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Failure dependence and cascading failures: A literature review and research opportunities

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ABSTRACT

The complexity of technical systems is escalating, and components within the systems are becoming more vulnerable to failure dependence. Failure dependence implies that the failure of one component or more components can influence the degradation of other components or trigger their failures. To provide a comprehensive understanding of failure dependence issues, a systematic literature review is carried out and critically analyzed in this article, specifically focusing on engineering and technical systems. An overview of key terminologies commonly associated with failure dependence is firstly provided. And then, studies from various perspectives, including reliability, maintenance, resilience, and sustainability are reviewed, with an emphasis on failure dependence models for each research area. Additionally, this study examines the related works applied to four types of complex engineering systems, including subsea systems, chemical industrial clusters, power grids, and traffic networks. The review investigates the failure dependence issues by screening both classical and state-of-the-art methodologies from holistic perspectives and various application fields, identifying future challenges and potential opportunities, which paves the way for future research.

1. Introduction

Growing interest in developing and operating complex engineering systems is leading to more focus on failure dependence, where the failure of one component or more components tends to influence the degradation or failures of other components [1]. Complex systems are characterized by high interactive complexity, exhibiting diverse failure dependencies that add difficulty in modeling and applying failure dependence analysis [2]. Failure dependence can trigger cascading failures (CAFs) and considerably degrade the system performance, potentially resulting in catastrophic consequences to the environment and the society. Past accidents have proven the significance and desire of investigation on failure dependence. For example, in 2010, the blowout and explosion occurred in the Deepwater Horizon in Gulf of Mexico, triggering failures of several safety barriers and finally resulting in the oil spill, causing direct economic losses of over $65 billion and immeasurable environmental losses [3]. Another example is in 2015, the accident in Tianjin, China, was triggered by spontaneous ignition of nitrocellulose, and led to domino effects causing a series of explosions and fires, finally resulting in 165 deaths, 8 missing, and 798 injured [4]. In 2003, the Italy massive blackout affected the entire Italian Peninsula for 12 h and impacted about 56 million people [5]. The 2017 collapse of an I-85 bridge in Atlanta caused extensive traffic congestion by redirecting flow to other roads, resulting in an extended period of highway closure [6]. Although these accidents occurred in different systems and for different root causes, they have a similar pattern: A single-point failure influenced the other parts and escalated into a CAF due to dependence. Such failure dependence issues have been reviewed in recent years, as the listed articles in Table 1.

Based on this table, we can identify that although previous reviews have examined the works on failure dependence from different perspectives and guided the direction of subsequent research, the following limitations and research gaps (RGs) still exist:

- The first RG is that existing reviews only focus on manifestations of failures, such as CAFs and domino accidents, neglecting the root cause of failure escalation, which is failure dependence. The absence of a review of failure dependence is primarily due to the limited

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Table 1
Review papers related to failure dependence.

Topics and focuses	Authors	Application fields
Dependent failure behavior models for risk and reliability in different system hierarchies.	Zeng et al. [7]	Not identified
Definitions, approaches, criteria, and regulations of domino effects, damage and escalation thresholds, escalation safety distance thresholds.	Alileche et al. [8]	Chemical industrial clusters
Bibliometric analysis of publications on domino effects from perspectives of temporal distribution analysis, geographical distribution analysis, and co-citation analysis.	Li et al. [9]	
Constitutions of domino effects, research issues including vulnerability and risk assessment, safety and security management strategies.	Chen et al. [10]	
Overview of CAFs, analysis tools and models of CAF models in power systems, pros and cons of these models.	Guo et al. [11]	Power grids
Evolution, and categories of CAF models, comparisons of quasi-steady-state CAF model and dynamic CAF model.	Zakariya and Teh [12]	
Use of machine learning (ML) techniques in CAF analysis, and precisely in normal, precursor, escalation, and post termination phase.	Sami and Naeini [13]	
Classification, measures and properties, traffic flow characteristics, congestion analysis, and robustness of complex traffic networks.	Zhang et al. [14]	Traffic networks
Causes and models of CAFs, reliability analysis methodologies, and the resilience strategies against CAFs.	Xing [15]	Internet of Things (IoT)

research in this area. This scarcity stems from the significant challenges associated with identifying and quantifying failure dependence, which requires extensive data and complex analysis methods.

- The second RG relates to the single-side perspective of existing reviews, which typically focus on failure propagation caused by specific types of failure dependence. The primary reason is the lack of a unified concept and systematic research on failure dependence, despite its broad scope. In fact, various failure dependence impact system performance in varying manners within a complex system. For example, failure dependence may immediately lead to system shutdown or only result in reduced system performance. Therefore, a comprehensive review examining different failure dependence models within systems is needed in order to better understand the influence of various failure dependence on the system performance.

Apart from the two aspects mentioned above, it is notable that current reviews generally overlook the cross-disciplinary nature of failure dependence studies. Despite targeting specific research topics in a specific application domain enables a deeper investigation into the research advancements within specific fields, insights from different disciplines can inspire and inform one another. This highlights the need for a holistic perspective to explore commonalities in failure dependence, and thus to develop standardized metrics and methodologies for failure dependence across different systems.

Accordingly, this study aims to enhance the understanding of the mechanisms and types of failure dependence and to clarify the relationship between failure dependence and CAFs in complex systems. More specifically, it is expected to contribute from the following perspectives: (i) elucidating the definitions of terminologies related to failure dependence and clarifying delimitations for various types of failure dependence; (ii) discussing the current failure dependence analysis models based on the classification of two types of dependences and from the perspective of reliability, maintenance, resilience, and sustainability; (iii) examining the contributions in the emerging fields of failure dependence in complex engineering systems; (iv) identifying the current limitations and providing readers with insights to recognize emerging trends. The conceptual scheme of our study is presented in Fig. 1.

This review distinguishes itself via setting clear delimitations for various types of failure dependence at the underlying mechanism level. The originality of the study lies in its holistic classification of failure dependence models and cross-disciplinary analysis, which enhances the understanding of how different domains interrelate in the context of complex systems. By examining failure dependence across diverse engineering systems, the study provides insights broadly applicable across different types of complex systems, addressing unique engineering challenges, rather than being limited to a single domain. Furthermore, the paper provides insights into the current limitations and challenges within fields of failure dependence. Overcoming the limitations of previous studies, this review enables providing a comprehensive overview of the advancements of failure dependence issues and offers guidance for researchers and engineers working on complex systems.

The remainder of this paper is structured as follows. We start with a general review of related terminologies commonly associated to failure dependence and specify their definitions in Section 2, followed by the main research areas that require emphasis when investigating failure dependence in Section 3. Section 4 reviews different types of engineering systems where failure dependence generally exists. In Section 5, some identified challenges and suggested future work are proposed. Finally, conclusions are stated in Section 6.

2. Related terminologies and definitions

Modern infrastructure systems typically exhibit complex interactions or interdependencies rather than operating in isolation. As a result, these complex systems are prone to demonstrate a variety of features, e.g., multiplicity, diversity, and interactivity. Within such a *complex system*, a catastrophic scenario may occur where the failure of a single component can propagate, resulting in the failures of other components. This phenomenon is referred to as a *cascading failure* in the given reference. In complex systems where CAFs occur among certain components, these components are identified as *dependent components* or *coupled components*, exhibiting *failure dependence*. Expanding on that, the maintenance activities directed at mitigating failure dependences and decoupling the dependent components could be denoted as *decoupling maintenance activities*. In this section, we describe commonly used terms associated with failure dependence to provide a clearer understanding of its delimitation.

2.1. Complex systems

Over recent decades, there has been a rise in interest in complex technical systems due to the development of systems engineering approaches. However, a definitive and universally accepted definition for a complex system still proves elusive. Researchers from diverse fields strive to characterize complex systems in various ways. Table 2 provides a comparison of some widely accepted definitions.

The definitions reveal that complex systems commonly contain plenty of interconnected components and complicated connections among them. The complexity of these systems introduces difficulties in the design, illustration, comprehension, prediction, operation, management, and maintenance of these complex systems. Consistent with the objectives of investigating the interconnected nature of complex systems, particularly in terms of failure dependence, a complex system could be defined as a system composed of multiple components with failure dependence. Given the definition of the complex system, some typical examples include the subsea systems [1,23], chemical industrial clusters, power grids [24–28], and traffic networks [29–31] whose components are tightly interconnected and have failure dependence.

