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Yixin Zhao

System performance analysis of complex systems with failure dependence

Doctoral thesis

NTNU
Norwegian University of Science and Technology
Thesis for the Degree of
Philosophiae Doctor
Faculty of Engineering
Department of Mechanical and Industrial
Engineering

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Trondheim, April 2024

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Preface

This thesis is submitted to the Norwegian University of Science and Technology (NTNU) as a partial fulfillment of the requirements for the degree of Philosophy Doctor (Ph.D.). The main work of the Ph.D. thesis was carried out at the Department of Mechanical and Industrial Engineering (MTP) of the Faculty of Engineering in NTNU, Trondheim, Norway. Besides, I also spent two months at University of Bologna, Bologna, Italy as part of my Ph.D. study. The research was primarily accomplished under the supervision of professor Yiliu Liu and Professor Jørn Vatn in Norway, with additional supervision from Professor Valerio Cozzani in Italy.

This work's target readers include researchers and practitioners interested in the following fields: reliability engineering, safety engineering, maintenance management, sustainability evaluation, and subsea industry engineering. It is assumed that the readers have basic knowledge of reliability and maintenance, preferably related to complex systems.

Trondheim, Norway

December 2023

Yixin Zhao

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Acknowledgment

Reflecting on my Ph.D. journey, I acknowledge the plethora of challenges and obstacles, but more significantly, it was a period marked by substantial growth and profound satisfaction, both for academic research and personal development. Up until now, I can still recall the anxiety and confusion that enveloped me when I applied for the Ph.D. position. Faced with the challenges posed by the COVID-19 epidemic and the intense pressure to secure employment, I questioned the validity of my decision of Ph.D. application. Yet, in retrospect, I can unequivocally state that it could be the best decision I ever made. At the end of this journey, I would like to express my sincere gratitude to my supervisors, colleagues, co-authors, friends, and families who have contributed to the completion of this PhD thesis.

First and foremost, I would like to show my deepest appreciation to my main supervisor, Professor Yiliu Liu, for all his invaluable insights, patient guidance, and continuous support throughout the entire research journey. He shared with me his knowledge and his experience in doing research. He led the way as a guide, offering invaluable insights into my research direction. He also devoted tremendous time and continuous energy on reviewing my papers repeatedly. Besides the role of supervisor, he has proven to be a supportive friend. His readiness to extend help, rejoice in my accomplishments, and encouragement during my challenging times have been a source of power.

I would like to thank my co-supervisor, Professors Jørn Vatn, who has provided insightful and constructive comments and suggestions on my research. My sincere thanks are also extended to Valerio Cozzani, from University of Bologna, for his professional guides and hosting during my visiting period. It was a great and unforgettable experience to work with his group.

A warm thank to my wonderful colleagues in the RAMS group for the seminars, nice coffee breaks, social events, lovely dinners, and girls gathering we had and shared. To Aibo, Lin, Renny, Xingheng, Bahareh, Tianqi, Gibran, Jie, Wanwan, Emefon, Asmae, Federico, Dimi, Andrie, Farhana, Reem, and all dear others, I am deeply thankful for all your kind help and our happy times together. I would also like to express my gratitude to the administrative staff at the department, Kari, Linn, and Øyvind, for being helpful whenever I required assistance.

Some of the research presented in this thesis was conducted in collaboration with researchers from institutions distinct from my own. Specifically, I would like to extend my thanks to Professors Baoping Cai, and Henry Hooi-Siang Kang for their valuable feedback and suggestions for my research. Additionally, I appreciate postdoc Tao Zeng, who provided valuable insights into the methodology and software.

I am especially thankful to my closest friends, Chang, Shujun, Jiajia, Tingting, and Yunbo, for their steadfast supports, our warm friendship, and happy moments together.

In the long journey of life, joy and sorrow are inevitable companions. Throughout this path, it is consistently my families who share the most significant part of these moments with me. Therefore, last but not least, I would like to express my deepest appreciation to my beloved parents, Hua Meng and Yanhua Zhao, for their considerate understanding, enduring support and unconditional love in my whole life.

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Summary

Many technical systems are becoming more and more complex, consisting of multiple components and prone to failure dependences. Within such systems with failure dependences, the failure of a component or some components may accelerate the degradation of other components. Such failure dependences can significantly reduce system reliability and lead to catastrophic consequence if not well considered and effectively mitigated. In addition, within the complex multi-component systems, the failure dependences are commonly not expected to be single but multiple and heterogenous, which further complicates the investigation of system operation and maintenance management.

The subsea system is typical example of complex system with failure dependence. The subsea system is part of the offshore oil and gas industry that performs various tasks and operates in the seabed or underwater environment. Given the long-term exposure to hostile environmental conditions encompassing high pressure, low temperature, salinity, and corrosion, et. al, ensuring the normal operation of the subsea system via effective maintenances becomes very important. Additionally, due to the complex functions, the subsea system rarely operates independently by a single device. In many cases, the subsea system may inevitably suffer the coupling effect of natural degradation and failure dependences, resulting in more severe consequences. Therefore, to guarantee the system performance to ensure its long-term stable operation in extreme environments, it is crucial to deal with these complex failure dependence situations of the subsea system.

Currently, the effect of failure dependence has not been well studied neither in the reliability analysis, maintenance management of the complex system nor in its sustainable relationship with the surroundings. As a result, it is desirable to conduct a thorough investigation on the impacts of failure dependence in complex multi-component systems. Our research identifies the subsea complex system as an ideal case example for such investigation.

This Ph.D. thesis aims to propose comprehensive methodologies to conduct reliability analysis, maintenance management, and sustainability evaluation for the complex systems considering the failure dependence. The aim is refined into the following four specific research objectives that are addressed in one conference paper and four journal articles:

- Elucidate the definitions of terminologies related to failure dependence and clarify delimitations for various types of failure dependence. Based on that, mechanisms of component degradation and cascading process are better categorized and understood. The study could improve the recognition and comprehension of failure dependence during system design and operation phases.

- Develop a system reliability analysis model for complex systems with multi-state components considering overloads. The cascading process is examined with its stop scenarios and influencing factors. It is expected to present insights to optimize the design and maintenance of complex loading dependent systems with overloads.

- Establish a general maintenance model for complex systems subject to failure

dependences. Impacts of heterogeneous failure dependences on component degradation within the subsea system are explored by this model, with the aim of optimizing maintenance strategies to improve the system availability.

- Propose an integrated framework to conduct sustainability evaluation for complex systems subject to failure dependence. This framework is capable of thoroughly examining the coupling effect of component degradation, failure dependence and maintenance management on the sustainability. It concerns the sustainability evaluation of complex subsea systems from environmental, social, and economic perspectives. Thus, it provides guidelines for long-term and sustainable optimization of maintenance strategies.

From an academic standpoint, this thesis proposes approaches and models to assess the effects of failure dependences. The suggested approaches and models reveal the degradation patterns of components subjected to failure dependence and the development mechanisms of cascade processes. From the practical viewpoint, this thesis serves as a reminder to designers, operators, and safety personnels regarding the significance of acknowledging failure dependences in complex multi-component systems. Furthermore, it offers implications to minimize the failure dependence during the system design stage or implement effective measures to mitigate such dependences during system operation and maintenance stage.

To conclude, this thesis provides a comprehensive overview of failure dependence issues in complex multi-component systems, as well as contributes to the reliability analysis, maintenance management and sustainability evaluation of the subsea systems subjected to failure dependences.

Contents

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Acronyms and abbreviations

BN	Bayesian network
CAF	Cascading failure
CBM	Condition-based maintenance
CM	Corrective maintenance
CPT	Conditional probability tables
CTMC	Continuous-time Markovian chain
DBN	Dynamic Bayesian network
DM	Decoupling Maintenance activities
DMDM	Degradation model for dependent multi-component system
DRI	Degradation rate interaction
FD	Failure dependence model
FDM	Failure Dependence Mitigation Maintenance
FE	Finite element
FSD	Failure sequence diagram
FFTA	Fuzzy fault tree analysis
FTA	Fault tree analysis
HCM	Hierarchical Component Model
IMRs	Inspections, maintenances and repairs
LCSA	life-cycle sustainability assessment
MLEs	Maximum likelihood estimates
MTP	Department of Mechanical and Industrial Engineering
NM	No Maintenance activities
NTNU	Norwegian University of Science and Technology
OREDA	Offshore and Onshore Reliability Data
OSS	Overall sustainability score
PDF	probability density function
Ph.D.	Philosophy Doctor
PdM	Predictive maintenance
PM	Preventive maintenance

RAMS	Reliability, Availability, Maintainability and Safety
RO	Research objective
SDG	Sustainable Development Goal
WCED	World Commission on Environment and Development
3D	Three-dimensional

Part I

Main Report

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Chapter 1

1. Introduction

1.1 Background

The complexity of technical systems is increasing, primarily attributed to the growing integration of technologies and components. These complex systems normally comprise many components with varying degrees of interactions and dependences. Such systems can be observed in various industrial contexts, encompassing but not limited to, processing systems [1, 2], chemical clusters [3, 4], transportation systems [5-7], power grids networks [8-13]. In the complex system, when one component fails resulting from a root cause, and then the failure propagates to cause failures in other components, it is termed as a cascading failure (CAF) [14]. Previous accidents [15-17] have indicated that CAFs could cause extensive damages to complex systems and even the environment and the society.

The failure dependence is the primary cause that may easily trigger CAFs and negatively impact the system performance. The CAFs occur when failure dependences exist in such complex systems. Nevertheless, failure dependence may not only lead to a complete failure or manifest as an immediate failure in some cases, but also result in a gradual degradation of the components [2, 18, 19], which may also evolve into failures finally. Therefore, the failure dependence identifies the root cause both for an exact CAF and for a potential CAF. To better address all the CAFs issues that cause negatively impacts on the system performance, this thesis focuses on failure dependence effects of the complex system.

The subsea system is a typical complex system, consisting of a network of interconnected components operating in underwater environments, each component playing a crucial role in the operation of the entire system. In contrast to land-based systems, subsea components face not only mechanical wear and tear but also exposure to hostile conditions like corrosive elements, high pressures, and extreme temperatures [20, 21], which places higher requirements on the system performance. However, the components in the subsea systems are gradually logically or physically interdependent, and are susceptible to failure dependence, which amplifies the operational risks of the system should CAFs occur. Once CAFs occurs, the system could be significantly impacted from the aspect of reliability, and even cause hostile ecological and environmental impact [22] to the sea. Understanding and effectively managing failure dependence in complex subsea systems is thus vital for enhancing the performance of these systems.

System performance analysis encompasses various critical aspects such as reliability analysis, maintenance management, and sustainability evaluation. Each aspect plays an essential role in ensuring the inherent functionality of the system and its long-term relationship with surroundings.

Reliability analysis serves undoubtedly as a cornerstone in the evaluation of system performance, providing quantitative insights to the performance and efficiency of engineering systems [5, 23-26]. In the context of subsea systems, reliability analysis serves as a powerful tool to assess the failure probabilities [27, 28]. Maintenance management is crucial for preserving and optimizing system performance, ensuring that the system operates at peak efficiency throughout its lifecycle [25]. Specifically, maintenance is necessary to improve system reliability, availability, and productivity [29]. Effective maintenance practices contribute significantly to minimizing downtime and maximizing operational longevity. While reliability analysis and maintenance management focus on the technical aspects of system performance, the sustainability evaluation of the system reveals its performance in aligning with surrounding environments during long period [30]. In the engineering context, sustainability refers to the ability of a system to function efficiently while minimizing negative impacts on the environment and society over its entire lifecycle. The integration of sustainability evaluation into the analysis framework becomes imperative, considering the global push towards environmentally and socially responsible practices. Sustainability in the context of complex subsea systems involves not only operational efficiency but also environmental impact, safety, and economy.

Achieving an optimal balance between performance of the subsea system and its sustainable relationship with surroundings requires a holistic understanding of the natural degradation of components, the complex failure dependence among them and their maintenance activities. However, there are still challenges currently for the examination of system reliability considering failure dependences. Besides, the effect of failure dependence has not been well studied neither in the maintenance management of the complex system nor in its relationship with the surroundings. For example, the critical concepts related to failure dependence in complex systems are not clearly clarified and thoroughly explored. Further, the overloading components often receive less attention compared to failed components, even though overloading components can also significantly influence system performance. Another underestimated yet crucial concern is that failure dependences are often multiple and heterogeneous. In addition, there is a lack of comprehensive examination of the system performance from the aspect of inherent system performance and the aspect of its relationship with surrounding environments and society.

In the subsequent sections of this paper, we will delve into the theoretical basis of failure dependence, explore existing methodologies, and propose innovative frameworks that addresses the challenges posed by failure dependence in the complex systems. The research utilizes subsea complex systems as case studies to enhance the integration of theoretical methodologies with practical applications. The studies are expected to address the critical need for an integrated approach to system performance analysis in complex systems, considering the reliability, maintenance management, and sustainability evaluations in the context of failure dependence. Through this multidimensional lens, we aim to contribute valuable insights that will inform the design, operation, and maintenance of complex systems, fostering a more reliable and sustainable future for subsea industries.

