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Review

A Comprehensive Review on the Role of Artificial Intelligence in Power System Stability, Control, and Protection: Insights and Future Directions

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Abstract: This review comprehensively examines the burgeoning field of intelligent techniques to enhance power systems' stability, control, and protection. As global energy demands increase and renewable energy sources become more integrated, maintaining the stability and reliability of both conventional power systems and smart grids is crucial. Traditional methods are increasingly insufficient for handling today's power grids' complex, dynamic nature. This paper discusses the adoption of advanced intelligence methods, including artificial intelligence (AI), deep learning (DL), machine learning (ML), metaheuristic optimization algorithms, and other AI techniques such as fuzzy logic, reinforcement learning, and model predictive control to address these challenges. It underscores the critical importance of power system stability and the new challenges of integrating diverse energy sources. The paper reviews various intelligent methods used in power system analysis, emphasizing their roles in predictive maintenance, fault detection, real-time control, and monitoring. It details extensive research on the capabilities of AI and ML algorithms to enhance the precision and efficiency of protection systems, showing their effectiveness in accurately identifying and resolving faults. Additionally, it explores the potential of fuzzy logic in decision-making under uncertainty, reinforcement learning for dynamic stability control, and the integration of IoT and big data analytics for real-time system monitoring and optimization. Case studies from the literature are presented, offering valuable insights into practical applications. The review concludes by identifying current limitations and suggesting areas for future research, highlighting the need for more robust, flexible, and scalable intelligent systems in the power sector. This paper is a valuable resource for researchers, engineers, and policymakers, providing a detailed understanding of the current and future potential of intelligent techniques in power system stability, control, and protection.

Keywords: smart grid; artificial intelligence; power system stability; power system protection; wavelet transformation; neural network; evolutionary algorithms

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1. Introduction

A power system constitutes a network of electrical components facilitating electricity generation, transmission, distribution, and utilization. Power systems engineering, a branch of electrical engineering, encompasses studying and managing electric power systems and associated devices like generators, motors, and transformers [1,2].

The primary objective of power system operation and control is to furnish customers with high-quality electricity at reasonable costs while upholding system stability and reliability [3]. However, the demand surges as the electric power system evolves, necessitating enhanced monitoring and control. This surge in workload and operational responsibilities strains the existing energy management systems (EMSs), typically numerical analysis software, making targeted processing during power system operation, particularly during fault states, challenging [4]. Leveraging artificial intelligence (AI) tools to support operational personnel in monitoring and decision-making minimizes staff workload and enhances incident response efficiency [5]. This convergence of electric power operations and AI represents a significant trend in recent years.

AI, commonly characterized as the intelligence exhibited by machines and software, including robots [6,7] and computer programs [8,9], is a scientific discipline that explores, develops, and simulates human behavior and its underlying principles [10]. The term primarily denotes creating systems possessing human-like cognitive processes and attributes, such as reasoning, learning from experience, generalization, discrimination, and error correction. Artificial general intelligence (AGI) refers to the hypothetical intelligence of a machine capable of performing any intellectual task achievable by a human [11]. AI techniques have proven instrumental in addressing numerous challenges in power systems, and their effectiveness is further amplified when combined with traditional mathematical approaches. Examples of these techniques include artificial neural networks (ANNs) [12,13], fuzzy logic (FL) [14–17], adaptive-network-based fuzzy inference systems (ANFISs) [18,19], artificial intelligent techniques [20–24], and expert systems [25,26].

This research provides a detailed review of AI applications in power systems, particularly in stability, control, and protection, identifying key challenges and research gaps based on recent publications from 2017 to 2022. The main advantages of this review article are as follows.

1. The paper analyses AI and metaheuristic optimization applications in modern power system stability and protection, highlighting their role in enhancing predictive maintenance and fault detection.
2. It identifies critical research gaps and future directions in integrating intelligent techniques with smart grids and traditional power systems, offering a roadmap for advancing this crucial field.
3. This paper also discusses how AI integration improves smart grid operation and energy efficiency. AI algorithms analyze sensor, meters, and grid infrastructure data to find energy conservation and grid optimization opportunities. AI improves grid efficiency, energy savings, and environmental impact by adjusting power distribution, voltage, and routing in real time.

The article is organized as follows. Section 2 explains the need for AI in power systems. Section 3 defines four critical categories of AI and lists the types commonly used in power systems. Section 4 provides an overview of the AI techniques commonly applied to different aspects of power system problems. Section 5 compares the modulation approaches and intelligent techniques for power system stability, control, and protection. Section 6 discusses the various control methods employed by intelligent techniques. Section 7 covers recent intelligent strategies developed in the power system over the last two decades. Section 9 discusses challenges and offers recommendations for future work. Finally, Section 10 summarizes and concludes the main points of the article.

2. The Need for AI in Power Systems over Traditional Techniques

The integration of AI in power systems offers significant advantages over traditional techniques due to several key factors.

First, AI is better suited to handle modern power systems' increasing complexity and scale. Traditional methods like state estimation and optimal power flow (OPF) have limitations when dealing with the vast amounts of data and intricate interdependencies in today's power grids. In contrast, AI techniques such as neural networks and machine learning can efficiently process large datasets and uncover complex patterns, as shown in the table summarizing AI applications [27].

Second, processing data and making real-time decisions is crucial for maintaining system stability and control. Traditional PID control and automatic generation control (AGC) techniques rely on predefined rules and parameters, which may not adapt quickly enough to real-time changes. AI methods, including deep learning and reinforcement learning, enable real-time data processing and adaptive decision-making, enhancing the system's responsiveness to dynamic conditions [28].

Predictive capabilities are another area where AI outperforms traditional approaches. Traditional methods like load shedding and frequency response analysis typically address issues reactively after they occur. As detailed in the AI techniques table, AI techniques like predictive analytics and time series analysis allow for accurate forecasting of future conditions, enabling proactive measures to maintain stability and prevent faults.

Moreover, AI's ability to continuously learn and adapt is a significant advantage. Traditional techniques often involve fixed rules and settings, which might not be optimal under varying conditions. AI algorithms, particularly those involving reinforcement learning, can continuously improve by learning from new data and adjusting to changing system conditions.

Handling uncertainty effectively is another reason for AI's superiority. Power systems face various uncertainties, such as fluctuating demand and renewable energy variability. Techniques like fuzzy logic and Bayesian networks, part of AI, can model and manage these uncertainties more robustly than traditional methods.

Optimization capabilities provided by AI through metaheuristic algorithms like particle swarm optimization (PSO) and genetic algorithms (GAs) offer powerful solutions for complex problems in power systems. These algorithms can find optimal or near-optimal solutions for stability control, protection settings, and control actions, which are often challenging with traditional methods [29].

Finally, AI enhances monitoring and control through advanced tools like smart sensors and IoT devices. These tools provide real-time data that, when analyzed using AI, lead to more informed and effective control strategies, thereby improving the overall stability and protection of the power system. AI offers significant improvements over traditional techniques, which are presented in Table 1, in handling complexity, real-time processing, predictive accuracy, adaptability, optimization, and uncertainty management, making it indispensable for modern power system stability, protection, and control.

Table 1. Traditional techniques in power system stability, protection, and control [30–35].

Traditional Technique	Role in Stability	Role in Protection	Role in Control
Proportional–Integral–Derivative (PID) Control	Maintaining system stability by fine-tuning control parameters	Enhancing fault-tolerant control, maintaining protection under varying conditions	Maintaining stable voltage and frequency, fine-tuning control actions
State Estimation	Providing accurate system state information for stability assessment	Ensuring reliable protection by accurate system monitoring	Enhancing control decisions by providing accurate state data
Optimal Power Flow (OPF)	Ensuring stable and optimal operation of the power system by optimizing power flows	Minimizing system losses and enhancing protection by optimal resource allocation	Optimizing control strategies for efficient power distribution
Contingency Analysis	Evaluating system stability under different failure scenarios	Identifying potential protection issues and vulnerabilities	Preparing control actions for different contingency scenarios

Table 1. *Cont.*

Traditional Technique	Role in Stability	Role in Protection	Role in Control
Power System Stabilizers (PSSs)	Enhancing dynamic stability by dampening power system oscillations	Improving protection response by stabilizing system conditions	Stabilizing system frequency and voltage during disturbances
Load Shedding	Maintaining system stability by shedding load during critical conditions	Protecting the system from cascading failures by controlled load reduction	Controlling system load to prevent instability
Under-Voltage Load Shedding (UVLS)	Preventing voltage collapse and maintaining stability by shedding load during low voltage conditions	Enhancing protection by preventing voltage-related issues	Managing voltage levels to ensure stable operation
Under-Frequency Load Shedding (UFLS)	Maintaining system frequency and stability by shedding load during low-frequency conditions	Protecting the system from frequency-related issues	Managing system frequency to prevent instability
Power Flow Analysis	Assessing system stability by analyzing power flows through the network	Identifying protection needs by analyzing current and voltage profiles	Enhancing control by providing detailed power flow information
Frequency Response Analysis	Maintaining system frequency stability by analyzing and responding to frequency deviations	Protecting the system from frequency-related disturbances	Controlling system frequency through real-time adjustments
Reactive Power Compensation	Enhancing voltage stability by managing reactive power flows	Protecting the system from voltage instability	Controlling reactive power to maintain voltage levels
Fault Analysis	Ensuring system stability by identifying and analyzing fault conditions	Enhancing protection by accurate fault detection and classification	Preparing control actions for fault conditions
Relay Coordination	Ensuring coordinated operation of protection relays for system stability	Enhancing protection reliability by ensuring proper relay operation	Coordinating control actions to prevent system instability
Transformer Tap Changer Control	Maintaining voltage stability by adjusting transformer tap settings	Enhancing protection by managing voltage levels through transformer adjustments	Controlling voltage levels to ensure stable operation
Automatic Generation Control (AGC)	Maintaining system frequency and power balance by adjusting generation levels	Protecting the system from imbalances by controlling generation	Optimizing control of generation units for stable operation
Voltage Regulators	Maintaining voltage stability by regulating voltage levels at various points in the network	Enhancing protection by ensuring voltage levels remain within acceptable limits	Controlling voltage levels to prevent instability
Synchronous Condensers	Enhancing dynamic stability by providing reactive power support	Protecting the system from voltage instability by managing reactive power	Controlling reactive power for stable voltage levels
Capacitor Banks	Enhancing voltage stability by providing reactive power support	Protecting the system from voltage sags and swells	Managing reactive power to maintain voltage levels
Static VAR Compensators (SVC)	Enhancing voltage stability by dynamically managing reactive power	Protecting the system from voltage-related issues	Controlling reactive power to maintain stable voltage levels
Phasor Measurement Units (PMUs)	Enhancing system stability by providing real-time monitoring and analysis of system dynamics	Enhancing protection by providing accurate and timely system information	Improving control decisions by providing real-time system data

3. Artificial Intelligence (AI) Techniques in Power Systems

The growing complexity and volume of data used in power system analysis make traditional methods more challenging. This is because such data require more time and computational resources to process accurately, leading to increased computation time and a need for higher accuracy. Traditional methods may also struggle to adapt to the changing nature of such data. Due to the ever-increasing energy consumption and the expansion of the current electrical transmission networks and lines, the modern power system functions near its limits [36]. Therefore, it is essential to continuously examine the system states in a much more detailed manner than previously necessary to operate the power and control systems with less conservatism in this condition.

Power system planning, operation, diagnostics, and design are now tough challenges that must be solved using sophisticated computer technologies. Among these computer technologies, AI has recently become increasingly popular and used in various power system applications [3,6]. AI techniques exceed traditional methodologies regarding robustness, stability, and response speed. Traditional procedures, on the other hand, use memory to complete the tasks mentioned above. As a result, adding a few extra capabilities in AI controllers makes them more expensive than traditional ways. Figure 1 depicts four significant AI categories: artificial neural networks, fuzzy logic, evolutionary methods, and expert systems. These four techniques are widely used and will be briefly discussed in this section: artificial neural networks, fuzzy logic, expert systems, and evolutionary methods.

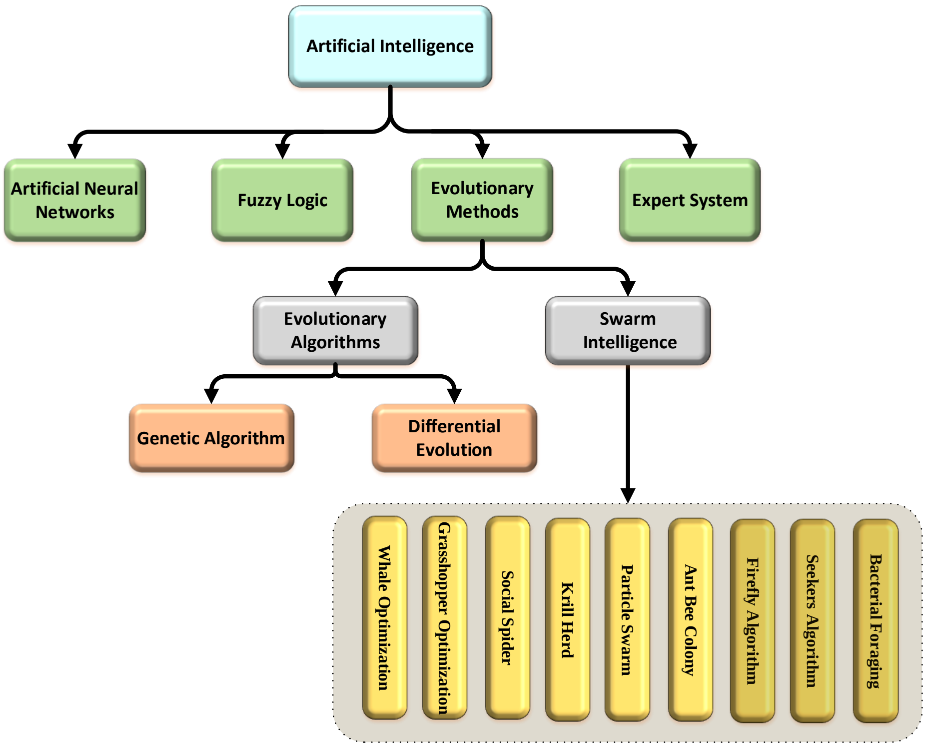

Figure 1. AI-based optimization techniques used to solve power quality issues [37].

3.1. Artificial Neural Networks

An artificial neural network (ANN) [38] is a system inspired by biology that converts one set of inputs into another set of outputs using a network of neurons. Each neuron in the network produces one output as a function of the inputs that it receives. A fundamental neuron can be considered a processor that performs a straightforward nonlinear operation on the information supplied to generate a single output. In order to construct computers that are capable of handling real-world problems that involve identifying patterns and pattern recognition, it is necessary to understand the behavior and interconnections of neurons. This can be achieved by examining the neural circuitry. Brinkman et al. [39]

have reviewed the experimental evidence for metastable dynamics in neural systems and explored the theoretical approaches for studying metastable activity in neural circuits.

Artificial neural networks (ANNs) are classified based on their structure and the way they process information [40]. The architecture of an ANN refers to the number of layers it has, while the topology refers to the pattern of connections between the layers. ANN can have either a feedforward or recurrent structure. In a feedforward ANN, the information flows in only one direction, as shown in Figure 2. In a recurrent ANN, the information is passed back and forth between layers. The typical structure of an artificial neural network is illustrated in Figure 3 below.

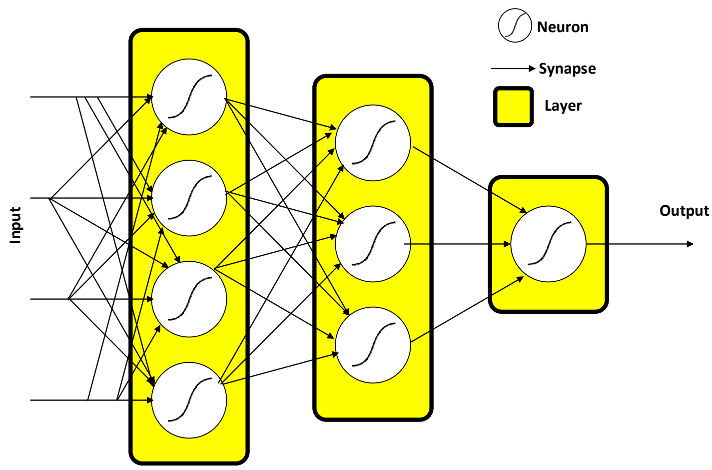

Figure 2. The architecture of a feedforward ANN [41].

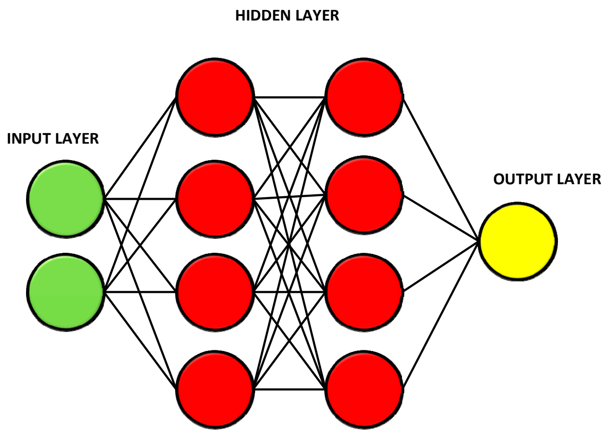

Figure 3. Typical structure of an ANN [41].

The issues with power generation, transmission, and distribution can be input to ANNs to find an appropriate solution. ANNs work on biological instincts and perform biological evaluations of real-world situations. It is possible to establish the precise values of the parameters given the limitations of a realistic transmission and distribution system. For instance, ANNs may numerically determine the values of inductance, capacitance, and resistance in a transmission line while accounting for variables such as environmental influences, imbalanced circumstances, and other potential issues [42]. Additionally, a transmission line's resistance, capacitance, and inductance values can be supplied as inputs to produce a composite normalized value for the parameters. The skin effect and proximity impact can be somewhat diminished in this way.

