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Applications of Artificial Intelligence and Machine Learning in Power System Operation and Control: A Comprehensive Review

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Abstract: The fields of artificial intelligence (AI) and machine learning (ML) have the potential to completely change a number of industries, including the operation and control of power systems. A detailed overview of the use of AI and ML approaches in power system operation and control is given in this review paper. Numerous subjects are covered, such as defect detection, voltage control, optimal power flow, renewable energy integration, predictive maintenance, and grid stability enhancement. In order to offer insights into the changing environment of smart grid technologies, problems, opportunities, and future directions in harnessing AI and ML for power system management are also covered.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Power System Operation, Renewable Energy Integration, Optimal Power Flow (OPF), Fault Detection and Diagnosis.

1. Introduction

In numerous industries, including power systems operation and control, the fusion of Artificial Intelligence (AI) and Machine Learning (ML) technologies has launched a new wave of innovation [1],[2]. As modern power systems become increasingly complex and interconnected, the need for intelligent solutions to manage grid operations efficiently, enhance reliability, and optimize resource utilization has become paramount. AI and ML offer a suite of powerful tools and techniques that enable data-driven decision-making, predictive analytics, and autonomous control, thereby transforming traditional power system management paradigms.

The aim of this review paper is to provide a comprehensive overview of the applications of AI and ML in power system operation and control. By synthesizing and analyzing recent research findings, methodologies, and case studies from academic literature, industry reports, and technical conferences, this review aims to elucidate the multifaceted role of AI and ML in addressing various challenges faced by modern power systems[3].

The review will cover a wide range of topics, including predictive maintenance, fault detection and diagnosis, optimal power flow, voltage control, renewable energy integration, and grid stability enhancement. Each topic will be examined in detail, exploring the latest advancements, methodologies, and practical implementations of AI and ML techniques in power system management[4].

Furthermore, the review will discuss the challenges, opportunities, and future directions in leveraging AI and ML for power system operation and control. This section will provide insights into the changing landscape of AI and ML applications in the electricity sector and identify important topics for future study and innovation. These will range from cybersecurity problems and regulatory consequences to data quality and model interpretability.

Overall, this review paper aims to serve as a comprehensive resource for researchers, practitioners, and policymakers interested in understanding the potential of AI and ML technologies to transform power system operation and control [5]. By elucidating the current state-of-the-art, identifying challenges, and outlining future research directions, this review seeks to facilitate the adoption of intelligent solutions for building smarter, more resilient, and sustainable power systems[6].

2. Predictive Maintenance and Asset Management:

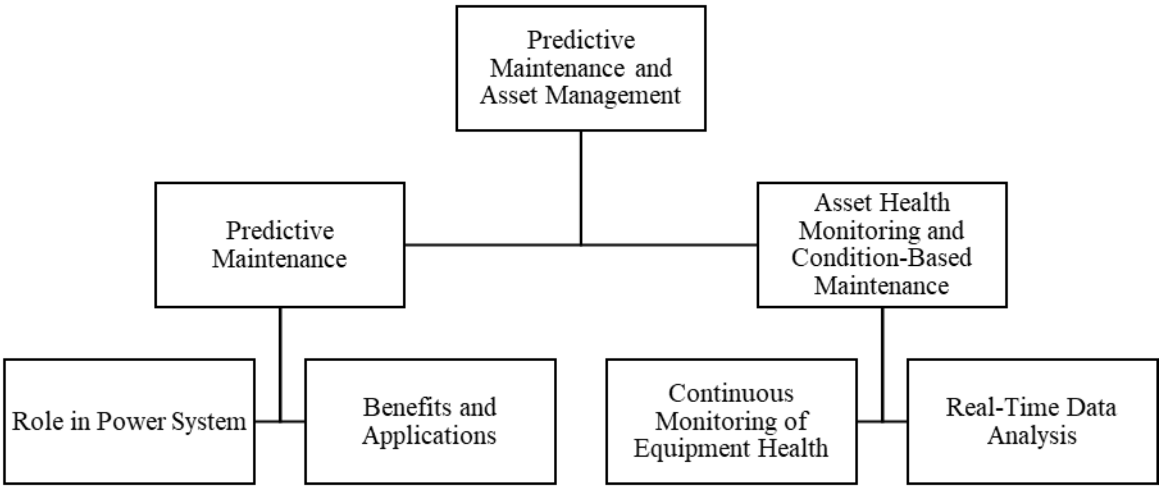

Figure-1:- Predictive Maintenance and Asset Management flow chart

In modern power systems, the efficient operation and maintenance of assets are paramount to ensure reliability, safety, and cost-effectiveness. Traditional maintenance strategies often rely on scheduled inspections or reactive responses to failures, leading to downtime, increased operational costs, and suboptimal asset performance. Predictive maintenance, empowered by Artificial Intelligence (AI) and Machine Learning (ML) techniques, offers a proactive and data-driven approach to asset management, enabling utilities to predict equipment failures, optimize maintenance schedules, and extend asset lifespan.

