CALIFORNIA STATE UNIVERSITY, NORTHRIDGE

Comprehensive Survey of Machine Learning Applications in Power Systems

A graduate project submitted in partial fulfillment of the requirements for Master of Science in Electrical Engineering

By

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ABSTRACT

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Master of Science in Electrical Engineering

This project presents a comprehensive survey of artificial intelligence in electric power system applications. It summarizes a general view of artificial intelligence in power systems in five chapters. The first chapter of This survey paper seeks to contribute to the literature by expanding on the existing research that has been published. A systematic review of the literature summarizes the practical applications of artificial intelligence to improve power systems in different areas such as control, security, distributed energy systems, control of load flow, and detecting faults. The second chapter is based on recent studies and research on artificial intelligence methods. It explains three critical categories of artificial intelligence: rule-based systems, machine learning techniques, and metaheuristic methods. The third chapter consists of the methodology for the literature review. It provides the databases that were used to search for the sources, as well as the screening procedure, time period for the search, and search string.

Chapter four describes Artificial intelligence applications. Finally, chapter five elaborates on the outlook for artificial intelligence in the power system.

1. INTRODUCTION

Modern society has developed a strong dependency on electrical energy. This dependency creates an important demand for ensuring that power system operators are functioning reliably to ensure that there is a readily available supply of electrical energy. However, energy transitions have presented challenges pertaining to the stability for maintaining energy grid operations. Given these challenges, there is a demand for system operators to identify solutions for maintaining a stable grid so that a reliable source of energy can be readily supplied. These solutions focus on ensuring that there is adequate energy supply available when deviating away from non-renewable energy sources through the adoption of carbon-neutral systems.

Given these challenges, numerous government agencies around the world are seeking to implement environmental solutions by working alongside grid operators. These government agencies are focused on integrating renewable energy from offshore sources. This is a strategy that the members of the European Commission have implemented. For example, the German government has implemented a strategy of optimizing its existing energy grid structures in an effort to reduce energy reserves, while also accelerating the development of new power lines.

In addition to these conventional strategies for improving the efficiency of power system operations, there are also data-driven strategies that can be incorporated. One of these strategies is the use of artificial intelligence to manage power systems operations using computational power. The literature provides data analysis from artificial intelligence measurement systems that utilize computational power to analyze data in real time. These research studies have led to interest in conducting additional research about the practical applications of artificial intelligence for improving the operational efficiency of distribution power systems. Online databases were used to collect and analyze data from the growing number of research studies published on artificial intelligence using data-driven systems to manage distribution power systems. The three online databases that were examined include Wiley's, IEEE, and Elsevier. The change in the number of monthly publications on AI-driven distribution systems is plotted in Figure 1 below. The figure demonstrates that there has been a 40% increase in the number of research studies published on the topic of artificial intelligence applications to power systems from the year 2016 to 2021.

The literature investigates the different applications that AI provides to power systems. For example, Zhao et. al discusses how artificial intelligence has applications to the three phases of the power electronics life cycle. These three phases include the design, control, and maintenance. The authors address the potential applications of AI in the management of electronic systems (AI). At least one activity can be handled by artificial intelligence in each stage of the design, control, and maintenance phases.

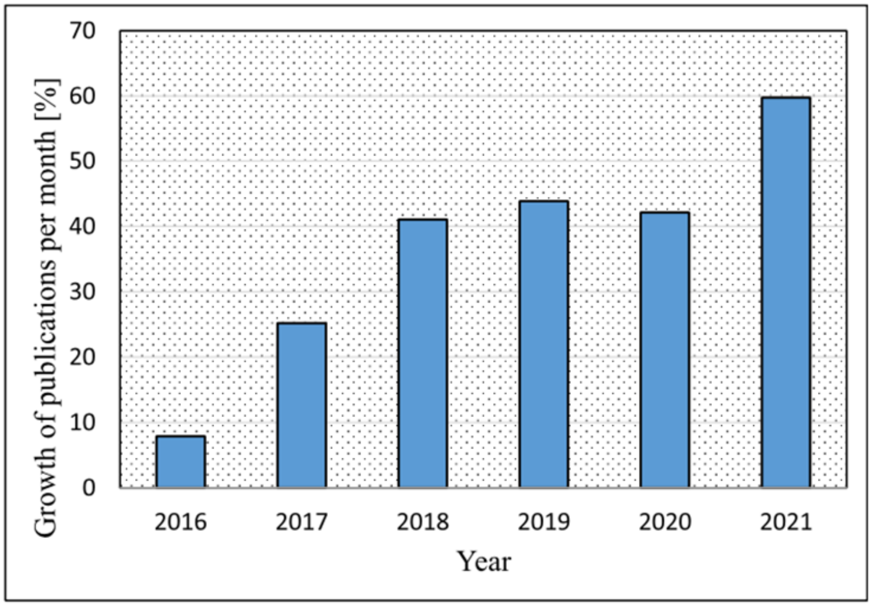

Figure 1. The number of publications on AI-driven distribution systems

These activities include optimization, categorization, regression, and data structure analysis. This article covers a wide range of artificial intelligence (AI) models, including but not limited to expert systems, fuzzy logic, met heuristic approaches, and machine learning, along with the applications of each model. More than five hundred publications were reviewed to determine the current state of public awareness, the difficulties associated with implementing AI, and the potential research issues. Alongside this article, you will find a link to a downloadable Excel sheet that contains a compilation of helpful materials on statistical analysis. This article goes into the many forms of AI that are now being implemented in electrical power systems. The following outlines some recent discoveries. Design, control, and maintenance of power electronic systems are the three primary applications of artificial intelligence that are now being explored. At each stage of the life cycle of the technology, researchers investigate the adoption rate of (AI) artificial intelligence its application pattern, features, and resource requirements. Expert systems, fuzzy logic, met heuristic techniques, and machine learning is the categories that can be used to categorize the artificial intelligence approaches implemented in power electronic systems nowadays. Comparisons between the suitable AI algorithms for each domain regarding their application patterns, advantages and disadvantages, and upper and lower bounds are made. Most software associated with AI is geared toward recognizing, categorizing, and improving data structures. By employing a chronology, we can examine the development of the most significant algorithms and the many applications to which they have been put. In addition to illustrative examples for every step of the life cycle, this article discusses the difficulties that need to be overcome and suggests future research fields. [1]. In a separate research study, Monti et. al investigates the different ways that distributed intelligence systems can control smart energy grids. This study presents a description of the issues, potential solutions, and recent breakthroughs in power distribution control that arise from multiple sources. These challenges have been identified as having several different origins. In the not-too-distant future, a considerable adjustment will be made to the electricity networks' organizational structure. There is not much space for debate on whether this will have the most substantial impact on distribution. This tutorial looks at the current state of affairs and explains how the grid might one day develop into something more intelligent and adaptable. To a significant extent, this idea depends on a varied collection of decentralized and renewable power plants. In the following sections, various subjects, including network-based control, distributed state estimation, and distributed intelligence, are broken down and examined in light of recent discoveries. The instruction explained that the electrical grid is in a state of constant change and that it is dynamic.

As a consequence of these shifts, it is more essential than ever to research new methods for the automation of the electrical system. Using this case study as an example, the authors focused on three critical areas: network-based control, distributed intelligent systems, and distributed state estimation. Each of these issues contains reports that provide a synopsis of the most recent findings from research on a range of specialized subjects [2]. A third example is Omitaomu's survey research that investigates the security risks and operational challenges to consider when relying on AI-driven smart grids [3].

