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Machine learning applications in cascading failure analysis in power systems: A review

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ABSTRACT

Cascading failures pose a significant threat to power grids and have garnered considerable research interest in the power system domain. The inherent uncertainty and severe impact associated with cascading failures have raised concerns, prompting the development of various techniques to study these complex phenomena. In recent years, advancements in monitoring technologies and the availability of large volumes of data from power systems, coupled with the emergence of intelligent algorithms, have made machine learning (ML) techniques increasingly attractive for addressing cascading failure problems. This survey provides a comprehensive overview of ML-based techniques for analyzing cascading failures in power systems. The survey categorizes these techniques based on the evolutionary phases of the cascade process in power systems, as well as studies focusing on cascade resiliency before the occurrence of cascades and problems related to cascades after their termination. By organizing these works into relevant categories, this survey aims to identify problems related to different phases of cascading failure in power systems that can be addressed by ML.

1. Introduction

1.1. Overview and significance

Despite the advancement of modern power grids, which are equipped with increasingly intelligent monitoring, control, and communication systems, historical data indicate that they remain susceptible to various cyber and physical stresses. The reliability-threatening stressors can affect all layers of these systems; however, stresses on transmission networks can have widespread and devastating effects such as large blackouts [1]. While the N-1 security criterion has traditionally been used to assess the reliability of power systems, it is important to recognize that power grids can still be susceptible to physical stresses, such as multiple contingencies arising from natural disasters or deliberate sabotage. Such failures along with the lack of timely and effective control actions can trigger a sequence of interdependent component failures in power systems, called *cascading failures*, leading to large blackouts. Cascading failures and diffusion phenomena manifest in a multitude of real-life complex systems, exhibiting diverse forms and scales [2,3]. While studies have demonstrated similarities in these processes across different systems, the contributing factors and underlying interaction mechanisms in cascades differ among systems. Generally, cascading failures and spreads are influenced by complex interactions of the large number of components within the system, which are further impacted by various attributes and characteristics unique to each system. In the context of power grids, analysis of historical data on cascading failures and blackouts, such as the 2003 Northeast blackout [4] and the 2011 Southwest blackout [5], highlights that the cascade process is not solely determined by physical component failures or associated physics-based interactions. Other factors, including the system's operating settings [6], cyber vulnerabilities [7] (e.g., computer server failures and communication issues), and human factors [8,9], also play a role in influencing the cascade process. Moreover, it has been discussed that failure of state estimator models and lack of situational awareness were significant contributors to these events and a timely reaction (such as load curtailment or islanding) could have significantly reduced the impact of these events [10].

Considering the complexity of these phenomena and challenges in controlling them, a large body of work has been formed in understanding cascading failures and mitigating their effects in power grids. Particularly, cascading failures in power grids have been studied using power physics-based techniques [11,12], simulation-based techniques [13,14], probabilistic models [15–17], and graph-based modeling and analyses [18,19]. Despite all the studies and developed techniques, due to the large size and geographical scale, complex and at-distance underlying interactions among the components, and new attributes and dynamics of modern power grids (for instance, deployment of stochastic renewable resources), cascading failures have remained, although not very common, but a complex and costly threat

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to these systems. With the emergence of new sensing and monitoring technologies, a wealth of data previously unavailable in power systems is now accessible. Additionally, advancements in the field of Artificial Intelligence (AI) and Machine Learning (ML) have enabled powerful descriptive and predictive analyses of this data, previously unattainable. While classical techniques remain valuable, they often rely on accurate system models which may not always be obtainable. The objective of ML techniques is not to supplant classical methods, but rather to complement them, enhancing their robustness, particularly in scenarios where system models are inaccurate. Furthermore, ML techniques facilitate the discovery of hidden patterns and relationships within the data, potentially uncovering new vulnerabilities or opportunities for mitigating cascading effects. In summary, ML techniques aim to expand the scope of cascade analysis beyond what is achievable through classical approaches, encompassing descriptive, predictive, and prescriptive analyses.

1.2. Motivation and contribution

Several surveys have reviewed various aspects of cascading failure studies, including historical cascade events [20,21], cascade methodologies and mechanisms [22], cascade models [20], public datasets and test cases available on cascading failures [20,23], tools for cascade analysis [24], risk assessment of grid components [25], and grid protection [21]. The reviewed works encompass various techniques for cascade analysis in power systems, including traditional power physics-based methods, power flow and contingency analysis, graph and game-theoretic approaches, and optimization techniques. Such classical solutions for cascade analysis, have been long-established and utilized for decades for their robustness and reliability under accurate system model assumptions, compliance with the existing grid standards, and scalability and integration with growing technologies for cascade analysis. However, unlike these conventional techniques, ML techniques facilitate the discovery of hidden patterns and relationships within the data, potentially uncovering new vulnerabilities or opportunities for mitigating cascading effects. Due to the intricate nature of cascading failures, characterized by complex interactions among system entities including physical, cyber, and human components, conventional models may struggle to adequately capture and analyze these interactions. Consequently, ML-based approaches emerge as promising candidates for capturing the intricate patterns of such complex interactions. As the use of such ML and AI-based intelligent algorithms in cascade analysis is on the rise, it is important for the scientific community to have a birds-eye view of the possible routes in addressing the complex problems related to cascading failures in power systems using such techniques. As power systems become more complex and exhibit stochastic behavior due to their expanding scale and the integration of renewable resources, and as the deployment of measurement devices generates vast volumes of data, the utilization of data-centric, ML-based techniques becomes crucial to support monitoring and decision-making processes before, during, and after cascading failures. Furthermore, the incorporation of stochastic renewable resources and energy storage systems adds more complexity to the dynamics of power systems. The utilization of ML techniques in analyzing cascading failures presents a great opportunity to enhance our comprehension of such complex dynamics and relationships. As such, the objective of this survey is to examine the utilization of data analytics and ML techniques in the analysis of cascading failures within power systems, while also addressing the existing gaps and unresolved issues pertaining to cascading failures in power systems that can be potentially addressed using these techniques. In addition to their application in cascading failures, ML techniques have been widely employed in various other domains within power systems such as system monitoring [26], state estimation [27], fault diagnosis and prediction [28], load forecasting [29], power system security [30], and energy management, and optimization [31,32]. Surveys exploring the application of ML and deep learning in diverse power system applications can be found in Refs. [33,34].

