

Review

Machine Learning and Artificial Intelligence Techniques in Smart Grids Stability Analysis: A Review

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Abstract

The incorporation of renewable energy sources in power grids has necessitated innovative solutions for effective energy management. Smart grids have emerged as transformative systems which integrate consumer, generator and dual-role entities to deliver secure, sustainable and economical electricity supplies. This review explores the important role of artificial intelligence and machine learning approaches in managing the developing stability characteristics of smart grids. This work starts with a discussion of the smart grid's dynamic structures and subsequently transitions into an overview of machine learning approaches that explore various algorithms and their applications to enhance smart grid operations. A comprehensive analysis of frameworks illustrates how machine learning and artificial intelligence solve issues related to distributed energy supplies, load management and contingency planning. This review includes general pseudocode and schematic architectures of artificial intelligence and machine learning methods which are categorized into supervised, semi-supervised, unsupervised and reinforcement learning. It includes support vector machines, decision trees, artificial neural networks, extreme learning machines and probabilistic graphical models, as well as reinforcement strategies like dynamic programming, Monte Carlo methods, temporal difference learning and Deep Q-networks, etc. Examination extends to stability, voltage and frequency regulation along with fault detection methods that highlight their applications in increasing smart grid operational boundaries. The review underlines the various arrays of machine learning algorithms that emphasize the integration of reinforcement learning as a pivotal enhancement in intelligent decision-making within smart grid environments. As a resource this review offers insights for researchers, practitioners and policymakers by providing a roadmap for leveraging intelligent technologies in smart grid control and stability analysis.

Keywords: smart grids; renewable energy resources; machine learning; artificial intelligence; stability analysis; grid stability; resonance stability; converter-based stability; grid control; sustainable energy; neural network; reinforcement learning; deep learning; support vector machine; power systems



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1. Introduction

It is essential to incorporate renewable energy sources into the power grid as energy systems are constantly evolving with growth in demand and the development of new technologies like large-scale hydrogen production plants [1,2]. This is rapidly advancing due to global concerns about fossil fuel usage, climate change, global warming and the decreasing costs of renewable technologies [3,4]. However, renewable energies, because of their uncertain and variable characteristics, present challenges that require innovative

and creative solutions for effective, efficient and sustainable energy management [5,6]. The emergence of smart grids is considered a major change in power grids in response to these challenges. These grids introduce an advanced model of energy systems in which consumers, producers and dual-role entities are intelligently connected, with the main goal of providing an integrated, economical, secure and sustainable source of electricity [7,8]. Smart grids strive to effectively manage various energy sources and help improve the overall efficiency and effectiveness of power grids [9].

The definition of a smart grid emphasizes its characteristics such as stability, flexibility, reliability, safety and efficiency as an electrical energy system. These characteristics include stability in transient and steady state, as well as the application of intelligent computing in power consumption, distribution, substations, transmission, and generation sectors [10,11]. The smart grid has a significant importance in increasing the share of renewable resources that are stochastic and intermittent in nature, which is effective in reducing pollution [11].

In the past, before renewable energy became popular, traditional systems consisted of a limited number of generating centers that supplied the energy needed by consumers and the energy flow was one-way. With the advent of renewable energy, a new role was created called the “prosumers”: individuals or entities that are both consumers and producers of energy [12,13]. To transform networks into two-way systems, there is a need to manage the flow of energy in both directions. The increase in the number of these consumers has made the process of energy production, distribution and consumption more complex [14]. This complexity has also affected economic decisions, especially in the field of buying or not buying energy at a certain price, which has now become much more difficult than in the past [15,16]. Smart grids enable two-way energy flow, facilitate both the consumption and sale of electricity and are compatible with new technologies such as microgrids [17], electric vehicles [18] and energy storage systems [19]. Energy market activation is also an important aspect of the smart grid, which helps optimize consumption and promote economic welfare [20].

Despite these advances, safe maintenance and sustainable operations remain fundamental requirements. The complexity of bidirectional flows and the diversity of energy sources make traditional methods of stability analysis and control ineffective. In this regard, artificial intelligence (AI) has been proposed as a promising solution that can respond to the stability challenges in smart grids and meet the high requirements of security and stability [21,22].

Power system stability is a key pillar for the reliable operation of today’s smart grids. This issue has become even more important with the vast changes in the global energy landscape and the introduction of renewable sources, such as wind and photovoltaic (PV), that are connected to the grid through power converters (PCs) [23,24]. Over the past twenty years, more than 1200 GW of these sources have been added to the power grid worldwide. This trend has transformed grid structures, control methods and operational procedures, and has created new challenges for maintaining stability [25,26].

In countries such as Denmark, Australia and Norway, the amount of energy generated from PC-interfaced renewable sources sometimes exceeds the total instantaneous demand that creates the need to export electricity [27,28]. For instance, Denmark often makes more electricity from wind and increasingly from solar than it uses at certain times of the day. In 2020, variable renewables in western Denmark met more than 100% of demand for 2117 h and even 213% of demand in a peak hour. During peak hours, they met up to 350% of local load [29]. Norway also exports about 15% of its annual generation (24.7 TWh in 2021) and imports about 7.6 TWh. This is possible because of interconnectors and a lot of hydropower [30]. In Australia, rooftop solar and large-scale PV now meet more than 40% of daytime demand. During sunny times, they even drive spot prices down [31]. In such

situations, system operators use advanced monitoring and control mechanisms such as SCADA systems and synchro phasor-based instruments. These instruments monitor key parameters such as voltage, frequency and rotor angle to maintain stability [32,33].

In the past, power system stability was defined based on the performance of networks dominated by synchronous machines and traditional turbine generators (TGs). In this classical framework, rotor angle, frequency, and voltage stability were the main axes and were well-suited for older systems [34,35]. However, with the rapid growth of PC-interfaced renewables and structural changes in modern networks, new instability phenomena have emerged that do not fit into the classical frameworks [36,37]. Therefore, there is a need to review and develop these classifications. In response to this need, IEEE formed a working group in April 2020 [38] and published a report titled “Stability definitions and characterization of dynamic behavior in systems with high penetration of power electronic interfaced technologies.” As shown in Figure 1, a new classification is presented while maintaining many of the traditional principles, and adding two important branches: resonant stability and converter-based stability [38,39].

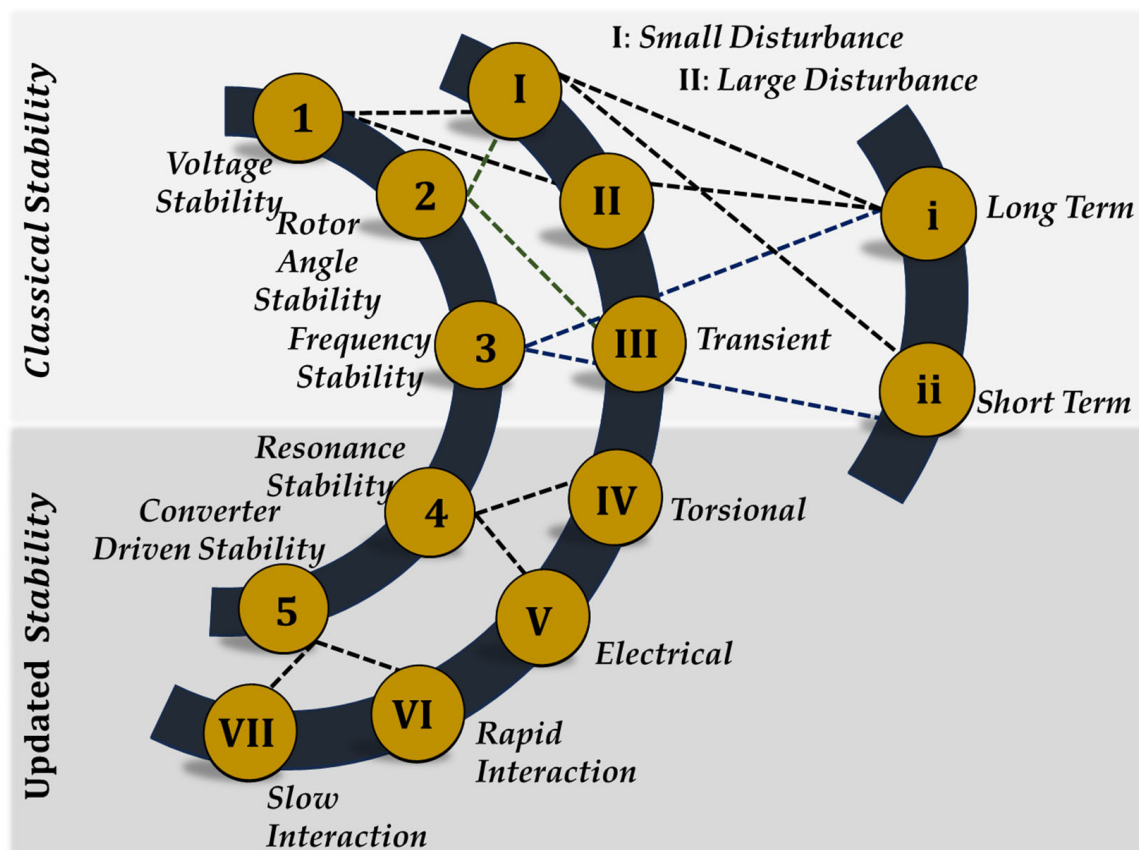


Figure 1. Updated stability classification framework for power systems with high penetration of power electronic interfaces: inclusion of resonant and converter-based stability.

Resonance stability includes phenomena such as electrical resonances, sub-synchronous control interactions (SSCI), induction generator effects and mechanical torsional vibrations. These phenomena often arise from the interaction between rotating machines and networks with series compensators or devices such as static synchronous compensators (STATCOMs) [40,41]. On the other hand, converter-based stability addresses instabilities that arise from complex, multiscale controls of converter-interfaced generators (CIGs). These instabilities can produce large frequency oscillations that arise from the interaction between electromechanical and electromagnetic behaviors [42]. This type of stability is divided into

two parts: slow interactions (less than 10 Hz) and fast interactions (from a few tens of Hz to kilohertz) [43,44]. As stated in [25,27], the key factors affecting the new generation of energy systems, of which smart grids are a small example, can be classified according to Figure 2.

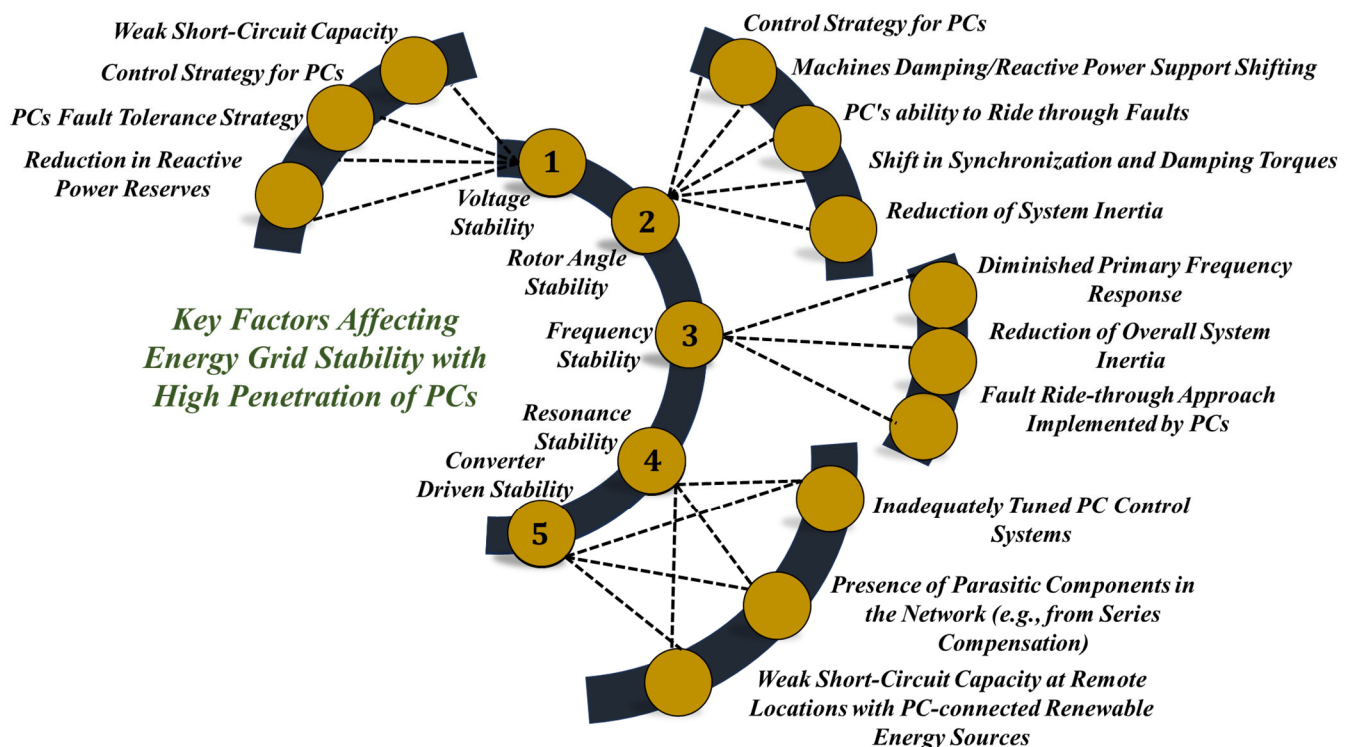


Figure 2. Classification of key factors affecting energy systems with high penetration of power electronic interfaces.

