AI-based solutions for grid stability and efficiency: Challenges, limitations, and opportunities.

ABDERRAHMANE EL RHATRIF, BOUCHRA BOUIHI, MOHAMMED MESTARI
2IACS Laboratory ENSET
Hassan II University of Casablanca
ENSET Mohammedia 28830,
MOROCCO

Abstract: - The complexity of managing power systems is increasing because of the dynamics and uncertainty introduced by the global transition toward deep decarbonisation as well as the growing volume of multidimensional data requiring rapid response times. Modern power grids face significant challenges owing to the increased penetration of distributed energy resources (DER). These challenges include maintaining power system stability, ensuring the proper functioning of protection and control systems, and balancing the supply and demand. Current technologies are insufficient to handle these future complexities. AI and ML technologies have emerged as transformative tools that offer new opportunities to improve the efficiency, reliability, and innovation in power system planning and operation.
This study examines recent and representative academic research on state-of-the-art AI/ML techniques applied to modern power systems, and examines their application across various power system domains, including fault detection, asset management, predictive maintenance, and oscillation detection. Despite the promising potential of AI to enhance the stability and protection of power systems, its limitations must be recognised. Key barriers to practical AI implementation were analysed, including reliance on synthetic data, scarcity of real measurement data, issues with protection selectivity, and the black-box nature of AI models. Factors such as safety, security, transparency, and trustworthiness are crucial for successful implementation and adoption of AI/ML solutions. To overcome these limitations, this study emphasises the need for further research on Explainable AI (XAI) and physics-informed machine learning (ML) to enhance the transparency and reliability of AI applications in power grids. The study also underscores the importance of advanced human–machine interfaces, which allow human operators to validate AI/ML solutions, thereby fostering trust and ensuring the effective deployment of these technologies in modern power systems.

Key-Words: - artificial intelligence; machine learning; power system; distributed energy resources; power system protection; power system stability; explainability AI; Inverter based resources

Received: March 8, 2024. Revised: August 11, 2024. Accepted: September 15, 2024. Published: November 1, 2024.

1.Introduction

Historically, traditional power systems have been distinguished by their centralised infrastructure and supply side management. However, the current global efforts towards decarbonisation and energy transition have led to a significant shift towards decentralised energy resources (DERs), characterised by increased distributed electricity generation and heightened consumer involvement in the electricity supply and management process.

A traditional power grid comprises synchronous generators, power transformers, transmission lines, substations, static compensators, and various loads. Power plants are typically located far from consumers, and electricity is transported via extensive transmission lines to distribution networks intended for unidirectional flow.

Modern power systems feature extensive integration of distributed energy resources (DER) and significant renewable energy sources (RES). This integration causes bidirectional power flow and intermittent availability owing to weather-dependent sources, such as solar and wind. These factors create new challenges for grid distribution networks, as bidirectional flow and intermittent RES threaten system stability because of the lack of inertia response and low short-circuit levels (SCL) compared to traditional plants. An increased share of RES may destabilise the system without proper mitigation. Grid protection and control systems may also malfunction because of the bidirectional flow and low short-circuit currents. Additionally, intermittent RES generation can disrupt the supply demand balance, causing load shedding without advanced forecasting systems. Other challenges include network topology changes, power quality, and voltage control, which complicate the transition to a sustainable, decarbonised energy system.

The volume of research exploring the application of artificial intelligence methods, particularly machine learning algorithms, in the power industry has experienced a substantial upsurge, encompassing domains such as power system stability analysis, system protection, load forecasting, state estimation, asset health monitoring, fault detection, renewable energy forecasting, cybersecurity, energy management, and energy optimisation. However, these AI-based techniques are generally confined to the simulation stages, disregarding the underlying physical phenomena and advancements in substation automation and protection technologies. Furthermore, they typically fail to consider the integration level of distributed energy resources (DERs) and demand more precise real-world measurement data for effective model training.

The degree to which distributed energy resources (DERs) are integrated into a power grid determines the complexity of the challenges faced by the grid operators and the overall effect of DER integration. A categorisation scheme for grids based on their DER share was used to gain a deeper understanding of the consequences of a high DER penetration. [3], this system aims to provide a concrete definition of a high DER penetration threshold and pinpoint the challenges and remedial measures for each classification, ranging from 0% to 100% renewable energy share.

This study investigates the challenges of operating modern electric systems with distributed energy resources (DERs) and reviews recent academic research on artificial intelligence (AI) techniques in power systems. Despite the lack of commercial AI applications for power system stability and protection, this study analyzes the opportunities, challenges, limitations, and barriers to AI implementation in power system operations. This paper overviews power grid evolution, categorises power grids by DER penetration levels, highlights challenges posed by DERs and their grid impact, reviews representative papers, and discusses the limitations and constraints for AI implementation in the power system domain, as well as opportunities for further development.