One of the primary contributions of this paper lies in its systematic organization of the review and the discussions, guided by different phases of cascading failures. Historical data and simulations of cascading failures have revealed that the time evolution of cascades exhibits three phases [4,5,8]. The first phase, known as the *precursor phase*, is characterized by a slow progression of failures. During this phase, control actions such as dispatching, load shedding, and intentional/controlled islanding can effectively mitigate the impact of disturbances. The second phase is the *escalation phase*, in which failures occur rapidly and preventing blackouts becomes significantly more challenging. The third and final phase is the cascade *phase-out*, where the rate of failures slows down as a significant number of components have already failed. In addition to reviewing works focused on various analyses during the cascade process, this paper also examines the application of different ML techniques developed for cascade resiliency before the cascade occurs, as well as problems related to cascades after their termination. Supervised, unsupervised, and reinforcement learning are the three major categories of ML that have been applied in cascading failure analysis, harnessing the distinct benefits that each category of algorithm has to offer. Supervised learning is mostly used with simulated or historical cascading failure datasets, where the labels of the attributes are available. On the other hand, unsupervised and reinforcement learning are more suited for unlabeled data, which requires the ML model to discover the inherent patterns and interactions within a given environment.

In this survey, a comprehensive overview of the state-of-the-art applications of ML in analyzing cascading failures in power systems is presented by reviewing a large number of journal and conference articles from reputable databases and categorizing them according to the problem they address related to different phases of the cascade and the type of ML algorithms used. This categorization based on cascade phases proves to be more useful in discussing the existing gaps in supporting critical functions for cascade mitigation and resiliency. The research studies incorporated in this review were sourced from various review papers, journals and conference papers, scientific books, and reports. A variety of databases, including IEEE Xplore, IET, Science Direct, Springer, Wiley publishers, Taylor & Francis, and MDPI have been considered for the exhaustive search. In order to maintain the quality of the research, it is ensured that the majority of the literature surveyed in this study is recent and has been published in peer-reviewed journals or conferences. Keywords such as "cascading failure", "machine learning", "outage", "blackout", and "power systems failure" have been utilized in the searching phase of the research. From a vast literature on power system failure, works on ML applications in power system cascading failure has been considered. Approximately forty reviewed works specific to ML-based analysis of cascades in power systems were categorized into four classes as illustrated in Fig. 1 and Table 1. The depiction of the categories and their association with different phases of the cascade are shown in Fig. 1. The upcoming sections provide a detailed discussion of the definition of each category and the applications of ML within those categories. The applications of ML in cascade analysis within these categories are summarized in Table 1 following the discussion of cascade phases.

2. ML-based cascade analysis in normal phase

This category reviews research that focuses on using ML to address issues related to cascades within the normal operating conditions of the power system, where no disturbances or disruptions are present. These works are further classified into vulnerability analysis, network hardening, and cascade modeling and simulations.

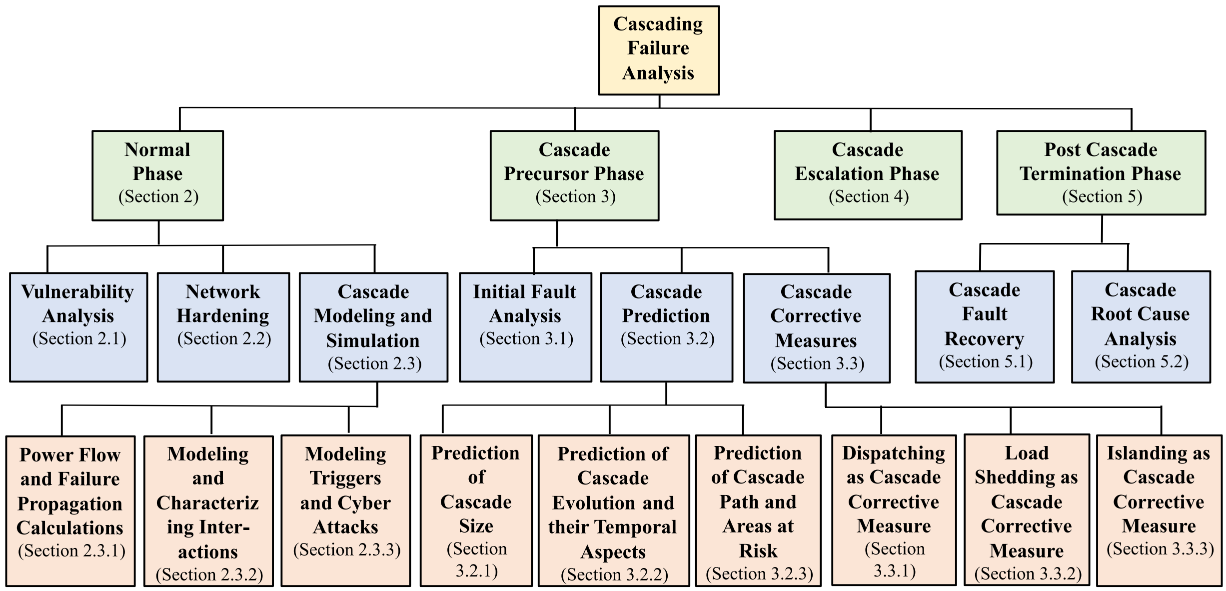

Fig. 1. Taxonomy of cascading failure analysis supported by ML techniques based on different phases before, during, and after cascading failures. The section numbers associated with the categories and sub-categories are marked in each element.