In this review paper, the importance of machine learning (ML) and AI strategies to improving the stability and efficiency of smart grids is investigated. As societies shift to the usage of clean and sustainable energy resources, the application of AI/ML algorithms to optimize the stability, structure and performance of smart grids accumulates growing significance. Since its emergence, artificial intelligence has advanced to the point where computers can simulate human behavior and thinking [44].

This technology has now become an integral part of many industries [45], economies [46] and everyday activities, providing solutions to complex problems such as natural language processing [47], machine vision [48], and autonomous driving [49]. Smart grids also benefit from AI innovations. The use of machine learning, deep learning and reinforcement learning methods in these networks have significant importance in maintaining sustainability, security and reliability [50,51].

The integration of AI-based methods into smart grids can manage the critical needs of these systems through fast and accurate computations and automated regulation. In the last few decades, the application of these techniques in areas such as security assessment [52], stability assessment [53], fault diagnosis [54] and stability control has been investigated, resulting in increased accuracy, speed and efficiency. These advances have reduced human workload and led to significant achievements [55].

In this review, the basic structures of smart grids are first introduced that emphasize their dynamic and changing characteristics. Then, conceptual models that have been proposed to address the specific challenges and needs of smart grids are discussed. Next, the paper reviews machine learning techniques and divides them into three categories: supervised/unsupervised and reinforcement learning. In this section, algorithms such as

Q-learning, State-Action-Reward-State-Action (SARSA) and the actor-critic algorithms are introduced, and their applications and roles in optimizing the performance of smart grids are reviewed. After that, advanced frameworks designed for the development of these networks are explained and the role of machine learning and artificial intelligence in solving challenges such as distributed energy resources, load management, and probabilistic scheduling are described.

Topics such as stability, voltage and frequency regulation and fault detection methods are also reviewed and their application in analyzing and improving the performance of smart grids is described. In the following, a set of machine learning algorithms and patterns is discussed that have led to the advancement of artificial intelligence in various applications of these networks. Also, the integration of reinforcement learning is introduced as an important step in expanding the capabilities of intelligent decision making in complex and dynamic environments.

Lastly, this review paper tries to give a full picture of how machine learning tools and artificial intelligence techniques can help smart grids become more stable and efficient. By examining structures, frameworks, and applications, this research can be a useful resource for researchers, professionals, and policymakers who are active in the field of smart grid stability analysis.

The subsequent sections of the paper are organized as follows: Section 2 illustrates the material and methods employed in this study. In Section 3, smart grids and dynamic structures are reviewed. Section 4 reviews machine learning methods in smart grid optimization. The Section 5 reviews the applications of machine learning and artificial intelligence in stability, frequency regulation, voltage control and fault detection in smart grids. Section 6 presents the discussion and a detailed exploration of the key challenges and future research trends. In Section 7, the main points are summed up and ideas for future research in the field of integrating machine learning, artificial intelligence and smart grids are given.

2. Materials and Methods

This review systematically investigates recent progress in the application of ML and AI techniques for stability prediction, classification and control in smart grids. To make sure comprehensive coverage, a structured literature search was done in major academic databases like IEEE Xplore, ScienceDirect and Google Scholar. The search used targeted keywords like smart grids, renewable energy resources, machine learning, artificial intelligence, stability analysis, sustainable energy and neural networks. Publications from the last ten years were prioritized to cover state of the art progress. Studies were selected based on their relevance to stability analysis and control in smart grids which has renewable energy sources. To give a balanced view, both theoretical contributions and practical implementations are included. The studied ML and AI approaches are classified into critical groups that reflect their underlying principles and applications: (i) Supervised learning that includes algorithms like support vector machines, decision trees, artificial neural networks, extreme learning machines and ensemble learning, primarily employed for fault detection, load forecasting and classification tasks. (ii) Unsupervised learning is used for clustering and anomaly detection to find unusual patterns that affect the stability of the grid. (iii) Reinforcement learning that includes dynamic programming, Monte Carlo methods, temporal difference methods and Deep Q-Networks. These are used in smart areas like advanced control and decision making in unstable conditions. (iv) Bayesian methods that utilized probabilistic graphical models to measure uncertainty and make predictions more reliable. (v) Additional approaches, such as probabilistic graphical models, active learning and transfer learning were also reviewed for their contributions to enhance model generalization and adaptability. This classification framework makes it possible to look at

how different AI and ML methods support smart grids to run smoothly and sustainably especially when it comes to using intermittent renewable energy sources.

3. Smart Grids and Their Structures

As societies have become modern, the power grid has an important role in transporting electricity from the point of production to the point of consumption. However, concerns about fossil fuel resources, climate change and the decreasing costs of renewable energy have increased the need to integrate sources like solar and wind power into energy systems [56]. The uncertain and variable character of renewable energy resources, being non-dispatchable, posed challenges for conventional power grids [56,57]. In response to these challenges, the smart grid emerged as a creative electric energy grid designed to facilitate large-scale integration of renewable power sources in a more economical, efficient, sustainable and effective manner [9,16,19].

Smart grids have brought about a significant transformation in power grid architecture. They provide intelligent connectivity between consumers, producers, and dual-roles with the advanced power grid [58,59]. The European Technology Platform defines a smart grid as a system that aims to provide affordable, secure and sustainable electricity. The National Institute of Standards and Technology (NIST) has expanded this definition. NIST emphasizes the integration of communication and computing services within energy systems. This integration enables bidirectional communication and intelligent control of energy flows [60,61]. The US Energy and Security agency also highlights the importance of smart grids in updating distribution and transmission systems. It emphasizes the creation of infrastructure that is secure, reliable, and ready for future growth [62]. Smart grid infrastructure is dynamic and constantly evolving to respond to new needs and capabilities [63]. The conceptual model provided by NIST divides smart grids into seven different areas. These areas include applications, actors, systems, partners and tools that make decisions and communicate critical information for application development [60]. Figure 3 depicts the relationship between these areas in the smart grid structure. Architecture has an important role in supporting various aspects of the smart grid.

Despite the complexity of the system, there is no single universal architecture. However, various models have been proposed to address specific challenges and functions [64,65]. Conceptual architectures, such as the model introduced in [63,66], focus on issues such as renewable energy sources' integration, optimization, adaptability, consumer interaction and self-healing capabilities. One key area is smart grid management. In this context, a model for key management in Advanced Metering Infrastructure (AMI) is introduced in [67] to address security concerns and ensure network authenticity. Reference [67] also proposes a network vision for smart transmission that includes smart interaction, substations, and related components. Smart grid models have also examined the use of different energy sources. These models use agent-based modeling to represent load, distribution, transmission, and integrated generators [68]. Also, in [69,70], a service-oriented and real-time event-based middleware framework is proposed that ensures security, reliability and collaboration between smart grid services. Probabilistic and stochastic evaluation structures have also been used in this context to address the uncertainties of distributed energy resources (DERs) [71]. In [72], an innovative method for dimensionality reduction in the application of heuristic optimization techniques to multi-objective problems is proposed. This method is designed to reduce peak loads and losses and increase the profits of electric vehicle (EV) owners. In [73], a stochastic hyper framework based on cloud theory is also developed to address DER uncertainties and distribution feeder reconfiguration. The results show the satisfactory performance of this model in IEEE distribution test systems. Decentralized frameworks in smart grids offer innovative solutions to optimize household load management and enhance user convenience

and privacy [74]. In [75], a non-cooperative iterative game theory is proposed to manage consumer load, achieve economic benefits, and reduce peak load. Finally, model predictive control as an intelligent control method was introduced by Lu et al. in [76]. They presented an eight-layer cloud-based decentralized model designed for applications such as direct load control, intensive energy management and direct data processing.

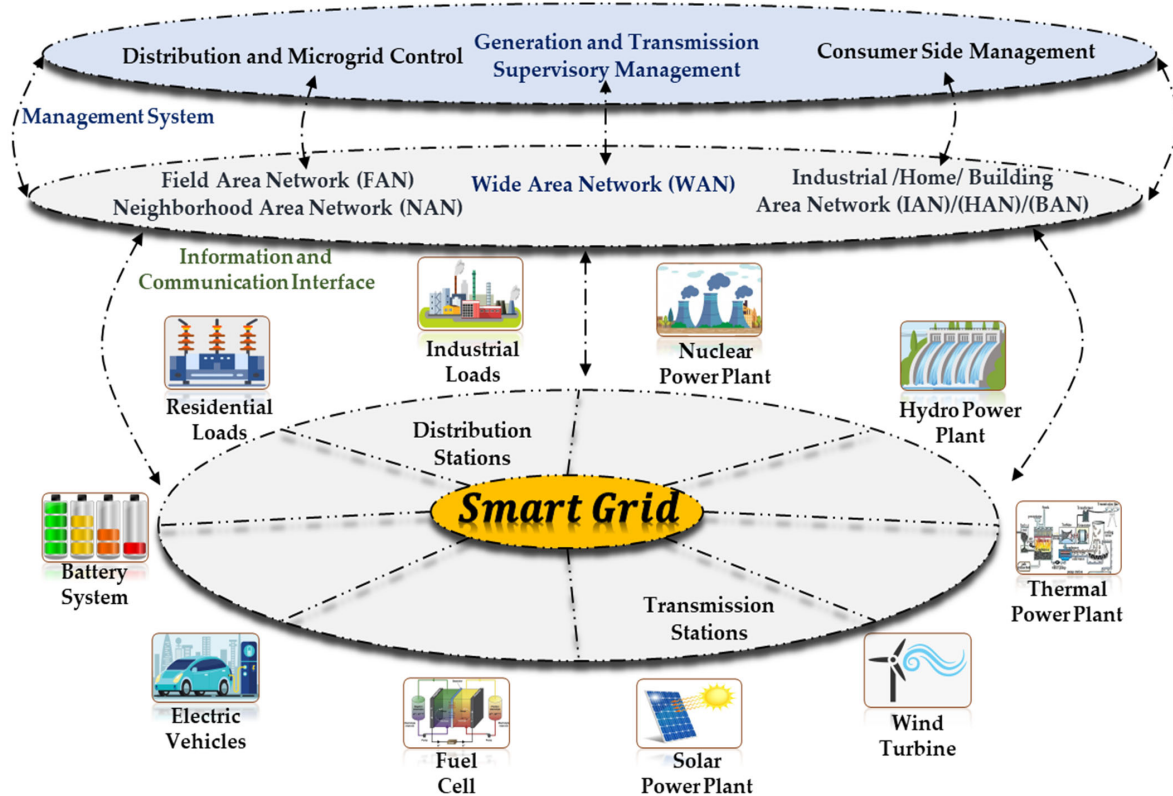


Figure 3. Structure of smart grid, including solar, wind, hydro, nuclear and thermal power plants.

Distributed hierarchical charge control structures in smart grids play a crucial role in coordinating EVs and generation units. EVs contribute significantly to DES and demand response (DR), as demonstrated in [77] where the authors present a smart grid structure which assigns charging limitations to EVs founded on charging preferences. Distributed hierarchical load control structures in smart grids play an important role in coordinating between EV and generation units. EVs are significantly effective in demand management and DES [78,79]. In [80], a structure for a smart grid is proposed that allocates charging control points to EVs based on charging priority. In [81], a distributed hierarchical load control architecture using bender decomposition is proposed. This framework reduces operating costs and improves network efficiency.

Markov frameworks provide a probabilistic approach to modeling components and interactions in a smart grid [82]. Authors in [82] proposed a dependent Markov chain model to make cascading faults/disturbances in cyber electrical infrastructures. Reference [83] have introduced a Markov decision strategy infrastructure for local inspection and online scanning of malware footprints in AMI networks. Risk management and vulnerability management are essential to maintain smart grid robustness [84,85].