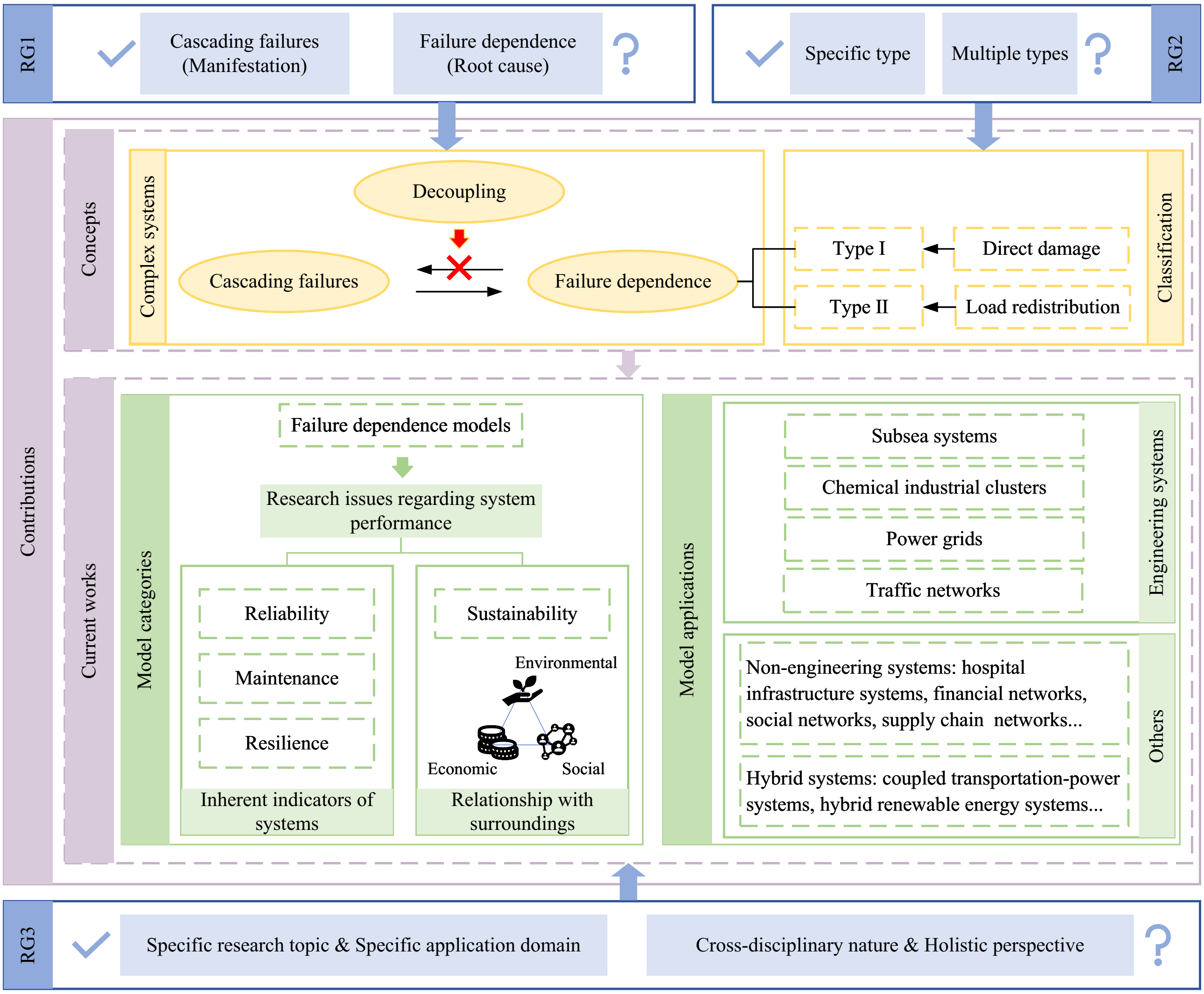

Fig. 1. Conceptual scheme of the study.

2.2. Cascading failure

CAFs occur in complex systems, where the malfunction of one component can affect the state and performance of other dependent components, leading to the subsequent failures of other components. In the current studies, CAFs are denoted by a variety of identities, each with a particular focus: induced failures [32–35], fault propagation [36,37], propagated failure [38,39], competing failure process [40,41], domino effects [42,43], and escalating scenarios/events [44,45]. Table 3 lists the definitions for these terms.

As shown in Table 3, although their definitions vary slightly, all terms refer to a phenomenon or scenario that includes three key elements: the initial event, the propagation process, and the escalation of the outcomes. Also, the root cause of these phenomena is inherently linked to the existence of failure dependences. CAF and failure dependence are an inseparable pair of concepts within the realm of complex systems. CAFs arise from the structural or functional interactions among multiple components within complex systems. Systems that exhibit a high degree of high failure dependence are particularly susceptible to CAFs. The presence of CAFs in a complex system indicates the existence of failure dependence. Conversely, while failure dependence exists in some complex systems, it does not necessarily result in CAFs, unless such failure dependence triggers a chain reaction of failures. The key distinction lies in the characteristics of these terms. The occurrence of CAFs is the direct result or manifestation of events, whereas the failure dependence among components is an inherent relationship stemming from their interactions. This inherent relationship may lead to performance degradation but may not result in complete failures that identify CAFs. Therefore, presence of failure dependence may not cause CAFs unless it precipitates a chain reaction of failures.

2.3. Coupling and decoupling

In the context of failure dependence, *coupling* and *decoupling* are a pair of concepts that can help understanding the relationships among components with failure dependence, and how to mitigate the failure dependence. Coupling refers to the dependent relationship between different parts or components of a system, describing how tightly two or more components are connected or interact. High coupling increases system complexity, vulnerability, and decreases maintainability. Specifically, high coupling facilitates failure propagation, thereby increasing the system vulnerability. Besides, systems with high coupled components are often difficult to maintain, as maintenance activities of one component may require interference to other components. Most current research concentrates on exploring the coupling mechanisms and their consequences, aiming to minimize the losses due to coupling, which will be presented in the following sections.

Decoupling, on the other hand, refers to the behavior of reducing the degree of dependence between the coupled parts or components of a system. Decoupling allows the parts or components to operate and be

Table 2
Definitions of the complex system.

Definitions	Authors	Year
Complex systems are certain technical systems that exhibit high interactive complexity.	Perrow [2]	1999, 2011
A complex system is a new approach of science investigating how parts of a system and their interactions give rise to its collective behaviors of the system, and how the system forms relationships with its environment.	Bar-Yam [16]	2002, 2014
A complex system is a system with numerous components and interconnections, interactions, or interdependencies that are difficult to describe, understand, predict, manage, design, and/or change.	Magee et al. [17]	2004
A complex system consists of a large number of non-linearly interacting non-decomposable elements.	Richardson [18]	2005
A complex system is a system characterized by: (i) comprised of many interacting agents; (ii) the manifestation of emergence–a self-organizing collective behavior that is challenging to predict based solely on the understanding of individual agent behavior; (iii) their emergent behavior does not have a central controller.	Boccara [19]	2010
A complex system is constructed from interconnected parts that as a whole exhibit one or more properties that are not inherent in the individual parts alone.	Snyder et al. [20]	2011
A complex system is a collection of numerous elements interacting in a disordered way, leading to robust organization and memory.	Ladyman et al. [21]	2012
The complex system is defined as a system where there exists a bidirectional non-separability between the identity of the whole and the identities of the parts.	Estrada [22]	2023

Table 3
Definitions of the terms synonymous with CAFs.

