

Review

AI Applications to Enhance Resilience in Power Systems and Microgrids—A Review

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Abstract: This paper presents an in-depth exploration of the application of Artificial Intelligence (AI) in enhancing the resilience of microgrids. It begins with an overview of the impact of natural events on power systems and provides data and insights related to power outages and blackouts caused by natural events in Estonia, setting the context for the need for resilient power systems. Then, the paper delves into the concept of resilience and the role of microgrids in maintaining power stability. The paper reviews various AI techniques and methods, and their application in power systems and microgrids. It further investigates how AI can be leveraged to improve the resilience of microgrids, particularly during different phases of an event occurrence time (pre-event, during event, and post-event). A comparative analysis of the performance of various AI models is presented, highlighting their ability to maintain stability and ensure a reliable power supply. This comprehensive review contributes significantly to the existing body of knowledge and sets the stage for future research in this field. The paper concludes with a discussion of future work and directions, emphasizing the potential of AI in revolutionizing power system monitoring and control.

Keywords: microgrid; energy-management system; Artificial Intelligence; deep reinforcement learning; machine learning; power system; forecasting; resilience



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1. Introduction

1.1. Background

In the European Union (EU), energy production is primarily based on fossil fuels. The share of gas in the total primary energy supply in 2022 amounted to 19.6%. Coal is the second largest energy source, accounting for 15%, and oil accounts for 1.6%. Nuclear energy constituted 21.9% and renewable energy resources 39.4% [1]. As seen in Figure 1, the fact that renewable energies accounted for the highest share of primary energy production in the EU in 2022 is a clear reflection of the EU commitment to reducing greenhouse gas emissions and transitioning to a more sustainable energy future.

The EU reliance on imported energy sources has led to an increased focus on renewable energy sources (RESs). This shift is evident in the introduction of several key directives in the area of energy policy. One such directive is the Energy Efficiency Directive 2012/27/EU, which was adopted in 2012 and updated in 2018 and 2023. This directive sets rules and obligations for achieving the EU ambitious energy efficiency targets. It establishes “energy efficiency first” as a fundamental principle of EU energy policy. In practical terms, this

means that energy efficiency must be considered by EU countries in all relevant policy and major investment decisions taken in the energy and non-energy sectors [2]. Another significant directive is the Renewable Energy Directive EU/2018/2001, which provides the legal framework for the development of clean energy across all sectors of the EU economy. Since its introduction, the share of renewable energy sources in EU energy consumption increased from 12.5% in 2010 to 21.8% in 2021. These directives reflect the EU commitment to reducing greenhouse gas emissions and transitioning to a more sustainable energy future. They set ambitious targets, such as reducing EU annual energy consumption by 38% and 40.5%, respectively, by 2030 and increasing the share of renewable energies in energy consumption to 32%. Additionally, at least 10% of the final consumption of energy in transport should come from RESs [3]. In October 2022, the National Recovery and Resilience Plans of 26 EU member countries were approved, paving the way for an investment of EUR 34 billion (USD 36.3 billion) in clean energy. These plans indicate the intention of the Member States to channel investments into various renewable technologies. This includes solar energy in countries like Austria, Bulgaria, the Czech Republic, Greece, Italy, Lithuania, and Spain. Offshore and onshore wind energy projects are planned in Belgium, Finland, Greece, Italy, and Poland. Biomass energy is a focus in Austria, Croatia, and Sweden. Seventeen Member States have plans for hydrogen energy, and Estonia, Latvia, and Romania are investing in energy infrastructure to improve the resilience of power systems [4].

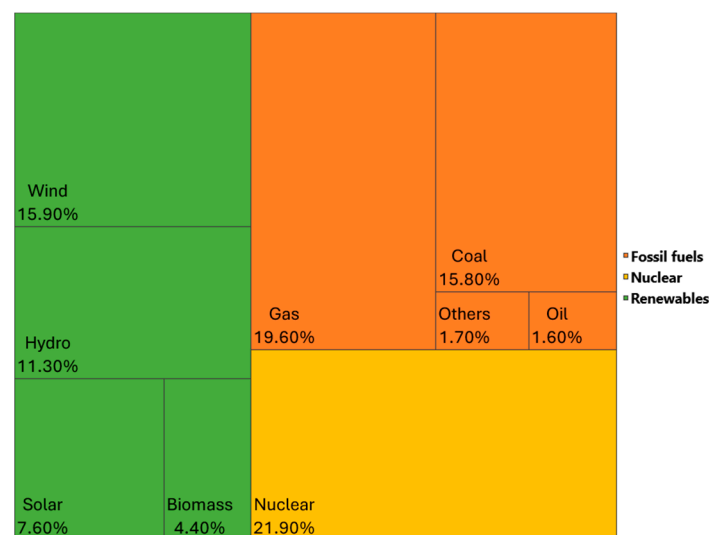


Figure 1. Share of energy production for EU countries in 2022.

In Baltic countries such as Estonia, the government has set a highly ambitious target to power the entire country with renewable energy sources by 2030. Moreover, the country is currently striving to ensure that 10% of its energy used in transport is derived from renewable sources, with a significant portion of this target expected to be covered through biomethane resources [5]. Electricity generation using renewable energy resources has continued to grow in Estonia. According to the statistics released by the Statistics Estonia Agency (Figure 2), since 2019, the total energy generation using renewable energy resources has continued to increase with a cumulative increase of 33.03% in 4 years [6]. This substantial growth rate places it among the top ten countries that have the largest increase in their share of renewable energy. This esteemed list includes nations such as Sweden, Norway, Denmark, Finland, Ecuador, Uruguay, Panama, and the United Kingdom. The remarkable progress in renewable energy utilization underscores the country's shift towards sustainable and eco-friendly energy solutions and zero-emission programs [4].

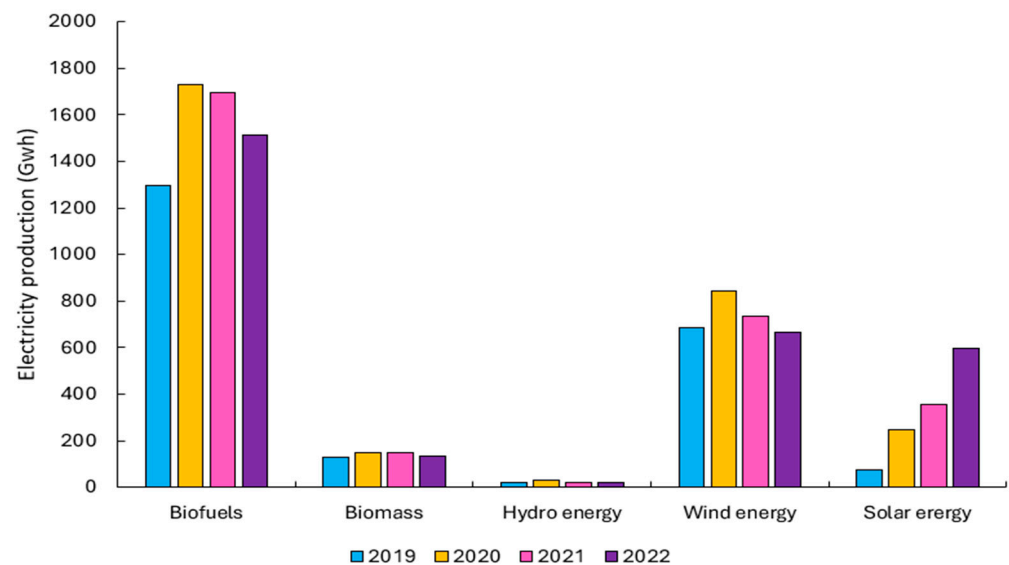


Figure 2. Share of renewable energy resources in Estonia between 2019 and 2022.

The shift towards a more electrified and digitalized society means that numerous vital sectors, such as communications, transportation, military, healthcare, and education, are either directly or indirectly dependent on a steady supply of electricity. Therefore, the uninterrupted provision of sufficient power is crucial for prosperity and sustainable growth. However, this reliance on power also increases susceptibility to significant disruptions in supply. These disruptions can be caused by different factors, including but not limited to, warfare, political unrest, extreme weather conditions, accidents, sabotage, technical malfunctions, or financial crises. The economic and security impact of such disruptions can be widespread beyond the directly affected region [7].

As previously stated, disasters or damage, whether caused by natural or human activities, can lead to power failures and outages. These power outages can have a significant financial impact across a variety of sectors and services, disrupting the daily lives of a large number of consumers, potentially in the millions, with each occurrence [8].

Between 2018 and 2023, the largest Distribution System Operator (DSO) in Estonia reported more than 68,026 power outages. Figure 3 provides a detailed breakdown of the factors causing power outages in Estonia between 2018 and 2023. These outages were caused by a variety of factors, including weather conditions, equipment failure, maintenance activities, etc. The impact of these outages was significant and affected numerous consumers across the country [9].

According to a recent study report from “Elektrilevi”, the largest distribution system operator in Estonia, the country faced a severe storm in October 2023 that caused widespread power outages. Similar weather events have caused power outages in different parts of Estonia where the size of the affected stakeholders reached up to 35,000 customers without power across the country. Moreover, the strong winds hampered repair efforts, and there were areas where operations had been halted for safety reasons. Despite challenging conditions, power was eventually restored to 17,000 customers. However, larger scale power restoration may take longer. For context, in a similar storm in October 2006, 42,000 customers were without power, and it took eight days to restore power to all customers [10].

The impact of severe weather events like storms extends beyond just unplanned power outages. Natural disasters can significantly impact and harm power system equipment and distribution lines, causing extensive damage. For example, a storm with relentless winds and torrential rain can cause physical damage to infrastructure, including poles, wires, and transformers. Furthermore, the effects of a natural disaster can increase demand as the system is restored, which leads to an imbalance in the network system. In particular, due to the continuous increase in greenhouse gas concentrations, the frequency, severity, and duration of severe weather events are expected to increase. This can potentially

lead to further outages and equipment failures if not managed properly. In this regard, the increasing frequency and intensity of extreme events is a matter of grave concern to energy infrastructure [8].

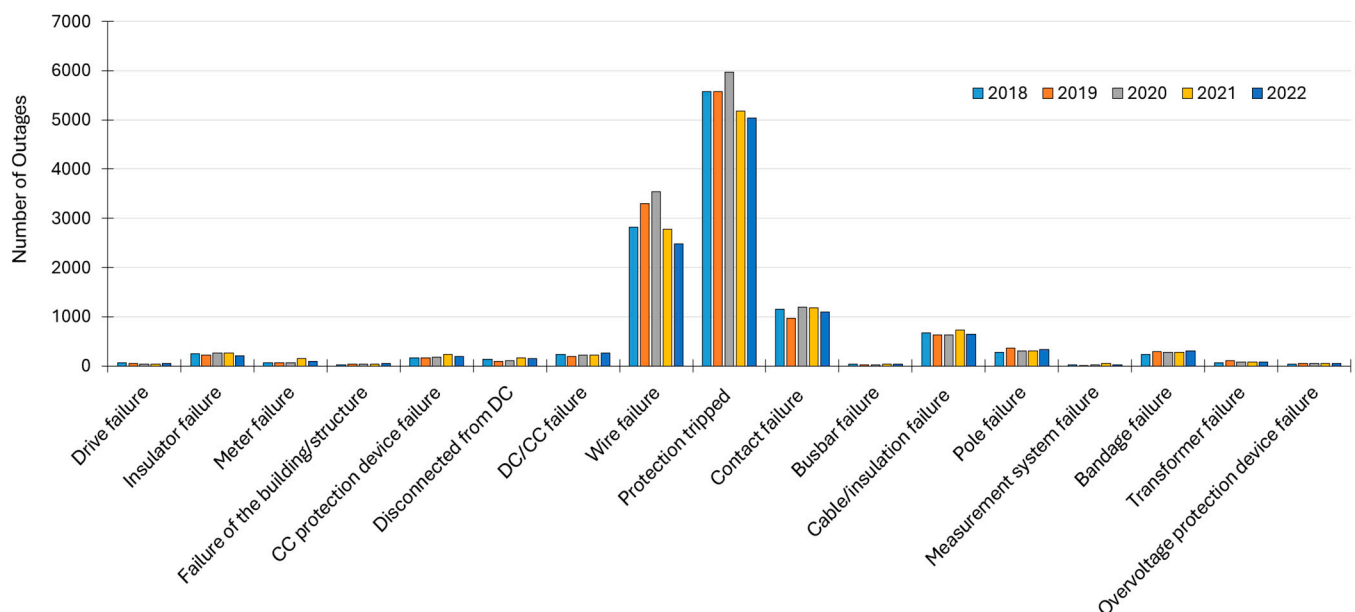


Figure 3. Analysis of factors causing power outages in Estonia (2018–2023).