Authors in [84] have designed a game-theoretic model that evaluates the impact of critical components on a cyber-physical system. Authors in [86] have also proposed a framework based on the multi-agent system (MAS). This model is applicable to fault location, recovery and isolation in self-healing distribution networks. Also, researchers in [87] have suggested an infrastructure employing the Internet of Things to predict user

behavior and mitigate risk in power systems. These frameworks, presented for smart grids, demonstrate the complexity of this domain and the need for multi-dimensional solutions. Every architecture solves a particular problem in smart grids and shows how the different parts of the system are connected. The next part talks about different ML strategies and how they affect the control and stability of smart grids.

4. Overview of Machine Learning Techniques

Machine learning is an important branch of AI that focuses on identifying patterns in existing data [88,89]. As depicted in Figure 4, ML algorithms analyze the characteristics of input signals to build benchmarks for tasks like prediction, classification and clustering. This field includes a diverse set of algorithms that are usually divided into three categories: supervised, unsupervised and reinforcement learning (RL) [90,91].

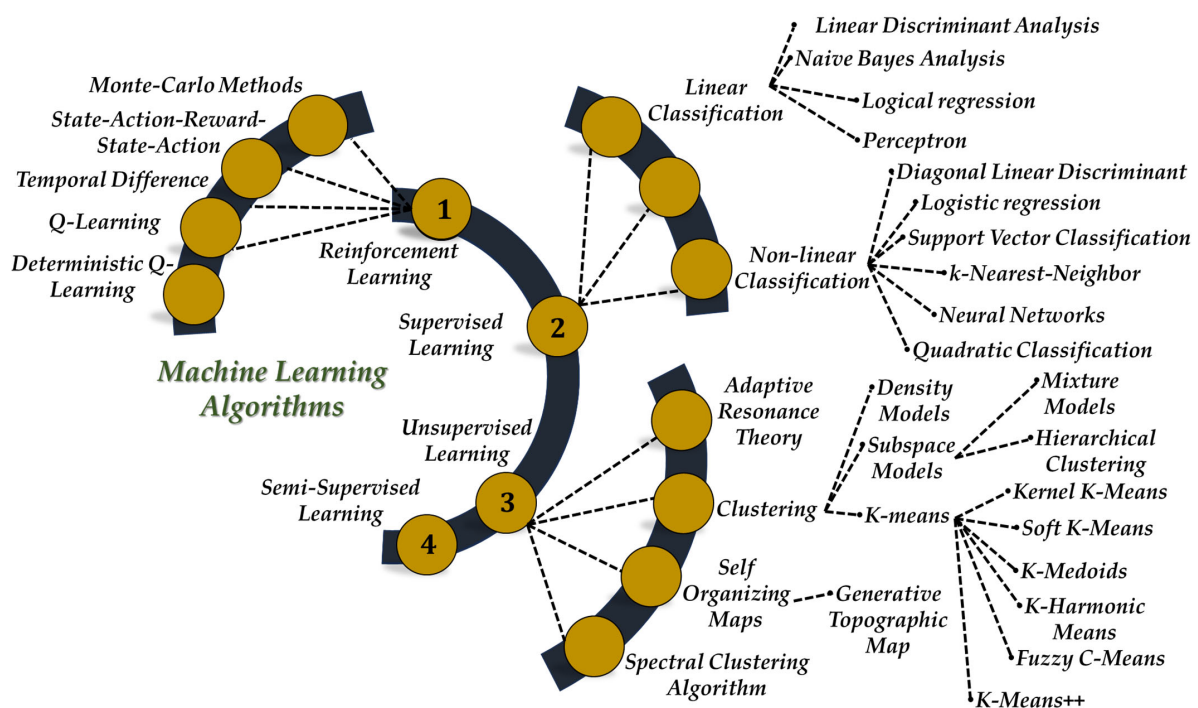


Figure 4. Classification of machine learning algorithms including supervised, unsupervised, semi-supervised and reinforcement learning.

In supervised learning, data consisting of target input and output values are used. The goal is to train a model that can create a map between the input and output. Linear regression, support vector machines and random forests are some of the most common algorithms in this group [92–96]. Unsupervised learning works with data that doesn't have labels. The purpose of this strategy is to find patterns and structures in the data that are not obvious. This field often has challenges with clustering and finding connections between data. Algorithms like k-means and autoencoders are utilized to solve these problems. RL takes a goal-oriented approach [97–100].

In this method, an agent interacts with the environment to maximize the long-term cumulative reward based on its experiences [93]. The main framework in RL is the Markov decision process (MDP). In this framework, the agent seeks optimal solutions for successive decisions [101]. RL takes a goal-oriented approach. In this method, an agent interacts with the environment to maximize the long-term cumulative reward based on its experiences [102,103]. The main framework in RL is the MDP. In this framework, the agent seeks optimal solutions for successive decisions [104]. One of the key elements in RL is

to strike a balance between exploration and exploitation. RL algorithms are divided into two groups: model-based and model-free. In model-based methods, such as dynamic programming (DP), the agent achieves optimal policies with complete knowledge of the environment [105]. In contrast, model-free RL is trained by interacting directly with the environment. Temporal difference (TD) methods, such as Q-learning and SARSA, are examples of this class [106]. The Q-learning algorithm is a model-free TD method that operates outside of the policy. It makes the next decision based on the highest Q value in the next state which enables learning through observation [51,107]. The SARSA algorithm is similar to Q-learning, but its updates are based on the current policy [108].

The actor-critic algorithm is a combination of policy based and value-based methods. It provides a balance between these two approaches [108]. Bayesian methods are used in RL to deal with uncertainty. They provide a solution to the conflict between exploration and exploitation by modeling uncertainty in the learned parameters. Models such as myopic sampling and Thompson help to increase the reward [109,110]. Deep Q-Network (DQN) offers a version of Q-learning in the context of deep learning by using neural networks to approximate functions. This approach has been able to overcome the challenges associated with large state spaces [111]. An overview of machine learning techniques, classifications, applications and remarks in the smart grid is presented in Table 1.

Table 1. Overview of machine learning methods, categories, applications and remarks.

Framework Category	Application	Descriptions/Remarks	References
Supervised Learning	Classification, Regression	Uses labeled data for training; finds mapping function from input to output.	[92–96]
Unsupervised Learning	Clustering, Association	May face challenges with very large datasets, complex training.	[97–100]
Reinforcement Learning	Decision Making, Exploration-Exploitation	Agent interacts with environment to maximize long-term rewards; involves Markov Decision Process (MDP).	[102,103,112]
Dynamic Programming	Optimal Policy in Sequential Decision Problems	Model-free approach using randomness for problem solution.	[105,113]
Monte Carlo Methods	Optimal Solutions through Direct Interaction	Requires careful tuning, may suffer from overfitting.	[101,114]
Temporal Difference Methods	Exploration-Exploitation Dilemma, Uncertainty Modeling	Utilizes Bayesian models to address uncertainty and guide exploration-exploitation.	[106,115]
Deep Q Network	Function Approximation in Large State Space	Uses neural network for function approximation in large state space; based on Q-learning.	[116,117]
Bayesian Methods	Exploration-Exploitation Dilemma, Uncertainty Modeling	Utilizes Bayesian models to address uncertainty and guide exploration-exploitation.	[109,110]
Support Vector Machine	Classification, Regression	Finds optimal hyperplane for classification and regression; supports nonlinear division.	[118,119]
Decision Tree	Decision Making, Classification	Utilizes tree-like structure for decision-making based on nested rules.	[120,121]
Artificial Neural Network	Nonlinear Relationships, Pattern Recognition	Represents relationships through layers of neurons; fits nonlinear relationships.	[122,123]
Extreme Learning Machine	Efficient Training of Neural Networks	Single hidden layer with random weights; efficient training without iteration.	[124,125]
Probabilistic Graphical Models	Bayesian Networks, Hidden Markov Models	Represents relationships between variables through graph-based probabilistic models.	[126,127]
Ensemble Learning	Improved Performance and Generalization	Combines diverse models to enhance performance and generalization.	[128,129]
Active Learning	Selective Labeling for Improved Model Performance	Queries the user for labels to achieve similar performance with fewer labeled data.	[130,131]
Transfer Learning	Knowledge Transfer for New Tasks, Transferring Model Structure and Parameters	Utilizes knowledge from related tasks for training models in new tasks. Adjusts weights based on similarity between source and target domain instances.	[132,133]

In the field of machine learning various algorithms are used in different applications. Support vector machine (SVM) [118], DT [120], artificial neural network (ANN) [122,123] and extreme learning machine (ELM) [124] are among the important algorithms. Furthermore, probabilistic graph models (PGM), such as Bayesian networks and hidden Markov models (HMM) [134], represent the relationships between variables in a probabilistic way. Ensemble learning paradigms like bagging and boosting algorithms including gradient boosted decision tree and Extreme Gradient Boosting (XGBoost) [135], improve the performance and generalizability of models. Active learning is a type of semi-supervised learning that reduces the problem of a lack of labeled data by purposefully selecting queries from a knowledgeable source to obtain labels [130,131].

Transfer learning also manages the issues of limited labeled samples by utilizing information from similar tasks that use approaches such as instance-based, feature-based, relational or model-based [132,133]. As shown in Table 1, machine learning encompasses a diverse set of algorithms and approaches that are contributing to the advancement of artificial intelligence in various fields. Figures 5–8 depict the general pseudocode for the algorithms that are listed in Table 1. Figure 5 illustrates basic learning paradigms, such as supervised learning which uses labeled data to learn a mapping function for classification and regression tasks; unsupervised learning which finds hidden patterns like clusters or associations in unlabeled complex data; reinforcement learning where an agent interacts with an environment to maximize cumulative rewards; dynamic programming which is used to solve sequential decision problems by breaking them down into smaller problems to find the best policies; and Monte Carlo methods which estimate solutions by taking random samples many times (although they need careful tuning and can be prone to overfitting). Figure 6 shows more specific methods, such as DQN, which employ neural networks to approximate Q-values in large state spaces; temporal difference methods which learn directly from raw experience without waiting for outcomes and help manage the exploration-exploitation trade-off; Bayesian methods that model uncertainty and guide exploration using probabilistic inference; SVM which are used for classification and regression by finding the best hyperplane even for nonlinear boundaries; and ELM which is a single-layer feedforward neural network with randomly initialized hidden nodes and efficient training.

Figure 7 shows ANNs that are built up of layers of connected neurons that learn complicated nonlinear patterns and DTs that make choices based on a hierarchy of rules. Probabilistic graphical models like Bayesian Networks and Hidden Markov Models, use graphs to show probabilistic connections. Transfer learning adapts models which have been trained on one task to work effectively on a similar task. Moreover, Figure 8 illustrates ensemble learning that combines multiple models to improve overall performance and generalization and active learning which enhances model efficiency by selectively querying the most informative data points for labeling, decreasing the need for large/labeled datasets. Combining reinforcement learning with these methods enables smarter decision making in complex and dynamic environments [72]. Figure 9 shows that the generalized machine learning flowchart has a number of structured processes like preparing the data, setting up the model, training and evaluating its performance.

