Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 3, Issue 2, 2025

ARTIFICIAL INTELLIGENCE IN THE POWER SECTOR: A GAME-CHANGING REVIEW OF AI TECHNIQUES FOR TRANSFORMING DUMP GRIDS INTO SMART POWER GRIDS

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DOI: https://doi.org/10.5281/zenodo.14880810

Keywords
Artificial Intelligence (AI); Smart Grid (SG); Microgrid (MG); Machine Learning; Deep Learning (DL); Distribution Network (DN); Power System (PS).

Article History
Received on 07 January 2025
Accepted on 07 February 2025
Published on 17 February 2025

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Abstract
The current electric power system is undergoing a substantial transformation towards the adoption of Smart Grids (SGs), which are viewed as a potential approach to improve grid stability and optimize management of energy. The current state of transition is characterized by dynamic and swift alterations, necessitating the utilization of numerous sophisticated approaches to effectively analyze the substantial volume of data produced by diverse entities. In this particular context, SG is closely associated with AI as an emerging technology that aim to establish a decentralized and intelligent energy paradigm. This study provides a groundbreaking assessment of a variety of artificial intelligence strategies that are turning outdated "dump" networks into intelligent, self-healing smart grids. This article also provides a comprehensive introduction to AI techniques and methods, followed by a detailed examination of how they are applied in the context of SG and microgrid (MG) systems. This analysis is conducted through a comprehensive examination of more than 90 recent scholarly articles. The primary aim of this analysis is to advocate collaboration between researchers and decision-makers in order to accelerate the actual implementation of strategies for Smart Grid systems.

INTRODUCTION

The traditional power system (TPS) functioned effectively from its establishment in 1870 until 1970. Despite the exponential growth in energy demand by consumers, it remained predictable. Since 1970, there has been a significant alteration in the patterns of electrical energy usage, wherein electronic devices have emerged as the most swiftly growing sector in relation to the total electricity demand. Electric vehicles (EVs) and other novel sources of elevated electricity consumption have surfaced [1-2]. Owing to multiple factors, such as the ineffectual appliances employed by consumers, inadequate adoption of smart technology, suboptimal routing and distribution of electrical power, inaccurate communication and monitoring systems, and the lack of an effective system for saving produced electrical power, TPSs experience substantial energy loss. Also, TPSs encounter various challenges such as escalating energy consumption, reliability, safeguarding, the emergence of renewable energy source (RES), and deteriorating infrastructure, increasing cost of electricity among others. From

1960 to 2021, there was a notable increase in the mean cost of electric energy use, rising from 2.6 to 13.19 ¢/kWh. In 2018, worldwide energy use increased by 2.3% from 2017, marking its largest annual increase since 2010, resulting in record-breaking levels of CO emissions from the energy industry. To meet conventional energy demand from 2010–2035, $11.7 T must be invested in the energy sector. By the year 2050, the average temperature of the Earth is expected to rise by 1.5 degrees Celsius compared to the temperature before the Industrial Revolution. The Earth faces grave danger if global warming continues to rise at this rate, surpassing the 2°C threshold [3]. Global electricity usage is to surge by nearly 70% over the next 30 years, rising from 25 to 42 TWh by 2050; 56% of the total output will be generated by RES, making them the most significant contributor to the global electricity supply [4].

In response to rising population, carbon dioxide emissions, and energy demand, Smart Grid (SG) has emerged as the most practical option, equipping utilities with the means to modernize their infrastructure by the utilization of ICT. The integration of field devices, information management, communication technologies, control technologies, and digitally based sensing enables the coordination of several electric processes inside the SG systems. SG's capabilities include the ability to share data among devices and systems, monitor or measure processes, and process, analyze, and assist operators in accessing and applying data from digital technologies throughout the grid. Also, utilizing low-carbon units and advanced metering infrastructure (AMI) alongside end-user engagement leads to the creation of smart distribution system (SDS), providing a wide range of techno-economic opportunities for system operators and end-users [5-8].

However, the incorporation of different distributed generations (DGs) presents numerous obstacles, including but not limited to analyzing faults and failures, predicting load demand, monitoring loads without intrusion, ensuring cybersecurity in the digital realm, managing demand from consumers, detecting electricity theft, and identifying islanding situations. Also, SG management faces the ever-increasing volume of high-dimensional, heterogeneous data being produced by a variety of sources. Traditional methods for analyzing, controlling, and making decisions in electrical power systems (EPS) face difficulties when dealing with limited information and variable conditions. These methods heavily rely on numerical calculations and physical models; thus, in the field of EPS, an increasingly prevalent and potentially economic development is the growing implementation of artificial intelligence (AI) methods [9-10]. Figure 1 shows a perspective of the applications of AI in SGs. The incorporation of AI with the IoT, Digital twins, blockchain technology in SGs can provide a multitude of benefits, such as data analysis, proactive maintenance, safeguarding of data and privacy, real-time simulation and monitoring, optimization of energy usage and management, decentralized energy trading, enhanced grid durability, and more. Thus, this integration improves efficiency, dependability, and security of the SG [11-13].