2.1. Vulnerability analysis

Vulnerability analysis in power grids involves identifying critical components in the system that carry a high risk of failure or that their failures can lead to higher reliability concerns including triggering or fueling cascading failures. The focus of the review in this section is particularly on the works for identifying vulnerable components that can lead to cascading failures in power systems. Identifying such components before failure is important to eradicate potential risks of system and service impairments and to implement protection and mitigation mechanisms.

Identifying combination of components that their simultaneous fault can trigger cascading failures [70–72] as well as identifying sequence of failures or attacks that can cause cascades [35,73], both in power systems and interdependent power and other critical infrastructures, such as communication systems [74] and gas systems [13], have been considered in the studies of cascading failure vulnerabilities. Moreover, the vulnerability of cyber components related to cascading failures has also been studied in the literature [75,76]. Another closely related problem to vulnerability analysis is identifying critical components, the protection of which can reduce the risk of cascades [36,39,74,77]. Although such components may not be the vulnerable ones triggering the cascade, their vulnerability can fuel the cascade process. Overall, various forms of cascade vulnerability analysis have been studied in the literature using simulation-based techniques [13,35,36,39], graph-theoretic techniques [78,79], game-theoretic techniques [76,80], and optimization techniques [72,74,81]. The research on the application of ML to vulnerability analysis has been classified into three categories, based on the modeling approach used for vulnerability analysis. These categories are search, classification, and regression.

Search Techniques: Searching power grids for vulnerable components that can trigger or fuel cascading failures is a daunting task due to the large number of combinations of failures that can be considered and can occur in cascades. The goal of ML-based techniques is to support these analyses for a more accurate and efficient search process over power systems. A large number of data-driven and intelligent algorithms for efficient search of vulnerable components and the most impactful attack sequences including greedy search algorithms [71], particle swarm optimization techniques [73], genetic algorithms [82] and random chemistry techniques [81] as well as reinforcement learning [35,36] and deep learning techniques [37,38] have been developed, creating a solid scope for the application of similar algorithms for efficient search over the power grids. Although the mentioned heuristic algorithms perform direct search over the grid topology, reinforcement, and deep learning-based search techniques took data-centric techniques for pattern learning. The work in [36] suggests a temporal difference reinforcement learning mechanism to learn the relation between faults and load loss to identify the fault chain that leads to the largest load loss. The authors in [35] use a Q-learning technique to search for the critical lines when the grid is under sequential attack. When the grid topology changes under such an attack, the technique learns the sequence of the lines that will lead the grid to a specific blackout size. In [37], a search framework with the aid of a graph convolutional network (GCN) is developed to identify critical cascading failures. The GCN model guides the search by classifying between normal and load shedding outcomes based on the state of the system defined through input features including the state of the lines. The work in [38] develops a deep convolutional neural network to classify the risk level of transmission lines based on their topological and operational characteristics, and the depth-first search algorithm is used to identify the critical lines that can trigger cascading outages.

Classification Techniques: Another group of works models the cascade vulnerability analysis as a classification problem to classify the components of the system as, for example, robust, normal, and vulnerable groups. For instance, the work presented in [39] utilizes features such as the centrality of the buses (i.e., betweenness centrality), and power flow information for vulnerability classification of buses using XGboost, which is an optimized distributed gradient boosting library. The latter approach has been compared with classification with logistic regression, support vector machine, and k-nearest neighbors in [39]. In [13], a steady-state energy flow model for a combined power-gas system has been considered and a random forest hybrid classification-regression is formulated to classify the vulnerable power and gas components. Specifically, the regression model is used to predict the vulnerability metric for each of the components enabling the classification of the vulnerable components.

Regression Techniques: Regression-based analysis of vulnerable components focuses on learning vulnerability metrics for the components of the system. Similar to the work in [13], which used a regression model to predict the vulnerability metric for each of the

Table 1
Classification of the references with a focus on the application of ML in cascading failure analysis based on the proposed categories and taxonomy in Fig. 1. The cascade escalation phase is not shown in the table as there is no current development relevant to this phase.

Phases	Applications	Categories	Algorithms with references
Normal Phase	Vulnerability Analysis	Search-based techniques	Q-learning [35,36], Graph Convolutional Network [37], Deep Convolutional Neural Network [38]
		Classification-based techniques	Random Forest [39], Logistic Regression, Support Vector Machine, and k-Nearest Neighbors [13]
		Regression-based techniques	Logistic Regression, Support Vector Machine, and k-Nearest Neighbors [13], Graph Neural Network [40], Neural Network [41]
	Network Hardening		—
	Model and Simulation	Power Flow and Failure Propagation Calculations	Graph Neural Network [42], Artificial Neural Network [43], Logistic Regression [44]
		Modeling and Characterizing Interactions in Cascading Process	Deep Convolutional Generative Adversarial Network [45], Spatiotemporal Graph Convolutional Network [46], Logistic Regression [44]
		Modeling Triggers and Cyber Attacks	Q-learning [47,48]
Cascade Precursor Phase	Initial Fault Analysis		Support Vector Machine [15], Feed-forward Neural Networks and Graph Neural Networks [49], Decision Tree, Support Vector Machine, and Multilayer Perceptron [50]
	Cascade Prediction	Prediction of Cascade Size	Linear and Polynomial Regression, Decision tree, and Deep Neural Network [18], Expectation Minimization [51], Logistic Regression, k-Nearest Neighbor, Decision Tree, Random Forest, Support Vector Machine, and Adaboost [52], Random Forest, Decision Tree, k-Nearest Neighbor, and Artificial Neural Network [53], Attention-based Graph Neural Network [54]
		Prediction of Cascade Evolution and Temporal Aspects	Markov chain [17], Neural Network [55], Attention-based Graph Neural Network [54]
		Prediction of Cascade Path and Areas at Risk	Markov chain [56], Bayesian Belief Network [57], Markov Search [58], Graph Recurrent Neural Network [59]
	Cascade Corrective Measures	Dispatching as Cascading Corrective Measure	Adaptive Immune Reinforcement Learning [60]
		Load Shedding as Cascading Corrective Measure	Deep Reinforcement Learning [14], Deep Neural Network [61], Neural Network [62], Graph Convolutional Network [63], Markov Decision Process [64]
		Islanding as Cascading Corrective Measure	Density-Based Spatial Clustering of Applications with Noise [65], Graph Convolutional Network [66]
Cascade Restoration Phase	Failure Recovery		Q-learning [67–69]
	Root Cause Analysis		—