Algorithm1: Supervised Learning Algorithm**Input**

- Training dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ where $x_i \in \mathbb{R}^m$: feature vector for sample i with m features and $y_i \in Y$: true label or output for sample i
- Model $f(x; \theta)$: a function parameterized by θ that maps input x to output $\hat{y}$
- Loss function $L(y, \hat{y})$: measures the error between predicted output $\hat{y}$ and true label y
- Hyperparameters: $\eta \in \mathbb{R}^+$ → learning rate → step size for parameter updates, $E \in \mathbb{N}^+$ → number of training epochs → full passes over dataset and $B \in \mathbb{N}^+$ → batch size → number of samples per training batch

Output

- Trained model $f(x; \theta^*)$ with optimized parameters θ^*

Protocol

- Initialize** model parameters θ randomly or using heuristic
- For epoch = 1 to E**:
 - Shuffle training dataset D randomly
 - Divide D into mini-batches of size B
 - For each mini batch $M \subset D$** :
 - For each (x_i, y_i) in mini batch M** :
 - Compute prediction: $\hat{y}_i = f(x_i; \theta)$
 - Compute loss for sample: $L_i = L(y_i, \hat{y}_i)$
 - Compute average mini batch loss:

$$L_{\text{minibatch}} = \frac{1}{|M|} \sum_{(x_i, y_i) \in M} L_i$$
 - Compute gradients of $L_{\text{minibatch}}$ with respect to θ :

$$\nabla_{\theta} L_{\text{minibatch}}$$
 - Update model parameters:

$$\theta \leftarrow \theta - \eta \nabla_{\theta} L_{\text{minibatch}}$$
- Return** trained model $f(x; \theta^*)$

(a)

Algorithm2: Unsupervised Learning**Input**

- Dataset $D = \{x_1, x_2, \dots, x_n\}$ where $x_i \in \mathbb{R}^m$: feature vector for sample i → with m features
- Model or method type → clustering, dimensionality reduction, ...
- Objective function $J(D, \theta)$: defines what structure the algorithm is trying to learn
 - Cluster compactness for clustering
 - Reconstruction error for dimensionality reduction
- Hyperparameters: $T \in \mathbb{N}^+$ → number of training iterations or convergence threshold, $\eta \in \mathbb{R}^+$ → learning rate → if applicable for model updates and $K \in \mathbb{N}^+$ → number of components/clusters

Output

- Learned model parameters θ or structure S

Protocol

- Initialize** model parameters θ or structure S
 - Randomly initialize K cluster centroids for clustering
 - Compute initial projection vectors
- Repeat** for $t = 1$ to T or until convergence:
 - For each sample x_i in D** :
 - Perform assignment or transformation step:
 - assign x_i to nearest cluster or compute lower-dimensional representation
 - Update model parameters θ or structure S based on current assignments or projections:
 - Update centroids, principal components or latent features
 - Recalculate objective function $J(D, \theta)$
- Return** learned structure S or model parameters θ

(b)

Algorithm3: Reinforcement Learning**Input**

- Environment E with S → set of possible states, A → set of possible actions and $R(s, a)$ → reward function that returns reward after taking action a in state s and $T(s, a) \rightarrow s'$ is transition function
- Policy $\pi_{\theta}(a|s)$: function defining the agent's behavior parameterized by θ
- Discount factor $\gamma \in [0, 1]$: determines the importance of future rewards
- Learning rate $\eta \in \mathbb{R}^+$: controls step size during learning
- Number of episodes $E \in \mathbb{N}^+$: total training episodes
- Max steps per episode $T \in \mathbb{N}^+$

Output

- Optimized policy $\pi_{\theta}(a|s)$ or value function $V(s)$ or $Q(s, a)$

Protocol

- Initialize** policy parameters θ or Q-values, if value-based
- For episode = 1 to E**:
 - Initialize starting state s_0 from environment
 - For $t = 1$ to T do**:
 - Select action:

$$a_t \sim \pi_{\theta}(a|s)$$
 - Execute action a_t in environment and observe:
 - Next state s_{t+1}
 - Reward $r_t = R(s_t, a_t)$
 - Store experience (s_t, a_t, r_t, s_{t+1})
 - Update policy or value function using learning rule:
 - Value-based (like Q-learning):

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \eta [r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)]$$
 - Policy-based (like Reinforce):

$$\theta \leftarrow \theta + \eta \nabla_{\theta} \log \pi_{\theta}(a_t|s_t) G_t$$
 - where G_t is the return (cumulative discounted reward)
 - Set $s_t \leftarrow s_{t+1}$
 - Stop if s_t is a terminal state
- Return** optimized policy $\pi_{\theta}(a|s)$ or value function $Q(s, a)$

(c)

Algorithm4: Dynamic Programming**Input**

- State space S → finite set of states
- Action space A → finite set of actions
- Transition probability function $P(s' | s, a)$ → probability of next state s' given current state s and action a
- Reward function $R(s, a)$ → expected immediate reward for taking action a in state s
- Discount factor $\gamma \in [0, 1]$ → importance of future rewards
- Threshold $\theta \in \mathbb{R}^+$ → small positive number for convergence criterion

Output

- Optimal state-value function $V^*(s)$ for all $s \in S$
- Optimal policy $\pi^*(s)$ derived from $V^*(s)$

Protocol

- Initialize** value function $V(s)$ arbitrarily for all $s \in S$
- Repeat**:
 - Initialize maximum change in value: $\Delta \leftarrow 0$
 - For each state $s \in S$** :
 - Store old value: $v \leftarrow V(s)$
 - Compute updated value:

$$V_{\text{new}}(s) \leftarrow \max_{a \in A} \left[R(s, a) + \gamma \sum_{s'} P(s' | s, a) V(s') \right]$$
 - Update $V(s) \leftarrow V_{\text{new}}(s)$
 - Update $\Delta \leftarrow \max(\Delta, |v - V_{\text{new}}(s)|)$
- Until** $\Delta < \theta$ (value function converged)
- Derive optimal policy $\pi^*(s)$:
 - For each state $s \in S$** :

$$\pi^*(s) = \arg \max_{a \in A} \left[R(s, a) + \gamma \sum_{s'} P(s' | s, a) V(s') \right]$$

(d)

- Return** $V^*(s)$ and $\pi^*(s)$

Algorithm5: Monte Carlo**Input**

- Environment E with states S and actions A
- Policy $\pi(a|s)$: the policy to evaluate or improve
- Discount factor $\gamma \in [0, 1]$: weighting of future rewards
- Number of episodes $N \in \mathbb{N}^+$: number of episodes to sample

Output

- Estimated state-value function $V(s)$, $\forall s \in S$
- action-value function $Q(s, a)$, $\forall (s, a)$

Protocol

- Initialize**
 - $V(s) \leftarrow$ arbitrary, $\forall s \in S$
 - $\text{Returns}(s) \leftarrow []$, empty list to store returns for each state s
- For episode = 1 to N**:
 - Generate an episode following policy π :

$$(s_0, a_0, r_1, s_1, a_1, r_2, \dots, s_T)$$
 - For each state s appearing in the episode**:
 - Let t be the first time step such that $s_t = s$
 - Calculate the return G_t from time t :

$$G_t = \sum_{k=t}^{T-1} \gamma^{k-t} r_{k+1}$$
 - Append G_t to $\text{Returns}(s)$
 - Update value estimate:

$$V(s) \leftarrow \frac{1}{|\text{Returns}(s)|} \sum_{g \in \text{Returns}(s)} g$$
- Return** $V(s)$

(e)

Figure 5. General pseudocode for machine learning algorithms: (a) Supervised Learning, (b) Unsupervised Learning, (c) Reinforcement Learning, (d) Dynamic Programming and (e) Monte Carlo Methods.

Algorithm6: Deep Q-Network (DQN)**Input**

- Environment $\mathcal{E}$ with states S and actions A
- Discount factor $\gamma \in [0, 1]$: weighting of future rewards
- Replay memory capacity $M \in \mathbb{N}^+$: maximum size of experience replay buffer
- Mini-batch size $B \in \mathbb{N}^+$: number of samples per training batch
- Learning rate $\eta \in \mathbb{R}^+$: step size for optimizer
- Number of episodes $N \in \mathbb{N}^+$: total training episodes
- Target network update frequency $C \in \mathbb{N}^+$: steps between target network updates
- Exploration parameters: $\epsilon_{start}, \epsilon_{min}, \epsilon_{decay}$

Output

- Trained Q-network with parameters θ

Protocol

- Initialize:**
 - Q-network $Q(s, a; \theta)$
 - Target Q-network $Q'(s, a; \theta) \leftarrow Q(s, a; \theta)$
 - Replay memory $D \leftarrow \emptyset$
 - Set $\epsilon \leftarrow \epsilon_{start}$
- For episode = 1 to N:**
 - Initialize** starting state s_0
 - For each time step t in episode:**
 - Select action a_t using ϵ -greedy policy:**

$$a_t = \begin{cases} \text{random action, with probability } \epsilon \\ \arg\max_a Q(s_t, a; \theta), & \text{otherwise} \end{cases}$$
 - Execute action a_t , observe reward r_{t+1} and next state s_{t+1}
 - Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in replay memory D
 - Sample mini-batch of B transitions $\{s_j, a_j, r_j, \tilde{s}_j\}$ from D
 - For each sampled transition compute target y_j :**

$$y_j = \begin{cases} r_j, & \text{if } \tilde{s}_j \text{ is terminal} \\ r_j + \gamma(\max_{a'} Q(\tilde{s}_j, a'; \theta)), & \text{otherwise} \end{cases}$$
 - Compute loss:**

$$L(\theta) = \frac{1}{B} \sum_{j=1}^B (y_j - Q(s_j, a_j; \theta))^2$$
 - Update parameters θ to minimize $L(\theta)$**
 - Every C steps: update target network $\theta' \leftarrow \theta$
 - Decay ϵ :**

$$\epsilon \leftarrow \max(\epsilon_{min}, \epsilon - \epsilon_{decay})$$
 - Update state $s_t \leftarrow s_{t+1}$**
 - If s_t is terminal, end episode**
- Return trained Q-network $Q(s, a; \theta)$**

(a)

Algorithm7: Temporal Difference Learning**Input**

- Environment $\mathcal{E}$ with states S and actions A
- Policy $\pi(a|s)$: policy used to select actions $\rightarrow$ can be fixed or improving
- Discount factor $\gamma \in [0, 1]$: weighting of future rewards
- Learning rate $\eta \in \mathbb{R}^+$: step size for updates
- Number of episodes $N \in \mathbb{N}^+$: total training episodes
- Max steps per episode $T \in \mathbb{N}^+$

Output

- Estimated state-value function $V(s), \forall s \in S$

Protocol

- Initialize** value function $V(s)$ arbitrarily, $\forall s \in S$
- For episode = 1 to N:**
 - Initialize** starting state $s_0 \sim \mathcal{E}$:
 - For $t = 0$ to $T-1$:**
 - Choose action a_t according to policy $\pi(a_t|s_t)$
 - Execute action a_t in environment and observe:
 - reward r_{t+1}
 - next state s_{t+1}
 - Update value function $V(s_t)$ using update rule:
$$V(s_t) \leftarrow V(s_t) + \eta [r_{t+1} + \gamma V(s_{t+1}) - V(s_t)]$$
 - Update state:
$$s_t \leftarrow s_{t+1}$$
 - If s_t is terminal stop:**
 - Return estimated value function $V(s)$**

(b)

Algorithm8: Bayesian Inference**Input**

- Dataset $D = \{x_1, x_2, \dots, x_n\}$ (observed data)
- Prior distribution $p(\theta)$ over model parameters θ
- Likelihood function $p(D|\theta)$: probability of data given parameters θ
- Model for predictions $p(y|x, \theta)$
- New input x^*

Output

- Posterior distribution $p(\theta|D)$
- Predictive distribution $p(y^*|x^*, D)$

Protocol

- Define prior belief about parameters θ :**

$$p(\theta)$$
- Collect observed data D**
- Compute posterior distribution using Bayes' rule:**

$$p(\theta|D) = \frac{p(D|\theta)p(\theta)}{p(D)}, \quad p(D) = \int p(D|\theta)p(\theta)d\theta$$
- For a new input x^* compute predictive distribution: assignments or projections:**

$$p(y^*|x^*, D) = \int p(y^*|x^*, \theta)p(\theta|D)d\theta$$
- Use approximate inference methods if posterior is intractable:**
 - Markov Chain Monte Carlo (MCMC)
 - Variational Inference
 - Laplace Approximation
- Make predictions or decisions based on the predictive distribution**

(c)

Algorithm9: Support Vector Machine (SVM)**Input**

- Training dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ where $x_i \in \mathbb{R}^m \rightarrow$ feature vector for sample i and $y_i \in \{+1, -1\} \rightarrow$ class label for sample i
- Regularization parameter $C \geq 0 \rightarrow$ soft-margin SVM
- Kernel function $K(x_i, x_j) \rightarrow$ nonlinear SVM

Output

- Optimal parameters $w \in \mathbb{R}^m$ and bias $b \in \mathbb{R}$ defining decision boundary
- Support vectors $\rightarrow$ subset of training samples

Protocol

- Formulate the optimization problem:**

$$\min_{w, b, \xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i$$

Subject to:

$$y_i (w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$
- Derive and solve the dual problem using Lagrange multipliers α_i :**
 - Maximize over α :**

$$\max_{\alpha} \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$
 - Subject to:**

$$\sum_{i=1}^n \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C$$
- Compute weight vector:**

$$w = \sum_{i=1}^n \alpha_i y_i x_i$$
- Compute bias term b using support vectors $\rightarrow$ Choose any support vector x_k with $0 < \alpha_k < C$:**

$$b = y_k - \sum_{i=1}^n \alpha_i y_i K(x_i, x_k)$$
- Define decision function for new input x :**

$$f(x) = \text{sign}(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b)$$
- Return w, b and support vectors (samples with $\alpha_i > 0$)**

(d)

Algorithm10: Extreme Learning Machine**Input**

- Training dataset $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$ where $x_i \in \mathbb{R}^m \rightarrow$ input features and $y_i \in \mathbb{R}^k \rightarrow$ target outputs
- Number of hidden neurons: N_h
- Activation function $g(\cdot)$

Output

- Output weights $\beta \in \mathbb{R}^{N_h \times k}$
- Trained input weights $W_{in} \in \mathbb{R}^{N_h \times m}$

Protocol

- Randomly initialize:**
 - Input weights $W_{in} \in \mathbb{R}^{N_h \times m}$
 - Biases $b \in \mathbb{R}^{N_h}$
- Compute hidden layer output matrix $H \in \mathbb{R}^{N_h \times N_h}$**
 - For each sample $x_i \in \mathbb{R}^m$ and hidden unit j :
$$H[i, j] = g(W_{in}[j]x_i + b[j])$$
- Calculate output weights β by solving the linear system:**

$$\beta = \text{Moore-Penrose pseudoinverse}(H^T) \times Y$$

where $Y \in \mathbb{R}^{N_h \times k}$ is the matrix of target outputs
- Prediction for new input $x^* \in \mathbb{R}^m$:**
 - Compute hidden layer output h^* :**

$$h_j^* = g(W_{in}[j]x^* + b[j]), \quad j = 1, \dots, N_h$$
 - Compute output:**

$$y^* = h^* \beta$$
- Return β and W_{in} and b for inference**

(e)

A) REINFORCE B) GRU C) LSTM D) RNN E) TDNN

A) REINFORCE B) GRU C) LSTM D) RNN E) TDNN

Figure 6. General pseudocode for machine learning algorithms: (a) Deep Q Network, (b) Temporal Difference Methods, (c) Bayesian Methods, (d) Support Vector Machine and (e) Extreme Learning Machine.