1.2 Objectives

The overall Research Objective (RO) of this Ph.D. thesis is to *develop models for the system performance analysis of complex systems with failure dependence*. The proposed models and methodologies in this study are expected to place particular emphasis on examining the effects of failure dependence on the system performance of complex systems. The research is decomposed into four main specific research objectives as below.

1. **Research Objective 1 (RO1):** Elucidate the definitions of terminologies related to failure dependence and clarify delimitations for various types of failure dependence.

2. **Research Objective 2 (RO2):** Develop a system reliability analysis model for complex systems with multi-state components considering overloads.
3. **Research Objective 3 (RO3):** Establish a general maintenance model for complex systems subject to failure dependences.
4. **Research Objective 4 (RO4):** Propose an integrated framework to conduct sustainability evaluation for complex systems subject to failure dependence.

1.3 Scope and delimitations

The thesis is driven by the aspiration to enhance the fundamental understanding of failure dependences and their influence on the system performance improvement of the complex systems. The methods and models presented in this thesis are tailored for complex systems and validated by the application in complex subsea systems, yet their applicability extends to other complex systems characterized by failure dependences. The system performance is thoroughly examined from aspects of reliability analysis, maintenance management, and sustainability evaluation. The results of the thesis are promising in the practical application, encompassing both qualitative and quantitative aspects.

The following delimitations apply:

- The complexity methodologies to study the complex systems are considered out of the scope.
- Other types of dependences such as structural dependence, economic dependences, and resource dependences within the complex systems are not covered.
- The proposed models are useful to analyze the fundamental complex systems with failure dependences, but we must realize that they are not sufficient for huge and extreme complex systems.
- Discussion of the reliability and credibility of purely software programs falls beyond the purview.

1.4 Structure of the thesis

This doctoral thesis consists of two parts: Part I is the main report, and Part II contains a collection of articles that provides a basis for this thesis.

Part I presents the objectives, scope, theoretical background, methodologies, main contributions, and conclusions of the research. The Part I is structured as follows:

- Chapter 1 introduces the topic of the thesis and presents the limitations.
- Chapter 2 covers the theoretical background of the research.
- Chapter 3 summarizes the main research questions and objectives of the thesis.
- Chapter 4 elaborates the research methodology and overall work process.
- Chapter 5 presents the main results and contributions.
- Chapter 6 concludes the research and suggests further works.
- References are in the last section of Part I.

Part II includes one research article published in an international conference and four research articles that have been published in international journals. The articles are listed in Table 1.

Table 1 List of articles in part II

No.	Type	Article	Reference
Article I	Conference	Zhao, Yixin; Liu, Yiliu. Condition-based maintenance for systems with dependencies: A review on related concepted, challenges and opportunities. *Proceedings of the 31st European Safety and Reliability Conference* (ESREL), Sep 19-23, 2021, Angers, France.	[31]
Article II	Journal	Zhao, Yixin; Cai, Baoping; Kang, Henry Hooi-Siang; Liu, Yiliu. Cascading failure analysis of multistate loading dependent systems with application in an overloading piping network. *Reliability Engineering & System Safety* (2023); Volume 231. 109007.	[14]
Article III	Journal	Zhao, Yixin; Sun, Tianqi; Liu, Yiliu. Reliability analysis of a loading dependent system with cascading failures considering overloads. *Quality and Reliability Engineering International* (2023).	[32]
Article IV	Journal	Zhao, Yixin; Cozzani, Valerio; Sun, Tianqi; Vatn, Jørn; Liu, Yiliu. Condition-based maintenance for a multi-component system subject to heterogeneous failure dependences. *Reliability Engineering & System Safety* (2023); Volume 239. 109483.	[2]
Article V	Journal	Zhao, Yixin; Cai, Baoping; Zeng, Tao; He, Zhengbing; Liu, Yiliu. Sustainability evaluation of multi-component subsea systems considering failure dependence and maintenance activities. *Ocean Engineering, 2024.*	[33]

Chapter 2

2 Theoretical background

The motivation of the theoretical background chapter is twofold. On one side, it aims to extract the research questions and reveals the challenges by a systematic review of the state of related field. On the other side, it intends to lay a foundation for selecting methodologies and approaches to address the research questions and challenges.

This chapter starts with a general review of definitions and current models of failure dependence. Followed by are the illustration and delimitation of the subsea system as an example of complex system with failure dependence. Then, it outlines the main perspectives that requires emphasis when examining system performance analysis of the complex system. The last part of this chapter states the summary.

2.1 Failure dependence

2.1.1 Failure dependence and cascading failures

Modern infrastructure systems typically exhibit complex interactions, interconnections, or interdependencies instead of existing in isolation, and these complex systems are thus prone to manifest the multiplicity, diversity, and interactivity [34]. In such complex system, a catastrophic situation may happen where a failure of one component can propagate, causing the failure of other components. This phenomenon is termed as a cascading failure in the reference [2, 14, 35, 36]. CAFs are recognized in the literature with various terms, each with a distinct emphasis, including induced failures [37-39], fault propagation [40, 41], propagated failure [23, 42], domino effect accidents [43, 44], and escalating scenarios [45]. But in general, they are all initiated by the deliberate activity carried out by a threat actor, or a random failure or event. CAF has been identified as one crucial cause contributing to the stability and reliability of numerous modern technical systems, such as subsea systems [1, 2], transportation systems [5-7], power grids networks [8-12], and other complex network systems [46-48]. Causes that can trigger CAFs include but not limited to behavioral and environmental factors [49], as depicted in Figure 1.

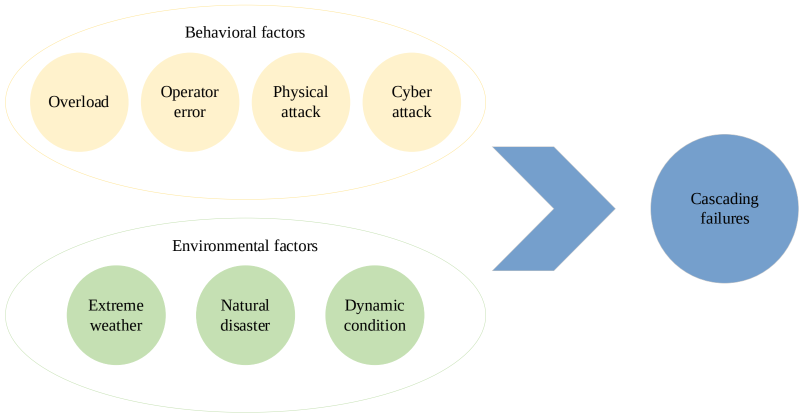


Figure 1 Causes of CAFs

The CAFs occur due to the structural or functional interactions of multiple components within complex systems. In complex systems where CAFs may occur among specific components, these components are referred to as dependent components or coupling components, and there exists failure dependence among them. Complex systems with high failure dependence are more susceptible to CAFs. In reverse, in complex systems where failure dependence exists, it is still plausible that CAFs might not occur. This is because that CAFs are the manifestation of the events while the failure dependence is inherent due to the interactions of components.

Nonetheless, CAF and failure dependence are still an inseparable pair of concepts related to complex systems, and understanding failure dependences is critical to predict the cascading process of the CAFs and identify the system failure modes.

2.1.2 Definition and classification of failure dependence

A notable finding in the literature is the absence of a universally accepted definition for failure dependence. The exploration of failure dependence could find its roots in the investigation of *failure interaction*. Murthy and Nguyen [37, 38] proposed the definition of failure interaction: failure interaction could be defined as the interaction between units where the failures of units can affect one or more of the remaining units. In addition, according to how components are affected by the failure interaction, the failure interactions are categorized into two types [50]:

- Induced failure: the failure of one component can trigger the simultaneous failure of other components with a given probability.
- Shock damage interaction: the failure of one component causes damage with a distribution to another component.

Later, this kind of classification is extended into three types [51]:

- Induced failure: the failure of one component can trigger the simultaneous failure of another component with a given probability.
- Failure rate interaction: the failure of one component can act as an interior shock to affect the failure rates of another component.
- Shock damage interaction: the failure of one component can cause a random amount of damage which could be accumulated and affect another component.

In addition, with emphasis on the failure mechanism dependent relationship, Chen et al. [52] proposed the concept *failure mechanism dependence* or *failure mechanism correlation*, and identified various failure process dependence effects for non-repairable system as shown in Figure 2.

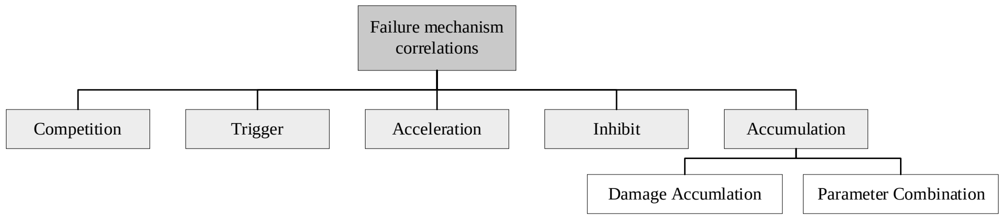


Figure 2 Classification of failure mechanism correlations [52]

Stochastic dependence is also a widely accepted concept to represent the dependence related with failures. Stochastic dependence applies when the deterioration process of one component is dependent on the state of one or more other components [53]. This type of dependence is classified into three ways:

- Failure-induced damage [50]: the failure of one component can trigger one-time damage to other components and cause an immediate degradation or failure of these components.
- Load sharing [14, 54]: multiple components in a system share the overall workload, so that if a component fails, the workload is automatically transferred to the remaining functional components and may cause degradation or failure of these components.
- Common-mode deterioration [55]: multiple components may experience simultaneous failure or deterioration due to similar working/environmental conditions.

Referring to the above definitions, failure interactions and failure mechanism correlation demonstrate dependence upon a complete failure of the component, while the stochastic dependence encompasses common-mode deterioration among components. In contrast to the preceding definitions, another type of dependence emerges that is not necessarily initiated by a component failure [18, 19] but rather centers more on the interactions among components due to degradation. This type of dependence is defined as *degradation interactions* [18, 19, 56, 57] and can be activated when the degradation behavior of a specific component can influence that of another component.

- Degradation state interactions [58, 59]: the degradation of a component triggers sudden state increment jump of the degradation process.
- Degradation rate interactions [19, 56, 57]: the degradation of a component triggers degradation rate acceleration of other components.

From the above discussion, many studies on failure dependence have been proposed to further understand the complex systems, with various definitions focusing on various aspects of the research issue. To summarize, common classification methods of failure dependence could be delineated in Figure 3.

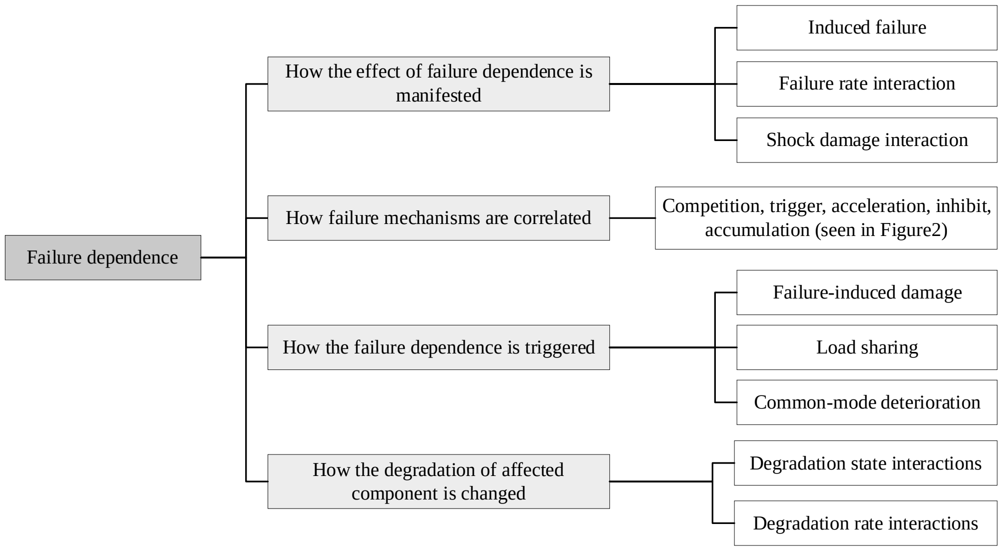


Figure 3 Classification of failure dependence

Subsequently, these terms gradually evolve into the term *failure dependence* [2, 60-62] to encompass the failure and degradation interactions more comprehensively and accurately. This shift can be attributed to the fact that the system dependences and internal interactions have been gradually spotlighted with the increasing system complexity. Dependence is characterized as the connection between two components, wherein change of one component may influence the other component. Within the complex multi-component systems, components exhibit varying types and degrees of dependences physically, logically, or economically [53]. Among them, failure dependence has been acknowledged as a critical category of dependence within the system because it directly affects the reliability, operational integrity, and overall system performance of the system.

