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Current Applications and Future Trends of Artificial Intelligence and Machine Learning in the Resilience of Interdependent Critical Infrastructures

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Abstract

Critical infrastructures, such as power and water networks, are vital for society and the economy. However, they are vulnerable to various disruptions such as component failures, cyber-attacks, and natural disasters. These disruptions can cascade across critical infrastructure networks (CINs), causing significant socioeconomic losses. Decision-makers face the challenge of protecting CINs before disruptions and restoring their functions afterward, considering interdependencies and uncertainties. Current methods struggle to model big data, complex interactions, and multilayer dependencies between CINs. Artificial intelligence (AI) and machine learning (ML) applications can be used to overcome these challenges, as they can model complex systems and discover data patterns representing a promising research trend that could benefit both private companies and governments. This article undertakes a comprehensive review of the literature on the applications of machine learning in improving the resilience of interdependent critical infrastructure systems (ICISs). The aim is to address the existing knowledge gap and dispersed research articles in this area, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The primary goal of this article is to assess the current state of ML applications in the ICISs resilience engineering field by examining the available literature, in order to discover future opportunities and trends. The findings are summarized, and potential future trends and opportunities are listed, aiming to inspire resilience engineering practitioners to explore these future directions in the field.

Keywords
Resilience Engineering, Artificial Intelligence, Machine Learning, Critical Infrastructures, Network Interdependencies.

1. Introduction
Machine learning (ML) is a data-oriented field of computing that allows computers to process and learn from data without explicit programming (Alkhaleel, 2024). According to Murphy (2012), ML can be defined as a group of techniques capable of detecting data patterns and using discovered information to forecast unseen data and improve the decision-making process. ML techniques excel in identifying hidden patterns in data, as well as complex systems modeling (Alkhaleel, 2024). Therefore, ML applications have expanded to various domains such as healthcare, education, transportation, e-commerce, and resilience engineering is next in line, especially applications related to critical infrastructure systems (CISs). Maintaining resilient infrastructure is important but requires costly investments in advanced systems (e.g., smart grids) (Meltzer et al., 2019). However, ML can offer innovative solutions to enhance resilience without extensive capital investments. ML applications in the resilience of CISs can improve decision-making and reduce socioeconomic losses caused by various possible disruptions.

Critical infrastructures (CIs) are systems that are responsible for the delivery of public services which are critical. Examples of critical infrastructure networks (CINs) include power networks, water distribution networks, and telecommunication systems. Disruptions of such systems incur severe socioeconomic losses; hence, governments tend to establish operational frameworks intended to guarantee that these critical systems can remain operational at satisfactory service levels even peri-disruptions (Karagiannis et al., 2017; Obama, 2013). Legislations governing CISs designs are included in such frameworks as well as repairability and maintainability requirements applied during periods of system failures (Obama, 2013). Falling below predefined resilience levels can lead to a significant impact on the economy, health, and public safety (Zio, 2016). Nonetheless, with all precautions made by the public and private sectors to maintain the resilience of CINs at acceptable levels, disruptions to such systems will not stop due to inevitable natural disasters and/or man-made events (Alkhaleel, 2024). Therefore, it is urgent to develop tools and techniques such as ML to improve the resilience of such critical systems.

1.1 CIs Interdependencies Classification

Infrastructure networks are interconnected and rely on each other for their proper functioning (Alkhaleel et al., 2022). This interdependence means that the state of one infrastructure network is affected by the state of another network in a bidirectional relationship (Peerenboom et al., 2002; Rinaldi et al., 2001). Figure 1 provides examples of interdependencies between electrical networks and other infrastructure networks. These interdependencies are critical for the resilience of critical infrastructures, as they can contribute to the spread of failures and impact the recovery process (Guidotti et al., 2016). Interdependencies between infrastructure networks can be categorized into four types: physical interdependency, where the output of one network serves as an input for another in a bidirectional relationship; geographical interdependency, where two networks are subject to a local area disruptive event; logical interdependency, which encompasses other kinds of dependencies such as social or legal connections between critical infrastructures; and cyber interdependency, where infrastructure networks exchange information unidirectional or bidirectional (Alkhaleel, 2024; Rinaldi et al., 2001).