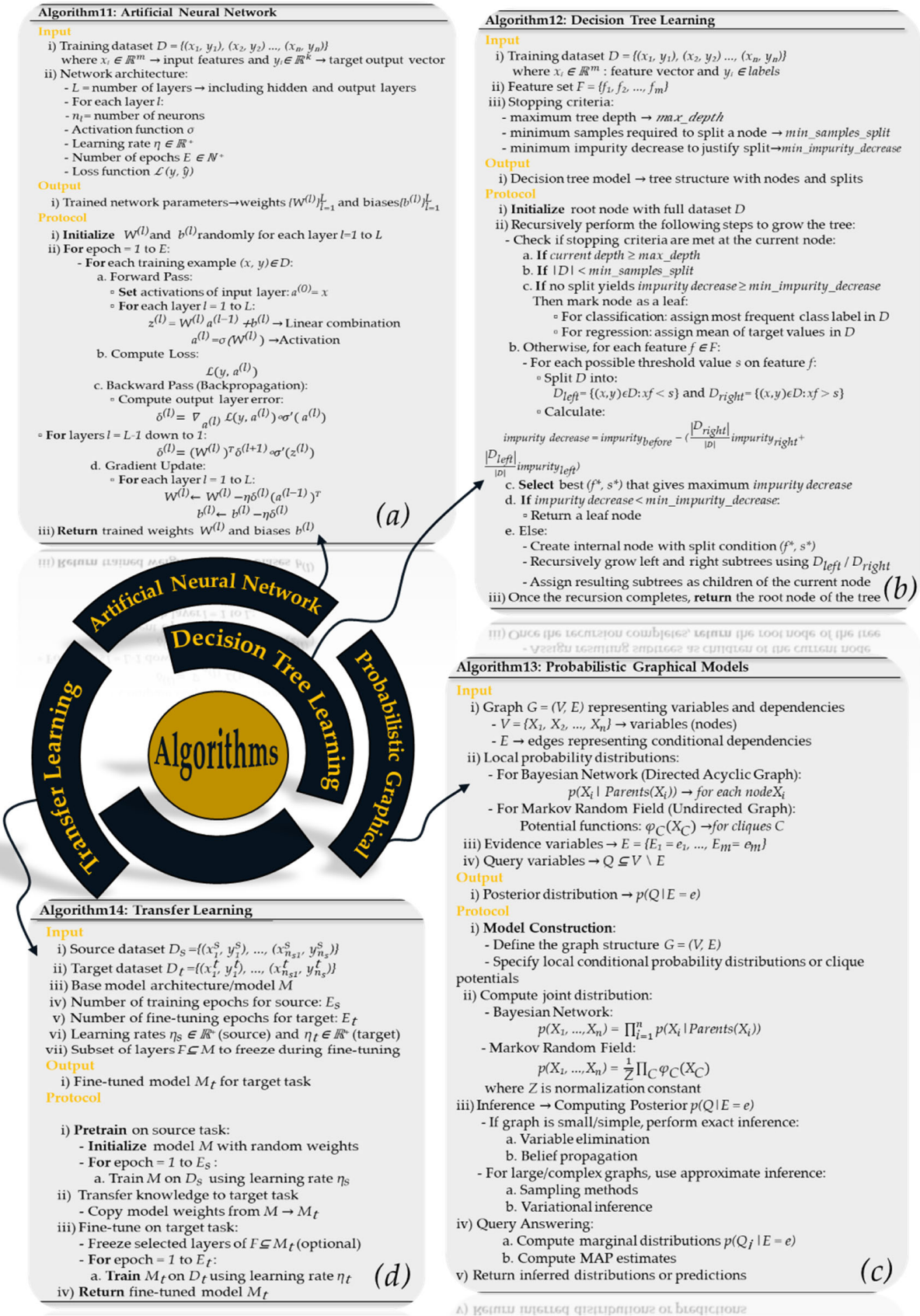


Figure 7. General pseudocode for machine learning algorithms: (a) Artificial Neural Network, (b) Decision Tree, (c) Probabilistic Graphical Models, (d) Transfer Learning.

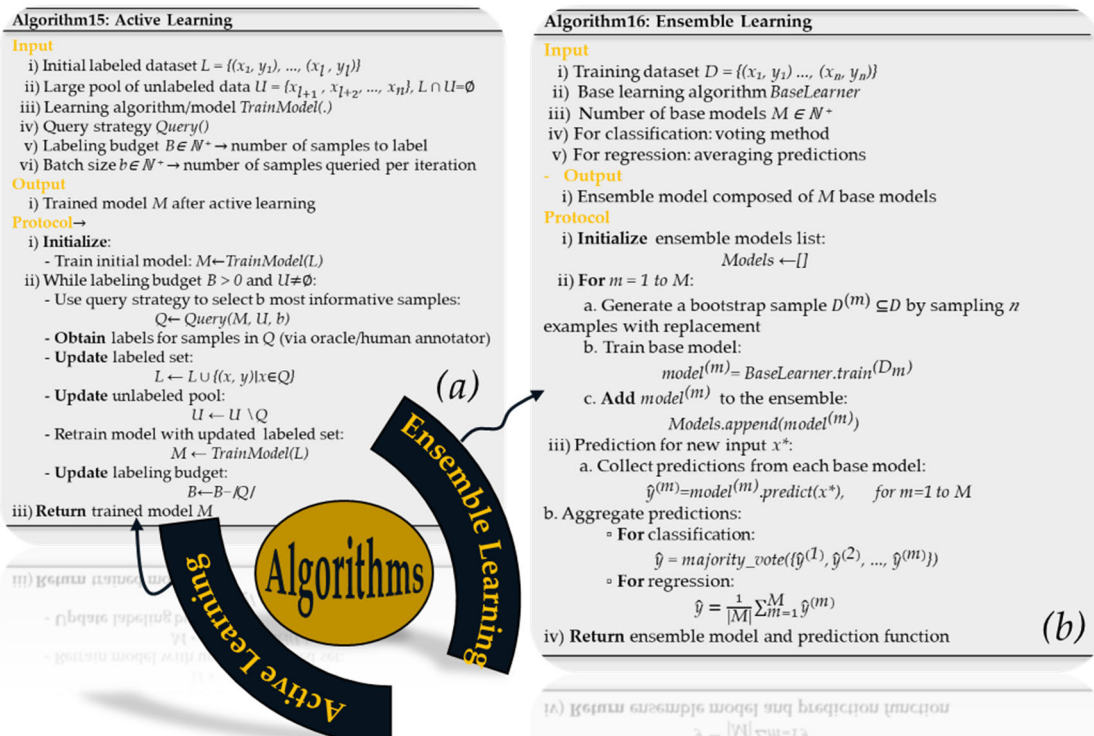


Figure 8. General pseudocode for machine learning algorithms: (a) Active Learning, (b) Ensemble Learning.

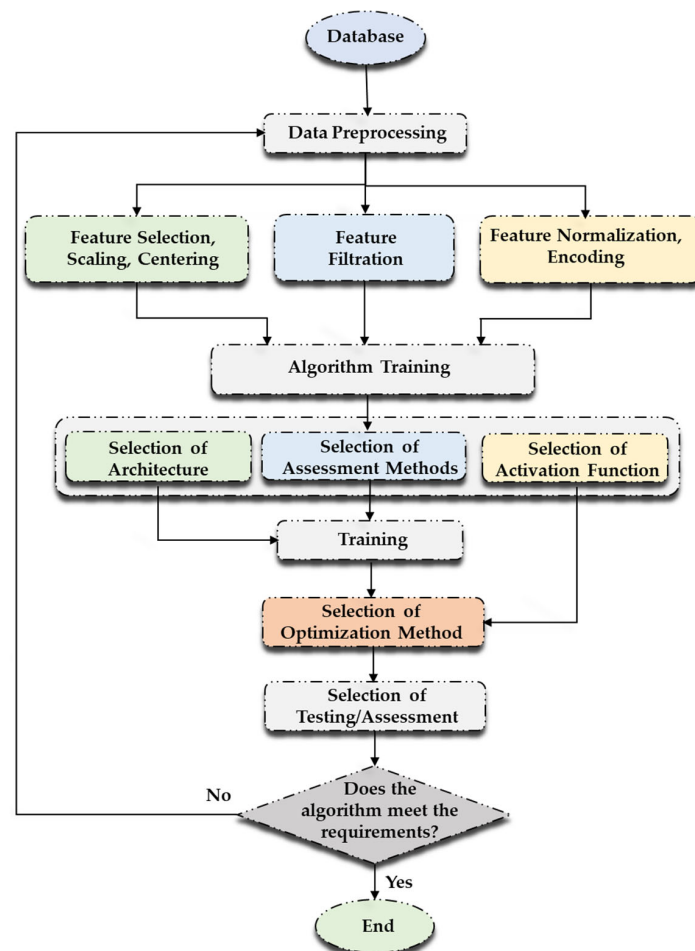


Figure 9. Systematic flowchart for machine learning algorithm design and development.

5. Artificial Intelligence Applications for Smart Grid Stability Analysis and Regulations

In recent years, the smart grid landscape has undergone significant changes because of factors such as the continuous increase in consumption demand, the introduction of volatile renewable energy sources, and the expansion of the liberalization of electricity markets and power electronics devices [136,137]. For this reason, the issue of stability has become one of the important concerns in these networks, which requires analysis and control with innovative approaches. Stability in a smart grid has three main dimensions that have been identified by the IEEE/CIGRE joint working group: rotor angle stability, voltage stability and frequency stability [138,139]. The investigation of these aspects requires methods that have the necessary speed and flexibility in addition to accuracy.

Rotor angle stability against severe disturbances is crucial for the coordinated operation of interconnected power systems. This has created challenges for conventional methods of stability assessment. Methods such as time-domain simulation and the use of transient energy functions have limitations in terms of computational complexity and conservatism [140,141].

Meanwhile, the application of artificial intelligence, especially ML, has given a new definition to the analysis of rotor angle stability. Machine learning enables fast online analysis by establishing a relationship between network variables and the stability state and provides the result immediately after receiving the data [142,143].

Several machine learning methods have been used in this field including SVM [118], ELM [144], deep belief networks (DBN) [145], denoising autoencoders (DAE) [146], Long Short-Term Memory (LSTM) networks [147] and convolutional neural networks (CNN) [148]. Shallow machine learning methods usually require manual or algorithmic feature extraction, such as the BinJaya binary model [99]. However, in deep learning (DL) like LSTM and CNN, the need for explicit feature design is eliminated.

Figures 10–15 show the architectures of the machine learning and deep learning methods mentioned above. Figure 10 depicts the structure of the SVM method and focuses on the idea of optimal hyperplane separation [118,149,150]. Figure 11 shows how the EML is built with a focus on its single hidden layer, with weights that are assigned randomly, and its ability to train fast [124,151]. Figure 12 illustrates the architecture of a deep belief network which is built up of stacked restricted machines that learn features without supervision [145,152]. The deep denoising autoencoder model is shown in detail in Figure 13 [146,153]. Figure 14 depicts the structure of a CNN with different layers like convolution and maximum pooling, that are used for hierarchical feature extraction [148,154]. Finally, Figure 15 shows the structure of the LSTM network. This network uses memory cells and gating mechanisms to find long-term dependencies in sequential data [147,155].

