add-on but an essential component in managing forecasting, control, and decision-making in modern power systems.

3. AI/ML APPLICATIONS IN POWER SYSTEM OPERATIONS

Artificial Intelligence (AI) and Machine Learning (ML) have become essential tools for handling the growing complexity of modern power systems. Their applications can be grouped into four major operational areas:

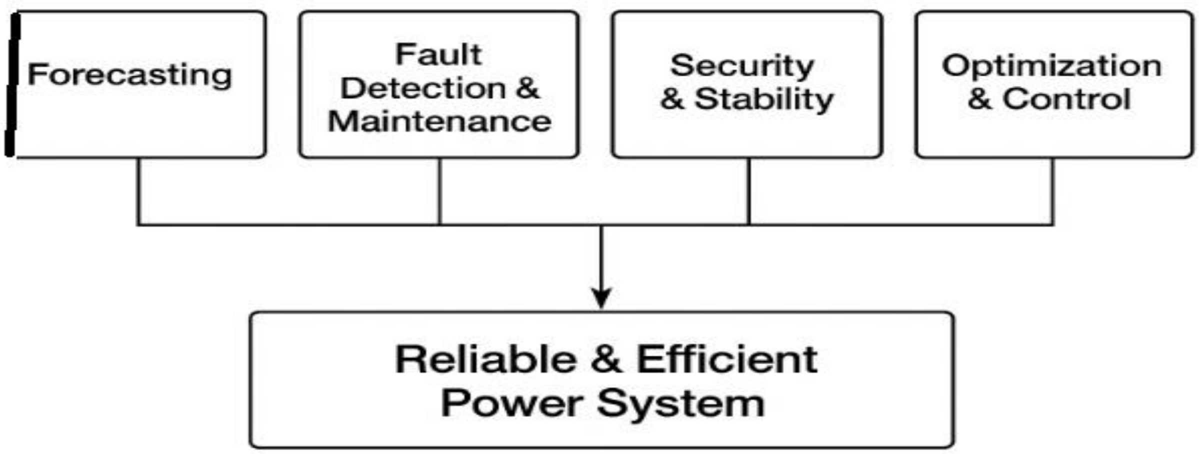

Fig. 3.1 AI/ML Applications in Power Systems

3.1 Forecasting: Dealing with Uncertainty

Reliable forecasting is central to both the economics and reliability of power systems.

3.1.1 Load Forecasting

Estimating future electricity demand is vital for unit commitment and economic scheduling. Unlike traditional statistical approaches such as ARIMA, ML models—especially Long Short-Term Memory (LSTM) networks—can better capture nonlinear relationships, seasonal variations, and the influence of weather and time-of-day patterns [3].

3.1.2 Renewable Generation Forecasting

The variable nature of solar and wind generation makes accurate forecasting critical. Convolutional Neural Networks (CNNs) are effective in processing weather-related spatial data, while LSTMs and Transformer models handle temporal sequences. Together, they provide highly accurate short-term predictions, often just hours ahead.

3.2 Fault Detection and Predictive Maintenance

Moving from reactive or routine maintenance toward predictive strategies helps reduce costs and prevent unexpected outages.

3.2.1 Condition Monitoring

AI models analyze sensor data such as dissolved gas readings in transformers, or vibration and temperature signals from transmission lines, to detect early indicators of equipment degradation.

3.2.2 Fault Diagnosis and Classification

When faults occur, ML techniques rapidly process waveform data from PMUs to identify the fault type (e.g., line-to-ground) and locate it precisely. This capability greatly reduces downtime and speeds up recovery.

3.3 Security and Stability Control

AI strengthens the grid's resilience against operational disturbances and cyber threats.

3.3.1 Real-Time Anomaly Detection

Unsupervised learning methods, such as Autoencoders, can establish a baseline of "normal" grid operations and highlight unusual behavior. This helps operators quickly spot potential instability or cyber intrusions like False Data Injection (FDI) attacks [4].

3.3.2 Voltage and Frequency Stability

Machine learning tools can provide rapid assessments of system stability. By identifying risks early, they enable corrective measures such as activating reserves or controlled load shedding, often faster than conventional techniques.

3.4 Optimization and Control

AI offers smarter and more autonomous ways to manage grid operations.

3.4.1 Energy Market Trading

Reinforcement Learning (RL) algorithms can learn and adapt to market conditions, allowing generators or consumers to optimize bidding strategies and improve profitability.

3.4.2 Demand Response

AI systems can coordinate distributed energy resources, such as smart appliances, electric vehicles, and thermostats, to shift consumption away from peak demand times. This results in a flatter and more balanced load curve.

3.4.3 Optimal Power Flow (OPF)

Deep learning models can approximate complex OPF calculations, making it possible to perform near real-time grid optimization that would otherwise be too computationally expensive.