components, the work in [40] uses a graph neural network-based prediction of avalanche centrality, which is the measure of the impact of a node on the avalanche dynamics of a Motter-Lai cascading failure model. A probabilistic risk index based on load shedding, voltage violation, and hidden failure is predicted in [41] using decorrelated neural network ensemble to understand $N-k$ contingency analysis considering potentially cascade-inducing outages.

2.2. Network hardening

The primary objective of network hardening in power systems is to enhance the resilience of the system against faults, attacks, and stresses that have the potential to trigger cascading failures. In this field, existing research includes various approaches to network hardening, some of which involve strengthening the system's structure through methods such as increasing redundancy (e.g., adding extra components and connections) [83] or resilient structure design [84,85], and improving the protective and preventive maintenance of vulnerable and critical components in the cascade process [70,86]. It is important to note that not all network hardening studies solely focus on cascading failures and they may have a broader scope that includes hardening efforts for the distribution systems [87,88]. Additionally, the literature on this topic includes investigations into severe weather impact analysis [89,90] and smart vegetation management [91,92] as means to harden grid components. The network hardening problem has been addressed through different techniques including optimization [84,93–95], network theoretic techniques [70,84,96], and game-theoretic techniques [97]. Nonetheless, as far as the authors are aware, the utilization of ML in the transmission network hardening against cascading failures remains an area to be explored.

2.3. Cascade modeling and simulations

Data plays a pivotal role in ML-based research, and the availability of cascade datasets is crucial for developing efficient ML models for cascade analysis. Notable publicly available power system test cases have been compiled in literature such as [20,23] to serve as benchmarks or validation sets for different cascading models. For example, Table I in [20] offers a thorough compilation of publicly available test cases, while Table III in [23] details cascade models and their related sources of cascade data. These literatures list several datasets with their corresponding references. Such available datasets serve as valuable resources for simulating cascade scenarios and generating or augmenting test case data, which can then be used to train ML models.

However, these data are in general limited and do not include a large variety of complex cascade scenarios. Cascading failures, which are infrequent occurrences resulting from rare interactions in large-scale power transmission networks, present a challenge when it comes to modeling and simulating them with the necessary level of detail for analysis. To address this, several cascade models and simulation platforms have been developed over the years [23,98–100]. Furthermore, numerous studies have focused on simulating various events like cyber attacks, natural disasters, and physical damages that can trigger cascading failures. This section provides a comprehensive review of ML-based techniques utilized in the modeling and simulation of cascading failures. As there is limited available public data related to cascading failure events to support developing ML models, developing representative databases from historical datasets through modeling, simulations, and testbeds is essential; both for understanding and studying cascading failures in general and also for developing ML models to address the related problems. Here, the review of the application of ML in the simulation and modeling of cascade in power systems is categorized into three main sections:

2.3.1. ML application in power flow and failure propagation calculations

Some research in the field of modeling and simulating cascading failures has primarily focused on efficient and rapid power flow calculations, as well as simulations of failure propagation, for example, based on line overloading mechanisms. For instance, in the work referenced as [42], a physics-informed cascade model is developed using a graph neural network. This model enables faster and more accurate calculation of the power flow values for dynamic power systems. In another study presented in [43], an ML approach is adopted to predict power flow values for all branches after each step of cascading failures. This is achieved by utilizing an artificial neural network in an iterative manner, where the output is fed back as input, enhancing the simulation of cascade evolution. Furthermore, in the research outlined in [44], a time series interaction model is learned using logistic regression to determine the interaction matrix for changes in line states. The obtained results are then subjected to a binary decision-making process to determine the line status at subsequent time steps to model failure propagation.

2.3.2. ML application in modeling and characterizing interactions in the cascade process

Comprehending the interactions among system components during the cascade process is crucial for understanding the cascade behavior within the system. Interactions among system components during cascading failures have been studied and modeled using various forms of interaction graphs [19]. ML techniques have been employed to capture the structures and patterns of interactions among components in power systems' cascades. For instance, in the study presented in [45], a deep convolutional generative adversarial network is used to learn the failure interaction matrix at each step of the cascading failures. It is discussed that the predicted matrix can either help recover missing data due to the lack of information during cascading failures or can help discover new interactions that can provide information about interactions in the next steps. In another instance, detailed in [46], a spatiotemporal GCN model is developed to learn the importance matrix to reveal power system interconnections for cascade predictions. Furthermore, in the research presented in [44], a logistic regression model is designed to learn indirect interactions between the states of lines in order to model failure propagation trajectories after the initial failures.