As the name suggests, *failure dependence* signifies that the failures of the components are dependent. The scope of failure dependence in this context could be extensive. Firstly, concerning failure mechanisms, it encompasses failures resulting from shock or damage and those arising from loading dependence. Secondly, in terms of failure manifestation, failure dependence triggers alterations in the states or the failure rates of the affected components. Finally, from the perspective of failure consequences, failure dependence can lead to complete failures, as well as degradation or malfunctions that may develop into failures. In practice, the failure dependences are commonly not expected to be single among the above types, but rather multiple and heterogenous [2], which further complicates the investigation of failure dependence. In our research, the failure dependences are generally categorized as follows [2]:

- Type I failure dependence: The direct damage triggered from the initial failure can result in other failures. A component suffered type I failure dependence may fail due to the combined impact of its inherent degradation and the shock from failures in other components.
- Type II failure dependence: The working load is redistributed in the overall system and the load redistribution leads to other failures. A component suffered type II failure dependence may fail due to the combined impact of its inherent degradation and the accelerated degradation caused by failures in other components.

To exemplify two categories of failure dependence, consider a system composed of five components arranged in a mixed (series and parallel) structure, as depicted in Figure 4. If the component 1 fails, it could be considered as triggering component. For the consequence of type I failure dependence, a cascading effect exerts on the components 2 and 4, causing degradation or failures of components 2 and 4. Despite this, the system continues to operate as components 3 and 5 remain functional. However, the excessive workload of components 3 and 5 accelerates their degradation. Therefore, in this system, there exist type I failure dependence between component 1 and components 2 & 4, along with type II failure dependence between component 1 and components 3 & 5.

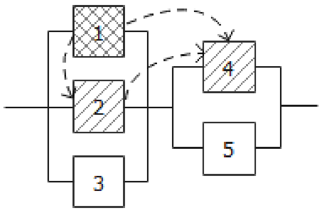


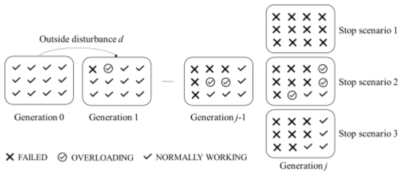
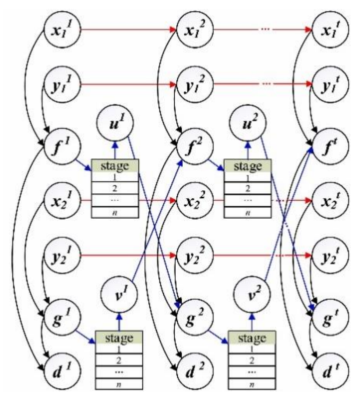
Figure 4 System structures with two types of failure dependence [31]

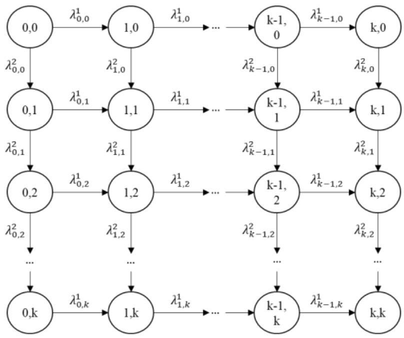
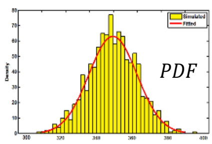
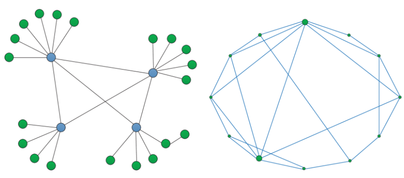
2.1.3 Models of failure dependence

Over the past decades, the failure dependence in complex systems have been extensively investigated and a widely range of models have been developed. The major contributions include, but not limited to shock damage model [37-39], Degradation rate interaction (DRI) model [19, 56, 57], CASCADE model [8, 9, 14, 24], Probabilistic models [63, 64], Bayesian networks (BN) [1, 4, 56, 65], Markov model [2, 13, 40, 66] Monto Carlo simulation [3], and Complex network model [67, 68]. These models above have their respective advantages and limitation. Comparisons of these models are performed and listed in Table 2.

Table 2 A comparison of the models for failure dependence

Model	Basics	Pros	Cons
Shock damage model	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
Degradation rate interaction (DRI) model	$S'_k = \Delta S_k$ S'_k: the degradation rate of component k 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

Model	Basics	Pros	Cons
CASCADE model	$$l_j = n_{f(j-1)} l_f + n_{o(j-1)} l_o$$  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
Probabilistic models	$$R_S = \sum P(F_i) \cdot P_r$$ R_S: system reliability $P(F_i)$: failure probability of component i P_r: cascading probability	• Easy for understanding and application	• Incapable of modeling maintenance or dynamic changes in complex systems • Inefficient for large-scale systems
Bayesian networks (BN)	 The blue line indicates failure dependence.	• Flexible • Efficient in computation • Applicable to specific types of distributions	• Difficult in acquiring sufficient data • Limitations of assumptions about conditional relationship between nodes

Model	Basics	Pros	Cons
Markov model	 $\lambda^i_{x_i,x_j} = \left(1 + D_{i,x_j}\right)\lambda_{x_i}$ $\lambda^i_{x_i,x_j}$: 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 D_{i,x_j}: failure dependence from component *j* on component *i* when component *j* is in state x_j λ_{x_i}: degradation rate of component *i* from state x_i to state $x_i + 1$ without failure dependence	• Flexible • Capable of integrating maintenance	• Inappropriate for large-scale systems
Monto Carlo simulation	 PDF: probability density function	• Suitable for large-scale systems	• Time-consuming • Susceptible to statistical errors during estimation
Complex network model	 (a) (b) The scale-free network (a) exhibits a power-law degree distribution, whereas the small-world network (b) is characterized by average short path lengths and high clustering coefficients.	• The topology of complex networks can be regular or random • Effective mitigation strategies	• Incapable of representing component behavior and characteristics

2.2 Subsea systems as an example of complex technical system

2.2.1 Complex system

The introduction of systems engineering methodologies has increased interest in complex technical systems over the last decades. Nevertheless, a clear and unambiguous definition for a complex system remains elusive. Researchers across diverse fields endeavor to characterize complex system in diverse ways. Table 3 includes various commonly used definitions for the purpose of comparison.

From the definitions listed in Table 3, it is found that complex systems generally consist of numerous components and complex interconnections among the components. Such complex systems pose challenges in terms of description, comprehension, prediction, design, management, and maintenance. Aligned with the goals of this dissertation, the focus is directed towards exploring the interconnected characteristics of complex systems, specifically the type of failure dependence. Therefore, the complex system in this thesis could be defined as a system composed of multiple components with failure dependence. Alternatively, the failure or degradation of two or more components within complex systems interacts unexpectedly owing to interactions. The discussion will be elaborated upon in the subsequent sections.

Table 3 Definitions of the complex system

Authors	Definition	Year
Perrow [69]	Complex systems are certain technical systems exhibit high interactive complexity	1999, 2011
Bar-Yam [70]	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.	2002, 2014
Magee et al. [34]	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.	2004
Richardson [71]	A complex system consists of a large number of non-linearly interacting non-decomposable elements.	2005
Boccara [72]	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.	2010
Snyder et al. [73]	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.	2011
Ladyman et al. [74]	A complex system is a collection of numerous elements interacting in a disordered way, leading to robust organization and memory.	2012
Estrada [75]	Complex system is defined as the system where there exists a bidirectional non-separability between the identity of the whole and the identities of the parts.	2023

2.2.2 Overview of subsea systems

The subsea system is a typical complex system, consisting of a network of interconnected components operating in underwater environments. As technology advancements are progressively made, the growing need for deepwater exploration has heightened the complexity of subsea system and presented superior challenges for all the subsea operating parties. Figure 5 shows the layout of a subsea production system, primarily consisting of wells, Christmas tree, separators, pipelines, manifolds, compressor, pumps, etc. [76, 77].

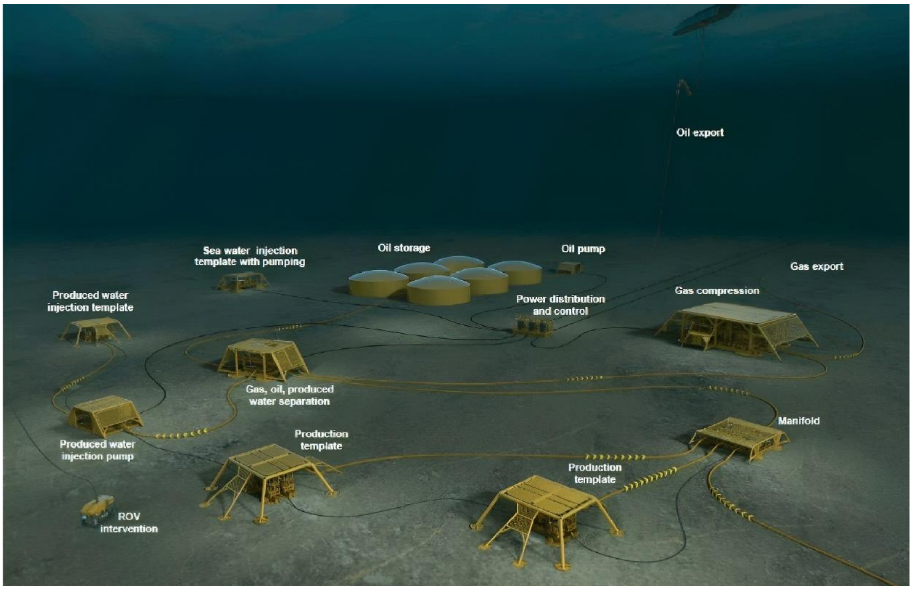


Figure 5 Example of subsea system [78]

Wells are the primary components for extracting oil and gas from the seabed or injecting the water back. Various types of wells are production wells and injection wells.

Subsea Christmas tree is installed on the wellhead of an oil or gas production well on the seabed. Key components of subsea Christmas tree contain pressure- and flow-control valves [79], connections for production and injection lines, chokes, tree cap, etc.

After the extraction of gas and oil, the separator is used to carry out the initial separation of well fluids into distinct phases. It is either a two-phase separator that separates gas and liquids or a three-phase separator that separates gas, oil, and water [76]. In some cases, a vertical scrubber may replace the separator vessel, primarily serving to capture liquid condensate during the dehydration process [80].

Multiple pipelines are used to transfer either produced or injected flows between the subsea completions and the subsea host facilities [79]. Following the separator outlet, several pipelines transport the separated substances to onshore or offshore facilities respectively.

The manifolds serve as distribution hubs from multiple wells, collecting, controlling, distributing, and directing the streams of oil and gas to appropriate destinations.

The compressor and pumps are utilized to transfer various substances. Compressors boost the pressure of the extracted gas and ensures that the gas reaches its destination in the topside. Oil pumps convey the separated oil to surface facilities in the topside for oil export, while the water containing sand are also transported through pumps for reinjection via the water injection or potential release into the sea.

Together, these devices form an integrated system that plays a crucial role in the offshore production industry.

2.2.3 Subsea pipeline networks

Subsea pipelines connect a set of the subsea facilities, and such interconnection, in turn, determines the pipeline networks and the system operation efficiency [81]. From the structural point of view, subsea pipelines may adopt either single wall pipe or pipe-in-pipe [21, 82, 83] configurations based on the specific application. From the boundary point of view, subsea networks schematically comprise reservoir pipelines (pre- and post-separation), injection pipelines, service pipelines (i.e. service for gas lift, chemical injection, monitoring, etc.) as well as hydraulic pipelines for actuated devices [79]. The boundary of subsea pipelines could be defined from a subsea production facility to a receiving facility, e.g. another subsea production facility or a topside production facility [84]. The boundary definition could be illustrated in Figure 6.

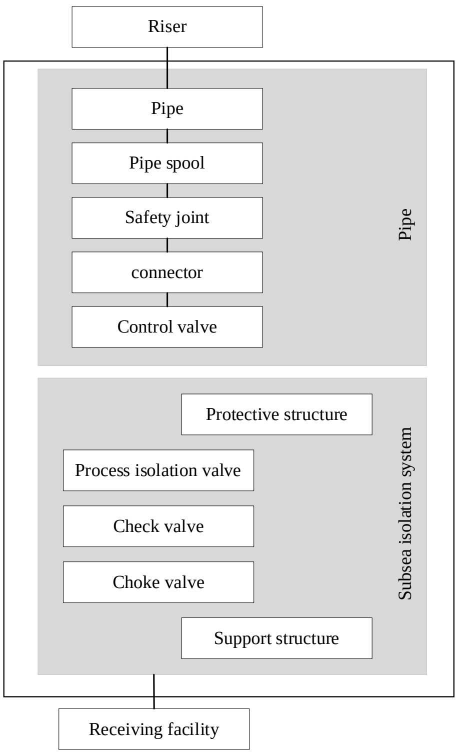


Figure 6 Boundary of the subsea pipelines [84]

Previous studies on subsea pipeline networks mainly focused on the layout optimization, structural instabilities, and safety analysis. The layout design of subsea pipeline networks determines the workload of installation and maintenance. Therefore, Wang et al. [85] proposed a mathematical model for the layout optimization of the pipelines and manifold. Besides, Hong et al. [81] developed an integrated optimization model for obtaining a minimum total pipeline length to optimize the layout design of subsea production system. In terms of structural instabilities, Gong et al. [86] conducted the experimental investigation and numerical simulation of the scenarios of buckles propagation for pipeline networks under the quasi-static steady-state circumstance. Liu et al. [87] compared the effects of various soil layers on dynamic response of the subsea pipelines, and established a dynamic finite element model. Azzam and Khalifa [88] identified the rupture, crack, fatigue, and burst of subsea oil pipelines and revealed their causes via experimental investigation.