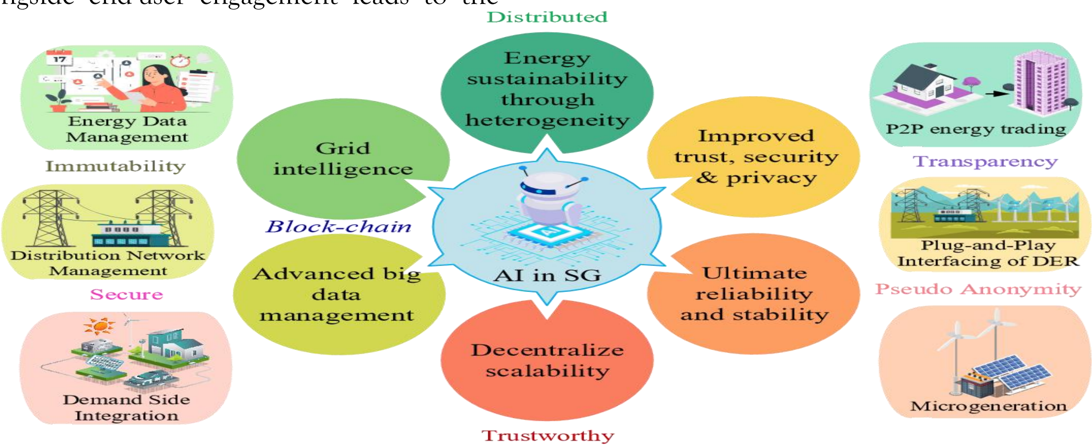

Figure 1: An Overview of AI's Potential Applications in SGs.

2- A basic overview to the world of Artificial Intelligence:

2.1- Exploring different definitions of Artificial Intelligence:

What is Artificial Intelligence? The evolution of artificial intelligence over the past several decades has been remarkable but the pursuit of a cohesive definition within academic circles continues to pose significant challenges. In 1955, American scientist John McCarthy (1927– 2011) established the foundation for AI's advancement by defining it as "the science and engineering of building intelligent machines" [14]. A Swedish-American scientist Nils John Nilsson (1933–2019) emphasized that artificial intelligence allows wise agents to learn superior human-like skills, like how to perceive, communicate, reason, and learn, especially in complex settings [15]. David Poole a Canadian scientist said that the fundamental The goal of AI is to create intelligent entities that can understand their surroundings and execute behaviours that enhance their likelihood of attaining designated objectives [16]. This underscores the primary aim of AI to develop systems capable of independently navigating and responding to complex situations, emulating humanlike decision-making and problem-solving skills [17]. The goal of modern AI research and development is to give computers the ability to think and act autonomously [18].

2.2- The Historical Development of Artificial Intelligence:

John McCarthy first used the term "Artificial Intelligence" at the famous Dartmouth Conference in 1956 [17]. Thereafter, AI began its first golden period, distinguished by a predominant emphasis on reasoning with the use of search engines and NLP [19]. The first winter of AI, however, occurred in 1970 due to computers were too slow and made it hard to make money because improvements didn't move forward. The emergence of ESAs in the 1980s marked the start of a new era of success for AI. Power systems' timing issues were addressed by these systems [20]. Because of the steep price of maintaining expert systems, a lack of enthusiasm for expenditure, and an abrupt decline popularity for AI technology, spending fell flat. But after a few years, AI went through the next winter. In 1990, the new idea of a "intelligent agent" became more widely accepted. Then AI quickly grew again, and the Deep Blue system beat the world chess king, Garry Kasparov. AI has advanced due to new applications like self-driving automobiles in the 21st century. Since 2011, the development of deep learning and large data has led to a dramatic increase in AI. Figure 2 illustrates the concise historical progression of artificial intelligence.