Artificial neural networks (ANNs) primarily address the skin effect and proximity impact through their pattern recognition capabilities derived from training data, including various scenarios. By processing historical data where these effects were significant, ANNs can learn to predict and mitigate their impacts under similar circumstances. The neural network accomplishes this by adjusting real-time operational parameters such as frequency, phase angle, and current amplitude to minimize these undesirable effects. Moreover, the application of ANNs extends to optimizing the physical configuration of cables and scheduling load operations, which can inherently reduce skin effects and proximity impact. For instance, ANNs can suggest alterations in the layout or the cross-sectional area of cables to reduce these effects without compromising the system's efficiency or safety.

The enhanced capability of ANNs to predict and manage such complexities arises from their layered structure, which can model intricate relationships within data much more effectively than traditional computational methods. This allows for a nuanced understanding and handling of the skin effect and proximity impact, ensuring more stable and efficient power system operations. In practical applications, a study detailed in [43] explored various neural network techniques for evaluating steady-state stability in power networks. This analysis included five algorithms: cascade-forward NN (CFNN), Elman NN (ENN), layer recurrent NN (LRNN), linear layer NN (LLNN), and feedforward NN (FFNN). Performance comparisons employed the regression learner algorithm (RLA) using root mean squared error (RMSE) and response plot graphs on IEEE 30-bus and NGP systems. FFNN and CFNN closely predicted both systems' stability, with FFNN ranking first for accuracy and predictability on the IEEE 30-bus system, followed closely by CFNN. Conversely, CFNN ranked first and FFNN second for the NGP system, with LLNN securing third place for both systems, while ENN and LRNN filled the remaining positions.

3.2. Fuzzy Logic (FL)

Fuzzy systems, often known as fuzzy logic [14], are logical frameworks for normalizing and standardizing approximative reasoning [44]. Fuzzy logic can generate precise and accurate answers from specific or even approximative facts and data, comparable to how humans make decisions. The benefits of using fuzzy logic compared to traditional approaches are highlighted in Figure 4. Carreon-Ortiz et al. [45] studied and explained the concept of fuzzy logic, which uses reasoning similar to human reasoning. The human brain functions through fuzzy logic, and we can employ this technology in machines to make them function like humans. Fuzzification improves the ability to represent complicated issues at low or moderate solution costs by enhancing expressive power, generality, and modeling capabilities. Fuzzy logic permits a specific degree of ambiguity during an analysis because this ambiguity can specify accessible information. Fuzzy logic is valuable in many applications because it reduces issue complexity. Fuzzy logic is appropriate for use in many aspects of power systems when there is uncertainty in the currently available information. For instance, a problem can be applied to numerical inputs and outputs instead of only symbolic ones and may entail logical reasoning. The conversions from numerical to symbolic inputs and back again for the outputs are provided by fuzzy logic.

3.3. Expert System

An expert system, as delineated by [25], refers to a computer program employing artificial intelligence techniques to replicate the decision-making prowess of a human expert within a particular domain. It translates the knowledge and proficiency of a human expert into a series of rules and procedures executable by a machine [26]. These systems are adept and well-versed in a specific subject matter. Figure 5 illustrates the structure of an expert system. Typically, the procedural aspect of the program is stored independently from the knowledge base and may be represented in various formats such as models, frames, decision trees, or rules. As rule-based or knowledge-based systems, expert systems utilize knowledge and interaction mechanisms to address challenges that exceed human intelligence and expertise.

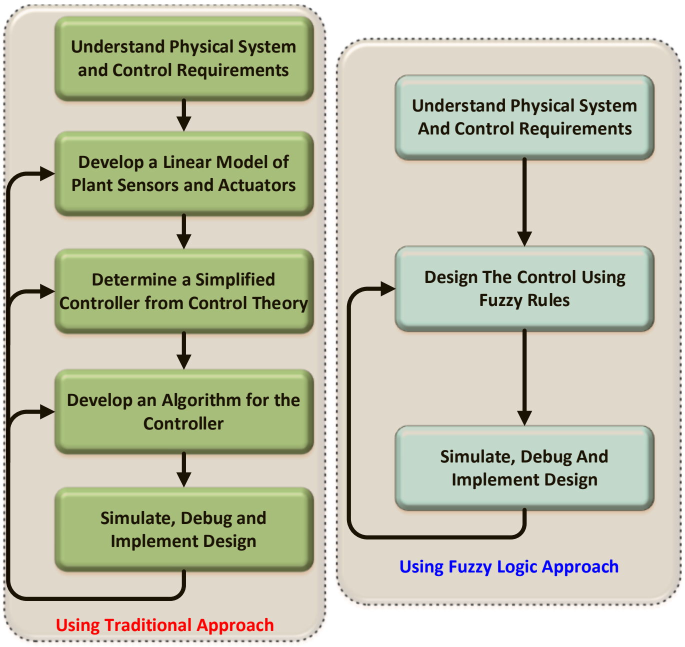

Figure 4. Benefits of using fuzzy logic [46].

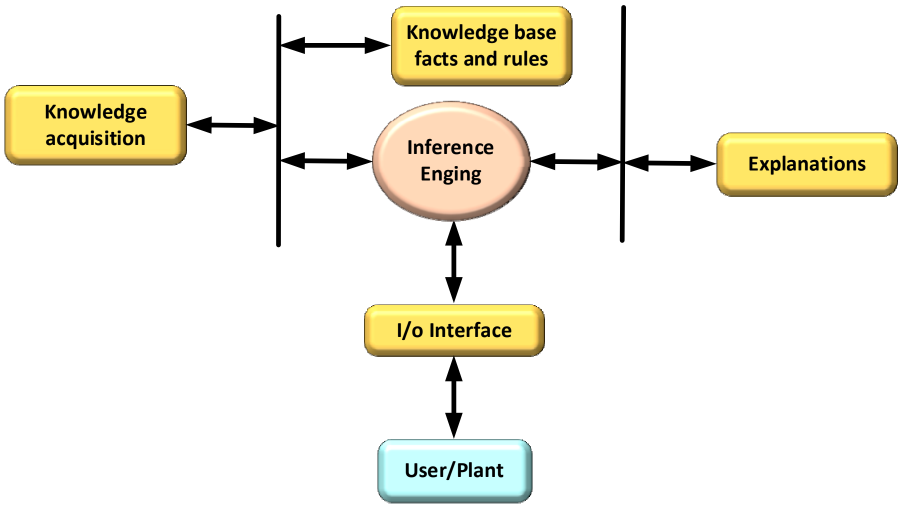

Figure 5. Structure of an expert system [47].

Expert systems are built on creating codes, which are more accessible than calculating and estimating the value of parameters because they are essentially computer programs. Therefore, it is simple to make changes even after completing the design. These systems are unable to accommodate brand-new issues or unplanned circumstances. Many power system applications mirror the capabilities of expert systems in areas including decision-making, knowledge archiving, and problem-solving using logic, heuristics, and judgment. Expert systems are beneficial for these issues when a large amount of data and information must be processed quickly.

Writing the codes for expert systems is more accessible than actually calculating and predicting the value of parameters used in generation, transmission, and distribution because expert systems are essentially computer programs. As computer programs, any changes may be easily made, even after completing the design. Estimating these numbers and performing additional studies to improve the procedure's efficiency is possible. Table 2 provides a summarized comparison of different AI approaches based on features.

Table 2. Comparison of different AI approaches based on features [48,49].

Feature	Expert Systems	Artificial Neural Networks	Fuzzy Logic (FL)
Knowledge used	Expert knowledge in the form of rules, objects, frames, etc.	Information extracted from the training set of cases.	Expert knowledge in the form of protection criteria.
Trouble- shooting and improving a relay	Change of rules required.	Complex—the internal signals are almost impossible to interpret.	Convenient—the internal signals arc understandable and analyzable.
Self-learning	Possible.	Natural.	Possible.
Handling unclear cases is Possible.	Possible.	Natural.	Natural.
Robustness	Non-critical and easy to ensure.	Difficult to ensure.	Non-critical and easy to ensure.
Setting a relay	Convenient.	A large number of simulations are required.	Convenient. Both knowledge and simulation are used.
Computations	Extensive.	Dedicated hardware.	Moderate.

3.4. Evolutionary Methods

Recently, the optimization of power systems has made use of evolutionary computation techniques, such as genetic algorithms (GAs), evolutionary programming (EP), and differential evolution (DE). Natural selection underlies evolutionary algorithms, which are a potent optimization approach. These algorithms can converge to the global optimum with less computational effort and are straightforward to implement. Evolving computation has many benefits, such as its conceptual simplicity, wide range of domain applications, effectiveness in solving real-world problems, adaptability in including domain knowledge, hybridization with traditional techniques, parallelism, robustness, self-adoption, and need for minimal human expertise. These methods can be applied to various problems without extensive mathematical knowledge. DE is quickly becoming one of the most popular evolutionary computation methods, and it is being used to solve many different kinds of complex optimization issues in power systems.

The method of numerical optimization known as differential evolution (DE) was developed by [50], and it is characterized by being straightforward, easily implementable, significantly faster than other methods, and highly reliable. In contrast to previous evolutionary algorithms, the fittest offspring competes directly with the fittest parent. Due to the nature of the competition, the convergence speed increases. DE combines a standard random generator's adaptive random search with the true coded GA. Points in a continuous space are better represented using floating point numbers used in DE. It has been proven that this strategy is a strong contender for resolving optimization problems with absolute values.

3.4.1. Genetic Algorithm

An optimization method based on the study of natural selection and natural genetics is known as a genetic algorithm (GA) [51]. Its fundamental tenet is that a population's fittest member has the best chances and potential for survival. Genetic algorithms provide a global approach based on biological metaphors. The genetic algorithm distinguishes itself from other optimization techniques in several ways:

- Rather than directly manipulating the variables, the genetic algorithm operates on coded representations.
- Instead of targeting a single optimal point, the genetic algorithm explores the population of potential solution points to identify optimal solutions.
- The genetic algorithm relies solely on information from the objective function.
- Unlike deterministic laws, the genetic algorithm employs probability transition laws.

Derived from a basic model of population genetics, the genetic algorithm comprises the following components:

- Individuals are represented by chromosomes encoding the variables.
- An initial population of individuals is established.
- An evaluation function acts as the environment, ranking individuals based on their fitness or survival ability.
- Genetic operators dictate the formation of a new population from the previous one through a defined procedure.
- Parameters for the genetic algorithm are predefined.

Applications in power systems encompass various areas:

- Planning tasks include wind turbine placement, reactive power optimization, network feeder routing, and capacitor positioning.
- Operational aspects include hydro-thermal plant coordination, maintenance scheduling, loss reduction, load management, and control of flexible alternating current transmission systems (FACTS).
- Analytical functions include reducing harmonic distortion, designing filters, controlling load frequency, and performing load flow analysis.

Since the survival of the fittest is the foundation of GAs, several strategies can be suggested to improve the effectiveness of power system operations and boost power output. The most effective strategy among these can be chosen using genetic algorithms, since it is the way that best withstands all restrictions (survival of the fittest) [52].

3.4.2. Metaheuristic Optimization Technique

Particle swarm optimization (PSO), a population-based evolutionary technique, offers several notable advantages over alternative optimization methods:

- PSO can handle objective functions that may not be continuous, convex, or differentiable, as it operates as a non-gradient, derivative-free approach, unlike deterministic methods [53].
- PSO utilizes the fitness function value to guide the search for optimality in the problem space rather than relying on derivative information (first and second order) to locate an optimal solution [54].
- By utilizing the fitness function value, PSO circumvents the need for approximations and assumptions often employed by conventional optimization techniques on problem objectives and constraint functions.
- Due to its stochastic nature, PSO can effectively address specific optimization problems characterized by objective functions with stochastic and noisy attributes.
- In contrast to deterministic approaches, the quality of a solution produced by PSO is not dependent on the initial solution.
- Being a population-based search technique, PSO enables the algorithm to evaluate multiple solutions in a single iteration, thereby reducing the risk of becoming trapped in local minima [55].
- The adaptability of the PSO algorithm allows for integration and hybridization with other approaches, whether deterministic or heuristic, when necessary.
- PSO requires fewer parameters to calibrate and adjust than many other metaheuristic approaches.
- Due to its utilization of straightforward mathematics and Boolean logic operations, the PSO method is generally easy to understand, implement, and program.

Various heuristic methods, such as genetic algorithms, simulated annealing, evolutionary programming, and ant colony optimization, compete with PSO alongside conventional gradient-based optimization algorithms. While these methods may handle various optimization challenges similar to PSO, they often have significant drawbacks:

- Additional parameter adjustment is necessary.
- They frequently demand longer computation times.

- Highly complex programming abilities are needed to create and adapt competing algorithms to fit various categories of optimization problems.

Most demand a sizeable population of members, resulting in more fitness evaluations. Some strategies involve binary conversion instead of working with actual valued variables directly.

The following algorithms have advantages over PSO: MATLAB's genetic algorithm, simulated annealing, and the commercial versions of Excel premium solver (evolutionary programming). However, it is worth noting that some of these methods are only available in commercial versions. An extensive collection of books and academic articles provides in-depth coverage of various competing approaches, particularly in the case of genetic algorithms and evolutionary programming [56].

The same category's additional heuristic methods are enumerated in [57]. These methods are becoming more widely used primarily because of their dependability, simplicity, and capacity to handle increasingly precise models without unpleasant approximations. Like other metaheuristic optimizers, PSO's main flaws are its lack of a solid mathematical foundation and inability to guarantee theoretically global optimum solutions. Many common benchmark optimization problems that academics use to test new global optimization strategies have shown that PSO performs well. Reference [58] is a valuable resource that has examined and investigated the promising convergence properties of the PSO algorithm, where Clerc and Kennedy were successful in laying the mathematical groundwork to describe how a simplified PSO model behaves while looking for the best answer. However, there is a need for further research to address the remaining challenges in the use of the particle swarm optimization (PSO) algorithm, such as the social influence component and the development of general guidelines for adjusting its parameters to suit various optimization problems.

In the initial discussion of evolutionary methods, it might have been understated how much expertise is required to effectively apply these algorithms within complex power systems. While evolutionary algorithms (EAs) such as genetic algorithms and differential evolution are conceptually straightforward, involving principles such as mutation, crossover, and selection, their practical application demands significant expertise in optimization techniques and power systems' domain-specific challenges. These challenges include accommodating nonlinear loads, adhering to regulatory constraints, and understanding the physical limitations of grid infrastructure. Moreover, optimizing the parameters of EAs, such as population size, mutation rates, and crossover methods, requires a deep understanding of both the algorithms and the system being optimized. Therefore, while the foundational elements of evolutionary algorithms are simple to grasp, their successful implementation in the context of power systems is a sophisticated process that necessitates substantial domain-specific expertise and meticulous customization.

The genetic algorithm is extensively utilized for reactive power optimization due to its ability to search for global optimal solutions through multiple paths, effectively addressing discrete and nonlinear problems. In [59], an enhanced genetic algorithm is introduced to tackle reactive power optimization issues, enhancing optimization outcomes. Using this improved genetic algorithm, standard test systems simulate reactive power optimization and compare results between the standard and enhanced genetic algorithms. Simulation outcomes indicate the proposed algorithm's feasibility and effectiveness, with the enhanced genetic algorithm exhibiting lower active network loss and superior global convergence performance and speed. Similarly, the study in [49] aimed to assess the efficiency of various versions of the differential evolution (DE) method concerning accuracy and speed for adequacy assessment in electrical power systems. Different DE methods were evaluated, including standard DE, composite DE, JDE, chaotic DE, and adaptive DE, employing mutation strategies like DE/rand/1, DE/best/1, DE/rand/2, etc. Independent software developed in C++ facilitated experimentation on systems with three and seven adequacy zones. The most effective bundles, aDE and DE/rand/1, exhibited universality, stability in objective function values, and computational efficiency, highlighting the necessity for precise method selection and parameter tuning in evolutionary algorithms to achieve optimal results in complex power systems. Various metaheuristic algorithms in power system aspects are highlighted in Table 3.

Table 3. Roles and applications of metaheuristic algorithms in power system stability, control, protection, and other aspects [60–67].