Safety analysis include risk assessment and reliability assessment. Bayesian theory [80, 89, 90], fault tree analysis (FTA) [91], fuzzy fault tree analysis (FFTA) [77, 92], and risk matrix [93] are generally used to characterize the probabilistic pipelines failures along with risk assessment or reliability assessment. Moreover, other methodologies are also applied to conduct the safety analysis. To assess the leakage risk of subsea pipelines, an integrated risk-based assessment scheme was developed by Aljaroudi et al. [94] to predict the failures and the consequences via limit state approach. Shabani et al. [95] analyzed the reliability of free spanning subsea pipeline by Probability of Failure theory, which is calculated by First-Order Reliability method and Monte-Carlo sampling. To seek for the optimal production system, Silva and Soares [96] proposed a robust optimization model decision-makers to minimize the risk of the pipeline system. Given the above works, main failure modes of subsea pipelines involve leakages, ruptures, blockage, bursting, corrosion, fracture, fatigue, vibrations, buckling etc. In addition, Stefani and carr [97] summarized the most probable failure modes of offshore pipelines: mechanical damage, external or internal corrosion, construction defect and mechanical or material failure, and natural hazards.

2.2.4 Subsea transmission system

The subsea transmission system (compressor and pumps), separation devices, and associated electrical power distribution devices together comprise of the subsea processing system. A scheme of the subsea processing system is reported in Figure 7.

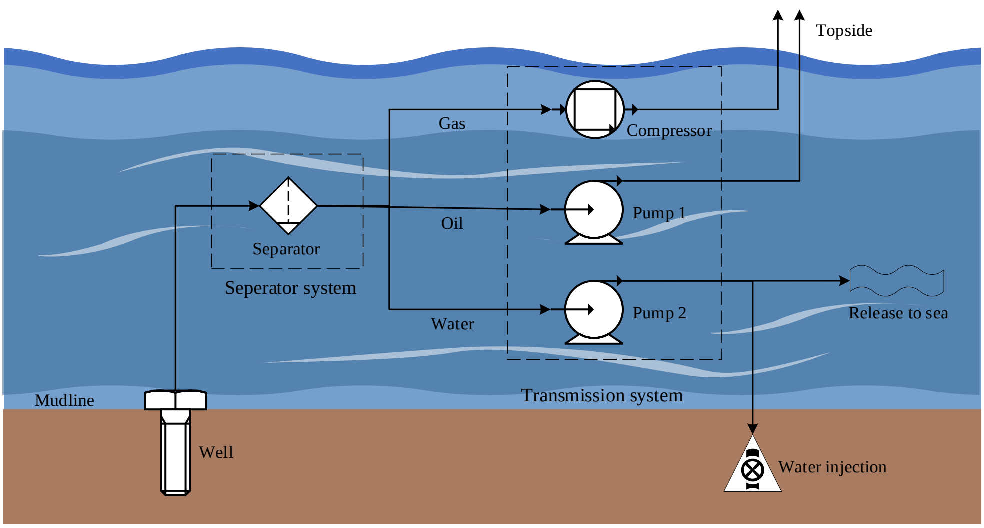


Figure 7 Scheme of subsea processing system (separator and transmission part) [33]

The subsea processing system is capable of gas-liquid separation, gas compression, pressure boosting, desanding, and water reinjection [79, 80]. A subsea separator is utilized for the initial separation of well stream into three distinct phases: gas, oil, and water. After the separator outlet, three pipelines transport the separated flows to a compressor and two pumps respectively, and then distribute the flows to distinct destinations.

The transmission devices within the subsea processing system, comprising the compressor and two pumps, can be regarded as an integrated and interrelated system abbreviated as the subsea transmission system. In the subsea processing system, the subsea transmission part is deployed mainly for treatment, transportation, and distribution of separated gas/liquid. In this general model of the subsea transmission system, a single compressor and two pumps operate in parallel. The gas is compressed by either the wet-gas compressor or dry-gas compressor, and then conveyed to the topside. In addition to the compressed gas, the separated oil is also transported directed topside by the pump. The separated water, on the other hand, is pumped either for possible release into the sea or for reinjection via the water injection system. The sand is transferred from the separator desander module and then mixed with the injected water to be deposited into a reservoir.

Such a system necessitates a reliable and stable system performance since any interruption during the operation stage results in prolonged production downtimes and financial losses. According to the OREDA handbook [84], failure modes of the subsea items could be given for each severity class, i.e., critical, degraded, incipient, and unknown. Meanwhile, this handbook also provides a concise overview of the distinct failure modes for the compressor and pumps, along with their corresponding failure rates, maintenance activities, and failure mechanism. The failure modes [84] for compressor and pumps in the subsea transmission system involve abnormal instrument reading, breakdown, erratic output, external leakage, internal leakage, fail to start on demand, fail to stop on demand, high output, low output, minor in-service problems, noise, overheating, parameter deviation, plugged/choked, spurious stop, structural deficiency, vibration, etc. Their corresponding failure mechanisms [84] could be blockage/plugged, breakage, burst, clearance/alignment failure, combined causes, contamination, control failure, corrosion, deformation, earth/isolation fault, electrical failure, external influence, faulty power/voltage, faulty signal/indication/alarm, instrument failure, leakage, looseness, material failure, mechanical failure, no signal/indication/alarm, open circuit, out of adjustment, overheating, short circuiting, software failure, sticking, vibration, wear, etc.

2.2.5 Failure dependence in subsea systems

In this subsea system, some components are structurally or functionally interconnected with each other, whose degradation and failures may influence others. There arises a growing focus in research on the failure dependence in subsea systems. Cai et al. [1] 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 is also explored by Shao et al. [56]. The subsea Christmas tree is a typical complex system with multiple components, multiple parallel relationships, and multiple working states. 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.

There also exist failure dependences within the subsea pipelines networks and the subsea transmission system mentioned in the last two subsections, as explained below:

Concerning subsea pipeline networks, loading dependence constitutes the primary form of failure dependence. If one of the pipelines is deformed or plugged, causing a reduction in flow, the pipeline will be not capable of operating as expected. The overall workloads of the system will therefore be redistributed to other pipelines via manifolds and valves. The additional workloads imposed on these pipelines expedite their degradation and could result in failures. Such failure dependence is identified as type II failure dependence.

In terms of the subsea transmission system, the compressor and pumps should operate at the desired power under ideal circumstances to transfer various substances. Nevertheless, these devices experience natural degradation, resulting in diverse failure modes, as discussed in the previous subsection. Some of these failures not only affect their individual operational efficiency but also contribute to the degradation of other devices in the system. For instance, if a compressor fails, some gas may be intermingled with liquid and enter the pumps, thus accelerating the degradation of pumps. Such failure dependence is influenced by the content of impurities present. Another case involves the vibration and overheating of one pump, which can directly impact the operation and degradation of another pump nearby. The nature of this failure dependence is related with the physical distance and the setup of safety barriers. Such failure dependence is identified as Type I failure dependence.

2.3 System performance analysis

2.3.1 The scope and basic concepts of system performance analysis

As the modern world continually advances into a complex and interconnected network of systems, enhancing the capacity to design such complex systems and improving the ability to sustain system performance becomes crucial. The system performance could be explored from three perspectives, as depicted in Figure 8.

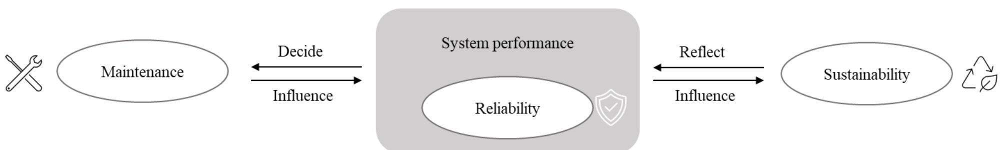


Figure 8 The relationship between system performance and related concepts

Reliability is the most important and widely adopted metric of system performance, which demonstrates the inherent system performance by design and manufacture. The system reliability, defined as the ability of a system to perform its intended function in a stated context over a specified period [25], stands out as the fundamental parameter that most accurately reflects the effectiveness, dependability, and stability of a system. Several manufacturers of technical systems have faced challenges and even collapsed due to flaws and failures. The key factors stimulating to enhanced reliability embraces safety issues, security issues, customer requirements, laws and regulations, environmental requirements, maintenance costs, warranty costs, market pressure, etc. [25] While reliability has shown improvement across almost all types of systems over the years, there is a growing expectation from customers for even higher reliability in new systems, especially the complex systems.

Maintenance management significantly impact the system performance during operation or after failures by planning and execution of maintenance activities. Conversely, the foundation of maintenance strategies should be grounded in the system performance. Maintenance management refers to the systematic process of planning, organizing, and controlling maintenance-related activities to ensure maximum efficiency of the system [98]. High maintainability improves the system reliability, but inappropriate maintenance policies or too much maintenance activities may also cause negative effects. Frequent maintenance activities, for instance, enhance system reliability while generating high costs and wasting resources. In addition, failure dependences may further complicate the maintenance policies [2]. Therefore, investigation to seek for the optimal maintenance policies is crucial for balancing the system performance, asset longevity, resource allocation, and cost efficiency within the complex systems.

Sustainability evaluation further broadens the spatial dimension beyond the system itself to incorporate its relationship with surroundings, as well as enhances the examination of the long-term system performance from a time dimension. Sustainability development aims to meet the needs of the present without compromising the ability of future generations to meet their own needs [99]. In the engineering context, sustainability refers to the ability of the system to maintain a long-term process continuously over time, considering the incorporation of environmental, social, and economic aspects [33]. Integrating sustainability into system performance analysis provides a comprehensive framework for decision-makers to navigate the failure dependence of complex systems.

2.3.2 Reliability analysis

Reliability describes the ability of a system to sustain its regular operation in a specific period without failures. System reliability analysis can offer important information to guide design, operation, and maintenance strategies. To analyze the system reliability, several models are proposed, which are basically based on two kinds of definitions:

- The structural reliability [100] is measured as the probability that the strength is greater than the load at a certain time or in a period, as shown in Figure 9.

$$R(t) = \Pr\big(Load(t) \leq Strength(t)\big)$$

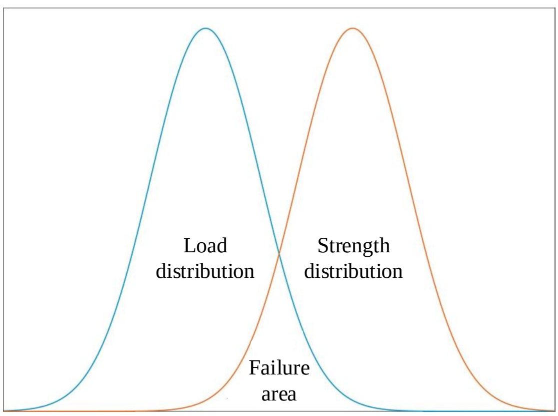


Figure 9 The load and the strength distributions

- The actuarial reliability [25] is measured with the occurrence probability of a failure in a period, no explicit modeling on load and strength.

For the complex systems, the reliability analysis is even more crucial to minimize the failure probability and downtime, as well as enhance the safety and improve product design. Over the recent years, there has been an uprising interest in the field of reliability analysis for complex systems. The related researches could be summarized in Table 4. It is worth noting that the investigations outlined in Table 4 may employ their own method to classify the failure dependence. However, in this context, the categorization of failure dependence solely relies on the methodology presented in this thesis, referring to subsection 2.1.2 for comprehensive details.

Table 4 Reliability analysis of complex systems with failure dependences

Authors	Brief description	Methods	Type of failure dependence
Xu et al. [101]	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. [18]	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. [102]	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 et al. [24]	Developed three CAF models of system reliability based on the normalized CASCADE model, by introducing the corresponding system reliability indices.	CASCADE model	Type II
Duan et al. [5]	Developed an innovative CAF model to investigate how route-choosing behavior influence the traffic network reliability.	Network topology	
Zhao et al. [103]	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. [104]	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. [105]	Introduced an analytical model for calculating reliability of consecutive k-out-of-n systems where the workload and shock load of failed components are redistributed.	Probabilistic model	
Che et al. [106]	Proposed an analytical reliability model for the load-sharing man-machine system,	Probabilistic model	

Authors	Brief description	Methods	Type of failure dependence
	incorporating the human errors with degradation processes and random shocks.		
Li et al. [107]	Derived the failure rate function for multi-units system with a dominate unit and numerous secondary units, as well as established the transient reliability of the system.	Markov model	Not identified
Kong et al. [59]	Proposed explicit forms of system reliability functions by employing factor analysis to characterize the degradation interactions.	Factor analysis	
Wang et al. [108]	Proposed a reliability assessment model of multi-state reconfiguration pipeline system considering failure interaction based on cloud inference.	Markov model	
Torrado et al. [109]	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	

According to Table 4, some researches [5, 24, 59, 101, 103, 104, 107-109] focus on the internal degradation of the components within the complex systems, while some other works [18, 24, 102, 105, 106] incorporate both the internal degradation and external shocks. Despite the diverse methodologies, the aforementioned contributions collectively underscore the significance of reliability analysis for a wide range of complex systems with failure dependence. This motivation has prompted us to examine the system performance by integrating a system reliability perspective.