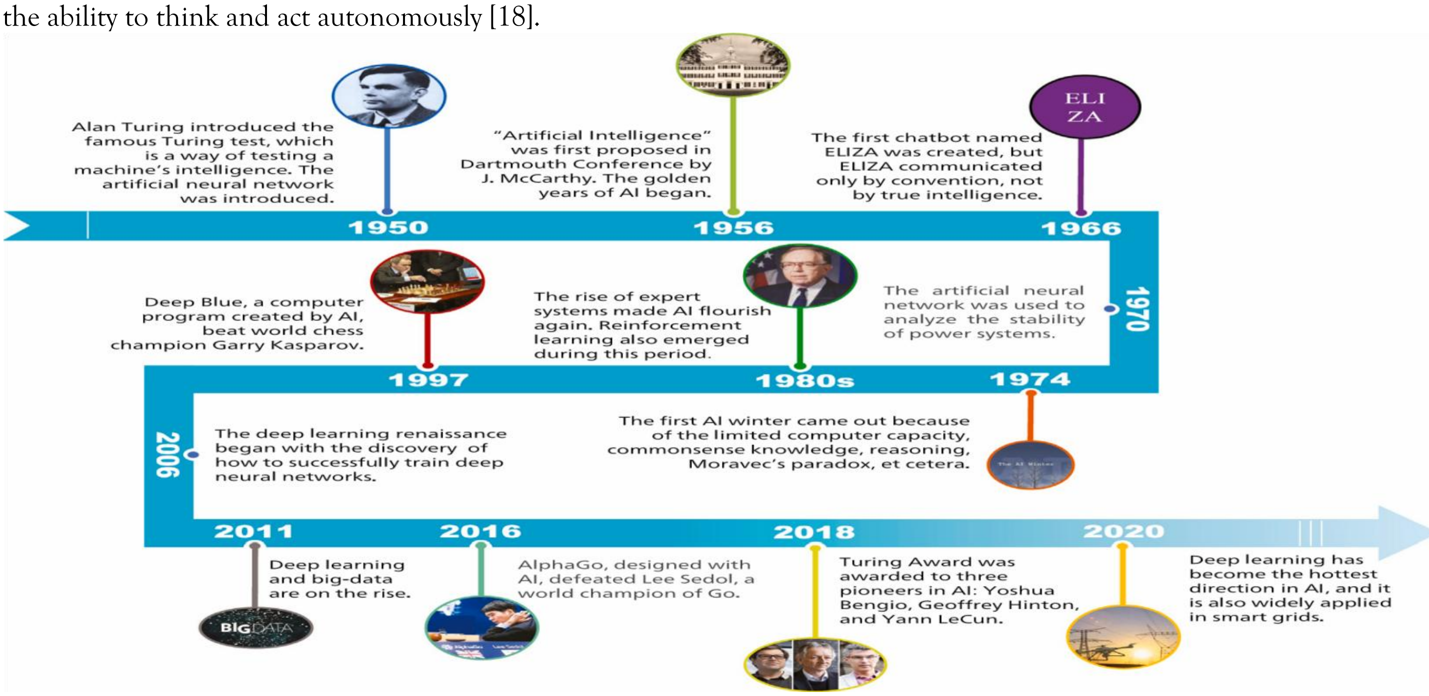

Figure 2: The brief development

HISTORY OF AI.

1- Techniques of Artificial Intelligence:

The swift progression of contemporary power systems has facilitated the cohesive incorporation of diverse distributed smart grid components, such as intelligent metering facilities communication networks, distributed sources of energy, and electric automobiles, within a comprehensive electrical power network supported by a fundamental communication system. These components generate substantial data to improve and automate smart grid performance, enabling various applications such as decentralized energy administration, system status forecasting, defect detection, and cybersecurity [21]. Standard computer methods are insufficient for managing the vast data produced by smart grid networks, leading to considerable interest in AI technologies [22]. A significant amount of research efforts concentrated on analyzing these AI solutions to address the issues, since they utilize vast data to improve smart grid performance. AI approaches in the smart grid may often be classified into the following categories, as illustrated in Figure 3 [23].

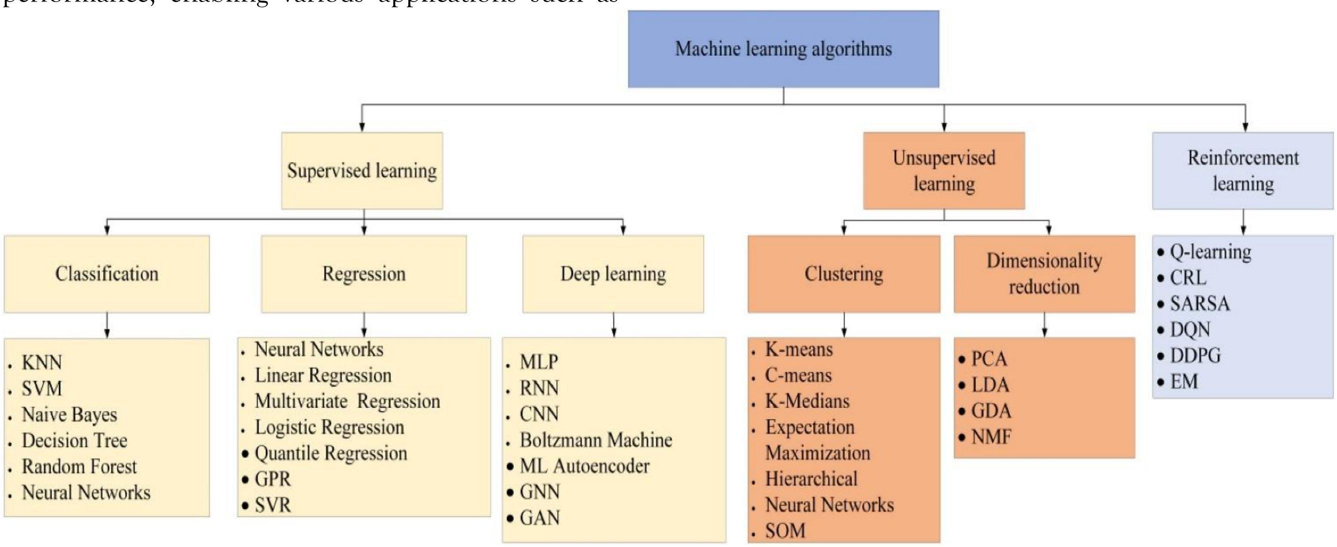

Figure 3: Different types of machine learning algorithms [24].