2.3.3. ML application in modeling triggers and cyber attacks

The design of failure and attack models, as well as the identification of the most impactful triggers for cascading failures, are key problems in cascade modeling and simulation. This problem is closely related to vulnerability analysis discussed in Section 2.1. Modeling such triggers for generating cascading failure has been explored using different approaches such as physics-based [101] and game-theoretical techniques [80]. For example, [102] provides a general overview of how cyber attacks on power grids can lead to cascading failures and blackouts. This study highlights critical cyber–physical factors including the loss of transmission lines, synchronization disruption, and voltage and frequency instability, which attackers can exploit to initiate cascading failures. ML techniques have emerged as a recent approach to detect triggers and potential attacks capable of inducing cascading failures within power systems. As another example, in the study referenced as [47], reinforcement learning techniques, specifically double Q-learning, are employed to model sequential attacks that have a significant impact. The work proposes an attacking scheme that determines the minimum number of attacks needed to cause large cascades, taking into account factors such as line tolerance, the probability of line disconnection, and hidden failures. To enhance the efficiency of the search process, the approach described in [48] utilizes candidate pool-based Q-learning to shrink the search space by focusing on the nodes with the highest loads and degrees.

3. ML-based cascade analysis in precursor phase

This category includes studies that focus on addressing challenges related to cascades occurring after the system has undergone disturbances. This phase of the cascade is one of the most critical stages to react to the process, prompting extensive investigations and studies to support crucial functions during this period. The aim of these efforts is to enhance the understanding of cascade risks and facilitate informed decision-making regarding corrective actions. Studies falling within this category can be further classified into three classes: initial fault analysis, cascade prediction, and cascade corrective measures.

3.1. Initial fault analysis

After the occurrence of initial failures in a power system, it becomes crucial to evaluate the system's state and identify potential risks of cascading failures. Analyzing the impact of initial stresses on the cascade process has been studied using a probabilistic method in [103] and using physics-based techniques in [104]. Examples of ML approaches to stability assessment [105–107] include transient stability assessment [108–111], and the acceleration of N-1 contingency screening [112]. Another related problem is identifying the risk of cascade after the initial failures. For instance, research presented in [113] proposes a combined GCN and long short-term memory model to approximate risk parameters as regression targets to evaluate the risk of cascading failures in real time after the initial failures. The work presented in [49] proposes using feed-forward neural networks and graph neural networks to perform binary classification of a given graph into safe or unsafe to estimate the risk of cascading failure after the initial failure. Classification of the system state datasets enables proactive early warning for cascades. For instance, the work in [15] suggests a Support Vector Machine (SVM)-based classification method to classify a given power loading level into normal or potential blackout cases. A binary classification of normal versus cascade scenarios given the loading level of the lines and the outage stages is performed in [50] using decision tree, support vector machine, and multilayer perceptron techniques.

3.2. Cascade prediction

When the power system experiences initial disturbances and the risk of cascading failures is assumed, the prediction of cascade attributes can facilitate the understanding of the state of the system and identify potential mitigation strategies to subdue the failures. Predictive analysis of the cascade in power systems involves the prediction of cascade size, cascade evolution and its temporal aspects, and propagation path and regions. Although the utilization of ML for outage prediction and power system resilience has been reviewed in [105,114], respectively, to the best of the authors' knowledge, there is no review of data-driven and ML applications in predictive analytics related to cascade attributes in power systems to date. This section is focused on reviewing such literature.

3.2.1. Cascade size prediction

Once the risk of a cascade has been identified, a key challenge is to predict the potential size or magnitude of the cascade. This problem can be approached by characterizing the distribution of cascade sizes as a function of the number of component failures (e.g., transmission lines, generators), the amount of load shed, or the number of affected customers. The study of cascade size distribution has been extensively explored in the context of power systems, taking into account both historical and simulation data. Researchers have investigated the general form of the distribution of cascading failures and have observed its heavy-tailed power-law nature [17,51,52,115,116]. Similarly, the study of interdependent power and communication systems has also contributed to the understanding of cascade size distributions in interdependent systems [18,117]. Characterizing the cascade size distribution unique to each state of the system and the initial disturbances is one of the focuses in this category of problems. In a study presented in [118], the cascade size distribution is examined based on the location of initial failures in various communities identified within the power system. A Markov chain model is utilized to analyze and understand the cascade size distribution in this context. The cascade size distribution and the effects of influential component failures on cascade size distribution are studied using an influence-based model in [119]. The prediction of cascade sizes allows operators and decision-makers to assess the severity of the system's state and initial disturbances to mitigate cascade and improve grid resilience.

The majority of the work in characterizing the probability distribution of cascade sizes primarily relies on data-driven and statistical methods, while the direct application of ML to this problem remains limited. From the available works, the work in [18], applies linear and polynomial regression, decision tree, and deep neural network to predict the total number of components that failed after the initial faults while considering the topological features such as degree and betweenness among the nodes. In [51], the interaction among the lines of the grid is learned by the expectation minimization algorithm to characterize the probability of small, medium, and large cascade sizes for the number of line failures. In [52], the size of the cascade is predicted through a classification problem with three classes of cascades including no cascade, small, and large cascades using different ML algorithms including logistic regression, k-nearest neighbor, decision tree, random forest, SVM, and Adaboost. The work in [53] performed the prediction of cascade severity and minimum cascade size as classification tasks using various ML models such as random forest, decision tree, k-nearest neighbor, and artificial neural network. This study illustrated that the prediction accuracy is unsatisfactory at the very beginning of the cascade but gradually improves, eventually reaching an acceptable level after just a few initial steps.

3.2.2. Prediction of cascade evolution and temporal aspects

As mentioned in Section 1.2, the analysis of historical data indicates that the propagation of cascading failures can be categorized into distinct phases over time. Understanding the temporal aspects and the evolution process of cascades is crucial for operators to recognize the temporal division between these phases and estimate the remaining time available to respond to the situation effectively. This knowledge becomes particularly valuable in assessing the urgency of the situation and taking appropriate actions before the cascade transitions into the escalation phase. Despite its significance, there is a limited body of existing research in this domain. For instance, the work in [17] uses a data-driven Markov model to characterize the evolution of the blackout probability over time. In another work, [55], a neural network-based classifier is applied to predict the onset time of the cascading acceleration phase. The problem is formulated as a multi-class classification task, where a neural network is employed to classify a given scenario into urgent, relatively urgent, or non-urgent categories based on the predicted onset time. The authors in [54] predicted the failed status of branches within each cascade time step and determined the final grid status using an attention-based graph neural network. The cascade failure size is then evaluated as the total number of failed branches from the predicted final grid status. While this work focuses on categorizing the temporal urgency of cascade scenarios, the detailed exploration of onset time itself and the broader evolution aspects of cascades remain relatively unexplored. The limited existing work highlights the need for further research and development in understanding and predicting the temporal dynamics and evolution process of cascading failures.