Table-3.1 Summary of AI/ML Applications in Power Systems

Application Area	Key Objective	Common ML Techniques	Data Sources
Load Forecasting	Predict electricity demand	LSTM, Transformer, Gradient Boosting	Historical load, weather, time data
Renewable Forecasting	Predict solar/wind output	CNN, LSTM, RNN	Weather forecasts, satellite imagery, historical generation
Predictive Maintenance	Predict equipment failure	Anomaly Detection, SVM, CNNs	Sensor data (vibration, temperature, gas levels)
Fault Diagnosis	Identify and locate faults	Supervised Learning, CNN	PMU/SCADA data (voltage, current waveforms)
Cybersecurity	Detect cyber-attacks	Anomaly Detection, Clustering	Network traffic, SCADA data logs
Grid Optimization	Efficient power distribution	Reinforcement Learning, DNN	Grid topology, load, generation data

4. EMERGING CHALLENGES AND BARRIERS TO ADOPTION

While AI offers enormous opportunities for transforming power systems, its large-scale deployment still faces several obstacles:

4.1 Data Quality and Accessibility

The performance of ML models depends heavily on the quality of input data. If data is noisy, incomplete, or inconsistent—especially from older legacy systems—the accuracy of predictions suffers. Moreover, information is often stored in isolated silos across utilities, which prevents the creation of more reliable and generalized models.

4.2 Model Transparency (The "Black-Box" Issue)

Many deep learning models operate as highly complex systems with limited interpretability. For grid operators, trusting such models during emergencies is difficult if the reasoning behind a decision cannot be clearly explained [5]. Lack of transparency remains a critical barrier to adoption in safety-critical environments.

4.3 High Computational Demands

Training advanced AI models requires powerful computing resources. While large organizations may have access to such infrastructure, smaller utilities often struggle to meet these requirements, creating inequality in adoption.

4.4 Cybersecurity Risks

As AI becomes embedded in the grid, it introduces new vulnerabilities. Malicious actors can attempt "model poisoning" by corrupting training data or launch adversarial attacks designed to mislead deployed models. Such threats could lead to serious errors in system operation if not properly mitigated.

5. FUTURE DIRECTIONS

Looking ahead, the advancement of AI in power systems will depend on how effectively current challenges are addressed and how emerging innovations are adopted:

5.1 Explainable AI (XAI)

Future research must focus on making AI models more transparent and interpretable. By providing clear reasoning behind their decisions, XAI can help operators build confidence in AI-assisted grid operations.

5.2 Federated Learning

Instead of requiring centralized data sharing, federated learning enables multiple utilities to collaboratively train models while keeping sensitive raw data secure. This approach improves model robustness while protecting privacy.

5.3 Physics-Informed Neural Networks (PINNs)

By embedding the physical principles of power systems (such as Kirchhoff's laws) into neural network design, PINNs ensure that predictions remain consistent with engineering realities, increasing trustworthiness and reliability.

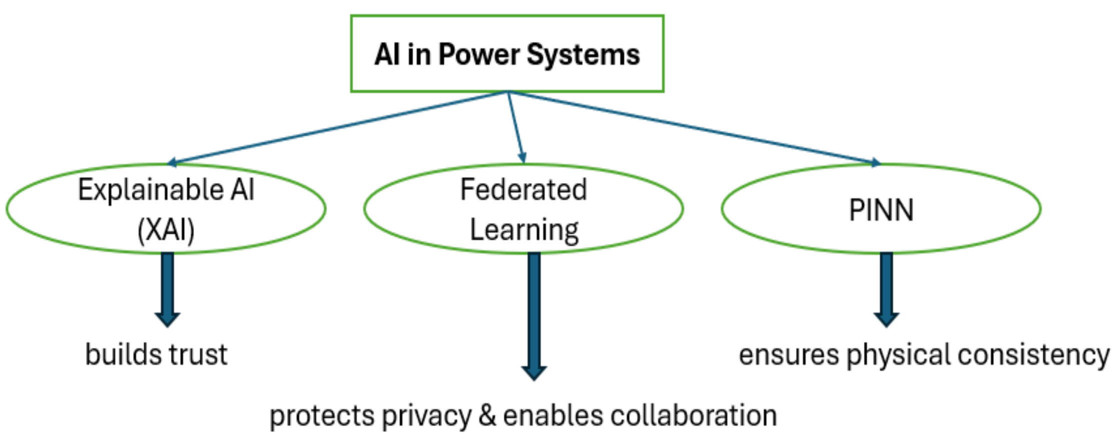

Fig. 5.1 Future Directions of AI in Power Systems

CONCLUSION

Artificial Intelligence and Machine Learning represent more than incremental tools—they are transformative technologies shaping the future of smart grids. Their ability to improve forecasting, enable predictive maintenance, strengthen security, and optimize operations makes them essential for managing increasingly complex energy networks. Still, their widespread success depends on overcoming barriers related to data quality, transparency, and cybersecurity. Moving forward, close collaboration between power engineers, data scientists, and policymakers will be vital to create AI systems that are not only powerful but also explainable, secure, and resilient—ultimately ensuring a sustainable and intelligent energy future.all.