3- Artificial Intelligence Techniques in Smart Grid:

3.1- Forecasting:

3.1.1- Load Forecasting (LF):

A LF methodology known as Hybrid Ensemble DL (HEDL) is introduced in [25]. The two-phase pressure breakup method is employed to efficiently simplify the complex structures of the reported pressure series across the spatial and harmonic domains. It facilitates the realignment of target prediction objectives and the extraction of necessary input attributes. Diverse feature matrices are used to address the discrepancies in the decomposed components, taking into account different feature types and window lengths. The predictive models employ Temporal Convolutional Networks characterized by unique receptive fields. These models are engineered to successfully record both immediate and distant relationships within diverse component sequences. A proportional programming-based weighted ensemble approach enhances the accuracy of outcome predictions for residual components with significant uncertainty. A unique deep learning model based on Seq2Seq is presented in [26] for multistep forward LF. The model has interlinked basic blocks, with residuals linking them. The ultimate residual output is included into the loss function. The Seq2Seq framework employs a deconstruction approach to develop the trainability and convergence in terms of the structural depth. The model employs a dynamic approach to break down into various parts of the initial time series, which effectively alleviates the general forecast load and enhances forecast precision. Every fundamental block utilizes a TCN for the encoding process and an LSTM for the decoding phase.

3.1.1.1 - Short-Term Load Forecasting (STLF):

[27] formulates a model that integrates an encoder-only A Time-Series Transformer-Framed, Temporal Convolutional Network (PatchTCN-TST). This

model employs a channel-independent method to foretell the energy use on an hourly basis and interior environmental conditions of a multi-load office block in Bangkok, Thailand. The forecasting is conducted for time horizons from one to three hours in advance. The model can do what it does thanks to the channel-independent strategy to provide distinct predictions for multivariate data, using common parameters for multivariate forecasting. Partitioning the input sequence into many sub-series reduces the work required to process the attention mechanism and enhances the extraction of local dependencies. Furthermore, the embedding process uses the TCN block to extract temporal characteristics in place of the original CNN. A load prediction system is developed in [28] using the Hybrid Deep Learning and Beluga Whale Optimisation (LFS-HDLBWO) approach. The approach is mostly intended to predict the load in the SG environment. The input dataset is normalised using Z-score normalisation and scaled using a Long-Term Short-Term Memory Convolutional Network (CB-LSTM) model that includes an Autoencoder (AE).

3.1.1.2- Medium-Term Load Forecasting (MTLF):

A hierarchical MTLF model is introduced in [29]. The model incorporates a distinct element for time series data, with exponential smoothing (ETS) coefficients and starting seasonal components. A global component is derived from several time series using LSTM weights. It simultaneously transforms TS models and input vectors into output vectors via stochastic gradient descent. For the purposes of deseasonalization and normalisation, formulae derived from ETS extract the primary components of particular time series. LSTM with residual dilation is used to forecast pre-processed time series. Through the use of dilated recurrent skip connections and a spatial shortcut pathway from lower layers, LSTM enhances training effectiveness and is adept at recalling long-term seasonal correlations. To alleviate forecast bias, a pinball loss function and a parameter regulating its asymmetry are used. The model employs two regularisation techniques: three-level assembly and a penalised loss function. [30] introduces a Multi-Task Learning Framework (MTLF) that combines Deep Learning (DL) with manifold learning. The local linear embedding (LLE) approach is used to extract the intrinsic load pattern, which includes the main factors of load change. The LSTM model predicts low-dimensional load manifolds, with the ultimate load prediction value derived from the LLE reconstruction approach. The main challenge in manifold learning is the appropriate integration of temporal stress information. A connection exists between load samples collected at successive periods and those gathered on subsequent days, indicating that the burden data are significantly time-dependent. The LLE approach collects characteristics by preserving spatial distance invariance, focussing on the spatial configuration of load. The ability of LLE to extract essential load features might be improved by optimising the use of temporal load information.

A two-stage forecasting technique is presented in [31]. Initially, a series of Back Propagation Neural Network (BPNN) models is used to provide very precise predictions for the initial timesteps of the forecast horizon, using the most current available data. In the second step, the accurate predictions produced by BPNN, together with other relevant attributes, serve as input for a set of radial basis function neural network (RBFNN) models to estimate the remaining time intervals of the predicted timeframe. A unique strategy is proposed to aggregate historical data embedded with noise to provide supplementary training data for the training of RBFNN models.

3.1.1.3- Long-Term Load Forecasting:

[32] presents an innovative concept for long-term strategic planning of a real-world gearbox system. The model seeks to significantly improve the accuracy of monthly peak load predictions. Incorporating the power production pattern of photovoltaic (PV) systems and accounting for the medium-term effects of persistently high temperatures may substantially enhance the model's accuracy. A CNN-LSTM model is presented for forecasting the frequency of long-term point loads for a duration of up to 3 years. Block bootstrapping is used to establish a long-term probabilistic LF framework. This strategy involves generating scenarios using economic, demographic, and climatic data. The framework emphasises the creation of scenarios to provide precise probabilistic forecasts for long-term strategic planning. A comprehensive

methodology for distribution feeder LTLF is defined in [33]. A hybrid model, integrating both bottom-up and top-down information, is used to seamlessly combine multiple layers of data. Consequently, it encapsulates the relationships among feeder load specifics, regional and overarching factors, and feeder peak demand. To improve forecast accuracy, advanced sequence prediction models, including LSTM and GRU, are used to effectively capture and utilise the sequential characteristics of multi-year data. The method of a virtual feeder generated very precise estimates for both summer and winter. The variability of output across successive years affects the performance of many-to-many and many-to-one sequential setups.