2.1. Predictive Maintenance Techniques:

AI and ML algorithms play a pivotal role in predictive maintenance by analyzing historical data, sensor measurements, and operational parameters to detect anomalies, identify degradation patterns, and predict impending failures. Supervised learning algorithms, such as Support Vector Machines (SVM) and Random Forests, are commonly used for classification tasks[7], while unsupervised learning techniques like clustering and anomaly detection algorithms aid in identifying abnormal behavior in asset performance data[8]. Furthermore, reinforcement learning algorithms enable adaptive maintenance strategies by optimizing maintenance actions based on real-time feedback and performance data[9].

2.2. Asset Health Monitoring and Condition-Based Maintenance:

AI and ML-based asset health monitoring systems continuously analyze sensor data, operational logs, and environmental conditions to assess the condition of critical assets such as transformers, generators, and transmission lines. These systems can detect early indications of deterioration or aberrant behaviour by using methods including time-series analysis[10], pattern recognition[11], and feature extraction[12]. This enables operators to conduct preventative maintenance measures before breakdowns happen.Condition-based maintenance strategies prioritize maintenance activities based on asset health assessments, optimizing resource allocation and minimizing downtime[13].

2.3. Remaining Useful Life Prediction:

It is crucial to estimate the assets' remaining usable lives (RUL) in power systems in order to maximize asset longevity, minimize expenses, and optimize maintenance schedules[14]. Regression analysis, survival analysis, and deep learning models are a few of the AI and ML techniques used to estimate the RUL of equipment based on environmental conditions, maintenance records, and previous performance data. By leveraging advanced data-driven models, utilities can forecast the time to failure of assets with greater accuracy, enabling proactive maintenance interventions and reducing the risk of unexpected downtime.

2.4. Anomaly Detection and Fault Diagnosis:

Anomalies and faults in power system assets can have significant operational and safety implications, making timely detection and diagnosis critical for maintaining system reliability. AI and ML algorithms, such as auto encoders, deep belief networks, and Bayesian networks, are applied to detect anomalies and diagnose faults by analyzing patterns in sensor data, operational logs, and historical maintenance records [15]. These methods aid in the quick discovery and resolution of asset-related problems by enabling the early detection of anomalous behaviour and facilitating root cause analysis.

2.5. Integration with Asset Management Systems:

Integrating AI and ML-based predictive maintenance solutions with existing asset management systems enhances decision-making capabilities, streamlines maintenance workflows, and optimizes resource allocation[16]. By combining predictive analytics with asset performance data, maintenance histories, and business constraints, utilities can develop data-driven maintenance strategies that prioritize critical assets, optimize spare parts inventory, and minimize operational risks. Furthermore, advanced analytics techniques, such as prescriptive maintenance and dynamic risk assessment, enable utilities to proactively mitigate potential failures and optimize asset performance in real-time[17,18].

In conclusion, AI and ML-enabled predictive maintenance and asset management have a lot to offer power system control and operation. By enabling utilities to predict equipment failures, optimize maintenance schedules, and extend asset lifespan, these techniques contribute to improving reliability, reducing costs, and enhancing overall system performance. To fully realize the potential of intelligent asset management in contemporary power systems, solve new issues, and improve predictive analytics skills, further research and innovation in AI and ML-based predictive maintenance are required.

3. Fault Detection and Diagnosis

Power system malfunctions can cause serious disruptions that put the grid's stability and dependability in danger. Prompt corrective action and downtime reduction depend on early defect detection and precise diagnosis. By providing sophisticated data-driven methods for issue detection and diagnosis in power system management and control, artificial intelligence (AI) and machine learning (ML) techniques enable utilities to increase system dependability, optimize maintenance plans, and boost operational effectiveness[1].

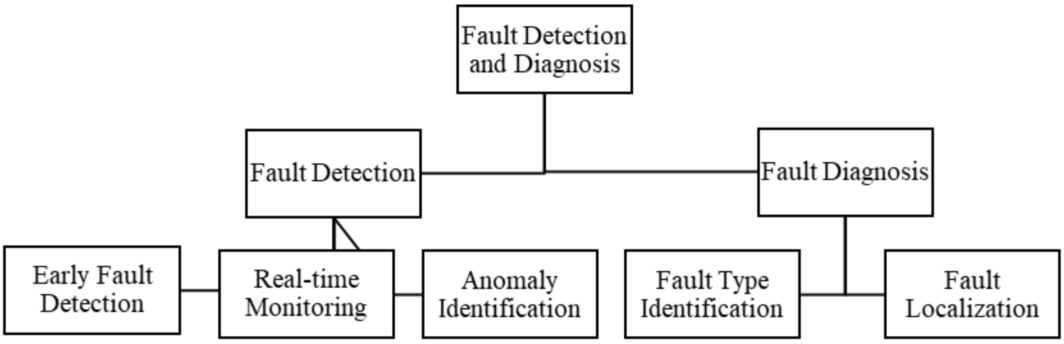

Figure-2 Fault Detection and Diagnosis

3.1. Data-Driven Fault Detection:

AI and ML algorithms leverage historical operational data, sensor measurements, and system parameters to identify abnormal behaviour indicative of faults [19]. Supervised learning algorithms, such as Support Vector Machines (SVM) and Decision Trees, are trained on labelled datasets to classify normal and faulty conditions based on features extracted from sensor data [20]. Unsupervised learning techniques, including clustering and anomaly detection, are utilized to identify patterns of deviation from normal operation without requiring labelled data [21]. These approaches enable utilities to detect faults proactively and initiate timely interventions to prevent cascading failures and minimize outage durations.