The literature also includes research studies that investigate the specific applications of AI-driven power systems. Cao et. al applies deep reinforcement learning as a means of solving challenging problems for the use of current power systems [4]. Glavic et. al also investigates how reinforcement learning can be used to improve the control and decisions made by power systems [5]. Another topic investigated by Sun et. al is the opportunities and challenges for using voltage control [6]. Similarly, Aldhelou et. al investigate the opportunities and challenges for the integration of artificial intelligence to improve the control of load flow. The paper concludes with a section that discusses current and future research requirements and emerging research trends in LFC. The article discusses the present situation of load frequency regulation in power networks worldwide. Because of this, all mathematical models of frequency response for traditional and intelligent power systems are subjected to substantial research. There are various innovative system models; examples are distributed generation, microgrids, smart grids, and modern power systems that use multiple renewable energy sources. In addition, both traditional and adaptive control strategies are thoroughly examined in this study. Studies also study cutting-edge control strategies for load frequency management in power systems, such as optimum control theory, resilient control, and a control strategy based on soft computing. These theories and strategies include optimum control and robust control. In conclusion, we look at a few unanswered questions and some future avenues of investigation for load frequency control systems [7].

Darab et. al and Chai et. al have also contributed to the applications of artificial intelligence in smart grids by investigating the different methods that can be applied for detecting faults and making diagnoses for power systems [8]. Kumar et. al also investigates the use of emerging techniques to integrate resources of distributed energy systems to improve smart grids. Following this, they covered the benefits and drawbacks of utilizing AI approaches and their basic principles, characteristics, and practical implementations within the realm of power grid FD. They discussed how artificial intelligence (AI) may be utilized shortly to identify and fix faults in the nation's electrical grid. This step is intended to encourage future research in the field, as mentioned above. Some minor adjustments have been made to the Grid FD approach that is dependent on AI. This research suggested several different artificial intelligence methodologies for locating issues with electricity grids. The authors examined the positive and negative aspects of the currently available AI power grid FD techniques. This study estimates the future of AI-powered power grid FD in light of recent breakthroughs in AI technology (like AlphaGo) and the significant emphasis given to AI research and deep learning. At this point, most power grid FD techniques based on artificial intelligence (AI) are still in the experimental phase. On the other hand, because of the speedy advancement of AI technology, brand-new AI-based power system FD solutions are anticipated to be produced and put into action in the future [9]. Cai & Lu also investigate the applications of metaheuristic algorithms to improve power systems [10].

The objective of this survey paper is to provide a systematic review of the existing applications that artificial intelligence provides to distribution power systems while also discussing the potential concerns for their practical applications. These findings are summarized based on the following:

The systematic review of the literature discusses the practical applications of artificial intelligence systems to improve the operations of distribution power systems. The systematic review also includes an analysis of the requirements needed for artificial intelligence to provide applications to distribution systems while also discussing the key functions of artificial intelligence when applied to distribution power systems. Based on the analyzed data from the literature, the four key metrics to consider are the dynamics, adaptability, dataset, and runtime of artificial intelligence systems. In this survey paper, each of these four metrics is evaluated based on a 5-point Likert scale. The metrics are rated from their practical applications derived from analyzing the selected research studies.

A set of guidelines is created to outline the techniques for different artificial intelligence applications. These guidelines are derived from a performance analysis that considers the effectiveness of AI tools in creating AI solutions.

The structure of this survey paper begins with Section II, which includes a brief overview of commonly used artificial intelligence techniques. This includes a discussion of the concepts of machine learning, fuzzy logic, metaheuristic, and the control phase. Section III includes literature review that analyzes the research methodologies of the selected studies, and introduces the four metrics used to evaluate these studies. Section IV includes a discussion of the practical applications of artificial intelligence techniques to improve power system operations. Section IV is broken down into two sections that discuss closed-loop and decision-support systems. Section IV concludes with the guidelines for selecting suitable artificial intelligence techniques for each application to distributed power systems. Section V discusses the future outlook of artificial intelligence for improving distributed power systems. Section V also provides a brief overview of the key concepts applicable to artificial intelligence. Lastly, Section VI provides a summary for the key contributions of this survey paper to the literature. This survey paper aims to provide an overview of systematic research studies in order to provide guidelines for choosing artificial intelligence algorithms to enhance the operational efficiency of distribution power systems.

2. ARTIFICIAL INTELLIGENCE METHODS

The literature has provided an extensive discussion of artificial intelligence. In the 1940s, Turing introduced the definition of artificial intelligence [11]. However, recent research studies demonstrate disagreements about the definition of artificial intelligence. Despite these disagreements, there is a consensus that artificial intelligence consists of information processing systems that influence an environment through an ability to learn and adapt. The next part lays out four criteria for a good working definition, including how basic it should be, how it should reference relevant research, and how it should have a clear limit. These criteria are used to assess general field definitions. Adapting with limited information and tools is the essence of intelligence. Comparisons are made between this meaning and another to show how the effects of this term vary. The goal of this concept is to offer a solid foundation for the profession while resolving several problems. The concept of "Intelligence" within the field of artificial intelligence requires more study than has been conducted so far. Different scenarios necessitate different research paths; therefore, a working definition is crucial. Today's AI is a synthesis of many multiple areas of study, each with its theoretical underpinnings, practical applications, and other defining characteristics. The term "AI," is used to describe them all, but not in a theoretical sense. Losing all of these under the umbrella term "AI." is a mistake, although there are certain commonalities between them. One does not need a theoretical background to use this strategy effectively. Questions about artificial intelligence (AI) are not immediately apparent. When asked, "How to build AI" and "Is AI useful?" Because so many different kinds of AI can have such different outcomes, the question requires a definition of AI. It is essential to distinguish between systems whose knowledge, including moral and ethical understanding, is entirely predetermined in their design and development (their nature) and those whose knowledge is primarily derived from their own experience once they start operating when discussing the security of artificial intelligence (its nurture). Each type of AI requires its own unique set of guidelines. It is argued from this perspective that the theoretical and practical repercussions of any definition of AI render it impossible to arrive at a single, operationally valid definition. To paraphrase the article's requirements, not all workplace definitions are created equal. Although there is no agreed-upon definition (and I seriously doubt there ever will be), it is nonetheless essential to acknowledge the diverse perspectives. When results are published, researchers should note any AI's role, but ultimately, it is up to the individual researcher to decide if and how AI is used. Many researchers find helpful information, but it may not be exactly what they want. However, the same theories and methodologies were used to address problems that had nothing to do with AI. One factor contributing to this is people's ignorance of the assumptions used in AI programs. Each research topic may be given its name in the future for the sake of the organization when an accurate definition of AI has been made. We can define AI and figure out its limits before that occurs. People who "don't much care" where they are headed can get there if they walk far enough no need to start over [12]. Basic components of artificial intelligence techniques are demonstrated from different applications in this paper. Figure 2 outlines the three key categories of artificial intelligence, which are rule-based systems, machine learning techniques, and metaheuristic methods. Standard algorithms are commonly modified, but are classified as a single category.

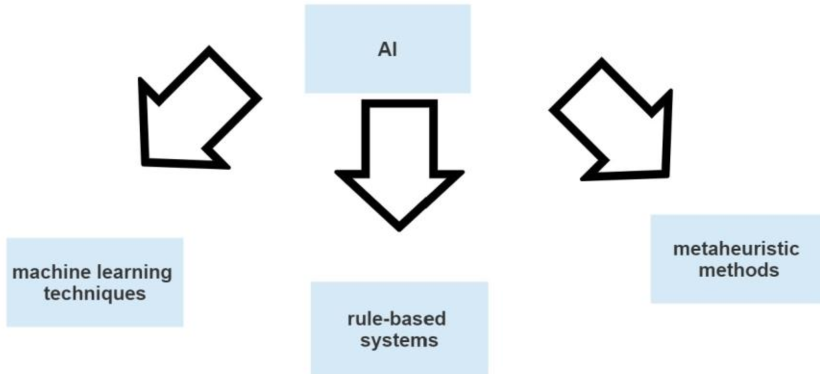

Figure 2. The Three Categories of Artificial Intelligence

2.1 Machine Learning Techniques

Machine learning is a technique that is commonly used in contemporary research studies. Machine learning can be classified into three categories: reinforcement learning, unsupervised, and supervised. These three categories are outlined in Figure 3 below. The supervised learning technique consists of a dataset with input and output data for mapping strategy. This includes neural networks that have applications for training and validating networks. The training process consists of an optimizer that minimizes the error function based on distance measurement between target values and output value for the dataset. Regular neural networks utilize supervised learning and convolutional neural networks that provide an added filter layer to data inputs [13]. Unsupervised learning doesn't include target values in the dataset, which consists of a training process where learning algorithms are used to identify the target value. The methods used for unsupervised learning are the Support Vector Machine (SVM) and k-means clustering algorithm. These two methods provide applications for detecting anomalies and classifying images. The performance of the detection systems was analyzed using ROC charts, which take a comprehensive look at how well the systems function across all thresholds. Establishing a localized threshold requires extensive work but is essential [14]. Another learning technique to consider is reinforcement learning, which relies on agent-based methods for learning a specific action strategy. In this case, the agent must choose the action for specific situations, which yields a reward for performing the action. This creates a utility function that provides an approximated value for the specific action. However, reinforcement learning helps us to understand our environment and find better solutions to problems [15].