2.3.3 Maintenance management

Widely adopted maintenance activities could be categorized into three classes as: *Corrective Maintenance (CM)*, *Preventive maintenance (PM)*, and *Predictive Maintenance (PdM)*. According to *EN 13306* [110], **CM** denotes tasks carried out as a result of a detected item failure or system failure to restore the item to a specified condition; **PM** is maintenance carried out to mitigate degradation and reduce the failure probability of an item; **PdM** is extended Condition-based maintenance (CBM) carried out following a forecast derived from repeated analysis or known characteristics and parameters evaluation of the degradation of the item. More detailed classification could be described in Figure 10.

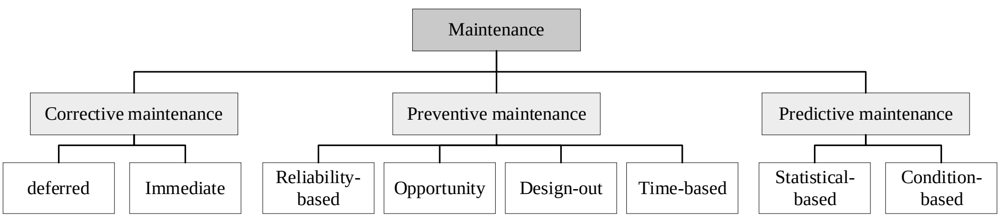


Figure 10 Classification of maintenance types [111]

For the complex systems, there exist various failure dependences, necessitating the maintenance activities to uphold optimal the system performance. Therefore there have been numerous contributions on the maintenance management of complex systems with failure dependences, as listed in Table 5.

Table 5 Maintenance management of complex systems with failure dependences

Authors	Brief description	Methods	Type of failure dependence
Satow and Osaki [50]	Studied a two-parameter maintenance policy for a two-component system where failures of component 1 follow a Poisson process and induces a stochastic amount of damage to component 2.	Stochastic model	Type I
Lai [51]	Developed an optimal periodical replacement policy for multi-unit systems subject to failure rate interaction by incorporating replacement costs and minimal repair.	Stochastic model	
Liang and Parlikad [112]	Established a modelling approach for 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 [19]	Presented a CBM optimization model for state-rate interactions components in the system using regression.	Regression	
Zhang et al. [113]	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. [114]	Proposed a CBM policy for systems subject to economic and stochastic dependence, incorporating a utility/reward function.	Stochastic model	
Zhao et al. [115]	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. [116]	Developed and extended Split System Approach for interactive failures and examine the impact of failure interactions on the intervals of preventive maintenance actions.	Extended Split System Approach	Not identified
Rasmekomen and Parlikad [117]	Presented a general approach to optimize the maintenance for multi-component systems with degradation interactions using General Path Degradation Modelling and regression techniques.	Regression	
Gao and Ge [118]	Presented periodical maintenance cost models for a two-state series system and a	Probabilistic model	

Authors	Brief description	Methods	Type of failure dependence
	three-state series system with failure interactions.		
Zhang et al. [119]	Developed two different shock models and three maintenance policies for a two-component system with failure interactions.	Virtual age method	
Zhang et al. [61]	Proposed a CBM model for two-unit system with failure dependence under imperfect inspection.	Stochastic model	
Rezaei et al. [120]	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. [2]	Developed a comprehensive framework to evaluate heterogeneous failure dependences and a CBM model for maintenance optimization.	Markov model	Both

According to Table 5, CBM stands out as one of the most extensively employed maintenance strategies Among all these maintenance activities, CBM is considered as a proactive approach preceding system failure and shows more cost-effective, compared to other traditional maintenance solutions [121]. Condition-based maintenance [110] is defined as preventive maintenance including assessment of physical conditions and possible ensuing maintenance actions. It can identify the current degradation and predict behavior patterns, and thereby determine optimal timing and approach for maintenance to fulfill the system performance while minimizing cost. Key steps of CBM are outlined as following and depicted in Figure 11.

1. Data acquisition, to collect data related to system.
2. Data processing, including data selection (data examination, data cleaning) and data analysis.
3. Maintenance decision making, to provide the optimal solution for system maintenance.

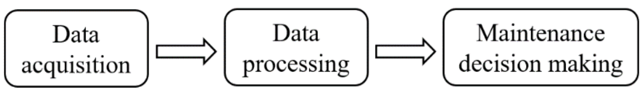


Figure 11 Three steps in CBM [122]

The studies mentioned above provide inspirations to examine the failure dependence when exploring reliability analysis and optimizing maintenance strategies. However, to the best of our knowledge, there are few papers that proposed the model to mitigate the failure dependence even though the components decoupling could show notable efficiency in preventing unexpected CAFs.

2.3.4 Sustainability evaluation

In 1972, Meadows et al. [123] claims that "it is possible to establish a condition of ecological and economic stability that is sustainable far into the future.", which could be regarded as the mark of the appearance of the term sustainability [124]. Later, the World Commission on Environment and Development (WCED) [99] clarified it as development that meets the needs of the present without compromising the ability of future generations to meet their own needs. This definition has been widely accepted in a broad point of view. In the usage across various fields, the sustainability centers around diverse aspects. Nevertheless, when referring to sustainability evaluation, three main pillars are generally examined involving environmental, economic, and social aspects [124]. Furthermore, the sustainability could be represented as the synergy among three pillars, such as social economic aspects (e.g., business ethics, fair trade), social environmental aspects (e.g., conversation policies, environmental justice), environmental economic aspects (e.g., energy efficiency, renewable fuels) [125].

In the engineering context, three pillars of sustainability are holistic enough to basically encompass the requirements needs of the system, as presented in Figure 12. Explanations for three pillars are listed below.

- Environmental sustainability: the ability to conduct activities that can protect and preserve the natural environment over time, ensuring the fulfillment of current needs without compromising the availability of resources for future generations.
- Economic sustainability: the ability to conduct activities with the goal of promoting long-term economic well-being and achieving a balance between economic growth, resource efficiency, social equity, and financial stability.
- Social sustainability: the ability to conduct activities that prioritize the well-being of individuals and communities, aiming at promoting equity, upholding human rights, ensuring access to education and health care, as well as fostering decent work.

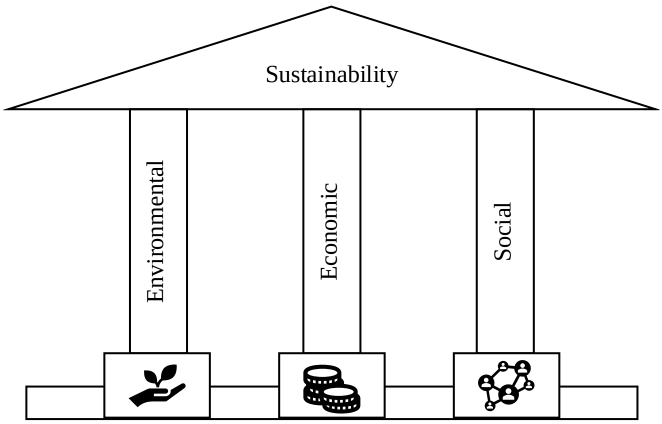


Figure 12 Three pillars of the sustainability

Considerable contributions have been made to models for estimating sustainability and strategies for enhancement [126-128]. In terms of specific research questions, some studies consider the sustainability evaluation not only during system operation, but also associated with the maintenance interventions. Nezami et. al. [129] presented a fuzzy framework that incorporates an effective sustainability program to provide appropriate decision-makings for maintenance strategies among a set of maintenance alternatives. Zheng et. al. [130] presented a comprehensive four-step structure for pavement life-cycle sustainability assessment (LCSA), including the maintenance phase. On the basis of above studies, some works focus on the assessment of the impact of maintenance activities themselves on the asset sustainability. Ghaleb et. al. [131] proposed an approach for quantifying and measuring the impact of maintenance activities on overall sustainability, which shows suitability being implemented in a sustainability dashboard (user interface). Saihi et. al. [132] established a fourth-order Hierarchical Component Model (HCM) to evaluate the sustainable performance of maintenance practices, and conduct a model validation through a survey of the Oil & Gas industry.

The trend of industrial engineering gradually expanding from land to ocean has also inspired more and more investigation [133-137] on the sustainability of the marine environments. Building on the frontiers of ocean science, Virto et al. [133] examined the framework for the most appropriate Sustainable Development Goal (SDG) 14 indicators and proposed the challenges and opportunities for future research. Kappenthuler et al. [134] developed a material selection framework to analyze the long-term potential of five common metal types in marine construction and provided the evaluation of their durability, economics, sustainability and future availability. Qiu et al. [135] developed a three-dimensional (3D) nonlinear finite element (FE) framework to systematically examine the time-dependent seismic resilience and sustainability of bridges under aggressive marine environments.

The above studies evaluated the sustainability of the system from different aspects, but they do not investigate the phenomenon of failure dependence even though the complex systems are more vulnerable and riskier. Particularly, for some complex systems, the coupling impact of components degradation, failure dependences and the maintenance activities on sustainability is complicated, and how to construct a comprehensive model to evaluate the overall sustainability of the system is still a challenging issue.

2.4 Summary

In summary, this chapter clarifies the basic concepts, classifications, and concluded various models of failure dependences in complex systems. Furthermore, an overview is provided on the configuration and functions of subsea systems, exemplifying as a typical complex system. Key parts prone to failure dependence in subsea systems, including pipeline networks and subsea transmission systems, are also outlined. Subsequently, an exploration is conducted into research scrutinizing the influence of failure dependence on the system performance of complex systems, encompassing aspects such as reliability, maintenance management, sustainability, and more, etc. These contributions are inspiring both in quantitative and qualitative analysis.

However, the research in failure dependence in the complex systems is still encountering some limitations which is worthy investigating. Detailed explanations about the research limitations and gaps are provided in subsection 3.1, and inspirations from the current contributions for our research objectives are presented in subsection 3.2. To solve the research problems, section 4 offered the explanation of solution tools regarding the research gaps.

Chapter 3

3 Research questions and objectives

3.1 Research questions

The examination of theoretical background in Chapter 2 underscores the significance of failure dependence in complex systems, which has received increasing attention in recent years. Nevertheless, there remains certain research questions concerning the failure dependence issues and its influence on the system performance, which are outlined in this section.

3.1.1 Failure dependence

Research gap 1: Comprehension of failure dependence

Numerous researchers have delved into the examination of CAF and failure dependence. As far as CAF and failure dependence are concerned, they are a pair of closely interrelated concepts. CAF emerges as a consequence of failure dependence. Failure dependence serves as a crucial prerequisite for the manifestation of CAF and constitutes the fundamental source influencing system performance, warranting primary attention. However, even though many researchers have studied failure dependence, their investigations generally concentrate on a specific aspect, presenting a somewhat one-sided perspective. Currently, there is no unified concept for failure dependence. In fact, the concept for failure dependence is quite broad, encompassing diverse failure causes, mechanisms, and characters, which stimulates a thorough definition.

Moreover, within a complex system, various failure dependence impacts system performance in varying manners. For example, a complete failure due to type I failure dependence may immediately lead to system shutdown, while some accelerated degradation due to type II failure dependence may only result in reduced system performance. To better understand the influence of failure dependence on the system performance, it is required to identify the way that failure dependence poses an effect, and to model the different types of failure dependence within the system.

To summarize, whether form a conceptual perspective or from a practical application perspective, it is imperative to furnish comprehensive definition and accurate classifications for failure dependence. This poses several research questions:

Q1: How to define and classify the failure dependence in complex systems?

Q2: What are the related concepts of failure dependence?

3.1.2 System performance

In general, the system performance can be reflected through reliability analysis, can be affected by maintenance management strategies, and can further include its sustainable relationship with the surroundings. Identifying the influencing factors of the failure dependence and exploring how they manifest their influence on system performance remains a challenge. The following detailed illustrations provide insights into this issue from three perspectives.

Research gap 2: Explorations into reliability analysis

The contributions outlined in subsection 2.3.2 collectively emphasize the importance of reliability analysis in a diverse array of complex systems characterized by failure dependence. Several models can be found in these works to explore the reliability of the complex systems. Certain methods have already reached a relatively mature stage, capable of simulating various states of components and diverse levels of failure dependences. Nonetheless, the CASCADE model, a commonly employed classic model for analyzing type II failure dependence in loading dependent systems, faces limitations in effectively simulating components in various states in the cascading process. An overlooked aspect is that overloading components may also accelerate the failure propagations in a manner similar to failed components. In practice, the failure dependence induced by overloading components is thought to influence state of other components. The reliability of the component and the system will be overestimated if such influence is neglected. Therefore, the CASCADE model is needed to be extended to analyze the performance of loading dependent system subjected to type II failure dependence affected by overloads.

The relevant research questions related to reliability analysis issues can be summarized as follows:

Q1: How to model the CAFs within loading dependent systems subject to type II failure dependence when considering overloads?

Q2: What factors related to failure dependence influence system reliability?