3.1.2- Renewable Generation Forecasting:

3.1.2.1- Solar Forecasting:

Solar Forecasting: [34] anticipated sun energy in rainforest ecosystems over a thirty-day period with neural networks. The data from the Brazilian segment of the Amazon basin, comprising twelve cities, is employed over a decade (2013-2023), in alignment with global energy matrix transformation trends, particularly attributable to heightened deforestation. Although the boundary conditions of the cities are comparable, considerable discrepancies, such the relative humidity, may account for the variances across the models. By adopting an LSTM_GRU model, the minimal MAPE reaches 19.2. The LSTM_GRU model produces the minimal RMSE (0.75) and the minimal MAE (0.61) when used in an MLP model. [35] presents a deep learning system that employs a hybrid Transformer-LUBE architecture to enhance the accuracy of photovoltaic power production forecasts one day ahead. The model integrates pre- and post-processing methodologies. XGBoost is used for missing data imputation, the Pearson Correlation Coefficient is utilised for feature engineering, and a GRU model is merged with an error compensation approach that amalgamates numerical daily error correction curves. The technique incorporates probabilistic or interval forecasts via the use of LUBE to assess the uncertainty associated with forecasting, while also producing deterministic predictions. A hybrid prediction model incorporating the PSO technique, signal decomposition (WT), and support vector machine (SVM) is proposed in [36] for a 480 kW photovoltaic facility situated in Beijing, China. The SVM model is trained by decomposing and filtering historical photovoltaic power data and meteorological parameters utilising wavelet transform. The PSO method is used to optimise the internal parameters of the SVM by applying it to the noise-processed subcomponents.

3.1.2.2- Wind Power Forecasting (WPF):

The long-term WPF hybrid model is proposed by [37] through the adjustment of wind speed (WS) data derived from numerical weather prediction (NWP) and the application of multiscale deep learning data mining techniques. A data refinement methodology is developed that utilises WS power curves to efficiently and straightforwardly purify the raw data. Power prediction combines many methodologies and the multi-scale deep learning prediction model to condense forecast findings. A nonparametric technique for producing predictive distributions of forecasting uncertainty is presented in [38] using a combination bootstrap and cumulant (CBC) methodology grounded in maximum likelihood (ML). A recommended strategy to adequately reflect both the epistemic and aleatory uncertainty is to employ a bootstrap-based conditional moment estimation method using ML. The predictive distribution of RE is first constructed using higher-order cumulants and calculated conditional moments. The CBC method effectively characterises overall uncertainty through three series expansions and the additive properties of cumulants. Reference [39] delineates a hybrid short-term WPF approach that integrates the weighed-voting-based DL model selection (DLMS) technique with the multiparameter similarity wind process matching (MSWPM) theory. Comparable historical wind processes obtained from MSWPM are used to ascertain, using a hybrid technique, the best suitable NN-based WPP model for each segment of the predicted target wind process. The MSWPM method employs four similarity indices to gather pertinent data from prior wind processes to identify correspondences for each forthcoming target wind process. A detailed historical record may be used to differentiate the analogous historical wind patterns of each individual wind process for guidance. The forecast target sample's DLMS utilises the WPP results of analogous historical wind patterns as predicted by each DL model.

3.1.2.3- Wind Speed Forecasting (WSF):

A nonparametric method for WSF concerning extremely short-term probability is proposed in [40]. It employs non-linear quantile regression (NQR) in conjunction with an integrated criteria (IC) and adaptive LASSO (ALASSO). ALASSO is used to guarantee appropriate variable selection and coefficient shrinkage, as confirmed by numerical analysis in comparison to the LASSO-based approach and NQR. The numerical comparison substantiates the notion of an IC using CWLP to optimise the NQR cost function for improving the composite's performance. The MFCM is used to increase sample sizes for various models, hence improving prediction accuracy. [41] presents a two-stage short-term wind power forecasting model based on a wind power curve (WPC) and wind speed factor (WSF). After the calculation of the WSF values, preliminary power forecast values are derived using WPC conversion. A two fully-connected layer artificial neural network (ANN) is then developed to provide the final power forecast value. A short-term WSF model using machine learning, empirical mode decomposition, and K-means clustering is proposed to improve the accuracy of input water supply during water production conversion. Historical wind speed measurements are decomposed into intrinsic mode functions (IMFs) by empirical mode decomposition (EMD), followed by the extraction of frequency domain information from each IMF using fast Fourier transform (FFT). The IMFs are classified into three categories high-, medium-, and low-frequency components utilizing the Kmeans clustering technique. Three machine learning strategies, specifically Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and LASSO regression, are used to individually train these components, taking into account their sensitivity to intricate data. The WSF is derived by aggregating the projected values of each component.

