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Applications of Machine Learning in Modern Power Systems: A Comprehensive Review

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Abstract—**The demand for electrical power has increased due to population growth, electronic technology advancements, and environmental concerns. This has led to a significant modernization of the power system that incorporates renewable energy sources and electronic components for measurement, communication, and control. However, these changes have added new challenges to the management and control of modern power systems that cannot be overcome using traditional analytical methods. Artificial Intelligence (AI), specifically Machine Learning (ML) techniques, have recently been deployed by a wide number of researchers from different fields thanks to their adaptability and learning ability at a higher speed. These techniques are adequate for large, non-linear, and multi-variable problems such as modern power systems. Therefore, this paper aims to provide an extensive review of recent ML techniques as well as their usage in modern power systems in terms of power quality, power stability, energy and load forecasting, protection and fault diagnosis, and cybersecurity. Finally, the main challenges associated with the implementation of ML techniques for future modern power systems are pointed out.**

Keywords—Modern power systems; artificial intelligence; machine learning.

I. INTRODUCTION

Population development demands an increment in power generation and the expansion of its infrastructure. Although current power generation is highly reliant on fossil fuels, contributing to global warming, countries are attempting to modernize their electric grid systems to be cleaner [1],[2]. The incorporation of intermittent Renewable Energy Sources (RESs), advanced power electronics, and Information Communication Technology (ICT) allows for a reliable, secure, and efficient electric grid. However, this modernization has added new challenges owing to the integration of multi-variable and non-linear electrical components [3]. One solution is to adopt a "Smart Grid" (SG), which refers to a diversified and complex Cyber-Physical System (CPS) network composed of multiple source-load elements electronically controlled based on data through an information management system [1]-[4].

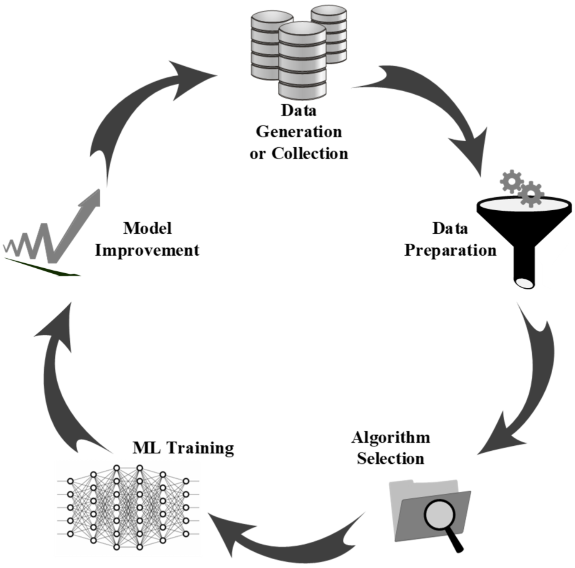

Fig. 1. General machine learning workflow.

Traditional systems are conceived as unidirectional power flow networks, whereas modern grids have bidirectional power and information flow using distributed resources, communication delivery, and automated integration [1]-[3]. These key elements generate massive amounts of data which are crucial for enhancing and optimizing operations as well as supporting automatic decision-making [1],[3],[4].