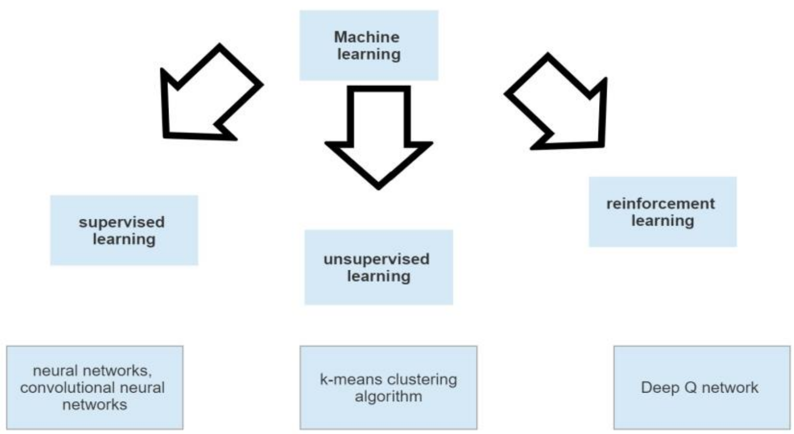

Figure 3. The Three Categories of Machine Learning

2.2 METAHEURISTIC METHODS

Metaheuristic methods consist of groups of algorithms that are used to solve optimization problems. The algorithms commonly find hyperparameters for controllers and models. There are two subgroups of algorithms that include population-based and trajectory-based methods known as swarm intelligence. Figure 4 provides an outline of the process for these two methods.

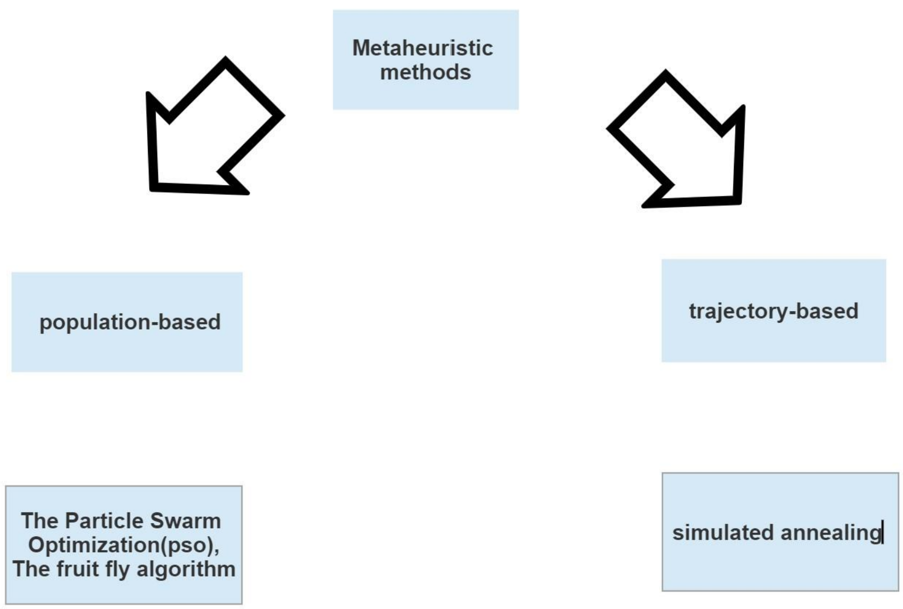

Figure 4. The Two Categories of Metaheuristic Methods

The Particle Swarm Optimization (PSO)is the most popular population-based method. The PSO method was created by Kennedy and Eberhart in 1995, and developments have resulted in improved versions. The basic PSO version relies on swarms of particles that has an initial velocity and position relative to a search field. The PSO functions to find a global optimum with particles determining the best individual and global positions [16]. The fruit fly algorithm is also a popular metaheuristic optimization algorithm. When compared to PSO, the fruit fly algorithm is limited to building geometrical representations [17]. Ant colony optimization is an alternative method that mimics the foraging behaviors of ant colonies. The ant colony optimization algorithm was created in the 1990s with the purpose of solving complex problems in a relatively short time. There is also the Genetic algorithm, which follows the process of natural evolution. In the Genetic algorithm, the fittest individuals are selected for genes to be passed down to the next generation [18]. The differential evolutionary optimization model follows this concept of the survival of the fittest [19]. There is also the immune algorithm that is derived from the genetic algorithm. The immune algorithm consists of an immune operator that is developed based on the selection of vaccination and immunity [20]. Another popular metaheuristic algorithm is the Tabu search method, which provides guidance for local heuristics processes to identify global solutions. The Tabu search method process consists of adaptive memory and exploring responsive mechanisms [21]. There is also simulated annealing that integrates the physical properties of solid materials during their cool-down phase after they have been annealed by solving optimization problems [22].

2.3 RULE-BASED SYSTEMS

The third category of artificial intelligence are rule-based systems that consist of groups of AI techniques that work together to integrate human knowledge. These rule-based systems operate based on a set of "if-then" rules, which enables the system to make decisions based on the rules implemented by the developer. As a result, the rule-based system is perceived as a modularized version of "know-how" systems [23]. In several other research studies, rule-based systems are described as expert systems. As shown in Figure 5, these rule-based systems rely on processes such as Boolean logic, control, and fuzzy logic.

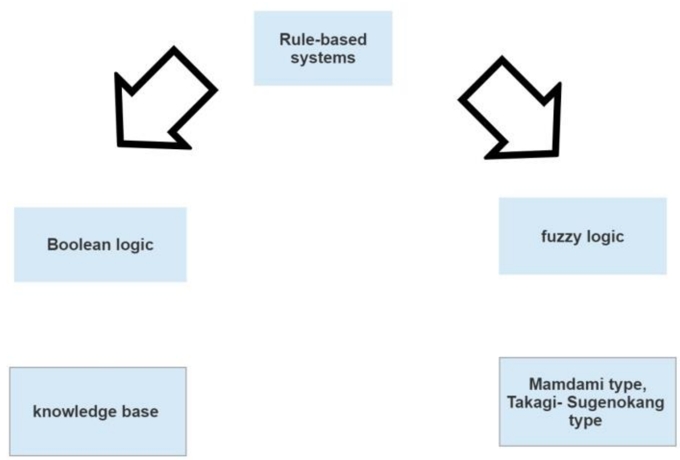

Figure 5. The Two Categories of Rule-Based Methods

The key advantage of utilizing logic and fuzzy theory is that variables can be described in relation to human language. The fuzzy system consists of three key elements. The first is fuzzification, which provides input signals that are mapped into a function of fuzzy membership based on membership degrees. These functions can take on different shapes, such as Gaussian, trapezoidal, and triangular. The second is the inference model, which consists of calculating the degrees of memberships that are integrated into the code of fuzzy rules based on "if-then" processes. These fuzzy rules have to be developed by experts that are knowledgeable about the processes. The third element is defuzzification, which consists of creating an output signal tied to a physical system [24]. Based on these three elements, there are different types of combinations and categories that can be created [25]. Some of these techniques don't have to be tied to a single category, and can be grouped into multiple categories at once. In summary, this chapter has introduced artificial intelligence techniques, as well as an outline of the advantages and limitations for grouping these techniques. These findings have been summarized in Table 1 along with a discussion of applications.