3.2- Operational Control:

3.2.1- Autonomous Voltage Control (AVC):

A data-driven multi-agent AVC (MA-AVC) framework based on DRL is developed in [42] to address voltage concerns in a large-scale energy system. The MA-AVC problem is represented as a Markov Game, in which agent division is performed heuristically. Alterations and enhancements are implemented in the MADDPG algorithm to enable it to acquire a centralised effective policy from the operational data. Agents using sufficiently trained DRL get effective performance in managing voltage profiles in a decentralised way. The degree of collaboration may be flexibly adjusted by the coordinators based on the conditions of the learning system. In [43], a parallel augment random search (PARS) derivative-free DRL algorithm is designed and executed to regulate the voltage stability of PSs through the load shedding. PARS may be easily modified to achieve optimum performance by using a restricted set of hyperparameters. A model-free and decentralised MADRL architecture for DS-VR with significant PV penetration is presented in [44]. The sparse pseudo-Gaussian process (SPGP) initially reconstructs the mapping relationship between the voltage magnitude at each node and the active and reactive power injections utilising limited recorded data as a surrogate model; this model is further integrated with the multi-agent deep reinforcement learning to facilitate the formulation of a coordinated control strategy. The DRL method addresses each subaddress within the capabilities of an agent. [45] delineates a hierarchical multitimescale framework including three phases, using smart inverters from energy storage systems (ESSs) and/or photovoltaic (PV) systems to implement peak shaving and voltage and var control (VVC) inside active distribution networks (ADNs). Optimisation and model-free online safe deep reinforcement learning methods are used. The first phase tackles a day-ahead scheduling challenge with a resolution of 30 minutes to ascertain the optimal charging and discharging schedules for energy storage systems to mitigate peak power consumption. The DRL algorithm, in conjunction with the safety module, significantly mitigates voltage violations that may arise during the training phase when the DRL agent interacts with the real world. The last step entails fast local voltage regulation with an accuracy of 0.1 seconds; real-power compensation PI controllers are used by the intelligent inverter to quickly address local voltage discrepancies resulting from fluctuating photovoltaic production output.

3.2.2- Load Frequency Control (LFC):

[46] presents a method called self-tuning fractional gradient descent (FGD), using a single-input interval type-2 fuzzy logic controller (SIT2-FLC) as the main regulator. It reduces grid frequency oscillations in a hybrid microgrid with a Tidal Power Unit (TPU) and electric car accommodation. A technique using adaptive DDPG-based AC is developed to enhance the main controller with additional learning capabilities, effectively addressing the control problems in the isolated MG. A substantial amount of isolated MG data is used during the training of the actor and critic networks. This training enables automated adjustment of the control parameters for enhanced compensatory control of the relevant system. [47] formulates a methodology for the systematic regulation of PS emergency frequencies (PSEFC) using off-policy reinforcement learning-based model-free control (MFC). The framework may be used to teach optimal control actions for many contexts. In reinforcement learning, multiQ learning is implemented across several constrained scenarios; when certain emergency situations occur online, a corresponding set of actions aligned with the most analogous scenarios is conducted immediately. To diminish excessive dimensionality and facilitate synchronous execution, the several agents associated with diverse regulatory mechanisms are consolidated into a singular agent. In certain situations, a DDPG is implemented to maintain continuous emergency frequency regulation using a DQN. A data-driven cooperative load frequency control approach for multi-area power systems is delineated in [48]. The methodology is based on Multi-Agent Deep Reinforcement Learning (MADRL). To improve the effectiveness of LFC using MADDPG, the controller settings are optimised in coordination during centralised learning. The MADRL operation is accelerated by initialising the agents' settings. The derivation of the parameter update algorithm using DDPG takes into account physical restrictions, including generation rate limitations and generation deadband. The obtained controllers are restricted to using local area state data to cooperatively alleviate unplanned tie-line power fluctuations and frequency variations across all regions.

3.3- Power Grid Stability Assessment:

3.3.1- Transient Stability Assessment:

[49] suggests redefining the function of gridfollowing inverters (GFLIs) at the grid-edge by using an AIbased power reference correction (AI-PRC) mechanism. This approach aims to improve the transient response and resilience of power electronic dominated grids (PEDGs). The Bayesian regularization algorithm (BRA) is used to train a two-layer feedforward ANN. This network is part of the AI-PRC module, which is responsible for predicting the trajectory of the system frequency and determining the appropriate amount of correction power for GFLIs during grid disruptions. The dynamics of GFLI and grid forming inverters (GFMI) are thoroughly examined to provide a precise data mining method for training the ANN. To tackle the issue of opacity in ML algorithms that have higher accuracy, [50] uses the SHapley Additive exPlanations (SHAP) approach. SHAP calculates an estimation of Shapley values, representing the individual contributions of features in a model towards the prediction for a local explanation, which can be expanded to cover all occurrences, thereby offering a in-depth interpretation of the entire model. Applying SHAP to transient stability assessment (TSA) exposes the influence of PS factors on the forecast of the stability threshold of an ML model, measured in seconds. The advantage of this can be two-fold: to acquire heightened assurance in ML models and to uncover patterns that would otherwise be challenging to comprehend due to the escalating intricacy and unpredictability of PS operating. Also, a method is suggested to utilize SHAP values to detect patterns in the stability border by evaluating the covariance between a specific variable of interest (VOI) and the related SHAP value at different locations. Thus, the overall effect on the stability limit of modifications to that VOI becomes apparent. [51] employs a distinctive method relying on data analysis to integrate online transient stability monitoring and enhancement (TSMAE). It allows for the efficient and collaborative execution of TSA and critical generator identification (CGI) in real-time, thereby aiding in the stabilization of the system