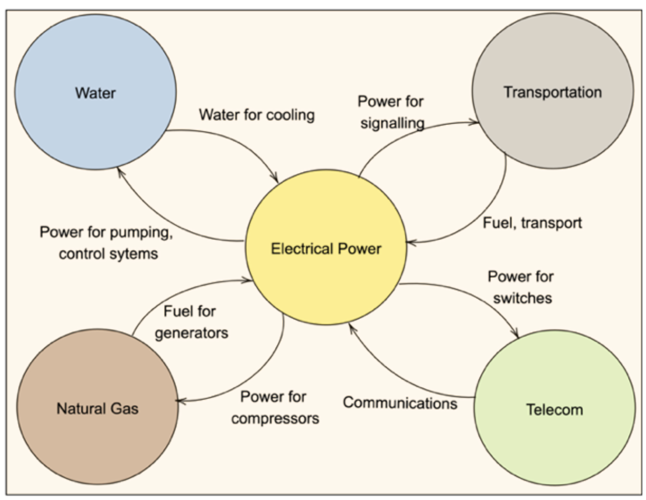

Figure 1. Examples of dependencies between electric power networks and other CIs (Alkhaleel et al., 2022)

Complex systems with complex human and technical interactions such as CINs pose difficulties in assessing vulnerabilities and understanding risks (Alkhaleel, 2024; Zio, 2016). Indeed, interdependencies among CINs can lead to cascading effects of a single failure on multiple networked systems. Effective risk analysis requires an integrated approach considering various interdependencies (e.g., physical and cyber) (Min et al., 2007; Rinaldi et al., 2001). Research on modeling interdependent critical infrastructure systems (ICISs) is a growing field with several challenges, including the complexity of interdependencies, the need for secure and resilient systems, limited data, diverse system components, and uncertainties (Alkhaleel et al., 2022; Danziger et al., 2016; Karakoc et al., 2019). It is essential to develop new tools, strategies, and methodologies, such as ML, to model and improve ICIS resilience to overcome the current various challenges and to discover future directions of research and opportunities.

1.2 Machine Learning Summary

In this subsection, we provide a concise overview of ML and its main categories, especially for readers who may not be familiar with this concept. ML encompasses a wide range of algorithms, but it can be broadly categorized into four main types: supervised learning (SL), unsupervised learning (USL), semi-supervised learning (SSL), and reinforcement learning (RL) (Anandakumar & Ramu, 2020). ML categories and their main branches are depicted in Figure 2. The following briefly describes these categories.

(i) Supervised learning: in this category, labeled data, which are a group of pairs of correspondent inputs and outputs are used to train the ML model. The model learns to map such inputs to the correct output(s) by generalizing from the provided examples. It can then make predictions or classify new unseen data based on its learned patterns. Popular algorithms for supervised learning include decision trees, random forests, support vector machines (SVM), and artificial neural networks (ANN).

(ii) Unsupervised learning: in this category, unlabeled data, where the input data do not have corresponding output labels are fed into the model. The goal is to find relationships within the data such as common patterns or similar structures, without prior knowledge. Common subcategories include clustering, where similar data points are grouped based on similarities in data, and dimensionality reduction, which represents data in lower-dimensional spaces to lessen data complexity. Examples of USL algorithms include k-means clustering and principal component analysis (PCA).

(iii) Semi-supervised learning: this category combines aspects of both SL and USL. In this approach, the training data consist of a combination of labeled and unlabeled data samples. The labeled data contains input samples paired with corresponding output labels, similar to supervised learning. The unlabeled data helps to capture the inherent data structure, reduce the overfitting possibility, and generalize the model for different data. By using both labeled and unlabeled data, semi-supervised learning can potentially achieve higher accuracy with fewer labeled examples compared to purely supervised learning.

(iv) Reinforcement learning: in this category, an agent is trained to interact with an environment to maximize a reward signal. The agent learns through trial and error by taking actions and receiving feedback as rewards for correct actions or penalties for bad decisions. The aim is to find a policy that is optimal in the sense it can guide the agent over time to take correct actions to achieve the maximum cumulative reward. Algorithms such as Q-learning and Deep Q-Networks (DQN) are commonly employed in reinforcement learning.