Algorithm	Advantages	Limitations	Applications
Metaheuristic (Population based)	global convergence	convergence speed	Improve PSO algorithm
Metaheuristic (trajectory based)	Implementation simplicity	parallel capability	improved objective function and genetic algorithm
Fuzzy Systems	Integration of expert knowledge	elaborate design of rules	Based on fuzzy set theory
Supervised learning	runtime after training	large dataset	small signal stability using artificial neural networks
Unsupervised learning	no label data	time of training	low voltage distribution network based on fuzzy C-means clustering algorithm
Reinforcement learning	no dataset needed, learn interaction of system	adaptation can be time consuming	double deep Q-learning networks approach

Table 1. Artificial Intelligence Algorithms

3. REVIEW METHODOLOGY

This chapter consists of the methodology for the literature review. Table 2 provides a list of the databases that were used to search for the sources, as well as the screening procedure, time period for the search, and search string.

search index	content
data	Google scholar, IEEE Xplore, Sciencedirect, MDPI, Wileys (IET)
Search String	Each technique/Methodology and app e.g. Neutral network state, distribution system and AI
Search Time	2010-2021
Procedure	Relevant Judge by abstract, introduction and conclusion

Table 2. Review of Research Methodology

The studies have been classified based on their applications to distribution systems. General metrics have been established and defined to provide clarification for artificial intelligence and distribution grid operation designs. This provides a process for reviewing each research study based on clearly defined metrics to provide a basis for AI guidelines. The metrics demonstrate the importance of the requirements for each AI application. The metrics are rated from a Likert scale between a score of 0 to 5. A score of 0 corresponds to a low rating for the severity of the requirements, whereas a score of 5 corresponds to a high rating. After reviewing each of the research studies, a rating was provided for each of the metrics. Based on these results, the requirements are discussed to define AI approaches.

At the conclusion of reviewing these research studies, general guidelines have been established to demonstrate their applications to different methods. These methods are discussed in chapter 2 based on their applications. The outcomes are demonstrated in a table that summarizes the general rating based on the review of the literature and corresponding metrics. The metrics are described in further detail:

Dataset: Most research studies are data-based approaches, and the database are presented along with the required measurements.

Runtime: The AI approaches have a runtime and operating timescale, as well as practical applications that are reviewed based on their applications to real-time operations.

Dynamic: Some AI applications consider system dynamics to be mandatory for efficient operations.

Adaptability: Effort is provided to adapt the research designs to new situations, which include training time. This leads to a strong correlation between large datasets and long training times.

Table 3 provides a list of the times needed for adaptability based on rating, dataset, runtime, dynamic, and adaptability. In Table 3, rating provided to metrics are clearly defined. The reviewed papers are evaluated using a quantitative evaluation system with defined ranges to evaluate adaptability, runtime, and dataset. These values are then classified into 5 groups with defined outer limits.

Rate	Data	Runtime	Dynamic	Adaptability
0	1-10 samples	2h-24h	—-	millisec-sec
1	10-10^2 samples	30m-2h	min to hr	sec-min
2	10^2-10^3 samples	1m-30m	sec to min	min
3	10^3-10 ^4 samples	10s-1m	10^-2s-10s	min-hr
4	10^4-10^5 samples	10^-2s-10s	10^-6s-10^-3s	hr-day
5	10^5-10^6 samples	10^-9s-10^-3s	10^-9s-10^-6s	day-week

Table 3. Defined Metrics

4. AI APPLICATIONS TO DISTRIBUTION POWER SYSTEMS

There are two types of distribution grid operations that are demonstrated in Figure 6. The left side of Figure 6 demonstrates the process of decision support systems that rely on measurements to visually represent different situations into the grid. The operator is capable of manually controlling the actions in this case. In this paper, the decision support system functions through an open-loop control process that is not fully automatic.

On the right of Figure 6, the closed-loop system functions through an automated process. This automated process is completely self-reliant without a need for humans to interact with the system. The closed-loop system in Figure 6 includes a grid and control. Visualization from the decision support system plays a role in checking to ensure that the control is functioning effectively without human intervention.

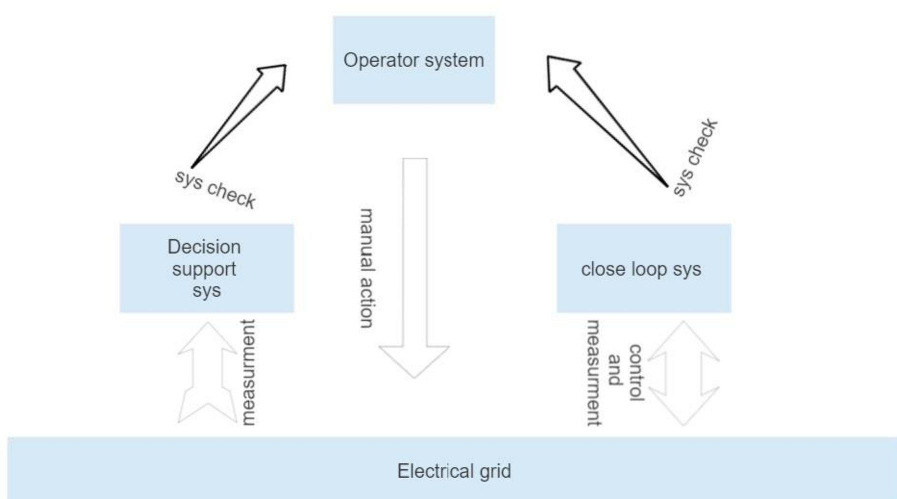

Figure 6. Operations of Distribution Systems

The literature demonstrates that there are varying degrees of automated processes for managing distribution grids. However, these distribution grids are commonly run by decisions from manual operators. Section A demonstrates some of the common applications for artificial intelligence to decision support systems. Section B provides an investigation of these applications to a closed-loop control system. However, it is important to note that not all the reviewed research designs were designed for distribution systems, but these designs are still discussed because they are applicable to distribution systems.

Recent research studies have investigated the use of frequency ancillary services to improve the connectivity of distribution generation in distribution systems [26]. Fast generation changes influence the investigation of fast generation grids. There is a need for investigating the impact of fast generation changes to improve distribution grids. Assessing the frequency leads to improving the interest of future grids. One of the areas of interest is to examine how the dynamics of distribution systems change based on modifications to distributed generation [27]. Tasks also need to be considered for their applications to distribution system operations. However, these tasks are primarily used for modern transmission systems.

4.1 AI in Distribution Decision Support

4.1-1 Distribution nodal loads and mode circuit connectivity models

Digital twin concepts have been applied for modeling distributional nodal loads using lower time periods. Digital twin is growing in popularity in research studies given its rapid growth in AI distribution systems [28]. The digital twin provides a digital representation for physical systems where state and behavior can be changed based on measurements and parameter information. The digital twin concept is primarily used in manufacturing processes, but there has been growing interest for using digital twin as applications for power systems. Some of the applications of digital twin in power systems is monitoring, control, maintenance, and design for power plants [29]. Figure 7 demonstrates the basic requirements for establishing circuit connection and nodal loads for power system operations. The process speed and accuracy are needed to demonstrate the system's behavior in other states. The process speed and accuracy also play a role in providing a representation of system behaviors in all the system's possible stages. This requires a broad dataset with multiple situations.