during different emergency scenarios. A smart computer-generated imagery (CGI) scheme is developed, utilizing advanced DL methods, to accurately forecast the impact of tripping individual generators on system stabilization.

3.3.2- Frequency Stability Assessment:

In [52], A transfer and CNN-LSTM-based method are devised to enhance the efficiency of the optimal load reduction and dynamic frequency prediction process. By using the spatial-temporal information of the system and extracting local features from inputs, the method significantly enhances performance. Also, the implementation of the TL process greatly enahnces the capacity of CNN-LSTM for generalization. Also, it addresses the issues posed by inadequate data and operational condition changes in actual PSs, resulting in exceptional training while minimizing sample generation. To use the data-driven and model-driven methods, [53] devised the integration of a modelbased system frequency response (SFR) and AI-based ELM serial integration, aiming to enhance the frequency stability assessment (FSA) and control capabilities. The SFR model incorporates transfer functions that aim to maintain the essential frequency response properties of the system. The inaccuracy resulting from the simplicity of SFR is corrected by using ELM, involving fitting the correlation between the reduction in load and the operational status of the system.

3.3.3- Small Signal Stability Assessment:

A dynamic security assessment (DSA) of SSSA is executed via an Online Gaussian Process (OGP) method in [54]. To predict transient and small-signal rotor angle stability (RAS) in PS, [55] devises a temporal and topological embedding DNN (TTEDNN) model. Coupled with graph convolution (GC) modules, it extracts temporal features from the PMU data and maps the spatial information of the PS topology to the temporal convolution (TC) modules. The model exhibits great predictive capability in minor disruptions and *N-1* contingencies. Owing to its viability for online deployment, it generates a rapid forecast using solely the PMU data from the initial five cycles after disturbance. Practical applications require its resilience to the measurement disturbance that encompasses PMU data. Finally, it transforms transient RAS conditions into small-signal RAS conditions with superior TL capability.

3.3.4- Voltage Stability Assessment:

[56] presents a graphattention (GATT)-based MARL algorithm for decentralized GEVC in multi-area PSs. By utilizing the topological data of each subnetwork, GCN allows the agents to acquire a more profound comprehension of the subgraph's structure, resulting in a more effective learning procedure. In addition, a sophisticated attention mechanism is utilized to facilitate effective information selection among the agents' interactions and the various subnetworks. This combination facilitates a collaborative learning environment for addressing the dynamic control problem. [57] presents a novel approach called Disagreement-based DL technique for the aim of static VSM (DVSM). To address the obstacles posed by restricted flexibility to topological modifications, challenges related to sample labeling, and inefficiencies in managing small datasets, [58] presents a method using PMU measurements (PMU-Ms) and deep TL. It extensively studies the correlation among various fault datasets, showing its versatility and originality within the domain of short-term VS assessment (STVSA). The method greatly tackles the difficulties related to labeling samples and managing small datasets by utilizing temporal assembly for sample labeling and least squares GANs (LSGANs) to generate high-quality synthetic samples, thus enhancing the performance of the model.

The use of PMUs during the online evaluation phase permits the VSA in real time. Continuous monitoring system (CMS) for online rapid and precise long-term VSA (LTVSA) is developed in [59] through the acquisition of knowledge from sequential state images of multiple cases. Temporal and spatial information regarding the topological structure and VPQ, respectively, are contained in these state images after bus reordering using the annealing algorithm. Every case is distinguished by three dimensional data. Next, the CMS employs a 3D-CNN to train a classifier designed for an online application, employing the modified images that have been filtered using a sliding window. The CMS is exceptionally versatile for unforeseen situations, because to its translation invariance and logical sequencing. Also, it is highly resilient against PMU-M faults and data losses.

3.4- Cybersecurity (Attack and Defense):

To defend against GAN-based evasion attacks, a clusteringbased approach to electricity fraud detection is proposed in [60]. Multiple detectors can be utilized to detect electricity fraud from all consumers. A utility company can categorize its customers into clusters according to reliable indicators that impact their electricity usage, such as residential area, square footage, and contracted power. For each cluster, a distinct electricity fraud detector is then constructed; the cluster-specific detector is not susceptible to the GAN-based evasion attack, as the electricity use levels of all consumers within the cluster are comparable. Yet, false readings of low-use consumers in the remaining clusters are unsuccessful attempts due to the cluster-specific detectors' ability to readily identify the fabricated samples.