2.Modern power grid characteristics

Conventional electrical power systems are composed of numerous interconnected components including synchronous generators, power transformers, transmission lines, transmission substations, static compensators, distribution lines, distribution substations, and diverse loads. Generally, power generation facilities are located at a distance from areas of consumption, necessitating the transmission of electricity over extended transmission lines to distribution networks configured for one-way power flow.
Recent advancements in grids have involved the integration of novel distributed energy resources including solar power, wind power, and energy storage. These DERs are Inverters Based Generations, connected to the grid electronically through inverters, and introduce fresh difficulties (new challenges) for grid operators, such as diminished system inertia, alterations in fault current magnitude, bi-directional power flow, modifications in grid topology, the presence of harmonics, waveform distortion, and Inverter-Based Stability issues.

Radial design is no longer appropriate because of the bidirectional power flow in the system. The unpredictability of energy availability arises from the intermittent nature of power from weather-dependent resources such as solar and wind. The stability of the power system may be threatened by a decline in system inertia, whereas the protection and control system may face difficulties owing to the low levels of short-circuit current (SCL) provided by the inverter-based DERs.
The challenges faced by grid operators in distribution networks cannot be resolved using current protection and management systems. The application of artificial intelligence (AI) can be beneficial for resolving these challenges by offering

tools for various tasks in modern grids, including distributed energy management, renewable energy generation prediction, load forecasting, grid health monitoring, power system state estimation, grid stability assessment, and fault detection.

Table 1. Characteristics of Traditional and Modern Grids.

Traditional Grid	Modern Grid
Generation:	
Centralized	Centralized and distributed
Dispatchable	More stochastic (Increased share of DER)
Large thermal plants	Efficient and flexible units
Mechanically coupled	Electronically coupled
Transmission:	
Operator-based controls	Automatic controls
Congestion, despite underutilized capacity	Flexible network to relieve capacity constraints
Distribution:	
Limited visibility	Enhanced observability
Limited controllability	Increased communications and controls
Radial design (one-way flow)	Two-way flow
Aging assets (unknown effects)	Active asset condition monitoring
Customers:	
Uniformly high reliability,	Customer-driven reliability
Energy consumers (kWh)	Energy producers
Predictable behavior based on historical needs and weather	Variable behavior
Growing intolerance to sustained outages	Informed on system conditions, Data access

In Table 1, we outline the differences between modern and traditional grids. Modern grids feature bidirectional power flow, consumer involvement in energy production, and stochastic dispatchable energy generation. In contrast, the traditional grid relies on large plants with synchronous machines that provide a sufficient inertia response and fault current magnitude. Although the synchronous machines in the traditional grid can provide up to seven times their nominal current as an SCL, the electronically coupled DERs in the modern grid can only provide up to 1.5 times their nominal current as an SCL.

3.Key challenges of DER on the grid

3.1 Classification of DER

Distributed energy resources can be classified based on three main criteria: grid connection, application, and supply type. The grid connection can be either on- or off-grid. DERs connected to the power grid in real time are considered on-grid, whereas those that are not connected to the power grid are classified as off-grid. In terms of applications, DERs can be used in residential, commercial, or public buildings, as well as in urban areas for utility-scale applications. Finally, the supply type can be either intermittent, such as solar PV and wind turbines, or firm, including diesel generators, gas turbines, and hydropower.

This study focuses on Distributed Energy Resources (DERs), primarily comprising Renewable Energy Sources (RESs) connected to the grid through inverters or inverter-based resources (IBRs).

3.2 Grids Classification according to RES' share

The integration of renewable energy sources (RESs) into a power grid and the associated challenges depend on the level of RES penetration in overall power generation. The share of RES in total power generation serves as an indicator of the extent of RES integration into the grid.

Four classes were defined in [3] to qualify power grids with high DER penetration. These classes delineate the grid's evolution from 0% to 100% RES penetration, which is a crucial goal of energy transition and decarbonisation policies.
This categorisation clarifies the "high penetration of DERs" and challenges faced by grid operators at each RES integration stage. It also identified the specific impacts, challenges, and mitigation measures associated with DER integration for each category, spanning from 0% to 100% RES.