REFERENCES

[1] Y. Wang, D. Zhang, Y. Liu, B. Dai, and L. H. Lee, "Enhancing Smart Grid with Machine Learning," IEEE Access, vol. 7, pp. 157842-157856, 2019.

[2] T. M. Index and S. S. Venkata, "Artificial Intelligence in Power Systems: A Survey," IEEE Power Engineering Review, vol. 12, no. 11, pp. 41-41, Nov. 1992.

[3] Z. Liang, et al., "Short-Term Load Forecasting Based on Long Short-Term Memory Model," in 2018 IEEE International Conference on Energy Internet (ICEI), Beijing, China, 2018, pp. 229-234.

[4] Y. Zhang, J. Wang, and B. Chen, "Detecting False Data Injection Attacks in Smart Grids: A Deep Learning Approach," IEEE Transactions on Industrial Informatics, vol. 15, no. 7, pp. 4065-4074, July 2019.

[5] Adadi and M. Berrada, "Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)," IEEE Access, vol. 6, pp. 52138-52160, 2018.

[6] Garg, V., Jangid, R., Jain, C., Sisodiya, M. "Performance Analysis of a PV-BESS-Grid Integrated Fast EV Charging System", Journal of Emerging Technologies and Innovative Research (JETIR), Volume 12, Issue 6, 2025.

[7] Jain, C., Jangid, R., Sisodiya, M., Garg, V. "ANN-Based DVR for Fault Mitigation and Performance Optimization in Hybrid PV-Wind Energy Conversion Systems", International Journal of Technical Research & Science. Volume X, Issue VI, June 2025. DOI Number: https://doi.org/10.30780/IJTRS.V10.I06.007

[8] Sisodiya, M., Jangid, R., Jain, C., Garg, V. "Short-Term Load Forecasting (STLF) Using Machine Learning Models: A Comparison Based Study to Predict the Electrical Load Requirements", International Journal of Technical Research & Science. Volume X, Issue VI, June 2025. DOI Number: https://doi.org/10.30780/IJTRS.V10.I06.007

[9] Sharma, S.S., Joshi, R.R., Jangid, R. et al. "Intelligent Techniques for Mitigation of Transient Over-Voltages in Gas Insulated Sub-Station and Effects of VFTO", Journal of Critical Reviews, Volume 7, Issue 14, pp. 3378-3392, 2020.

[10] Bhatnagar, S., Jangid, R., et. al. "Modeling and Design of Maximum Power Point Tracking System Control Algorithm for PMSG Based Grid Connected Wind Power Generating Unit", International Journal of Technical Research & Science. Volume IV, Issue VII, July 2019. DOI Number: https://doi.org/10.30780/IJTRS.V04.I07.002

[11] Verma, C., Jangid, R. "Smart Household Demand Response Scheduling with Renewable Energy Resources", IEEE Third International Conference on Intelligent Computing and Control System (ICICCS-2019), Organized by Vaigai College of Engineering during May 15-17, 2019 at Madurai, India. (Scopus index) DOI: 10.1109/ICCS45141.2019.9065908.

[12] Y. Joshi, J. K. Maherchandani, V. K. Yadav, R. Jangid, S. Vyas and S. S. Sharma, "Performance Improvement of Standalone Battery Integrated Hybrid System," 2021 7th International Conference on Electrical Energy Systems (ICEES), Chennai, India, 2021, pp. 250-255, doi: 10.1109/ICEES51510.2021.9383636

[13] Kumar, S., Jangid, R., Parikh, K. "Comparative Performance Analysis of ANFIS & ANN Algorithms Based MPPT Energy Harvesting in Solar PV System", International Journal of Technical Research & Science. Volume VIII, Issue III, March 2023. DOI Number: https://doi.org/10.30780/IJTRS.V08.I03.001

[14] Gaur, S.S., Bahrani, P., Jangid, R. "Performance Analysis of Standalone Solar Generation System with Fuzzy and ZVS Converter", International Journal of Technical Research & Science. Volume IV, Issue II, Feb. 2019. DOI Number:10.30780/IJTRS.V04.I02.003

[15] Aarif, M., Joshi, D., Jangid, R. "Grid Power Smoothing Management for Direct Drive PMSG Variable Speed Wind Energy Conversion System with Multilevel Converter", IEEE 7th International Conference on ICT for Sustainable Development (ICT4SD 2022), Organized by Global Knowledge Foundation during 29-30, July 2022 at Goa, India. (Springer Scopus index) https://doi.org/10.1007/978-981-19-5331-6_3

[16] Sharma, S.S., Joshi, R.R., Jangid, R. et al. "Mitigation of Transient Over-Voltages and VFTO Effects on Gas Insulated Substation", Solid State Technology, Volume 63, Issue 5, 2020.