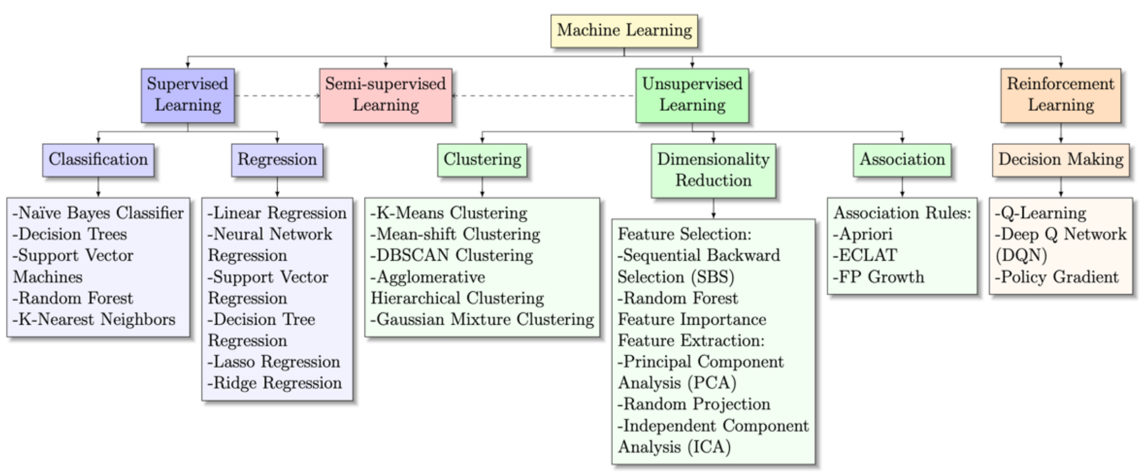

Figure 2. ML main categories, subcategories, and known algorithms

1.3 Overview and Research Contribution

The previous discussion highlighted the challenges associated with the field of resilience in ICISs. Efficient approaches are needed to address these challenges, and ML emerges as a suitable solution given its potential to explore various opportunities to alleviate the difficulties encountered in this research field. Additionally, ML can surpass the capabilities of traditional analytical tools and improve the complex modeling and decision-making processes in ICISs resilience by uncovering unseen data patterns (Alkhaleel, 2024). To address the existing knowledge gap and dispersed research articles in this area, this article adopts a systematic literature review approach. The primary goal of conducting this study is to assess the current state of ML applications in the field by systematically analyzing relevant literature using the well-known PRISMA protocol (standing for Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Liberati et al., 2009). The article's main contributions can be summarized as follows: (1) synthesizing and outlining the existing applications of machine learning in the field of ICISs resilience engineering, (2) identifying possible trends and potential opportunities in this field, and (3) inspiring resilience engineering practitioners to explore these future directions in the field. Subsequent sections of the article are ordered as the following. Section 2 presents the methodology and results of the systematic review. Section 3 outlines and discusses the objectives and categories of the reviewed applications. Section 4 suggests potential future trends and opportunities. Finally, Section 5 shows the concluding remarks.

2. Systematic Literature Review

Systematic reviews play a crucial role in consolidating research on a particular subject in a systematic and efficient manner. This method of review relies on evidence and seeks to assess the accuracy and relevance of the available studies (Alkhaleel, 2024). In recent years, systematic reviews have gained popularity as they offer a systematic and transparent approach to assessing research. Throughout the current section, a thorough review of the current utilization of ML applications in the resilience of ICISs is analyzed through a PRISMA-based systematic review of the literature based on our previous work (Alkhaleel, 2024). We searched two databases (ScienceDirect and Google Scholar) yielding an aggregate of 960 outcomes, after removing deduplicating 5 outcomes. Thus, the number of unique findings was 960. Terms used for searching the selected databases were ("machine learning" OR "deep learning") AND ("interdependent network" OR "interdependent networks" OR "interdependent critical infrastructure") AND "resilience". Note that to ensure the inclusiveness of research terms, interchangeable terms were used to allow the consideration of a wide range of results.

2.1 Selection of Studies

In the selection phase, a predetermined inclusion and exclusion criteria is followed to evaluate each piece of literature. These criteria primarily consider the time frame and research areas covered in the search to determine whether a study should be included or excluded. The selection process mainly consists of three phases. First, the search results were filtered based on the inclusion and exclusion criteria, focusing on the timeframe and research areas relevant to the field. Specifically, studies conducted between 2010 and 2023 were selected to encompass a comprehensive range of relevant research. The inclusion criteria contain peer-reviewed articles, PhD and Master dissertations, and conference proceedings, aiming to capture the potential trend in research directions. Among the searched databases, a total of 965 results were identified (906 from Google Scholar and 59 from ScienceDirect), with 5 duplicates. After the deduplication process, 960 studies remained for the subsequent phase. For the screening phase, only titles and abstracts were used to assess the fond results from the first phase in relevance to the study's field. During this phase, 277 results are kept for further evaluation after excluding 683 results. The preserved results were then subjected to a full examination to determine their relevance to the research scope. Based on a detailed examination, only 17 studies were considered suitable for the final phase with the exclusion of the remaining 260. Finally, the 17 studies' quality was assessed to find any potential eliminations based on quality criteria, but no exclusions were made on these grounds. The final set of results was thoroughly explored for the systematic review. The steps of the selection process and the review protocol findings are illustrated in Figure 3 and the keywords number of occurrences in the selected studies is shown in Figure 4.

2.2 Summary of Results and Applications

The reviewed resilience-based applications in the literature are categorized based on the application phase: pre-, peri-, and post-disruption. The studies presenting these applications are reviewed and described in chronologically, starting from the earliest.