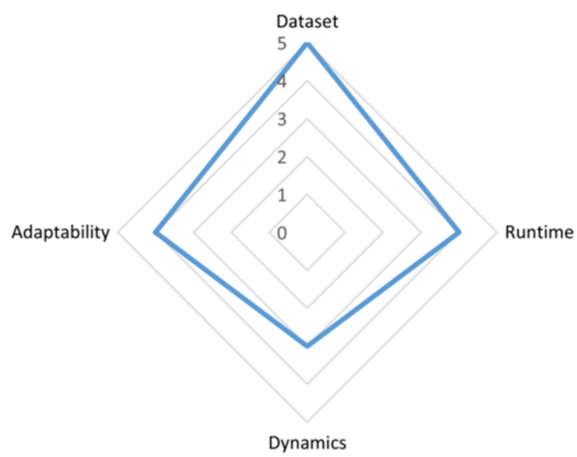

Figure 7. Severity for basic requirements needed for modeling distribution modes

The model extracts data related to the system's be heavier to determine how to provide an adaptive response to different types of operational scenarios. This leads to high adaptability with the digital twin approach that includes an ability to change behaviors while online and estimate dynamic parameters. AI techniques build digital twins to provide a range of applications.[30] demonstrates how the digital twin can be used to provide an online grid analysis. In this application, the digital twin consists of a virtual model that includes a bus, nose, breakers, and branch model that can be updated using state estimation and SCADA data. Any changes that are detected in the model results in the engine conducting a situation awareness analysis in which data is fed into a machine learning system. A neural network conducts an online security assessment, which can be conducted in an online environment. Field tests have been conducted and reveal that the computational time required for the entire process is 300 ms or less.

[31] recommends using the digital twin to conduct power flow calculations for artificial neural networks. This neural network includes P and Q as grid inputs and complex voltage as outputs. Also, designed a 9-bus system using 9,600 samples in MATPOWER to train and test the system. An operator is needed to monitor power flow within power systems using real-time operational data. This can be used to perform a series of conventional flow calculations to create a mode of the system. [32] recommends using a linear first-order load model to compute power flow calculations in a parameter fitting algorithm known as Powerfit. Linear models are used to provide convergence to power flow algorithms that search for any cut points in datasets. This can be used to detect drastic changes in load data in which load parameters can be adapted to new situations.

[33] recommends using a two-stage approach to create a load model that provides a dynamic load response using the Western Electricity Coordinating Council Composite Load Model (WECC). Each of these load components provide a different aggregate for load components. A Double deep Q-learning Network (DDQN) learning agent is used to investigate the load composition for each bus during the first stage. I'm the second stage, Monte Carlo simulations are used to identify parameter sets. DSATools and TSAT are used to create training concepts based on the 39-bus grid. [34] proposes the use of LSTM to estimate parameters based on the

ZIP model. This is useful for extracting measurements related to the temporal relationship between the target bus and load model parameters.

[35] proposes a digital twin approach to identify load dynamics by combining identification methods for systems and their corresponding neural networks. It is possible to optimally utilize DERs and EVs, as well as topology identification systems to improve calculations for the system's structure and parameters.

[34] recommends using a neural network structure with binary classifieds to conduct online identification. The network can be trained using inputs from measurements, such as PMUs. This problem-solving approach is binary because the neural network output can either have a value of 1 or 0. A value of 1 corresponds to connected and a value of 0 corresponds to not connected.

recommends using deep neural networks as an alternative approach for conducting topology identification. The deep neural networks include using DER management systems to conduct measurements. [36] suggests that fuzzy e-means clustering can be used to check LV distribution grid topologies with smart meter data collecting individual household data for correlation analysis. The collected data is then compared using a GIS system to determine if a user is located using the correct transformer area based on the fuzzy e-means algorithm.

4.1-2 State Estimation

The growing increase in distributed generation has led to more emphasis on controllability and measurability for distribution grids. Operation grids experience changes to their operation practices, which causes the ability to estimate the grid states to be important for grid modeling and control. Conventional approaches are difficult to implement because ere is undermined measurement sets and topology information that is missing. AI techniques are more effective because they can extract data in real time. Figure 8 provides a visual depiction of how AI techniques can be used to perform state estimation. According to figure 8, state estimation relies on large datasets that are highly adaptable to changes in system states.

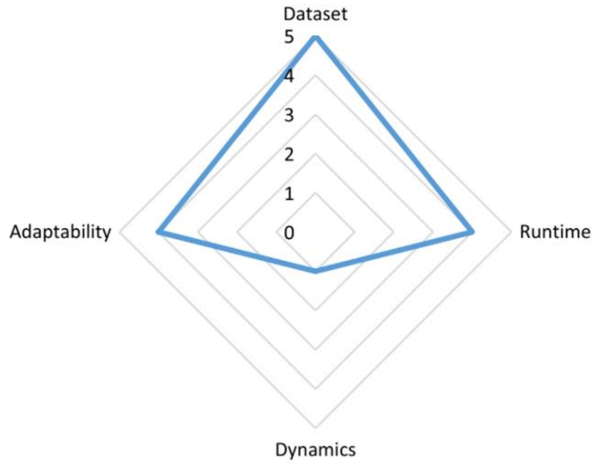

Figure 8. Severity for basic requirements for state estimation

[37] recommends using a machine learning with physics methods to create a hybrid model that improves the ability to explain data-driven models. This includes a temporal relationship between states to achieve improvements to state estimation. This considers factors such as the system's dynamics. The Deep Neural Network model incorporates LSTMs with measurements for time steps from the present and past. The system's state is estimated based on this data and provided to an AC power flow model that provides the system with physical parameters.

[38] offers an alternative approach for incorporating physical structures into neural networks. This approach consists of graphing a structure based on the electrical grid, and copying it into a neural network. This approach is effective in reducing the complexity and training ability of network parameters.[39] demonstrates a deep learning-based framework that provides real-time distribution for state estimation based on machine learning methods. This deep learning-based

framework includes an offline component that trains DNN and online component that copies the offline DNN. Smart meter data is used to facilitate the offline learning process, and this data is then injected into Gaussian and Weibull models. With this process, bad data can be detected by identifying the differences between learned distribution parameters and measurements. [40] proposes that forecasting systems should be added to improve state estimation in real time. This can be achieved by implementing two DNNs systems. The first DNNs system is used to conduct estimations and the second is used to conduct predictions.

4.1-3 Stability

One of the important aspects of power system operations is analyzing the stability of power systems. This subject presents several research studies that apply AI techniques to conduct stability assessment tasks for distribution system operations because of their capability to effectively acquire nonlinear data from dynamic systems with short runtimes.[41] reveals that these AI techniques are commonly applied to provide frequency stability in transmission system operators.[42] states that when generation transitions to distribution systems, the generators' non-frequency and frequency ancillary services play a role in connecting to the distribution system.

Figure 9 demonstrates how a model can be used to detect stability in dynamic systems. The model requires a large dataset and fast runtime based on rapid changes to the stability of the system. However, this model doesn't work well for dynamic systems striving to achieve long-term voltage stability. This is because achieving voltage stability is challenging because the time behavior fluctuates.[43] Suggests utilizing a method of data analysis that is self-adaptive with a hierarchy for assessing short-term voltage stability. In this model, PMU measurements are taken to evaluate whether there is stability in the propagation of voltage. When a stable status is detected, the Fault-Induced Voltage Delayed Recovery (FIDVR) and root-mean-squared voltage severity dip (RVSI) is used to predict voltage recovery performance. This results in an assessment system based on a hierarchy. In this hierarchal model, the first tier in the hierarchy detects a stable point in the dynamic system, which then activates the second tier in the hierarchy. This creates a regression model that can be used to solve complex machine learning processes. ELMs are aggregated separately in each stage of the model, but performance validation is aggregated following the training step. This creates an optimization problem used to evaluate the accuracy and timeliness of the dynamic system. For the model used in this paper, the date was generated by measuring pre-fault conditions for the 39 buses in the New England bus system. The data generation process consists of 10,000 Monte Carlo simulations that contribute 700 MW to loads and wind power plants. The simulations are carried out using Transient Stability Assessment Tools (TSAT) using 0.01 seconds for the step size. The ReliefF algorithm is used to select different features for the simulation [44].