Metaheuristic Algorithm	Role in Stability	Role in Protection	Role in Control	Other Roles
Particle Swarm Optimization (PSO)	Optimizing stability control strategies, tuning stability parameters	Designing optimal protection schemes, fault diagnosis	Optimizing control parameters, load flow optimization	Renewable energy scheduling, grid optimization
Artificial Bee Colony (ABC)	Enhancing stability through optimized control actions, tuning system parameters	Fault detection and classification, adaptive protection schemes	Real-time control optimization, voltage control	Energy management, resource allocation
Genetic Algorithms (GAs)	Optimization of stability control strategies, tuning of control parameters	Designing optimal protection settings, fault diagnosis	Solving complex control optimization problems, load flow optimization	Renewable energy scheduling, grid optimization
Ant Colony Optimization (ACO)	Enhancing system stability by finding optimal paths for power flow	Fault detection, designing robust protection schemes	Control parameter optimization, dynamic load balancing	Network optimization, resource scheduling
Differential Evolution (DE)	Stability optimization through parameter tuning, dynamic stability analysis	Designing adaptive protection schemes, fault classification	Control strategy optimization, real-time system adjustments	Demand forecasting, renewable energy integration
Simulated Annealing (SA)	Stability enhancement by optimizing control actions, mitigating stability issues	Optimizing protection settings, fault detection	Control parameter tuning, load flow optimization	Preventive maintenance, energy management
Harmony Search (HS)	Stability control optimization, tuning system parameters	Fault diagnosis, designing adaptive protection schemes	Real-time control optimization, voltage, and frequency control	Resource allocation, demand response management
Firefly Algorithm (FA)	Stability enhancement through optimized control strategies, parameter tuning	Fault detection, adaptive protection schemes	Control optimization, load flow management	Smart grid operations, energy storage management
Bat Algorithm (BA)	Optimizing stability control parameters, enhancing dynamic stability	Fault classification, designing robust protection schemes	Real-time control adjustments, optimizing control actions	Renewable energy management, asset optimization
Cuckoo Search (CS)	Stability optimization, enhancing system resilience	Designing optimal protection settings, fault detection	Control parameter tuning, dynamic load balancing	Energy management, predictive maintenance
Grey Wolf Optimizer (GWO)	Stability control optimization, enhancing system stability	Fault detection and classification, adaptive protection settings	Control strategy optimization, voltage, and frequency regulation	Resource scheduling, demand forecasting
Whale Optimization Algorithm (WOA)	Stability enhancement through parameter optimization, dynamic stability analysis	Fault diagnosis, designing adaptive protection schemes	Real-time control optimization, load flow management	Smart grid operations, energy storage management

Table 3. *Cont.*

Metaheuristic Algorithm	Role in Stability	Role in Protection	Role in Control	Other Roles
Dragonfly Algorithm (DA)	Enhancing stability by optimizing control parameters, dynamic stability enhancement	Fault detection, adaptive protection schemes	Control optimization, dynamic load balancing	Resource allocation, demand response management
Salp Swarm Algorithm (SSA)	Optimizing stability control actions, enhancing system resilience	Fault classification, designing robust protection schemes	Real-time control adjustments, optimizing control actions	Renewable energy management, asset optimization
Crow Search Algorithm (CSA)	Stability control optimization, enhancing system stability	Fault detection and classification, adaptive protection settings	Control strategy optimization, voltage, and frequency regulation	Resource scheduling, demand forecasting
Sine Cosine Algorithm (SCA)	Stability enhancement through parameter optimization, dynamic stability analysis	Fault diagnosis, designing adaptive protection schemes	Real-time control optimization, load flow management	Smart grid operations, energy storage management
Elephant Herding Optimization (EHO)	Optimizing stability control parameters, enhancing dynamic stability	Fault detection, adaptive protection schemes	Control optimization, dynamic load balancing	Resource allocation, demand response management
Moth-Flame Optimization (MFO)	Stability control optimization, enhancing system resilience	Fault detection and classification, adaptive protection settings	Control strategy optimization, voltage, and frequency regulation	Resource scheduling, demand forecasting
Grasshopper Optimization Algorithm (GOA)	Enhancing stability by optimizing control parameters, dynamic stability enhancement	Fault detection, adaptive protection schemes	Control optimization, dynamic load balancing	Resource allocation, demand response management
League Championship Algorithm (LCA)	Stability enhancement through parameter optimization, dynamic stability analysis	Fault diagnosis, designing adaptive protection schemes	Real-time control optimization, load flow management	Smart grid operations, energy storage management
Flower Pollination Algorithm (FPA)	Optimizing stability control actions, enhancing system resilience	Fault classification, designing robust protection schemes	Real-time control adjustments, optimizing control actions	Renewable energy management, asset optimization
Jaya Algorithm	Stability control optimization, enhancing system stability	Fault detection and classification, adaptive protection settings	Control strategy optimization, voltage, and frequency regulation	Resource scheduling, demand forecasting
Quantum PSO (QPSO)	Enhancing stability through quantum-based parameter optimization	Fault detection, adaptive protection schemes	Real-time control optimization, dynamic load balancing	Smart grid operations, energy storage management
Teaching–Learning-Based Optimization (TLBO)	Stability control optimization, enhancing dynamic stability	Fault detection and classification, adaptive protection settings	Control strategy optimization, voltage, and frequency regulation	Resource scheduling, demand forecasting
Shuffled Frog-Leaping Algorithm (SFLA)	Optimizing stability control parameters, enhancing system resilience	Fault detection, designing adaptive protection schemes	Control optimization, dynamic load balancing	Resource allocation, demand response management

4. Applications of AI Techniques in Power Systems

AI tools can effectively solve power system problems when the characteristics of the problem align well with those of the AI tool. It is worth noting that the nonlinear behavior of various components and the entire system is an essential aspect of power system problems that are often relevant to AI applications. Nonlinearities in power systems can be classified into three categories: near linear, continuous nonlinear, and discrete. Many power system problems can be treated as near linear during regular operation, allowing for numerical approaches to minimize solution times.

As power systems experience increased stress due to larger loads and power transfers, the nonlinearities may become too significant to ignore, and control limits may become necessary [68]. Both near-linear and nonlinear power systems can also experience planned and unplanned discrete changes due to switching operations, which can be automatic or manual. The nonlinear behavior of components in power systems can make it challenging to address each component individually. However, at the same time, nonlinear problems are well suited for AI tools to tackle.

Regarding the application of artificial intelligence (AI) in power systems as case studies, real-world applications demonstrate the practicality of AI technologies and highlight their successes and limitations. For instance, a case study involving a major power utility's use of machine learning algorithms to predict and manage load distribution could be detailed, illustrating the positive impact on operational efficiency and energy savings. Conversely, a discussion of a situation where AI failed to predict a system failure due to unforeseen circumstances, such as extreme weather conditions, would provide valuable lessons on the limitations of current AI implementations. Including such examples would offer readers a clearer understanding of AI technologies' practical applications, challenges, and real-world performance in managing complex power systems. These enhancements will ensure the discussion is theoretical and grounded in practical evidence reflecting AI's current state and potential in this field.

AI tools can be used to train personnel to solve problems in various areas of power systems. Experience and good heuristics often improve the quality and efficiency of solutions. Power system personnel can participate in simulations that utilize AI tools to apply stored knowledge and gain experience and insights from others. To determine which characteristics of power system problems are suitable for AI tools, the problems can be categorized based on power system operation, restoration, power system security, power system stability and stabilizer, voltage stability, and protection. Table 4 presents AI's critical roles in various aspects of power system stability, control, and protection, highlighting the AI techniques used and the benefits they bring to the power system.

Table 4. Roles and applications of AI techniques in power system stability, control, protection, and other aspects [69–74].

AI Techniques	Role in Stability	Role in Protection	Role in Control	Other Roles
Machine Learning	Predicting system behavior under various conditions, fault prediction	Fault detection and classification, adaptive protection schemes	Optimizing control parameters, real-time adjustments	Demand forecasting, load balancing
Neural Networks	Modeling and predicting dynamic system responses, stability assessment	Pattern recognition for fault diagnosis, real-time fault location	Voltage and frequency control, predictive control strategies	Renewable energy integration, energy storage management
Fuzzy Logic	Handling uncertainties in stability analysis decision-making under imprecise conditions	Adaptive protection settings, fault tolerance	Control of nonlinear systems, voltage control	Demand response management, grid management

Table 4. *Cont.*

AI Techniques	Role in Stability	Role in Protection	Role in Control	Other Roles
Reinforcement Learning	Learning optimal strategies for system stability enhancement, dynamic stability control	Adaptive and self-learning protection schemes	Autonomous control actions, real-time system optimization	Preventive maintenance, energy management systems
Predictive Analytics	Forecasting stability margins, predicting critical system conditions	Predicting potential faults, preventive protection measures	Anticipating control needs, optimizing control actions	Demand forecasting, asset management
Genetic Algorithms	Optimization of stability control strategies, tuning of control parameters	Designing optimal protection settings, fault diagnosis	Solving complex control optimization problems, load flow optimization	Renewable energy scheduling, grid optimization
Expert Systems	Utilizing expert knowledge for stability analysis, decision support	Implementing rule-based protection schemes, fault analysis	Providing control decisions based on expert rules	Energy management, smart grid operations
Deep Learning	Detailed stability modeling, high-dimensional data analysis for stability prediction	Advanced pattern recognition for fault diagnosis, self-learning protection schemes	Complex control scenario analysis, predictive control	Predictive maintenance, demand forecasting
Time Series Analysis	Forecasting stability-related parameters, trend analysis	Historical data analysis for fault prediction, trend-based protection measures	Anticipating control needs based on historical data	Demand forecasting, energy consumption analysis
Recurrent Neural Networks (RNNs)	Predicting future stability conditions, handling time-dependent stability data	Time-dependent fault pattern recognition, dynamic protection adjustments	Control decisions based on time-series data	Demand forecasting, energy management
Long Short-Term Memory (LSTM)	Long-term stability forecasting, handling sequential stability data	Sequential fault pattern recognition, time-sequence-based protection adjustments	Control strategies considering long-term dependencies	Long-term demand forecasting, energy storage management
Data Mining	Extracting stability-related patterns, identifying stability risks	Discovering hidden fault patterns, enhancing protection measures	Extracting control patterns from large datasets, optimizing control actions	Preventive maintenance, asset management
Clustering Algorithms	Grouping similar stability conditions, identifying critical stability clusters.	Clustering fault events, identifying common fault characteristics	Grouping similar control scenarios, optimizing control based on clusters	Customer segmentation, demand response management
Bayesian Networks	Probabilistic stability assessment, handling uncertainty in stability data	Probabilistic fault diagnosis, enhancing protection reliability	Decision-making under uncertainty, probabilistic control strategies	Predictive maintenance, risk management
Proportional–Integral–Derivative (PID) Control	Fine-tuning control parameters for stability and maintaining system stability under varying conditions	Enhancing fault-tolerant control, maintaining protection under varying conditions	Maintaining stable voltage and frequency, fine-tuning control actions	System automation, process control
Model Predictive Control (MPC)	Predictive stability management, optimizing control actions for future stability	Predictive protection measures, optimizing protection actions based on future predictions	Anticipating future control needs, optimizing control strategies	Energy management, process optimization

Table 4. *Cont.*

AI Techniques	Role in Stability	Role in Protection	Role in Control	Other Roles
Support Vector Machines (SVMs)	Classifying stability conditions, identifying stability threats	Fault classification, enhancing protection reliability	Classifying control scenarios, optimizing control actions	Fault diagnosis, pattern recognition
Ensemble Learning	Combining multiple models for robust stability prediction, improving stability assessment accuracy	Enhancing fault detection accuracy, combining multiple protection models	Combining multiple control strategies for robust control decisions	Demand forecasting, predictive maintenance
Smart Grids	Enhancing overall grid stability, integrating stability-enhancing technologies	Intelligent protection schemes, self-healing grids	Dynamic control of distributed energy resources, real-time grid optimization	Grid management, renewable energy integration
IoT Integration	Real-time stability monitoring, enhancing situational awareness	Real-time fault detection and location, enhancing protection responsiveness	Real-time control based on sensor data, optimizing control actions	Smart grid operations, asset management
Big Data Analytics	Analyzing large volumes of stability data, identifying stability trends	Analyzing fault data for protection improvement, enhancing fault detection	Analyzing control data for optimization, improving control decisions based on big data insights	Customer behavior analysis, demand forecasting
Multi-Agent Systems	Coordinated stability control, enhancing system-wide stability	Coordinated protection actions, enhancing system-wide protection	Distributed control actions, enhancing system-wide control coordination	Smart grid operations, distributed energy resource management

4.1. Power System Operation

The matching of total generation with load demand and related system losses is necessary to operate automatic generation control (AGC) efficiently in interconnected power systems. A power system's operational point may eventually experience variations from the nominal system frequency and planned power exchanges to other places, which could have a negative impact [75]. Older techniques relied on linearized linear models or approximations of nonlinear processes, neither of which could produce accurate results. A higher level of precision was achieved with the use of AI technology. Approximately in the early 1990s, ANN applications began, and they are still in use today. The flight controller (FC) is primarily utilized in the design of regulators. Genetic algorithms (GAs) also optimize complex nonlinear AGC problems. In load frequency controllers, fuzzy membership functions are also tuned using GAs. Alhelou et al. [75] mentioned that the solution to some AGC issues exhibits FL and ANN hybridization. There is a discussion of contemporary approaches to AGC issues [76]. In order to combine the robustness of GA with the simplicity of linear matrix inequalities (LMIs), a GA and LMI are utilized in the study [77]. The rapid development of AI has extensively developed AGC research by using different soft computing such as improved stochastic fractal search (ISFS), hybrid bacteria foraging (HBF), grasshopper optimization algorithm [78], pattern search (PS) [79], differential evolution (DE) [80], whale optimizer (WO) [81] and bacterial foraging algorithm (BFA) [82]. Additionally, there are some hybrid approaches such as PSO–BFA [20], hybrid crow search (hCA) combined with PSO [21], and others [22–24].

4.2. Power System Restoration

Electricity blackouts are uncommon, but their effects on numerous industries must be dealt with immediately to speed up restoration. This has been the use of AI approaches for a long time. A review of ANN applied to this issue is conducted by [83] comparing several AI methodologies. A few writers proposed other techniques, such as reconfiguring the distribution system based on evolutionary algorithms (EA). Reference [84] introduced an heuristic reconfiguration algorithm. Ant colony search (ACS)-based techniques are covered in [85]. According to fuzzy-heuristic approaches, hybridization and multi-objective FL are detailed in [86]. Evolutionary algorithms (EA) such as genetic algorithms (GAs), Tabu search (TS), and simulated annealing (SA) tend to have longer computation times. At the same time, evolution strategies (ESs) and FL are not primarily optimization algorithms. Combining these methods is expected to yield better results in the future.

4.3. Power System Security

Power system security refers to a system's capacity to keep customers' energy flowing from generating stations, mainly when chaotic. Authors widely compare reliability and security. According to the regulations set forth by governing systems, a desirable reliability level is frequently anticipated to be maintained as the value. A human operator for this procedure may not always be practical, but constant monitoring can often do this. AI approaches, which mimic human thought, may be helpful [87]: they mentioned in their study that recent developments include using ANN to maintain steady-state security and FL applications for determining the reliability of power systems using the interrupted energy assessment rate given in [88]. Aside from monitoring voltage profiles, ES has also been utilized to monitor security simultaneously. More applications are anticipated to emerge to sustain desirable dependability levels.

4.4. Power System Stability and Stabilizers

A power system is constantly subjected to disruptions, which can be event- or load-related. Power systems must be adequately planned to resist the occurrence of disruptions and constantly monitored to minimize the negative impacts. The classification of power system stability varies based on factors such as the involved variables, the disturbance's extent, and duration, as depicted in Figure 6 and more details highlighted in Table 5. AI approaches have been utilized for all of this almost since their earliest application in electric power systems. The effects of temperature rise on brake resistors for transient stability have recently been discussed [89]. An ANN-based approach was recently discussed for a generalized neuron-based stabilizer [90] and a multilayer perceptron for transient stability assessment [91]. The second method is not affected by the location or type of failure. SA can be found in the robust design of stabilizers for multimachine power systems [92]. The article in [93] discusses hybridization, such as the neuro-fuzzy approach for excitation control for voltage and dampening control. Because the stability problem needs continual monitoring, AI techniques suited for it have been widely used, although optimization algorithms and memory-based gravitational searches such as GA, TS, and ant colony optimization (ACO), among others, have not found many applications. Higher-stability limitations can be achieved using more advanced procedures.

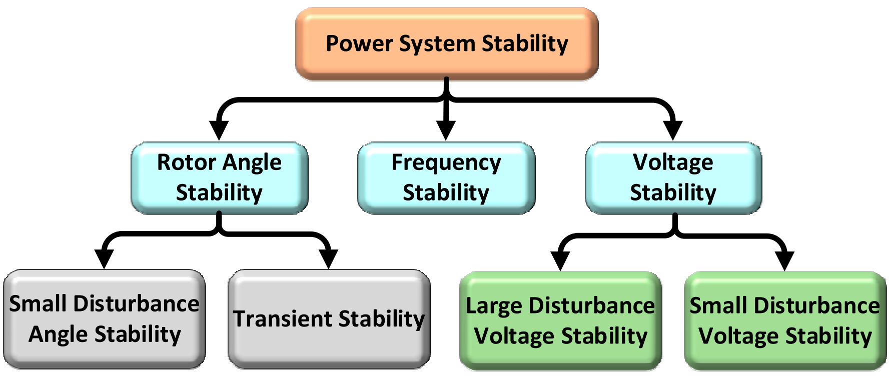

Figure 6. Classification of power system stability [94].

Table 5. Types of control and focus areas for stability in power systems [32,95].

Type of Stability	Focus Area	Control Types	Associated Problems
Angular Stability	Rotor angular stability at small signals	Damping controllers, power system stabilizers (PSSs)	Oscillations in rotor angle, loss of synchronism
Voltage Stability	Maintaining acceptable voltage levels	Voltage regulators, static VAR compensators (SVCs), FACTS devices (flexible AC transmission systems)	Voltage collapse, voltage fluctuations
Frequency Stability	Maintaining system frequency	Frequency controllers, load frequency control (LFC), automatic generation control (AGC)	Frequency deviations, frequency oscillations

4.5. Voltage Stability

Voltage must be kept within specific limits to preserve system stability and avoid voltage collapse. Continuous monitoring is critical for this. Recently, ANN-based systems have been presented [96] for ANN-based coordinated control of the under-load tap changing (ULTC) transformer and static synchronous compensator (STATCOM). Because of its complexity and ambiguity, FL can be employed efficiently in reactive power and voltage regulation. Recently, Jafarian et al. developed a strategy for controlling regional voltage profiles using a knowledge base [88]. You et al. [97] have proposed ES-based approaches for supervisory control and data acquisition (SCADA) systems. Heuristic search and predictive control have recently been applied [98] to achieve a coordination strategy to prevent voltage collapse. Zhao et al. [99] proposed neuro-fuzzy systems, which rank several contingencies for voltage stability, while Zhao et al. [99] proposed hybrid systems employing FL-ES. Because they are relatively slow for continuous monitoring, optimization techniques such as GA, SA, ACS, and TS have not been widely used for voltage stability concerns. FL and ES are projected to lead in the coming years, with hybridizations being possible. Voltage control may benefit from the hybridization of optimization methods and control approaches.

4.6. Protection

Integrating artificial intelligence (AI) into power system protection has revolutionized how modern power systems operate, offering substantial improvements in reliability, speed, and precision. AI techniques such as machine learning, neural networks, fuzzy logic, and expert systems are extensively utilized to enhance power system protection. For instance, machine learning models, including support vector machines (SVMs) and decision trees, are employed for fault detection and classification, providing higher accuracy and faster identification of faults by analyzing vast amounts of historical and real-time data. Neural networks, including intense learning models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are instrumental in real-time monitoring and control, enabling the system to learn from data patterns and make informed decisions quickly [100].

Fuzzy logic systems are used in adaptive relaying, where they adjust relay settings dynamically to account for uncertainties in power system parameters, ensuring optimal performance under varying conditions. Expert systems, which incorporate knowledge from human experts, are pivotal in accurately locating faults within transmission and distribution networks, significantly reducing the time needed for repairs. Genetic algorithms and other optimization techniques facilitate the coordination of protection devices by finding the best settings to minimize outage areas and enhance system reliability. Predictive analytics, powered by AI, plays a crucial role in predictive maintenance by analyzing sensor data to forecast potential equipment failures, allowing for proactive interventions and reducing downtime. Furthermore, AI-driven intrusion detection systems (IDSs) are essential for cybersecurity, detecting and responding to cyber threats that target power system protection infrastructure [101]. Table 6 showcases AI's practical applications in power systems.