Pre-disruption Applications

The literature contains various applications focusing on the proactive phase of ICISs resilience. One early work by Buxton et al. (2010) emphasized the significance of interdependency modeling among CINs to guarantee their effective operation. A Bayesian belief networks (BBNs) methodology using interdependency-mapped conditional probability tables was proposed to model interdependent. This approach enables decision support to benefit from both prognostic and diagnostic reasoning. Wang et al. (2021) proposed a methodological framework that utilizes deep learning to analyze the resilience of ICISs by identifying network topology attributes. This framework enables the classification of interconnected networks into different types (e.g., scale-free) based on their topology. By analyzing the classified functional characteristics, the vulnerabilities of various disruption scenarios can be examined. Based on that, mitigation approaches and optimum defense tactics can be developed to aid the decision-making process. Elvas et al. (2021) introduced a resilience framework for smart cities capable of connecting ICISs to improve their resilience. Their approach employs a data-driven methodology, utilizing ML techniques (although the specific algorithms used are not clearly stated) to improve pre-disruption resilience through risk evaluation. Early event detection is supported by the proposed system through the use of Internet of Things (IoT) collected data. Pattern recognition approaches are applied to identify patterns in textual or spatial datasets. Hence, disaster management applications can benefit from an effective information analysis framework.

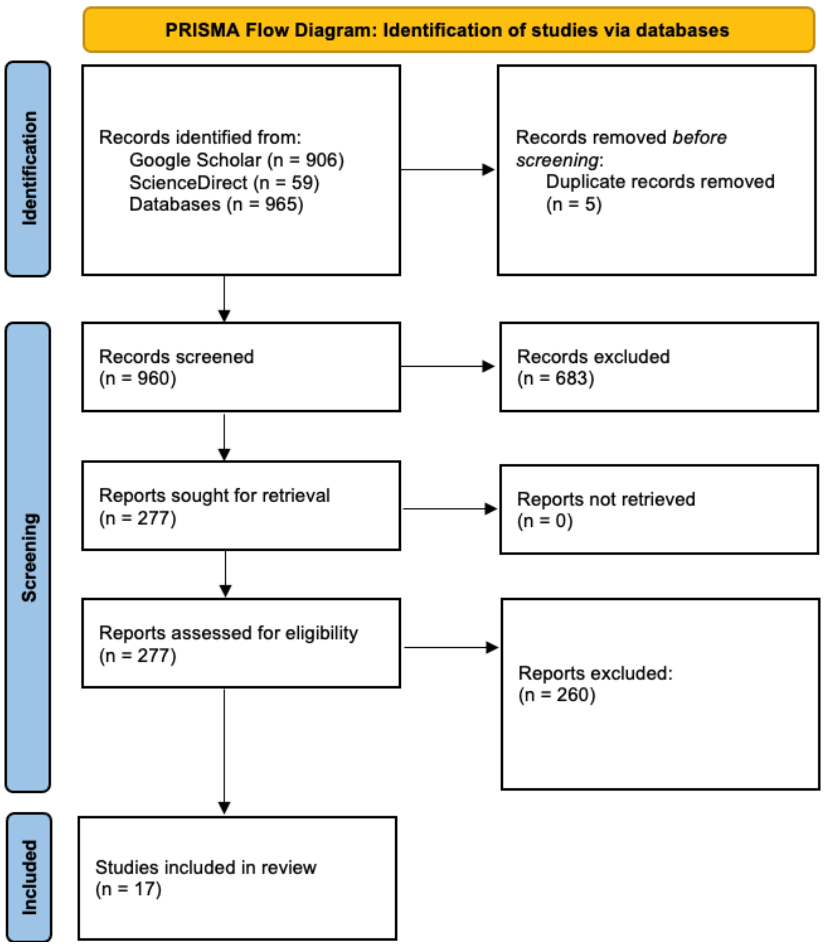

Figure 3. The flow process for the PRISMA review protocol

Almaleh and Tipper (2022) introduced a comprehensive approach that utilizes network indicators and applies linear regression algorithms to evaluate geographic zones' criticality within a large area. Through the introduction of several network measures (e.g., centrality and community), vital zones were recognized within a city (Alkhaleel, 2024). The model is capable of improving readiness by evaluating the critical nodes of ICISs, which allows the implementation of risk mitigation strategies pre-disruptions. Wu and Wang (2023) proposed a graph learning-based generative design method to facilitate the efficient design of a resilient system of ICISs. The proposed framework consists of a design generator, which employs an unsupervised learning graph variational autoencoder (GVAE) algorithm, and an estimator of performance, which utilizes a semi-supervised graph convolutional networks (GCN) algorithm (Alkhaleel, 2024). This framework intelligently extracted characteristics from current systems and generated better designs with predefined conditions.