- Class1 (0% to 15%): DERs are not relevant at the power system level
- Class 2 (15% to 30%): DER output starts to be noticeable for Grid operation
- Class 3 (30%–50%): The flexibility of conventional generation is a priority for grid operation.
- Class 4 (50% to 100%): Power system stability becomes the priority

3.3 Key challenges of DER on the grid

Operating a safe and secure power system requires meeting five key requirements: inertia, short-circuit level, voltage control, system restoration, and supply–demand balance [3]. Inertia measures a system's resistance to frequency changes linked to the kinetic energy in the rotating masses of turbogenerators, which is essential for network stability and rapid active power injection during disturbances. Currently, only synchronous generators provide inertia in the transmission networks. The short-circuit level (SCL), along with inertia, is crucial for protection and system stability.

Voltage control and reactive power are vital for safe and efficient power transport, akin to frequency control, which focuses on reactive power generation or absorption. System restoration addresses total or partial shutdowns by gradually re-energising parts of the network before full system recovery, requiring generators that can quickly activate independently of the external electricity sources. Lastly, supply and demand imbalances affect network frequency; if the frequency deviates beyond acceptable limits, there is a high risk of load shedding disconnecting parts of the system.

Table 2: Challenges that renewables pose for key system requirements

System Requirements	Impact of distributed RES	Consequence
Supply and demand balance	Intermittence of power	System Stability
Inertia	Decrease in inertia.	Frequency Stability
Short circuit level	Low Short Circuit Levels	Prtection dependability
Voltage control	Degraded Voltage control	Voltage Stability
System restoration	No restoration services.	System stability

The proliferation of distributed energy resources and the increased share of RES in the energy mix present new challenges for grid operators, such as topological changes, power flow, and power quality. The configuration of components, such as generators, transformers, lines, substations, and loads, defines the power system topology. Real-time insight into grid topology is crucial for effective monitoring, control, and protection. Modern power systems with more distributed generation exhibit bidirectional current flow. Power quality is impacted by the power-electronic-based devices used to connect PV plants and wind farms to the grid, as these nonlinear devices generate harmonics.

In Table 2, we outline the consequences of distributed energy resources on the five essential requirements of safe and reliable power system operation.

Additionally, DERs have an impact on more than the five power system requirements. Table 3 succinctly summarises the influence of DERs on grid topology, power flow, and power quality and outlines the corresponding risks for each scenario.

Table 3. Challenges that renewables pose for Grid

Power System Need	Impact of DER	Consequence
Topology change	Intermittence of power	dependability and stability
Power flow	Bidirectional flow of power	dependability
Power quality	harmonics and distortion	Voltage stability

4.Power systems protections

A protection system is a vital component of power grids and is responsible for detecting and isolating faults. To ensure the proper functioning of a protection system, five requirements must be satisfied. These requirements are essential for ensuring the reliability and resilience of a power system and preventing significant outages that could lead to cascading effects.

Historically, protection schemes have relied on commercial relays to issue tripping commands when specific thresholds are reached. However, the large-scale deployment of DERs has resulted in rapid and substantial changes in the power grid topology, creating gaps in system conditions. Consequently, traditional relays can no longer provide dependable or secure protection against faults or transients in certain situations.

In recent years, adaptive protection has emerged as a promising solution for adjusting protection responses in real time based on prevailing system conditions. However, traditional power system state estimation methods face challenges owing to the increasing complexity of modern power grids resulting from the high penetration of DERs. In this context, machine-learning techniques offer a potential solution to enhance the accuracy and performance of state estimation by leveraging real-time and historical data.

4.1 Protection System Requirement

To ensure a dependable and stable power system, the NERC proposed five design principles to guide the operation of protection systems.

These principles include [1]:

- Dependability: This refers to the level of assurance that a protective relay functions accurately and within a specified timeframe when required.
- Security: This principle ensures that protective relays do not operate erroneously in the absence of system faults.
- Redundancy: This involves the use of multiple functionally equivalent protection systems to safeguard each element of an electric system.
- Selectivity and Coordination: In the event of a fault, the primary protective device should be activated first, which is designed to interrupt the minimum number of customers. If the primary protection fails to clear the fault, remote backup protection should be activated to clear the fault while still limiting the number of affected customers.
- Speed: In certain applications, it is essential to clear faults in tens of milliseconds.

4.2 Protection Relays

Protection relays advanced significantly from their early stages in the 1900s when electromechanical relays were used. These relays were limited to basic settings and had a single function of relying on physically moving parts. In the 1960s, solid-state relays were introduced that used analogue electronic components and new protection techniques with multifunctional features. In 1982, the first microprocessor-based digital protective relay was invented, which marked a significant advancement in technology. The second generation of microprocessor relays, released in the early 21st century, feature powerful multifunction multi-setting devices with advanced communication capabilities and special protection schemes, as well as SER and oscillography capabilities. The most recent generation of digital relays is equipped with the universal and comprehensive communication protocol IEC61850.