Table 6. Practical applications of AI in power systems [2,27,102].

Application	Description	Examples
Demand Forecasting	Predicts energy demand to optimize power generation and distribution.	Siemens and General Electric (GE) use AI algorithms to forecast energy demand accurately.
Grid Management	Real-time monitoring and control of power grids to detect and predict faults, manage loads, and optimize electricity flow.	AI techniques are used in smart grid projects for real-time monitoring and fault detection.
Renewable Energy Integration	Predicts the generation capacity of renewable sources based on weather conditions, improving grid stability and optimizing renewable use.	Google DeepMind collaborates with the UK National Grid to predict wind energy output.
Energy Storage Management	Optimizes charging and discharging cycles of energy storage systems, prolonging battery life and reducing costs.	AI models manage battery energy storage systems for efficient use and extended battery life.
Predictive Maintenance	Analyzes sensor data to predict equipment failures before they occur, reducing downtime and maintenance costs.	ABB and Schneider Electric use AI-driven predictive maintenance solutions to monitor equipment health in power plants and grids.
Energy Efficiency	AI-driven systems in buildings and industries optimize energy use by learning consumption patterns and implementing efficiency measures.	Smart thermostats and building management systems use AI to reduce energy consumption.
Fault Detection and Diagnosis	Quickly identifies and diagnoses faults in the power system, enabling faster responses and preventing equipment damage.	AI systems are employed in fault detection and diagnosis in smart grids.
Smart Grid Development	Uses digital technology to monitor and manage electricity from all generation sources to meet varying electricity demands.	Smart grid projects globally incorporate AI for enhanced grid management and efficiency.
Customer Management and Services	Enhances customer services through chatbots, predictive analytics for billing, and personalized energy-saving recommendations.	Utilities use AI for customer support chatbots and to provide personalized energy-saving tips.
Energy Trading	Forecasts prices, optimizes trading strategies and manages risks in energy trading platforms.	For better financial outcomes and risk management, AI models are used in energy trading platforms.

5. Modulation of Intelligent Techniques for Power System Stability, Control and Protection

Inverters and controlled converters are switched on and operated using modulation techniques to create output voltages and currents of superior quality for various loads. We can regulate the switching electronic device by applying these modulation approaches to obtain the desired amplitude, frequency, and quality. Numerous modulation approaches have been previously examined. A single-phase matrix converter's use as a cycloconverter and cycloinverter was described in [103]. The matrix converter switches were controlled by sinusoidal pulse width modulation (SPWM) pulses, which produced output. Ismail et al. [103] described the creation of a microcontroller-based single-phase sinusoidal pulse width modulator (SPWM) inverter. This configuration's usage of a microprocessor to produce sinusoidal pulse width modulation (SPWM) pulses makes it appealing.

Reference [104] used MATLAB-Simulink tools to compare the space vector pulse width modulation (SVPWM) and sinusoidal pulse width modulation (SPWM) approaches, and they concluded that the SVPWM method is the most trustworthy one. To address this gap, it is essential to clarify that Ahmed and Ali utilized MATLAB's SimPowerSystems toolbox, which is particularly suited for simulating and modeling power systems in the time domain. This choice was driven by the toolbox's robust capabilities in handling complex calculations required for accurately comparing the performance of SVPWM and SPWM methods. This toolbox allows for a realistic simulation of electrical circuits and power system dynamics, providing a trustworthy basis for their conclusion that SVPWM is the superior method. The recently constructed buck-boost type Z-source inverter was controlled by five modified pulse width modulation schemes, which were compared and evaluated [105]. For uninterruptible power supply (UPS) systems, Ismail et al. [105] proposed a modified algorithm of pulse width modulation (PWM) inverter deadbeat control. It was confirmed that the proposed control scheme increased output voltage amplitude while offering a superior transient response and precise phase positioning for various load conditions. This technique is appropriate for high-power UPS applications where fine control of the power flow is needed, and the switching frequency is in the region of a few kilohertz. Two well-known methods for switching multilevel converters are phase-shifted pulse width modulation (PS-PWM) and level-shifted pulse width modulation (LS-PWM). Because it assures equal power distribution and switching frequency on all of the switches inside a particular module, PSPWM is typically selected for cascaded multilevel inverters. However, the absence of appropriate switching is a drawback of this method.

On the other hand, the LS-PWM technique guarantees the best switching patterns, but does not evenly distribute power among the switches in the modules. SVPWM, LSPWM, and PS-PWM are contrasted in this research regarding switching patterns and power distribution across modules. A proposed modified carrier-based PWM approach combines the advantages of fair power distribution, equal switch consumption, and the best switching sequences. Line voltage and switching sequence analyses have been performed on each one to close the gap between the three approaches and demonstrate their similarity. Results from simulations are used to support the suggested approach. According to a proposal by Peyghambari et al. [106], random pulse width modulation (RPWM) can lower acoustic noise in loads powered by power electronic converters. The switching period in this method depends on the duty ratio, which is in contrast to standard RPWM systems. In other words, the switching time in each switching cycle depends on the duty ratio and the switching periods of the previous switching cycles. The experimental findings supported the proposed method's capability to lower noise power at a chosen frequency in the voltage spectrum.

Zahraoui et al. [107] analyzed a random PWM method for three-phase voltage-controlled inverters with randomized pulse positions. Experiments were conducted to generate and validate closed-form equations for the inverter's line-to-line and line-to-neutral voltages' discrete and continuous power spectra. The theory presented makes it possible to optimize the voltage spectra of randomly modulated inverters numerically. Chiu et al. [108] suggested a two-stage, three-phase, wavelet-modulated isolated AC-DC converter for use in electric vehicle (EV) charging systems. A half-bridge resonant CLLC converter was put forward due to its high efficiency, broad gain range, galvanic isolation, and bidirectional power flow. The outcomes demonstrated that the suggested bidirectional converter may be built with wavelet modulation. The performance of the suggested converter results in an output current with less than 10% total harmonic distortion and shallow output voltage ripple, which is in line with expectations.

6. Control Methods of Intelligent Techniques

It is possible that utilizing a power system stabilizer (PSS) to increase one generator's dampening will not be enough to increase the dampening of the other generators in multi-machine power systems. Following severe faults, post-fault conditions may differ from pre-fault conditions, leading to inadequately damped swings. Therefore, it may be necessary to integrate PSS into the turbine governor system to dampen local and inter-area oscillations [109]. Many control strategies have been used in designing PSSs. The linearized machine model is the foundation for stabilizers built using traditional and contemporary control theories. Various disturbances can affect the power system, which is a nonlinear, complex system. These disturbances can lead to a variety of unresolved problems and unpredictable outcomes. Given these constraints, it is challenging to stabilize power system efficiency using these kinds of PSSs. Different contemporary control approaches, such as adaptive controllers and H control systems, were employed to attain higher operating performance than standard stabilizers. Modern control theory-based stabilizer design has some technical limitations, requiring extensive knowledge of the power system, extensive processing time for online parameter determination, and significant implementation cost [110,111].

6.1. Fuzzy Control

In 1963, Zadeh developed the idea of fuzzy logic. Fuzzy set theory is where fuzzy logic comes from. There is no limit to the number of members in a fuzzy set. There is a number between 0 and 1 that represents the degree of each membership for each element.

A straightforward controller based on a state-feedback control system was presented by Poongodi et al. [112]. The excitation control signal includes both the output signals from the fuzzy controller and the traditional PI controller.

A stabilizer in heavy and light circumstances can function more effectively than a traditional power system stabilizer (PSS) [113]. To account for the situations above, two linear power system stabilizers (PSSs) based on the traditional frequency domain technique were constructed. Fuzzy reasoning was developed to select a stable signal that best matched the operational state.

A fuzzy power system stabilizer that is indirectly adaptive was developed by [114]. Two unsolved nonlinear differential equations served as the power system representation. The stabilizer was created by two fuzzy logic systems based on these equations. The fuzzy logic systems were modified using the Lyapunov synthesis method.

A direct adaptive fuzzy logic stabilizer presented in [115] has a smaller rule base than a typical one. The rule base for single-machine infinite bus (SMIB) and multi-machine power systems was tweaked online to adjust the stabilizer to various operating scenarios. Here, the variable-structure approach was used to estimate the controller settings.

Intelligent fuzzy controller implementation in load frequency controllers (LFCs) is increasing yearly. In [116], two intelligent load frequency controllers (LFCs) were created to manage system frequency and power output by regulating the generator's speed using fuel rack position control. Fuzzy logic (FL) alone creates the first controller, whereas neural networks, genetic algorithms, and FL are combined to create the second. The suggested controllers were discovered to have sufficient overall dynamic performance and circumvent potential limitations related to other competing approaches. On the other hand, Kalyan et al. [21] proposed a fuzzy controller based on a water cycle algorithm (WCA) for LFCs in multi-area systems. With the combination of LFC and AVR, Kalyan et al. [22] also proposed a fuzzy PID controller using the hybridized artificial electric field algorithm (HAEFA) approach.

A fuzzy power system stabilizer with novel input signals was proposed by [92]. These signals include the speed deviation and the tie line linking two locations. The method outperformed conventional PSS and fuzzy PSS with typical speed deviation and acceleration input signals regarding dynamic performance. The approach's costs and scanning times were cut because the same signal could be sent to all fuzzy logic PSSs.

A new global tuning method was suggested for fuzzy power system stabilizers to reduce oscillations in a multi-machine power system [117]. The iterative adaptive, efficient partition algorithm is the foundation for this method. According to numerical findings, this method can locate the ideal global solution more quickly than a traditional GA.

The performance of a large-scale power system can be improved by wide-area measuring systems (WAMS). Signal transmission and reception delays have the potential to impede system performance [118]. The delay-independent robust control problem was presented to address this shortcoming based on WAMS employing the H fuzzy control approach. Similar T-S fuzzy models depict this case's vast, interconnected, nonlinear power networks. Using a feedback decentralized control technique, the model stabilized.

6.2. Artificial Neural Networks

Due to the nonlinear mapping characteristics of neural networks, ANNs have been successfully employed for many years to identify and control complex systems. Neural networks may be employed as controllers rather than traditional PSSs when suitably trained. The neural network (NN) must be trained for various operating situations to fine-tune the traditional PSS parameters and obtain reasonable performance. Interference is created during learning using a traditional backpropagation network under many circumstances. A modular NN was proposed by [119] in place of a backpropagation network to address this flaw. Three local expert networks and one gate network, each having three layers, make up this model. The ANN was trained directly from a traditional PSS's input and output. According to the simulation results, the modular PSS is more efficient at dampening system oscillations and delivering high-quality outcomes.

A neural adaptive power system stabilizer was created by [120] using a feedforward neural network with a single hidden layer. This made use of several methods. The two subnetworks comprise each stabilizer, an adaptive neuroidentifier (ANI) and an adaptive neurocontroller (ANC). A backpropagation technique was used to train both subnetworks. The second strategy was modified online and is based on an indirect adaptive control scheme instead of the previous approach's direct adaptive control system.

In order to fine-tune PSS parameters online based on real-time assessment of machine loading conditions, [120] designed a radial basis function network (RBFN). The suggested stabilizer was trained for various operating scenarios and changes in system parameters. The orthogonal least squares learning approach was used to obtain the network parameters and a collection of significant radial basis functions.

The neural network employed in the approach described by [119] needs significant training. An ANN-based self-tuning PSS was suggested by [97] to circumvent this issue. This method included the ANN allowing real-time adjustment of the traditional PSS parameters. A novel method chose the number of neurons in the hidden layer.

Alanazi et al. [111] suggested a recurrent neural network (RNN) stabilization controller to enhance the transient stability of power systems under various operating conditions and parametric uncertainties. The suggested additional RNN controlled the governor and the automatic voltage reactor (AVR). Online adjustments were made to the controller's weight. For excitation control, the signal output of the first RNN was combined with the PSS signal output. The governor system's stabilizing signal came from the second RNN's output. The suggested method worked with a single-machine infinite bus.

Designing intelligent controllers based on ANNs requires a significant investment in time and resources due to the complexity of large-scale power systems. These encourage [90] employment generalized neurons (GNs) to create an adaptable PSS based on generalized neurons. Offline training covered a variety of operating situations and disturbance types for the stabilizer. After that, I taught it the power system online. The simulation results of the single-machine infinite bus (SMIB) system show that the proposed stabilizer works well under solid shocks.

A PSS was created using the gain scheduling technique to improve system performance. This stabilizer works better than the traditional PSS. A neural power system stabilizer that is taught using a set of gain scheduling PSS parameters was proposed by [93]. These characteristics were acquired by utilizing the pole-placement approach for various operating situations. They concluded that stabilizers would be more useful when generators absorb reactive power.

Rana et al. [121] used the single-neuron model to improve resilient PSS parameter optimization by probabilistic eigenvalue analysis. By constructing a helping PSS gain from the single-neuron model, the PSS performance was self-adjusted to follow the system operating state. The method was successfully applied to an eight-machine system with six PSSs [122]. Adaptive critics and neural networks were employed to build and implement an optimal wide area control system (WACS) in real time. A real-time digital simulator is connected to a digital signal processor (DSP) to implement the WACS (RTDS). In this method, neural network systems were designed to calculate the dynamics of the power system and create nonlinear optimal control. According to the simulation results, adding PSS to the WACS improved the dampening of interarea oscillation under various operating situations and eventualities.

6.3. Particle Swarm Optimization (PSO) Technique

Le et al. [96] suggested the PSO approach for adjusting a lead–lag power system stabilizer and brushless exciter parameters. The simulation results showed the stabilizer's actions in dampening oscillations in a multi-machine power system.

6.4. Tabu Search (TS) Technique

Syahputra and Soesanti [123] suggested a TS method to determine the ideal parameters for a traditional lead–lag power system stabilizer. This technique performs well when tested on SMIB and multi-machine power systems under various operating conditions.

6.5. Hybrid Artificial Intelligent Controller

Combining two or more artificial intelligence algorithms creates a hybrid intelligence system. Such strategies are used in series or integration through cooperative interactions to achieve good results. Hybrid systems have been used in engineering applications for the last 20 years.

To improve the stability of power systems, the studies of [114,124] suggest a gain-scheduling PID stabilizer. Ref. [99] employed a hybrid conventional PSS, a fuzzy logic-based PSS, and simple switching criteria. This method dealt with an SMIB experiencing faults and other transitory disruptions. In [125], the speed error signal and its derivative were used to tune the parameters of the proposed stabilizer online. This controller was used in multi-machine power systems and SMIB.

Ekinci and Hekimoglu [125] introduced adaptive fuzzy control based on unsupervised learning neural networks to enhance the producing unit transient of a hydropower system. Using the proper tools, an ideal state-feedback regulator-design language control method was changed into a variable control strategy. Fuzzy logic-based controller modules and a neural network classifier are both included in the proposed controller. The fuzzy associative matrix stores the relationship between the controller inputs and outputs created via unsupervised NN learning. The main state-of-the-art methods are given in Table 7.

Table 7. Method presented by researchers.

No.	Methods Presented	References
1	Presented a straightforward controller based on a state-feedback control system	[115]
2	Developed an indirect adaptive fuzzy power system stabilizer	[116]
3	Presented a direct adaptive fuzzy logic stabilizer	[117]
4	A fuzzy power system stabilizer with novel input signals was proposed	[93]
5	Suggested a new global tuning method for fuzzy power system stabilizers to reduce oscillations in a multi-machine power system	[126]
6	Using a feedforward neural network with a single hidden layer, a neural adaptive power system stabilizer was created	[99]
7	Suggested an ANN-based self-tuning PSS	[97]
8	Suggested a recurrent neural network (RNN) stabilization controller to enhance the transient stability of power systems under various operating conditions and parametric uncertainties	[90,127]
9	Suggested a PSO approach for adjusting a lead–lag power system stabilizer and brushless exciter parameters	[125]
10	To improve stability of power systems, some authors have suggested a gain-scheduling PID stabilizer	[124]

7. Recently Proposed Intelligent Techniques for Power Systems

In order to solve the optimal power flow (OPF) problem, a unique method based on a modified sine–cosine technique was proposed [128]. The modified sine–cosine algorithm (MSCA) seeks to shorten calculation time while improving the practicality and ability to identify the best answer. The OPF problem is solved for several benchmark test systems to validate the MSCA. To demonstrate the efficacy and potential of the sine–cosine algorithm (SCA) and MSCA algorithms, the proposed MSCA is contrasted with alternative optimization techniques. Ref. [128] presented a novel hybrid algorithm that combines atom search optimization with simulated annealing algorithms. A power system stabilizer used in a single-machine infinite-bus power system was proposed to be optimized using the newly created enhanced algorithm, the improved atom search optimization algorithm. The assessments were initially carried out by comparing the outcomes with those of the genetic algorithm, the simulated annealing technique, particle swarm optimization, the gravitational search algorithm, and the original iteration of the atom search optimization algorithm. The outcomes demonstrated the created hybrid algorithm's significant potential in striking a balance between the exploration and exploitation stages. The suggested approach outperformed other recently reported top-performing power system stabilizer design algorithms. Deveci et al. [129] introduce a multi-criteria decision-making strategy based on interval type-2 fuzzy sets for choosing the ideal site for electric charging stations. Simulated annealing, which combines two separate aggregation operators—linguistic weighted sum and average—with the interval type-2 membership function parameters, improves this approach. An actual issue with public transportation faced by the municipal bus business in Istanbul is addressed using the suggested overall reusable multi-stage solution strategy. The outcomes show that the method does enhance the model by better capturing the associated uncertainties embedded in the interval type-2 membership functions, creating a fuzzy system with greater efficacy. These findings are supported by experts who also found that the SA-improved interval type-2 fuzzy approach produces more trustworthy outcomes when choosing the optimal locations for electric bus charging stations. Ref. [130] suggested a particle swarm optimization (PSO)-based tuning methodology for power system stabilizers (PSSs) that is effective for systems with 10 or even more units. The commercial simulation program Dig Silent Power Factory's source language was used to build our novel methodology. The methodology was used on various test systems, demonstrating the efficacy and potential of the suggested method. In order to ensure the safe and reliable operation of a power system, Ref. [131] attempted to resolve the problem of anomaly detection. The one-class support vector machine (OCSVM), which is appropriate for classifying imbalanced data, is used, since the fraction of aberrant data in the operation of the power system is relatively low. OCSVM's performance depends on the given parameters, so making the wrong decision will reduce its classification precision and generalizability. The author optimized the parameters of the OCSVM using PSO. The original PSO method readily reaches the local optimum and converges slowly. This problem is addressed by the author's modified PSO method for parameter optimization, which introduces adaptive population splitting and adaptive speed weighting to speed up convergence and aid in algorithmic escape from the local optimal location. The efficiency of the suggested approach is demonstrated in tests using natural power system experimental data sets and standard benchmarks. One more technique is ant colony algorithms, which are inspired by the actions of natural ant colonies in working together to solve problems by changing the environment and utilizing indirect communication. Each ant wants to pursue a pheromone-rich direction because natural or genuine ants release a specific quantity of pheromone while moving. This straightforward game shows how ants can adapt to environmental changes, such as new barriers obstructing the previously shortest path. The fundamental concept is to create fresh solutions to optimization issues by repeatedly and frequently simulating artificial ants. The ants use experience to guide their search, and the environment makes this knowledge available and modifies it. Positive reinforcement for excellent solutions, distributed computation, beneficial heuristics, and many more features are characteristics of ACO. However, its lack of computability is a drawback that may not be considered for some issues with electric power systems for which it has been employed, such as in unit commitment, economic dispatch, planning, and many more issues still to come.