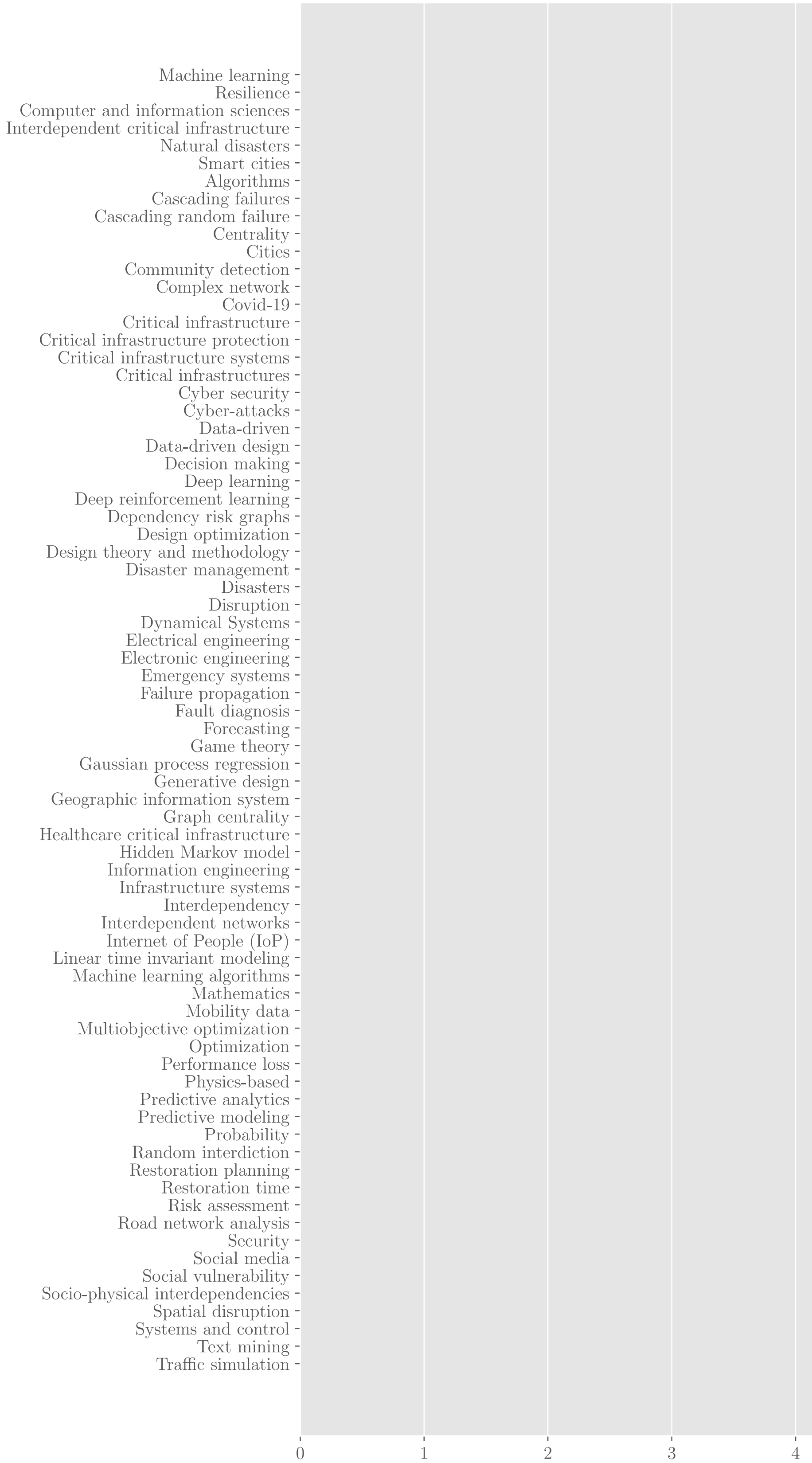

Figure 4. The frequency at which keywords appeared in the selected studies

Peri-Disruption Applications

One of the early applications focusing on the peri-disruption resilience of ICISs was proposed by Ntalampiras et al. (2015). A stochastic model was presented to examine malicious events affecting ICISs by establishing a USL hidden Markov model (HMM) that captures the relationship between data streams originating from two network nodes. The objective is to analyze and understand the state of the system of ICISs under attack. Cascading failures among ICISs were studied by Zhou et al. (2020) who developed a framework that combines data with physics-based methods to recognize the propagation of such failures. By analyzing unstructured text data from several sources, including news articles and social media, infrastructure failure patterns can be identified. This approach can be used for both historical data analysis to improve preparedness and real-time decision-making during disruptions.