Terms	Definitions	Authors
Induced failures	The phenomenon that a nature failure of a component induces failures of one or more of the remaining components.	Satow and Osaki [35]
Fault propagation	The phenomenon that an accelerated degradation of critical components induced by the failure of non-critical components.	Liang and Parlikad [36]
Propagated failure	The case when the common cause failures stem from system elements and have an influence on other system elements.	Levitin and Xing [38]
Competing failure process	The process that soft failure mode and hard failure mode compete with each other and result in the whole system failure.	Cao et al. [41]
Domino effect	The propagation in time and space and the escalation resulting in an increased severity of accidents in the chemical and process industry.	Cozzani et al. [43]
Escalating scenarios/ events	A scenario in which the initial event escalates into a larger event or set of events with more severe outcomes.	Casson Moreno et al. [44]

maintained more independently, thereby enhancing system reliability and maintainability while reducing vulnerability. Decoupling strategies are the strategies carried out during the whole lifecycle of systems to mitigate the failure dependence, including design, manufacturing, operation & maintenance, and continuous improvement phases. By implementing appropriate decoupling strategies, it is possible to build a system that is both reliable and flexible, as well as easy to maintain and easy to expand. Some efforts are directed toward decoupling strategies such as link-addition strategies [46,47], safety barriers [48,49], and safety distance [8,50]. These strategies essentially work by creating redundancies, implementing physical separations, or ensuring adequate space to mitigate the failure dependence among coupled components. Additionally, given that the system may already be operational in certain instances, applying decoupling activities in the maintenance phase becomes the optimal choice, which referred to as decoupling maintenance activities. Zhao et al. [51] explicitly proposed the concept of Decoupling Maintenance activities and characterized them via Bayesian networks (BNs), particularly aiming at eliminating failure dependences among coupled components. While the research offers guidance for developing decoupling methods in complex systems, it remains deficient in providing more detailed practical maintenance activities specifically targeting heterogenous failure dependences.

2.4. Failure dependence

In the existing research, a universally accepted definition for failure dependence is still lacking. Failure dependence is often recognized with various terms, such as failure interaction, failure mechanism dependence/correlation, stochastic dependence, and degradation interaction. These terms were typically categorized rather than merely defined to aid understanding and investigation. Therefore, this subsection primarily addresses the classification of terms synonymous with failure dependence.

The roots of exploring failure dependence can be traced back to the investigation of *failure interaction*. Murthy and Nguyen [32,33] firstly introduced the concept of failure interaction and characterized it as follows: there is failure interaction in the case where if item 1 fails, it can induce a failure of item 2 with a certain probability. Furthermore, the classification of failure interaction into two types, as suggested in [35], is determined by the specific manner in which components are impacted by these interactions.

- Type 1 failure interaction: a nature failure of one component could induce the subsequent failure of one or more remaining components with a given probability.
- Type 2 failure interaction: the failure affects the performance of one or more remaining components.

This kind of classification was subsequently broadened into three distinct categories [52]:

- Type-I failure interaction: a nature failure of one component can trigger simultaneous failure or no influence on one or more remaining components, wherein the probabilities associated with these two events remain constant all the time.
- Failure rate interaction: the failure of one component can act as an interior shock and may affect or modify the failure rates of one or more remaining components.
- Shock damage interaction: the failure of one component can cause a random amount of damage which could be accumulated and affect one or more remaining components.

In addition, with emphasis on the failure mechanism correlations, Chen et al. [53] introduced the concept of *failure mechanism dependence* or *failure mechanism correlation*, and identified diverse effects of failure process dependences in non-repairable systems, as depicted in Fig. 2.

Referring to the aforementioned definitions, the failure interaction and the failure mechanism dependence/correlation rely primarily on the dependence among complete failures of the components, whereas stochastic dependence includes not only complete failures but also degradations. The concept of *stochastic dependence*, broadly acknowledged, depicts the dependence associated with failures. Specifically, this dependence arises when the deterioration process of a particular component is dependent on the state of one or more remaining components. This type of dependence is grouped into three distinct categories.

- Failure-induced damage [35]: when a component fails, it can trigger one-time damage on one or more other components, resulting in their immediate degradation or failures.

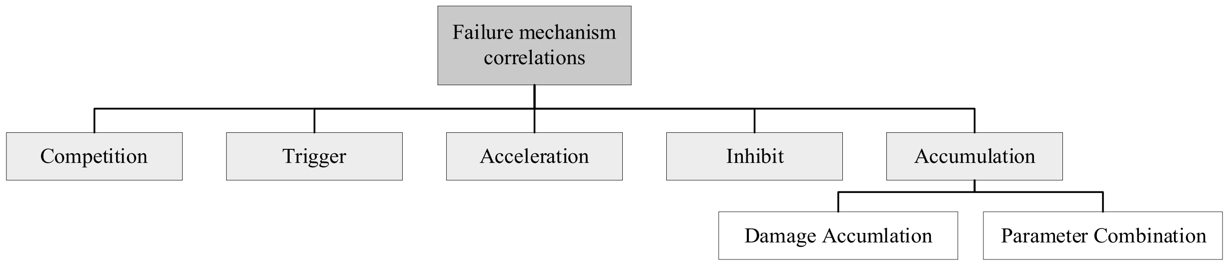

Fig. 2. Classification of failure mechanism correlations [53].

- Load sharing [54,55]: involves the distribution of the overall workload among multiple components within a system. In the event of a component failure, the workload is automatically redistributed to the remaining operational components, potentially leading to degradation or failures of these components.
- Common-mode deterioration [56]: multiple components may fail or degrade simultaneously as a result of similar operational or environmental factors.

In contrast to the definitions mentioned earlier, another type of dependence that is not solely triggered by a component failure [57,58], but rather focuses more on the interactions among components due to degradation. Termed as *degradation interaction* [57–60], this type of dependence can be triggered when the degradation of one component impacts the degradation of one or more other components. This kind of dependence is classified into two ways:

- Degradation state interaction [61,62]: the degradation of a component leads to a sudden increase in the degradation process state of other components.
- Degradation rate interaction [58–60]: the degradation of a component results in the acceleration of degradation rates of other components.

Based on the preceding discussion, numerous studies have been conducted on failure dependence to enhance the comprehension of complex systems, offering diverse definitions that address different aspects of the research issue. Fig. 3 provides an overview of typical classification approaches for failure dependence derived from the literature sources analyzed.

Subsequently, the term *failure dependence* [1,63–65] emerged as an evolution of these terms, which effectively captures a broader and more precise understanding of the interactions between failure and degradation. This evolution can be attributed to the fact that the dependences and internal interactions in complex systems have been gradually spotlighted as the system complexity continues to increase. Dependence is characterized as the relationship between two components, where a change in one component can impact the other. In complex multi-component systems, components manifest various types and degrees of physical, logical, or economic dependences [66]. Notably, failure dependence stands out as a crucial category of dependence within the complex systems as it holds significant implications for the reliability, operational integrity, and overall performance of the system. Failure dependence, as implied by its terminology, indicates the relationship between components that the failures of the components are dependent. In this context, the scope of failure dependence could be extensive. Firstly, with regard to failure mechanisms, failure dependence identifies failures caused by shock or damage, as well as those that stem from loading dependence. Secondly, concerning failure manifestation, failure dependence induces changes in the states or failure rates of the components affected. Finally, in the context of consequences, failure dependence has the potential to result in not only complete failures but also degradation that may ultimately evolve into failures. In practical applications, the failure dependences are often expected to be multiple, diverse, and heterogeneous [1], rather than singular among the aforementioned types. This heterogeneous nature adds complexity to the study of failure dependence. Therefore, the failure dependences are typically classified as follows [1]:

- Type I failure dependence: the direct damage caused by the initial failure can trigger other failures. Specifically, a component subject to type I failure dependence may fail because of the cumulative effect of

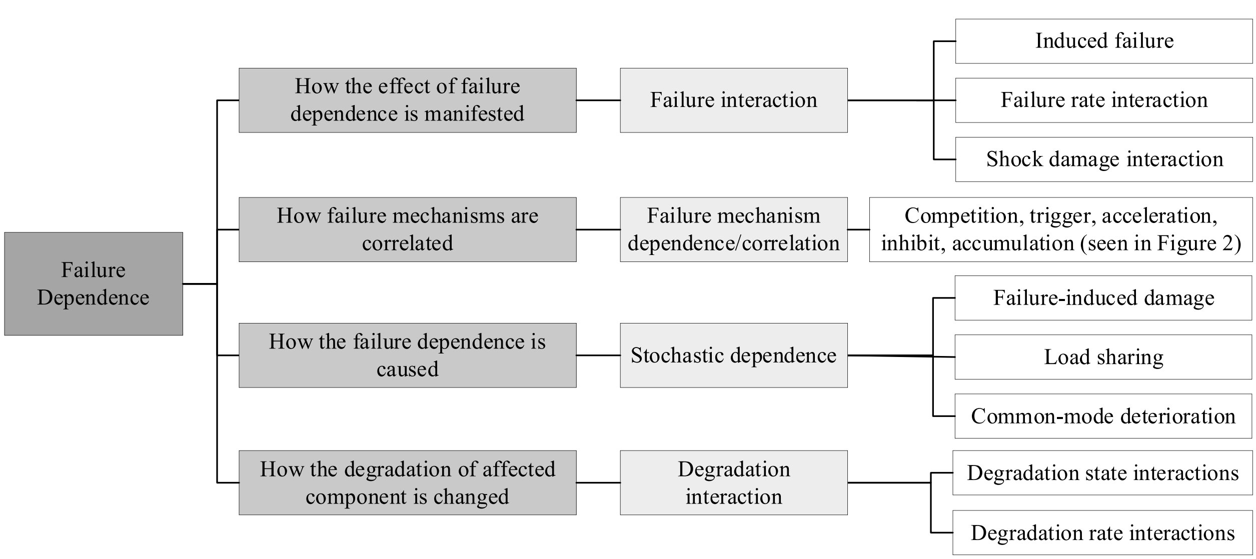

Fig. 3. Classification of failure dependence.

its inherent degradation and the shock stemming from the failures of other components.