The concept of resilience of the power system is described in the literature in different manners. Generally, resilience is defined as the ability to prepare and adapt to changing conditions, reconfiguration, resistance, and rapid restoration of the network system if events occur. This definition includes all active and passive aspects of this concept [11]. However, the concept adds complexity to the existing power system. To improve the ability of power systems to cope with major events, various studies and works addressing resilience have been conducted. These works include creating prediction models for the disaster location, enhancing the reconfiguration structure, studying the restoration performance, analyzing resilience, developing general methods to enhance resilience, and planning for resilience in the short and long term [12]. Some types of natural disasters may impact large geographic regions over long durations; therefore, various researchers have studied resilience-enhancement measures considering their local geographic location, and the pre-, during, and post-event impact is analyzed [13]. Moreover, some common solutions include using line hardening, using resilience infrastructure, and creating multi-microgrids.

1.2. Related Work

A comprehensive review of various studies has been conducted to understand the different characteristics of enhancing resilience using microgrids [14]. These studies span across various developing countries worldwide, providing a diverse perspective on the subject. In this section, we intend to review and explore several review papers that discuss the techniques used to improve the resilience of the network system.

In [12,15,16], the role of microgrids in enhancing power system resilience is explored, including the formation of microgrids, networked microgrids, and dynamic microgrids. Strategies used by microgrids to enhance resilience during major outage events are examined, including proactive scheduling, outage management, feasible islanding, and advanced operation strategies. Research gaps are identified and future directions for improving resilience-oriented operation methods are suggested. In [13], threats and vulnerabilities to microgrids, including cyberattacks and physical interruptions, are analyzed, and a methodology for designing resilient microgrids is proposed. Various mitigation strategies for different disaster recovery stages are suggested, focusing on enhancing micro-

grid attributes such as robustness, redundancy, resourcefulness, response, and recovery. In [17], the impacts of various events on generation, networks, and loads are analyzed, and quantitative metrics for these impacts are presented. Adaptation options and optimal strategies for resilience improvement from both component-level and system-level perspectives are discussed. The potential of smart/responsive loads in improving power system resilience is explored. In [18,19], the concept of networked microgrids (NMGs), clusters of physically connected and functionally interoperable microgrids, is discussed. The state-of-the-art methodologies for the operation and control of NMGs are reviewed, including the notion of dynamic boundaries for advanced microgrid applications. The opportunities, challenges, and potential solutions for improving grid resilience, robustness, and efficiency through NMGs are explored. In [20], the increasing importance of cybersecurity for enhancing microgrid resilience is discussed, addressing the existing approaches to cyber-physical security in power systems from a microgrid-oriented perspective. The rapid evolution of microgrid equipment poses a significant challenge for cyber defense mechanisms, particularly in the absence of contemporary standards.

1.3. Motivation for This Work

The rapid evolution of power systems towards decentralized systems such as microgrids, characterized by the integration of state-of-the-art technologies in power electronics, computers, information, communication, and cyber technologies, presents a compelling motivation for the current research. However, the complexity, nonlinearity, and large amounts of measurements and data inherent in these advanced power systems necessitate the development of novel analytical techniques, as the conventional methods and approaches for analyzing power systems are no longer sufficient.

In this context, the incorporation of Artificial Intelligence (AI) to address the current microgrid research requirements has emerged as a significant research direction in this digital era.

In microgrids, a variety of AI models have been employed for numerous applications. These include energy management, load forecasting, predicting renewable energy output, detecting and classifying faults, and identifying cyberattacks. Furthermore, AI plays a pivotal role in various aspects of microgrid and power system operations, including information, digital, intelligent operation mechanisms, protection, control, and planning to realize practical analyses. In essence, the integration of AI in microgrids not only enhances their operational efficiency but also significantly improves their resilience, making them better equipped to handle uncertainties and disturbances. AI has the capacity to learn from data with low dependence on physical models of the systems, which provides an effective solution to break through technical challenges. Unlike traditional mathematical algorithms, AI can effectively handle the nonlinearities and discontinuities inherent in power system problems. The term “AI-based solution” is generally used to describe solution technology that uses data, which is usually applied in large quantities to construct models.

Practically in power systems, AI models can be classified into five main categories: machine learning (ML) methods, probabilistic learning methods, statistical methods, search and optimization techniques (such as genetic algorithms and particle swarm optimization), and game theory and decision-making algorithms [21]. The ML approach is a subset of AI that equips systems with the capability to autonomously learn from extensive historical or synthetic data, eliminating the need for human intervention. Neural network and ML algorithms and their variants, such as Artificial Neural Networks (ANNs), and Recurrent Neural Networks (RNNs) have gained significant attention and have been implemented in various power system domains. Among these, deep learning has become an integral component of state-of-the-art systems across various applications, forecasting, control, and fault diagnosis [22].

There are several papers in the literature that review some applications of AI techniques in smart grids and power systems such as energy management [23,24], energy market [25,26], security and stability assessment [27], and cyber security systems [28]. The

aforementioned trend necessitates creating a systematic overview of the application fields of AI to enhance the resilience of microgrids. Unlike existing works, our paper is a comprehensive review of the application of AI techniques for enhancing microgrid resilience. This paper presents an updated review based on application of state-of-the-art resilience approaches for microgrids, in addition to providing an overview of the general mechanisms of AI applications in microgrid resilience. In this paper, we cover recent advances and applications made to enhance the effectiveness and efficiency of these applications. This paper highlights more applications of AI, and similarly, the behavior with respect to the event's occurrence time (pre-event, during event, and post-event). This paper contributes significantly to the existing body of knowledge and paves the way for future research in this field.

1.4. Methodology and Structure

The research methodology aims to explore, categorize, and evaluate the AI-based solution used for microgrid applications, with a focus on studies conducted from 2016 to now. The methodology comprises five main steps:

1.4.1. Keyword Search

Initial research was conducted using Google Scholar, utilizing keywords related to resilience in power systems, AI models, microgrids, review papers, and the application of AI, machine, and deep learning in microgrids.

1.4.2. Paper Screening

The papers retrieved were then screened based on whether the papers were review papers or research papers. Then, classification methodology is conducted to classify the proposed AI model based on the model used and its application.

1.4.3. Additional Article Identification

Additional relevant articles were identified from the citations within the selected papers and from papers that cited the selected works.

1.4.4. Review

All selected articles from steps 2 and 3 were reviewed to understand the objective of each paper, the methods used, the type of application (event's occurrence time), data source and type, modeling performance, and compared approaches.

1.4.5. Analysis of Review Results

Finally, the review results were analyzed to identify superior approaches for restoration and reconfiguration after the occurrence of the faults, as well as to pinpoint research gaps and future opportunities.

The remaining sections of this paper are presented as follows: In Section 2, we delve into the concept of the microgrid and resilience. We explore the idea of resilience and High Impact Low Probability (HILP) events, and we analyze and evaluate resilience. We also examine threats in power systems and microgrids. Section 3 introduces various Artificial Intelligence (AI) techniques, providing a foundation for the subsequent sections. In Sections 4 and 5, we apply these AI techniques to power systems and microgrid resilience, respectively. We analyze the design aspects of AI applications in these contexts, drawing from existing practices worldwide to identify best practices. Section 6 discusses the challenges of applying AI to microgrid resilience. We examine the limitations of current AI applications in resilience and suggest directions for future research. Finally, Section 7 provides a summary of the work and outlines the path forward. This comprehensive examination of resilience in microgrids, the application of AI techniques, and the challenges and future directions of this research form the core of our review paper.

2. Microgrid and Resilience

This section provides a comprehensive overview of the resilience concept in power systems, with a particular focus on microgrids. It introduces the main concept of resilience, assessing the threats in the power system, and resilience analysis.

2.1. Microgrid Concept

Microgrids have been deeply studied in many previous research papers like [29–32]. These studies have covered all aspects of microgrids, such as their design, how they work, and where they can be used. This extensive research is very important and provides a lot of information about microgrids. However, this paper will not go into the details of microgrids.

Generally, the microgrid is characterized as a local network of Distributed Energy Resources (DERs), and is a small-scale, self-controllable power system. It interconnects DERs and loads within clearly defined electrical boundaries [33]. It also facilitates the integration of renewable energy sources, such as solar and wind power, and can play a crucial role in energy conservation and demand response strategies [29].

Microgrids connect with the main grid via Points of Common Coupling (PCCs) located at their boundaries as shown in Figure 4. Microgrids can operate in two different modes: either a grid-connected mode, where the system works in connection with the main grid, or an island mode, where the system functions independently. A notable feature of microgrids is the smooth transition between these two modes which provides enhanced reliability, flexibility, and security [30]. Microgrids, equipped with advanced technologies and energy-management systems for effectively utilizing local renewable energy, contribute to environmental conservation and climate change mitigation [34]. As a link between local users and the main grid, microgrids operate as adjustable, controllable loads, optimizing power system functionality. The advantages are improved power quality, reduced costs, and a reliable power supply during emergencies, enhancing resilience. In case the main grid fails, microgrids significantly increase the survivability of the local power supply [35].

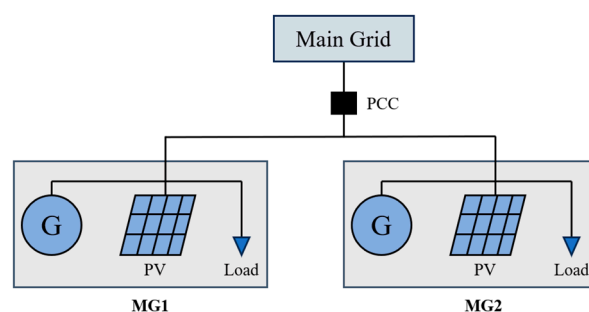


Figure 4. Microgrid structure with the main grid.

A microgrid controller (MGC) is utilized to strategically manage each microgrid under different operating conditions. The typical functionality of an MGC is depicted in Figure 5. Several local controllers (LCs) are implemented within the microgrid to achieve detailed monitoring, control, and management functions of the DERs, and Battery Energy Storage System (BESS). Under LCs' control, DERs are categorized into grid-following and grid-forming DERs. Grid-following DERs, typically not dispatchable energy resources (like photovoltaic panels and wind turbines), follow microgrid voltages and frequency instead of directly controlling them. Conversely, grid-forming elements, usually dispatchable (like generators and energy storage devices), possess adequate real and reactive power capacity to regulate microgrid voltages and frequency [36].