A system that utilizes various sources of data including data from social networks was proposed by C. Lee (2020) to monitor ICISs. Data found on social media are processed and classified in order for the developed system to be capable of detecting damages to critical infrastructures. C. Lee (2020) demonstrated the application of the proposed methodology by employing three SL classifying approaches, namely decision trees, Support Vector Machines (SVM), and naïve Bayes models, on word-based X (formerly known as Twitter) data to identify damages to ICISs. Furthermore, to validate the approach, unlabeled data (acquired from a known past event) were used to evaluate the best-performing classifier in order to simulate live detection scenarios in a particular system. Yuan et al. (2021) proposed a framework utilizing the Internet of People (IoP), where individuals using social media platforms act as sensors by providing information on the state of a particular system or event, for assessing road networks' performance peri-disasters. The resilience of road networks, particularly their connections to other infrastructures such as hospitals, is evaluated using the rate of performance loss. Sentiment analysis (SA), a USL algorithm, using a Lexicon-based approach was employed to determine if the posts on the social network contain road names; hence, damages to the road network are assessed based on found information. Lastly, Srikanth et al. (2021) proposed a simulation model using MADRL, standing for multi-agent deep reinforcement learning, to model healthcare critical infrastructure systems and their interdependencies under disruptive events, such as disease outbreaks similar to COVID-19. The developed model utilizes a spatiotemporal long short-term memory approach that forecasts the infection cases trajectory within a geographic area (Alkhaleel, 2024). This predictive capability enables the development of response activities and contingency plans for different scenarios of disease growth levels.

Post-disruption Applications

In the work of Yabe et al. (2021), a data-oriented framework was introduced to enable the inference of social and physical interdependencies within municipal systems and their impact on recovery planning after disruptions (post-disaster resilience). The framework utilizes wide-ranging mobility data (i.e., point of interest (POIs)). By leveraging the location information of mobile phones, the daily number of visits to each POI was estimated. Subsequently, clusters of data points were generated to identify "stay points" through the use of a USL algorithm, namely Density-Based Spatial Clustering of Applications with Noise (DBSCAN), to improve post-disruption recovery decisions. A framework aimed at evaluating resilience for interdependent water and transportation infrastructures was introduced by Rahimi-Golkhandan et al. (2022). Both social vulnerability indicators and physical network characteristics of these infrastructures are included in the framework. The resilience of the system is computed as the service level retained following disruptions considering various possibilities of high-risk incidents and possible random failures using several SL algorithms including multivariate adaptive regression splines (MARS) and Bayesian additive regression trees (BART). The study reveals a notable correlation between community and infrastructure resilience, emphasizing the vital importance of social and economic aspects in the context of resilience applications.

Ramineni et al. (2023) conducted a study exploring various SL methods for predicting the time required to restore an interdependent network following a disruption. Such SL predictive algorithms include decision trees and gradient boosting, and others. In their study, the affected components' restoration rates were assumed to be the independent variables, and a model that optimizes restoration activities generated the time-dependent variable representing network restoration. The work of Aslani and Mohebbi (2022) focused on the restoration activities following cascading failures of ICISs that exhibit functional dependencies as well as spatial ones. They proposed a multi-objective model to optimize objectives covering cost, community, and environmental aspects. To solve the proposed model, a learn-to-decompose methodology was proposed, and an SL Gaussian process regression module was incorporated to lead the optimization search direction and tune the decomposition algorithm. An application of Deep Operator Networks (DeepONets) was introduced in Dhulipala and Hruska (2022) to expedite the recovery modeling of interdependent networks. Such deep operator networks are supervised machine learning architectures capable of identifying arithmetical operators from analyzed data with the advantage of accurately predicting the system underlying interactions with minimum computational power (Alkhaleel, 2024). To identify components of ICISs that exhibit similar susceptibility characteristics, and introduce resilience-based projection models accordingly, Balakrishnan et al. (2022) proposed a clustering-based framework for that purpose. This framework groups together components with comparable characteristics to improve prediction models. Lastly, the work of Rangrazjeddi et al. (2022) tries to incorporate predictions regarding the actions of different decision-makers into a restoration-based optimization model of ICISs. To achieve their goal, they employed a game theory approach (within an environment of limited shared information) to incorporate the expectations of various decision-makers' actions into the developed model.