A multi-machine power system's low-frequency oscillations and voltage deviations are dampened utilizing an innovative control strategy described by [132] using an ant colony optimization-based static synchronous compensator. The control system uses two proportional–integral controllers to control the gate signal in the static synchronous compensator. This uses the ant colony optimization metaheuristic swarm-based optimization technique to modify the gain parameters. Without a controller, with a static synchronized compensator, and with the proposed ant colony optimization-based static synchronous compensator, the time-domain results of the rotor dynamics and deviation in generator voltage demonstrate the potential of the proposed controller in reducing the overall oscillations in the power system.

Moreover, when the issue is about power system protection, most researchers have implemented different techniques for protecting it in their studies. Since they serve as the primary conduit between energy generation and its use, this study considers an example of transmission lines, an essential component of the power system network. However, these have the most significant fault occurrence rate because they are immediately exposed to the environment. Transmission line faults are primarily divided into symmetrical and unsymmetrical faults. As the reliance on energy grows steadily, customers are becoming increasingly aware of the issue, since they need a reliable, nearly interruption-free power supply. In order to facilitate speedy repair and restoration of the defective line, increase dependability, and bring the line back into operation as soon as possible, it is crucial to identify and precisely pinpoint a transmission line's defects. Transmission line protective relays typically employ current and voltage input signals to identify, categorize, and locate problems on a protected line segment. The relay will transmit a trip signal to a circuit breaker in cases of faults in the transmission line's protected segment, so the system's damaged portion may be quickly disconnected. Widely utilized as primary and secondary transmission line protection, distance relays are based on the electrical distance along a transmission line to a defect. Their operation is based on the voltage-to-current ratio, which the relay perceives as impedance [133]. Early techniques for fault classification relied on variations in voltages, currents, and impedances concerning predetermined values to classify different fault types. However, these techniques had shortcomings in not covering faults caused by changes in fault resistance, angles at which faults originate, mutual coupling from adjacent lines, the magnitude of the DC offset, and the presence of harmonics in the transient signal of the damaged transmission line. Earlier, the traveling wave approach was employed to locate faults in transmission lines. The idea rested on recognizing when forward and backward waves arrived at terminals. For transmission line protection, Refs. [134,135] used a traveling wave-based fault classification approach. However, this has certain drawbacks, including the need for a high sampling rate, difficulties separating traveling waves reflected from the fault spot from the far end of the line, and noise in the input signals [136]. To address these issues, various intelligent strategies have been developed over the past two decades, including artificial neural networks (ANNs), fuzzy methods, a neuro-fuzzy approach, support vector machine (SVM)-based techniques, and a combined wavelet–ANN approach.

7.1. Wavelet Transformation

Fourier transform (FT) was employed to analyze faults in transmission lines, although it has drawbacks such as fixed resolution and frequency localization. Wavelet transform has lately become a potent technique for removing crucial information from voltage and current signals for transmission line relaying. It can get over the restrictions of FT. Wavelets are mathematical operations used to create a model for a nonstationary signal with several tiny wavelike components.

Wavelet transform and its use in the power system are discussed in [121]. Wavelets are time- and frequency-localized by dilation (through translation). Wavelet transform offers a quick and efficient method for examining nonstationary voltage and current waveforms. It is also ideally suited for irregular wideband signals and may contain both sinusoidal and impulsive transients. It may be used to quickly and precisely find defects in parallel transmission lines. Zhang et al. [136] compare the discrete wavelet transform (DWT) and discrete Fourier transform (DFT) for locating and categorizing transmission line problems. The authors utilized Matlab simulation to compare DFT with DWT, and the findings reveal that the DWT approach performs better for fault classification and for determining the location of faults when more than one phase is involved in the fault, while in the instance of a line-to-ground fault, the DFT technique performs better at predicting the location of faults. In order to locate faults in transmission lines, ref. [137] presented an approach based on wavelet transform. For this aim, wavelet transform analyzes fault-generated traveling waves to expose their journey periods between the fault and the relay sites. Wavelet transform was introduced by [138], and an online application for power system relaying was suggested. It can use a tiny data window to isolate the impulse and high-frequency components and extract the fundamental frequency component. Ref. [139] suggested a method based on wavelet transform for transmission line distance protection. In order to identify flaws, the observed current signals were first decomposed using a db1 wavelet, and the norm of the detail coefficients (D1) for each current was determined. When a norm value exceeds a predetermined threshold, there is a disturbance in that phase. Wavelet transform-based digital transmission system protection and wavelet MRA-based fault diagnostics have been proposed by [140,141]. Wavelet transforms and first-level high-frequency information of currents and voltages were employed to extract features from the fault transients. Single faulty phase current information from both ends was utilized to locate faults, and local terminal information was used for categorization. To protect transmission lines using series compensation, wavelet transform was proposed by [127]. To identify fault zones, the scientists employed db4 (Daubechies) mother wavelets, and to classify faults, they used Harr. The simulation results demonstrate that the suggested approach has a very high accuracy in fault detection, zone identification, and faulty phase identification. Faults of various sorts, conditions, and locations have been tested. Di Giorgio et al. [142] suggested a wavelet-based method for locating, classifying, and detecting faults in transmission lines. The scientists sampled a line's three-phase voltage and current data using a global positioning system with synchronizing clocks at both ends. The three-phase voltages and currents of the local terminal are decomposed with the help of the Bior4.4 mother wavelet for location ANN, which is utilized for defect detection, classification, and estimate. To detect high impedance problems in an EHV transmission line, Ref. [143] presented a discrete wavelet-transformed approach. The authors tested the suggested approach to display voltage signals of one pre-fault cycle and another cycle after the fault occurred using ATP-EMTP simulation, and the findings had several benefits over conventional HIF (high-impedance fault) detection techniques. The suggested method is straightforward, precise, and quick, independent of load change and imbalanced situations. Wavelet transformations are used in [144] categorization techniques for faults in double-circuit lines. The six current signals were preprocessed using wavelet transform Daubechies, which isolates distinguishing characteristics for feeding an artificial neural network. PSCAD was utilized for the simulation. The wavelet transform based on preprocessors helped to increase the algorithm's dependability and effectiveness. A novel method for locating faults in transmission networks was suggested by [40]. It is based on wavelet multi-resolution analysis combined with a cubical interpolation technique. The suggested method could be used at any voltage level and was unaffected by fault impedance, inception angle, or fault distance. However, the categorization of distinct line faults has not been considered. Wavelet MRA analysis was used by [145] to demonstrate how to identify and categorize defects in transmission networks. The peak absolute value, its mean, and the total of the third-level output of MRA signals of the currents in each phase were utilized as the decision criteria for identification and classification of the three-phase line currents provided from both ends using Daubechies eight (Db-8) wavelet transforms. Identifying and categorizing transmission line faults utilizing a wavelet multi-resolution analysis technique is also covered by [146].

7.2. Wavelets with Fuzzy Logic

A novel method for locating and categorizing faults in transmission lines has been presented by [147] and is based on a mix of wavelet and fuzzy approaches. Fuzzy logic was used to extract significant features from wavelet MRA coefficients to determine the fault's precise position in the lines. Dynamic properties of fault signals (line current) are retrieved using wavelet MRA coefficients. Wavelet and neuro-fuzzy-based fault-finding techniques have been addressed by [148] for an integrated transmission system. The neuro-fuzzy system for fault localization was divided into two sections: one to determine the location of faults in overhead power lines and the other for subterranean cables. Wavelet transform approximates the coefficients of current and voltage signals, and two FIR filters remove the DC offset components of current signals. The fault was located by comparing a predetermined value with the summation of the D1 coefficient of current over half a cycle. A novel method for classifying problems in power transmission systems utilizing a mixed fuzzy logic and wavelet approach has been developed [149]. The approach's inherent benefit was the capacity to deal with uncertainty caused by continually changing power system factors.

7.3. Wavelet with Artificial Neural Network

Khavari et al. [149] suggested a wavelet-based ANN technique for safety in transmission systems. In the suggested method, the relaying point's input signals were fed into a DWT to extract distinguishing characteristics, which were then supplied to an ANN system for fault classification. Manarikkal et al. [150] have suggested a method for wavelet and probabilistic neural network (PNN)-based online fault detection in a power system. Multi-resolution analysis (MRA) wavelet transform divides the signal into several resolutions, which the authors utilized to analyze the signal behavior in various spectral bands. PNN is used to classify and locate faults using the characteristics from wavelet analysis. A wavelet-assisted neural network-based distance relaying system has been suggested [151,152]. The suggested plan uses a discrete wavelet transform (DWT) and neural network in Matlab, as well as an electromagnetic transient software to simulate a transmission line model. The authors employ DWT to extract fault signal characteristics and a backpropagation neural network classifier to determine the kind and location of the problem. Wavelet transforms and neural networks were proposed by Reda et al. [153], who suggested a system for faulty phase selection on double-circuit transmission lines. For the goal of training a neural network, the authors utilized the Levenberg–Marquardt method. The suggested technique employs wavelet transform to extract distinguishing characteristics from the input signal and feed them to the neural network for classification. Torres et al. [143] suggested using a DWT with a backpropagation neural network (BPNN) method for fault detection on single-circuit transmission lines. The authors extracted the fault current's high-frequency component using DWT, and the high-frequency component of signals was divided up using the Daubechies 4 (db4) mother wavelet. After a DWT investigation of the defect, a decision-making algorithm called BPNN was created. Wavelet entropy and neural networks were used in a novel method by [154] for classifying and locating transmission line failures. The entropies of the wavelet decompositions were supplied to a neural network for fault classification and placement, and the authors employed the Db4 mother wavelet to analyze defective voltage signals. The suggested approach uses an Elman backpropagation architecture for fault identification and a probabilistic neural network (PNN) architecture for fault classification.

8. AI Applications in Smart Grids

Implementing intelligent grid technologies has led to the integration of AI methods in power systems, as illustrated in Figure 7 [155]. Voluminous, fast-paced, and diverse data characterize these systems. For instance, devices like phasor measurement units (PMUs) capture data with millisecond precision.

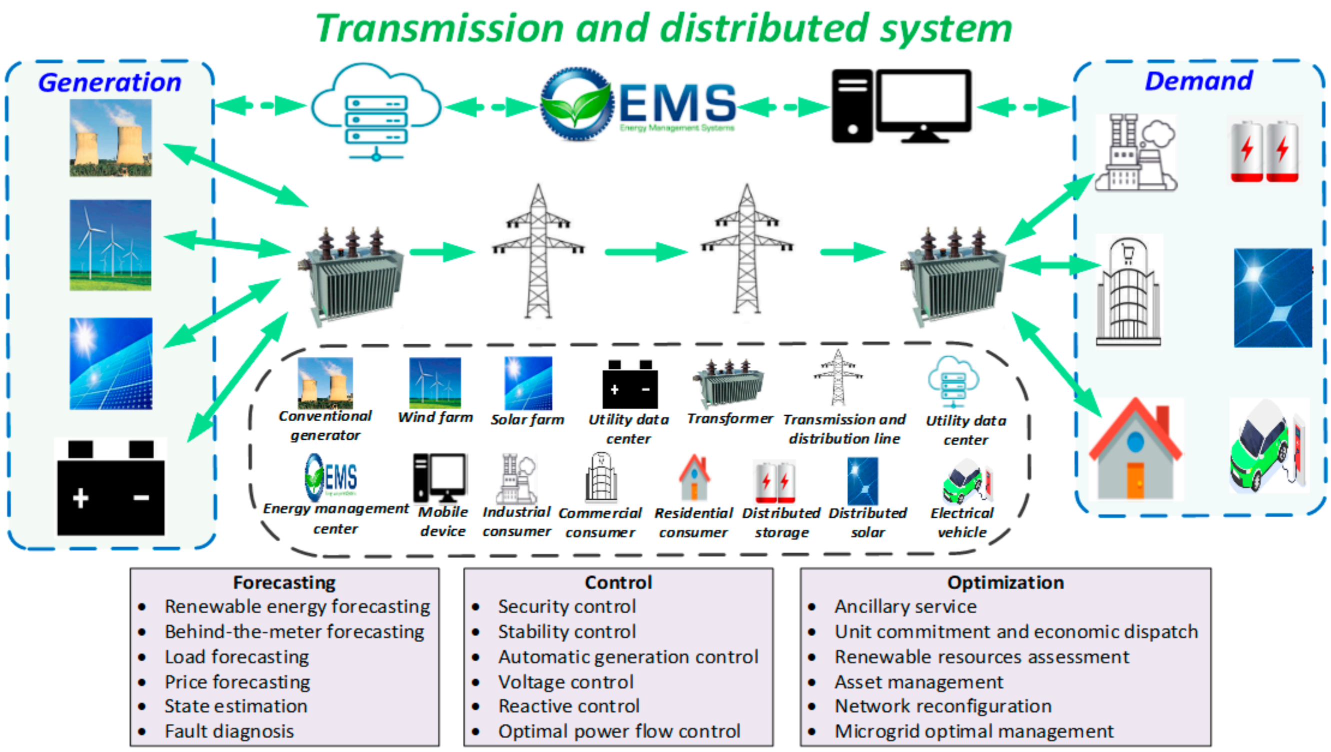

Figure 7. AI applications for smart grids [155].

8.1. Stability Control in Smart Grids

AI is essential for stability control in smart grids. AI can utilize sophisticated algorithms to predict and react to power supply and demand fluctuations, ensuring equilibrium for grid stability. It leverages extensive datasets from sensors, Internet of Things (IoT) devices, and historical patterns to anticipate potential stability concerns. The ability to predict is crucial in anticipating fluctuations that have the potential to disrupt the grid. In addition, AI facilitates the mechanization of decision-making processes in real time. It regulates control parameters, oversees the allocation of energy resources, and mitigates system overloads, guaranteeing consistent and uninterrupted power provision. The proactive implementation of stability control is essential for optimizing the operational efficiency of smart grids [156]. There are various controllers to mitigate stability issues that are highlighted in Table 5. The challenges will be discussed in Section 9.

8.2. Load Forecasting in Smart Grids

Artificial intelligence dramatically improves load forecasting in smart grids. The system uses advanced machine learning algorithms to examine past electricity usage data, weather trends, economic factors, and consumer habits to forecast future electricity demand. The precision of these forecasts is essential for maximizing the efficiency of electricity generation and distribution. AI aids in effectively allocating resources, reducing wastage, and preparing for situations of high demand. In addition, AI-driven forecasting tools such as neural networks excel at adjusting to evolving consumption patterns and seasonal fluctuations. Adaptability ensures that the forecasts remain dependable and precise, assisting in smart grids' strategic planning and operational effectiveness [128].

8.3. Protection in Smart Grids

AI greatly enhances the defensive capabilities of smart grids in security applications. It quickly detects and diagnoses malfunctions, isolates impacted regions, and expedites restoration procedures. Artificial intelligence algorithms can identify irregularities in the flow of power, voltage levels, and other crucial factors, indicating possible problems before they escalate into significant issues. Early detection is crucial for preventing power outages and ensuring the integrity of the grid. Furthermore, AI can examine patterns in past power outages to improve future strategies for safeguarding the grid, thereby increasing its ability to withstand faults and external disruptions. Incorporating artificial intelligence (AI) into intelligent grid protection not only enhances the dependability of the power supply but also augments the overall safety and sustainability of the energy system.

AI has the potential to resolve many problems that have resisted the best attempts of conventional mechanism-based approaches, with favorable performance, as indicated in Table 8. Most papers reviewed in this current study mentioned a few common challenges. We will talk about the challenges in the following paragraphs. In order to overcome the difficulties and close the gap between research and practice, we also offer recommendations for possibly significant future research directions. Numerous AI applications are data-driven and primarily rely on the quantity and quality of data, especially machine learning (ML) and deep learning (DL), and thus using AI on electrical grids may present problems. Many AI algorithms need data before producing accurate and helpful results. The current power system applications typically require thousands of instances. Additionally, the more instances are required, the more complicated the AI agent. Simulation can fill the gaps left by traditional modeling methods, providing a more dynamic and flexible approach to understanding complex system behaviors under varied conditions.

Table 8. Methods presented by researchers.