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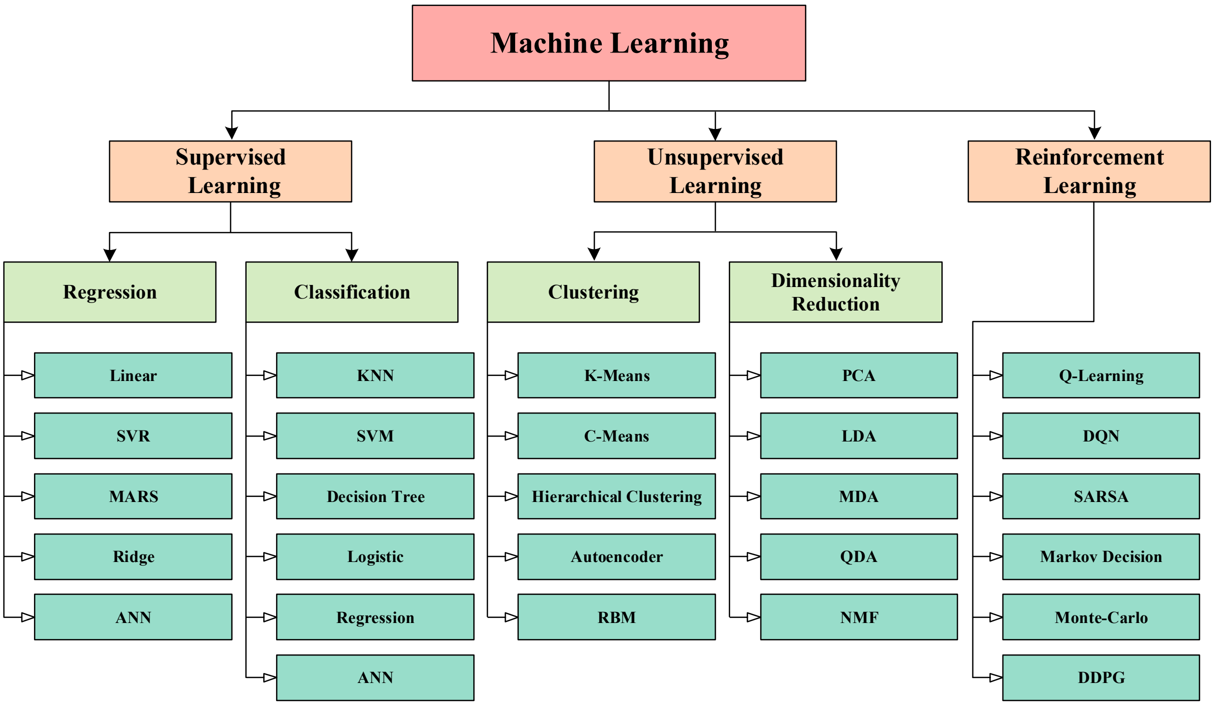


Fig. 2. Classification of machine learning paradigms.

Conventional techniques supported by physical modeling are unable to deal with complex novel networks dispossessed of a detailed model or precise parameters. In addition, they have several limitations and constraints in processing such quantities of big data [3]-[5].

To obviate the abovementioned challenges, intelligent tools such as Artificial Intelligence (AI) techniques have recently been adopted which are promising candidates for fast and accurate decision-making to ensure reliability and efficiency in modern power grids [3],[4]. ML is a subset of AI, sometimes used interchangeably with it [4]. With the purpose of increasing the overall effectiveness of multiple undefined systems, ML approaches have been explored in disciplines such as computer vision, autonomous car driving systems, stock forecasting, and cancer detection [5].

ML is a mathematical and computational method based on data. It learns from previous records, considering the statistical characteristics of input data, improving its performance over time and with the increase in data availability [6]. The core ML steps are the execution of implying data analysis instruction and a variety of algorithms to provide a “smart” decision. This makes it an intelligent tool suitable for modern power systems.

There exist several review articles in the field of application of ML in power systems [7],[8]. However, some are oriented toward one specific aspect within the power systems field, such as fault diagnosis to Electric Vehicle (EV) motors [9] or smart grid infrastructure [10], and others do not consider aspects like power quality or advanced schemes such as Transfer Learning (TL) or Deep Learning (DL). In [4], ML applications in load forecasting, stability assessment, fault detection, and security are discussed, although advanced ML models are barely mentioned. In [11], the energy system reliability of bulk power is reviewed integrating ML algorithms including Decision Trees, and Artificial Neural Networks (ANNs).

The authors acknowledge that a single study cannot provide an in-depth examination of all ML applications in power systems. Therefore, the main objectives of this paper are as follows: (a) to provide an overview of ML paradigms including supervised, unsupervised, and reinforcement learning, as well as some advanced ML techniques; (b) to discuss various ML applications in power systems by focusing on power quality, power stability, energy and load forecasting, protection and fault diagnosis, and cybersecurity; and (c) to point out the main challenges associated with ML techniques.

This paper is structured as follows. Section II presents a classification of ML techniques and their main features; Section III discusses the applications of ML in modern power systems; in Section IV, the main challenges of ML applications in the context of power systems are examined; and finally, Section V concludes the study.

II. ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

AI concept was initially developed in 1956. It describes the potential of computer systems to mimic human intelligence and acquire knowledge equivalent to humankind [12]. Since then, academics from different fields have carried out numerous research from diverse disciplines and perspectives. This interest has led to paradigms such as symbolism, connectionism, and actionism [12],[13].