5.Power System Stability

5.1 Time Scales of Power System Dynamic Phenomena

Electric power systems have undergone a major transformation, marked by an increase in power electronic converter interfaced technologies, including wind and photovoltaic generation, various storage technologies, flexible AC transmission systems (FACTS), high-voltage direct current (HVDC) lines, and power electronic interfaces. The substantial integration of inverter-based generation technologies (IBGs) has made the dynamic response of power systems increasingly complex and reliant on fast-response power electronic devices, thereby altering their dynamic behaviour.

Fig. 1 illustrates the timescales of different dynamic phenomena in power systems. The time scale for CIG controls spans from microseconds to milliseconds, covering both wave and electromagnetic phenomena. With the increasing presence of CIGs, faster dynamics will become more significant in future power system analyses compared with phenomena occurring over several milliseconds to minutes. [2]

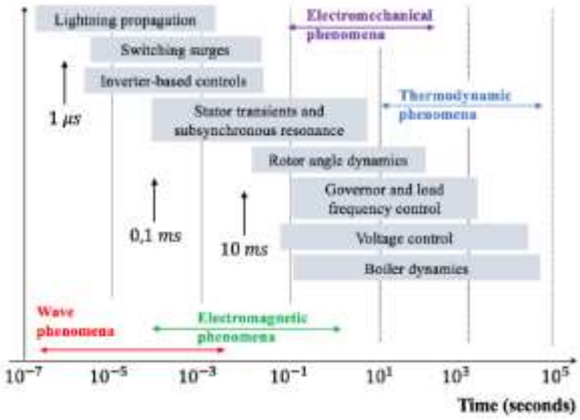

Fig. 1. Power system times scales - Source: [2]

5.2 Definition and Classification of Power System Stability

The stability of an electric power system refers to its capacity under a specific initial operating condition to recover a state of balance following a physical disturbance while ensuring that the majority of system variables remain within reasonable limits to preserve the integrity of the entire system. [2]

A modern power system is a complex multivariable process and its dynamic response is influenced by various devices with distinct characteristics and response times. Stability indicates a balance between opposing forces. Depending on the network topology, operating conditions, and disturbances, imbalances may cause different types of instabilities. Figure 2 illustrates the seven classes of power system stability: frequency stability, voltage stability, transient stability, small signal stability, resonance stability, and converter-based stability. The latter two classes were recently introduced due to the increasing proportion of CIGs in the power generation mix.[2]

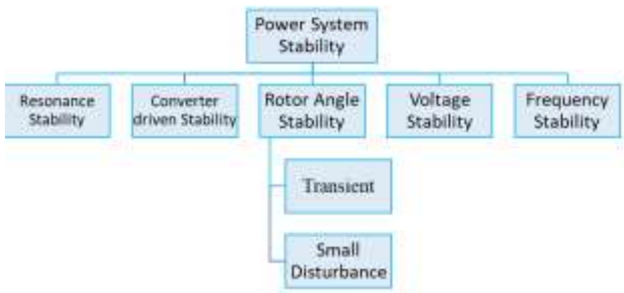

Fig. 2. Power system stability - Source: self-made

6. Artificial intelligence techniques and their applications in power system

6.1 A Brief Introduction to Machine Learning Techniques

Machine-learning methods in power systems can generally be classified into three categories: supervised learning, unsupervised learning, and reinforcement learning.

6.1.1 Supervised learning

Supervised learning algorithms require labelled data during training and require more processed data than other methods because of the inclusion of information representing output classes. This reliance on labelled data enhances the accuracy compared to unsupervised learning. However, labelling requires time and expert knowledge. For power system applications, amassing high-quality large-scale data is challenging. Supervised learning applications in power grids include load and renewable energy forecasting, state estimation, fault detection and location, asset health monitoring, power system security assessment, and stability analysis.

6.1.2 Unsupervised learning

Unsupervised learning involves tasks using unlabelled data, eliminating the need for data labelling, and simplifying the input preparation. However, they cannot estimate or map new sample results. In power systems, it is applied to fault detection, asset health monitoring, load profiling, nonintrusive load monitoring (NILM), renewable energy generation, and demand-side scenarios.

6.1.3 Reinforcement Learning

Reinforcement Learning (RL) focuses on mapping situations to actions to maximise a numerical reward signal using environmental reinforcements. RL problems are formalised through dynamic systems theory, particularly the optimal control of Markov decision processes. This machine learning approach has been applied in various power and energy system contexts, including residential demand response, power system control, and electricity markets, as discussed in detail in the subsequent sections.