3.2.3. Predicting cascade path and areas at risk

Given the non-local nature of cascade propagation and the complex interactions among components in power systems [116], accurately predicting the specific areas and components that will be affected by the cascade process poses a significant challenge. Consequently, research in this category is dedicated to predicting the components or regions in the system that are at a higher risk of failure following the initiation of a cascade. Within this area, there are various subproblems that researchers address. For instance, [57] focuses on predicting the next component failure, while [56] aims to predict the next k failures. Additionally, [58,59] seek to predict the complete path of the cascade, including all subsequent failures.

In the work presented in [118], the focus is on identifying the locality of cascading failures in relation to the underlying communities within data-driven interaction graphs of the power system. By examining the interaction patterns among components, the localized areas where failures tend to occur are identified. Another observation regarding the localization of failures can be seen in the tree structure of the power grid [120]. It has been noted that when a non-cut set of lines fails simultaneously, the resulting failure tends to be localized within that non-cut area. On the other hand, if the failure occurs in an interconnecting line between multiple trees within the grid, it has the potential to propagate globally and impact a wider area of the system [120].

Predicting the next k-failures and predicting the next immediate failure (which is a special case of the next k-failures) in the cascade process in power systems have been studied in the literature using ML techniques. For instance, the work in [56] develops a general event precedence model, which builds a first-order absorbing Markov chain over the event streams and a run-time causal inference mechanism, which learns causal relationships between the events to predict k failures that are most likely to occur next. The work in [57] performs next-step failure prediction in the cascades in general networks via a Bayesian belief network and a multi-attribute decision-making method to perform a ranking of the lines based on a scoring strategy relative to the features of the lines. Prediction of the complete path of the cascade after the initial trigger is also studied in the literature. For instance, in [58], the authors formulate the path prediction as a Markov search problem, which is built based on a large number of failure scenarios and DC power flow calculations. Prediction of the sequence of failures based on fault chains is proposed in [59] using a time-varying graph recurrent neural network. In this work, the search for the sequence of failures is formulated as a partially observable Markov decision process and the temporal features are captured through a graph recurrent Q-learning algorithm to predict vulnerable fault chains with respect to the amount of cumulative load loss in the system.

3.3. Cascade corrective measures

Corrective measures play a crucial role in preventing the spread of failures and mitigating their impact on power systems. Implementing these measures during the slow precursor phase is particularly effective in enhancing the resilience of the system. The corrective measures include power dispatching and load shedding with the aim of balancing the load and demand within the system and maintaining a stable frequency [121]. Another control action that can be employed to prevent the propagation of failures is intentional islanding. This involves isolating a specific portion of the power system to prevent further cascading effects. The related research on these three corrective measures is reviewed in the subsequent subsections.

3.3.1. Dispatching as the corrective measure

Dispatching is the process of managing the output levels of power generators to meet the real-time demand for electricity. It can help prevent further damage due to cascading failures by bringing additional generation capacity online to compensate for the loss due to outages. Implementing the dispatching decisions can take several minutes; hence, it is essential to make dispatching decisions and identify its necessary parameters quickly to prevent the situation from escalating [122]. ML-based algorithms can play a key role in searching the best dispatching parameters (e.g., generator variables and set points) and profiles (e.g., generator combination and schedule) with respect to specific circumstances. Some of the existing work, such as [123,124], have considered dispatching as an optimization problem to offer a preventive and resilient solution to cascading failures. ML-based optimization for generation dispatch is also used for generation control, and smart dispatching, as seen in the review presented in [125]. However, the application of ML in generation dispatching to address cascading failures is limited. One example is the application of an adaptive immune system reinforcement learning-based algorithm, which is presented in [60]. Similar to the response of an immune system to destroy an antigen by an antibody, an overloading in the power system is treated as an antigen, and the success of the generation dispatching is treated as an antibody, based on which a reward-penalty scheme is built to select the combination of the generators for optimum power dispatching.

3.3.2. Load shedding as the corrective measure

Load shedding can play a critical role in stopping the propagation of failures by preventing the overloading of transmission lines and generators and restoring the balance between supply and demand. Automating and optimizing the load shedding decision process and improving the accuracy and speed of the decision-making process are examples of the problems in this category. These problems have been studied in the literature using various techniques including game theory [126], optimization algorithms [127], and heuristic algorithms [128,129]. In the literature, ML has been used for determining the optimal load shedding amount [61–63], optimal load shedding policy (i.e., sequence of load shedding actions) [14,64] and the location of load shedding [62] for mitigating cascading failures. For instance, the work in [61] employs a deep neural network with a specialized loss function for predicting the required load shedding amount. The proposed network captures the non-linear and non-convex relationship of the real-time operating states and acts as a multi-input multi-output model for the risk-averse emergency load shedding (ELS) scheme. Similarly, [62] uses a neural network for ELS to capture the relation between the generation and load loss, spinning reserve capacity, and sustaining frequency of the system to determine the total required load shedding amount. The work in [63] proposes a GCN model for predicting the optimal load-shedding for minimizing the line overload. GCN captures the correlation between AC power flow values along with the topological information to determine the values of power dispatch and suggest the appropriate amount of required load shedding. The work in [14] proposes a deep reinforcement learning framework to guide the control processes including generator dynamic braking and under voltage load shedding events. The work involves modeling the power system as a Markov decision process (MDP) and using a deep neural network as the Q-function approximator to estimate the control parameters. In [64], an MDP is developed to learn the optimal load shedding policy to minimize the expected cumulative cost in terms of the number of line failures and load shedding.