After almost six decades, AI is an interdisciplinary field that integrates multiple disciplines including pattern recognition, expert systems, game theory, robotics, intelligent control, and machine learning [12]-[14]. The general ML workflow consists of five stages, i.e. data generation or collection, data preparation, algorithm selection, ML training, and model improvement, as shown in Fig. 1. The first stage implies data generation based on the system model; the subsequent stage is to preprocess the data; the third stage implies the choice of the algorithm and its hyperparameters besides the input features for the ML; the next stage corresponds to the actual training session; and finally, the last stage involves a cyclic update and improvement of the training parameters in order to minimize the error difference [15].

A. *Machine Learning Classification*

The following learning paradigms are used to classify machine learning techniques, as illustrated in Fig. 2:

1) Supervised Learning (SL): It consists of input/output samples fed to an ML algorithm. Given a provided labeled dataset, the main aim of SL is to identify a mapping relationship between the inputs and their intended results [4],[15]. There are two main categories of SL: when the output is a continuous value, it is referred to as a regression problem. Multivariate Adaptive Regression Spline (MARS), Ridge Regression, Linear Regression, Support Vector Regression (SVR), and Artificial Neural Network (ANN) are some algorithms that are used for regression problems; when the results are discrete or in classes, it is a classification problem. For instance, SVM, Logistic Regression, DT, and K-Nearest Neighbor (KNN) are deployed for classification problems [4],[16].

2) Unsupervised Learning (UL): In this type of ML, no corresponding output label is required for every input, there is no direct dependency of the dataset on output, and training is organized based on similarities or hidden patterns [6],[15]. UL performs more complex tasks but with unpredictable results due to key attributes selected by the algorithm designer [4],[16]. One UL method is clustering which groups data points into a set of clusters or patterns. K-Means, C-Means, Autoencoder, Restricted Boltzmann Machine (RBM), and Hierarchical Clustering are examples of UL methods. Dimensionality Reduction (DR) is another UL paradigm. It transforms the data from a higher dimension to a lower dimension space. Some main DR techniques are Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Principal Component Analysis (PCA), Non-negative Matrix Factorization (NMF), and Multiple Discriminant Analysis (MDA) [4]-[6].

3) Reinforcement Learning (RL): This paradigm works with an agent interacting within an environment, and subsequently adjusts its behavior in response to its movements according to the signals it receives. Similar to UL, it does not require a labeled dataset [6]. The goal of RL is to enhance the reward in a limited environment and to give feedback through an ongoing scheme of rewards and penalties for every move performed which can be helpful in unforeseen scenarios. Some RL algorithms used in power systems are Monte Carlo, Q-learning, Markov Decision, State-Action-Reward-State-Action (SARSA), Deep Deterministic Policy Gradient (DDPG), and Deep Q-learning Network (DQN) [4]-[6].

B. *Advanced Machine Learning Techniques*

Conventional ML models have the limitation of extracting the relevant information from the raw data for training. Owing to this fact, ML performance is dependent on data input quality. Therefore, much of the effort goes into the design of preprocessing and data transformation techniques, known as Feature Engineering (FE). It is one representation learning way to take advantage of human creativity and specific domain knowledge and integrate it into the machines to discover the main features. However, it leads to a rise in memory complexity and time [17]-[20]. The ML aims at designing more powerful algorithms that are less dependent on FE and intrinsically implement prior data representations. The deep learning algorithm is an example of a representation technique with multiple levels of transformation from input into higher and abstract ones [19]. Other advanced ML models are ensemble methods [21], Extreme Machine Learning, Transfer Learning [21],[22], Hybrid Learning [23], and Adversarial Learning [24], among others described in [17],[19].

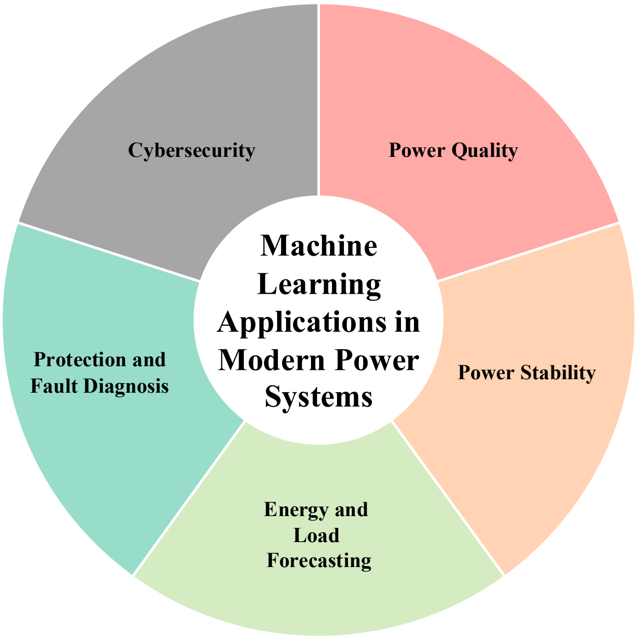


Fig. 3. Various machine learning applications in modern power systems.