3. Discussion and Applications Categories

The previous section provided an overview of the selected number of studies covering the applications of ML in the area of resilience of ICISs. The applications covered the different phases of resilience, including the proactive phase (pre-disruption) and the reactive phases (peri-disruption and post-disruption). Among the ML applications, SL algorithms were the most commonly used, with a focus on classification as well as regression subcategories. USL applications emerged as the second most frequently employed approach, with the subcategory of clustering being the most utilized. Moreover, only one application per the subcategory of SSL and RL was found in the selected studies.

Among the reviewed studies, various algorithms were used in the different resilience phases. For instance, in the post-disruption phase, algorithms such as regression models, random forests, and decision trees were frequently used for predicting the post-disruption time of restoration and measuring resilience, leading to efficiently supporting the decision-making process. In addition, to model and expedite recovery activities a deep learning algorithm known as CNNs, standing for convolutional neural networks, was employed in a single application. Regarding the resilience in the pre-disruption phase, ML applications often focus on design optimization and vulnerability assessment. To achieve both goals, clustering algorithms, dimensionality reduction techniques, and graph-based algorithms have been applied. In peri-disruption studies, the objectives of the reviewed applications were to improve decision-making in real-time by examining and analyzing information on social media through RL, sentiment analysis, and text mining approaches. It is worth noting that several applications integrated different ML algorithms to improve resilience.

The goals of ML applications varied according to the phase of resilience. For example, the objectives in the pre-disruption phase include modeling interdependencies, quantifying and assessing geographical criticality, detecting network topology attributes, recognizing interdependencies, and generating new resilience-based designs for existing systems. In the peri-disruption phase, the main objective was to monitor and analyze real-time data, especially social network posts, to improve situational understanding and decision-making. Moreover, quantifying resilience and optimizing restoration activities were the main goals of post-disruption applications.

Overall, the potential to improve the resilience of ICISs through ML applications is viable across all resilience phases. ML algorithms can help find solutions and opportunities to improve overall ICISs resilience by mitigating disruptions, optimizing resource allocation, and improving the decision-making process. It is important to note the lack of use of RL techniques among the reviewed applications, despite their potential for developing optimal control policies for resilience-based objectives covering resource allocation, maintenance prioritization, and peri-disruption rerouting needs. To sum up, the selection and application of ML algorithms should consider system features, available data, resilience phase type, and the strategic objectives of the resilience plan.

3.1 Applications Categories

In general, the reviewed ML studies could be categorized into four groups: interdependency and network topology modeling, IoT data analysis, IoP and textual analysis, and game theory and optimization. The first category involves using graph learning algorithms as well as statistical models to identify weaknesses in network design and identify dependencies between network components. Furthermore, the optimization of post-disruption recovery and restoration activities based on topological features and dependencies is a major goal in this category. For instance, to analyze components of ICISs data and interconnected dependencies, deep learning algorithms can be employed for that purpose in order to construct accurate network models. In addition, to simulate and analyze cascading failures in ICISs, ML can be utilized to incorporate disaster scenarios, past disturbance data, and graph topology to predict failure propagation in interdependent networks. These predictions can help identify critical network components that significantly impact the overall system resilience. Finally, to develop iterative resilience strategies that learn the best possible decision to make in order to maximize system resilience, RL can be employed.

The second category covers IoT applications that are capable of detecting disruptions and cascading failures through data pattern identification and recognition algorithms. For instance, IoT data from deployed sensors in power grids can be analyzed by ML algorithms to predict power failures, enabling a wide set of preventive actions (e.g., controlling power flow, rerouting power and isolating damaged components) (Alkhaleel, 2024). Another application is to examine real-time IoT streams of data to improve the awareness of the current conditions of the system, detect abnormalities, predict the behavior of the system, and provide immediate alerts to accelerate proactive actions and improve the overall response to disruptions. The third category involves IoP and textual analysis, which are used to detect network failure patterns and component states pre- and post-disruptions. Collected data from social networks can be analyzed using natural language processing (NLP) approaches to extract meaningful information, identify damages to ICISs components, and detect emerging concerns. For instance, posts on social media and IoP data (e.g., emergency calls and crowd-sourced information) can help identify power and water networks' failures and classify emergency events by severity. Lastly, The fourth category focuses on using ML to propose improved optimization algorithms and frameworks, particularly in post-disruption restoration actions. For instance, ML algorithms can optimize problems covering the allocation of resources in ICISs, and linking game theory with ML can simulate the behavior of stakeholders, resolve conflicts, optimize grouped decisions, and propose organization schemes for resilience improvement.