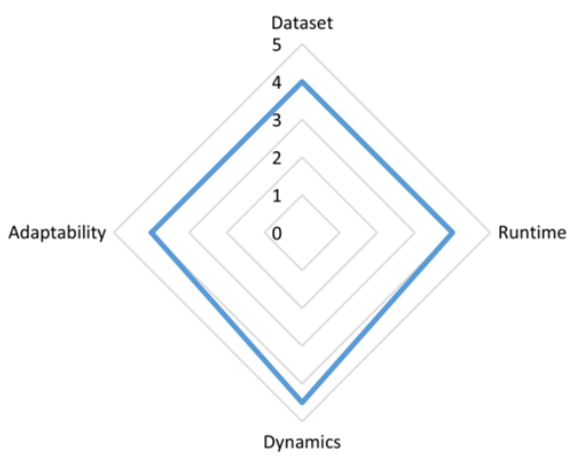

Figure 8. Severity for basic requirements for power quality analysis.

[45] offer a similar strategy that consists of a two-stage system for conducting voltage stability assessment. The first stage consists of detecting the stability of the system. The second stage focuses on making an accurate prediction about the trajectory of the system based on the stability assessment results. [46] recommend using a Support Vector Machine (SVM) to assess the voltage stability of the power system based on PMU measurements. There are two key optimization goals for the processing of measurement data. The first is to determine the SVM misclassification rate. The second is to use the nonlinear relationship between data measurements and voltage stability to reduce the number of SVM input features. This leads to increasing the accuracy of predictions, while also focusing on reducing the processing time needed to make these predictions.

A biogeography-based optimization algorithm (BBO) is used to process the dataset, which is known as an evolutionary optimization algorithm. In the first simulation conducted on the New England 39 bus system, the database is created by measuring load patterns from 506 pre-fault operation conditions. This leads to checking the stability for power flow convergence. The PMUs are used to calculate the angles of voltage phases, squared voltages, line currents, the flow of reactive power, and fault location. Iran's 66 bus power grid is then used to carry out additional tests. A total of 26 operation conditions were established across 15 days of collected load data. There are 24 PMUs positioned throughout the power grid.

The operations of power systems must also consider transient stability. The short timescales of detection algorithms make them suitable for achieving transient stability. [47] suggests that a transient stability is conducted by using PMU data with different ratios of signals to noise. Stacked autoencoders (SAE) are used to extract features, and convolutional neural networks (CNN) are used to carry out representational learning in order to filter noise. This process occurs with offline training by using historical data. CNN relies on unsupervised learning to facilitate its features and supervised learning to provide the classification of data. PMUs rely on real-time data to perform online operations for conducting transient stability analysis. In this case, the simulation database is generated from the 39 New England bus system grid and a PSD-BPA software that conducts calculations for power flow for different load levels. Using SNR, a total of 4,000 data samples were collected. [48] recommends the use of ML systems to indirectly perform PCA to reduce input dimensions when conducting stability assessments. This approach leads to only retaining necessary data points. This approach is more effective then direct PCA, which reduces data points with a cutoff set by lowest eigenvalues. The process of direct PCA is ineffective because the reduction of low eigenvalues doesn't necessarily lead to stability assessment in power systems. The indirect PCA is utilized to calculate the difference between stable and unstable dimension projections after acquiring the data values needed as inputs. In its application to the New England 39 bus system, datasets are created using Monte Carlo simulations for bus voltage and power generation with 165 measurements (i.e. branch power flows).

4.1-4 Analysis of economic efficiency

It is important to consider the economic aspect of distribution systems for optimal generation. [49] demonstrates how the economics of optimal generation are significant in DOMA, as well as other optimization goals for power systems. One of the traditional problems is economic dispatch, which focuses on minimizing costs. One of the other top goals is to reduce carbon emissions. A cost function can be generated to incorporate each of these optimization goals [50]. Figure 10 demonstrates that this cost function has problem variables that undergo slow changes, which enables the power system to achieve optimization without needing adaptability or fast runtimes. This is demonstrated in Figure 10, this cost function still requires enough data to achieve desired optimization levels.

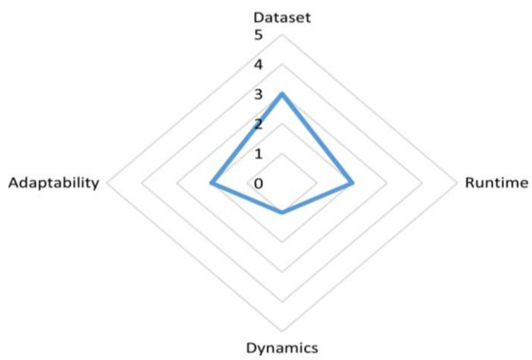

Figure 9. Severity for basic requirements for analyzing economic efficiency

Decision-support systems require models of online adaptability and analysis to achieve long-term applications for power systems as they undergo permanent changes. As a result, the model requires training and adaptation to be conducted routinely, which requires datasets and updated system data. Given these requirements and usage statistics, applied AI methods require suitable algorithms for each application, which are outlined in Table 4.

Applications	Algorithms					
	Metaheuristic (population based method)	Metaheuristic (trajectory based method)	Fuzzy systems	Supervised learning	Unsupervised learning	Reinforcement learning
Modeling of distribution nodal loads	–	+-	+-	++	+-	+-
Circuit connectivity and power flow	+-	+-	+-	++	++	+-
Analysis of Economic Efficiency	++	+-	–	+-	–	++
State estimation	+-	+-	+-	++	–	++
Power quality analysis	++	+-	+-	++	++	+-

++: convenient; +-: feasible; –: constrained

Table 4. AI Applications for decision-support systems.

4.2 Application in distribution system closed-loop control

4.2-1 VOLT/VAR/WATT Optimization

The oscillations of low voltage systems are caused by transmission system operators with more than one voltage regulator. However, inverter-based generation with a connection to distribution grids using voltage-controlled mode offers improvements to the operators of distribution grids. Integrating voltage regulators that are continuously acting leads to the most conventional outcome for generation units that improve the steady-state stability for power systems. However, additional controls are needed because there are dangers with using a system that has small magnitude oscillations and low frequency. [51] developed a supplementary excitation control called a power system stabilizer that is designed to achieve synchronous generation. Figure 11 demonstrates how the controller runtime must be fast to provide a reaction for system's dynamic behavior. Figure 11 demonstrates that the optimization for controller parameters can be significantly slower since they don’t have to occur in real time. [52] recommends the use of Neuro-Fuzzy controller (NFC) to replace traditional PSS and coordinated multi-power system stabilizers. This allows the power system to achieve stability by reducing low frequency oscillations.

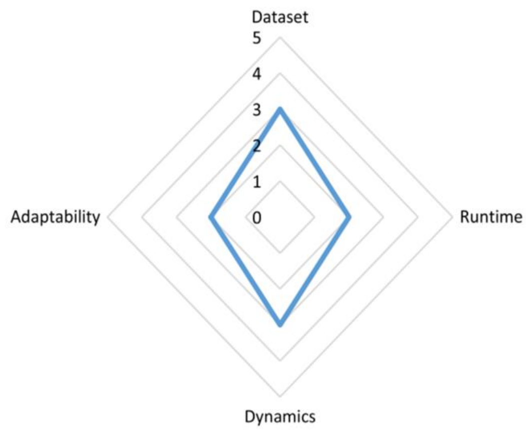

Figure 10. Severity for basic requirements for power system stabilizer.

In the next part, the distribution systems’ reactive power and voltage control are briefly discussed. This includes providing an overview and analysis of the challenges associated with voltage control for smart grids. Some of the recent approaches that researchers are taking will be discussed. Figure 12 demonstrates the large and comprehensive dataset that power systems require to manage multiple generation and load situations. According to Figure 12, voltage control is dependent on high adaptability and short runtime.

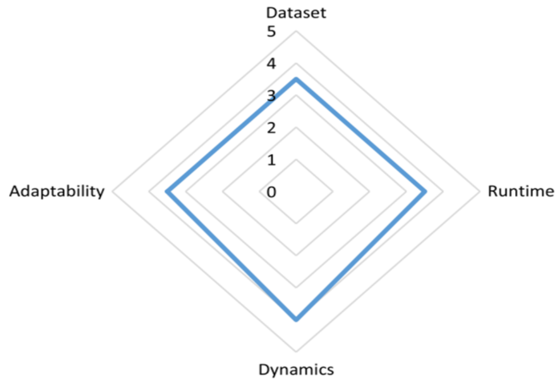

Figure 11. Severity for basic requirements for reactive power and voltage control.