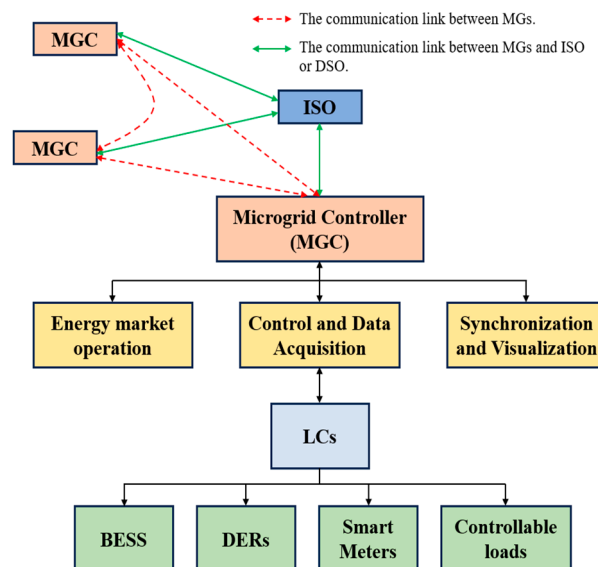


Figure 5. The interaction between the MGC with the local and global elements.

2.2. Resilience in Power System and Microgrid

In the past few years, the idea of resilience has emerged as an enhancement of earlier principles, aiming to guarantee the best possible functioning of the power system under circumstances or events. System resilience is described as the ability to prepare and adapt to changing conditions, resistance, and rapid return of disorders [29]. This concept of resilience not only strengthens the power system's ability to withstand disruptions but the ongoing procedure for improving robustness and operational flexibility to deal with uncertainties and recover from these events to ensure the continuity of power service, especially for critical loads such as hospitals, fire departments, and data centers.

Resilience in power systems acts as a defense line for guarding the system against various types of natural and human threats as planning efforts provide human operators. To make generation more resilient and more able to endure and recover from low-probability, high-impact events, such as natural disasters and human-induced attacks, certain adaptive measures could be applied to specific components [37]. These measures could include the integration of advanced technologies, the implementation of robust design principles, and the development of contingency plans. Furthermore, the use of DERs for power generation and operation, along with optimization techniques, could bolster the resilience of power generation against severe weather conditions. This comprehensive approach ensures the power system's robustness and adaptability under extreme weather events [38].

The focus on hardening of electrical network components to reduce the probability of failure including the type, placement, and size of DERs can significantly influence the system's robustness. Moreover, the BEES is another crucial factor in enhancing system resilience against various natural disasters. It helps maintain the balance between power supply and demand during disruptions. Moreover, energy storage allows for localized repairs without the need for a complete system recovery, thus minimizing the effects of unwanted outages [39].

2.3. Assessing Threats in Power Systems and Microgrids

Threats to power systems and microgrids can be broadly categorized into two types: natural hazards and human-induced hazards. These threats have the potential to damage, destroy, or disrupt the operation of utility grids or microgrids, and it is these threats that the systems aim to guard against. Natural hazards such as wildfires, hurricanes, floods, and earthquakes are environmental phenomena and beyond human control. These events can cause significant physical damage to power infrastructure, leading to disruptions in power supply [40]. For instance, wildfires can damage overhead transmission lines, while

floods can inundate substations and other ground-level infrastructure. Climate change is exacerbating these threats, with rising global temperatures leading to more frequent and intense extreme weather events. Conversely, human-induced hazards encompass both physical attacks and cyberattacks. Physical attacks on power infrastructure can cause immediate and tangible damage. This could range from vandalism to coordinated acts of terrorism. Cyberattacks, on the other hand, pose a more insidious threat. As power systems become increasingly digital and interconnected, they become more vulnerable to such attacks. Cyber threats can disrupt the operation of power systems, cause erroneous data readings, and even result in physical damage to equipment.

When evaluating the security and resilience of power systems and microgrids, it is crucial to assess the potential threats they face. Threat assessment involves identifying and analyzing various factors that could compromise the integrity, availability, or functionality of the energy infrastructure. By understanding the risks posed by various threats, stakeholders can implement mitigation strategies to reduce vulnerabilities and enhance the overall resilience of the energy infrastructure. Risk quantification involves assigning numerical values to the impact of identified threats. Risk quantification refers to the probability of a threat eventuating, while impact pertains to the severity of the consequences should the threat materialize. These values are often represented using qualitative scales (e.g., low, medium, high) or numerical scales (e.g., 1–10). This includes quantifying the extent of physical damage, the duration of disruptions, financial losses, environmental impacts, and social consequences.

2.4. Resilience Analysis

The resilience of a power system, especially in the face of critical events, can be effectively visualized using a system functionality curve (SFC), as demonstrated in Figure 6. An SFC provides a coherent depiction of how a resilient power system decreases the withstanding, adaptation, and recovery times compared to a conventional power system without resilience features. A range of parameters, including the proportion of load supplied, the count of customers served, the active percentage of system equipment such as overhead power transmission lines, and quality metrics like voltage and frequency [41]. These parameters can be used individually or in combination to achieve the desired SFC. This visualization underscores the importance of incorporating resilience features into power systems to enhance their ability to withstand, adapt to, and recover from extreme events [42].

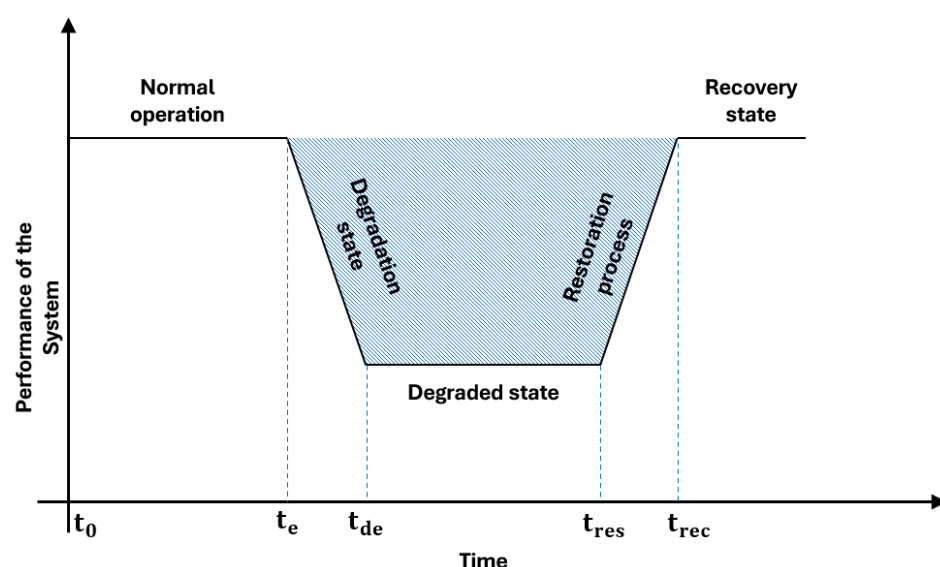


Figure 6. A conceptual resilience curve before, during, and after the event.

The enhancement of resilience in a power system is a process that involves five distinct phases. Initially, we have the pre-event state, which is the power system's condition before

any event occurs t_e , and the normal model operation at t_0 . During this phase, measures are taken to fortify the power system's resilience such as energy scheduling and planning. Following an event, the system enters the degradation state which is a transition from the pre-event state to the degraded state, characterized by a gradual decline in system performance to the degraded state t_{de} . During the degraded state, the system enters the during event state, where the aim is to re-establish system operation and maintain operational security to enter the restoration process. The restoration state is a transition from the degraded state at t_{res} to the post-event state t_{rec} , to restore the system to its original condition. The recovery state, also known as the post-event state, aims to restore the power system to its normal operation, as it was before the event occurred. The smooth transition between the five stages of enhancing the resilience of a power system is ensured through a combination of proactive planning, real-time monitoring, and post-event analysis using optimal control and proper monitoring tools.

Resilience metrics in power systems are evaluated based on different phases such as during event, post-event, and restoration periods. During event resilience is particularly important as it directly influences system degradation. However, most existing studies either focus on the restoration period or do not differentiate between various phases of a disruption event. Despite this, resilience during a disruption event is critically important as it determines the level of system degradation and therefore the required restoration time and effort. A comprehensive resilience metric should take into account the progression of failure scenarios during the disruption event.

3. Introduction to AI Techniques

Artificial Intelligence (AI) involves creating systems, such as computers or software, that mimic human intelligence or natural inspiration, including reasoning, learning from past experiences, and problem-solving. These intelligent agents perceive their environment and act to achieve their goals or optimize performance, with the ability to enhance their performance through learning [43]. In the context of power systems, which generate vast amounts of data due to system evolution and the integration of various components, conventional computational methods fall short. Therefore, AI methods are employed to efficiently handle and process these big data. This is particularly relevant in microgrids, where resilience can be enhanced through the effective use of AI [44]. A diagram illustrating AI subfields and techniques, along with a classification of the references reviewed in this survey, is presented in Figure 7. This section explores various AI subfields that have been successfully applied in this context, providing a comprehensive overview of the techniques.

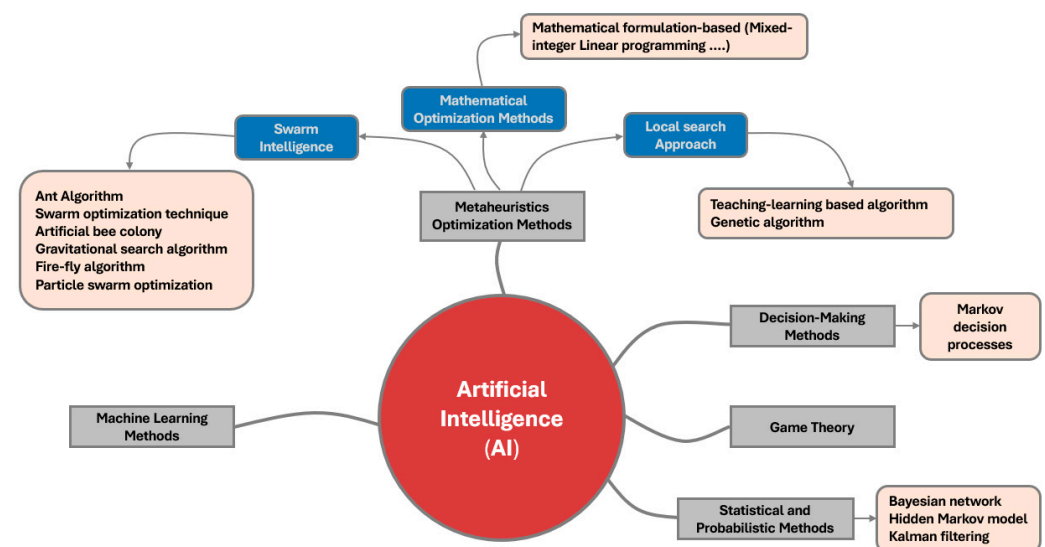


Figure 7. Diagram illustration for the AI subfields and techniques.

AI approaches are information driven in that they utilize existing information to carry out different tasks, and they can be generally gathered into five groups, as follows:

3.1. Metaheuristic and Optimization Methods

Search algorithm and intelligent optimization technique theories are key elements of the AI area and are capable of efficiently delivering optimal solutions to challenging and intricate real-world optimization problems, a task that would have been unfeasible with conventional or exact optimization methods. There is a wide class of optimization techniques based on mathematical approaches such as Linear Programming (LP), Quadratic Programming (QP), Convex Optimization (CO), evolutionary algorithms, heuristic methods, and metaheuristic approaches. As such, there is a comprehensive suite of both exact and heuristic approaches available for tackling optimization problems [45]. Recently, the advent of AI has spurred the evolution of numerous renowned metaheuristic and global optimization techniques inspired by nature and biology. Metaheuristic is a term that refers to high-level heuristic designed to solve a wide range of optimization problems. In recent years, several metaheuristic algorithms have been successfully applied to solve intractable problems.