- Type II failure dependence: the working load is redistributed throughout the system, ultimately leading to additional failures. Specifically, a component subject to type II failure dependence may fail because of the cumulative effect of its inherent degradation and the accelerated degradation triggered by the failures of other components.

For the sake of uniformity, the following discussion is based on the definition and categorization of failure dependence.

3. Failure dependence in different research areas

Based on the classification of failure dependence, this section discusses the current failure dependence models and their applications when conducting investigations on different research areas. Notably, while the studies may adopt different approaches to categorize failure dependence, in the present context, the discussion of failure dependence is solely grounded on the classification into type I and type II failure dependence, referring to subSection 2.4 for comprehensive details. Following the discussion of failure dependence models, their applications in several areas, including reliability, maintenance, resilience, and sustainability, are presented. Fig. 4 depicts relationships among these indicators. Reliability is the inherent capacity to reflect the system performance. Maintenance impacts the system performance during operation or after failures. Conversely, the foundation of maintenance strategies should be grounded on the system performance. Resilience reflects the system performance during a process of a system to absorb, adapt to, and restore from any disruptions. Sustainability reflects the system performance with broadened spatial dimension and time dimension. In detail, it not only includes the system itself, but also incorporates its relationship with surroundings. From a time dimension, it highlights the examination in the long-term process from our generation to future generations. To better understand the failure dependence issues in complex systems, literature was examined from these four perspectives.

3.1. Models for failure dependence

In recent decades, extensive research has been conducted on failure dependence in complex systems, leading to the development of a wide range of models. Major contributions encompass, but are not confined to, shock damage model [32–34], CASCADE model [24,25,55,67], degradation rate interaction model [58–60,68], probabilistic models (e.g., risk analysis models [42] and reliability analysis models [38,69,70]), simulation methods (e.g., Monte Carlo simulation [71,72]), state-transition model (e.g., BNs [23,51,59,73,74] and Markov model [1,36,75,76]), and topological model (e.g., complex network model [77,78]). Each of these models has its own advantages and limitations. A comparative analysis of these models is presented in Table 4.

3.2. Failure dependence in reliability analysis

Reliability refers to the capacity of a system to maintain its normal functionality over a defined period without failures [79]. Improving reliability can reduce safety and security issues, increase customer satisfaction and environmental friendliness, comply with laws and regulations, and control maintenance and warranty costs [79]. System reliability analysis provides valuable insights to inform design, operation, and maintenance strategies. Recently, the field of reliability analysis for complex systems with failure dependences has gained significant interest. The relevant research findings are summarized in Table 5.

3.3. Failure dependence in maintenance analysis

Maintenance management involves the systematic process of planning, organizing, and controlling maintenance activities to maximize the efficiency of the system [90]. Exploration to identify the most effective maintenance policies is imperative for achieving a balance

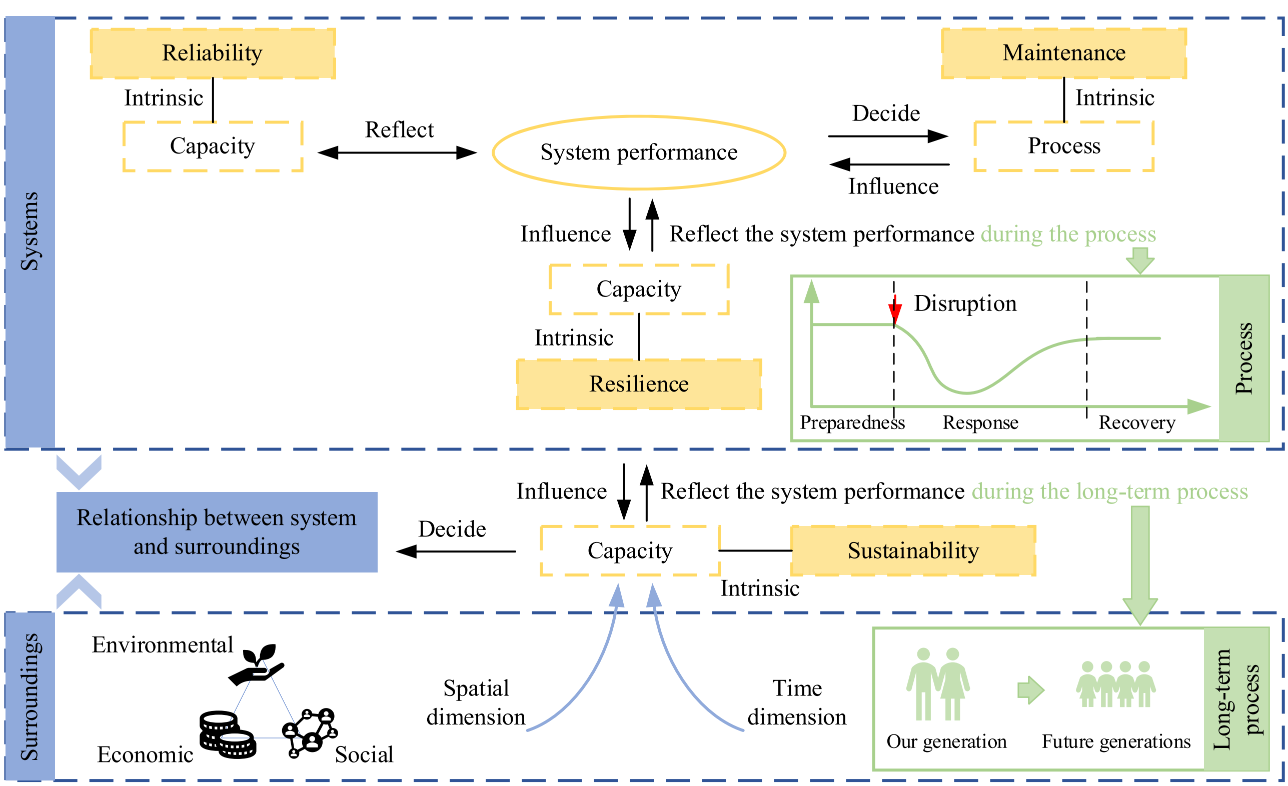

Fig. 4. Relationship between different research areas.

Table 4
A comparison of the models characterizing the failure dependence.