3.2. Pattern Recognition and Feature Extraction:

AI and ML techniques facilitate pattern recognition and feature extraction from high-dimensional sensor data, enabling the identification of fault signatures and distinguishing between different fault types. Reducing dimensionality and improving fault detection accuracy, feature extraction techniques like Principal Component Analysis (PCA) and Wavelet Transform extract pertinent characteristics from unprocessed sensor data. Additionally, to capture complex fault patterns and enhance classification performance, deep learning architectures like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) learn hierarchical representations of data.

3.3. Fault Classification and Localization:

Once a fault is detected, AI and ML algorithms classify the fault type and localize its location within the power system. Classification models trained on labelled fault datasets categorize faults into different classes such as line faults, transformer faults, or generator faults based on distinctive features extracted from sensor data [22]. Localization algorithms utilize spatial and temporal information to pinpoint the exact location of the fault, aiding operators in directing maintenance crews to the affected area promptly. These capabilities enable utilities to expedite fault restoration processes, minimize service disruptions, and enhance grid resilience.

3.4. Fault Severity Assessment and Risk Analysis:

AI and ML techniques enable utilities to assess the severity of faults and prioritize response actions based on their potential impact on system reliability and safety [23]. Predictive models trained on historical fault data and operational parameters quantify the severity of faults, considering factors such as fault magnitude, duration, and proximity to critical assets [24]. Risk analysis frameworks integrate fault severity assessments with probabilistic modelling techniques to evaluate the likelihood and consequences of various fault scenarios, enabling utilities to allocate resources efficiently and mitigate operational risks [25].

3.5. Integration with SCADA and EMS Systems:

The integration of artificial intelligence (AI) and machine learning (ML) fault detection and diagnostic algorithms with energy management systems (EMS) and supervisory control and data acquisition (SCADA) improves situational awareness and decision-making in power system operations[26]. Real-time data streams from SCADA systems provide valuable input for AI and ML models to continuously monitor system conditions and detect emerging faults. EMS platforms leverage fault diagnosis outputs to assess system stability, optimize control actions, and implement remedial measures to mitigate fault impacts [27]. This integration facilitates seamless coordination between automated fault detection algorithms and control systems, enabling utilities to respond rapidly to dynamic grid conditions and ensure reliable operation [28].

4. Optimal Power Flow and Energy Management:

Optimal Power Flow (OPF) and energy management are critical components of power system operation and control, aiming to optimize the allocation and utilization of resources while satisfying operational constraints and ensuring system stability. In order to solve challenging optimization issues in power systems, artificial intelligence (AI) and machine learning (ML) techniques have become increasingly potent tools [29]. These solutions allow utilities to improve grid dependability, reduce operating costs, and dispatch energy more efficiently. This section provides an overview of the applications of AI and ML in optimal power flow and energy management, highlighting key methodologies, challenges, and advancements in the field.

4.1. Role in Power System Operation:

Optimal Power Flow (OPF) is a fundamental optimization problem in power systems, involving the simultaneous optimization of generation dispatch, voltage levels, and reactive power flows while satisfying system constraints. AI and ML techniques offer efficient and scalable solutions for solving OPF problems in real-time, considering factors such as generation capacity, transmission line limitations, and demand variability [30]. By leveraging advanced optimization algorithms, utilities can achieve optimal energy dispatch, reduce generation costs, and minimize grid congestion, thereby improving overall system efficiency and reliability.

4.2. AI and ML Techniques for OPF:

AI and ML techniques such as neural networks, genetic algorithms, and reinforcement learning are applied to solve OPF problems in power systems. Neural network-based models learn complex relationships between input variables and system parameters, enabling accurate prediction of optimal generation schedules and voltage profiles [31]. Genetic algorithms and evolutionary optimization techniques provide robust solutions for multi-objective OPF problems, considering conflicting objectives such as cost minimization, environmental constraints, and system security. Reinforcement learning algorithms enable adaptive control strategies, learning optimal control policies through interaction with the environment and feedback from system dynamics.

4.3. Energy Management in Microgrids:

Micro grids present unique challenges and opportunities for energy management, requiring intelligent control strategies to optimize energy generation, storage, and distribution within localized grid networks. AI and ML techniques play a crucial role in microgrid energy management, facilitating dynamic scheduling of distributed energy resources (DERs), demand-side management, and grid balancing [32]. Reinforcement learning algorithms enable autonomous decision-making in micro grid operation, adapting to changing environmental conditions, load profiles, and energy prices to maximize grid efficiency and reliability. Furthermore, predictive analytics techniques such as time-series forecasting and probabilistic modeling aid in short-term and long-term energy planning, enabling utilities to anticipate demand fluctuations and optimize resource allocation accordingly.