The metaheuristic algorithms make almost no prior assumptions about the problem, can integrate several heuristics inside, and usually finds the best/optimal solutions by improving the global and the local best solutions of particles in the population [46]. These algorithms are attractive due to their ability to find the best or optimal solutions for even single and multi-objective problems, continuous and discrete constrained to unconstrained problems, and the largest problem sizes in a relatively short time frame. The majority of the state-of-the-art metaheuristics have been developed from the year 1990 until now such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Optimization (ACO), Cuckoo Search (CS), Differential Evolution (DE), Simulated Annealing (SA), Tabu search (TS), Frog-Leaping Algorithm (SFLA), Horse herd Optimization Algorithm (HOA), and crow learning algorithm (NCCLA). In addition, combining different metaheuristic algorithms is one of the most successful techniques in optimization. In addition, combining different metaheuristic algorithms has proven to be one of the most effective strategies in optimization. This includes hybridization models like GA-PSO, GA-ACO, CS-DE, ACO-CS, etc. [47].

3.2. Decision-Making Methods

The core principle driving this approach is the maximization of expected utility. This involves defining a utility function that assigns a numerical value to the desirability of a state, with the agent's decisions aimed at maximizing its objective function. In practice, agents have to deal with things that are not certain, and their success often depends on a series of choices and several decisions. As such, decision making can be modeled as sequential decision problems within uncertain environments [48].

Markov Decision Processes (MDPs) offer a solution to these problems when an agent's actions depend solely on the current state, more than the historical data. MDPs are characterized by a transition model, which outlines the probabilistic outcomes of actions, and a reward function, which specifies the reward in each state. The solution to an MDP is a policy that delivers a decision for every state the agent might reach. An optimal policy then maximizes the utility of the state sequences encountered during its execution [49]. These techniques are very popular in the design and development of applications in various fields, such as healthcare, where an AI algorithm might take in patients' vital signs and output a diagnosis, or in finance, where a stock-trading system might synthesize daily market prices and suggest stock buys. Decisions can be made by individual agents. In essence, these algorithms are designed to make optimal choices in complex scenarios, often involving uncertainty and a large number of variables. By leveraging the principles of maximization of expected utility and Markov Decision Processes, they provide robust and optimal solutions to sequential decision problems in uncertain environments. Thus, these

techniques represent a powerful tool for tackling complex decision-making problems in a wide range of contexts [50].

3.3. Game Theory

Game theory is a mathematical methodology that provides a strategic framework for analyzing scenarios where multiple individuals interact. A typical game in game theory includes the players, the strategies available to them, and the payoff each player receives for each combination of strategies. The players in a game are assumed to be rational, meaning that each player always tries to maximize their own payoff. Each type of game has its own set of assumptions and requirements, and the appropriate type of game to use will depend on the specific situation being modeled [51]. Game theory approach has two main branches: non-cooperative and cooperative game theory. Non-cooperative game theory deals with how rational economic agents deal with each other to achieve their own goals. On the other hand, cooperative game theory analyzes how groups of rational individuals can work together to achieve a common goal. Despite the variety of games and settings, the underlying goal of game theory is to predict the outcome of a game and to provide strategies for players to use to maximize their payoffs [52].

3.4. Statistical and Probabilistic Model-Based Method

Statistical modeling is a pivotal methodology in AI which is applied for the statistical models that navigate complex data, thus decomposing and inferring relationships between data variables. This approach is particularly useful in cases where data are abundant, and the patterns are hidden within the noise. Models follow a frequentist statistic and provide a fixed prediction amount, simply based on historical data and the effects of input variables on the output. A Bayesian statistic is a probabilistic approach which is based on judgments from multiple sources, such as experts' opinions, model simulations, and historical records. Moreover, this technique can provide the probability distribution of possible outcomes, considering the interrelation and causal inferences of input variables on each other [53].

Bayesian Networks (BNs) are the most commonly used probabilistic graphical model in the field of civil engineering. These networks are a statistical method that combines probability and graph theory to depict the causal connections between variables and their probabilities. BNs are represented as graphs, with nodes symbolizing random variables and directed edges indicating causal relationships between these variables. This representation is known as the Directed Acyclic Graphical model (DAG). The model includes a Conditional Probability Distribution (CPD) for continuous variables or a Conditional Probability Table (CPT) for categorical variables, which demonstrate the influences between the nodes. The structure and parameters for CPD or CPT can be determined through algorithms using extensive historical data, expert opinion, or a combination of both. BNs are extensively used in modeling, identifying, and analyzing risks related to different fields such as fault detection, power, and demand prediction [54].

3.5. Machine Learning

Machine Learning (ML) is a powerful tool that uses data-driven algorithms to 'teach' computers to perform tasks in a manner similar to humans and animals. This technology leverages algorithms that 'learn' directly from data. As the volume of data increases, these algorithms can adapt and improve their performance [22].

ML educates computers to learn from time series data or historical datasets and extract insights about the system for which the data were collected, without the need for mathematical models. The efficiency of these algorithms progressively improves as the dataset size increases [55].

ML is a cross-disciplinary field of study that amalgamates insights and expertise from various domains, with the objective of devising solutions to specific problems. ML paradigms find applications in a wide array of fields including medical diagnosis, disease spread forecasting, stock market analysis, search engines, recommender systems, gaming,

navigation, weather forecasting (like wind speed prediction), image and speech recognition, energy load forecasting, fraud detection, input selection, parameter estimation, and system identification of nonlinear and stochastic environments. ML is particularly effective in solving complex problems that involve large training datasets with numerous variables. Depending on the diversity of data and their target responses, ML can adopt unsupervised, supervised, or reinforcement learning paradigms [22]. These learning methods comprise various intelligent models that can be applied for classification, regression, or clustering problems, as depicted in Figure 8.

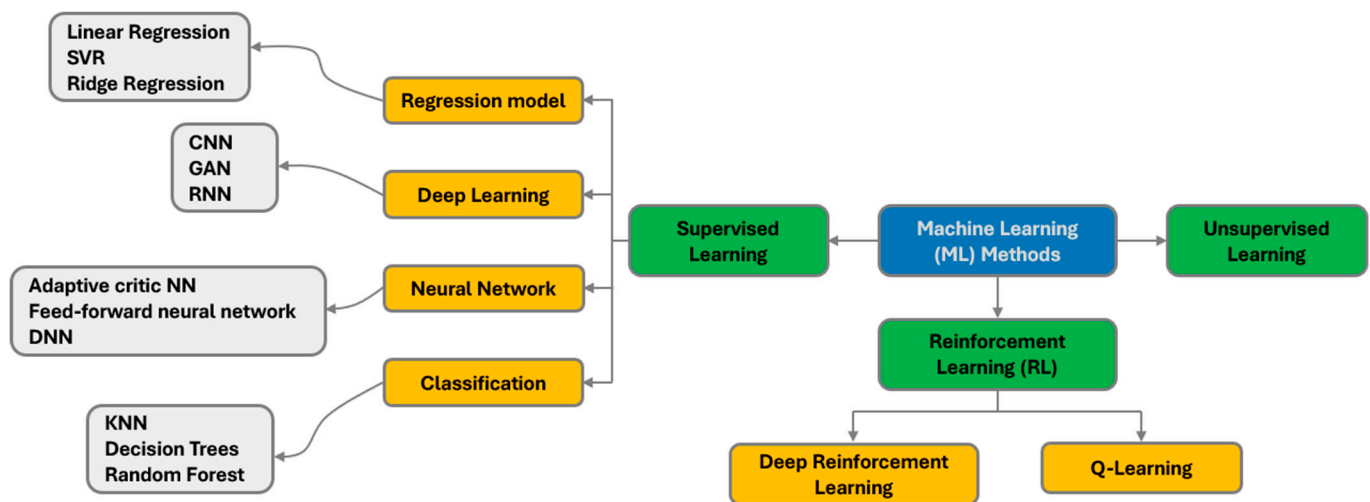


Figure 8. Diagram illustration for the various ML techniques.

ML methodologies are driven by data, utilizing existing information to perform a variety of tasks. These methodologies can be broadly categorized into three groups:

3.5.1. Supervised Learning

This is a type of machine learning which is able to learn from labelled data and predict responses for unknown data and offer solutions for a wide range of problems. It aims to achieve minimal error performance and is applicable in scenarios where both input and output data are available for model training. The trained model is then capable of predicting responses for unknown data. This task-driven learning technique can perform either classification or regression, depending on the requirements. The essence of supervised learning lies in its ability to learn a mapping from inputs to outputs based on a labelled set of input/output pairs present in the training set. The prediction performance of the model improves as the depth of model learning increases and the hyperparameters are optimized [56]. However, for accurate prediction of responses for predicted data, the existing dataset must contain a prototype for such cases. Models used in supervised learning include decision trees, random forests, and support vector machines, among others. For instance, decision trees are used for classification and regression tasks, providing interpretable results. Random forests, an ensemble of decision trees, offer robustness and improved accuracy. Deep learning models are effective for high-dimensional data and binary classification tasks [57].

3.5.2. Unsupervised Learning

This is a type of ML that operates on unlabelled data, seeking to uncover hidden patterns or intrinsic structures within the data. Unsupervised learning algorithms can perform more complex processing tasks compared to supervised learning but can be more unpredictable compared with other natural learning methods. This method is particularly useful when the available data consist of unique input variable, without any corresponding labelled responses [57]. As such, unsupervised learning is typically employed for problems

where only input data are available, and there are no target class labels to provide additional context. This data-driven learning technique aids in data exploration and leads to the formation of clusters within the dataset. Clustering has found significant applications in various fields such as market research, gene sequence analysis, and object recognition. Another application of unsupervised learning is anomaly detection, which identifies unusual data points in the dataset. This is particularly useful in fields like cybersecurity, where it can help detect fraudulent activities, and in healthcare [55].

3.5.3. Reinforcement Learning (RL)

This is a dynamic learning approach where an agent interacts with its environment, adapting actions based on the feedback received. Unlike supervised learning, RL does not rely on labelled data; instead, the agent navigates through rewards or penalties linked to its actions within the environment. This makes RL closely resemble the way humans and animals learn [55]. RL comprises goal-oriented algorithms that guide software agents to take actions in an environment to maximize cumulative rewards. In RL, a critic is present to administer rewards for correct actions and penalties for incorrect ones [56]. This reward/punishment-based learning technique includes four elements: critic, environment, reward/punishment, and action. The algorithm strives to maximize rewards, making RL popular in game designs, control applications, information theory, navigation, and robotics. Notable RL algorithms include Monte Carlo, Q-learning, SARSA, DQN, DDPG, A3C, NAF, TRPO, PPO, TD3, and SAC [56].

4. AI Approaches in Power System

AI has been increasingly applied in the field of power systems, offering innovative solutions and improvements in various areas. Figure 9 illustrates the broad spectrum of AI applications in power systems. It provides a visual representation of the various areas where AI has been applied, from operation cost mitigation and generation forecasting to fault detection and energy transactions. This section delves into the specific applications of AI in power systems. Each subsection provides a detailed exploration of how AI techniques have been utilized and the impacts they have had.