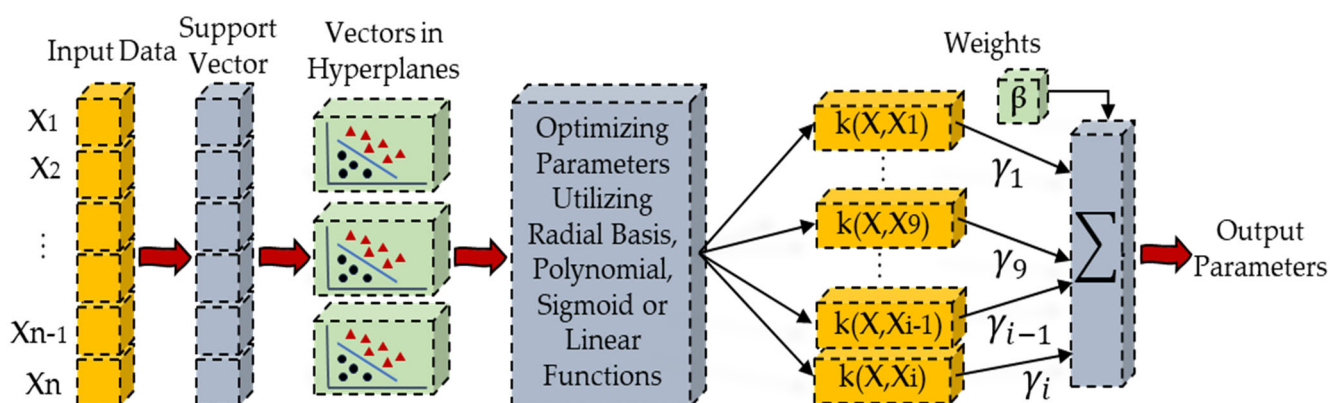


Figure 10. Architecture of the support vector machine method.

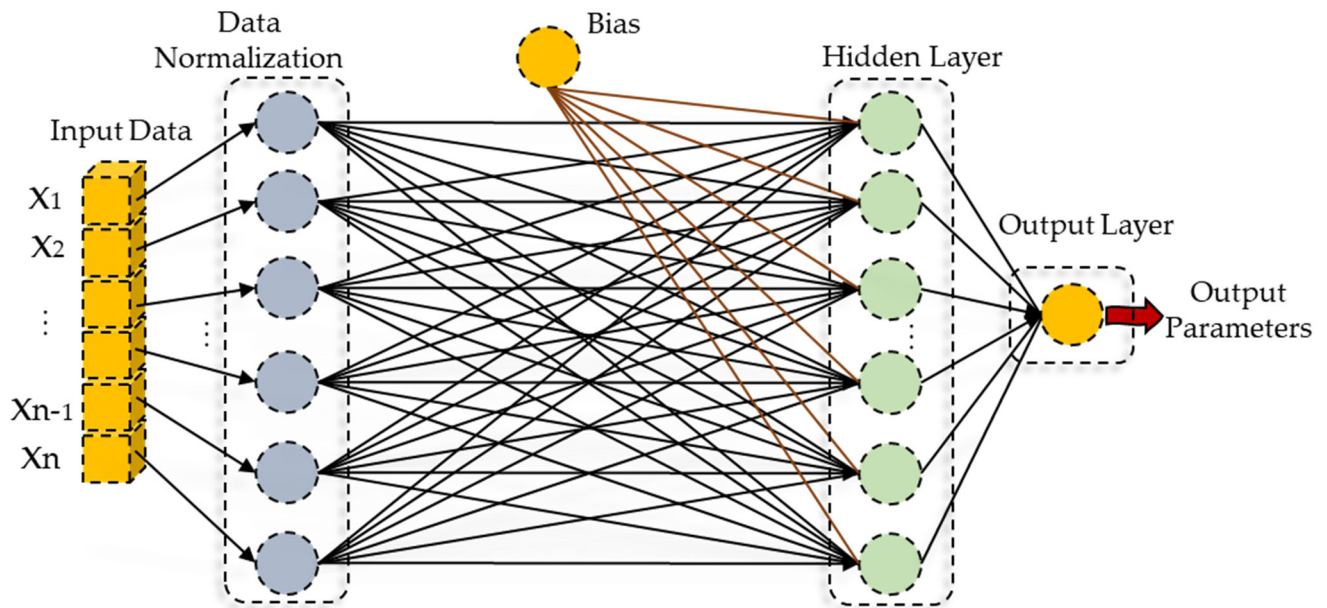


Figure 11. Structure of the extreme learning machine method.

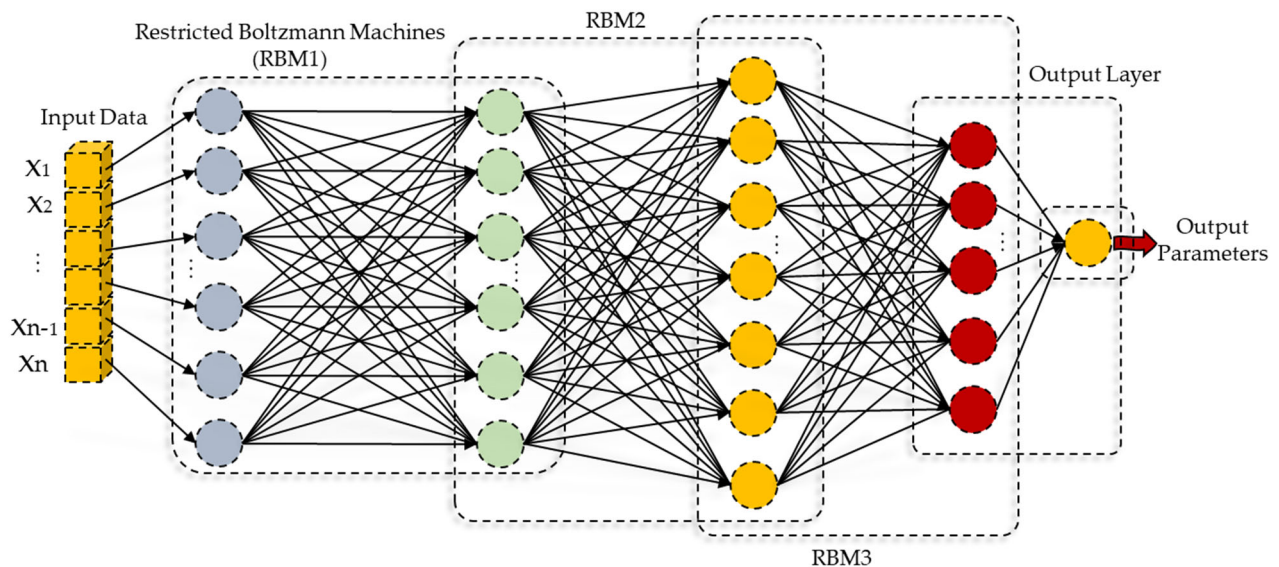


Figure 12. Architecture of the deep belief networks method.

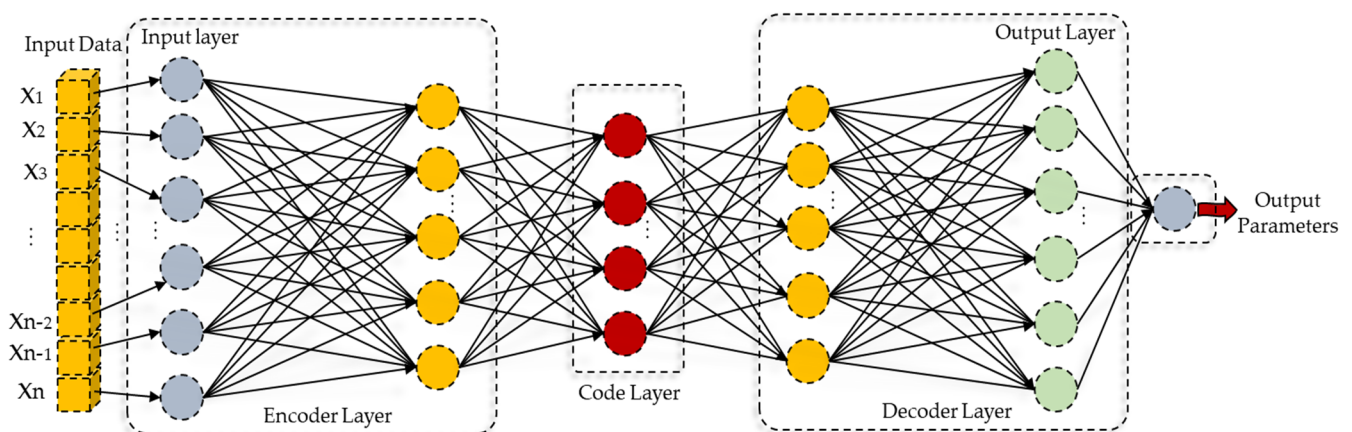


Figure 13. Detailed architecture of the deep denoising autoencoder model.

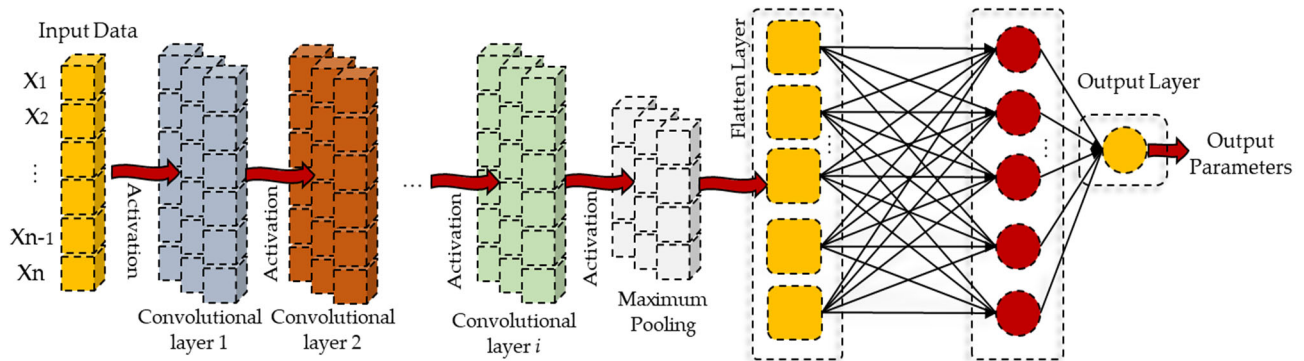


Figure 14. Structure of the convolutional neural network method.

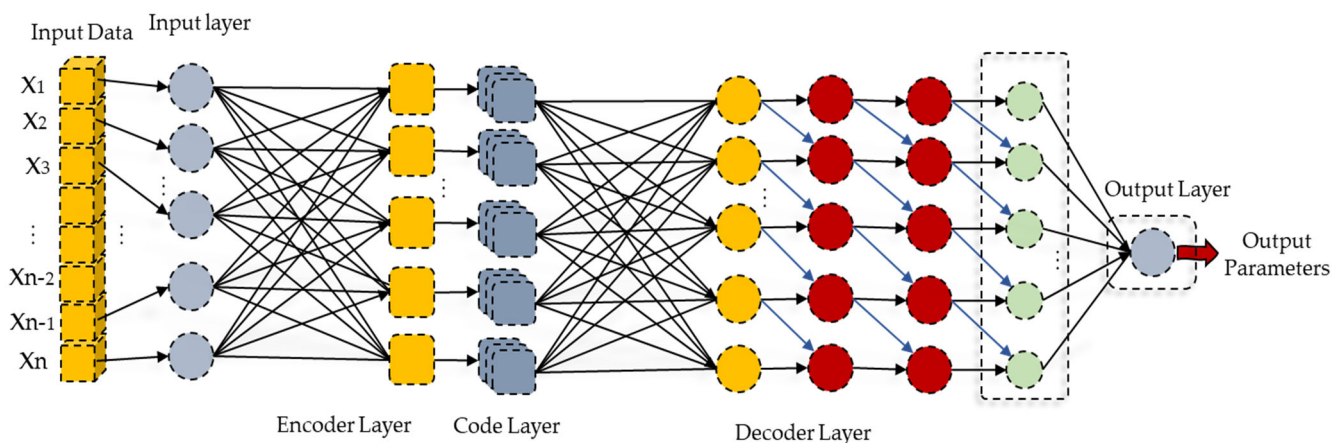


Figure 15. Architecture of the Long Short-Term Memory method.