4.4. Challenges and Future Directions:

Despite the significant advancements, several challenges persist in the application of AI and ML techniques in optimal power flow and energy management [29]. These include computational complexity [33], model interpretability [34], data quality [35], and cyber security concerns [36]. Future research directions include the development of hybrid optimization algorithms combining AI and traditional optimization techniques [37], the integration of distributed intelligence for decentralized energy management [38], and the adoption of advanced data analytics methodologies for real-time decision-making in dynamic grid environments. Additionally, efforts to standardize data formats, establish interoperability standards, and address regulatory barriers are essential for accelerating the adoption of AI and ML-based solutions in power system operation and control [39].

5. Voltage Control and Reactive Power Optimization:

Voltage control and reactive power optimization are crucial aspects of power system operation and control, aimed at maintaining voltage stability, improving power quality, and ensuring efficient utilization of resources. In today's power systems, artificial intelligence (AI) and machine learning (ML) methods have shown to be useful instruments for tackling problems with reactive power optimization and voltage control. This section provides an overview of the applications of AI and ML in voltage control and reactive power optimization, highlighting key methodologies, advancements, and contributions in the field.

5.1. Importance of Voltage Control and Reactive Power Optimization:

Reactive power optimization and voltage management are essential for preserving system stability and dependability, especially in transmission and distribution networks that have a high concentration of dynamic loads and renewable energy sources [40]. By adjusting reactive power resources such as capacitors and reactors, utilities can regulate voltage levels and minimize voltage deviations, thereby enhancing power system performance, reducing losses, and improving grid efficiency.

5.2. AI and ML Techniques for Voltage Control:

AI and ML techniques offer versatile solutions for voltage control in power systems, enabling utilities to predict voltage fluctuations, identify voltage control devices' optimal settings, and optimize voltage regulation strategies. Utilizing past data and system settings, supervised learning algorithms—like support vector machines and neural networks—are used to model voltage profiles and forecast voltage deviations [41]. Reinforcement learning algorithms enable autonomous voltage control actions, learning optimal control policies through interaction with the grid environment and feedback from system dynamics.

5.3. Reactive Power Optimization Strategies:

Reactive power optimization involves determining the optimal allocation and operation of reactive power resources to maintain voltage levels within specified limits while minimizing system losses and improving power quality. AI and ML techniques facilitate reactive power optimization by analyzing system data, identifying reactive power support needs, and optimizing reactive power dispatch schedules [42]. Large-scale power systems with nonlinear restrictions and uncertainties are solved using evolutionary optimization techniques, like particle swarm optimization and genetic algorithms, to find the best solution.

5.4. Integration with Smart Grid Technologies:

The integration of AI and ML-based voltage control and reactive power optimization strategies with smart grid technologies enhances grid flexibility, resilience, and self-healing capabilities [43]. Advanced metering infrastructure (AMI), synchrophasor measurements, and distribution automation systems provide real-time data streams for AI and ML algorithms to monitor system conditions, detect voltage anomalies, and implement corrective actions [44]. Coordinated voltage control and reactive power optimization across distributed energy resources (DERs), such as renewable production, energy storage, and electric cars, are made possible by decentralized control structures, such as distributed energy resource management systems (DERMS) [45].

5.5. Challenges and Future Directions:

Even with these tremendous advances, there are still a number of obstacles to overcome when using AI and ML techniques for reactive power management and voltage control. These include issues with cybersecurity, data quality, interpretability of models, and computational complexity [46, 47]. Future research paths include adopting advanced data analytics methodologies for real-time decision-making in dynamic grid environments, integrating distributed intelligence for decentralized voltage control [48], and developing hybrid optimization algorithms that combine artificial intelligence and conventional optimization techniques [49]. Further, to expedite the implementation of AI and ML-based solutions in power system operation and control, initiatives to standardize data formats, create interoperability standards, and remove regulatory obstacles are critical.

6. Renewable Energy Integration and Grid Stability Enhancement:

The incorporation of renewable energy sources (RES) into power networks has distinct difficulties with operational flexibility, grid stability, and reliability. Effective management and control mechanisms are necessary to achieve easy integration while preserving grid stability because renewable generation fluctuates depending on weather conditions [50]. Innovative approaches to these problems are provided by artificial intelligence (AI) and machine learning (ML) techniques, which allow utilities to maximize integration of renewable energy sources, improve overall system resilience, and improve grid stability. This section provides an overview of the applications of AI and ML in renewable energy integration and grid stability enhancement, highlighting key methodologies, advancements, and future directions in the field.

6.1. Renewable Energy Forecasting:

For efficient grid operation and planning, accurate forecasting of renewable energy generation is essential. Renewable energy forecasting makes extensive use of AI and ML techniques like ensemble approaches, support vector machines, and neural networks [51]. These techniques utilize historical weather data, generation patterns, and other relevant factors to predict future renewable energy output with high accuracy. By providing reliable forecasts, utilities can better anticipate fluctuations in renewable generation and optimize resource allocation, facilitating efficient grid management and integration.