[17] G. Liang, S. R. Weller, J. Zhao, F. Luo, and Z. Y. Dong, "The 2015 Ukraine Blackout: Implications for False Data Injection Attacks," IEEE Transactions on Power Systems, vol. 32, no. 4, pp. 3317-3318, July 2017.

[18] L. Xie, Y. Mo, and B. Sinopoli, "Integrity Data Attacks in Power Market Operations," IEEE Transactions on

Smart Grid, vol. 2, no. 4, pp. 659-666, Dec. 2011.
[19] R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 12-19, Feb. 2011.
[20] J. E. Contreras-Ocaña, M. A. Khan, B. Chen, and Z. Zhang, "Reinforcement Learning for Electricity Market Operation," IEEE Power and Energy Magazine, vol. 18, no. 3, pp. 66-77, May-June 2020.
[21] H. Sun, Q. Guo, J. Qi, V. Ajjarapu, R. Bravo, and J. Chow, "Review of Challenges and Research Opportunities for Voltage Control in Smart Grids," IEEE Transactions on Power Systems, vol. 34, no. 4, pp. 2790-2801, July 2019.
[22] Sujit Kumar, Himani Paliwal, Shripati Vyas, Sasanka Sekhor, Vikramaditya Dave and Srawan Singh Rao. Dynamic Wireless Power Transfer in Electric Vehicles. 2021 J. Phys.: Conf. Ser. 1854. https://doi.org/10.1088/1742-6596/1854/1/012014
[23] et. al., S. V. (2021). Life Extension Of Transformer Mineral Oil Using AI-Based Strategy For Reduction Of Oxidative Products. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12(11), 264–271. https://doi.org/10.17762/turcomat.v12i11.5869
[24] Tirole, R., Joshi, R.R., Yadav, V.K., Maherchandani, J.K. and Vyas, S. (2022). Intelligent Control Technique for Reduction of Converter Generated EMI in DG Environment. In Intelligent Renewable Energy Systems (eds N. Priyadarshi, A.K. Bhoi, S. Padmanaban, S. Balamurugan and J.B. Holm-Nielsen). https://doi.org/10.1002/9781119786306.ch4
[25] Chhipa, A.A., Vyas, S., Kumar, V., Joshi, R.R. (2021). Role of Power Electronics and Optimization Techniques in Renewable Energy Systems. In: Kumar, R., Singh, V.P., Mathur, A. (eds) Intelligent Algorithms for Analysis and Control of Dynamical Systems. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-15-8045-1_17
[26] Abrar Ahmed Chhipa, Shripati Vyas, Vinod Kumar, and R.R. Joshi. MPPT optimisation techniques and power electronics for renewable energy systems: wind and solar energy systems. International Journal of Swarm Intelligence 2022 7:2, 141-167
[27] Vyas, M., Yadav, V.K., Vyas, S., Swami, R.K. (2022). An Intelligent Control Strategy for Power Quality Improvement of DFIG-Based Wind Energy Conversion System. In: Kumar, J., Tripathy, M., Jena, P. (eds) Control Applications in Modern Power Systems. Lecture Notes in Electrical Engineering, vol 870. Springer, Singapore. https://doi.org/10.1007/978-981-19-0193-5_21
[28] X. Fang, S. Misra, G. Xue, and D. Yang, "Smart Grid — The New and Improved Power Grid: A Survey," IEEE Communications Surveys & Tutorials, vol. 14, no. 4, pp. 944-980, Fourth Quarter 2012.
[29] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving Nonlinear Partial Differential Equations," Journal of Computational Physics, vol. 378, pp. 686-707, 2019.
[30] McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-Efficient Learning of Deep Networks from Decentralized Data," in Proceedings of the 20th International Conference on Artificial Intelligence and Statistics (AISTATS), Fort Lauderdale, FL, USA, 2017, pp. 1273-1282.
[31] S. Wang, et al., "A Review of Deep Learning for Renewable Energy Forecasting," Energy Conversion and Management, vol. 198, 2019, Art. no. 111799.
[32] International Electrotechnical Commission (IEC), "White Paper: Artificial Intelligence Across Industries," IEC, Geneva, Switzerland, 2020.