For example, LSTM networks using raw data of synchro phasor measurements [156] and CNNs processing generator voltages as RGB images [157], have well demonstrated the adaptability of AI in dealing with intermittent and oscillatory instabilities. In online rotor angle stability systems, time-sensitive approaches [156,158] are used that allow for gradual adjustment of the response time to achieve a balance between accuracy and speed. To deal with the challenge of unbalanced data, methods are used at the data level, such as data partitioning, and at the model level, such as applying more weight to unstable examples in the classification process.

These measures increase the ability of AI to adapt to the real-world conditions of the smart grid. Finally, the integration of AI in rotor angle stability assessment not only increases computational efficiency, but also paves the way for stable, adaptive and timely analysis in smart grids [53,159]. Frequency stability in smart grids has become an important issue due to the integration of renewable energy sources and power electronics. Frequency stability assessment (FSA) is an essential mechanism to maintain stable grid performance [160,161]. In the meantime, artificial intelligence has been considered as an effective solution to increase the speed and accuracy of the computations. Real-time approaches in FSA which are designed based on extreme learning machines [162], ensemble algorithms [163] and model-based methods [125], show that AI has a high ability to predict stability under different conditions.

The use of model inheritance, with the help of historical information, allows for the improvement of the prediction accuracy with only a few new examples [164]. The combination of emergency control and FSA, as seen in event-based approaches [165] and the combination of model-based and AI-based methods [166], provides a complete picture of the new solutions. The future direction of this field also includes the study of coordination

between voltage regulation methods and strengthening the security of AI-based systems. Applications of AI in frequency stability analysis increase the adaptability of smart grids to the challenges posed by the integration of renewable energy resources and power system disturbances, faults and uncertainties.

In smart grids the Energy Management System (EMS) has a critical importance in optimizing the generation, distribution, and consumption of electricity [167]. The Smart Grid Central Controller (SGCC) and Supervisory Control (SGSC) are adapted for broader grid operations, which creates a centralized control infrastructure for distributed energy resources, demand balancing and real-time monitoring [168,169]. These systems enhance the grid's flexibility, reliability and efficiency by integrating advanced Information and Communication Technology (ICT) tools and intelligent automation across the network [170]. Figure 16 depicts hierarchical control schemes within a smart grid system including different levels of control.

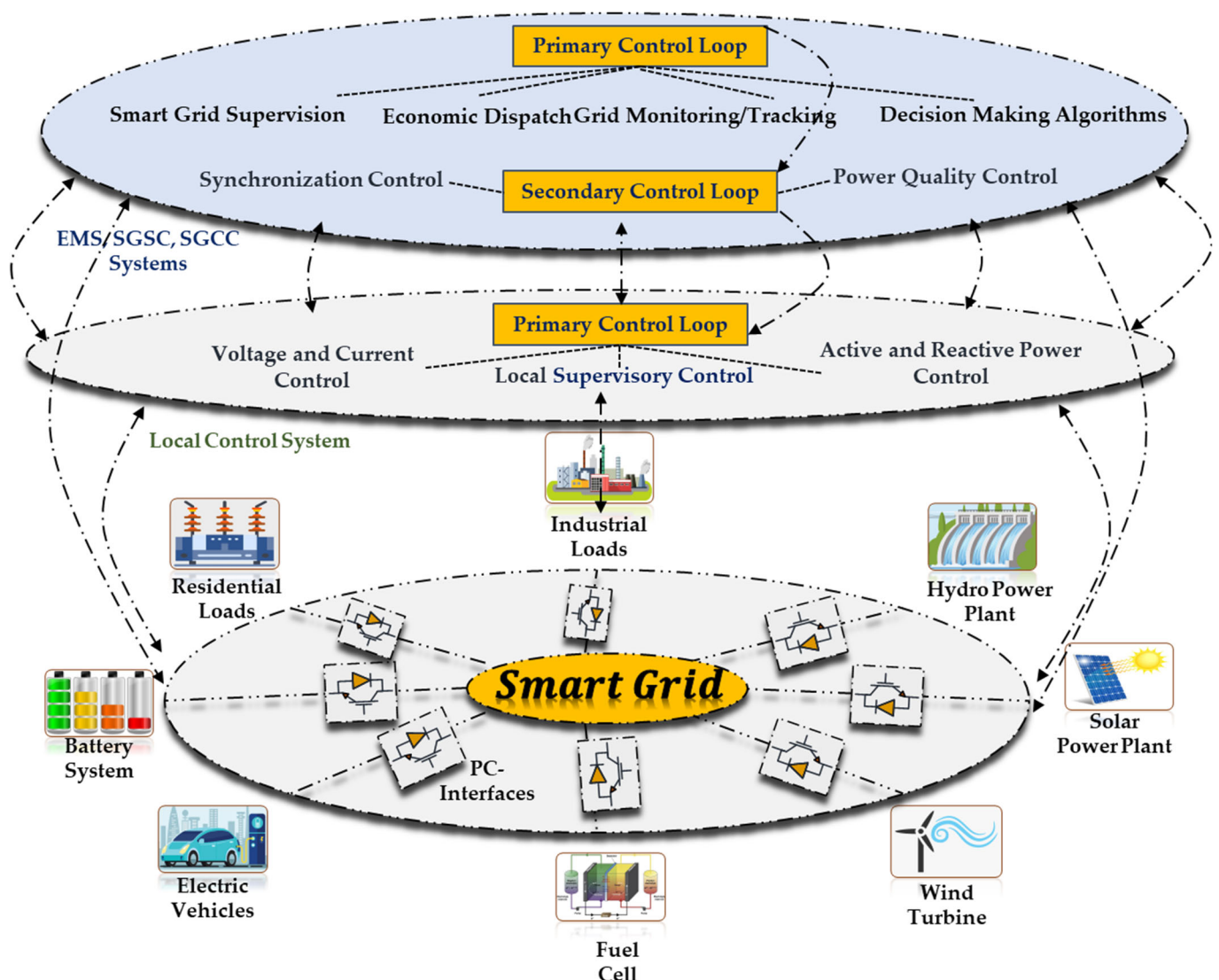


Figure 16. The hierarchical control schemes within a smart grid system including different levels of control.

In the field of voltage stability that is also faced with growing demand and dynamic loads, AI-based voltage stability assessments (VSA) offer suitable solutions. Traditional methods like energy functions and bifurcation examination face limitations in large networks and online applications, especially in the trade-off through computational time, com-

plexity and precision [171,172]. On the other hand, AI offers flexible solutions with the investigation of the nonlinear relationships of energy grid stability and variable states. Short-term VSA approaches like configuration classification [173], unbalanced learning [174] and transient voltage stability index (TVSI) prediction [119], help to improve the accuracy of the analysis and reduce the processing time. A study reported in [175] has also investigated delayed voltage recovery after a fault and categorized stable states for better management. VSA demonstrates the flexibility of AI methods in dealing with different stability scenarios by using techniques such as local regression [176] and online random forest models [177]. Automatic voltage control (AVC) is a key component in real-time voltage and reactive power optimization. It contributes to system stability and reduces transmission losses [178,179]. Reinforcement learning has been applied in the optimization of proportional-integral-derivative (PID) controllers and the development of new algorithms like “network intelligence”. Authors in [180] have proposed a teach-and-learn algorithm for optimal tuning of PID controller parameters which has shown efficient control performance under parameter uncertainties and large disturbances.

Researchers in [181] have proposed a network intelligence algorithm using deep reinforcement learning (DRL) for AVC in smart grids. This DQN/deep deterministic policy gradient (DDPG)-based method was able to quickly generate voltage regulation schemes under different operating conditions. This paper tests the suggested methods on a real 200-bus energy system that focuses on a local subsystem of 30 buses and five nearby generators. Power system analysis toolbox creates 14,000 scenarios with load changes of 60% to 110%. A participation factor list is used to re-dispatch generator outputs. The agents learn from about 10,000 cases and are tested on 4000 of them. In over 95% of the cases, they can keep the voltage between 0.95 and 1.05 pu. The use of DRL in AVC opens new avenues for research on the coordination of different voltage regulation methods [181,182].

Local power system stabilizers (PSS) and wide area damping controllers (WADC) with lead-lag link structure face challenges such as accurate parameter estimation and adaptation to changing conditions [183,184]. Authors in [184] have tested the proposed WADC strategy on the IEEE 16-machine 68-bus system utilizing MATLAB/Simulink using modal analysis and eigenvalue calculation. There are five connected areas in the system, and two 200 MW wind farms. Even with PSSs, two poorly damped inter-area oscillation modes (0.52 Hz and 0.78 Hz) are located. The results of this paper show that both WADCs greatly improve the damping of critical modes (by more than 10%). Note that adaptive switching makes sure that the best controller is chosen, quickly damping oscillations and keeping the system stable. To overcome these problems, artificial intelligence algorithms have been proposed. Examples of these methods include Q-learning-based controllers [107], RL tree-based clustering [120] and RL combined with artificial neural networks (NN) [185] that have shown effective performance.

The Q-learning-based vulnerability analysis suggested in [107] is tested on three IEEE benchmark systems, including the 5-bus test system, the 24-bus RTS-79 system and the 300-bus system. The size of a blackout (the number of failed lines) shows how insufficient a cascading outage is. Each system has its own threshold: 100% for the 5-bus, 20% for RTS-79 and 2.5% for the 300-bus. To deal with random hidden line failures, Monte Carlo simulations are run with 100 experiments per system, each with up to 1000 trials. The Q-learning agent starts with a positive outlook ($Q = +1.0$) and improves its strategy over time through ϵ -greedy exploration. It successfully finds attack sequences that cause critical system blackouts. A small-scale case study is employed in [120] to find power theft by using a dataset that shows how much power households use, with 20% of the entries being fake. A 2 MW generation unit sends power through a simplified city-level distribution network that makes realistic assumptions about power flow, transformer loads and 5% losses.

A hybrid SVM method is used to find theft. A decision tree uses feature entropy and information gain to figure out Priority Estimates (PE), and then SVM uses PE and other features (like the number of appliances, the time of day and the season) to classify the data. The method that was suggested gets 95.5% of the training right and 87.5% of the tests right. When trained with DT outputs, these numbers go up to 97.5% and 92.5%, respectively. The proposed algorithm in [185] combines ANN-based price forecasting with a decentralized multi-agent RL strategy to lower electricity bills. The suggested method moves controllable and shiftable loads to off-peak times that lowers peak demand and cuts electricity costs by up to 72.3%. It was tested on real data from February 24, 2017. The results of the comparison show that the MILP solver shows a good performance first, but the RL-based method gets better over time by learning and changing its policies. This method meets real-time requirements because it takes 80 s to train and 50 s to choose an action. It is an efficient and smart solution that does not require any prior knowledge of the system.

Another paper in [186] recently proposed a DC power supply unit for commercial buildings in smart grids. It is based on a multilevel power converter and can support EV charging stations and 5G communication infrastructure. The control infrastructure main part is an Interval Type-2 Fuzzy PD+I controller. A DDPG algorithm is utilized to optimize its input/output scaling factors and voltage regulation. The DDPG consists of two deep neural networks on how to learn the best control policies. This process lets the controller keep the DC output voltages stable and the power factor at one under changing grid voltages. The experimental results show that a DDPG-driven controller is strong enough to handle multi-DC terminal power systems in smart city applications. The current total harmonic distortion (THD) is now only 2.6%, which is well below the IEEE-1547 and IEC 61727 limits. This shows that the power is of high quality and can be used in smart city applications.

Traditional fault diagnostics frameworks, like impedance-based and traveling wave techniques, have limitations in dealing with modern power grid conditions. These limitations are especially evident in adapting to the increase in distributed renewable energy sources and the development of high-voltage direct current (HVDC) transmission lines [187,188]. In these circumstances, AI methods have emerged as an effective and flexible alternative due to their ability to eliminate the need for complex modeling and traditional fault mechanism analysis [189]. Various artificial intelligence algorithms, including artificial neural networks [190], support vector machines [191], convolutional neural networks [192], Bayesian networks [193] as well as Petri nets [194], have been widely used in fault detection, classification and location applications. These algorithms are able to identify fault patterns and pinpoint their locations with high accuracy using data recorded from the network. Authors in [195] investigate how to predict solar power in Saudi Arabia using ML ensemble models. They do this by using meteorological data (irradiance, module/ambient temperature and real power) that was collected every five minutes from a commercial building between September 2021 and August 2022. The authors used a number of statistical measures to test four ML models including xGBoost, Random Forest (RF), K-Nearest Neighbor (KNN) and Extra Trees (ET). The xGBoost model accomplished better results than the others in both training and testing, with a Mean Squared Error (MSE) of 0.0036, Root Mean Squared Error (RMSE) of 0.019, Mean Absolute Error (MAE) of 0.013, Mean Absolute Percentage Error (MAPE) of 0.689 and Coefficient of Determination (R^2) of 0.975.