3.3.3. Controlled islanding as the corrective measure

Controlled islanding is the process of dividing the power system into smaller, independent sections, which can continue operating independently using local resources. Such islanding can help mitigate cascading failures by containing the effects of the disturbance to a localized area and preventing the spread to other parts of the system. Controlled islanding to prevent cascading failures has been studied in the literature in different forms including as an optimization problem [130,131] and graph-theoretic problem [132,133]. ML techniques have also been applied to the problem of controlled islanding to improve the decision-making process and speed it up instead of relying on time-consuming calculations of a large number of real-time variables. For instance, [65] suggests a density-based spatial clustering of applications with noise (DBSCAN) combined with non-linear programming to identify groups of coherent generators. The clustered generators are considered the core of the islands and the nearby generators and loads are identified to construct the sub-network of the islands using the Dijkstra algorithm. The work in [66] proposes a deep GCN for graph partitioning to mitigate the load-generation imbalance within the islands. A specialized loss function is designed to cluster each bus into an island based on the generator coherency and to assign independent components in different islands depending on their distances in the topology.

4. ML-based cascade analysis in escalation phase

The escalation phase in the cascade process of power systems is characterized by the rapid propagation of failures throughout the system, limiting the available options for intervention. Due to the severity of the escalation phase, there is a scarcity of studies specifically focused on addressing this particular phase. However, the importance of studying and addressing the escalation phase should not be underestimated. Despite the challenges, gaining insights into the dynamics and behavior of cascades during this phase is crucial for enhancing the resilience and robustness of power systems. By understanding the underlying mechanisms and identifying potential measures to halt or slow down the cascade's progression, operators can improve their response capabilities and enhance the overall resilience of power systems.

5. ML-based cascade analysis in post termination phase

The focus of this category is on addressing the challenges that arise after the cascade process has concluded and a blackout has already occurred. The primary focus of these studies is on cascade fault recovery, service restoration, and conducting root cause analysis of the cascade event. Cascade fault recovery and service restoration include assessing the extent of the cascade and identifying the root causes of the failures, restoring the power through black-starting the generators using auxiliary power sources, repairing or replacing damaged components such as transmission lines and transformers, and synchronizing the restored sections of the system [134]. The utilization of ML techniques to support post-cascade operations is still relatively limited. In this section, the existing work related to cascade restoration has been reviewed under two categories of failure recovery process and root-cause analysis.

5.1. Cascade failure recovery

In the cascade recovery process, one of the key challenges is determining the optimal order for restoring the failed components. Identifying the order of restoration is critical, and involves considering various factors, such as the criticality of the component, the availability of resources and personnel, the time required for repairs, the dependencies between components, and the overall system stability. This problem has been studied in the literature through optimization-based techniques [124] and heuristic techniques [135]. ML techniques can also be employed to address this problem by analyzing historical data, system topology, and real-time information to identify patterns and dependencies among the failed components and to predict the optimal order of component restoration. For instance, the works in [67–69] find the bus/branch recovery sequences after a cascading failure using a Q-learning mechanism, to achieve topological restoration with the minimum number of repairing steps. The purpose of the Q-learning is to obtain maximum restoration with minimum component recovery.

5.2. Cascade root cause analysis

Root cause analysis (RCA) is an important process, which enables understanding the causalities in the system and supports fault mitigation, system upgrade, and investment decisions. The ML-based techniques to RCA can allow tracing the potential chain of cascade to identify the causes, triggering, and fueling factors by extracting and inferring causality and interaction information from large, complex, and incomplete cascade and system data. Many RCA approaches are based on statistical analysis to infer association among variables and identify dependencies among time-series [136,137]. Probabilistic graphical models [138,139] have also been adopted for RCA; however, they require specifying conditional dependency structure among variables. Recently, various ML models have been used to enable inferring the dependencies and interactions in data for RCA [140]. In power systems, many of the RCA approaches are focused on fault cause identification. The examples include RCA for power transformers fault [141], transmission line fault [142], and fault cause identification using waveform measurements in distribution networks [143]. These works mainly perform individual waveform or time-series analyses for RCA to classify the causes of faults and do not consider interactions or dependencies among components and their failures. RCA has also been applied to cascading failure problems in interdependent power and communication systems with an algorithmic approach in [144]. In the latter work, the node measurements are not considered and instead, the RCA is carried out over interdependency relations in the form of Boolean Logic relations, which are assumed to be known. The application of ML to RCA in power systems with regard to cascading failures is still very limited and has significant scope to be explored further.

The applications of ML in cascade analysis across the mentioned categories are summarized in Table 1. It is to be noted that the cascade escalation phase is not outlined in the following table as there is currently no literature available on this phase.

6. Challenges and recommendations

Within this review, key functions in the analysis of cascading failures in power systems have been identified that can benefit from or be complemented by ML techniques. These functions have been systematically classified based on the corresponding phases of the cascade. However, it is noteworthy that the application of ML to support these functions is a recent advancement and still warrants further exploration. Consequently, each of the identified problems represents an open and promising domain for further investigation. Next, some of the challenges and opportunities associated with refining ML techniques for the purpose of cascade analysis are discussed.

High Dimensional Data and Feature Selection: Cascading failures are complex phenomena with large contributing factors to their complex interactions. Considering various sources of data, including measurement data, simulation data, and historical data, about various power system components and their attributes, the cascade analysis models often deal with high dimensional data. In general, dimensionality reduction and feature selection are important functions that can improve ML models. The examination of the existing literature has unveiled that the ML algorithms employed in cascade analysis heavily rely on the type and mode of the data being utilized. Effective feature selection is highly beneficial in excluding redundant features and extracting relevant and important features for ML models.