4.2-2 Fault identification, isolation, and service restoration

Another crucial aspect for the operation of power systems is to detect and diagnose faults. This includes the detection of anomalies and losses for different short circuited other threats to consider are cyberattacks or communication outages that can result in power outages. Figure 13 demonstrates that detection of faults and anomalies are dependent on providing accurate models for system dynamics. Additionally, a fast runtime is required because systems are rapidly changing their system states. As a result, the adaptability of the system is important for being able to respond to different types of typologies [53].

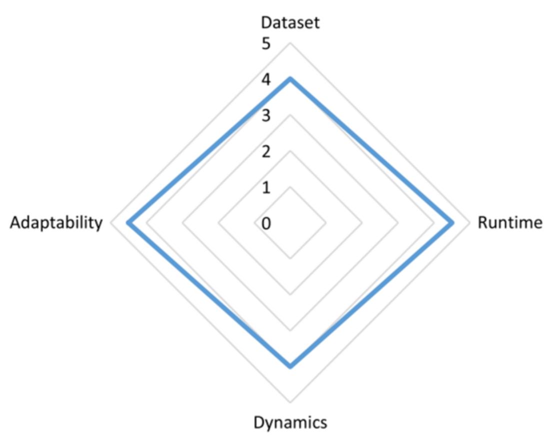

Figure 12 Severity for basic requirements for fault identification, isolation and service restoration.

4.2-3 Coordination of emergency actions

The coordination of emergency actions is important when the distribution grid is experiencing a critical mode. One of the potential emergency responses is to shed the loads in the event of a frequency drop. However, the low frequency of load shedding relays information that results in the disconnection of loads once a threshold is reached. Power systems are complex with dynamic behaviors, which makes it challenging to determine an optimal load shedding strategy. Figure 14 demonstrates a proposed algorithm that is adaptable without being dependent on a large dataset. The main purpose of this action is to reduce the time for the procedure of recovery and make the system stable in a shorter time. Also, it reduces the damages and help the system work more stable [54], [55].

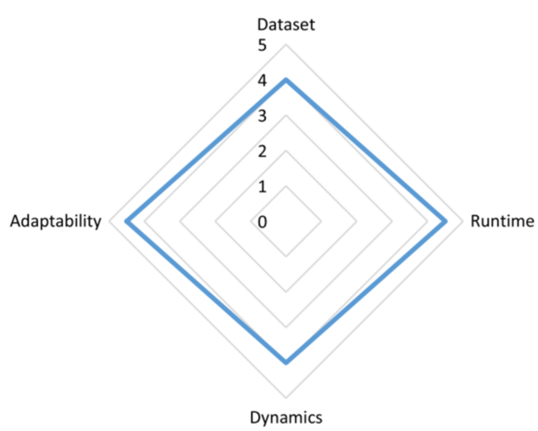

Figure 13. Severity for basic requirements for coordination of emergency actions.

4.2-4 Coordination of restorative actions

Distribution operators play an important role in providing restorative actions for blackouts because generation is becoming increasingly connected to distribution systems. [56]and [57] present ways that distributed generation can be incorporated into the restoration strategy of distributed power systems. [58] and [59] offer ways to incorporate energy storage for achieving these restorative actions. One of the proposed recommendations is to utilize EVs. Figure 15 demonstrates that blackouts can result in different types of outcomes following the emergency, which creates a need for adaptable approaches that can be readily applied to different types of situations. [60] recommends the use of multi-agent systems that provide a restorative distribution grid. In this model, two agent classes are considered: load and distribution substation agents. Load agents focus on the restoration of loads to provide energy and guidance to neighboring loads. The distribution substation agent monitors the flow of substation power and holds the load agents accountable.

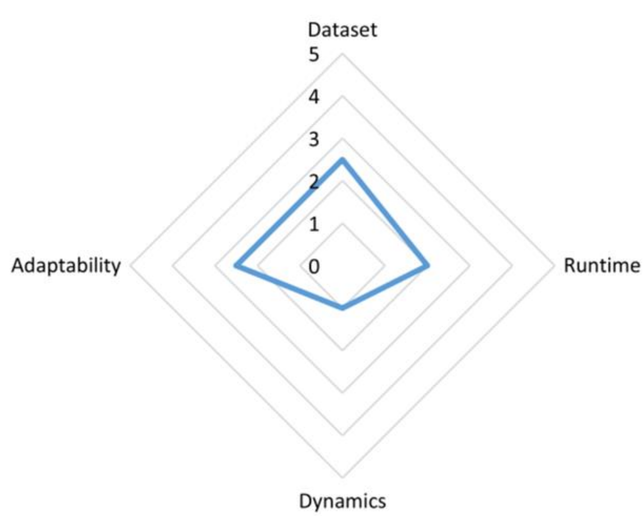

Figure 14. Severity for basic requirements for coordinating restorative actions.

Power systems are dynamic and change when the inverter-coupled participants are integrated [61]. This results in interactions across multiple controllers that lead to different optimization goals and runtimes. As a result, AI-based controllers must be further investigated

4.2.5 Load Forecasting

Forecasting is the process of estimating a variable's (or set of variables') value at a future time point. One of the main areas of electrical engineering research now is the forecasting of electricity demand. Artificial intelligence techniques have been the subject of extensive research in recent years when it comes to the load forecasting issue. Some artificial intelligence (AI) techniques used for load forecasting include expert systems, fuzzy, genetic algorithms, and artificial neural networks (ANN). In distributed systems, smart grid and buildings, next-day load demands, as well as autoregressive Artificial intelligence-based techniques such as ANN with exogenous vector inputs have been used for load forecasting. Because it does not require complex mathematical formulations, ANN has many applications in the areas of curve fitting, data mining, load forecasting, controls, system identification, and so on. The research, on the other hand, reveals two things. Electrical load forecasting and power system protection are two key applications of ANN in the context of the power system. ANN outperforms other forecasting methods in applications where non-linear relationships exist because of its ability to adapt to them. As a result, the use of artificial intelligence in load forecasting facilitates integration. of load switching, contract evaluation, energy generation and purchase, and infrastructure development. Additionally, it helps with precise load prediction, which is one of the key signs of power intelligence. Considering inputs based on loads, weather-related data, day type, and time of day is also beneficial. By maintaining current forecasting areas, this in turn helps to achieve a systematic approach to managing electric distribution. In the 1990s, load forecasting was widely acknowledged as an effective use of ANNs, but in the decade that followed, the field made little progress in terms of methodological innovation and enhancements to model accuracy and usability. While this was going on, other fields, like mathematical programming and computer vision, made significant methodological and practical advancements. In contrast to those thriving fields, the load forecasting literature from the 1990s to 2000s made slow progress for a number of reasons. Before the 2010s, benchmarking data and models were absent from the load forecasting literature, and many load forecasting papers lacked reproducibility. Therefore, artificial intelligence techniques have a lot of applications for load forecasting [62].

4.2.6 Stability control

This chapter's goal is to showcase the key artificial intelligence (AI) technologies that are employed in the power system to handle operational and dispatching tasks when conventional approaches fall short. Additionally, a brief summary of each technology covered in the chapter along with its precise application of the power system is provided. Furthermore, by regulating voltage, stability, power flow, and load frequency, these techniques enhance the efficiency and productivity of the power system. Furthermore, it permits network management of features like size, location, and management of equipment and devices. The automation of the power system ensures that network administration, security, and problem diagnosis are all possible. The ideal artificial intelligence strategy has to be discovered in order to use artificial intelligence for planning, monitoring, and control of the power system. The chapter also briefly discusses the use of artificial intelligence to the sustainable components of the power system. Furthermore, it emphasizes the four main artificial approaches, including neural networks, fuzzy logic, expert systems, and genetic algorithms. Each method aids in resolving problems with the power system. The article focuses on installation stability analysis and management via intelligence system, which is more significant. Sustainable energy practitioners must focus on the cautious operation of power channeling systems. communications. The authenticity and timely grading of any disruptions therefore prevents the handling of a later developed substituted system. Thus, this study addresses the challenges of selecting installation stabilizing structures and gives some rule solutions by examining reference works related to installation stability analysis and management.