No.	Aim of the Study	Algorithm Used	Achievements	Reference
1	Mentioned a unique method based on a modified sine–cosine technique	MSCA	Declared the solutions to OPF problems effectively after comparing them with other techniques.	[127]
2	Proposed a power system stabilizer used in a single-machine infinite-bus power system	Improved atom search optimization algorithm	The suggested approach outperformed other recently reported top-performing power system stabilizer design algorithms.	[128]
3	Introduces a multi-criteria decision-making strategy based on interval type-2 fuzzy sets for choosing the ideal site for electric charging stations	Simulated annealing	The outcomes show that the method does enhance the model by better capturing the associated uncertainties embedded in the interval type-2 membership functions, creating a fuzzy system with greater efficacy.	[129]
4	Suggested a particle swarm optimization (PSO)-based tuning methodology for power system stabilizers (PSSs) that is effective for systems with ten or even more units.	Particle swarm optimization	The suggested method showed effective and potential results over others.	[130]
5	Attempted to resolve the problem of anomaly detection by OCSVM.	Particle swarm optimization	The suggested strategy outperformed others in terms of effectiveness and potential results.	[131]

Table 8. *Cont.*

No.	Aim of the Study	Algorithm Used	Achievements	Reference
6	Described an innovative control strategy to dampen a multi-machine power system's low-frequency oscillations and voltage deviations.	Ant colony algorithms	Without a controller, with a static synchronized compensator, and with the proposed ant colony optimization-based static synchronous compensator, the time-domain results of the rotor dynamics and deviation in generator voltage demonstrate the potential of the proposed controller in reducing the overall oscillations in a power system.	[132]

There is a lack of data, although gathering data is typically time-consuming. Additionally, whether simulations can accurately reflect real-world operating conditions must be carefully considered. AI agents' accuracy is expected to decrease if they encounter real-world data that differ significantly from the data they used for training. To overcome these challenges, further advanced studies on these topics should be undertaken so that the challenges are met with relevant solutions, such as using the relevant tools to measure the power system applications and their associated aspects following stability and control. Challenges and future work recommendations for improving traditional and smart grids' stability, control, and security through intelligent techniques can be categorized into several essential domains (Table 9).

Table 9. Challenges and recommendations for traditional and smart grids.

No.	Challenge	AI-Based Future Work Recommendations	Reference
1	Integration of Renewable Energy	Develop AI-driven forecasting models and control strategies for accurate prediction and seamless integration of renewable sources.	[157]
2	Grid Stability and Reliability	Implement AI and machine learning-based grid management systems for real-time adaptation to load and generation changes.	[158]
3	Cybersecurity	Employ AI for advanced threat detection and response, including predictive analytics for intrusion detection and adaptive encryption strategies.	[159]
4	Aging Infrastructure	Use AI for predictive maintenance and to optimize the retrofitting process of existing infrastructure based on data-driven insights.	[160]
5	Regulatory and Policy Issues	Leverage AI for regulatory compliance monitoring and to simulate the impacts of policy changes on grid performance and stability.	[125]
6	Data Management and Analytics	Develop AI-powered data analytics tools for processing and utilizing the vast data generated by smart grids, improving operational efficiency and decision-making.	[161]
7	Consumer Participation and Demand Response	Create AI-enabled demand response systems with intelligent algorithms to predict consumer behavior and adjust energy distribution accordingly. Incentive schemes could also be optimized using AI analytics to encourage consumer participation.	[162]
8	Interoperability and Standardization	Apply AI to analyze and manage the interoperability issues between smart grid technologies and systems, ensuring seamless communication and integration.	[163]

9. Challenges and Future Directions for AI in Power Systems

AI and ML are essential in power systems for advanced monitoring, control, operation, and integrating renewable energy. They manage uncertainty, adapt to changing conditions, and address new smart grid aspects. Incorporating these approaches into legacy infrastructure is crucial for optimization. Therefore, AI challenges and future directions for power systems can be categorized into four groups, as shown in Figure 8 and Table 10. In considering these challenges, it is possible to identify key issues and prioritize solutions, enabling more effective AI integration in energy systems [164,165].

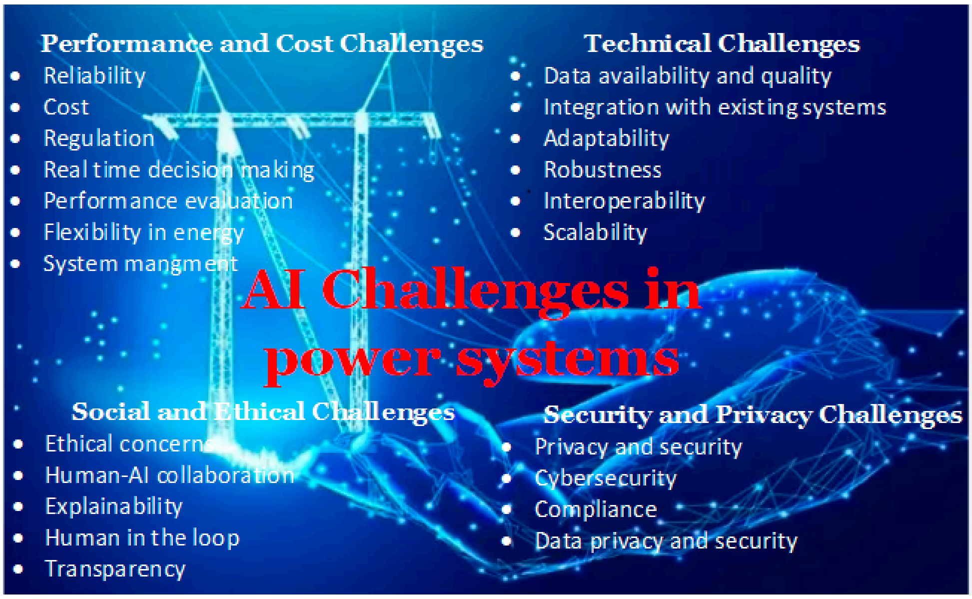

Figure 8. AI challenges in power systems [165].

Table 10. Main AI challenges and future directions for some important application areas in power systems.

Application Area	Achievements	Challenges	Future Directions
Predictive Maintenance	AI algorithms analyze sensor data to predict equipment failures, reducing downtime and maintenance costs.	Data quality and availability.	Improving data collection and preprocessing techniques.
Load Forecasting	Machine learning models provide accurate load forecasts, helping better grid management and reducing the risk of blackouts.	Scalability of AI solutions to large power systems.	Developing scalable AI models for large power systems.
Grid Optimization	AI optimizes the operation of power grids, improving energy distribution and reducing losses.	Interpretability of AI models.	Enhancing the interpretability of AI models.
Fault Detection	Neural networks and expert systems detect and diagnose faults in the grid, enhancing reliability.	Cybersecurity vulnerabilities introduced by AI integration.	Integrating robust cybersecurity measures with AI solutions.
Renewable Energy Integration	AI helps manage the variability and uncertainty of renewable energy sources, improving their integration into the grid.	Regulatory and ethical issues related to data privacy and AI decision-making.	Developing regulatory frameworks and addressing ethical concerns in AI deployment.

The integration of AI into power systems relies on several factors, including data accuracy, algorithm selection, project management, integration with existing systems, monitoring and evaluation, budget and resources, realistic expectations, and ethical and social considerations. Key aspects for successful AI implementation in power systems include high data availability and quality, privacy, security, and seamless integration with both new and existing setups. High costs and investment requirements can pose barriers, making scalability a significant concern [166].

While factors such as human–AI collaboration, explainability, human involvement, and performance evaluations are given medium to low priority, they still contribute to the overall success of AI strategies. High priority is given to privacy and security, explainability, reliability, regulation, and scalability to ensure that AI approaches are technically sound and adhere to ethical and legal standards. Medium-priority factors like human involvement, ethical concerns, cybersecurity, and transparency help build trust and confidence in AI systems. Although factors like human–AI collaboration, data availability and quality, integration with existing systems, cost and investment, and performance evaluation are considered lower priorities, they still play a role in the overall impact of AI on optimal power system operations. Table 10 summarizes the main AI challenges and future directions for some important application areas in power systems [27,158,167,168].

10. Conclusions

This review underscores the significant strides made in artificial intelligence (AI) towards enhancing power systems' stability, control, and protection. The growing complexities in power system operations, compounded by the increasing integration of renewable energy sources and the push for sustainable, efficient energy practices, have driven the need for advanced AI solutions. These technologies are improving the predictive capabilities of power systems and developing innovative methods for managing and mitigating operational risks. Particularly effective in this realm are artificial neural networks (ANNs), fuzzy logic systems, metaheuristic optimization techniques, and other emerging technologies like reinforcement learning and big data analytics.

ANNs excel in handling nonlinear issues and analyzing vast datasets, providing a solid basis for predicting and averting potential system faults and instabilities. Fuzzy logic systems, adept at managing the intrinsic uncertainties within power systems, offer a flexible, human-like approach to decision-making. Additionally, metaheuristic algorithms bring new efficiencies in optimizing power system operations, enhancing adaptability and operational efficiency. Reinforcement learning contributes to dynamic stability control, while big data analytics play a crucial role in real-time monitoring and optimization of grid performance.

Integrating these AI techniques has also propelled grid operation and energy efficiency advancements. AI algorithms are crucial in optimizing grid functionality by analyzing data from sensors and other infrastructure, identifying opportunities for energy savings, and improving grid performance. These improvements are vital for environmental sustainability and the economic performance of power grids. However, AI technologies also bring new challenges and complexities. The dependency on high-quality, extensive data for practical AI applications means that any shortfall in data quality or availability can impair the performance of AI systems.

Furthermore, integrating AI into essential infrastructure like power grids raises significant cybersecurity concerns, as these systems become more susceptible to novel cyber threats. This review highlights the critical need for continued research in AI to navigate these challenges. Future research should aim to develop more sophisticated AI models that can function effectively with limited or imperfect data and bolster the cybersecurity of AI-integrated power systems. As the power industry evolves, there is a growing requirement for AI systems that can dynamically adjust to changes in grid conditions and energy demands. Looking ahead, the field should also explore the potential of hybrid AI systems that combine various AI methodologies to capitalize on their unique strengths. For example, merging ANNs with fuzzy logic systems could yield more resilient power system operations, while hybrid metaheuristic algorithms could further enhance system efficiency and reliability.

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References

1. Boroyevich, D.; Cvetkovic, I.; Burgos, R.; Dong, D. Intergrid: A Future Electronic Energy Network? *IEEE J. Emerg. Sel. Top. Power Electron.* **2013**, *1*, 127–138. [CrossRef]
2. Zhao, S.; Blaabjerg, F.; Wang, H. An Overview of Artificial Intelligence Applications for Power Electronics. *IEEE Trans. Power Electron.* **2020**, *36*, 4633–4658. [CrossRef]
3. Omitaomu, O.A.; Niu, H. Artificial Intelligence Techniques in Smart Grid: A Survey. *Smart Cities* **2021**, *4*, 548–568. [CrossRef]
4. Cao, D.; Hu, W.; Zhao, J.; Zhang, G.; Zhang, B.; Liu, Z.; Chen, Z.; Blaabjerg, F. Reinforcement Learning and Its Applications in Modern Power and Energy Systems: A Review. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 1029–1042. [CrossRef]
5. Grover, P.; Kar, A.K.; Dwivedi, Y.K. Understanding Artificial Intelligence Adoption in Operations Management: Insights from the Review of Academic Literature and Social Media Discussions. *Acad. Manag. Ann.* **2022**, *308*, 177–213. [CrossRef]
6. Ashrafian, H. Artificial Intelligence and Robot Responsibilities: Innovating Beyond Rights. *Sci. Ethics* **2015**, *21*, 317–326. [CrossRef] [PubMed]
7. Yang, D.; Oh, E.-S.; Wang, Y. Hybrid Physical Education Teaching and Curriculum Design Based on a Voice Interactive Artificial Intelligence Educational Robot. *Sustainability* **2020**, *12*, 8000. [CrossRef]
8. Qin, Z.Z.; Naheyan, T.; Ruhwald, M.; Denkinger, C.M.; Gelaw, S.; Nash, M.; Creswell, J.; Kik, S.V. A New Resource on Artificial Intelligence Powered Computer Automated Detection Software Products for Tuberculosis Programmes and Implementers. *Tuberculosis* **2021**, *127*, 102049. [CrossRef]
9. Harris, M.; Qi, A.; Jeagal, L.; Torabi, N.; Menzies, D.; Korobitsyn, A.; Pai, M.; Nathavitharana, R.R.; Khan, F.A. A Systematic Review of the Diagnostic Accuracy of Artificial Intelligence-Based Computer Programs to Analyze Chest X-Rays for Pulmonary Tuberculosis. *PLoS ONE* **2019**, *14*, e0221339. [CrossRef]
10. Glikson, E.; Woolley, A.W. Human Trust in Artificial Intelligence: Review of Empirical Research. *Acad. Manag. Ann.* **2020**, *14*, 627–660. [CrossRef]
11. Glavic, M.; Fonteneau, R.; Ernst, D. Reinforcement Learning for Electric Power System Decision and Control: Past Considerations and Perspectives. *IFAC-PapersOnLine* **2017**, *50*, 6918–6927. [CrossRef]
12. Kushvaha, V.; Kumar, S.A.; Madhushri, P.; Sharma, A. Artificial Neural Network Technique to Predict Dynamic Fracture of Particulate Composite. *J. Compos. Mater.* **2020**, *54*, 3099–3108. [CrossRef]
13. Saeed, A.; Rashid, A. Development of Core Monitoring System for a Nuclear Power Plant Using Artificial Neural Network Technique. *Ann. Nucl. Energy* **2020**, *144*, 107513. [CrossRef]
14. Zadeh, L.A. Is There a Need for Fuzzy Logic? *Inf. Sci.* **2008**, *178*, 2751–2779. [CrossRef]
15. Vlamou, E.; Papadopoulos, B. Fuzzy Logic Systems and Medical Applications. *AIMS Neurosci.* **2019**, *6*, 266.
16. Alam, M.S.; Chowdhury, T.A.; Dhar, A.; Al-Ismail, F.S.; Choudhury, M.S.H.; Shafiullah, M.; Hossain, M.I.; Hossain, M.A.; Ullah, A.; Rahman, S.M. Solar and Wind Energy Integrated System Frequency Control: A Critical Review on Recent Developments. *Energies* **2023**, *16*, 812. [CrossRef]
17. Ezhilarasu, C.M.; Jennions, I.K. A System-Level Failure Propagation Detectability Using Anfis for an Aircraft Electrical Power System. *Appl. Sci.* **2020**, *10*, 2854. [CrossRef]
18. Karaboga, D.; Kaya, E. Adaptive Network Based Fuzzy Inference System (Anfis) Training Approaches: A Comprehensive Survey. *Artif. Intell. Rev.* **2019**, *52*, 2263–2293. [CrossRef]
19. Panwar, A.; Sharma, G.; Bansal, R.C. Optimal Agc Design for a Hybrid Power System Using Hybrid Bacteria Foraging Optimization Algorithm. *Electr. Power Compon. Syst.* **2019**, *47*, 955–965. [CrossRef]
20. Babu, N.R.; Bhagat, S.K.; Saikia, L.C.; Chiranjeevi, T. Application of Hybrid Crow-Search with Particle Swarm Optimization Algorithm in Agc Studies of Multi-Area Systems. *J. Discret. Math. Sci.* **2020**, *23*, 429–439. [CrossRef]
21. Kalyan, C.N.S.; Goud, B.S.; Reddy, C.R.; Ramadan, H.S.; Bajaj, M.; Ali, Z.M. Water Cycle Algorithm Optimized Type Ii Fuzzy Controller for Load Frequency Control of a Multi-Area, Multi-Fuel System with Communication Time Delays. *Energies* **2021**, *14*, 5387. [CrossRef]