Table 3 presents a succinct summary of the primary applications for each category of machine learning (ML) algorithms employed in the power industry.

Table 3 AI in power systems. Source: self-made

Category	Power System Applications
Supervised Learning	- Renewable energy forecasting - Power system stability analysis - Load forecasting - Fault diagnosis - Nonintrusive load monitoring - Electricity market forecasting - Electricity theft detection - Power system state estimation
	- Power system stability analysis - Demand response - Load profiling - Nonintrusive load monitoring - False data injection detection
Reinforcement Learning	- Power system control - Demand response - Electricity market operation - Power system economic dispatch

6.2 AI/ML Applications in Power System

The integration of AI and machine learning has recently enhanced various applications in power systems. A number of studies have explored the impact of these technologies on power systems, and this section focuses specifically on the improvements made to power systems through the use of AI and machine learning in transmission systems, such as grid monitoring, management, and planning. Relevant publications were selected to illustrate the advancements made in these areas using AI and machine learning methods.

6.2.1 Fault Detection/Protection

Traditional protection schemes rely on commercial relays to trigger tripping commands by exceeding the preset thresholds, balancing sensitivity, and security. However, this can lead to protection gaps, and conventional relays sometimes fail to provide reliable or secure protection against faults or transients. Advances in computing, enhanced measuring equipment, and improved training algorithms have prompted researchers to explore artificial intelligence (AI) machine learning methods to address these gaps in power system protection.

Manohar et al. [4] introduced a CNN-based protection scheme to differentiate between inverter faults in PV systems and symmetrical versus unsymmetrical faults in distribution lines, as well as to detect/classify faults and identify the faulty section; This scheme, validated on a hardware-in-the-loop platform, outperforms decision tree (DT) and SVM-based methods. However, it has been tested with a limited number of power flow scenarios and lacks adaptability to various configurations. The dataset was generated from microgrid measurements using the OPAL-RT digital simulator, which is synthetic and does not represent an actual grid.

Gao et al. [5] developed an RL-based algorithm to enhance the performance of doubly fed induction generator (DFIG) converters in wind turbines during grid faults, using a surrogate-gradient-based evolution strategy to control DFIG power and capacitor DC-link voltage by optimizing reference signals. The proposed method shows improved repeatability and adaptability for DFIG control interfaces but requires testing on larger network models beyond PSCAD's limitations of PSCAD. The dataset was generated from simulations of a grid-connected DFIG system using PSCAD software and is synthetic and does not represent an actual grid.

Jones et al. [6] demonstrate that embedding an SVM in each relay to classify grid faults, determine tie line switch positions, and estimate fault locations eliminates the need for communication and offers high accuracy and settings-free relay usage. The data were obtained through simulations using the synthetic IEEE 123-bus benchmark system, which does not represent a real grid. ML algorithms embedded in each relay at the grid edge achieve high selectivity and sensitivity, and enhance system safety. Nonetheless, further testing is required under distributed energy resource (DER) scenarios and active reconfiguration.

Poudel et al. [7] examined the coordination between local adaptive modular protection (LAMP) units and conventional relays. Using an SVM within LAMP, they accurately estimated the circuit topology, identified fault types, and detected fault zones. Their findings suggest that LAMP can operate without setting; however, its application is limited to small network models and testing systems. The data were simulated using the IEEE 123-bus benchmark system, which is synthetic and not representative of the actual grid.

Yu et al. [8] introduced a fault diagnosis approach utilizing tensor computing and meta-learning to detect and analyze potential faults in smart grid and power communication networks. This method notably enhances the fault diagnosis performance in smart grid environments by combining these techniques, allowing for more accurate fault identification and diagnosis with less data compared to traditional methods. The dataset, sourced from the current grounding fault simulation model in MATLAB Simulink, was synthetic and not representative of an actual grid.

6.2.2 State Estimation

Power system state estimation (SE) is a core task in monitoring and controlling distributed power networks. Power grids face significant challenges owing to the frequent voltage fluctuations caused by the widespread adoption of renewable energy sources, electric vehicles, and demand response programs. Monitoring real-time grid conditions is becoming increasingly vital. By utilising valuable insights from vast amounts of real-time and historical data, AI and machine learning techniques can significantly improve the monitoring precision and enhance the state estimation performance.

Zamzam et al. [9] introduced a joint optimization/learning method focusing on initialising a Gauss-Newton solver. This involves a specially designed learning cost function that allows a shallow neural network (NN) to initialise the solver efficiently. This approach maintains low sample and runtime complexity while leveraging the high accuracy of the initialised Gauss-Newton solver. The hybrid machine learning/optimization method outperformed traditional optimisation-only techniques in terms of stability, accuracy, and runtime efficiency. In addition, a well-designed neural-network training cost function enhances the overall SE performance. However, this approach is only effective for small LV networks and faces scalability issues. The data were generated through simulations using the IEEE 37-bus benchmark system, which is a synthetic dataset that does not represent an actual grid.