Research gap 3: Optimizations of maintenance

The studies mentioned in subsection 2.3.3 offer insights into investigating failure dependence while delving into optimizing maintenance strategies. It is found that the maintenance management for the complex systems are examined for both types of failure dependence. However, the majority of current approaches focus on either a two-component system or an n component system with identical failure dependence, deviating from the complexity and heterogeneity present in practical multi-component systems. Heterogeneous failure dependences occur in the situation where at least two types of non-identical failure dependence exist in a multi-component system. Consequently, there is a need for a general framework that can capture the diverse and heterogeneous failure dependences in the context of maintenance optimization.

On the other side, although there is an acknowledgment of the necessity to investigate failure dependence, the field lacks research that addresses maintenance measures aimed at mitigating failure dependence. As far as we are aware, there are scarce publications proposing models to mitigate the failure dependence among components despite the potential notable efficiency in preventing unexpected CAFs. Hence, there is also a necessity for proposing maintenance activities to mitigate the failure dependence and decouple the dependent components.

To summarize, the relevant questions regarding maintenance management include:

Q1: How to develop a maintenance model for complex systems with heterogeneous failure dependences?

Q2: How do the failure dependences influence the system availability and maintenance costs?

Q3: What maintenance activities could be adopted to mitigate the failure dependence?

Q4: What suggestions can be derived concerning maintenance management in complex systems with failure dependence?

Research gap 4: Research on sustainability evaluation

Sustainability assessment is an effective tool for understanding the long-term performance of a system and its long-term relationship with the surrounding environment and society. The studies presented in subsection 2.3.4 assessed the sustainability of varying systems from different perspectives. However, nearly none of them explored the phenomenon of failure dependence, despite the heightened risk and potential challenges to sustainability associated with complex systems subject to failure dependence. Consequently, there is a need to develop a sustainability evaluation framework tailored for complex systems with failure dependence.

Furthermore, there is a notable absence of research examining system sustainability while considering the coupling impacts of component degradation, failure dependencies, and maintenance activities. From a respective standpoint, it is undeniable that research concerning component degradation and failure dependence is inherently complex. Regarding maintenance activities, their complexity arises from their potential to influence sustainability directly or indirectly. For instance, maintenance activities impact the sustainability in two ways: indirectly improve the sustainability by enhancing system performance, or directly cause sustainability changes by carrying out activities. Consequently, constructing a comprehensive model to evaluate the overall sustainability of the system, considering the coupling impact of component degradation, failure dependencies, and maintenance activities, poses a more challenging issue.

Hence, there is a desire for investigation on sustainability issues in complex systems with failure dependence. Potential research questions could be summarized as follows:

Q1: How to construct a sustainability evaluation framework for a complex system with failure dependence?

Q2: How to incorporate the effect of degradation process and maintenances on the sustainability of the complex system?

Q3: What suggestions can be derived concerning sustainability issues of complex systems with failure dependence?

3.2 Research objectives

The overall objective of this Ph.D. thesis is to develop models for analyzing the system performance of complex systems with failure dependence. Driven by the overall objectives and the summarized research gaps in subsection 3.1, the specific research objectives are proposed as below.

Research question 1 concerning failure dependence identifies a research gap aligned with a specific research objective.

- RO1: Elucidate the definitions of terminologies related to failure dependence and clarify delimitations for various types of failure dependence.

Research question 2 regarding system performance reveals three distinct research gaps, each corresponding to a separate research objective.

- RO2: Develop a system reliability analysis model for complex systems with multi-state components considering overloads.
- RO3: Establish a general maintenance model for complex systems subject to failure dependences.
- RO4: Propose an integrated framework to conduct sustainability evaluation for complex systems subject to failure dependence.

The relationships between two research questions, four research gaps, and four research objectives are presented in Figure 13.

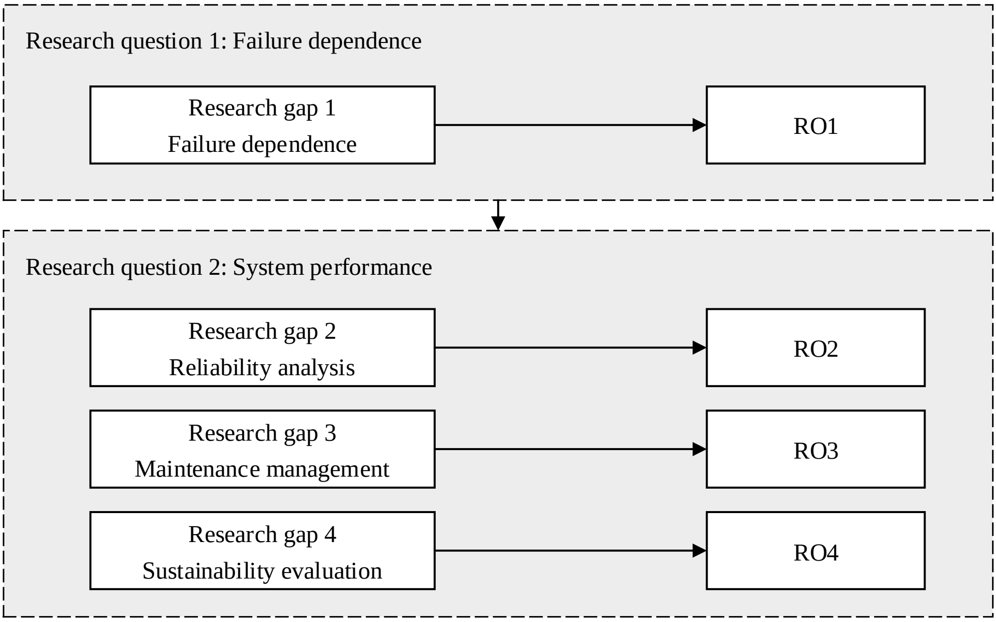


Figure 13 Relationships between research questions, research gaps, and research objectives

Chapter 4

4 Research approaches

4.1 Research methodology

Research is defined as the search for knowledge through objective and systematic method of finding solution to a problem [138]. Research consists of various academic activities and could be classified into a number of broad groupings. This section documents the research during the Ph.D. project from the perspective of methodologies.

Methodology is the philosophical evaluation of how knowledge and inquiry are framed within an academic discipline or school of thought [139]. Research methodology is a way to systematically solve the research problem [138], characterized as a structured and scientific approach to collect, analyze, and interpret quantitative or qualitative data to answer research questions or test hypotheses. According to studies by Kothari [138] and Zhang [140], the basic classifications of research methodology are summarized in Figure 14.

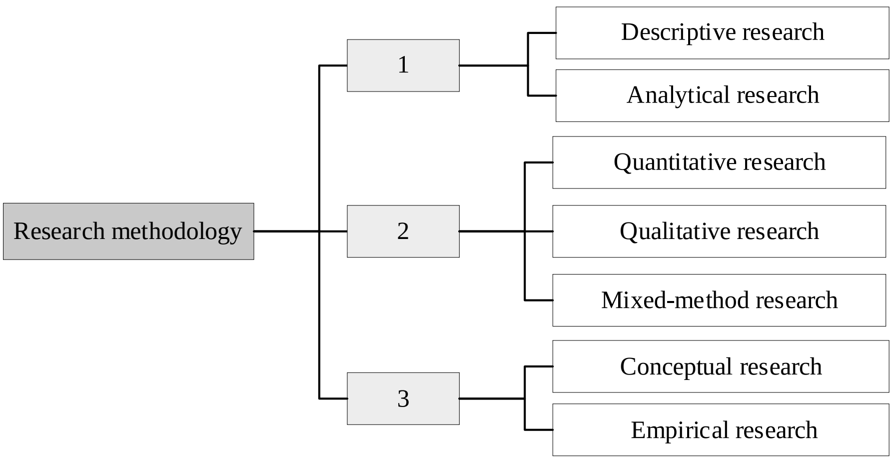


Figure 14 Classification of research methodology

Detailed explanations are as follows:

1. Descriptive research and Analytical research. Descriptive research includes different kinds of s surveys and fact-based enquiries, aiming at describing the current state of the affairs/components/systems. On the contrary, the analytical research requires the researchers to perform analysis based on the existing facts or information.

   This thesis is a mixture of descriptive and analytical research. For example, Article I describes the main contributions of some literatures. Article IV and Article V introduce the complex subsea transmission system and identify different types of failure dependence. The above works are completed by descriptive research. In addition, all the articles are analytical. Based on the contributions of literatures, research questions and potential challenges are extracted and proposed in Article I. The process of developing models and case studies in other articles are all analytical.

2. Quantitative research, Qualitative research, and Mixed-method research. Quantitative research is used to represent phenomena that can be expressed in terms of quantity or amount measurement. Qualitative research is concerned with phenomenon relating to or involving quality, aiming at underlying motives and desires. Mixed-method research uses the characteristics of both quantitative and qualitative research methodologies in the same study.

   In this thesis, Article I reviews and analyzes the literatures qualitatively. Based upon the qualitative results, the models and analyses are carried out in a quantitative manner. For instance, Article II and Article III use the probabilistic method to develop a multi-state CASCADE model and a reliability analysis mode; Article IV calculates the system availability and maintenance cost by Markov mode; Article V qualifies the impact of component degradation, failure dependence, and maintenance activities on the overall sustainability by dynamic Bayesian network (DBN).

3. Conceptual research and Empirical research. Conceptual research is generally conducted to develop new concepts when the existing ones require to be reinterpreted. Empirical research is data-based research, which is generally conducted based on experience or observation, often without due regard to theories.

   This thesis is mainly conceptual, with various concepts within the area of complex systems and reliability engineering in five articles. Aside from conceptual research, the experience of experts guides qualification of failure dependence in Article IV and contributes to the evaluation of sustainability in Article V. These research activities could be classified as empirical research.

This thesis starts from providing an overview of the current related contributions, followed by several analysis models to find solutions for the research questions. In general, there is a mixture of several types of research methodologies mentioned above in this thesis, which are illustrated in Figure 15.

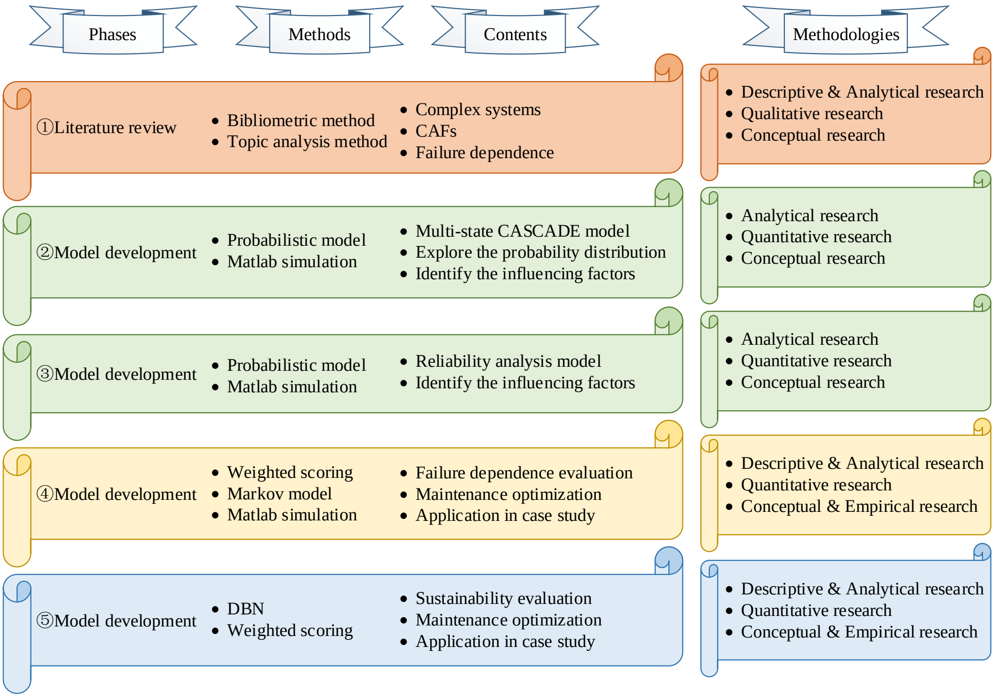


Figure 15 Overview of research methodologies in articles enclosed in this thesis

4.2 Overall process of work

The process of the Ph.D. project can be divided into four main phases, i.e., (1) foundation of Ph.D.; (2) literature review; (3) model development; and (4) finalize the thesis and defense. The respective results and specific research activities are depicted in Figure 16.

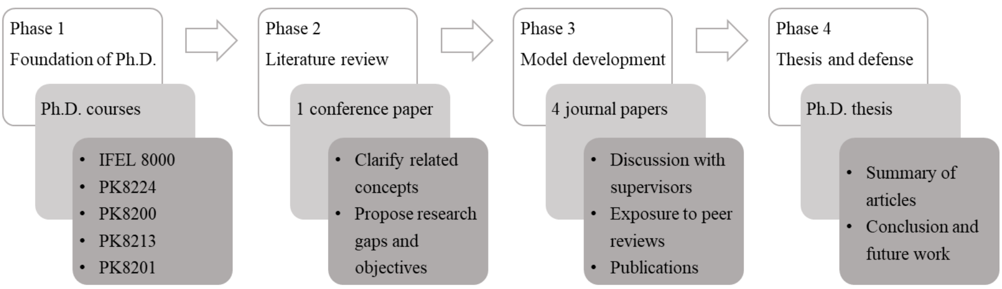


Figure 16 Overall process of the Ph.D. project

(1) **Foundation of Ph.D. project.** By taking fundamental PhD courses, a thorough insight on the theoretical foundation of reliability analysis and maintenance optimization is obtained. Acknowledged reliability analysis models and maintenance algorithms lay a solid theoretical foundation for further investigation. During this period, collaborative activities such as seminars and academic discussions among PhD candidates within the RAMS group played a crucial role in ideas inspiration and misunderstandings correction.