22. Kalyan, C.N.S.; Goud, B.S.; Reddy, C.R.; Bajaj, M.; Sharma, N.K.; Alhelou, H.H.; Siano, P.; Kamel, S. Comparative Performance Assessment of Different Energy Storage Devices in Combined Lfc and Avr Analysis of Multi-Area Power System. *Energies* **2022**, *15*, 629. [CrossRef]
23. Mohanty, M.; Sahu, R.K.; Panda, S. A Novel Hybrid Many Optimizing Liaisons Gravitational Search Algorithm Approach for Agc of Power Systems. *Ain Shams Eng. J.* **2020**, *61*, 158–178. [CrossRef]
24. Benetis, D.; Vitkus, D.; Janulevičius, J.; Čenys, A.; Goranin, N. Automated Conversion of CVE Records into an Expert System, Dedicated to Information Security Risk Analysis, Knowledge-Base Rules. *Electronics* **2024**, *13*, 2642. [CrossRef]
25. İpek, M.; Selvi, H.; Findik, F.; Torkul, O.; Cedimoğlu, I.H. An Expert System Based Material Selection Approach to Manufacturing. *Mater. Des.* **2013**, *47*, 331–340. [CrossRef]
26. Sun, H.; Guo, Q.; Qi, J.; Ajjarapu, V.; Bravo, R.; Chow, J.; Li, Z.; Moghe, R.; Nasr-Azadani, E.; Tamrakar, U. Review of Challenges and Research Opportunities for Voltage Control in Smart Grids. *IEEE Trans. Power Syst.* **2019**, *34*, 2790–2801. [CrossRef]
27. Cheng, L.; Yu, T. A New Generation of Ai: A Review and Perspective on Machine Learning Technologies Applied to Smart Energy and Electric Power Systems. *Int. J. Energy Res.* **2019**, *43*, 1928–1973. [CrossRef]
28. Gao, D.W.; Wang, Q.; Zhang, F.; Yang, X.; Huang, Z.; Ma, S.; Li, Q.; Gong, X.; Wang, F.-Y. Application of Ai Techniques in Monitoring and Operation of Power Systems. *Front. Energy* **2019**, *13*, 71–85. [CrossRef]
29. Eslami, A.; Negnevitsky, M.; Franklin, E.; Lyden, S. Review of Ai Applications in Harmonic Analysis in Power Systems. *Renew. Sustain. Energy Rev.* **2022**, *154*, 111897. [CrossRef]
30. Zahraoui, Y.; Korõtko, T.; Rosin, A.; Zidane, T.E.K.; Agabus, H.; Mekhilef, S. A Competitive Framework for the Participation of Multi-Microgrids in the Community Energy Trading Market: A Case Study. *IEEE Access* **2024**, *12*, 68232–68248. [CrossRef]
31. Zahraoui, Y.; Korõtko, T.; Rosin, A.; Zidane, T.E.K.; Mekhilef, S. A Real-Time Simulation for P2P Energy Trading Using a Distributed Algorithm. *IEEE Access* **2024**, *12*, 44135–44146. [CrossRef]
32. Machowski, J.; Lubosny, Z.; Bialek, J.W.; Bumby, J.R. *Power System Dynamics: Stability and Control*; John Wiley & Sons: Hoboken, NJ, USA, 2020.
33. Omar, Y.R.; Abidin, I.Z.; Yusof, S.; Hashim, H.; Rashid, H.A.A. Under Frequency Load Shedding (Ufls): Principles and Implementation. In Proceedings of the 2010 IEEE International Conference on Power and Energy, Kuala Lumpur, Malaysia, 29 November–1 December 2010.
34. Abood, H.G.; Sreeram, V.; Mishra, Y. A New Algorithm for Improving the Numerical Stability of Power System State Estimation. *IEEJ Trans. Electr. Electron. Eng.* **2019**, *14*, 358–365. [CrossRef]
35. Lee, Y.; Song, H. A Reactive Power Compensation Strategy for Voltage Stability Challenges in the Korean Power System with Dynamic Loads. *Sustainability* **2019**, *11*, 326. [CrossRef]
36. Krogh, A. What Are Artificial Neural Networks? *Nat. Biotechnol.* **2008**, *26*, 195–197. [CrossRef] [PubMed]
37. Jumani, T.A.; Mustafa, M.W.; Alghamdi, A.S.; Rasid, M.M.; Alamgir, A.; Awan, A.B. Swarm Intelligence-Based Optimization Techniques for Dynamic Response and Power Quality Enhancement of Ac Microgrids: A Comprehensive Review. *IEEE Access* **2020**, *8*, 75986–76001. [CrossRef]
38. Maoz, O.; Tkačik, G.; Esteki, M.S.; Kiani, R.; Schneidman, E. Learning probabilistic neural representations with randomly connected circuits. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 25066–25073. [CrossRef]
39. Brinkman, B.A.W.; Yan, H.; Maffei, A.; Park, I.M.; Fontanini, A.; Wang, J.; La Camera, G. Metastable Dynamics of Neural Circuits and Networks. *Appl. Phys. Rev.* **2022**, *9*, 011313. [CrossRef]
40. Amiruddin, A.A.A.M.; Zabiri, H.; Taqvi, S.A.A.; Tufa, L.D. Neural Network Applications in Fault Diagnosis and Detection: An Overview of Implementations in Engineering-Related Systems. *Neural Comput.* **2020**, *32*, 447–472. [CrossRef]
41. Rezapour, M.; Nazneen, S.; Ksaibati, K. Application of Deep Learning Techniques in Predicting Motorcycle Crash Severity. *Eng. Rep.* **2020**, *2*, e12175. [CrossRef]
42. Soufi, M.D.; Samad-Soltani, T.; Vahdati, S.S.; Rezaei-Hachesu, P. Decision Support System for Triage Management: A Hybrid Approach Using Rule-Based Reasoning and Fuzzy Logic. *Int. J. Med. Inform.* **2018**, *114*, 35–44. [CrossRef]
43. Badrudeen, T.U.; Nwulu, N.I.; Gbadamosi, S.L. Neural Network Based Approach for Steady-State Stability Assessment of Power Systems. *Sustainability* **2023**, *15*, 1667. [CrossRef]
44. Khan, M.R.; Haider, Z.M.; Malik, F.H.; Almasoudi, F.M.; Alatawi, K.S.S.; Bhutta, M.S. A Comprehensive Review of Microgrid Energy Management Strategies Considering Electric Vehicles, Energy Storage Systems, and AI Techniques. *Processes* **2024**, *12*, 270. [CrossRef]
45. Carreon-Ortiz, H.; Valdez, F.; Castillo, O. Comparative Study of Type-1 and Interval Type-2 Fuzzy Logic Systems in Parameter Adaptation for the Fuzzy Discrete Mycorrhiza Optimization Algorithm. *Mathematics* **2023**, *11*, 2501. [CrossRef]
46. Singh, N.; Sharma, A.K.; Tiwari, M.; Jasiński, M.; Leonowicz, Z.; Rusek, S.; Gono, R. Robust Control of Sedcm by Fuzzy-Pso. *Electronics* **2023**, *12*, 335. [CrossRef]
47. Lee, H.-J.; Oh, J.-H. Restoration Aid Expert System for Power Systems. In *E3S Web of Conferences*; EDP Sciences: Les Ulis, France, 2020.
48. Franki, V.; Majnarić, D.; Višković, A. A Comprehensive Review of Artificial Intelligence (Ai) Companies in the Power Sector. *Energies* **2023**, *16*, 1077. [CrossRef]
49. Taherdoost, H.; Madanchian, M. Ai Advancements: Comparison of Innovative Techniques. *AI* **2023**, *5*, 38–54. [CrossRef]

50. Ahmad, M.F.; Isa, N.A.M.; Lim, W.H.; Ang, K.M. Differential Evolution: A Recent Review Based on State-of-the-Art Works. *Alex. Eng. J.* **2022**, *61*, 3831–3872. [CrossRef]
51. Albadr, M.A.; Tiun, S.; Ayob, M.; Al-Dhief, F. Genetic Algorithm Based on Natural Selection Theory for Optimization Problems. *Symmetry* **2020**, *12*, 1758. [CrossRef]
52. Yang, X.-S. *Nature-Inspired Optimization Algorithms*; Academic Press: Cambridge, MA, USA, 2020.
53. Gandomi, A.H.; Yang, X.-S.; Talatahari, S.; Alavi, A.H. Metaheuristic Algorithms in Modeling and Optimization. *Metaheuristic Appl. Struct.* **2013**, *1*, 1–24.
54. Ari, Ç.; Aksoy, S. Unsupervised Classification of Remotely Sensed Images Using Gaussian Mixture Models and Particle Swarm Optimization. In Proceedings of the 2010 IEEE International Geoscience and Remote Sensing Symposium, Honolulu, HI, USA, 25–30 July 2010.
55. Peška, L.; Tashu, T.M.; Horváth, T. Swarm Intelligence Techniques in Recommender Systems-a Review of Recent Research. *Swarm Evol. Comput.* **2019**, *48*, 201–219. [CrossRef]
56. Alhamrouni, I.; Salem, M.; Rahmat, M.K.; Siano, P. Bacterial Foraging Algorithm & Demand Response Programs for a Probabilistic Transmission Expansion Planning with the Consideration of Uncertainties and Voltage Stability Index. *IEEE Can. J. Electr. Eng.* **2021**, *44*, 179–188.
57. Chen, X.; Xu, B.; Du, W. An Improved Particle Swarm Optimization with Biogeography-Based Learning Strategy for Economic Dispatch Problems. *Complexity* **2018**, *2018*, 7289674. [CrossRef]
58. Jia, L.; Thomas, R.J.; Tong, L. On the Nonlinearity Effects on Malicious Data Attack on Power System. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012.
59. Zhu, R. The Approach of Genetic Algorithms Application on Reactive Power Optimization of Electric Power Systems. In Proceedings of the 2017 4th International Conference on Machinery, Materials and Computer (MACMC 2017), Xi'an, China, 27–29 November 2017.
60. Momoh, J.A. Electric Power System Applications of Optimization: CRC Press: Boca Raton, FL, USA, 2017.
61. Tran, A.-T.; Duong, M.P.; Pham, N.T.; Shim, J.W. Enhanced Sliding Mode Controller Design Via Meta-Heuristic Algorithm for Robust and Stable Load Frequency Control in Multi-Area Power Systems. *IET Gener. Transm. Distrib.* **2024**, *18*, 460–478. [CrossRef]
62. Saini, A.; Rahi, O.P. Optimal Power Flow Approaches for a Hybrid System Using Metaheuristic Techniques: A Comprehensive Review. *Int. J. Ambient. Energy* **2024**, *45*, 2345839. [CrossRef]
63. Hassan, M.H.; Kamel, S.; El-Dabah, M.A.; Abido, M.A.; Zeinoddini-Meymand, H. Optimizing Power System Stability: A Hybrid Approach Using Manta Ray Foraging and Salp Swarm Optimization Algorithms for Electromechanical Oscillation Mitigation in Multi-Machine Systems. *IET Gener. Transm. Distrib.* 2024; *in press*. [CrossRef]
64. Rezk, H.; Olabi, A.G.; Wilberforce, T.; Sayed, E.T. Metaheuristic Optimization Algorithms for Real-World Electrical and Civil Engineering Application: A Review. *Results Eng.* **2024**, *23*, 102437. [CrossRef]
65. Diab, A.A.Z.; Abdelhamid, A.M.; Sultan, H.M. Comprehensive Analysis of Optimal Power Flow Using Recent Metaheuristic Algorithms. *Sci. Rep.* **2024**, *14*, 13422. [CrossRef] [PubMed]
66. Akter, A.; Zafir, E.I.; Dana, N.H.; Joysoyal, R.; Sarker, S.K.; Li, L.; Muyeen, S.M.; Das, S.K.; Kamwa, I. A Review on Microgrid Optimization with Meta-Heuristic Techniques: Scopes, Trends and Recommendation. *Energy Strategy Rev.* **2024**, *51*, 101298. [CrossRef]
67. Sahli, Z. Optimal Planning of Reactive Power in Electrical Networks Using Metaheuristics. Ph.D. Thesis, Ferhat Abbas University, Setif, Algeria, 2024.
68. Tielens, P.; Van Hertem, D. The Relevance of Inertia in Power Systems. *Renew. Sustain. Energy Rev.* **2016**, *55*, 999–1009. [CrossRef]
69. Sarker, I.H. Ai for Critical Infrastructure Protection and Resilience. In *AI-Driven Cybersecurity Threat Intelligence: Cyber Automation, Intelligent Decision Making Explainability*; Springer: Cham, Switzerland, 2024; pp. 153–172.
70. Zahraoui, Y.; Korõtko, T.; Rosin, A.; Mekhilef, S.; Seyedmahmoudian, M.; Stojcevski, A.; Alhamrouni, I. AI Applications to Enhance Resilience in Power Systems and Microgrids—A Review. *Sustainability* **2024**, *16*, 4959. [CrossRef]
71. Strielkowski, W.; Vlasov, A.; Selivanov, K.; Muraviev, K.; Shakhnov, V. Prospects and Challenges of the Machine Learning and Data-Driven Methods for the Predictive Analysis of Power Systems: A Review. *Energies* **2023**, *16*, 4025. [CrossRef]
72. Ongsakul, W.; Dieu, V.N. *Artificial Intelligence in Power System Optimization*; CRC Press: Boca Raton, FL, USA, 2016.
73. Aygul, K.; Mohammadpourfard, M.; Kesici, M.; Kucuktezcan, F.; Genc, I. Benchmark of Machine Learning Algorithms on The Need for AI in Power Systems Transient Stability Prediction in Renewable Rich Power Grids under Cyber-Attacks. *Internet Things* **2024**, *25*, 101012. [CrossRef]
74. Li, Y.; Cao, J.; Xu, Y.; Zhu, L.; Dong, Z.Y. Deep Learning Based on Transformer Architecture for Power System Short-Term Voltage Stability Assessment with Class Imbalance. *Renew. Sustain. Energy Rev.* **2024**, *189*, 113913. [CrossRef]
75. Alhelou, H.H.; Hamedani-Golshan, M.-E.; Zamani, R.; Heydarian-Forushani, E.; Siano, P. Challenges and Opportunities of Load Frequency Control in Conventional, Modern and Future Smart Power Systems: A Comprehensive Review. *Energies* **2018**, *11*, 2497. [CrossRef]
76. Ali, S.S.; Choi, B.J. State-of-the-Art Artificial Intelligence Techniques for Distributed Smart Grids: A Review. *Electronics* **2020**, *9*, 1030. [CrossRef]

77. Kumar, R.; Sharma, V. Automatic Generation Controller for Multi Area Multisource Regulated Power System Using Grasshopper Optimization Algorithm with Fuzzy Predictive Pid Controller. *J. Int. J. Numer. Model. Electron. Netw. Devices* **2021**, *34*, e2802. [CrossRef]
78. Kumar, L.S.; Kumar, G.N.; Madichetty, S. Pattern Search Algorithm Based Automatic Online Parameter Estimation for Agc with Effects of Wind Power. *Int. J. Electr. Power Energy Syst.* **2017**, *84*, 135–142. [CrossRef]
79. Rout, U.K.; Sahu, R.K.; Panda, S. Design and Analysis of Differential Evolution Algorithm Based Automatic Generation Control for Interconnected Power System. *Ain Shams Eng. J.* **2013**, *4*, 409–421. [CrossRef]
80. Hasanien, H.M. Whale Optimisation Algorithm for Automatic Generation Control of Interconnected Modern Power Systems Including Renewable Energy Sources. *IET Gener. Transm. Distrib.* **2018**, *12*, 607–614. [CrossRef]
81. Nasiruddin, I.; Bhatti, T.S.; Hakimuddin, N. Automatic Generation Control in an Interconnected Power System Incorporating Diverse Source Power Plants Using Bacteria Foraging Optimization Technique. *J. Electr. Power Compon. Syst.* **2015**, *43*, 189–199. [CrossRef]
82. Wang, P. On Defining Artificial Intelligence. *J. Artif. Gen. Intell.* **2019**, *10*, 1–37. [CrossRef]
83. Toorajipour, R.; Sohrabpour, V.; Nazarpour, A.; Oghazi, P.; Fischl, M. Artificial Intelligence in Supply Chain Management: A Systematic Literature Review. *J. Bus. Res.* **2021**, *122*, 502–517. [CrossRef]
84. Chowdhary, K.R. Fundamentals of Artificial Intelligence: Springer: Berlin/Heidelberg, Germany, 2020.
85. Chao, L.; Lei, Z.; Yuhang, L. Topology Checking Method for Low Voltage Distribution Network Based on Fuzzy C-Means Clustering Algorithm. In Proceedings of the 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), Dalian, China, 27–29 June 2020.
86. Hotz, C.; Becker, C. Online Monitoring of Power System Small Signal Stability Using Artificial Neural Networks. In Proceedings of the NEIS 2019; Conference on Sustainable Energy Supply and Energy Storage Systems, Hamburg, Germany, 19–20 September 2019.
87. Hatziargyriou, N.; Milanovic, J.; Rahmann, C.; Ajjarapu, V.; Canizares, C.; Erlich, I.; Hill, D.; Hiskens, I.; Kamwa, I.; Pal, B. Definition and Classification of Power System Stability–Revisited & Extended. *IEEE Trans. Power Syst.* **2020**, *36*, 3271–3281.
88. Jafarian, M.; Soroudi, A.; Keane, A. Distribution System Topology Identification for Der Management Systems Using Deep Neural Networks. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020.
89. Robak, S.; Gryszpanowicz, K. Comprehensive Dimensioning of Series Braking Resistor for Transient Stability Improvement. *Electr. Power Syst. Res.* **2018**, *154*, 59–66. [CrossRef]
90. Zamzam, A.S.; Sidiropoulos, N.D. Physics-Aware Neural Networks for Distribution System State Estimation. *IEEE Trans. Power Syst.* **2020**, *35*, 4347–4356. [CrossRef]
91. Mestav, K.R.; Luengo-Rozas, J.; Tong, L. Bayesian State Estimation for Unobservable Distribution Systems Via Deep Learning. *IEEE Trans. Power Syst.* **2019**, *34*, 4910–4920. [CrossRef]
92. Douidi, B.; Mokrani, L.; Machmoum, M. A New Cascade Fuzzy Power System Stabilizer for Multi-Machine System Stability Enhancement. *J. Control Autom. Syst.* **2019**, *30*, 765–779. [CrossRef]
93. Masrob, M.A.; Rahman, M.A.; George, G.H. Design of a Neural Network Based Power System Stabilizer in Reduced Order Power System. In Proceedings of the 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, Canada, 30 April–3 May 2017.
94. Abro, A.G.; Mohamad-Saleh, J. Control of Power System Stability-Reviewed Solutions Based on Intelligent Systems. *Int. J. Innov. Comput. Inf. Control* **2012**, *8*, 6643–6666.
95. Alajrash, B.H.; Salem, M.; Swadi, M.; Senjyu, T.; Kamarol, M.; Motahhir, S. A Comprehensive Review of Facts Devices in Modern Power Systems: Addressing Power Quality, Optimal Placement, and Stability with Renewable Energy Penetration. *Energy Rep.* **2024**, *11*, 5350–5371. [CrossRef]
96. Le, T.N.; Nguyen, N.A.; Quyen, H.A. Emergency Control of Load Shedding Based on Coordination of Artificial Neural Network and Analytic Hierarchy Process Algorithm. In Proceedings of the 2017 International Conference on System Science and Engineering (ICSSE), Ho Chi Minh City, Vietnam, 21–23 July 2017.
97. You, S.; Zhao, Y.; Mandich, M.; Cui, Y.; Li, H.; Xiao, H.; Fabus, S.; Su, Y.; Liu, Y.; Yuan, H. A Review on Artificial Intelligence for Grid Stability Assessment. In Proceedings of the 2020 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Tempe, AZ, USA, 11–13 November 2020.
98. Xu, Y.; Zhang, R.; Zhao, J.; Dong, Z.Y.; Wang, D.; Yang, H.; Wong, K.P. Assessing Short-Term Voltage Stability of Electric Power Systems by a Hierarchical Intelligent System. *IEEE Trans. Neural Netw. Learn. Syst.* **2015**, *27*, 1686–1696. [CrossRef]
99. Zhao, Y.; Chen, J.; Poor, H.V. Efficient Neural Network Architecture for Topology Identification in Smart Grid. In Proceedings of the 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Washington, DC, USA, 7–9 December 2016.
100. Bojjawar, S.; Shanmugasundaram, R.; Benakop, P.G.; Raj, C.M.; Babu, W.R. Intelligent Modular Controller for Implementing the Digital Protection of Transformers as Ai Algorithms Techniques. In Proceedings of the 2024 2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), Bengaluru, India, 4–6 January 2024.
101. Wei, J.; Chammam, A.; Feng, J.; Alshammari, A.; Tehranian, K.; Innab, N.; Deebani, W.; Shutaywi, M. Power System Monitoring for Electrical Disturbances in Wide Network Using Machine Learning. *Sustain. Comput. Inform. Syst.* **2024**, *42*, 100959. [CrossRef]
102. Gorjian, A.; Eskandari, M.; Moradi, M.H. Conservation Voltage Reduction in Modern Power Systems: Applications, Implementation, Quantification, and AI-Assisted Techniques. *Energies* **2023**, *16*, 2502. [CrossRef]