Without using assault samples, [61] proposes a real-time *FDIA* detection scheme. The results of this process were state quantiles serving as upper and lower detection bounds, which are derived from state features extracted in spatial and temporal dimensions using a spatiotemporal GNN. Also, an enhanced temporal data for detection learning is achieved through the formation of a CNN-ResNet-based super-resolution perception network that reconstructed high-frequency state estimation outcomes. The SDN-cloud-fog architecture for multi-MGs is devised in [62]. The master controller in the application plane, managing the performance of each local controller, increases the resilience of network communications against human error and attack. Local controllers on a fog server are outfitted with an SVM algorithm to detect *DDoS attack*; upon identifying them, the corresponding local controller modifies the forwarding information topology to exclude the compromised switch. A method to efficiently assess the impact of *delay attack* is devised in [63]. ML is used to tackle the state explosion issue in safety classification when the safety of the system is contingent on the multi-dimensional system state. The use of the tandem stabilitysafety design expedites the overall assessment process and enhances the precision of the unsafety detection. Also, a two-tier attack impact mitigation strategy is devised, involving adjusting the control gain as an initial line of defense and only using load reduction when the gain tuning fails to restore safety. Due to the limited availability of faulty and FCA samples in practical power systems for training DL models, a novel framework called GBSS is devised in [64]. GBSS is a triple network that combines a conditional GAN (CGAN) with a semisupervised learner. This framework aims to learn from partially labeled data to diagnose *false command attacks* and faults related to PMUs. A framework for a proactive defense and black-box attack against DL-based soft sensors (DLSSs) is devised in [65]. It considers real-life situations that attackers may confront and uses a proxy model and attack transferability to accomplish these goals. The adversarial attack method called the *knowledge-guided adversarial attack* (KGAA), have the qualities of imperceptibility, stability, and rationality. The approach resolves the ill-posed optimization dilemma of DLSSs that arises from the unavailability of labels during the testing phase. The DLSS shows a degree of resilience against additional attacks while experiencing a reduced decline in prediction accuracy due to the KGAA adversarial training method, which effectively implements defense against KGAA. Using a POMDP to *attack an* AGC system fortified with numerous fault and attack detection methods was formulated in [66]. The attacked sensor measurements were computed using an RL solution based on the proximate policy optimization algorithm. The outcomes show that the DRLAs are formidable in terms of both the damage they cause to the power grid and their ability to evade detection by a broad spectrum of sensors; they are capable of circumventing current detection systems and directing the grid frequency along critical trajectories. A critical transmission line overloading *coordinated topology attack* strategy based on deep Q-learning is devised in [67]. Physical- and cyber-attacks are combined in the attack strategy to trip a transmission line and create a sham line, respectively. Load uncertainty in power systems can be managed by the RL-based method. Also, a deepQ-learning-based strategy is used to allocate minimal attack resources to inject the attack with such constraints. Critical transmission lines' susceptibilities are exposed by the attack strategy, which is applicable when devising safeguards.

In [68] devised a model based on GNNs that detects and localizes *FDIA* in PSs simultaneously. To account for the network's physics, the model incorporates the spatial correlations of the measurement data and the underlying graph topology of the grid. Due to the rational type filter composition of the IIR type ARMA graph filters (GFs) implemented in the model's hidden layers, the frequency response is more adaptable than that of FIR type polynomial GFs. Using *moving target defense*, [69] devised a method to detect coordinated CPAs. A subset of links is designated for the deployment of D-FACTS devices, providing the defender with the capability to identify physical assaults targeting any link within the system. Also, to minimize the price of defense for the operator, a game-theoretic approach is utilized to determine the optimal set of connections whose reactances must be perturbed during operation. By using an RL algorithm characterized by low complexity and low data requirements, it is possible to compute a robust solution against an adversary. ACIL, a generative-adversarial class-imbalance learner that learns from biased class training samples, is devised in [70]. To categorize *cyberattacks and defects* in cyberphysical power transmission systems, ACIL is then modified; by integrating CGAN with an auxiliary classifier, ACIL generates new synthetic minority samples via the generator as a result of interactions between the auxiliary classifier, discriminator, and generator. The produced minority samples resemble the initial minority samples, yet they diverge from samples representing opposing classes. Auxiliary classifier performance is influenced by these samples throughout the training session.

4- Conclusion:

In recent times, there has been a significant surge in global interest surrounding AI, particularly in the realm of DL methods. The utilization of DL and DRL techniques is more focused on practical applications; thus, complex industries, like Smart Grid, have witnessed an increase in the rate of adoption of these methods. This comprehensive analysis has scrutinized the prevailing AI techniques employed in SG and MG applications, deriving ideas from recent progressions in computational neuroscience. The analysis is based on a thorough examination of 90 relevant scholarly papers. Yet, the advancement of AI in addressing electrical domain issues remains a nascent and promising area of research. Despite its numerous benefits, there are still obstacles to overcome to effectively implement AI models in practical SGs and MGs. These challenges must be addressed to attain outcomes characterized by heightened precision, improved efficiency, and enhanced reliability.

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