In [196], a CNN-based fault classification method is presented, whose input consists of features extracted through the Hilbert–Huang transform (HHT). This method has been applied to energy grids and has shown high performance in detecting various types of

faults. Also, the use of graph convolutional networks (GCN) in fault-location methods, as mentioned in [197], preserves the spatial structure of the data and increases the accuracy of fault identification. In another study, [198] used a combination of hidden Markov models (HMM), matched pursuit analysis and other ML procedures. In these methods frequency and voltage waveforms are used to perform the identification and planning process. In addition, the construction of line maps in that network buses are clustered based on the degree of fault susceptibility has made fault analysis more accurate and targeted [199,200]. Despite the positive results and promising performance of AI-based methods, some fundamental challenges remain. These include the need to combine information from different sources to increase accuracy design high performance parallel algorithms for application in complex power networks and use multiple methods in combination to take advantage of their advantages while reducing limitations [201,202]. Thus, the application of AI algorithms in fault detection, classification and location has created a fundamental change in facing the challenges of the growing concept of smart grids. These approaches pave the way for the development of more accurate, faster and more reliable strategies for managing network faults.

6. Discussion, Challenges and Future Trends

The integration of machine learning and artificial intelligence strategies in smart grid stability research has shown considerable potential to improve system control, modeling, reliability as well as smart grid fault detection and predictive maintenance. The studies that were looked at demonstrate that ML models like RL, SVM, ANN, decision trees and deep learning architecture have been used extensively to model complex system behaviors and make accurate forecasts for grid stability. For example, RL presents a dynamic and adaptive approach to smart grid control, making it effective in controlling variable and uncertain loads, the variability of renewable energy sources, and unexpected disturbances that are more visible in the smart grids due to its presented structure. Most traditional machine learning models use static or labeled data and try to make the best decision for a single step. Note that RL learns and updates its control policies over time based on current conditions and future outcomes. RL can improve long-term performance instead of just getting quick results because it can make decisions in a row. In addition, RL balances the need to explore new strategies with the exploitation of proven ones that enable smart grids to become more responsive and resilient. Since, in smart grids with plenty of renewable energy resources and different loads, monitor devices are growing at an exponential rate, RL is a promising tool for finding faults in power systems. Another benefit during the implementation phase is that it is comfortable to use programming languages that are prominent in data science and engineering areas like Python, MATLAB, C++. There are also specialist platforms that offer RL libraries, such as Petting Zoo, Stable-Baselines3, RLlib, Gymnasium, TensorFlow and Keras. One important advantage of ML and AI approaches is their ability to process large volumes of real-time data that enable dynamic and adaptive stability investigation. This capability is critical given the increasing penetration of distributed energy resources, new generation of loads like EVs, heating and cooling systems and the addition of storage systems like batteries that are large in scale and result in variability and uncertainties in power system operations.

Despite these improvements, challenges can remain in terms of model interpretability, data quality as well as the demand for standardized benchmark datasets. Also, the blackbox character of many AI and ML algorithms can limit their accuracy in important applications where explainability is paramount. Thus, in order to fully realize the potential of ML and AI in smart grids the following challenges must be considered:

- A. **Data Quality and Data Understanding:** There are a lot of complicated time series and spatial data in smart grids that come from different measurement/monitoring systems. Compressing, combining, storing and displaying this diverse data in an efficient manner is an important challenge. Problems like noise, missing values and inconsistencies make data quality worse that affects the performance of AI and ML algorithms. The fact that there is not a full understanding of the structure of data and semantics makes this problem worse. This can lead to choosing the wrong model and getting results that are not the expected outcomes.
- B. **High Computational Time and Inefficient Learning:** AI and ML techniques must have resources that take long time to train and lot of data to converge. This characteristic is inefficient for smart grids where being capable of controlling and adapting in real time is very important. Learning through trial and error even in simulated environments does not always work well with the rapid transients and changes that happen in modern smart grids. Experience replay and meta-learning are two methods that have come up to speed up convergence, but they still need powerful computer systems and may not work well in new situations or when there are unexpected problems with the grid.
- C. **Optimization Algorithm's Structure Design:** In order to get AI and ML agents to operate accurately in smart grids, the reward functions should be well-designed. Simple reward structures may not lead to the best learning outcomes and overly complicated ones may cause the agent's goals to not match up with real-world control goals. Also, smart grid environments often have sparse or delayed rewards, like failures that happen long after wrong decisions, which makes learning even harder. Deep Inverse Reinforcement Learning (DIRL) and reward shaping have made progress recently that solves these problems by using expert demonstrations and domain knowledge to infer or add to reward signals.
- D. **The Difference Between Simulated Procedures to Real-World Application:** AI and ML training is usually accomplished through high-fidelity simulators that simulate a smart grid close to reality. However, these simulators cannot fully simulate the noise, operational variability and uncertainty of real-world grid environments. This difference that is often called the simulation-to-reality gap, can make trained methods less effective when they are used in real systems. An ML algorithm could be naive or insufficiently tuned to certain operating conditions if it does not have the right methods to make sure that it can generalize like sensitivity analysis, domain randomization or digital twins/shadows.
- E. **Scaling, Reliability and Data Privacy:** A lot of the current AI and ML frameworks for controlling smart grids use centralized framework which can cause problems with scaling, reliability and data privacy. Centralized learning not only makes it easier for things to go wrong, but it also makes it harder to send sensitive operational data. In addition, different nodes or substations can have local learning without sharing raw data because of federated learning and distributed reinforcement learning frameworks. Therefore, the system is more robust and complies with data protection regulations. There are drawbacks to distributed setups like the extra effort needed to take care of synchronization, communication problems and security holes.
- F. **Complex Dynamics in Smart Grids:** Smart grids are inherently complex and multi-agent environments. In this system, different subsystems like renewable energy sources, different loads, storage systems and controllers work together in a coordinated and dynamic manner. Some AI and ML methods often make these interactions too simplified that skip out on real behaviors or localized instabilities. Multi-agent machine learning (MML) gives us a better framework because it lets agents learn

together and compete with each other. But it also adds non-stationarity, coordination complexity and a lack of interpretability that make it hard to use in real applications.

- G. **Lake of Standardization and Benchmarking:** It is difficult to compare and produce results when there are different experimental tests, parameter tuning strategies and operating scenarios used in AI and ML research for smart grids. There is not a single set of benchmarks or standardized datasets that can be used to test how well AI and ML models work in different smart grid structures. Therefore, it is difficult to compare new algorithms that slows down development in this area. Inconsistent metrics and random performance also make AI and ML findings less reliable in critical areas like stability analysis.

In order to evaluate AI and ML techniques more efficiently for analyzing smart grid control and stability the following future research directions are promising:

- A. **Online and Real-Time Learning:** Future research on using AI and ML in smart grids can move from offline model training to real time/online learning frameworks. These models can be updated using real-time data streams. They can handle grid problems and changing system conditions without having to be fully retrained. This change will make smart grids more stable in real-time and lower latency.
- B. **Human-based AI and ML:** Human-based AI and ML: Using knowledge graphs and other methods to directly include domain knowledge in the learning process of the AI and ML techniques in order to improve the efficiency and accuracy of the approach. Models need to give explanations that are appropriate for the user's level of knowledge so that users can see clear and personalized insights. It will be very important to make AI and ML models easy to understand for making decisions in important situations.
- C. **Robust Time-Series Models:** Future research could focus on building AI and ML models that can understand how smart grids behave over time. This would make it possible to get more accurate, clear and useful information from complicated and variable data patterns.
- D. **Scalability and Robustness of AI and ML:** AI and ML algorithms need to be able to handle complex smart grid environments with a lot of different state-action spaces and contingencies. Risk-aware learning, hierarchical architectures and safe decision-making strategies should be the main focus of future research.
- E. **Data Fusion and Big Data Analytics:** Smart grids are relying more than before on data from multiple sources like measurement systems, different control levels, monitoring systems, weather forecasts, etc., which requires strong fusion, real-time processing and visualization approaches. In order to be safe, prompt and private insights from huge and varied datasets in future platforms need to use standardized models, in-memory databases and parallel computing.
- F. **Digital Twins and Digital Shadows in Smart Grids:** Future research can look into how digital twin and digital shadow technologies can be employed to build real-time, high-fidelity copies of smart grids. These virtual models can accurately simulate a wide range of grid operating conditions that give AI and ML algorithms large datasets to work with. Using these concepts will make models more accurate, help with stability analysis and let the control system get feedback and test scenarios all the time.
- G. **Improved Feature Engineering and Preprocessing:** In order to overcome the problems with conventional feature extraction approaches, future AI and ML models can investigate faster strategies, handle more data and are less sensitive to noise. These methods need to work with real-size smart grids and be able to accurately classify disturbance in faulty conditions.

- H. Security and Reliability of AI and ML: As AI and ML become more involved for controlling smart grids that need to be capable of managing failures, cyberattacks and non-ideal learning behaviors. To protect against instability and make sure that the system operates safely and reliably in the real world, future research can use safety constraints, adversarial training and resilient optimization strategies.
- I. Broader Application Scope for Interpretability: Interpretability can go beyond making predictions to include different features such as power dispatch, system protection and detecting cyberattacks. Models must provide clear and useful explanations in high-impact areas to support system operators.

7. Conclusions

This review focuses on the growing landscape of smart grids and their key importance in managing the challenges posed by the integration of power converter-based renewable energy sources. Given the increasing complexity of these power networks, the utilization of ML and AI techniques has materialized as a promising solution to handle the sustainability, security and stability requirements of smart grids. This review paper begins with an introduction to the dynamic configurations of smart grids and provides an overview of various machine learning techniques which discusses their capabilities and applications in optimizing grid performance. Along the way, various algorithms are examined in detail to provide a clear concept of how they can be employed in the effective management of distributed resources, load control and contingency planning. The frameworks introduced demonstrate how machine learning and artificial intelligence has an active role in solving complex grid problems, especially in areas such as stability maintenance, voltage and frequency regulation as well as fault detection. This work also discusses how these techniques can improve analytics and enhance grid operational capabilities. Different machine learning algorithms and paradigms that have been effective in the development of AI in various smart grid applications are highlighted. Among them, the integration of reinforcement learning is highlighted as one of the prominent advances that can enhance the ability of intelligent decision-making in dynamic and complex grid environments. This work can be used by researchers, technical experts and policymakers. It also provides a roadmap for the effective utilization of intelligent technologies to analyze and improve the stability of smart grids. As the energy landscape is developing, the perspectives and frameworks introduced in this study furnish a platform to guide future research at the intersection of machine learning, artificial intelligence and smart grids.

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Abbreviations

AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
AVC	Automatic Voltage Control
BN	Bayesian Network
CIG	Converter-Interfaced Generators
CNN	Convolutional Neural Network
DAE	Denosing Autoencoder
DBN	Deep Belief Networks
DDPG	Deep Deterministic Policy Gradient
DER	Distributed Energy Resource
DIRL	Deep Inverse Reinforcement Learning

DL	Deep Learning
DP	Dynamic Programming
DQN	Deep Q-Network
DR	Demand Response
DRL	Deep Reinforcement Learning
DT	Decision Tree
ELM	Extreme Learning Machine
EMS	Energy Management System
ET	Extra Trees
EV	Electric Vehicle
FSA	Frequency Stability Assessment
GCN	Graph Convolutional Network
HHT	Hilbert-Huang Transform
HMM	Hidden Markov Model
HVDC	High Voltage Direct Current
ICT	Information and Communication Technology
IoT	Internet of Things
KNN	K-Nearest Neighbor
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAS	Multi-Agent System
MDP	Markov Decision Process
ML	Machine Learning
MML	Multi-agent machine learning
NIST	National Institute of Standards and Technology
NN	Neural Network
PE	Priority Estimates
PGM	Probabilistic Graph Model
PID	Proportional-Integral-Derivative
PSS	Power System Stabilizer
RL	Reinforcement Learning
RMSE	Root Mean Squared Error
SARSA	State-Action-Reward-State-Action
SGCC	Smart Grid Central Controller
SSCI	Sub-Synchronous Control Interaction
STATCOM	Static Synchronous Compensator
SVM	Support Vector Machine
TD	Temporal Difference
TG	Turbine Generator
THD	Total Harmonic Distortion
TLBO	Teach-Learn-Based Optimization
TVSI	Transient Voltage Stability Index
VSA	Voltage Stability Assessment
WADC	Wide Area Damping Controller
XGBoost	Extreme Gradient Boosting

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