(2) **Literature review.** To fully understand the results of previous studies and comprehensively grasp the basic background related to the topic, literature review is conducted in the beginning. The literature review has been published as a conference paper. In this literature review, several key concepts in this field are clarified, and investigations of CBM implementation in the complex systems with dependences are reviewed. Based on the review, several research gaps and potential objectives are identified.

(3) **Model development.** One key part of this Ph.D. project is developing approaches and models to achieve the research objectives. To investigate the system performance of complex systems with failure dependence, reliability analysis model, maintenance optimization model and sustainability evaluation model are proposed. These models are constructed with the help and instructions of supervisors. Furthermore, the establishment procedures, application verification, and the significance of these models have been documented in articles that underwent expert review. These models addressing research questions provide the basis for the publication of research articles.

(4) **Thesis and defense.** The last phase of Ph.D. project is to finalize the thesis and prepare for doctoral defense. This is a process of highlighting the motivation, research questions, and research objectives of the Ph.D. project. Besides, it is also a process to reevaluate how the research results in Part II are interconnected by summarizing them through this thesis.

4.3 Quality assurance

In general, the research in the thesis underwent initial scrutiny through critical reviews from supervisors, co-authors, and colleagues within the relevant research domain.

Quality assurance was further ensured by the publications of the research in international journals. These publications underwent thorough peer review processes, with subsequent revisions based on valuable feedback and comments from reviewers.

Additionally, some research works were presented at seminars and international conferences, after evaluation for acceptance. Thus, the thesis benefited from insights gained in brainstorming seminars, which brought together individuals with diverse expertise in fields such as reliability engineering and maintenance optimization, contributing valuable input to the research results.

Chapter 5

5 Main results and contributions

5.1 Overview

This chapter presents the summary of main results of the Ph.D. thesis and contributions that are structured in the form of five articles. Among these articles, four have been published in relevant international journals, and another one has been published in the peer-reviewed international conference proceedings. These articles are organized to achieve the research objectives identified in Section 3. Their corresponding main topics are listed in Table 6.

- Regarding Research Objective 1, theoretical basis regarding system dependence, and classification of failure dependence are clarified. Specifically, Article I is a literature review that serves as basis for fundamental understanding of complex systems and system dependences; Article II categorized the CAFs into two types; and Article IV further explains the definitions and classifications of failure dependence.
- Concerning Research Objective 2, reliability analysis model of complex loading dependent system considering overloads is developed. In detail, Article II develops a multi-state CASCADE model to examine the probability distributions of CAFs, and Article III further explored the reliability analysis model based on the proposed model.
- With respect to Research Objective 3, Article IV proposed the CBM models of complex systems subject to heterogeneous failure dependences to optimize the maintenance policies; Article V discussed the effects of maintenances on the overall sustainability.
- For Research Objective 4, Article V constructed an integrated sustainability evaluation framework of complex systems considering failure dependence.

Table 6 Overview of the contributions and relevant Research Objectives

Research Objective	Main topic	Article
RO1	Theoretical basis regarding system dependence, and classification of failure dependence	Article I Article II Article IV
RO2	Reliability analysis of complex systems considering overloads	Article II Article III
RO3	Maintenance management of complex systems subject to failure dependences	Article IV Article V
RO4	Sustainability evaluation of complex systems considering failure dependence	Article V

Further elaborations on the contributions to each Research Objective are presented in the subsequent sections. The complete versions of articles are incorporated in Part II.

5.2 Main results

5.2.1 Article I

Topic

Condition-based Maintenance for Systems with Dependencies: Related Concepts, Challenges and Opportunities

Purpose and novelty

Many critical systems with dependencies do not collapse immediately due to single-point failures but are more vulnerable to the cascading effects of these failures. Condition-based maintenance has been found useful not only in improving availability of technical system but also in reducing the risks related to unexpected breakdowns, including those events related to dependencies, such as cascading failures. The serious disasters created by such failures and increased requirements for CBM policy due to dependencies urges a comprehensive study on current research and future challenges.

The main purpose of Article I is to review the literatures systematically related with the CBM implementations in the systems with dependencies. The novelty of the work lies in its examination of CBM implementation from three perspectives: the procedure of CBM, the types of system dependencies, and the expected benefits of CBM. Additionally, this work proposed potential research directions for the future implementation of CBM.

Methodology

The Bibliometric method is used in conjunction with Topic Analysis method to examine the CBM implementations in the systems with dependencies. Concerning the Bibliometric method, relevant papers are selected and analyzed via the VOSviewer program, to identify co-occurrences of keywords of CBM. As for Topic analysis method, literatures are organized based on topics to explain various issues related with CBM, including the CBM procedure, the definition and exploration of various system dependencies, and the expected benefits of CBM.

Results and discussion

Regarding the related concepts of CBM, a co-occurrences network is visualized based on related works in the last 30 years to present the occurrence frequency of keywords and their relationships, as shown in Figure 17. Followed by the definitions of key concepts according to the standard *EN 13306*.

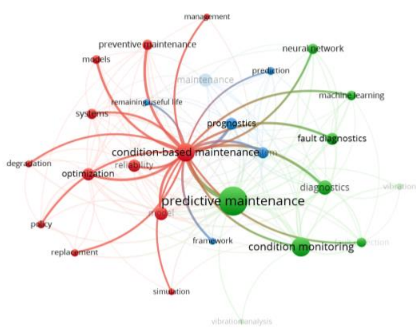


Figure 17 Co-occurrence of related concepts in CBM [31]

Besides, the CBM related papers literatures are organized based on three topics.

- Summarized according to the process of its implementation procedure: 1. Data acquisition; 2. Data processing; 3. Maintenance decision making.
- Reviewed according to the characteristics of systems subject to three types of dependencies: economic dependency, structural dependency, and evolution dependency.
- Examined according to expected benefits of CBM: improving productivity, cost minimization, and acceptable level of risk.

Drawing upon the research above, some recommendations are highlighted for CBM investigation. System dependencies and cascading failures triggered by that are supposed to be addressed in future. Also, a new, more comprehensive maintenance policy, Risk-informed Condition-based Maintenance, is introduced and requires further research.

5.2.2 Article II

Topic

Cascading failure analysis of multistate loading dependent systems with application in an overloading piping network

Purpose and novelty

Many production and safeguard systems consisting of multiple components are susceptible to the cascading failures, where one possibility is that the failure of a component leads to more workloads of other components. Such loading dependence can result in failure propagation, make the systems more vulnerable and decision-makings for maintenances more difficult.

The main purpose of Article II is to explore the cascading process and analyze the performance of loading dependent system subjected to CAFs affected by overloading components. The novelties of the work are 1) an extended multi-state CASCADE model is developed considering overloading component; 2) the situation that components degrade gradually are considered.

Methodology

To achieve the goal of investigating the cascading process in loading dependent systems with CAFs where the cascading process could be affected by overloading components, we developed a probabilistic model, multi-state CASCADE model, with the extended quasi-multinomial distribution. The mechanism for a cascading process to proceed is shown in Figure 18. An initial outside disturbance to all components triggers the initial event followed by cascading process. The algorithm for the multi-state CASCADE model refers to the flowchart of Figure 19, which also demonstrates how the cascading process proceeds until it stops. When the cascading process stops, there are three types of scenarios, denoted as stop scenarios.

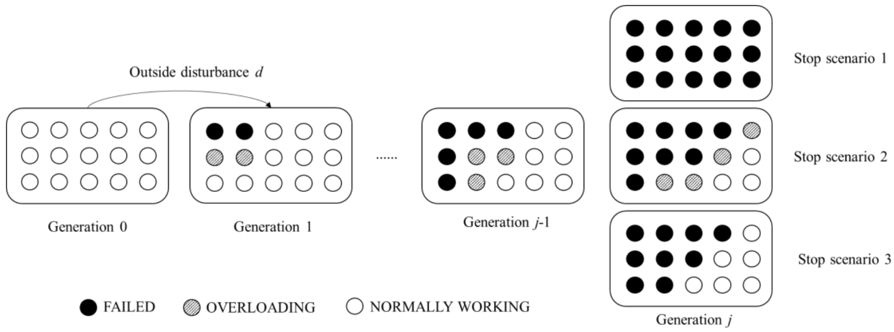


Figure 18 Failure cascading process and stop scenarios of multi-state CASCADE model [14]

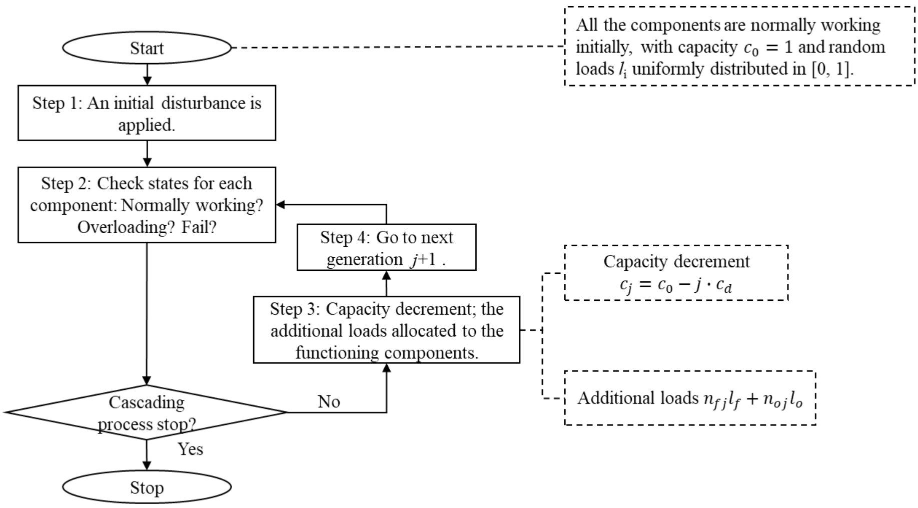


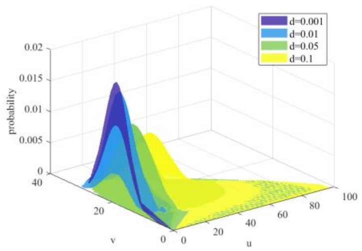
Figure 19 Algorithm of multi-state CASCADE Model [14]

Results and discussion

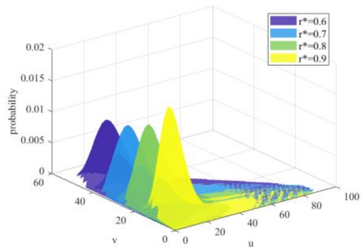
Firstly, a practical case in piping network is investigated to illustrate the analysis procedure, and to compare the effectiveness of the proposed model with those of the existing methods. The results of the practical case indicate that the performance of components and the system would be overestimated if the components degradation and the influence of overloading components are ignored.

In addition, numerical analyses are conducted to evaluate the factors influencing the probability distributions of total number of failed- and overloading components, as well as the occurrence frequencies of different stop scenarios. The numerical results are shown in Figure 20. According to Figure 20, the initial disturbance and loading increments affects the probability distributions. More failures may occur as the initial disturbance and loading increments increase, but the maximum values of probability distributions decrease. A novel finding is that the overloading threshold affects the probability distribution range of number of overloading components rather not the failed components.

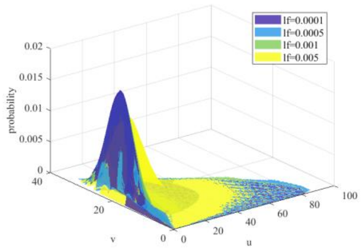
In conclusion, the proposed model can provide a more accurate characterization of the cascading process of the multistate loading dependent systems, and thus to help maintenance crew and managers to make more reasonable maintenance policies.



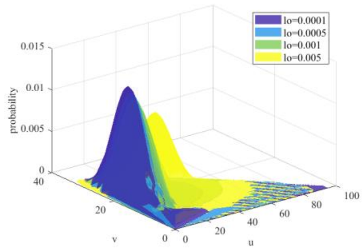
(a) Initial disturbance



(b) Overloading threshold



(c) Additional load from a failed component



(d) Additional load from an overloading component

Figure 20 Integration of probability distributions with different influencing factors [14]

5.2.3 Article III

Topic

Reliability analysis of a loading dependent system with cascading failures considering overloads

Purpose and novelty

In many production facilities, multiple components have to work together to share the overall workload on the entire system, leading to loading dependence and higher vulnerability to cascading failures. Additionally, overloading of one component can expedite the failures of others, exemplifying another form of loading dependence.

This article primarily aims at extending the multi-state CASCADE model and conducting system reliability analysis for loading dependent systems considering overloads based on the preceding work. The novelties of the work are 1) a system reliability analysis model is developed considering overloading component and components degradation; 2) the reliability of k-out-of-n systems are discussed.