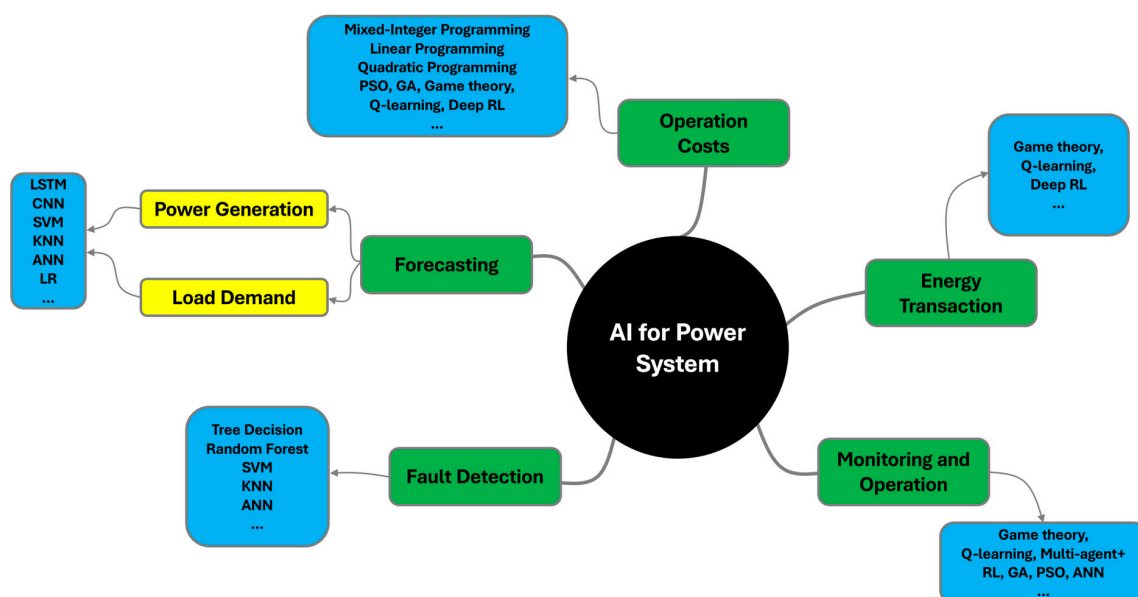


Figure 9. Overview of AI techniques in various power system applications.

4.1. Cost Operation

An efficient optimal operation strategy for DER in power systems is required and it is essential to coordinate and ensure the economical and optimal power dispatch from each

DER unit minimizing the operational cost. An optimal operation for the power system allows efficient energy consumption scheduling through coordination of the assets in the system, such as PV generation, storage, EVs, and flexible loads via demand response programs. This optimal operation aims to reduce the operational cost of DER, minimize emission costs and maintenance costs, optimize the start-up and shut-down processes of the DER, and minimize the degradation cost for the BESS [29]. The operation model problem in power systems solves the optimum objective function for the electrical network with given constraints like the cost function for the DER and the asset operational limits. AI techniques have been proposed to effectively schedule and plan alternative energy resources or energy storage, maintaining stability and optimally dispatching power to enhance economic benefits. AI models have been shown to support the automatic optimization of energy power systems at both transmission and distribution levels [58].

Several studies proposed a different AI model in their research to minimize the cost; in [59], a bi-level optimal dispatching model for a community integrated energy system (CIES) with an electric vehicle charging station (EVCS) is proposed. The model aims to balance energy supply and demand while maintaining user satisfaction. Moreover, the objective function is modeled to minimize the operating costs of the CIES and EVCS and incorporates a dynamic pricing mechanism. The model is solved using sequence operation theory, converting it into a mixed-integer linear programming formulation. In [60], an optimal power scheduling controller for energy management of distributed energy resources in a power system was developed. The controller uses a metaheuristic approach based on a lightning search algorithm to provide optimal power delivery with minimum cost. The study demonstrated that the controller reduced power consumption significantly, leading to substantial cost savings and a reduction in CO₂ emissions. The approach outperformed other techniques in terms of operating cost and solving complex optimization problems. The authors in [33] applied a modified gravitational search algorithm (GSA) to minimize the cost operation of the DER including PV power plants, combined heat power (CHP) systems, and diesel generators. The authors concluded that the proposed method has higher performance in solving the optimal power generation problem compared to other methods in terms of the computation cost and optimal value. In [61], a novel data-driven method for power system management in interconnected local power systems is proposed. The method uses a deep neural network to simulate operations under dynamic retail price signals, protecting customer privacy. A model-free Monte Carlo reinforcement learning method is applied to optimize pricing strategy, aiming to maximize profit and minimize the peak-to-average ratio. The method demonstrates considerable accuracy and computational efficiency, making it a promising tool for studying power system problems with hidden information or vast search spaces. In [62], a DRL-based Stackelberg game model is proposed for virtual power plants (VPPs) with electric vehicle charging stations. The model optimizes the scheduling of distributed energy resources and bidding strategies for market participation, while also learning scheduling strategies for charging and discharging electric vehicles. This approach achieves energy complementarity and improves the overall operating economy, including minimizing the operation cost and the start-up and shutdown costs of conventional energy resources. In [63], a two-stage optimization framework for microgrids' daily energy management was proposed, considering renewable energy sources, energy storage systems, and demand response programs. The framework uses a deep learning artificial neural network for forecasting the energy production and a cooperative game method for daily dispatch and energy transactions. The study demonstrated that this approach led to more accurate predictions and significant energy cost savings. The impact of energy storage systems on power system operations was also analyzed.

4.2. Power Forecasting

The integration of renewable energy resources into power systems poses significant challenges due to their unpredictable and intermittent nature. However, these challenges can be effectively addressed through the use of prediction methodologies [64]. These

methodologies play a crucial role in ensuring optimal scheduling, approximating reserves, managing the generated electrical power, facilitating efficient operation with the grid utility, reducing the cost of produced electrical energy, and handling congestion management [65]. Furthermore, the data collected through advanced technologies, such as meteorological devices and smart meters, can be incredibly useful for a range of forecasting applications. Once these data are collected, processed, and analyzed, they can help in forecasting real-time electricity prices, predicting power demand, estimating the output of renewable energy sources, and understanding consumer and power provider behavior. Therefore, the integration of highly accurate forecasting with thorough data analysis can greatly improve the incorporation and management of renewable energy resources in power systems [57]. Power generation and load demand forecasting are considered a solution to improve the stability and reliability operation of the system. Based on the time horizon of the studies, power generation and load demand forecasting can be categorized into short-term (i.e., prediction of load from minutes to hours), mid-term (i.e., prediction of load from hours to weeks), and long-term (i.e., prediction of load for years) [43].

4.2.1. Generation Forecasting

The authors in [66] compared various machine learning (ML) models such as linear regression, random forest (RF) regression, K-nearest neighbors, and support vector machines (SVMs) for short-term solar generation forecasting using solar radiation and temperature. The results indicate that RF and SVM outperform other models in short-term forecasting of solar irradiation and temperature, with SVM showing a slight edge over RF. In [67], a novel hybrid deep learning model is proposed for very short-term wind power generation forecasting. The model, which combines convolutional layers, gated recurrent unit (GRU) layers, and a fully connected neural network, outperforms other advanced models in terms of forecasting accuracy. The study uses data from two real wind farms in Australia and demonstrates the model's superior performance, improving the accuracy of wind power forecasting by up to 8.13% in mean absolute percentage error. In [68], a deep learning model based on physics-constrained long short-term memory (PC-LSTM) is proposed for accurate photovoltaic power generation (PVP) forecasting. This deep learning-based framework incorporates domain knowledge of PV, overcoming the limitations of data-driven machine learning algorithms. The PC-LSTM model demonstrated superior forecasting accuracy and robustness compared to the standard LSTM model and other conventional methods, particularly in scenarios with sparse data. The study emphasizes the importance of integrating domain knowledge into deep learning for improved accuracy, robustness, and interpretability. In [69], a novel algorithm is proposed for predicting PV power generation using an LSTM neural network. The algorithm creates a synthetic weather forecast by integrating historical solar irradiance data with the publicly available type of sky forecast. This approach improves forecasting accuracy by up to 33% compared to the hourly type of sky forecasts and 44.6% compared to daily forecasts. The superiority of the LSTM network with the proposed features is also verified against other machine learning models. In [70], novel hybrid deep learning neural network is proposed for 24 h ahead wind power forecasting. The method combines a Convolutional Neural Network (CNN) and a Radial Basis Function Neural Network (RBFNN) with a double Gaussian function. The CNN extracts wind power characteristics, which are then processed by the RBFNN to handle uncertainties. The proposed method outperforms traditional methods in accuracy, offering significant potential for efficient wind power operation. Another study in [71] proposed a novel hybrid model, RF-CEEMD-DIFPSO-BPNN, for accurate forecasting of PV power generation. This model integrates random forest (RF), improved grey ideal value approximation (IGIVA), complementary ensemble empirical mode decomposition (CEEMD), dynamic inertia factor particle swarm optimization (DIFPSO), and backpropagation neural network (BPNN). The model was empirically tested on a PV power plant and showed promising results in terms of forecasting accuracy, especially under rainy or snowy weather conditions. The error evaluation index Mean Absolute Percentage Error (MAPE) of the proposed model was

83.66% lower than the BPNN, indicating its superior forecasting efficiency for complex and nonlinear data sequences of PV power generation.

4.2.2. Demand Forecasting and Flexibility

An ML approach based on a Binary Genetic Algorithm (BGA) was applied in [72] to enhance the accuracy of the short-term electricity demand-forecasting model. The approach uses a Gaussian Process Regression (GPR) fitness function for predictor selection. The method was applied to various building energy systems in Espoo, Finland, and outperformed other feature-selection techniques. A Feedforward Artificial Neural Network (FFANN) model was used to evaluate the forecast performance, achieving a MAPE of 1.96%. In [73], a scalable big data framework is proposed for Short-Term Load Forecasting (STLF) using ML algorithms. The framework collects data from smart meters and weather sensors, processes them, and uses seven ML algorithms for forecasting. The best-performing algorithm is selected based on Root Mean Square Errors (RMSE). The methodology also includes dimensionality reduction, clustering, and automatic selection of relevant meteorological factors as input. The approach was tested on a residential smart building, demonstrating improved performance. In [74], a Bayesian deep learning technique is proposed for residential probabilistic load forecasting. The approach includes a three-step pipeline: clustering customers into groups, pooling load profiles within each group, and leveraging these groups in a multitask learning framework. This method addresses overfitting and improves predictive performance. The proposed approach is particularly suitable for practical applications such as residential demand response and network reliability analysis. Reference [75] addressed a deep learning-based framework for electricity demand forecasting, addressing long-term historical dependencies. The approach uses cluster analysis, load trend characterization, and LSTM network multi-input multi-output models. It also incorporates a moving window-based active learning strategy. The model, tested on data from Chandigarh, India, outperformed other methods in prediction accuracy and adaptability. In [76], a Deep Recurrent Neural Network with a Gated Recurrent Units (DRNN-GRU) model is proposed for forecasting the load demand of residential buildings. The model, which considers the complexity and variability of load demand, demonstrated higher accuracy compared to conventional methods when tested on residential load data measured hourly in Austin, Texas. The DRNN-GRU model also effectively filled missing data by learning from historical data. Reference [77] proposed a novel deep ensemble learning model using LSTM networks for ultra-short-term industrial power demand forecasting. The model, which employs a hybrid ensemble strategy and a new loss function, outperforms existing models in accuracy and robustness. The study also suggests further improvements in peak demand forecasting for longer time horizons.

4.3. Fault Detection and Analysis

Ensuring the stability of power systems is of utmost importance and requires the immediate detection of faults. Various factors such as equipment malfunctions, unusual conditions, human errors, and environmental factors can trigger faults in a power system. These faults can result in substantial economic losses and power outages. As a result, early and precise identification, localization, and categorization of faults are critical to improve safety and reliability, and minimize downtime and financial losses [56].