Model	Basics	Pros	Cons	Type of failure dependence
Shock damage model [32]	When component 1 fails, it causes shock damage with distribution $G(x)$ to component 2. The damages are accumulated and lead to a failure of component 2 when exceeding a failure threshold.	• Flexible for systems with various structures	• Incapable of representing other failure modes • Sensitivity to distribution assumptions	Type I
CASCADE model [55]	$l_j = n_{f(j-1)}l_f + n_{o(j-1)}l_o$ l_j: loading increments from all the failed and overloading components in the jth generation $n_{f(j-1)}, n_{o(j-1)}$: number of failed/overloading components in the generation $j-1$ l_f, l_o: load increment from a failed/overloading component	• Dynamically demonstrate the cascading process • Explicitly consider loading dependence	• Require remodeling for systems with various structures • Incapable of representing other failure modes	Type II
Degradation rate interaction model [58]	The Degradation rate of Component k is dependent on the states of Component 1 to k-1. $S_k' = \Delta S_k/\Delta T$ S_k': the degradation rate of component k at ΔS_k: the amount of degradation during ΔT	• Realistic consideration of failure dependence • Capable of understanding the system temporally and dynamically	• Inefficient for large-scale systems	Not identified
Reliability analysis model [70]	$R_S = \sum P(F_i)\cdot P_r$ R_S: system reliability $P(F_i)$: failure probability of the component i P_r: cascading probability	• Flexible for systems with various structures • Applicable to specific types of distributions	• Incapable of mdodeling maintenance or dynamic changes • Inefficient for large-scale systems	
Bayesian networks [23]	Use the directed arcs among the nodes of the BNs to denote the failure dependence among components.	• Easy for understanding and application • Flexible for systems with updated info in real time • Applicable to specific types of distributions	• Sensitive to prior probabilities • Difficult in acquiring sufficient data • Limitations of assumptions about the conditional relationship between nodes	Both
Monte Carlo simulation [71]	Transforms practical problems into probabilistic models and simulates them via statistics to obtain approximate solutions.	• Flexible for systems with various behavior • Suitable for large-scale systems	• Time-consuming • Limited cascading evolution paths • Susceptible to statistical errors during estimation	
Markov model [1]	Transition rates of the component subject to failure dependence: $\lambda^i_{x_i,x_j} = (1 + D_{i,x_j})\lambda_{x_i}$ $\lambda^i_{x_i,x_j}$: degradation rate of component i from state x_i to state $x_i +$ 1 influenced by failure dependence between it and component j whose state is x_j λ_{x_i}: degradation rate of component i from state x_i to state $x_i +$ 1 without failure dependence D_{i,x_j}: failure dependence from component j on component i when component j is in state x_j	• Flexible for systems with various behavior • Capable of integrating maintenance	• Inappropriate for large-scale systems	
Complex network model [77,78]	The scale-free network exhibits a power-law degree distribution, whereas the small-world network is featured by short path lengths and high degree of clustering.	• The topology of complex networks can be regular or random • Effective mitigation strategies	• Incapable of representing component behavior and characteristics • Limitations of modeling maintenance intervention	

between system performance, asset lifespan, resource allocation, and cost-effectiveness within complex systems. Regarding complex systems, there are diverse failure dependences, which can complicate maintenance policies [1] and affect system performance. Consequently, numerous contributions addressed the field of maintenance analysis for complex systems with failure dependences, as outlined in Table 6.

Based on Table 6, CBM emerges as one of the most widely applied maintenance strategies. Among these maintenance activities, CBM is recognized as a proactive approach preceding system failures, and is proven to be more cost-effective, compared to traditional maintenance solutions, as noted in [99]. The research mentioned above offers valuable insights into examining failure dependence in the context of maintenance strategy optimization. Nevertheless, to our understanding, there is a lack of investigations on proposing models to mitigate the failure dependence, despite the potential efficiency of decoupling activities in preventing unexpected CAFs.

3.4. Failure dependence in resilience analysis

Resilience refers to the inherent capacity of a system to absorb, adapt to, and restore from any disruptions or changes [100], whether accidental or intentional. When conducting resilience assessment and improvement, three distinct phases are typically evaluated: preparedness, response, and recovery, with respective highlights of absorbability, adaptability, and recoverability. A complex system possessing higher resilience exhibits a strong ability to withstand both the disturbances and the failure dependence [101]. Exploring resilience issues facilitates a holistic understanding to mitigating failure dependences to optimize system performance of complex systems. Table 7 presents some current research from the perspective of resilience improvement for complex systems.

3.5. Failure dependence in sustainability analysis

Sustainability development strives to fulfill the requirements of the current generation while ensuring that future generations remain capable of satisfying their own necessities [113]. In the realm of engineering, sustainability pertains to the system capacity to sustain a continual long-term process, considering the integration of environmental, social, and economic factors [114]. Incorporating sustainability into the analysis of system performance offers decision-makers a more holistic approach to navigating the failure dependence issues in complex

Table 5
Reliability analysis of complex systems with failure dependence.

Authors	Brief description	Methods	Type of failure dependence
Xu et al. [80]	Explored the reliability model with the failure interaction coefficients characterized by the Copula function and the Grey model.	Copula function & Grey model	Type I
Shen et al. [57]	Investigated the reliability of the multi-component system featuring interacting components affected by both a continuous degradation process and categorized shocks.	Markov model	
Sun et al. [81]	Developed a general reliability model for the system considering dependence among the degradation processes as well as the dependence between degradation and random shocks.	Copula function	
Dong and Cui [67]	Developed three CAF models of system reliability based on the normalized CASCADE model, by introducing the corresponding system reliability indices.	CASCADE model	Type II
Zhao et al. [82]	Estimated the system reliability for loading dependent systems with overloads based on the Multi-state CASCADE model.	CASCADE model	
Duan et al. [29]	Developed an innovative CAF model to investigate how route-choosing behavior influence the traffic network reliability.	Network topology	
Zhao et al. [83]	Examined a framework to conduct reliability analysis of load-sharing systems comprising identical components subject to continuous degradation.	Maximum likelihood estimates (MLEs)	
Nezakati et al. [84]	Explored the conditional distribution, considering the dependent competing soft and hard failures, and formulated a reliability function for the load-sharing k-out-of-n system.	MLEs	
Guo et al. [85]	Introduced an analytical model for calculating the reliability of consecutive k-out-of-n systems where the workload and shock load of failed components are redistributed.	Probabilistic model	
Che et al. [86]	Proposed an analytical reliability model for the load-sharing man-machine system, incorporating human errors with degradation processes and random shocks.	Probabilistic model	
Li et al. [87]	Derived the failure rate function for the multi-unit system with a dominant unit and numerous secondary units, as well as established the transient reliability of the system.	Markov model	Not identified
Kong et al. [62]	Proposed explicit forms of system reliability functions by employing factor analysis to characterize the degradation interactions.	Factor analysis	
Wang et al. [88]	Proposed a reliability assessment model of a multi-state reconfiguration pipeline system considering failure interactions based on cloud inference.	Markov model	
Torrado et al. [89]	Introduced a reliability analysis model of hierarchical system structures where the dependence exists among the components, as well as among the modules of the system.	Copula function	

systems. Zhao et al. [51] constructed a comprehensive model to evaluate the overall sustainability of the system considering the coupling impact of components degradation, failure dependences, and the maintenance activities on sustainability. The research was the first to introduce the concept of decoupling maintenance, and innovatively focuses on the effect of failure dependence on the sustainability, which contributes to insightful reference for engineers seeking for sustainable maintenance practices. However, this study still has constraints that necessitate further investigation, e.g., consideration of more complex and heterogeneous failure dependences, as well as extended period with multiple changes in the BNs.

4. Failure dependence in engineering applications

This section mainly reviews investigations on failure dependence in some complex engineering systems, including subsea systems, chemical industrial clusters, power grids, and traffic networks. In the context of failure dependence, these application fields share commonalities and have their own distinctive features. These systems are all highly interconnected and exhibit pronounced failure dependences, making them ideal examples to examine the mechanisms and methodologies of failure dependence. Therefore, there is a substantial body of existing research available for these systems, providing a robust foundation for a systematic literature review and allowing for a comprehensive analysis to identify challenges in current approaches. Failure dependence in complex systems also presents unique characteristics across different fields. Subsea systems typically exhibit two types of failure dependences, whereas chemical industrial clusters are mainly dominated by type I failure dependence. In both subsea and chemical industrial clusters, CAFs resulting from failure dependence can lead to numerous casualties and significant environmental pollution. In contrast, power grids and traffic networks primarily experience type II failure dependence. In these application fields, CAFs primarily impact daily life and society functions, and are typically mitigated through load control.

4.1. Subsea systems

The subsea system [1,23] represents a typical example of a complex system, comprising a network of interconnected components functioning within underwater environments. A subsea production system typically includes wells, Christmas trees, separators, compressors, pumps, pipelines, manifolds, etc. [115,116]. With the continuous progression of technological advancements, the growing demand for deepwater exploration has significantly amplified the complexity of subsea systems and posed superior challenges for all subsea devices. Within this subsea system, certain components are functionally or structurally interconnected, leading to two types of failure dependence,

Table 6
Maintenance analysis of complex systems with failure dependence.