4. Future Trends and Opportunities

Numerous prospects await the integration of machine learning applications in the area of resilience for ICISs. In this endeavor, we endeavor to delineate forthcoming trends and openings for ML in this domain. Drawing insights from the literature review, we try to explore these trends and opportunities:

- **Uncertainty Reduction:** The majority of post-disruption recovery studies assume deterministic conditions, where complete information is available on available resources and activity durations (Alkhaleel, 2024). However, restoration actions of ICISs are often complex and occur in highly uncertain environments, influenced by the disaster itself, human reactions, and limited information gathering capabilities (Fang and Sansavini, 2019). Therefore, ML offers potential solutions by integrating data from multiple sources to enumerate disruption uncertainty in terms of overall impact, network and traffic states, and risk levels. The quantification of such information can help in prioritizing recovery and restoration actions. ML aligns with the current research trend of incorporating stochastic optimization modeling in post-disaster resilience-based restoration models (Alkhaleel et al., 2022; Kong et al., 2023). Indeed, ML can be part of the process of reducing uncertainty by improving the algorithms that reduce the number of possible scenarios with minimum loss of information and also can help improve the algorithms of stochastic optimization (Alkhaleel et al., 2022).
- **Decision Support Systems:** ML can support decision-making processes before and after emergencies or dis-ruptions. By analyzing real-time data, historical patterns, and relevant contextual information, ML models can provide insights and recommendations to aid in de-cision-making, resource deployment, and crisis response. Moreover, ML can op-timize the allocation of resources within CINs and between authorities to achieve high levels of resilience and efficient spending.
- **Cybersecurity and Intrusion Detection:** ML algorithms can be used to analyze network traffic, detect anomalies, and identify potential cyber threats or attacks on critical infrastructure systems. By continuously learning from new data and adapting to evolving threats, ML mod-els can improve cybersecurity measures and protect critical infrastructure net-works.
- **ML integration of disaster and disaster databases to understand ICISs interdependencies:** To examine the interdependencies among infrastructure systems, it is important to maintain databases containing records of past and present disasters. Resilience planning strategies can be improved by analyzing historical disruption data through various ML techniques. By leveraging ML algorithms, it becomes possible to investigate various interdependencies within a given system and prioritize them based on their relevance to particular types of disruptions (Alkhaleel, 2024). Furthermore, ML-based algorithms such as graph learning and classification can be employed to identify the most vulnerable components within networks or the weakest networks within complex network systems (Alkhaleel, 2024). As a result, data-oriented ML methodologies will be capable of improving the decision-making processes by providing valuable insights and recommendations.
- **Integration of human factors:** The role of human factors in CINs covers the effect of various human characteristics on operating and managing these systems (Magoua et al., 2023). It is a significant set of factors contributing to failures that impact the functioning of ICISs. In order to understand man-made catastrophes in ICISs and suggest proper resilience-based measures and optimization models, unconventional methodologies are

needed to model the dynamic interaction concerning human factors and technical properties. ML presents itself as a viable solution for this purpose. For instance, it can help identify potential points of failure related to human factors, suggest proper decisions for mitigation, categorize disruptions (e.g., man-made, natural, and others), and assess the effect of human factors on system operational state and vulnerabilities caused by interdependencies across the entire system. For a comprehensive review of the role of human factors in modeling CINs resilience, refer to Magoua and Li (2023).

- **IoT Utilization through Wearables:** One of the significant applications of IoT for resilience objectives can involve the utilization of wearable devices, commonly known as wearables (Alkhaleel, 2024). These smart devices include smartwatches, fitness trackers, and smart rings. As wearables are located on the human body, various information generated by them can be used to improve resilience planning, especially during disruption. Examples of such useful information might include information about the movement of people around a disrupted area, the location distribution of communities, the traffic conditions (Rizzo et al., 2022), the health status, including the number of injured people and deaths, and the current conditions of the environment (Alkhaleel, 2024; Cureau et al., 2022). However, it is important to acknowledge challenges related to privacy, security, and other considerations (Alkhaleel, 2024; Sterbenz, 2017). Nonetheless, the decision-making process with the aid of ML could be improved by the integration of such data from sensors deployed across the affected geographical region with other data streams.

5. Conclusion

ML is a valuable and versatile tool with broad applications across various disciplines. In the context of resilience engineering, the field of ICISs resilience can significantly benefit from ML, as it enables data-driven decision-making under high-risk conditions. This article presents a comprehensive examination of different ML categories and a summary of the diverse types of interdependencies documented in the literature concerning ICISs. In addition, It also presents a review and exploration of the current literature covering ML applications in interconnected critical systems' resilience. The discussed applications encompass areas such as interdependency and network topology modeling, IoT data analysis, IoP and textual analysis, and game theory and optimization. It is important to note the limited amount of research available in this domain, leaving many potential applications unexplored. Therefore, several future opportunities are highlighted, aiming to help the resilience engineering community embrace and utilize ML for the diverse applications available in this domain.

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