Garcia et al. [10] proposed an ML-based circuit topology estimation for adaptive protection systems, demonstrating high accuracy in classifying circuit topology. The study found that SVM with a linear kernel outperformed logistic regression and SVM with other kernels in the power distribution network topology estimation. Data were obtained from simulations using the synthetic IEEE 123 bus test system rather than an actual grid.

Zhang et al. [11] designed a learning method by unfolding an iterative solver for the least-absolute-value formulation of the state estimation problem; Prox-linear nets integrate NNs with traditional physics-based optimization for power system state estimation, and deep RNNs forecast power system states from historical voltages. Real load data tested numerically on IEEE 57- and 118-bus systems revealed that the proposed method is easy to train and computationally efficient, but its performance on larger transmission networks remains unverified and may face scaling challenges.

Kurup et al. [12] investigated the application of deep neural networks (DNN) and support vector machines (SVM) for power distribution systems' topology estimation and fault detection. The results indicated that a convolutional neural network (CNN)-based topology estimation model outperformed the SVM in power system topology estimation. Furthermore, the authors suggest that additional fault detection prior to fault classification may help reduce the overall test error. The effectiveness of the proposed method was tested using data obtained from power simulations on a modified IEEE 123 bus system using MATLAB Simulink.

6.2.3 Power System Stability

There are three primary stability evaluation methods: time-domain simulation, direct methods, and AI-based methods. Time-domain simulation is accurate, but time-consuming for large power systems, making it impractical for real-time use. Direct methods are applied only to simplified system dynamics. Owing to these limitations, machine-learning (ML) methods have been proposed to improve the speed and scalability of real-time stability assessments for large power systems.

Zhao et al. [13] introduced a deep Koopman inference network (DKIN), a conditional VAE-like structure with an embedded Koopman layer. Based on the Koopman operator theory, the trained DKIN framework provides an accurate linear approximation of high-dimensional nonlinear power system dynamics during postcontingency transients. The approach was tested only on small cases with data derived from simulations of the IEEE 68 bus system using MATLAB Simulink.

Moya et al. [14] developed automated uncertainty quantification (UQ) for a Deep Operator Network (DeepONet) to reliably support power system post-fault trajectories. They proposed two methods for quantifying uncertainty: a Bayesian framework (B-DeepONet) and a probabilistic framework (Prob-DeepONet). Both methods used DeepONet and provided confidence intervals in their results. Training and testing datasets were generated using time-domain simulations of the New York-New England power grid model.

Nandanoori et al. [15] proposed combining GNN and Koopman models to create a Spatial-Temporal graph convolutional neural network, demonstrating high temporal and spatial accuracy in PMU data training and testing. Datasets for model training and testing were generated by simulating various load-change events in the IEEE 68-bus system. The results confirm that the predictive models can accurately forecast the post-disturbance transient evolution of the system.

Zhao et al. [16] introduced a novel Deep-learning Neural Representation (DNR) using a GNN to learn network topology dependencies and generator dynamics, achieving over 98% accuracy in predicting grid events like load variation, topological changes, and transient contingencies. Datasets were generated using power simulations on IEEE 39-Bus and IEEE 300-Bus systems, demonstrating the effectiveness and scalability of the proposed DNR framework.

Zhang et al. [17] introduce a novel deep reinforcement learning (DRL) algorithm with automatic entropy adjustment (AEA) for voltage stability control in grid emergencies. This approach enhances the adaptivity and efficiency of power system responses under a voltage load shedding scheme compared with traditional fixed-parameter settings and DQN-based methods. Datasets for training and testing were generated through time-domain simulations using the New York-New England power grid model.

7. AI/ML Opportunities and Challenges in Power Systems

7.1 AI/ML Opportunities in Power Systems

The integration of artificial intelligence (AI) and machine learning (ML) in power systems offers significant opportunities for further development of gride-edge solutions, managing uncertainty, explainability AI, physics-informed ML, and meta-learning approaches.

7.1.1 Grid Edge

Implementing smart sensing, communication, and control at the grid's edge rather than central operations enhances the reliability, availability, and efficiency of the electric grid amid the rise of decentralised energy resources (DERs). This approach leverages edge devices, such as smart meters and IoT sensors, aiming to manage the power supply-demand balance adaptively and effectively. Historically, raw data from terminal meters and sensors have been collected via utility communication channels, analysed on a central server, and decisions conveyed to controllers. However, this method suffers from long response latency and inefficient communication, leading to significant power outages owing to delayed grid status awareness and slow responses to power disturbances.