Authors	Brief description	Methods	Type of failure dependence
Satow and Osaki [35]	Studied a two-parameter maintenance policy for a two-component system where failures of component 1 follow a Poisson process and induce a stochastic amount of damage to component 2.	Probabilistic model	Type I
Lai [52]	Developed an optimal periodical replacement policy for multi-unit systems subject to failure rate interaction by incorporating replacement costs and minimal repair.	Probabilistic model	
Liang and Parlikad [91]	Established a modeling approach for Condition-based maintenance (CBM) optimization for complex industrial assets with load-sharing interaction and fault propagation using a two-tiered approach.	Markov model	Type II
Rasmekomen and Parlikad [58]	Presented a CBM optimization model for state-rate interaction components in the system.	Degradation rate interaction model	
Zhang et al. [92]	Proposed three maintenance policies for a two-component load-sharing system and conducted the theoretical propositions to examine the optimal average costs.	Probabilistic model	
Oakley et al. [93]	Proposed a CBM policy for systems subject to economic and stochastic dependence, incorporating a utility/reward function.	Probabilistic model	
Zhao et al. [94]	Investigated the reliability and inspection optimization model for a k-out-of-n system with failure dependence under load sharing effect using a coupling search failure sequence diagram (FSD) and sampling algorithm.	Coupling search FSD and sampling algorithm	
Sun et al. [95]	Developed and extended Split System Approach for interactive failures, and examined the impact of failure interactions on the intervals of preventive maintenance actions.	Extended Split System Approach	Not identified
Gao and Ge [96]	Presented periodical maintenance cost models for a two-state series system and a three-state series system with failure interactions.	Probabilistic model	
Zhang et al. [97]	Developed two different shock models and three maintenance policies for a two-component system with failure interactions.	Virtual age method	
Zhang et al. [64]	Proposed a CBM model for a two-unit system with failure dependence under imperfect inspection.	Probabilistic model	
Rezaei et al. [98]	Established a novel formulation of the linear consecutive k-out-of-n: F system model subject to failure dependence and optimized maintenance intervals.	Probabilistic model	
Zhao et al. [51]	Proposed an integrated framework to explore the impact of common maintenance strategies and decoupling maintenance activities on the overall sustainability of complex systems.	BNs	
Zhao et al. [1]	Developed a comprehensive framework to evaluate heterogeneous failure dependences and a CBM model for maintenance optimization.	Markov model	Both

requiring a mounting concern in this field.

Cai et al. [23] examined the CAFs in a subsea transportation system, consisting of oil pipelines, transfer stations, and some auxiliary production facilities. This subsea transportation system is divided into three areas and three levels. In their model, the transfer station and its related equipment are integrated into a whole node, whose overall degradation influences the degradation of other nodes and causes CAFs.

Additionally, the failure dependence in subsea Christmas tree was also explored by Shao et al. [59]. The subsea Christmas tree is a typical complex system with multiple components, multiple parallel relationships, and multiple working states. In this study, the failure dependence in various parts (including the electronic control system, the hydraulic control system, and the valves) of the subsea Christmas tree, is individually modeled to establish the overall performance degradation model of the whole system. Based on the degradation and interaction model, a multi-stage remaining useful life (RUL) prediction model is developed.

Regarding the subsea transmission system, Zhao et al. [1] proposed a framework for heterogeneous failure dependences in multi-component systems and developed a general CBM model to optimize the maintenance strategies. The developed model was applied to a practical parallel subsea transmission system consisting of one compressor and two pumps. Besides, an integrated framework [51] was also introduced for the subsea transmission system to thoroughly examine the coupling effect of component degradation, failure dependence, and maintenance management on the sustainability evaluation. In this framework, decoupling maintenance activities to mitigate failure dependences were innovatively suggested. The proposed framework was constructed based on a dynamic Bayesian network (DBN) model and applied in a case study, which provides valuable insights for decision-makers in seeking sustainable maintenance practices.

In terms of subsea pipelines, Liu et al. [117] proposed a reliability model considering parameter uncertainty for dependent competing failure processes. The authors established two DBNs to analyze the dependence between degradation failure and sudden failure. The

Table 7
Resilience analysis of complex systems with failure dependence.

Authors	Brief description	Methods	Type of failure dependence
Cincotta et al. [102]	Introduced an optimal firefighting identification methodology for the fire escalation scenarios to increase the resilience of process plants.	BNs	Type I
Habib et al. [103]	Derived the analytical limitation on the maximum number of interconnection links required to guarantee resilience for the dependent power grid - optical network against the CAFs.	Network topology	
Goldbeck et al. [104]	Developed a multi-stage stochastic programming model to optimize the network capacities, dynamic network flows, and repair resource logistics regarding resilience planning.	Input-output modeling	
Zeng et al. [105]	Established a barrier management framework for the Natech domino accidents to improve the resilience of the barrier system during the whole cycle.	BowTie	
Li et al. [101]	Suggested the resilience reinforcement strategies for the network with potential CAFs based on nodal capacity redundancy.	Scale-free network & random network	Type II
Fan et al. [47]	Presented a connectivity link addition strategy to improve the resilience for multiplex networks against CAFs and attacks.	Network topology	
Lian et al. [106]	Constructed a resilience index for the power system based on a CAF graph under persistent disturbances.	Monte Carlo simulation	
Zhou et al. [107]	Examined a resilience optimization framework considering the mixed CAFs from load redistributions in local and global networks.	CASCADE model	
Salama et al. [27]	Examined the risk mitigation strategies including dispatch, load shedding, and intentional controlled islanding to improve the robustness and resilience of the power grid.	Complex network model	
Dui et al. [108]	Proposed a time-varying algorithm to achieve resilience optimization regarding CAFs in unmanned vehicle distribution network.	Complex network model	
Zhang et al. [109]	Explored a two-stage recovery model after mixed CAFs to improve resilience for cyber-physical supply chain networks.	Network topology	
Yu et al. [110]	Developed a CAF graph and a resilience index scheme for the electric-thermal energy networks considering both the ice disasters and CAFs.	Complex network model	
Dui et al. [111]	Proposed a propagation model to illustrate the cascading process of COVID-19, and a CAF model for the hospital infrastructure system (HIS). Based on the two models, a resilience optimization was established.	Scale-free network & Markov model	Both
Fu et al. [112]	Developed a CAF model and a two-stage recovery strategy to improve the resilience for automotive manufacturing supply chain networks.	Complex network model	

models were developed based on variable degradation increments and degradation rates.

4.2. Chemical industrial clusters

In the chemical industrial clusters, the ever-increasing complexity and interactions of the facilities have brought economic effects and simultaneously exacerbated the severity and extent of potential consequences. Failure dependences exist due to the significant concentration of hazardous chemical process plants and equipment in a confined region. Therefore, any fire or explosion incident in one unit may propagate, triggering accidents in adjacent units, thereby leading to CAFs, which are well known as domino accidents [42] in the chemical industry. Such domino accidents are generally induced by fires or explosions, or coupled factors [10]. In domino accident scenarios in the chemical industrial clusters, type I failure dependence primarily contributes to the cascading process, since the failures of a pipe or of an equipment item due to a fire or an explosion generally has the potential to directly affect the other nearby units.

In the cases of domino accidents triggered by fires, the primary failure could be a loss of containment resulting in a pool fire [118,119], jet fire [120,121], fireball [122], flash fire [122], etc. The cascading factors that contribute to fire-induced domino accidents include radiation [123] or fire engulfment or impingement [121]. For domino accidents caused by an explosion, the primary failure could be a confined explosion, a physical explosion, a loss of containment resulting in a Boing Liquid Expanding Vapor Explosion (BLEVE) [124,125], or in a Vapor Cloud Explosion (VCE) [125,126], etc., and the cascading factors can be projected fragments [127] or overpressure [123,125].

The failure dependence in the chemical industrial clusters has been attracting significant attention as it often leads to more severe consequences and substantial losses compared to the systems mentioned above. Therefore, many studies have also been conducted on how to mitigate failure dependence to reduce the probability and severity of domino accidents. To mitigate the type I failure dependence of domino accidents, safety barriers [48,49] and safety distances [8,50] are the two methods that are mostly considered. Safety barriers are essential in mitigating and preventing catastrophic consequences, which can significantly decrease the probability of failure propagation by multiple orders of magnitude. Safety barriers basically include [128] passive barriers (such as fireproofing protection [129,130] and protective layer [131]), active barriers (such as water/foam sprinklers [132], emergency shutdown/blowdown/drainage systems [133,134], etc.), as well as procedural and emergency measures (such as emergency response teams [128,133]). Another effective approach is to keep the hazardous units far away from each other. However, such measure is hardly applicable considering the limited land availability, the high cost of land, and the increased costs of pipeworks and pipe racks needed to connect the units [135]. Actually, cost considerations make a no-risk arrangement not feasible, adhering to "safe distance" norms and codes presents options to minimize risks and optimize land usage, thereby striking an optimal balance. The investigations of safety barriers and safety distance could provide insightful references for establishing safety measures or developing decoupling maintenance activities to reduce failure dependence in other types of systems.