6.2. Demand Response and Flexible Load Management:

Demand response programs and flexible load management strategies play a vital role in balancing supply and demand in renewable-rich grids. AI and ML algorithms enable utilities to analyze consumption patterns, identify demand flexibility opportunities, and optimize load scheduling to align with renewable generation patterns [52]. Reinforcement learning algorithms facilitate dynamic demand response actions, allowing customers to adjust their energy consumption in response to real-time price signals or grid conditions [53]. By leveraging demand response and flexible load management, utilities can enhance grid stability, reduce peak demand, and maximize the utilization of renewable resources.

6.3. Grid-Friendly Renewable Energy Integration:

Integrating renewable energy sources into the grid while ensuring grid stability and reliability requires advanced control and coordination strategies. AI and ML-based control algorithms enable grid-friendly integration of renewable resources, facilitating seamless synchronization with grid operations and mitigating potential grid disturbances. Predictive analytics techniques, such as state estimation and dynamic modeling, aid in real-time monitoring and control of renewable energy assets, enabling proactive grid management and optimization [54]. By implementing grid-friendly integration strategies, utilities can minimize the impact of renewable variability on grid stability and enhance system resilience.

6.4. Adaptive Grid Control and Stability Enhancement:

Voltage control and grid stability are challenged by the dynamic nature of renewable generation as renewable penetration rises. AI and ML techniques offer adaptive grid control solutions, enabling real-time monitoring, prediction, and control of grid dynamics. Reinforcement learning algorithms facilitate adaptive voltage control actions, optimizing reactive power management and voltage regulation to maintain grid stability under varying operating conditions [55]. Furthermore, distributed control architectures and decentralized control strategies enhance system resilience and responsiveness, enabling autonomous coordination among grid assets and enhancing overall grid stability.

6.5. Cyber-Physical Security and Resilience:

To protect against potential cyber threats and physical attacks, renewable energy-rich grids must ensure their cyber-physical security and resilience [56]. AI and ML-based anomaly detection techniques enable utilities to detect and mitigate cyber security threats in real-time, enhancing grid resilience and reliability. Furthermore, advanced analytics algorithms facilitate proactive risk assessment and threat prediction, enabling utilities to pre-emptively address vulnerabilities and strengthen grid security measures. By integrating cyber security and resilience considerations into renewable energy integration strategies, utilities can mitigate risks and ensure the robustness of the grid infrastructure.

7. Challenges, Opportunities, and Future Directions in AI and ML for Power System Operation and Control:

Both opportunities and obstacles arise when Artificial Intelligence (AI) and Machine Learning (ML) techniques are integrated into power system management and control. Encouraging improvements in grid sustainability, dependability, and efficiency can be made possible by recognizing and tackling these obstacles [57]. The main obstacles, prospects, and future directions in the application of AI and ML to power system control and operation are examined in this part.

7.1. Challenges:

7.1.1 Data Quality and Accessibility:

The effectiveness of AI and ML models heavily relies on the quality and accessibility of data. Challenges such as data heterogeneity, incompleteness, and noise can hinder the performance of models and lead to inaccurate predictions.

7.1.2. Model Interpretability:

Complex AI and ML models often lack interpretability, making it challenging for operators to understand the underlying mechanisms driving the decisions. Ensuring transparency and interpretability of models is crucial for gaining trust and acceptance from stakeholders.

7.1.3. Computational Complexity:

Many AI and ML algorithms require significant computational resources and time for training and inference. Addressing computational complexity is essential for real-time applications in power system operation, where timely decision-making is critical.

7.1.4. Regulatory and Ethical Considerations:

The integration of AI and ML technologies into electricity systems gives rise to ethical and regulatory concerns about security, fairness, and privacy of data. Ensuring adherence to ethical and regulatory standards is crucial for the conscientious application of AI and ML technologies.

7.2. Opportunities:

7.2.1. Improved Grid Resilience:

AI and ML techniques offer advanced monitoring, prediction, and control capabilities, enabling utilities to enhance grid resilience and mitigate the impacts of disturbances, such as extreme weather events and cyber-attacks.

7.2.2. Optimized Resource Allocation:

AI and ML algorithms can optimize resource allocation by intelligently scheduling generation, transmission, and distribution assets, leading to cost savings, improved efficiency, and reduced environmental impact.

7.2.3. Enhanced Situational Awareness:

AI and ML-based monitoring and diagnostic tools provide utilities with enhanced situational awareness, enabling proactive identification and mitigation of grid anomalies, faults, and vulnerabilities.

7.2.4. Integration of Renewable Energy:

By streamlining energy generation, storage, and distribution, artificial intelligence (AI) and machine learning (ML) approaches help the grid's integration of renewable energy sources and the shift to a more sustainable and clean energy mix.

7.3. Future Directions:

7.3.1. Hybrid AI and Physics-Based Models:

Integrating AI and ML techniques with physics-based models can combine the strengths of both approaches, leveraging domain knowledge while capturing complex nonlinear relationships in power systems.

7.3.2. Explainable AI and Model Transparency:

Developing explainable AI techniques and transparent ML models can enhance trust and acceptance among stakeholders by providing insights into model decisions and predictions.

7.3.3. Edge Computing and Decentralized Control:

Leveraging edge computing and decentralized control algorithms can enable real-time decision-making at the edge of the grid, reducing reliance on centralized control systems and enhancing grid resilience.