For instance, [18] involves utilizing a recursive feature elimination algorithm to identify crucial features for pinpointing critical nodes, with the objective of protecting these nodes and enhancing network robustness. In [45], a deep convolutional generative adversarial network is employed to capture implicit features related to failure propagation. In the analysis of interconnected power systems, the dimensionality of the data expands, underscoring the importance of ranking and sorting critical features for the ML models [13].

Moreover, large datasets in this context may exhibit class imbalances, where the number of cascade failure scenarios is smaller compared to nominal scenarios. To address this issue, data preprocessing algorithms, such as, the synthetic minority oversampling technique (SMOTE) can be employed to manage class imbalances in cascade classification problems, as demonstrated in [50]. Moreover, despite the abundance of data available from the system, the necessary features for the ML models may not be readily available in the data. Crafting new features from the existing data and attributes that effectively encapsulate grid dynamics during the cascade process can enhance the performance of ML models. As an example, [39] integrated diverse features from grid topology, node embeddings, and power flow distributions to augment those obtained from the complex network model. Introducing such combined features enables crafting new features that can enhance the model performance.

Computational Cost: Just like in other application domains, ML techniques used for cascade analysis encounter computational challenges. The vast scale of power systems and the growing volume of collected data present challenges in terms of scalability for training and conducting cascade analysis on these systems. Approaches like transfer learning offer potential solutions by training the model on one system and transferring the knowledge to similar power systems [145,146]. Furthermore, researchers in the ML domain have focused on optimizing algorithms and ML models to improve computational efficiency. Examples of such techniques applied to ML models in cascade analysis include the design of more efficient model architectures, such as novel network architectures for ANN [43], CNN [112] or GNN [37] models, as well as the development of tailor-made optimization algorithms. These algorithms aim to reduce the need for exhaustive traversal of large datasets and decrease the computational cost of models, as seen in the reduced search early termination techniques presented in [18].

Robustness: Similar to ML models in other application domains, ML models used for cascade analysis are expected to exhibit robustness and maintain their performance in the face of various challenges including input changes, noise, unforeseen scenarios, and cyber attacks. However, due to the complexity and stochastic nature of cascading failures, as well as the inability to consider all possible combinations of events during model training, ML models may encounter robustness challenges. Unforeseen scenarios, in particular, present a significant challenge akin to open-set recognition problems, where the ML model must classify unknown categories of scenarios that the model did not exhibit during training phase and adapt accordingly. Addressing such scenarios can involve leveraging statistical and deep learning methods [147], which aid in consistently handling trained cascading scenarios while segregating unforeseen cases to refine model training over time. In such instances, enhancing robustness can be achieved by exposing the model to augmented cascading scenarios by feasibly modifying existing datasets [42] and incorporating human-in-the-loop ML approaches [148] into the systems.

As a special case of robustness challenges, the ML models developed for cascade analysis can face cyber-attack challenges. Intentional manipulation of input data or model parameters can degrade the performance of cascade analysis, resulting in inaccurate associated risk assessment or incorrect recommendations with potentially severe consequences [149,150]. Malicious actions like data poisoning and the insertion of adversarial examples during training can mislead ML models, putting the accuracy of cascade analysis at risk. In [151], it is noted that ML-based cascade prediction models can be susceptible to False Data Injection Attacks (FDIA), which can adversely affect prediction accuracy. These approaches can improve the model's adaptability and resilience in dynamic and complex cascade scenarios. The adoption of explainable and trust-worthy ML models [152], and enhanced adversarial training [153] in power systems can also be deemed a viable solution for addressing cyber-security issues in ML-based cascade analysis, by enhancing the transparency of the models. Due to such security risks, it is important to recognize the vulnerability of cascade models to cyber-attacks and support them with countermeasures, including robust design and attack detection. However, assessing the impact of cyber-attacks on ML models for cascade analysis and devising attack mitigation mechanisms have not been explored adequately in the literature, which is suggesting a promising avenue for future research exploration.

In summary, these open challenges and corresponding recommendations in the domain of ML-based cascading failure analysis present opportunities for impactful research to support various functions in different phases of the cascade to improve the resiliency of the power systems to cascading failures.

7. Conclusion

Cascading failures present a significant threat to power grids, necessitating extensive research efforts in their analysis and understanding. The combination of advancements in monitoring technologies, the availability of vast amounts of power system data, and the emergence of intelligent algorithms have made ML techniques increasingly appealing for analyzing cascading failures. The presented review in this survey provides a comprehensive overview of ML-based techniques employed in the analysis of cascading failures in power systems. By categorizing these techniques based on the different phases of the cascade process and examining research on cascade resiliency prior to and after the occurrence of cascades, this survey offers new insights and a systematic understanding of ML's role in modeling, analyzing, and mitigating cascading failures. The organization of these works into relevant categories contributes to a better understanding of the strengths and limitations of ML techniques in addressing cascading failures. The gaps in the existing research also show the importance of further research in this domain to fully exploit the potential of ML in cascade analysis. Leveraging the wealth of historical and simulation data via big data analysis and data mining tools, identifying and incorporating relevant features that can augment and bolster these models, reducing computational costs with effective online and transfer learning techniques, and implementing explainable and trustworthy ML to design secure ML models for cascading analysis can be notable recommendations that can contribute to the resolution of current research gaps and fortify the robustness of ML applications in power system cascade analysis. As power systems continue to evolve and face new challenges, for instance, due to stochastic and uncertain renewable resources and the incorporation of energy storage systems, the integration of ML techniques holds great potential for advancing our understanding of cascading failures and improving preventive and corrective measures under new circumstances.

CRediT authorship contribution statement

Naeem Md Sami: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Mia Naeini:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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