Historically, research in this area has concentrated on developing faster and more precise methods for detecting fault events in grids. This is accomplished by using both historical and real-time measurements as input data for ML algorithms. The goal is to increase the probability of an appropriate response from the grid's protection control system. This approach not only enhances the efficiency of fault detection but also contributes to the overall resilience of the power grid [55]. The application of AI techniques can further enhance this process. AI techniques can process large amounts of data quickly and accurately, making them ideal for real-time fault detection and response. Generating large volumes of fault data through simulation calculations is possible, but ensuring

consistency and accuracy in these simulated data can pose a challenge. It is often necessary for the results of these simulations to align closely with the exact fault outcomes for effective analysis of real-world power grid incidents [78]. The process of fault detection and prediction involves analyzing historical data to identify potential faults in the power system, which is crucial for maintaining the power system's reliability and stability. This approach not only enhances the efficiency of fault detection but also contributes to the overall resilience of the power grid and increases the economic benefits by minimizing the revenue loss owing to non-supplied power [79]. Several fault-prognosis and -diagnosis models are considered to detect and classify faults in power systems. Table 1 illustrates some of the research that was conducted using AI techniques for detecting and diagnosing faults in power systems.

Table 1. AI techniques are used for detecting and diagnosing faults in power systems.

Technique	Ref.	Description	Algorithm	Advantage	Disadvantage
Supervised Machine Learning	[80]	This study used the DT, KNN, and SVM models as part of a comparative analysis of different machine learning algorithms for fault classification in power systems. The SVM model was found to be the most effective in this study, outperforming the other two models. The study used an SVM with a radial basis function kernel, achieving a test accuracy of 91.6% for the generated dataset.	Decision Tree (DT)	Simple to understand and interpret	Prone to overfitting
Supervised Machine Learning	[81]	The study investigated the use of four powerful machine learning classifiers to detect and predict fault types and locations over a 750 KV, 600 km long power transmission line. The findings suggest that using machine learning techniques could be feasible for such tasks and may represent a great opportunity to increase power system protection and efficiency. However, results for location prediction accuracy may need to be improved in order to locate the fault precisely.	Naïve Bayesian Classifier (NBC)	High prediction accuracy for both fault type and location	Did not achieve enough accuracy for fault-type prediction
			Boosting	High prediction accuracy for fault type	Did not achieve enough accuracy for fault-type prediction
Supervised Machine Learning	[82]	This study proposed the use of IES-ML for fault detection in China's energy-based district heating system. The system was used to effectively boost the economy in contrast with the traditional power supply scheme. In addition, multi-energy coupling safety, durability, flexibility, and power have been validated. The experimental results indicate that IES-ML achieves the best accuracy of 98.67% in the identification and control of faults.	Integrated Energy System using Machine Learning Technology (IES-ML)	High accuracy of 98.67% in fault detection and control	Does not perform well when we have a large dataset because the required training time is higher
Supervised Machine Learning	[83]	This study proposed a deep learning-based diagnostic method for power quality disturbances (PQDs) in electric power systems (EPSs) using a CNN. The CNN model was trained with end-to-end learning and supervised learning approaches, and it successfully classified the type and location of the faults. The study demonstrated that the CNN model trained through the simulation of PQD data enables the accurate classification of faulty types and locations in the EPS.	Convolutional Neural Network (CNN)	High accuracy of over 99% in fault detection and control, reduced time required for diagnosing faults	Needs a lot of datasets to perform well.

Table 1. Cont.

Technique	Ref.	Description	Algorithm	Advantage	Disadvantage
Supervised Machine Learning	[84]	This study proposed a novel fault diagnosis method called multi-dimensional aggregation and decoupling network (MADN) for power quality disturbances (PQDs) in electric power systems (EPSs). The MADN architecture is designed fundamentally with three sequential stages: A multi-dimensional image building (MIB) stage, a feature decoupling mapping (FDM) stage, and a system fault state classification (SSC) stage. The proposed MADN can make a precise analysis of power system even with the transmission loss or unsynchronized multiple signals.	Multi-Dimensional Aggregation and Decoupling Network (MADN)	High accuracy in fault detection and control, adapts to complicated and alterable input, learns implicit features from multiple signals	Needs to be fine-tuned if great changes occur in the power system
Supervised Machine Learning	[85]	The study used Sequential Deep Learning (SDL) through Long Short-Term Memory (LSTM) to model spatiotemporal sequences of high-dimensional multivariate features to achieve accurate classification and prediction results.	Long Short-Term Memory (LSTM)	Models spatiotemporal sequences of high-dimensional multivariate features to achieve accurate classification and prediction results	Needs to be fine-tuned if great changes occur in the power system
Reinforcement Learning	[86]	This study proposed a DRL fault diagnosis model based on a CNN. The model outperforms traditional deep learning models and classic SVM in both initial sample size and small sample scenarios.	Deep Reinforcement Learning	High accuracy of over 99% in fault detection and diagnosis, slow convergence but better stability after reaching convergence status	Needs a prefect environment to perform well.
Reinforcement Learning	[87]	The study introduced a DRL model for fault detection and diagnosis in transmission lines. The DRL model outperformed the CNN model in all test cases, achieving a correlation coefficient of $R = 98.04\%$ in fault identification and $R = 96.61\%$ in early detection of single-phase to ground short circuit fault location (high impedance).	Deep Reinforcement Learning	High accuracy of over 99% in fault detection and diagnosis, more effective than CNN	Needs a prefect environment to perform well.

4.4. Monitoring and Control

The deployment of the IOT and sensor devices in the distribution network is truly remarkable in increasing its observability of dynamic and transient events and collecting information about the actual state of the power system, thus achieving a higher level of monitoring, observability, and control beyond the substation level. A huge amount of data is attained and employed in power network operation, control, and monitoring [88]. The application of AI techniques to analyze these data can lead to the identification of different patterns and the overcoming of complex control and monitoring tasks. AI plays a crucial role in addressing the transient stability problem of power systems, which includes determining the transient stability post-failure, predicting the status of critical parameters such as system frequency, power angle, and voltage post-failure, and quantifying emergency control measures after a transient failure, and monitoring the power system before, during, and after the fault occurs [57]. In particular, Fault State (FS) source location and

classification can be solved efficiently by AI and soft computing techniques which provide intelligent monitoring systems for the operation and planning of power systems [22].

In terms of power system operation, AI can assist in control, optimization, and decision-making problems. AI can bolster dynamic visibility for power system monitoring and control. This is particularly advantageous in systems; AI approaches provide a strategy for monitoring and controlling energy-consumption and energy-generation patterns, maintaining the comfort of the clients, monitoring the state of the power grid and its parameters, health monitoring of physical components, detecting anomalies in power flow, stability control, automatic generation control (AGC), voltage control, EM, and self-turning control [89].

While AI techniques in control and monitoring in power systems are still in their early stages, several studies have demonstrated immense potential; reference [90] presents a data-driven approach to reduce the cost of power quality (PQ) monitoring in power networks. Algorithms have been proposed to strategically place PQ meters on selected power links, reducing the uncertainty of PQ estimation on unmonitored links. The study demonstrated the efficiency of the meter-placement solution in various simulated networks, highlighting its potential to significantly decrease PQ monitoring costs. Reference [87] presents a deep learning approach for identifying and locating single-phase to-ground short circuit faults in power networks. The study utilized a hybrid model of DRL and CNN to interpret Time-Frequency (TF) traces related to these faults. The accuracy of the proposed hybrid model is higher than the simple CNN model and the use of such hybrid models improves monitoring issues in the power system. In [91], a goal representation heuristic dynamic programming (GrHDP) controller was developed to enhance the transient stability of a doubly fed induction generator (DFIG) based a wind farm. The GrHDP controller, tested on two cases, demonstrated improved low voltage ride through (LVRT) capability and transient stability under grid fault conditions. The controller's weights were adjusted based on back-propagation, requiring sufficient sampling time for real power system applications. Reference [92] introduced a DRL constraint encoding method for the frequency-constraint microgrid scheduling problem. The method uses an ANN to approximate the nonlinear function between system operating conditions and frequency control, which is then integrated with the scheduling problem. The method ensures both islanding success and adequate frequency response and also can be applied to any dynamic-constrained optimization problem. In [93], a data-driven online scheduling method for microgrid energy optimization was proposed, leveraging continuous-control DRL. The method, which uses a GRU-based network and proximal policy optimization (PPO), effectively handles uncertainties in renewable energy sources, load demand, and electricity prices. It outperforms existing DRL-based methods and closely matches the Mixed Integer Quadratic Programming (MIQP) method's performance. The authors in [94] proposed a disagreement-based deep learning method (DVSM) for static voltage stability monitoring. The DVSM uses a small amount of labeled data and a large amount of unlabeled data to train a DNN. The method can swiftly adapt to changes in network operating conditions or topology, achieving over 94.03% accuracy with only 300 labeled samples, and over 95.48% accuracy after line tripping with only 5 samples per category.

4.5. Energy Transaction and Energy Market

In the Transaction Energy (TE) concept, the community allows for energy transactions between its peers which is typically implemented through local energy markets (LEM). In addition, TE also encompasses the transactions between the energy community and the large national power system through the wholesale electricity markets [95]. TE is gaining popularity as a design framework for the demand response (DR) program in power systems and is a control mechanism that allows the dynamic balance of supply and demand across the entire power system infrastructure [96]. DR programs encourage consumers and energy providers to adjust their energy usage in response to incentive payments designed to induce lower power usage during peak hours. However, the stochastic nature of demand and generation provides a vital function when managing energy flows within the system [74].

This leads to a set of operation-optimization problems in planning generation, energy system operation within consumption, device control, and market interaction, which are deemed as the main applications of AI tools. AI approaches could be employed in several applications in different energy transactions and energy markets and play a significant role in the maximization of social welfare by determining the price of electricity via fair and competitive market transactions in the LEM.

AI methods can be utilized in resolving such problems as market clearing, as reported in [97,98], where the authors present an LEM for prosumers, formulated as a generalized game theory. A network operator enforces operational constraints, and a semi-decentralized Nash equilibrium-seeking algorithm is used to ensure an economically efficient, strategically stable, and operationally safe configuration. The approach is scalable, and active market participation is beneficial for both prosumers and network operators, and internal price calculation, as reported in [99], which represents an MDP formulation for joint bidding and pricing in the LEM. The DRL algorithm is used to solve the MDP for optimal policies. ANN is employed to learn dynamic bid and price response functions from historical data, which are used to generate state transition samples, reducing the violating line flow. In [100], a decentralized energy trading scheme was proposed for electricity markets with high penetration of DERs. The scheme allows market players to maximize their welfare through bilateral energy trading, using a primal-dual gradient method for market clearance. The method respects line flow constraints and requires lower data exchange, with faster convergence compared to similar methods. And price prediction was introduced in [101], where a hybrid model, WT-Adam-LSTM, was proposed for electricity price forecasting. The model combines wavelet transform and an Adam-optimized LSTM neural network. The wavelet transform stabilizes the variance of the nonlinear electricity price sequence, while the Adam optimizer enhances LSTM's performance.

5. AI Approaches in Microgrid Resilience

The integration of microgrids into the main power grid has shown promising potential in enhancing power system resilience, particularly during outages. However, the complexity of managing multiple interconnected microgrids and the challenges posed by switching operations necessitate innovative and intelligent solutions. At present, AI technology has better adaptability and flexibility with respect to solving the problems of nonlinearity, strong uncertainty, strong coupling, and multi-variables contained in microgrid systems [23]. In the following sections, we delve into how AI can be leveraged in microgrids to enhance resilience in various aspects:

5.1. Service Restoration

At present, the service restoration for the microgrids after major disasters mainly considers using available generation resources to maximize the restoration of critical loads and ensure that the restored loads can be provided with a sustained and stable power supply during the operation. The integration of distribution generators including microgrids in the distribution systems provides new opportunities to maintain the power supply at critical loads and enable faster restoration [102]. In order to maintain customer satisfaction and enhance the reliability of the network, it is imperative to implement a robust service-restoration strategy that ensures swift recovery following the characteristics of the distribution system [103]. In fact, service restoration accomplishes the self-healing operation in microgrids; thus, this problem is crucial and sensitive. Mathematically, service restoration is a combinatorial problem with the objective of maximizing the supply of power for as many loads as possible which must be carried out violating the constraints of distribution system operation, while still preserving the radial topology and satisfying the constraints of the problem. The mathematical constraints applied are for the service restoration including the client weight, restoration and switching cost, current and voltage limits, and the radial characteristics for the distribution network.