4.3. Power grids

The major reason for large blackouts of power grids could be CAFs because the power grids are highly complex and vulnerable to strong failure dependence. Typical examples include the blackout that occurred in America in 1996 [25], the massive power outage in Northeast in 2003 [136], the blackout in Italy in 2003 [5], the power outage in Venezuela in 2019 [137], etc. In the power grids, key components such as transformers, generator buses, and load buses are interconnected as a network by transmission lines. The circuit laws govern the electrical variables, e.g., current, voltage, power, and others that are associated with the components. The initial failure of some components can significantly alter electrical variables, potentially causing redistribution of power flow and removal of failed components, which eventually results in CAFs [137]. Such a cascading process due to redistribution of power denotes that there typically exists type II failure dependence in power grids.

Various models have been established to characterize the mechanism of CAFs in power grids. The commonly accepted models include but are not limited to the CASCADE model, the branching process model, ORNL-PSerc-Alask (OPA) model, the simulation model, and the topological model. There are also other models addressing diverse perspectives of CAF issues in power grids, which were summarized in [11].

The CASCADE model was firstly proposed by Dobson et al. [24,25,138] to examine the criticality of blackouts for loading dependent power grids. The basics of this model are as follows. The initial load of each component is uniformly distributed within a range. After the outside disturbance is applied to every component, some components may fail and start the cascading process. Then the failures allocate the additional loads to the remaining components, and such load redistribution drives the unfolding of the cascading process. This process stops when there are no more new failures. Based on the normalized CASCADE model, Dong and Cui [67] developed the extended CASCADE models to investigate the reliability of power transmission system by 1) introducing cascading time; 2) applying to a k-out-of-n system; and 3) considering a series outside disturbances.

The branching process model approximates the CASCADE model. By approaching the failure propagation as a Poisson branching process, Dobson et al. [139] developed a probabilistic model that examines CAFs in the loading dependent electric power transmission systems. Kim and Dobson [140] also measured the approximation accuracy between two generic high-level probabilistic models of CAFs, and their results verified the feasibility of using the branching process as an approximation.

The OPA model [141] is a Direct Current (DC) power flow-based model widely used for predicting CAF sequences. The model features two time-scale dynamics: the slow dynamics (take years/decades to model grid upgrade) and the fast dynamics (take hours/days to model CAFs due to line outages or overloads) [15,141]. The origin DC-OPF-based OPA model shows some limitations such as inaccurate simulation [11] and unmatchable results with the utility data. To address the limitations, the model was improved [142] to capture more realistic cascading scenarios. Later, other kinds of modifications based on the model were also made: Alternating Current-OPA (AC-OPA) model, AC-OPF model [143], AC optimal power flow model considering frequency deviation (AC-OPFf model) [144], and enhanced OPA model [145].

The simulation models may encompass several traditional methods such as Monte Carlo simulation, as well as some intelligent algorithms such as ML) techniques. For example, Cadini et al. [72] constructed a Monte Carlo framework to realize the integration of an extreme weather stochastic model with the realistic power grid fault dynamics in a power transmission grid. ML techniques have become increasingly appealing for handling CAF issues, owing to the trend of Big Data, the advancements in monitoring technologies, and the development of intelligent algorithms. ML techniques can contribute to initial fault analysis [146,147], cascade prediction [148,149], root cause analysis [150], etc.

The topological model is mainly used to describe the structure of the system and the internal connection relationships. The modified topological model is typically used for power grids owing to the consideration of essential electrical properties, e.g., line impedance, line capacity, and flow-based analysis [11]. By defining the weights and attributes of nodes and connections, and setting the initial failure and failure propagation rules, the cascading process of the CAFs in the power grids can be observed.

The above models support the analysis of the mechanism and prediction of CAFs in power grids and thus constitute the cornerstone of investigations on mitigating CAFs. Common mitigation strategies include intentional controlled islanding, generation redispatch, load-shedding, adding redundancy, hardening critical components, etc. [27,151], among which the first two strategies highlight the failure dependence issue. Tortós et al. [152] established a unified framework based on the graph theoretic cut-set matrix to evaluate the risk of intentional controlled islanding scheme. To showcase its adaptability and robustness, the proposed framework was implemented and tested on the operational power system of Cyprus. Besides, Salama et al. [27] proposed the integrated strategy (dispatch & load shedding, integrated with intentional controlled islanding) strategy to mitigate the CAFs of power grids and prevent catastrophic blackouts. The intentional controlled islanding method was developed through a constrained spectral clustering algorithm. Moreover, these strategies can be realized through more advanced methods. For example, Zhang et al. [137] presented an intelligent method that uses deep reinforcement learning techniques to promptly generate adequate remedial actions in response to CAFs in real time. The method was achieved through a CAF simulation model to accurately depict the dynamic cascading process, a Markov decision process to decide the remedial actions, and the Proximal Policy Optimization algorithm to train the underlying policies.

4.4. Traffic networks

In traffic networks, failure dependence often exists between routes or roads [153]. The damage of one link tends to trigger a chain reaction, leading to subsequent failures through the network and finally causing CAFs of other links [154]. Taking the urban traffic network as an example, the damage or congestion of one or more roads could be considered as the initial failure of the cascading process, which can be generated by extreme climate change, terrorist attacks, temporary road closures, or rush hour congestion. Once the road is jammed or unavailable, other routes/nodes will suffer additional traffic flow. If these routes/nodes cannot handle the extra traffic flow, overloads and failures occur. This is how the failure propagates through the whole network. In this cascading process, type II failure dependence accelerates the failure propagation of the cascading process. Another type of failure dependence, although not widely studied, still exists in traffic networks, demonstrated by chain reaction accidents between vehicles. In this cascading process, type I failure dependence promotes the failure propagation.

Regarding the failure dependence in traffic networks, many studies concentrated on developing models to characterize the cascading process and reliability. Deng et al. [153] introduced a causal inference methodology to uncover the failure dependences among road sections, leveraging information theory and real-time velocity data. The findings help reveal CAF patterns in road networks. By constructing a data-driven physical model, Dekker and Panja [155] analyzed the spreading of train delays across the network, revealing that large-scale disruptions depend on the dynamic dependences in the network. For other types of traffic networks, such as highway bridge network [156] and global container shipping network [157], CAFs may also occur, stimulating investigations on the cascading process and reliability modeling. Extending from the single type of public traffic mode to the complex coupling dynamics in the multi-modal public transit network, Zhang et al. [158] proposed a cascading reliability model to measure and control the CAFs, with consideration of various types of failure load dynamic redistributions. Furthermore, given the coupling trend of traffic networks and power grids, Wu et al. [159] creatively proposed a load–capacity model for the coupled networks to describe the failure propagation between two networks.

Normal operation and recovery after failures are essential for sustainable traffic networks. Some studies focused on the mitigation of CAFs, e.g., prevention, control and recovery strategies. In terms of the CAF prevention, link-addition strategies [46,47] are commonly applied, primarily focusing on adding new links prior to CAFs, especially those with strong failure dependence. While link-addition strategies offer passengers more routing options and enhance the overall network performance, they unfortunately come with increased delivery time and management costs. Later, utilizing topological and operational knowledge, Zhang et al. [160] designed relinking strategies for non-emergency and emergency routes to compare the prevention and emergency control strategies. The results show that emergency control surpasses prevention strategies, with operational knowledge outperforming topological knowledge. The study offers guidance for the rail network and other similar traffic networks at different stages. For the period after CAFs, Guo et al. [161] proposed a cascading and recovery model for metro–bus double-layer network to illustrate the dynamic evolution mechanisms of the cascading and recovery process. The study discussed the effect of some factors on the recovery process, including station capacity, load redistribution rules, repair speed, etc., which provides insightful inspiration for decoupling the routes with failure dependence and developing a sustainable and stable traffic network.