In modern AI, pre-processing of raw data from terminal sensors is crucial to avoid unnecessary information accumulation and redundant processing. Local data processing is often more efficient than the automatic transmission to a central server. Ideally, raw data should be intelligently preprocessed at terminal sensors to transmit only essential information. Edge intelligence shifts knowledge discovery and applications from cloud-to-edge devices, where data are generated or acquired. This enables local data processing and decision making, thereby reducing delays and energy consumption. [18]

AI and machine learning at the grid edge require distributed computing, decentralised AI/ML models, a robust communication infrastructure, and interoperability. These elements work together to enhance the grid's efficiency and responsiveness to the operational conditions and consumer requirements.

7.1.2 Risk Control Under Uncertainty

As power systems become more complex and variable energy resources increase, understanding the impacts of generation and load uncertainties on grid reliability, robustness, and security is crucial. Advanced algorithms are required to manage variables that affect fluctuations in generation, loads, and contingencies. However, many variables that influence grid security remain unknown, necessitating the identification of their impact on the accuracy of evaluations under uncertainty. This task is central to uncertainty quantification (UQ), specifically forward UQ or uncertainty propagation (UP), which quantifies how input uncertainties affect the model outputs. [19]

Power systems are complex entities with high levels of nonlinearity and dimensionality, making it difficult to predict their dynamics owing to their stochastic nature and large amounts of measurement data, including PMU and SCADA data. However, advanced deep learning methods for uncertainty quantification can enhance the assessment of power grid dynamic security. These methods can create high-fidelity prediction models to forecast uncertain variables in the power grid for both short-term (seconds ahead) and short-term (minutes ahead) periods. In addition, they can identify a concise input sample set for AI-based learning and control, capturing the essential features of the operating conditions of the power grid.

7.1.3 Explainable Artificial Intelligence

Explainable AI (XAI) is defined in [20] as AI systems that can explain their rationale to a human user, characterise their strengths and weaknesses, and convey an understanding of how they will behave in the future.

Decision-making in areas such as power grids and energy management is of utmost importance as it has a direct impact on people's lives. Decisions must be transparent, comprehensible, and dependable [20]. However, current AI methods are viewed as black boxes, making it challenging for grid operators to understand and explain their actions, particularly in critical situations. Explainable Artificial Intelligence (XAI) aims to improve AI transparency and comprehensibility, help clarify the reasoning behind AI decisions, and foster trust among users [21].

7.1.4 Physics Informed Machine Learning

PINNs were introduced five years ago, and since then they have experienced high popularity [22]. In contrast
to normal NNs, PINNs integrate the governing differential equations of the system into the loss function and find the required derivatives through automatic differentiation. This enables faster convergence, robustness to noise, and the generation of additional data points, the so-called collocation points [23] [24].
Physics-informed neural networks require substantially less training data and can result in simpler neural network structures while achieving high accuracy.

7.1.5 Meta-Learning

AI and machine learning methods have achieved impressive results in various modern power grid applications. Nevertheless, these approaches are designed for a specific system configuration and may lose effectiveness when the system topology changes. Furthermore, they can struggle with changes in system conditions and scarcity of training data.

Meta-learning, intends to design ML methods and models that could improve the process of learning new tasks or adapting to new environments rapidly with a few training examples. [25]

Meta-learning is an essential concept in the domain of power grid control and operations, particularly in circumstances where DERs are prevalent. It presents innovative strategies and methods for the real-time control and adaptation of power grids in response to changing grid operation scenarios, which are characterised by uncertainties arising from the high penetration of DER [26], [27].

7.2 AI/ML Challenges in Power Systems

Despite numerous opportunities, significant challenges persist in the application of AI/ML to power systems. Utilities acknowledge the importance of AI/ML but require convincing results before further investment. Thus, cross-domain synergy is crucial. Concerns regarding ML methods and result interpretability exist, and incorporating domain knowledge and physics representation into ML frameworks remains challenging in this evolving field.

The major challenges in applying AI/ML technologies to power systems can be summarised as follows:

7.2.1 Data Quality and Availability

The efficiency of AI and machine learning models is heavily dependent on the quality and accessibility of data. The diversity, quantity, and currency of the data used in the training, validation, and ongoing learning of AI models are crucial for determining their effectiveness and flexibility.
Obtaining comprehensive and accurate data in power systems, particularly from diverse sources, can be challenging. Ensuring the integrity and accessibility of such data remains a significant obstacle.