7.3.4. Advanced Data Analytics and Predictive Maintenance:

Utilities can reduce downtime and maintenance costs while increasing grid reliability by anticipating and preventing equipment breakdowns through continued research in predictive maintenance and advanced data analytics.

7.3.5. Interdisciplinary Collaboration:

Fostering interdisciplinary collaboration between power system engineers, data scientists, and domain experts is essential for developing holistic solutions that address the complex challenges of power system operation and control effectively.

8. Conclusion:

The in-depth analysis offered here offers a thorough investigation of the uses of machine learning (ML) and artificial intelligence (AI) in power system control and operation. We have looked at a variety of approaches, strategies, and developments in using AI and ML to leverage these technologies to solve a range of issues and improve power grid performance throughout this assessment. Power systems monitoring, management, and optimization could undergo a radical change thanks to AI and ML, which have shown enormous promise in areas like voltage control, renewable energy integration, and predictive maintenance.

9. Key Findings:

- AI and ML techniques offer powerful tools for predictive maintenance, enabling utilities to anticipate equipment failures, optimize maintenance schedules, and enhance asset reliability.
- Voltage control and reactive power optimization benefit from AI and ML algorithms, allowing for real-time monitoring, adaptive control, and optimization of voltage levels and power flows.
- The integration of renewable energy sources into power grids is facilitated by AI and ML, enabling efficient energy generation, storage, and distribution while ensuring grid stability and reliability.
- Challenges such as data quality, computational complexity, and regulatory concerns must be addressed to realize the full potential of AI and ML in power system operation and control.

10. Implications and Future Directions:

Looking ahead, the adoption of AI and ML in power system operation and control is expected to continue expanding, driven by ongoing advancements in data analytics, computational algorithms, and grid automation technologies. Future research directions include the development of hybrid AI and physics-based models, the integration of edge computing and decentralized control strategies, and the deployment of explainable AI techniques to enhance model transparency and interpretability.

Interdisciplinary collaboration between power system engineers, data scientists, policymakers, and industry stakeholders will be essential for fostering innovation, addressing challenges, and driving the adoption of AI and ML solutions in power grids. By embracing these technologies responsibly and ethically, utilities can unlock new opportunities for enhancing grid resilience, optimizing resource allocation, and accelerating the transition towards a cleaner and more sustainable energy future.

In conclusion, the integration of AI and ML holds immense promise for transforming power system operation and control, empowering utilities to build smarter, more efficient, and resilient grids that meet the evolving needs of society while advancing the global transition towards sustainable energy systems.

Refrences

[1] Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y., Li, Y.-F., Lundberg, S. M., Nori, H., Palangi, H., Ribeiro, M. T., & Zhang, Y. (2023). Sparks of Artificial General Intelligence: Early experiments with GPT-4. ArXiv, abs/2303.12712.

[2] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., Wicke, M., Yu, Y., & Zhang, X. (2016). TensorFlow: A system for large-scale machine learning. USENIX Symposium on Operating Systems Design and Implementation, 265-283.

[3] Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J., Nair, B., ... & Lee, S. (2020). From local explanations to global understanding with explainable AI for trees. Nature Machine Intelligence, 2, 56-67.

[4] Hu, X., Tang, T., Tan, L., & Zhang, H. (2023). Fault Detection for Point Machines: A Review, Challenges, and Perspectives. Actuators.

[5] Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. Applied Energy, 137, 511-536.

[6] Malik, O. (2013). Evolution of Power Systems into Smarter Networks. Journal of Control, Automation and Electrical Systems, 24, 139-147.

[7] Battineni, G., Chintalapudi, N., & Amenta, F. (2019). Machine learning in medicine: Performance calculation of dementia prediction by support vector machines (SVM). Informatics in Medicine Unlocked.

[8] Aibar, S., González-Blas, C. B., Moerman, T., Huynh-Thu, V. A., Imrichová, H., Hulselmans, G. J., ... & Aerts, S. (2017). SCENIC: Single-cell regulatory network inference and clustering. Nature methods, 14, 1083-1086.

[9] Kaur, J., Choppadandi, A., Chenchala, P. K., Nakra, V., Kirupa, P., & Pandian, G. (2023). AI Applications in Smart Cities: Experiences from Deploying ML Algorithms for Urban Planning and Resource Optimization. Tuijin Jishu/Journal of Propulsion Technology.

[10] Wu, H., Hu, T., Liu, Y., Zhou, H., & Wang, J. (2022). TimesNet: Temporal 2D-Variation Modeling for General Time Series Analysis. ArXiv, abs/2210.02186.

[11] Takeuchi, O., & Akira, S. (2010). Pattern Recognition Receptors and Inflammation. Cell, 140, 805-820.

[12] Musleh, D., Alotaibi, M., Alhaidari, F., Rahman, A., & Mohammad, R. (2023). Intrusion Detection System Using Feature Extraction with Machine Learning Algorithms in IoT. J. Sens. Actuator Networks, 12.

[13] Martins, A., Fonseca, I., Farinha, J., Reis, J., & Cardoso, A. (2023). Online Monitoring of Sensor Calibration Status to Support Condition-Based Maintenance. Italian National Conference on Sensors, 23.