III. MACHINE LEARNING APPLICATIONS IN MODERN POWER SYSTEMS

Fig. 3 depicts various machine learning applications in modern power systems which are discussed in detail in the following subsections. A compendium of these applications and their main features is provided in Table I.

TABLE I. COMPENDIUM OF MACHINE LEARNING APPLICATIONS IN MODERN POWER SYSTEMS AND THEIR MAIN FEATURES.

Application	Machine Learning	Improvement Tool	Highlight	Reference	Year
Power Quality	MLP	FFT/DWT	7-class power quality classifier	[27]	1997
	DT	VMD	Detection and classification of PQD	[28]	2018
	ELM	VMD	Multi-power quality classifier	[29]	2019
	ELM	CT/MDE	Power quality classification under noise conditions	[30]	2021
	ANN/DT	ST	Single and multistage power quality disturbances	[31]	2015
Power Stability	CNN	SGDR	Predict transient stability and instability modes	[34]	2020
	SVM	K-Means	Stability accuracy analysis	[35]	2018
	Active Learning	-	Voltage stability margins	[36]	2017
	RF	WMVT	Online voltage stability assessment	[37]	2018
	GAN	-	DCA accuracy under missing conditions	[24]	2019
Energy and Load Forecasting	WRELM	SSA/FEEMD/VMD	Wind speed prediction	[23]	2018
	SVM/UC-3M	OCCUR	1-hour-ahead solar forecasting	[38]	2019
	MARS	-	Complex weather conditions forecast	[39]	2019
	DRL	CNN	Optimize energy trading policy scheme exchange	[40]	2019
	DT/SVM	WA/TS	Short-term forecast metropolitan-scale electric load	[41]	2020
Protection and Fault Diagnosis	ANN/MLP	-	Fault diagnosis in multiterminal HVDC	[42]	2017
	LSTM	-	Fault diagnosis in large-scale multi-machine	[43]	2021
	GCN	-	Fault location in distribution systems	[44]	2020
	KNN	L2-Norm/L1-Norm	Adaptive compressive method for classifying power faults	[45]	2020
Cybersecurity	SVM/RBK	PCA/GA	Classification of malicious control commands	[47]	2021
	ELM	GRD/LHS	Classifier for contaminated state separation caused by FDIAs	[48]	2021
	RF/SVM	-	Intrusion detection in SCADA	[49]	2018
	FFNN/LSTM	-	Intrusion Detection in SCADA	[50]	2021

A. Power Quality

The integration of RESs and power electronics into the power systems has brought more complexity and uncertainty to the grid, raising global concern since they are the predominant factors for Power Quality Disturbances (PQDs) [25],[26]. A PQD can be described as "any sudden change in the normal operation of voltage, current, or frequency that triggers malfunction or failure to the consumer equipment". They can be categorized into three groups, i.e. steady-state harmonics, sudden transients, and magnitude variations. Severe PQDs may also cause a huge economic loss due to equipment failure [20],[26]. ML techniques for power quality have been used for the classification of PQDs. For instance, a 7-class power quality classifier based on Discrete Wavelet Transformation (DWT) and Fast Fourier Transform (FFT) for feature extraction and Multi-Layer Perceptron (MLP) is studied in [27]. A detection and classification approach of PQD based on DT and Variational Mode Decomposition (VMD) is studied in [28]. Another approach using VMD is proposed in [29] in combination with two Extreme Learning Machines (ELM) to improve the generalization of the power quality multiclassifier and reduce the training time. Similarly, an ELM approach enhanced with Curvelet Transform (CT) for FE and a Modified Differential Evolution (MDE) is studied in [30]. A hybrid ANN and DT with Stockwell's Transform (ST) is proposed in [31] and tested against single and multistage disturbances.