7.2.3 Field expertise Incorporation

Incorporating field knowledge into scientific machine learning requires interdisciplinary collaboration between experts in machine learning and power systems. This process requires a thorough comprehension of both the underlying physics principles and machine-learning techniques. Transforming power system knowledge into actionable features or input representations for machine-learning models can be a challenging task.

7.2.4 Explainability and Trust

The challenges posed by the intrinsic complexity of AI/ML algorithms extend to generating conclusions that are both interpretable and comprehensible as well as extracting actionable insights from ML predictions to reinforce confidence in the outcomes. To foster trust among stakeholders, it is crucial to invest in measures such as XAI methods that promote transparency and comprehensibility of these systems.

7.2.5 Robustness:

Developing dependable and sturdy scientific machine learning methods is essential to ensure that the outcomes are not overly sensitive to any disruption in training data or model selection. This involves the ability to handle different configurations and uncertainties in power systems and the capacity to remain resilient to changes in the training data and model selection. To achieve robustness, extensive testing and validation are required.

7.2.6 Interoperability/

Power systems are typically comprised of a multitude of equipment and technologies from various manufacturers. The challenge lies in achieving interoperability and standardisation across these diverse components, thereby enabling the seamless integration of AI/ML solutions.

7.2.7 Human-machine interactions

Human-machine interactions are essential for the successful integration of AI/ML techniques in the power industry. Establishing clearly defined roles, interfaces, and workflows for human operators and machines is necessary to ensure the collection of high-quality data and high-fidelity models, which will improve the system resilience and responsiveness while addressing human factors.

8 Limitations in Applying Artificial Intelligence to Power Systems

Over the past two decades, extensive research has focused on applying artificial intelligence (AI) to power systems with a significant integration of renewable energy sources (RES). This section critically examines the primary limitations hindering the practical implementation of AI in addressing the challenges within power systems. Key issues include the proportion of RES within grids, reliance on synthetic data, scarcity of real measurement data, challenges related to protection selectivity and coordination, and inherent "black box" nature of machine learning models.

A significant limitation of academic research is the lack of precise quantification of the proportion of RES in power grids. Studies often refer to the "high penetration of Distributed Energy Resources (DER)" without providing specific metrics. However, empirical evidence suggests that power systems can effectively operate with 30-50% distributed generation from RES without necessitating the development of new AI-based techniques for stability and protection.

Another challenge arises from the prevalent use of simulation-generated data, as opposed to real-world observations, for training machine-learning models. The authenticity and complexity of these synthetic data are often insufficient, raising concerns about the applicability and effectiveness of machine learning-based protection systems in real-world power grids.

The scarcity of relevant real measurement data further complicates the development and training of machine-learning models for power system protection and stability. Even when real data are available, they may not be ideal for training purposes, as power systems are typically engineered to maintain stable operations over extended periods, resulting in a limited amount of data from unusual fault situations.

Additionally, current research on machine-learning-based protection methods frequently overlooks the critical aspects of selectivity and coordination across different levels of the grid. Many studies have failed to address the interactions between protection systems at various voltage levels, leading to a lack of comprehensive research in these areas. This oversight significantly hampers the practical application of AI in power-system protection.

Finally, the " black-box nature of machine-learning models poses a significant challenge within power systems, where high standards of accountability and transparency are required. The opacity of AI decision-making processes can undermine operator trust, complicating the acceptance, validation, and justification of AI-driven recommendations in power system management.

4 Conclusion

Machine learning methods have been used to address the challenges of integrating distributed energy resources in modern power grids. Although effective in load forecasting, renewable energy prediction, and energy optimisation, these methods struggle with power system stability and protection issues. Synthetic datasets are often inadequate to ensure the applicability of simulated solutions to real-world power systems. Categorising power grids based on distributed energy resources is essential for efficiently identifying and solving these issues, saving time, and enabling precise and tailored strategies. Physics-informed machine learning models and meta-learning methods can be integrated to address data scarcity and quality issues. The black box effect in AI systems for power grids can be mitigated through advancements in Explainable Artificial Intelligence (XAI). The implementation of grid edge computing offers a unique opportunity to improve the reliability and efficiency of the power grid in the context of distributed energy generation.

The future appears to hold the potential for advanced AI systems to be comprehensively understood and efficiently utilised in the operations and management of power grids and energy systems.

In summary, harnessing AI/ML in power system applications is characterised by both promising prospects and intricate obstacles. The implementation of strategic measures that tackle data challenges, interoperability issues, and transparency will be crucial for realising the transformative potential of AI/ML and shaping the future of power systems.

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