[14] Rambe, R. M. A., Ahmar, N., & Sailendra. (2023). Dampak Rate Of Return, Investor Trust, Fund Longevity Terhadap Kinerja Reksa Dana Dengan Moderasi Asset Under Management. Jurnal ilmiah manajemen bisnis dan inovasi Universitas Sam Ratulangi, JMBI UNSRAT (Jurnal Ilmiah Manajemen Bisnis dan Inovasi Universitas Sam Ratulangi).

[15] Vincent, P., Larochelle, H., Lajoie, I., Bengio, Y., & Manzagol, P. (2010). Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion. Journal of machine learning research, 11, 3371-3408.

[16] Logeshwaran, J., Shanmugasundaram, N., & Lloret, J. (2023). Energy-efficient resource allocation model for device-to-device communication in 5G wireless personal area networks. International Journal of Communication Systems, 36.

[17] Tzitziou, G., Dimara, A., Papaioannou, A., Krinidis, S., Anagnostopoulos, C. N., Ioannidis, D., & Tzovaras, D. (2023). Is the residential sector ready for prescriptive maintenance? A short analysis. 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC).

[18] Su, Z., Zhang, K., & Liu, C. (2022). Dynamic risk assessment of slope stability of homogeneous earth-rock dam under action of multiple hazards. SIMULATION, 98.

[19] Wang, J., Sun, Z., Bao, B., & Shi, D. (2019). Malicious synchrophasor detection based on highly imbalanced historical operational data. CSEE Journal of Power and Energy Systems.

[20] Graf, R., Zeldovich, M., & Friedrich, S. (2022). Comparing linear discriminant analysis and supervised learning algorithms for binary classification—A method comparison study. Biometrical Journal.

[21] Iparraguirre-Villanueva, O., Guevara-Ponce, V., Sierra-Liñan, F., Beltozar-Clemente, S., & Cabanillas-Carbonell, M. (2022). Sentiment Analysis of Tweets using Unsupervised Learning Techniques and the K-Means Algorithm. International Journal of Advanced Computer Science and Applications.

[22] Rajesh, K. N. V. P. S., Rao, U., Fofana, I., Rózga, P., & Paramane, A. (2023). Influence of Data Balancing on Transformer DGA Fault Classification With Machine Learning Algorithms. IEEE Transactions on Dielectrics and Electrical Insulation, 30, 385-392.

[23] Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. SSRN Electronic Journal.

[24] Rasool, A., Bunterngchit, C., Luo, T., Islam, M. R., Qu, Q., & Jiang, Q. (2022). Improved Machine Learning-Based Predictive Models for Breast Cancer Diagnosis. International Journal of Environmental Research and Public Health.

[25] Zhang, D., Malkin, N., Liu, Z., Volokhova, A., Courville, A. C., & Bengio, Y. (2022). Generative Flow Networks for Discrete Probabilistic Modeling. International Conference on Machine Learning.Lorem ipsum dolor sit amet, consecteturadipiscingelit, sed do eiusmodtemporincididuntut labore et dolore magna aliqua.

[26] Tian, C., Xu, Z., Wang, L., & Liu, Y. (2023). Arc fault detection using artificial intelligence: Challenges and benefits. Mathematical biosciences and engineering: MBE, 20(7), 12404-12432.

[27] Hack, K., Levy, M., Garfinkel, E., & Margolis, A. M. (2022). Establishing consensus-based high-acuity low-occurrence skills for EMS physicians: A pilot survey of EMS fellowship faculty. AEM Education and Training, 6.

[28] Savinykh, A., Kurenkov, M., Kruzhkov, E., Yudin, E., Potapov, A., Karpyshev, P. A., & Tsetserukou, D. (2022). DarkSLAM: GAN-assisted Visual SLAM for Reliable Operation in Low-light Conditions. 2022 IEEE 95th Vehicular Technology Conference: (VTC2022-Spring).

[29] Sayed, A., Wang, C., Anis, H. I., & Bi, T. (2023). Feasibility Constrained Online Calculation for Real-Time Optimal Power Flow: A Convex Constrained Deep Reinforcement Learning Approach. IEEE Transactions on Power Systems, 38, 5215-5227.

[30] Huang, B., & Wang, J. (2023). Applications of Physics-Informed Neural Networks in Power Systems - A Review. IEEE Transactions on Power Systems, 38, 572-588.

[31] Tan, M., & Le, Q. V. (2019). EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In International Conference on Machine Learning (pp. abs/1905.11946). ArXiv.

[32] Van, L. P., Do Chi, K., & Duc, T. N. (2023). Review of hydrogen technologies based microgrid: Energy management systems, challenges and future recommendations. International Journal of Hydrogen Energy.

[33] Ali, Y. A., Awwad, E. M., Al-Razgan, M., & Maarouf, A. (2023). Hyperparameter Search for Machine Learning Algorithms for Optimizing the Computational Complexity. Processes.

[34] Kokhlikyan, N., Miglani, V., Martin, M., Wang, E., Alsallakh, B., Reynolds, J., ... Reblitz-Richardson, O. (2020). Captum: A unified and generic model interpretability library for PyTorch. arXiv.org.