The service-restoration problem is classified as a single- and multi-objective function problem. Several AI approaches based on different methods have been applied to solve the service-restoration problem in microgrids. The traditional AI methods of service restoration in microgrids mainly include the mathematical methods referenced in [104]; in that study, a mathematical model for restoring balanced radial distribution systems was proposed. This model, a mixed integer second-order conic programming problem, optimizes several objectives, prioritizing demand satisfaction, minimizing switch operations, and supplying the critical loads. The model demonstrated robustness, efficiency, and flexibility in tests on a 53-node system. In [105] a Colored Petri net (CPN) model was developed for efficient service restoration in distribution systems. The system prioritizes key customers and integrates operation rules from Taipower, ensuring compliance with regulations. The effectiveness of this approach was demonstrated through simulations on a Taipower distribution system with 18 feeders, a metaheuristic approach as referenced in [106]. That study introduced a novel self-healing topology for micro-grids, enhancing resilience during faults by prioritizing critical loads. It operates in two modes: normal and self-healing. The normal mode minimizes generation costs, while the self-healing mode maximizes power from undamaged Distributed Energy Resources (DERs) during faults. The Binary Teaching-Learning-Based Optimization (BTLBO) technique is used to optimize the switching action sequence. The proposed topology outperforms traditional methods in priority selection and computation time, and the fuzzy approach as in [107]; the authors of that study presented a fuzzy logic-based methodology for managing microgrids in islanded conditions to maximize power supply duration. It considers load shedding, fossil fuel dispatch, and demand response actions. The EMS controls microgrid variables and manages grid operation. The approach is validated using a modified IEEE 34 node sample system. The results demonstrate the effectiveness of the proposed methodology in enhancing the reliability and resilience of power systems.

Recently, the above methods achieved an effective solution to enhance the resilience of the microgrids and distribution systems; however, they cannot ensure the optimal solution in an effective time because of the computation burden. To overcome the computational issue, several techniques based on learning algorithms have been proposed such as machine learning in [108,109], and deep reinforcement learning in [110,111], which can be a good alternative to solve the service-restoration problem for the microgrid.

5.2. System Reconfiguration

The process of network reconfiguration, which involves changing the open/closed status of switches, has become a prevalent feature in microgrids and modern power systems. This process, also known as distribution network reconfiguration, is defined as the method of altering the status of normally open/closed switches in the distribution network. One of the key benefits of network reconfiguration is its effectiveness in reducing potential damages caused by natural disasters. By changing the system topology, networks can be made less susceptible to such disasters. In the event of a distribution network failure, system reconfiguration for microgrids and the distribution network can minimize power loss by optimizing the switching combination scheme [112]. The goal is to achieve a configuration that optimizes desired objectives while satisfying all operational planning constraints of the network, without isolating any functioned network nodes.

Network reconfiguration contributes significantly to enhancing power system resilience. It does this by redirecting faulted areas to alternative supply sources through sectionalizing switches within a feeder or tie switches between feeders. In addition to volt/var support, loss reduction, and load balancing, reconfiguration is also used for restoration purposes. However, reconfiguration in resilience is a combinatorial problem that involves searching an enormous space of solutions [7].

The advent of advanced technologies, such as phasor measurement units, remote controls, and AI, has significantly facilitated the implementation of network reconfiguration. AI approaches, capable of analyzing complex data, predicting potential issues, and

optimizing network performance in real time, have revolutionized this process. These advancements have made today's power systems smarter than traditional networks, with DNR being recognized as a flexible solution in the modernization of power systems [113].

Recently, numerous research works have been published on the problem of network reconfiguration in microgrids. Generally, the authors of these papers have employed different AI methodologies and techniques to solve the problem. Reference [114] introduces a Maximum Likelihood Estimator (MLE)-based ensemble technique based on an unsupervised technique for enhancing the resilience of electric distribution systems against extreme weather and cyber events. Utilizing Distribution Phasor Measurement Units (D-PMUs) and data-mining techniques offers a proactive, resilience-driven reconfiguration strategy to minimize the impact of adverse events. The effectiveness of this approach demonstrated through real-world test cases, underscores the potential of such advanced techniques in ensuring grid resilience amidst the increasing frequency of extreme events. In [115], the ML approach for enhancing the observability of automated microgrid reconfiguration was introduced. The authors proposed a multi-stage strategy for positioning micro-synchrophasor units, considering the reconfigurable structure of distribution systems. The approach, formulated within an integer linear programming framework, leverages a whale optimization method to optimize topology and reduce costs. The authors demonstrate that their method ensures system observability pre- and post-reconfiguration, even under varying load levels and topologies. Reference [116] presents a novel Soft-Hard Optimal Convergence (SHOC) strategy that combines AI and algorithmic optimization to enhance the resilience of electrical distribution systems in large cities. The SHOC strategy, which uses machine learning to train an AI agent with offline scenarios, enables rapid calculation of optimal reconfiguration and recovery paths post-disaster. The authors demonstrate the effectiveness of this approach in a 70-node distribution system case, achieving significant speedups in solution times. Reference [117] proposes an RL model for reconfiguration to enhance the resilience of distribution systems following major outages. The model, which learns to efficiently restore systems, incorporates asynchronous information and uses a Monte Carlo Tree Search for expedited training. Validated on IEEE test feeders, the approach demonstrates scalability and effectiveness, offering a robust decision-making tool for large-scale systems under asynchronous and partial information scenarios.

5.3. Power System Stability and Load Frequency Control

The integration of DERs into the main grid, coupled with the uncertainties of the extreme weather conditions and randomness of renewable energy source production, can lead to power and frequency fluctuations, potentially causing system instability and even widespread power outages. Therefore, a resilient controller is needed to manage and improve the accuracy of active/reactive power-sharing and simultaneously control the voltage and frequency in networked microgrids. MGs typically employ automatic control mechanisms for their operation. This includes the operation of tap-changers, reactive shunt devices, Flexible AC Transmission Systems (FACTSs), Power System Stabilizers (PSS), and Load Frequency Control (LFC). These systems work in harmony to ensure the stability and efficiency of the power system.

A key control technique is to design a PSS and LFC law under different operation cases of the networked MG to maintain the voltage magnitude and the frequency at desired values. The implementation of the PSS in the MG application is a simple and cost-effective approach, and adds a supplementary stabilizing signal to the excitation system, enhancing both steady-state and transient stability. The crucial factor in achieving the appropriate action from PSS in time is the proper tuning of key parameters of PSS. The critical task in PSSs is addressed using AI approaches by the researchers to develop efficient control as, for example, in [118]

A PSO-based tuning methodology for PSSs in electric power systems has been proposed. This AI-based technique is implemented to enhance system stability by minimizing oscillations. Despite some limitations in certain systems, the methodology shows significant improvement in stability compared to conventional strategies. In [119], an ensemble approach, combining three machine learning techniques, for real-time tuning of PSS pa-

rameters to dampen unwanted oscillations in power systems is presented. The method was tested on two single-machine power system models under various loading conditions. The proposed model outperformed other approaches in all performance indicators, demonstrating its ability to predict PSS parameters instantly and enhance system stability. In [120], the authors introduced a Linear Neuro-Adaptive-Predictive Control Power System Stabilizer (LNAPC-PSS) as an alternative to the traditional power system stabilizer. This LNAPC-PSS, which utilizes a simple, linear neural identifier, minimizes computational demands and enables quick learning. The authors demonstrate its superior performance in damping oscillations across various operating conditions. They argue for the sufficiency of simple, linear neural networks for online system identification, negating the need for complex network structures and nonlinear activation functions, thus advocating for their model-free, decentralized approach. Reference [121] addressed the issue of low-frequency oscillations in interconnected power systems. The authors propose a Neuro-Fuzzy Controller (NFC) as a more efficient alternative to the traditional PSS and Interline Power Flow Controller (IPFC). The NFC, which reduces computational and simulation costs, demonstrated superior performance in damping oscillations and improving system stability in various operating conditions, outperforming the traditional controllers in both transient and steady-state areas.

On the other hand, the LFC maintains the desired frequency and power interchanges. In the context of enhancing the resilience in the MG, the application of AI in LFC can determine the transient stability pre-event, during event, and post-event and predict the status of critical parameters in the system such as voltage magnitude and frequency. Reference [122] introduced an emotional learning-based intelligent controller for improving LFC in a two-area interconnected power systems, considering generation rate constraints. The controller, which includes a neuro-fuzzy system and a fuzzy critic, outperforms proportional integral, fuzzy logic, and hybrid neuro-fuzzy controllers in damping frequency oscillations. Notably, it responds faster under a stringent 3% generation rate constraint. Reference [123] explores the integration of electric vehicles and renewable sources into multi-area power systems. They propose AI-optimized PI controllers, including Fuzzy logic, FOPID tuned by fuzzy, and model predictive control, for LFC. The new technique-based AI approaches, validated using simulation tools, enhance controller performance by reducing frequency deviation and overshoot, with the FOPID controller tuned by fuzzy showing the best performance. Reference [124] proposes a data-driven cooperative method for LFC in multi-microgrids, using multi-agent DRL. The method optimizes controller parameters through centralized learning and decentralized implementation, considering physical constraints. Simulations on a three-area system and the New England 39-bus system demonstrate its effectiveness in reducing frequency deviations and unscheduled tie-line power flows, validating its superior performance.

5.4. Cyber Security Enhancement

As mentioned earlier, microgrids as cyber-physical systems are increasingly reliant on information and communication technologies, making them vulnerable to cyber disruptions and attacks. These vulnerabilities can lead to incomplete information and control failures, particularly during extreme weather events. In addition, these threats can affect microgrid stability, reliability, and economy, and pose significant challenges to the safe and efficient operation of the system.

Cybersecurity, therefore, is a critical issue in MG studies. Recent advancements in digitalization have increased these risks, even with smart infrastructure at both the on-grid and end-user levels. AI models, particularly those using ML and DL, have been proposed as solutions to these security challenges. These models use the mathematical model combined with time-series prediction to identify manipulated meter readings at the distribution grid level. Most cybersecurity research in MGs focuses on threats such as false data injection (FDI), sensor attacks, communication latency, denial of service attacks, and control system attacks. Therefore, innovative control solutions and cybersecurity techniques are needed to ensure the safe operation of MGs and improve system resilience. Table 2 represents the AI techniques applied in cybersecurity to enhance the resilience of the microgrid.

Table 2. AI techniques used for cybersecurity to enhance the resilience in microgrid systems.