103. Ismail, B.; Taib, S.; Saad, A.R.M.; Isa, M.; Hadzer, C.M. Development of a Single Phase Spwm Microcontroller-Based Inverter. In Proceedings of the 2006 IEEE International Power and Energy Conference, Putra Jaya, Malaysia, 28–29 November 2006.
104. Vivek, G.; Biswas, J.; Nair, M.D.; Barai, M. Comparative Study on Svpwm Switching Sequences for Vsis. *J. Electr. Eng.* **2018**, *13*, 133–142.
105. Ismail, B.; Naain, M.M.; Wahab, N.I.A.; Awalin, L.J.; Alhamrouni, I.; Rahim, M.F.A. Optimal Placement of Dstatcom in Distribution Network Based on Load Flow and Voltage Stability Indices Studies. In Proceedings of the 2017 International Conference on Engineering Technology and Technopreneurship (ICE2T), Kuala Lumpur, Malaysia, 18–20 September 2017.
106. Peyghambari, A.; Dastfan, A.; Ahmadyfard, A. Strategy for Switching Period Selection in Random Pulse Width Modulation to Shape the Noise Spectrum. *IET Power Electron.* **2015**, *8*, 517–523. [CrossRef]
107. Zahraoui, Y.; Alhamrouni, I.; Mekhilef, S.; Khan, M.R.B.; Hayes, B.P.; Ahmed, M. A Novel Approach for Sizing Battery Storage System for Enhancing Resilience Ability of a Microgrid. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13142. [CrossRef]
108. Chiu, H.K.; Ramasamy, A.K.; Tan, N.M.L.; Teow, M.Y.W. Modelling of a Two-Stage Bidirectional Ac-Dc Converter Using Wavelet Modulation. *Int. J. Power Electron. Drive Syst.* **2018**, *2088*, 1007. [CrossRef]
109. Ibrahim, N.M.A.; El-Said, E.A.; Attia, H.E.M.; Hemade, B. Enhancing Power System Stability: An Innovative Approach Using Coordination of Fopid Controller for Pss and Svc Facts Device with Mfo Algorithm. *Electr. Eng.* **2023**, *106*, 2265–2283. [CrossRef]
110. Li, S.; Alanazi, M.; Abdulkader, R.; Salem, M.; Abdolrasol, M.G.M.; Mohamed, F.A.; Alghamdi, T.A.H. Improving the Time Delay in the Design of the Damping Controller with the Aim of Improving the Stability of the Power System in the Presence of High Penetration of Renewable Energy Sources. *Int. J. Electr. Power Energy Syst.* **2024**, *158*, 109922. [CrossRef]
111. Alanazi, M.; Salem, M.; Sabzalian, M.H.; Prabaharan, N.; Ueda, S.; Senjyu, T. Designing a New Controller in the Operation of the Hybrid Pv-Bess System to Improve the Transient Stability. *IEEE Access* **2023**, *11*, 97625–97640. [CrossRef]
112. Poongodi, T.; Mishra, P.P.; Lim, C.P.; Saravanakumar, T.; Boonsatit, N.; Hammachukiattikul, P.; Rajchakit, G. Ts Fuzzy Robust Sampled-Data Control for Nonlinear Systems with Bounded Disturbances. *Computation* **2021**, *9*, 132. [CrossRef]
113. Zahraoui, Y.; Alhamrouni, I.; Khan, M.R.B.; Mekhilef, S.; Hayes, B.P.; Rawa, M.; Ahmed, M. Self-Healing Strategy to Enhance Microgrid Resilience During Faults Occurrence. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e13232. [CrossRef]
114. Younes, Z.; Alhamrouni, I.; Mekhilef, S.; Khan, M.R.B. Blockchain Applications and Challenges in Smart Grid. In Proceedings of the 2021 IEEE Conference on Energy Conversion (CENCON), Johor Bahru, Malaysia, 25 October 2021.
115. Zahraoui, Y.; Alhamrouni, I.; Mekhilef, S.; Khan, M.R.B.; Seyedmahmoudian, M.; Stojcevski, A.; Horan, B. Energy Management System in Microgrids: A Comprehensive Review. *Sustainability* **2021**, *13*, 10492. [CrossRef]
116. Diao, R.; Wang, Z.; Shi, D.; Chang, Q.; Duan, J.; Zhang, X. Autonomous Voltage Control for Grid Operation Using Deep Reinforcement Learning. In Proceedings of the 2019 IEEE Power & Energy Society General Meeting (PESGM), Atlanta, GA, USA, 4–8 August 2019.
117. Tariq, R.; Alhamrouni, I.; Rehman, A.U.; Eldin, E.T.; Shafiq, M.; Ghamry, N.A.; Hamam, H. An Optimized Solution for Fault Detection and Location in Underground Cables Based on Traveling Waves. *Energies* **2022**, *15*, 6468. [CrossRef]
118. Alatshan, M.S.; Alhamrouni, I.; Sutikno, T.; Jusoh, A. Application of Static Synchronous Compensator and Energy Storage System for Power System Stability Enhancement. *Bull. Electr. Eng.* **2020**, *9*, 2222–2234. [CrossRef]
119. Cheng, L.; Wu, Z.; Xuanyuan, S.; Chang, H. Power Quality Disturbance Classification Based on Adaptive Compressed Sensing and Machine Learning. In Proceedings of the 2020 IEEE Green Technologies Conference (GreenTech), Oklahoma City, OK, USA, 1–3 April 2020.
120. Albatsh, F.M.; Ahmad, S.; Mekhilef, S.; Alhamrouni, I.; Hamid, M.F.A. Power Flow Control Using Fuzzy Based Upfc under Different Operating Conditions. *J. Electr. Syst.* **2017**, *13*, 398–414.
121. Rana, M.J.; Shahriar, M.S.; Shafiullah, M. Levenberg–Marquardt Neural Network to Estimate Upfc-Coordinated Pss Parameters to Enhance Power System Stability. *Neural Comput.* **2019**, *31*, 1237–1248. [CrossRef]
122. Ray, S.; Venayagamoorthy, G.K. A Wide Area Measurement Based Neurocontrol for Generation Excitation Systems. *Eng. Appl. Artif. Intell.* **2009**, *22*, 473–481. [CrossRef]
123. Syahputra, R.; Soesanti, I. Power System Stabilizer Model Using Artificial Immune System for Power System Controlling. *Int. J. Appl. Eng. Res.* **2016**, *11*, 9269–9278.
124. Ismail, B.; Naain, M.M.; Wahab, N.I.A.; Shaberon, N.S.M.; Awalin, L.J.; Alhamrouni, I. Voltage Stability Indices Studies on Optimal Location of Wind Farm in Distribution Network. In Proceedings of the 2017 IEEE Conference on Energy Conversion (CENCON), Kuala Lumpur, Malaysia, 30–31 October 2017.
125. Ekinci, S.; Hekimoglu, B. Parameter Optimization of Power System Stabilizer Via Salp Swarm Algorithm. In Proceedings of the 2018 5th International Conference on Electrical and Electronic Engineering (ICEEE), Istanbul, Turkey, 3–5 May 2018.
126. Samek, W.; Wiegand, T. Klaus-Robert Müller. Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models. *arXiv*, 2017; arXiv:1708.08296.
127. Attia, A.-F.; El Sehiemy, R.A.; Hasanien, H.M. Optimal Power Flow Solution in Power Systems Using a Novel Sine-Cosine Algorithm. *Int. J. Electr. PowerEnergy Syst.* **2018**, *99*, 331–343. [CrossRef]
128. Izci, D. A Novel Improved Atom Search Optimization Algorithm for Designing Power System Stabilizer. *Evol. Intell.* **2022**, *15*, 2089–2103. [CrossRef]
129. Deveci, M.; John, R. Interval Type-2 Fuzzy Sets Improved by Simulated Annealing for Locating the Electric Charging Stations. *Inf. Sci.* **2021**, *547*, 641–666.

130. Verdejo, H.; Pino, V.; Kliemann, W.; Becker, C.; Delpiano, J. Implementation of Particle Swarm Optimization (Pso) Algorithm for Tuning of Power System Stabilizers in Multimachine Electric Power Systems. *Energies* **2020**, *13*, 2093. [CrossRef]
131. Wang, Z.; Fu, Y.; Song, C.; Zeng, P.; Qiao, L. Power System Anomaly Detection Based on Ocsvm Optimized by Improved Particle Swarm Optimization. *IEEE Access* **2019**, *7*, 181580–181588. [CrossRef]
132. Kumar, R.; Singh, R.; Ashfaq, H. Stability Enhancement of Multi-Machine Power Systems Using Ant Colony Optimization-Based Static Synchronous Compensator. *Comput. Eng.* **2020**, *83*, 106589. [CrossRef]
133. Cairoli, P.; Dougal, R.A. New Horizons in Dc Shipboard Power Systems: New Fault Protection Strategies Are Essential to the Adoption of Dc Power Systems. *IEEE Electrif. Mag.* **2013**, *1*, 38–45. [CrossRef]
134. Zhu, X.; Jin, T. Research of Control Strategy of Power System Stabilizer Based on Reinforcement Learning. In Proceedings of the 2020 IEEE 2nd International Conference on Circuits and Systems (ICCS), Chengdu, China, 10–13 December 2020.
135. da Silva, M.; Coury, D.V.; Oleskovicz, M.; Segatto, Ê.C. Combined Solution for Fault Location in Three-Terminal Lines Based on Wavelet Transforms. *IET Gener. Transm. Distrib.* **2010**, *4*, 94–103. [CrossRef]
136. Zhang, L.; Wang, G.; Giannakis, G.B. Real-Time Power System State Estimation and Forecasting Via Deep Unrolled Neural Networks. *IEEE Trans. Signal Process.* **2019**, *67*, 4069–4077. [CrossRef]
137. Gururajapathy, S.S.; Mokhlis, H.; Illias, H.A. Fault Location and Detection Techniques in Power Distribution Systems with Distributed Generation: A Review. *Renew. Sustain. Energy Rev.* **2017**, *74*, 949–958. [CrossRef]
138. Cui, Y.; You, S.; Liu, Y. Ambient Synchrophasor Measurement Based System Inertia Estimation. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020.
139. Kathirgamanathan, A.; De Rosa, M.; Mangina, E.; Finn, D.P. Data-Driven Predictive Control for Unlocking Building Energy Flexibility: A Review. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110120. [CrossRef]
140. Meinecke, S.; Sarajlić, D.; Drauz, S.R.; Klettke, A.; Lauven, L.-P.; Rehtanz, C.; Moser, A.; Braun, M. Simbench—A Benchmark Dataset of Electric Power Systems to Compare Innovative Solutions Based on Power Flow Analysis. *Energies* **2020**, *13*, 3290. [CrossRef]
141. Sundararaman, B.; Jain, P. Fault Detection and Classification in Electrical Power Transmission System Using Wavelet Transform. *Eng. Proc.* **2023**, *59*, 71. [CrossRef]
142. Di Giorgio, A.; Giuseppi, A.; Liberati, F.; Pietrabissa, A. Controlled Electricity Distribution Network Black Start with Energy Storage System Support. In Proceedings of the 2017 25th Mediterranean Conference on Control and Automation (MED), Valletta, Malta, 3–6 July 2017.
143. Torres, J.A.; dos Santos, R.C.; Yang, Q.; Li, J. Analyses of Different Approaches for Detecting, Classifying and Locating Faults in a Three-Terminal Vsc-Hvdc System. *Int. J. Electr. Power Energy Syst.* **2022**, *135*, 107514. [CrossRef]
144. Furse, C.M.; Kafal, M.; Razzaghi, R.; Shin, Y.-J. Fault Diagnosis for Electrical Systems and Power Networks: A Review. *IEEE Sens. J.* **2020**, *21*, 888–906. [CrossRef]
145. Swaminathan, R.; Mishra, S.; Routray, A.; Swain, S.C. A Cnn-Lstm-Based Fault Classifier and Locator for Underground Cables. *Neural Comput.* **2021**, *33*, 15293–15304. [CrossRef]
146. Ali, M.S. Investigate the Effect of Artificial Neural Network Parameters to Improve Fault Distance and Impedance Accuracy. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2021.
147. Shaikh, M.S.; Ansari, M.M.; Jatoi, M.A.; Arain, Z.A.; Qader, A.A. Analysis of Underground Cable Fault Techniques Using Matlab Simulation. *J. Comput. Math. Sci.* **2020**, *4*, 1–10.
148. Masood, B.; Khan, M.A.; Baig, S.; Song, G.; Rehman, A.U.; Rehman, S.U.; Asif, R.M.; Rasheed, M.B. Investigation of Deterministic, Statistical and Parametric Nb-Plc Channel Modeling Techniques for Advanced Metering Infrastructure. *Energies* **2020**, *13*, 3098. [CrossRef]
149. Khavari, S.; Dashti, R.; Shaker, H.R.; Santos, A. High Impedance Fault Detection and Location in Combined Overhead Line and Underground Cable Distribution Networks Equipped with Data Loggers. *Energies* **2020**, *13*, 2331. [CrossRef]
150. Manarikkal, I.; Elasha, F.; Mba, D. Diagnostics and Prognostics of Planetary Gearbox Using Cwt, Auto Regression (Ar) and K-Means Algorithm. *Appl. Acoust.* **2021**, *184*, 108314. [CrossRef]
151. Sabug, L., Jr.; Musa, A.; Costa, F.; Monti, A. Real-Time Boundary Wavelet Transform-Based Dc Fault Protection System for Mtdc Grids. *Int. J. Electr. Power Energy Syst.* **2020**, *115*, 105475. [CrossRef]
152. Elmitwally, A.; Mahmoud, S.; Abdel-Rahman, M. Fault Detection and Identification of Three Phase Overhead Transmission Lines Ended with Underground Cables. *Mansoura Eng. J.* **2020**, *35*, 129–137. [CrossRef]
153. Reda, A.; Al Kurdi, I.; Noun, Z.; Koubyssi, A.; Arnaout, M.; Rammal, R. Online Detection of Faults in Transmission Lines. In Proceedings of the 2021 IEEE 3rd International Multidisciplinary Conference on Engineering Technology (IMCET), Beirut, Lebanon, 8–10 December 2021.
154. Rong, X.; Shek, J.K.H.; Macpherson, D.E.; Mawby, P. The Effects of Filter Capacitors on Cable Ripple at Different Sections of the Wind Farm Based Multi-Terminal Dc System. *Energies* **2021**, *14*, 7000. [CrossRef]
155. Feng, C.; Sun, M.; Dabbaghjamanesh, M.; Liu, Y.; Zhang, J. Advanced Machine Learning Applications to Modern Power Systems. In *New Technologies for Power System Operation and Analysis*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 209–257.
156. Shi, Z.; Yao, W.; Li, Z.; Zeng, L.; Zhao, Y.; Zhang, R.; Tang, Y.; Wen, J. Artificial Intelligence Techniques for Stability Analysis and Control in Smart Grids: Methodologies, Applications, Challenges and Future Directions. *Appl. Energy* **2020**, *278*, 115733. [CrossRef]

157. Onwusinkwue, S.; Osasona, F.; Ahmad, I.A.I.; Anyanwu, A.C.; Dawodu, S.O.; Obi, O.C.; Hamdan, A. Artificial Intelligence (Ai) in Renewable Energy: A Review of Predictive Maintenance and Energy Optimization. *World J. Adv. Res. Rev.* **2024**, *21*, 2487–2499. [CrossRef]
158. Alaerjan, A.; Jabeur, R.; Chikha, H.B.; Karray, M.; Ksantini, M. Improvement of Smart Grid Stability Based on Artificial Intelligence with Fusion Methods. *Symmetry* **2024**, *16*, 459. [CrossRef]
159. Yaseen, A. Ai-Driven Threat Detection and Response: A Paradigm Shift in Cybersecurity. *Int. J. Inf. Cybersecur.* **2023**, *7*, 25–43.
160. Baduge, S.K.; Thilakarathna, S.; Perera, J.S.; Arashpour, M.; Sharafi, P.; Teodosio, B.; Shringi, A.; Mendis, P. Artificial Intelligence and Smart Vision for Building and Construction 4.0: Machine and Deep Learning Methods and Applications. *Autom. Constr.* **2022**, *141*, 104440. [CrossRef]
161. Stecyk, A.; Miciuła, I. Harnessing the Power of Artificial Intelligence for Collaborative Energy Optimization Platforms. *Energies* **2023**, *16*, 5210. [CrossRef]
162. Gupta, R.; Chaturvedi, K.T. Adaptive Energy Management of Big Data Analytics in Smart Grids. *Energies* **2023**, *16*, 6016. [CrossRef]
163. Nouri, A.; Lachheb, A.; El Amraoui, L. Optimizing Efficiency of Vehicle-to-Grid System with Intelligent Management and Ann-Pso Algorithm for Battery Electric Vehicles. *Electr. Power Syst. Res.* **2024**, *226*, 109936. [CrossRef]
164. Dobbe, R.; Hidalgo-Gonzalez, P.; Karagiannopoulos, S.; Henriquez-Auba, R.; Hug, G.; Callaway, D.S.; Tomlin, C. Learning to Control in Power Systems: Design and Analysis Guidelines for Concrete Safety Problems. *Electr. Power Syst. Res.* **2020**, *189*, 106615. [CrossRef]
165. Danish, M.S.S. Ai in Energy: Overcoming Unforeseen Obstacles. *AI* **2023**, *4*, 406–425. [CrossRef]
166. Mortier, T. *Why Artificial Intelligence Is a Game-Changer for Renewable Energy*; Ernst Young Global Limited: London, UK, 2020.
167. Nix, A.; Decker, S.; Wolf, C. Enron and the California Energy Crisis: The Role of Networks in Enabling Organizational Corruption. *Bus. Hist. Rev.* **2021**, *95*, 765–802. [CrossRef]
168. Szczepaniuk, H.; Szczepaniuk, E.K. Applications of Artificial Intelligence Algorithms in the Energy Sector. *Energies* **2022**, *16*, 347. [CrossRef]