B. Power Stability

The aim of power stability assessment is to determine whether the power system can sustain a steady flow of power and regain a state of operating equilibrium after being affected by the disturbance, and categorize the type of instability. This analysis is known as Dynamic Security Assessment (DSA) [32],[33]. It has three categories, i.e. rotor angle, voltage, and frequency stability. Rotor angle stability is separated into two further subcategories, i.e. small signal and transient [33]. Due to the variability of RESs and the integration of electronic devices, conventional techniques have some limitations that AI can overcome [32]. A Convolutional Neural Network (CNN) with a Stochastic Gradient Descent with warm Restart (SGDR) optimization algorithm is used in [34] to predict the transient stability and instability modes. The approach receives the bus voltage taken by a Phasor Measurement Unit (PMU) after disturbance as input. To improve the accuracy of stability analysis, a two-stage SVM model is studied in [35]. This is merged with K-Means to lower the number of samples and enhance the speed. In [36], to decrease the time for training and eliminate redundant offline simulations, ANN, SVM, and DT are studied for voltage stability margin using an active learning technique. Similarly, an online voltage stability assessment is proposed in [37] based on Random Forest (RF) in combination with Weighted Majority Voting Technology (WMVT), enabling online updating and adaptability. Authors of [24] propose a Generative Adversarial Network (GAN) model to maintain the DSA accuracy under missing conditions, completing the data without dependency on the PMU observability.

C. *Forecasting*

RESs are highly variable and weather-dependent; therefore, predicting their behavior becomes an essential task to guarantee the security and effectiveness of the power source. In [23], to predict the wind speed, a hybrid strategy is used for FE based on VMD, Fast Ensemble Empirical Mode Decomposition (FEEMD), and Seasonal Separation Algorithm (SSA), and finally, a weighted regularized ELM (WRELM) is deployed. A UL model is developed in [38] for 1-hour-ahead solar forecasting. The proposed method uses a combination of an Optimized Cross-validated Clustering (OCCUR) method, SVM, and Unclustering Multimodel (UC-M3). In [39], for complex weather conditions, a model considering a Multivariate Adaptive Regression Spline (MARS) is applied. The model is compared against SVM, ARIMA, and ANN models, showing a similar accuracy but faster training time than an ANN. A Deep Reinforcement Learning (DRL), enclosing a CNN, is studied in [40] to optimize the energy trading policy scheme in a power plant connected to multiple microgrid network systems. The authors of [41] presented an ensemble ML approach based on load decomposition to forecast short-term metropolitan-scale electric load. The proposed technique uses DT and SVM for hourly seasonal attributes, a Weighted Average (WA) for daily seasonal, and a Time-Series (TS) method for weather-sensitive components.

D. *Protection and Fault Diagnosis*

Protection includes three distinct subtasks, i.e. location, classification, and detection. It is crucial for the regular maintenance of the electrical system and the prompt restoration of service. [32]. Smart devices can provide detailed information for power system protection. They can also be used to process and analyze the electric grid. In [42], an ANN-MLP system is studied for an FD at one Multi-Terminal High Voltage Direct Current (HVDC) system using only high-frequency components from current signals as inputs. In [43], a different FD is examined on an extensive scale with several machines. The approach relies upon three LSTM models using the transient data of current and voltage signals. Nevertheless, this approach is highly dependent on the advancement of the synchrophasors. Authors of [44] perform a comparative study for fault location between SVM, RF, and Fully-Connected NN (FCNN), as well as a combination of Spectral Graph Theory and CNN, known as the Graph Convolutional Network (GCN) methodology. The suggested framework learns to integrate data from several measurement units while preserving the spatial correlation of the buses, allowing it to be more robust to errors and noise. In [45], authors researched the feasibility of a modified KNN with adaptive compressive sensing and random projections optimized using L2-norm and L1-norm to attain higher levels of precision.

E. *Cybersecurity*

In an interconnected system with an exchange of information, cybersecurity becomes a critical issue. Data transmission is a key task in modern grids. However, it can be vulnerable to major attacks [46]. In [47], a hybrid approach composed of SVM and Radial Basis Kernel (RBK) is used for the classification of malicious control commands from normal operations. In this study, PCA and Genetic Algorithm (GA) are used for FE. In [48], a classifier for contaminated state separation is developed based on a series of ELMs to detect anomaly states caused by False Data Injection Attacks (FDIAs). In this work, the variety of the base learners and the initialization of input weights is enhanced with the aid of Latin Hypercube Sampling (LHS) and the Gaussian Random Distribution (GRD). In [49], authors assess SVM and Random Forest (RF) for intrusion detection in Supervisory Control And Data Acquisition (SCADA) systems using a real dataset collected from a gas pipeline provided by Mississippi State University. In [50], another approach for SCADA attacks regarding Onmi Intrusion Detection Systems (IDS) is studied using a hybrid LSTM and Feedforward Neural Network (FNN).