[35] Douglas, B. D., Ewell, P. J., & Brauer, M. (2023). Data quality in online human-subjects research: Comparisons between MTurk, Prolific, CloudResearch, Qualtrics, and SONA. PLOS ONE.

[36] Beyari, H., & Alrusaini, O. (2023). The two-step cluster analysis of pre-COVID-19 experience and cybersecurity concerns about online education for academic staff in Saudi universities. International Journal of ADVANCED AND APPLIED SCIENCES.

[37] Singh, G., & Banga, V. (2022). Combinations of novel hybrid optimization algorithms-based trajectory planning analysis for an industrial robotic manipulators. Journal of Field Robotics.

[38] Khalatbarisoltani, A., Boulon, L., & Hu, X. (2023). Integrating Model Predictive Control With Federated Reinforcement Learning for Decentralized Energy Management of Fuel Cell Vehicles. IEEE Transactions on Intelligent Transportation Systems.

[39] Rodbard, D., & Garg, S. (2021). Standardizing Reporting of Glucose and Insulin Data for Patients on Multiple Daily Injections Using Connected Insulin Pens, and Continuous Glucose Monitoring.

[40] Xu, B., Zhang, G., Li, K., Li, B., Chi, H., Yao, Y., & Fan, Z. (2022). Reactive power optimization of a distribution network with high-penetration of wind and solar renewable energy and electric vehicles. Protection and Control of Modern Power Systems, 7, 1-13.

[41] Baevski, A., Zhou, H., Mohamed, A., & Auli, M. (2020). wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations. Neural Information Processing Systems, ArXiv, abs/2006.11477.

[42] Hu, D., Ye, Z., Gao, Y., Ye, Z., Peng, Y., & Yu, N. (2022). Multi-Agent Deep Reinforcement Learning for Voltage Control With Coordinated Active and Reactive Power Optimization. IEEE Transactions on Smart Grid, 13, 4873-4886.

[43] Giannelos, S., Borozan, S., Aunedi, M., Zhang, X., Ameli, H., Pudjianto, D., Konstantelos, I., & Strbac, G. (2023). Modelling Smart Grid Technologies in Optimisation Problems for Electricity Grids. Energies.

[44] Biricik, S., & Redif, S. (2019). Detection of Grid Voltage Anomalies via Broadband Subspace Decomposition. ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP).

[45] Huo, Y., Li, P., Ji, H., Yu, H., Yan, J., Wu, J., & Wang, C. (2023). Data-Driven Coordinated Voltage Control Method of Distribution Networks With High DG Penetration. IEEE Transactions on Power Systems.

[46] Kaur, R., Gabrijelcic, D., & Klobučar, T. (2023). Artificial intelligence for cybersecurity: Literature review and future research directions. Information Fusion, 97, 101804.

[47] Arrieta, A. B., Rodríguez, N. D., Ser, J., Bennetot, A., Tabik, S., Barbado, A., ... & Herrera, F. (2019). Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges toward Responsible AI. Information Fusion, 58, 82-115.

[48] Liu, H., & Wu, W. (2022). Federated Reinforcement Learning for Decentralized Voltage Control in Distribution Networks. IEEE Transactions on Smart Grid, 13(7), 3840-3843.

[49] Singh, G., & Banga, V. (2022). Kinematics and trajectory planning analysis based on hybrid optimization algorithms for an industrial robotic manipulators. Soft Computing, 26, 11339-11372.

[50] Naeem, A., & Hassan, N. (2020). Renewable Energy Intermittency Mitigation in Microgrids: State-of-the-Art and Future Prospects. In 2020 4th International Conference on Green Energy and Applications (ICGEA) (pp. 158-164).

[51] Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., & Aslam, S. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. Renewable and Sustainable Energy Reviews.

[52] Parmar, A., & Darji, P. (2023). Novel Metaheuristic Optimizers Based Load Shifting and Flexible Load Curve Techniques for Demand-side Load Management. Smart Science, 11, 538-567.

[53] Haarnoja, T., Zhou, A., Abbeel, P., & Levine, S. (2018). Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor. ArXiv, abs/1801.01290.

[54] Song, X., Wu, N., Song, S., & Stojanovic, V. (2023). Switching-Like Event-Triggered State Estimation for Reaction–Diffusion Neural Networks Against DoS Attacks. Neural Processing Letters.

[55] Shi, Y., Feng, M., Wang, M., Zhou, W., & Li, H. (2023). Multi-Agent Reinforcement Learning with Safety Layer for Active Voltage Control. Adaptive Agents and Multi-Agent Systems.

[56] Cobilean, V., Mavikumbure, H. S., Mcbride, B. J., Vaagensmith, B., Singh, V. K., Li, R., Rieger, C., & Manic, M. (2023). A Review of Visualization Methods for Cyber-Physical Security: Smart Grid Case Study. IEEE Access, 11, 59788-59803.

[57] Noorollahi, Y., Kalantari, A. S., Saifoddin, A., & Yousefi, H. (2021). Distributed wind and solar power for grid sustainability and emission reduction. Environmental Progress & Sustainable Energy, 40.