4.5. Other systems

Some other applications in non-engineering systems are also reported in the literature, e.g., hospital infrastructure systems [111], financial networks [162], social networks [163], supply chain networks [112], etc. In addition, some hybrid systems such as coupled transportation-power systems [164] and hybrid renewable energy systems [165] are evolving, increasingly meeting market demands while also introducing more complex failure dependence. However, as these systems are newly developing, related research is still in the early stages, and theoretical frameworks or models for failure dependence in such hybrid systems are even rarer. An increased emphasis will be predictably directed towards investigations on the failure dependence of even more different systems in the future, as the technology progresses and evolution of the IoT are elevating system complexity.

5. Challenges identified and research opportunities

Based on reviews of failure dependence related contributions, some open questions and suggestions that are worthy of investigation can be identified. This section locates challenges and upcoming opportunities for future explorations in decoupling maintenance activities, research on sustainability, research on hybrid systems, prediction methods for the cascading process, and verification techniques.

5.1. Decoupling maintenance activities

Despite the importance of studying failure dependence has been recognized, the primary emphasis has been directed toward the propagation mechanisms and the subsequent impacts on system performance. Most of the existing work was devoted to avoiding failure dependences through layout optimization [50,166,167] and redundancy design [101] during the system design phase, which cannot support in the operation and maintenance phase. As for the maintenance strategies, even though there have been lots of studies considering failure dependence, as listed in Table 6, the investigations primarily concentrated on the system and its individual components, with limited attention to decoupling maintenance activities that specifically target failure dependence. Not to mention that due to the heterogeneity of failure dependence, different maintenance strategies can be adopted to mitigate the failure dependence better and reduce maintenance costs. Therefore, in contrast to the traditional maintenance strategies that merely address system and components, it is imperative to examine decoupling maintenance strategies tailored specifically for various types of failure dependences, which is the optimal solution for avoiding failure escalation.

5.2. Consideration on sustainability

Currently, there is rarely discussion on the relationship of the system and its surroundings, which could be characterized by sustainability. As discussed in the previous sections, numerous research studies have been conducted on the reliability analysis, maintenance analysis, and resilience improvement of complex systems with failure dependence. These works offer valuable references and assurances for ensuring the safe, stable, and long-term operation of such systems. Despite their importance, these works primarily focus on the system intrinsic performance and human interventions, without considering the relationship between the system and its surroundings. On the other hand, sustainability analysis aligns better with the strategic needs of the whole society and provides a more comprehensive perspective to reflect the impact of failure dependence on system performance. Despite its significance, limited research has explored failure dependence in complex systems through the lens of sustainability, which encourages further investigation.

5.3. Dependence within hybrid systems

The concept of a hybrid system is broad, indicating a complex system consisting of multiple interacting subsystems with diverse characteristics. For instance, in some cases, a subsea system can be regarded as a hybrid system because it contains functionally dependent subsystems such as Christmas trees systems, separator systems, manifold systems, etc. However, based on our classification of systems reviewed in this paper, a hybrid system refers specifically to a mixed system consisting of systems from different domains that interact with each other. For example, operation and failures of the electric road systems are constrained by the power distribution network in the coupled transportation-power systems [164]. Green hydrogen production relies on renewable energy systems, such as wind turbines and solar power panels, and electrochemical equipment, like electrolyzers. The failure causes and distributions of these systems are different, but failure dependence exist between them. Failure dependence in such hybrid systems is more complex. Furthermore, these hybrid systems are still evolving, leading to potentially limited resources for in-depth research on failure dependence.

Future research should focus on strengthening cross-disciplinary investigations and drawing from the research experiences of traditional systems, so as to establish a more complete theoretical framework and models of failure dependence in hybrid systems. Moreover, integrating advanced modeling techniques is crucial in capturing the dynamics of hybrid systems. Using big data and ML can provide deeper insights into failure patterns and dependences in such systems, offering identification capabilities that traditional methods lack.

5.4. Cascading process prediction

The presence of heterogeneous failure dependence among random components within the complex system results in a chaotic and unpredictable failure cascading process. Since CAFs are characterized by positive feedback and increasing complexity over time, if the unfolding trend of the cascading process can be predicted in the early stage and effective measures can be taken in advance, the system reliability can undoubtedly be significantly improved. Current studies mainly focus on the RUL prediction considering failure dependence [23,59], while relatively few studies address the prediction of unfolding scenarios for the cascading process in both the spatial and time dimension. As big data technologies continue to advance, the prediction of unfolding scenarios for the cascading process have become feasible [148,149]. However, these studies still have limitations due to simplifying the system structure and failure modes, making them unsuitable for more unique engineering systems. Specifically, it is challenging to use the incomplete operational and maintenance data [168] of the unique system to develop more precise prediction models, capable of forecasting even longer cascading processes. In order to better predict the unfolding scenarios of the cascading process for more engineering systems, a digital twin model based on physical reality data can be constructed in the future to provide early warning and decision support by updating the model state with real-time data.

5.5. Verification techniques

As mentioned in the previous subsection, the cascading process exhibits stochasticity and uncertainty, and conducting experiments to explore failure dependence issues thus poses significant difficulties. To investigate the failure dependence and the cascading process, numerical simulation methods are mostly adopted [1,23,148] and offer an effective solution with several advantages: First is repeatability. Numerical simulations can be executed repeatedly with the same scenarios or conditions to validate the results. Next comes the scenario diversity. Adjusting parameters and initial conditions can simulate various failure cascading scenarios, including diverse failure dependences and combinations. The third is cost-effectiveness. Numerical simulations are usually less costly compared to actual physical experiments. Then finally, visualization. Many numerical simulation tools support visualization capabilities, which can help researchers visually understand the dynamic cascading process and its consequences.

However, simulations rely on models that may not perfectly represent the real failure dependence of the system. Model assumptions and simplifications, as well as the sensitivity of simulation results can introduce inaccuracies. This is why experimental validation is also craved to be performed. The experimental validation can be mutually verified with the simulation method, thus ensuring the accuracy and robustness of the simulation model, which can truly reflect the failure cascading process. In addition, it helps to apply the theoretical research results to practical systems and guides the design and operation of complex systems with failure dependence.

When conducting experimental validation of failure dependence issues in complex systems, several technical difficulties need to be addressed in the future: 1) How to isolate and observe the precise failure dependence and mechanisms that lead to CAFs. 2) How to accurately replicate real-world conditions, including external disturbances, noise, and environmental variations, which can significantly influence the cascading process. 3) Advanced isolation techniques to systematically investigate the effects of different failure modes and different combinations of heterogeneous failure dependences.

6. Conclusions

Addressing failure dependence issues in complex systems, this paper conducted a systematic literature and identified existing challenges. The relationship between CAF and failure dependence was identified, spotlighting the concept of decoupling, and presenting definitions and classifications of various terms denoting failure dependence. This work also highlighted several research areas, examining not only the studies most relevant to the inherent system performance but also investigating research on sustainability, which focuses on the relationship between the system and the surroundings. Subsequently, the investigations into failure dependence in different engineering systems were also reviewed. The dominating type of failure dependence varies for various engineering systems. For engineering systems with similar types of failure dependence, there are some commonalities in the methodologies and models that can be borrowed from each other. It was found that the current studies on decoupling maintenance activities, the impact of failure dependence on system sustainability, the application of failure dependence models in hybrid systems, and the cascading process prediction are still in early stages and not yet fully developed. Moreover, regarding the theoretical approaches used in current studies, how to adopt experimental verification remains an open question.

Despite this paper is offering a thorough examination of failure dependence and CAF, it nevertheless has specific limitations and could be extended in three aspects. Firstly, while other research areas such as risk analysis, as well as other engineering systems, non-engineering systems, or hybrid systems also exhibit failure dependence, the scope of this paper is necessarily limited. Future research could expand to include other research areas and applications to further enrich the understanding of failure dependence in various fields. Furthermore, this work primarily draws from English journal articles, supplemented by a handful of monographs, reports, and web-based information. Some insightful works such as Master and Philosophy Doctor (Ph.D.) thesis, and non-English publications are not included. In addition, to illustrate the development of research in this field temporally, its geographical distribution, and the collaboration between institutions and authors, bibliometric analyses could be added.

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.

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