Security System	Ref.	Technique	Phase	Description	Limitation
False Data Injection (FDI)	[124]	SVM	Post-event	Investigated a novel method for detecting FDI attacks in Industrial IoT systems using autoencoders. Their approach outperformed ML-based methods, offering higher detection rates and lower false alarms. They also demonstrated the effectiveness of denoising autoencoders in recovering original data from corrupted data.	The proposed algorithm is able to detect attacks that ruin the correlation among sensor readings.
	[125]	ANN	During/Post event	Introduced a novel detection mechanism for false data injection attacks in AC state estimation using the ANN technique. the proposed approach demonstrated superior performance in detecting attacks and recovering system states. Despite the complexity, the proposed mechanism maintained less than 10% false positive/negative detection rate, proving its effectiveness in real-world power systems.	The model must be trained for each type of attack.
	[126]	DL	Pre/Post event	A novel strategy for FDI attacks on power systems is proposed, utilizing a Q-learning algorithm for online learning and attacking. The study also presents a mitigation method using kernel density estimation for bad data detection and correction, enhancing the security of the system. The tests reveal that the FDI attacks can cause system-wide voltage collapse and disrupt normal operations, even with limited knowledge of the whole power system. The mitigation method effectively enhances the security of the state estimation and the automatic voltage control (AVC) based on optimal power flow.	As a very sparse attack method, the proposed method may select target substations to guarantee its efficacy
Control System Attacks	[126]	ANN	During/Post event	A model predictive control (MPC) and ANNs is proposed to detect and mitigate false-data injection for control system attacks in the DC microgrids. The strategy effectively counteracts the effects of cyberattacks, ensuring secure operation. Tested under various conditions, including control attacks. The results show that the proposed strategy can calculate and remove the false data properly, with a very low estimation error, enhancing the performance of the system.	Solving an optimization problem, which can increase the computational burden
	[127]	ANN	Post-event	ANNs model is proposed to detect and mitigate control system attacks in DC microgrids. The decentralized approach, tested under various conditions, effectively estimates and removes the disruptive data, ensuring secure operation. Real-time simulations are used to validate the effectiveness of the proposed strategy in maintaining the stability of the DC microgrid.	This may limit its effectiveness in detecting and mitigating attacks under different or more complex scenarios
	[128]	DRL	During/Post event	a TSK fuzzy system-based DRL approach is proposed for the assessment and security control of interconnected microgrids. The study introduces an active defensive strategy to recover the microgrids to normal operation state. Simulation results validate the effectiveness of the proposed learning assessment strategy and the optimal defensive strategy in improving security levels and reducing security risk and economic cost.	The scalability of the method for larger or more complex microgrids

Table 2. Cont.

Security System	Ref.	Technique	Phase	Description	Limitation
Sensor Attacks	[129]	ML	During event	a robust framework was proposed to counteract sensor attacks in wireless sensor networks within microgrids. The study introduced an intelligent anomaly detection method, utilizing prediction intervals and a modified optimization algorithm, to identify varying degrees of malicious attack. The results underscored the model's accuracy and performance.	Needs a lot of datasets to perform well.
	[130]	DRL	During/Post event	the performance of the discordant cyberattack detection algorithm was evaluated under various conditions. The algorithm effectively detected sensor attacks on distributed current signals. The study highlighted the algorithm's ability to detect attacks even under load switchings and destabilizing conditions.	Needs a lot of datasets to perform well.
Denial of Service (DoS) Attacks	[131]	DRL	Pre/During the event	A novel data-driven decentralized secondary control scheme was proposed to manage multiple heterogeneous BESSs in microgrids. The scheme, based on an A3C multi-agent DRL, effectively balanced frequency regulation and state-of-charge. To mitigate the impact of DoS attacks on local communication networks, a dynamic event-triggered communication strategy was introduced.	The scalability of the method for larger or more complex microgrids
	[132]	ML	During event	proposed a resilient control scheme to mitigate the impact of hybrid cyberattacks, including DoS attacks, on modern marine microgrids. The scheme, based on adaptive ML and active disturbance rejection control, was designed to maintain system frequency performance under various attack scenarios. The effectiveness of the approach was demonstrated through real-time simulations, highlighting its robustness and ease of implementation.	Needs a perfect environment to perform well.

5.5. Multi Microgrids Coordination

The primary issue in the multi-microgrid pre-/during/post-events is coordinating and operating the interconnected microgrids in the optimal operation mode to minimize economic losses. The coordination of multi-microgrids requires careful consideration of several factors [12]. These include system stability, energy balance, microgrid connectivity, and hierarchical control of frequency and voltage, among others. One of the effective ways to address this issue involves linking multi-microgrids and managing each via a distributed or centralized control mechanism [58].

Additionally, the development of advanced algorithms for the control mechanism can significantly improve the coordination among the microgrids. This not only enhances the overall efficiency but also ensures a stable power supply during critical events. Furthermore, the implementation of a comprehensive regulatory framework can guide the operation of these interconnected microgrids, thereby ensuring a reliable and sustainable power system [41]. A wide range of studies has described coordination planning for multi-microgrid systems using AI applications to enhance the resilience of the power system as follows. In terms of economic losses, reference [61] presents a data-driven approach for energy management in multi-microgrids using deep neural networks and the RL model. The authors construct a model that simulates multi-microgrid operations under dynamic retail price signals, protecting customer privacy. The distribution system operator optimizes its

pricing strategy using a Monte Carlo method based on the AI model, aiming to maximize profit and minimize the peak-to-average ratio. The proposed method outperforms conventional models in computational efficiency and accuracy, showing promise for future power system studies with hidden information or large search spaces. Reference [133] proposed an energy-management system for multi-microgrids that ensures efficient coordination and fair energy cost allocation to enhance resilience. Unlike the previous studies, the application of a cooperative game for energy cost allocation is solved using a novel algorithmic approach. Additionally, they employ a DL model for daily operating cost estimation. Their method significantly outperforms existing models, achieving a reduction in daily operating costs of up to 87.86%. The study also presents a robust mechanism for equitable expense distribution among multi-microgrids.

On the other hand, to enhance the stability of the power system, the authors in [134] propose a resilience-oriented multi-objective two-stage scenario-based stochastic modeling approach for optimal energy management in multi-microgrids. This approach enhances the resilience of the distribution system during extreme power outages. The study also investigates the impact of charging and discharging electric vehicles on the resilience of interconnected microgrids and the distribution system. The authors demonstrate that limiting the charge of electric vehicles to 40% during emergencies can improve the resilience of microgrids without compromising the distribution system's resilience. In [135], a novel energy-management method for multi-microgrids using an improved Deep Q-Network (IDQN) was developed. The method leverages a Kriging surrogate enhanced GRU-TCN deep network and a k-crossover sampling strategy. This approach enhances the efficiency of action space exploration and reduces computational complexity. The results indicate that the proposed method significantly improves the economic efficiency of multi-microgrids, outperforming traditional methods in terms of accuracy and convergence speed. Reference [136] proposes a decentralized framework for resilience-oriented coordination of multi-microgrids using a novel multi-agent reinforcement learning (MARL) method. The method, called Shapley Q-value Deep Deterministic Policy Gradient (SQDDPG), leverages the Shapley Q-value and DDPG algorithm to accurately learn each agent's contribution to system resilience. The authors demonstrate the effectiveness of their approach through case studies on two modified IEEE distribution networks, showing superior performance in optimality, stability, and scalability compared to existing methods.

6. Challenges of AI for Microgrid Resilience and Future Direction

The adoption of AI technology to enhance the resilience of microgrids comes with significant challenges. Several challenges and selective suggestions are discussed in this section.

6.1. Limitations of AI Applications in Resilience

- The adoption of AI in microgrids is still in the early stages, and there are many difficulties that must be addressed. AI technology has not been adopted totally across all energy sectors. The primary deterrent appears to be the challenges for real application in microgrids.
- Primarily, dependence on conventional technologies poses a barrier to the implementation and acceptance of AI technologies in microgrids.
- Furthermore, the significant challenges faced by the energy providers to use AI technologies to enhance the resilience of the microgrids include the need for top management support regarding IT infrastructure, low investments, the mismatch between human goals and machine output, and lack of accountability. In addition, there are multiple technological challenges during adoption, such as the difficulty in algorithm readiness and the lack of technology provided.
- AI technologies play a pivotal role in enhancing grid resilience by preventing power interruptions and reducing disturbances. However, the effectiveness of a microgrid could be jeopardized if it lacks adequate protection for AI technologies against disturbances occurring within its boundaries or in the neighborhood.

- AI models require large amounts of data for training and building an optimal model, and the quality of these data is crucial for the performance of these models. However, the data related to renewable energy sources can be inconsistent and incomplete due to various factors such as weather conditions, geographical location, and time of year.
- In order to expand the widespread adoption of AI technologies in microgrids, there is a need to address the regulatory issues associated with enhancing resilience. These include ownership regulations, market regulation and policies, and strategic placement of the technologies.
- Previous literature underscores the need for proper training and testing for the rapid adoption of AI technology. In addition, the lack of government support, policies, regulatory framework, and incentives is another major challenge the organization faces in adopting AI.

6.2. Future Direction

This review presents crucial and targeted recommendations for advancing AI technology to enhance the resilience of microgrid applications:

- There is a need to establish the link with traditional theories. Therefore, future researchers can work on using resource-based views, dynamic capabilities, and other relevant theories to understand how AI can be effectively integrated into microgrids to enhance their resilience.
- The development and integration of advanced IoT technologies that are compatible with AI models could indeed be a promising avenue for enhancing the overall efficiency and resilience of microgrids.
- Indeed, the creation of comprehensive simulation models of interconnected microgrids, which include a variety of DG sources and types for diverse loads and fault conditions, is a crucial aspect of this research. These intricate models can facilitate the generation of synthetic data that closely mirror real-world scenarios, providing a rich dataset for ML and DL algorithms.
- The concept of a Digital Twin (DT) can indeed be leveraged to enhance the resilience of microgrids. A DT is a virtual model that replicates the physical system in digital space. When integrated with AI, it can provide a multiphysics mirror of the microgrid, allowing for real-time monitoring, control, and optimization.
- Future research should prioritize the practical validation of various proposed techniques through real-time experimental investigation to ensure the effectiveness and reliability of AI and IoT technologies in enhancing the resilience of microgrids.
- Future studies can focus on the application of AI to improve maintenance procedures in microgrids, thereby enhancing resilience after faults occur.
- Developing and implementing innovative feature-extraction methods could be a good choice to enhance the speed, precision, and resilience of ML and deep learning DL models used for safeguarding microgrids.
- Future research should explore the potential of integrating HPC in the development and deployment of AI models for microgrids. These powerful systems can handle complex computations at a much faster rate, which could significantly reduce the time required to train AI models. Once trained, these models could be stored in the cloud, allowing for easy access and scalability.
- The incorporation of the latest models of AI in microgrids such as the Explainable AI (XAI) technologies can lead to more transparent and reliable AI-driven solutions, fostering trust among stakeholders and promoting wider acceptance of AI technologies to enhance resilience.

7. Conclusions

The rapid evolution of power systems towards decentralized systems such as microgrids, characterized by the integration of state-of-the-art technologies, presents a compelling motivation for this research. In this paper, we have attempted to present and review major

new studies of AI techniques applied to the main problems of power system control in the context of microgrids. We introduced various AI techniques, including metaheuristic and optimization methods, machine learning methods, and deep learning. We explored AI approaches in power systems, including cost operation, power forecasting, fault detection and analysis, monitoring and control, energy transactions, and energy markets.

We further investigated AI approaches in microgrid resilience, including service restoration, system reconfiguration, power system stability, load frequency control, and cyber security enhancement. Despite the advantages of AI techniques, we also discussed the challenges of AI for microgrid resilience and future directions.

The literature shows that the application of AI in power system monitoring and control improves the performance of the controller in terms of speed, accuracy, and efficiency compared to its conventional counterpart. Although every AI technique has its own share of advantages and drawbacks, it was duly concluded that machine learning and deep learning methods are more suitable for monitoring and control.

This review presents a thorough examination of the current state of AI applications in power system monitoring and control. It highlights the potential of AI in this field, suggesting that it could bring about significant changes and improvements. The paper concludes by discussing potential future work and directions in this area, underscoring the promising role of AI in advancing power system monitoring and control.

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