IV. CHALLENGES OF USING MACHINE LEARNING IN MODERN POWER SYSTEMS

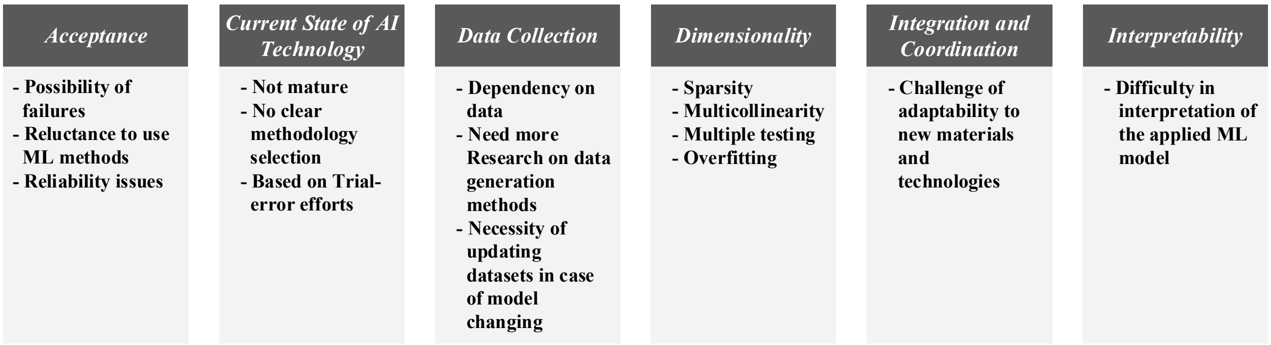
The current ICT environment as well as the interest in AI has pushed forward its evolution to AI 2.0, leading to smart power systems [12]. However, the implementation of ML techniques in power systems suffers from some main challenges as shown in Fig. 4 which are discussed in detail as follows:

- *Acceptance*: Due to the critical consequences of possible failures in AI techniques, conventional methods are always preferred, since they are based on well-known physical laws. As a result, the transition to ML techniques needs to convince experts and managers who are responsible for the reliability of modern power systems [15],[51].

- *The current state of AI technology*: Research on AI is still in its preliminary stage. As a result, there is no clear methodology selection for a specific ML algorithm and its hyperparameters for a determined power system task. In fact, most of the time, the researchers are dealing with a trial-error effort [14], [22].

- *Data collection:* The quality of the data used impacts ML effectiveness; therefore, more research on current data generation methods is required [22]. Moreover, any change in the topology of a large-scale grid necessitates updating all training datasets. This translates to an increase in costs and resources, either with physical or simulated models [52].

- *Dimensionality*: A common mindset while implementing any ML technique is that more information is better, but the challenge known as the Curse of Dimensionality (CoD) cannot be ignored. There are four main issues related to dimensionality: sparsity, multicollinearity, multiple testing, and overfitting. CoD can be affected by the amount of data and/or by the number of features used [53].



Acceptance	*Current State of AI Technology*	*Data Collection*	*Dimensionality*	*Integration and Coordination*	*Interpretability*
- Possibility of failures - Reluctance to use ML methods - Reliability issues	- Not mature - No clear methodology selection - Based on Trial-error efforts	- Dependency on data - Need more Research on data generation methods - Necessity of updating datasets in case of model changing	- Sparsity - Multicollinearity - Multiple testing - Overfitting	- Challenge of adaptability to new materials and technologies	- Difficulty in interpretation of the applied ML model

Fig. 4. Challenges in the implementation of machine learning techniques.

- *Integration and Coordination*: One key challenge in the implementation of ML techniques in power systems is its coordination with new materials and technologies in modern power systems such as RESs, EVs, etc. [14].
- *Interpretability*: ML models are seen as black-box solutions. With the increase of complex architectures, these become opaque solutions. An improvement in the understanding of these techniques can guide us to the correction of their deficiencies and biases when developing ML models [2],[54].

V. CONCLUSION

Power system modernization incorporating renewable sources and electric vehicles has brought some new control and protection challenges that cannot be overcome using traditional analytical methods. Therefore, the application of some advanced computer-based approaches such as machine learning techniques has attracted much attention in recent years. The aim of this article was to offer an extensive review of recent ML in terms of power quality, power stability, energy and load forecasting, protection and fault diagnosis, and cybersecurity. Lastly, the main difficulties of deploying ML techniques in modern power systems were presented which need to be taken into account for the development of future netowrks.

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