In conclusion, the main feature of power system design and planning is reliability, which was conventionally evaluated using deterministic methods. Moreover, conventional techniques don't fulfill the probabilistic essence of power systems. This leads to increase in operating and maintenance costs. Plenty of research is performed to utilize the current interest artificial intelligence for power system applications. A lot of research is yet to be performed to perceive full advantages of this upcoming technology for improving the efficiency of electricity market investment [63].

4.2.7 Energy Management

To attain energy management for hybrid renewable energy-based multi-area power systems, the distributed controllable loads are used. The distributed controllable loads are hinted as better alternative instead of costly energy storage systems. The need for an artificial intelligence-based nonlinear energy management becomes mandatory due to nonlinearity, high variability and uncertain nature of hybrid renewable energy-based multi area power systems based on distributed controllable loads. This paper hints a hybrid control strategy based on fuzzy reasoning and nonlinear sliding mode control to manage the energy of distributed controllable loads in a smart grid such as rooftop solar photovoltaic units and wind generating units. The identified hybrid control strategy fuses the unique features of both fuzzy logic and nonlinear sliding mode to handle the system nonlinearities and to standardize the humid characteristics of the system response against the uncertainties of the boundaries, as well as the high variability of renewable energy resources. Also, the acquisition of proposed fuzzy logic and nonlinear sliding mode controller is regulated by the imperialist rival probabilistic that is considered a powerful artificial intelligent procedure. This paper emphasizes that the energy management of the controllable loads is evolved based on a fuzzy sliding mode control strategy to maintain the output recurrence within the agreeable limits. The recommended procedure is applied in a multi-area smart grid, including renewable energy rather than the traditional. The addition of the hinted hybrid fuzzy logic and nonlinear sliding mode controller is honeyed by a new intelligent technique based on intelligent competitive rather than the trial and error conventional procedure. Also, the hinted control procedure can ensure system stability under the uncertainty of the boundaries [64].

5. OUTLOOK FOR AI IN POWER SYSTEMS

AI is becoming more prevalent in research for power systems. However, there is still potential for future research and improvements to current research. This chapter explores the outlook for AI in power systems and the current concerns for the practical applications of AI. These issues will be addressed in future research studies based on AI applications over the past few years.

5.1 . Explainability of AI

As AI becomes increasingly implemented in real-world systems, there are concerns about how AI systems can be simplified and explained. This is particularly challenging for closed-loop control systems in which the system makes control decisions and actions instead of an operator. The majority of AI approaches have a black-box structure where the operator can’t check if the system is taking actions as intended in each type of possible situation. [65] suggests reviewing the type of models learned by the AI to better understand its behavior in the system. [66] suggests that the operator should focus on explaining individual predictions of behavior. Several studies investigate the explanation of AI for power systems, which offers tremendous potential for future research.

5.2 Database

The database used by AI is crucial for the effectiveness of AI applications. This is particularly true for complex power systems, in which AI must rely on a larger database set to sort and test different types of algorithms and models. [67] offer open-source data collection models, but one of their challenges is that they lack general application to different types of systems and approaches. Another challenge is that there are privacy regulations that limit access to data that can be used to improve AI models and systems. This makes it challenging to gain access to central data collection and integrate this data into individual loads. In cases where date is protected, AI must rely on suboptimal datasets that limit the development of AI-driven models and systems.

5.3. Reducing Computational Loads

Although computational power has experienced a significant increase over the last 10 years, one of the limitations of AI systems is that they take a lot of time to acquire complex behaviors. This results in limiting the application of real-time behavior and tasks. This is particularly prevalent in cases where the AI system must perform learning processes online. For example, in cases where Deep Neural Networks carry out online adaptations. This is also a crucial step for metaheuristic approaches that are applied to optimization tasks that use a lengthy trial-and-error process for convergence. However, AI systems require the ability to adapt online because power systems have long time changes, primarily to the aging components of the system. Based on these challenges, there are three aspects that future power systems should consider. The first is to enhance the AI system’s explainability so that systems can be traced and applied to plausible solutions. Second, is to create robust AI systems so that all components of the system are safe and secure for system operations. Another important aspect is to ensure that comprehensive datasets are used to train and test AI models. A third objective is to reduce computational demand to improve real-world application and an ability to adapt to online environments [68].

5.4. Sector Coupling

In the last decade, there has been a source in research devoted to the coupling of energy sectors to achieve carbon neutrality. Integrated energy systems (IES), which link the electricity, heat, and gas industries, are seen as the benchmark for future energy systems that utilize a high percentage of renewable energies. IES also links the electricity industry to the heat and gas industries. Electricity, heat, and gas can be dynamically connected using two essential coupling technologies, power-to-gas, and power-to-heat. Despite this, the general stability of the system may be put at risk due to these interactions. As a potential methodology for conducting research, one option presented is to take the approach of combining grid reduction, steady state, and dynamic inquiry.

[69] Also, In recent years, multi-carrier micro grids, also known as MCMGs, have been increasingly popular because they can offer practical solutions that improve the operation and construction of power grids. The owners of MCMG have been searching for viable solutions to the problems that are now hurting the energy markets worldwide on the company's behalf. This study investigates how effective the Transactive Energy Management (TEM) mechanism, which is a unique method of energy sharing, could be in assisting in reducing the operational expenses incurred by each MCMG in energy markets characterized by intense competition. [70] However,

That researches demonstrate how energy quarters are used to provide energy coupling for buildings or entire neighborhoods on a distribution grid.

The urban energy network at the neighborhood level has the potential to offer more cost-effective and sustainable services to a large number of buildings through the integration of separate energy systems. It may not always be possible to guarantee the benefit of individual buildings within the network to achieve the highest potential network performance. There has not been much thought into whether energy networks' benefit allocation is fair. This work aims to provide unique cost and emission benefit distribution limitations based on cooperative game theory so that all participating buildings can reap the full benefits. The results show that the solution space is slightly reduced when benefit allocation is considered compared to when it is not.

[71] Because of the expansion of intermittent renewable energy sources, the power grid is finding it increasingly difficult to strike a balance between supply and demand. It is anticipated that buildings will play a more significant role in the future of the smart grid due to enhanced grid connections and increased end-use loads. Buildings may be able to make more efficient use of passive thermal mass, which functions as a versatile source of thermal energy if predictive control is used. [72] These examples demonstrate several ways in which AI can be used to incorporate control concepts to improve these algorithm.

5.5. Ancillary Services

Providing ancillary services is a popular research topic due to the volatility surrounding the generation of renewable energy. [73] demonstrates that EVs can be used as flexible loads can be used alongside DER for advanced loading. However, [74] reveals that one of the challenges of utilizing EVs to provide ancillary services is that the infrastructure is lacking. The rising use of asynchronous generation leads to concerns about system inertia because synchronous generators don't provide system stability. [75] raises several concerns about the behavior of low inertia systems and how AI techniques can be applied to improve these systems.

6. CONCLUSION

This project demonstrates the ways that AI is being integrated into the operations of distribution power systems. Some of the promising applications of AI include metaheuristics methods, machine learning, and rule-based systems to improve system efficiency. This survey classified the applications of AI into closed-loop and decision-support control systems. This literature review provides the guidelines for choosing the best algorithm for AI applications in distribution power systems. The four key metrics that are adaptability, dynamics, runtime, and the significance of database requirements. Each of these four metrics quantitatively evaluated for each AI application. Using these metrics, each of the AI techniques are rated based on their suitability for each application to distribution power systems.

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