Methodology

This article builds upon the previous work in Article II, characterizing the duration of each generation in the cascading process, along with the cumulative time of the whole cascading process by embedding a time variable to the multi-state CASCADE model. The new algorithm considering cascading time is shown in Figure 21. In step 3 of this algorithm, record the cascading time for every generation. Assume that the interval time of each generation in the cascading process follows an exponential distribution.

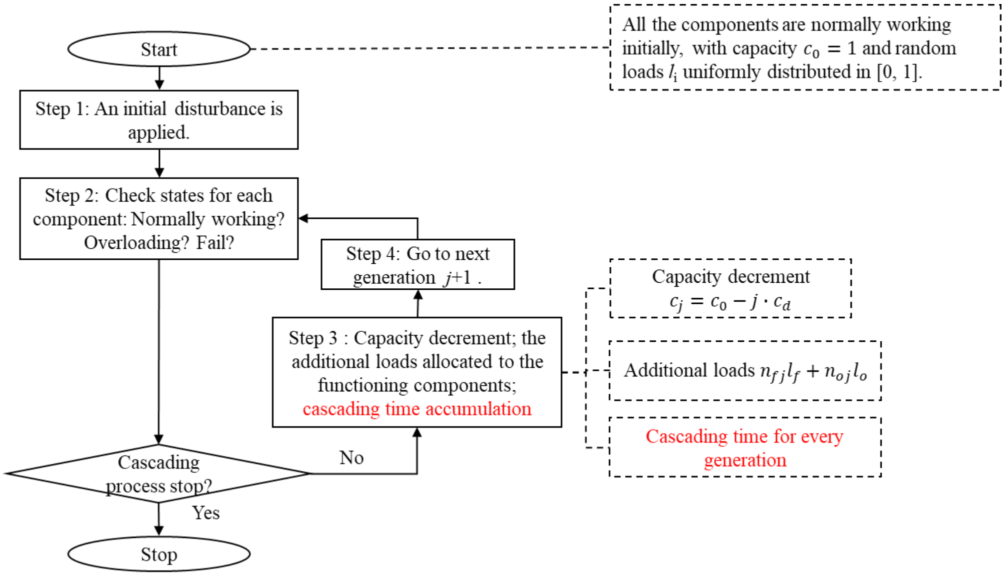


Figure 21 Algorithm of reliability analysis model based on multi-state CASCADE Model

The above algorithm could identify one stop scenario of the cascading process. Based on the multi-state CASCADE model, the probability of every stop scenario where the system fails in the *j*th generation could be obtained. Since the cascading process can evolve in various ways, there are several scenarios where the cascading process stops and the system fails in the *j*th generation. The overall system failure probability is accomplished by summing the probabilities of all the scenarios resulting in system failure in the *j*th generation.

Results and discussion

A new reliability index for evaluating the system reliability of a loading dependent system considering overloading state is proposed based on the multi-state CASCADE model. The numerical example is conducted to examine the system reliability model and demonstrate the impacts of different factors on the cascading process and the system reliability: Alterations in the initial disturbance, the total number of components, the cascading time distribution, and the parameter *k* in a k-out-of-n system all significantly influence both the system reliability and the duration of the cascading process. On the other hand, the variation of the loading increments only exhibits an influence on the system reliability when the cascading process approaches its end due to influence accumulation. Notably, neither the system reliability nor the duration of the cascading process remains unaffected by the overloading thresholds of the components.

These findings can help maintenance crews and managers make more informed decisions in terms of system design and operational management when considering cascade time and reliability.

5.2.4 Article IV

Topic

Condition-based maintenance for a multi-component system subject to heterogeneous failure dependences

Purpose and novelty

Many industrial facilities consisting of multiple components are prone to failure interactions and degradation interactions. In such systems, these interactions are frequently characterized by failure dependences that may accelerate the degradation of components. Due to system layout and functional interactions, not all components have the same failure dependence. In the general context of complex failure dependences in dependent multi-component systems, heterogeneous failure dependences further complicate the maintenance activities during operation.

Article IV aims to quantify the failure dependences and construct a general maintenance optimization framework with heterogeneous failure dependences. The novelties of this article are 1) a new framework to evaluate heterogeneous failure dependences is developed; 2) a general CBM model for systems with heterogeneous failure dependences is constructed.

Methodology

Figure 22 illustrates the main steps to develop the maintenance model considering heterogeneous failure dependence. In the present study, an independent general degradation model with a general degradation path is developed firstly to reflect the inherent independent degradation of components in a dependent system. This model serves as the foundation of the degradation model for dependent multi-component system (DMDM) when failure dependences are considered. When the degradation rates of the component are affected by other degrading or failed components, there exists failure dependence and should be evaluated to update the affected degradation rates. Based on the independent general degradation model and the failure dependence model, the DMDM is obtained. The degradation models and maintenance model are analyzed and integrated through Markov process. After integrating the degradation models with the maintenance model, the system availability is maximized, and the maintenance cost is minimized to seek for the optimal maintenance strategy.

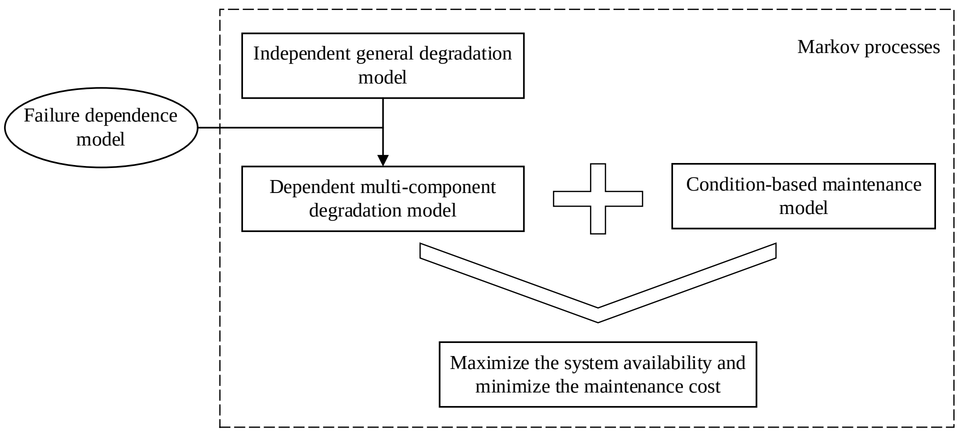
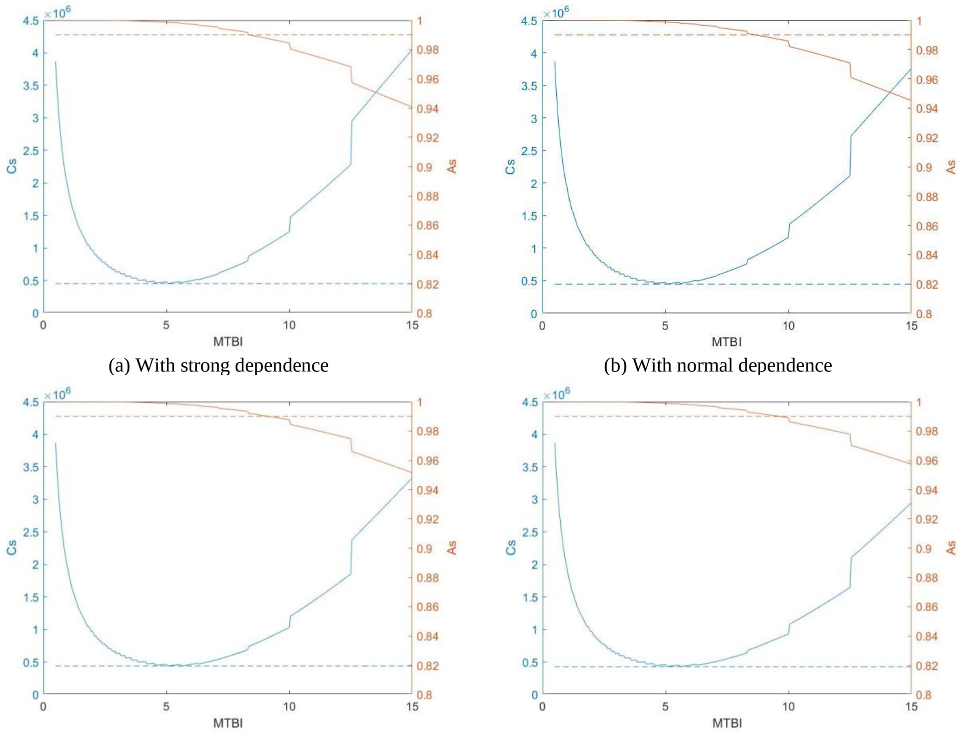


Figure 22 Framework of maintenance management considering failure dependence

Results and discussion

A case study case considering a parallel subsea transmission system is applied to illustrate the effects of heterogeneous failure dependences on the system availability and maintenance cost. Figure 23 shows the numerical results of the practical case that the availability of the system would be overestimated, and the annual inspections, maintenances and repairs (IMRs) costs would be underestimated if we neglect the influence of failure dependences. The work provides some references for the decision makers when the maintenance strategies should be implemented for a complex multi-component system with heterogeneous failure dependences.



(a) With strong dependence (b) With normal dependence

(c) With weak dependence (d) Without dependence

Figure 23 Availability and average life-time cost of the system with various dependence [2]

Notations: A_S -- The availability of the system; C_S -- The average life-time cost

5.2.5 Article V

Topic

Sustainability evaluation of multi-component subsea systems considering failure dependence and maintenance activities

Purpose and novelty

Technical systems operating in the subsea context are often with multiple components under complex failure dependences. Due to the hostile subsea environments, it is challenging to perform efficient maintenance for such systems to ensure their operational reliability while keeping the maintenance activities sustainably. A general approach has not been established yet for assessing impacts of failure dependences, effectiveness of maintenance activities, and sustainability.

The purpose of Article V is to propose a comprehensive framework to evaluate the system sustainability with consideration of failure dependence and maintenance activities. The novelties of this article are 1) models the maintenance activity that can decouple dependent components and mitigate failure dependence; 2) develops a comprehensive framework that enables engineers to conduct a thorough assessment of the overall sustainability of a complex system, considering the failure dependence and maintenances.

Methodology

Figure 24 illustrates the methodology to evaluate the system sustainability incorporating the failure dependences and maintenance activities. This integrated framework comprises three sub-models. Within this framework, the degradation model involves estimating the state of components and failure dependences among components using historical data and expert assessments. Furthermore, drawing from expert experience and maintenance records, it is possible to determine the traditional maintenance strategies and the formulation of a maintenance model. Finally, a universal sustainability model is employed to assess alterations in sustainability throughout the system operation and maintenances, enabling optimization of the decision-making scheme. Given that the research issue involves dynamics of a system, the DBN is selected to understand and handle the probabilistic events in complex systems.

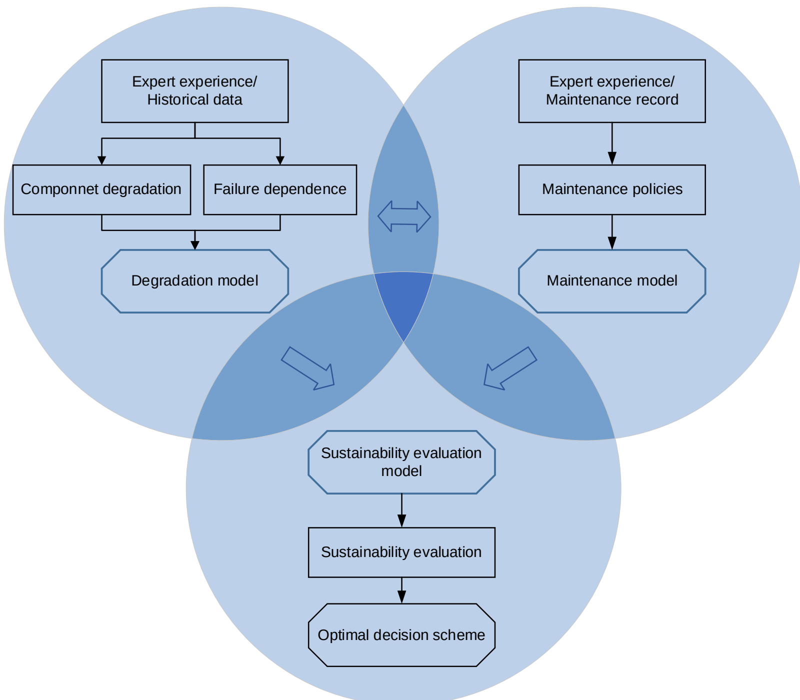


Figure 24 The integrated framework for sustainability evaluation

Results and discussion

Following the proposed framework, numerical analysis is conducted through a case study of subsea transmission system based on a DBN model. Figure 25 shows the overall DBN model with simple numerical results of the overall sustainability score (OSS) at time *t* and *t*+Δ*t*. In Figure 25, the failure dependence relationship linking the components are visualized by the red arcs. According to the established sustainability evaluation framework, the system sustainability can be confined within a range from -1 to 1. A lower value of the *OSS* closer to -1 signifies a lower degree of acceptance for the system sustainability, and a higher *OSS* indicates an increased level of acceptability for the system sustainability. Figure 25 suggests that, even after the application of maintenance activities, the overall sustainability still exhibits a declining trend in general over time activities because the maintenance activities themselves also cause certain damage to the sustainability.

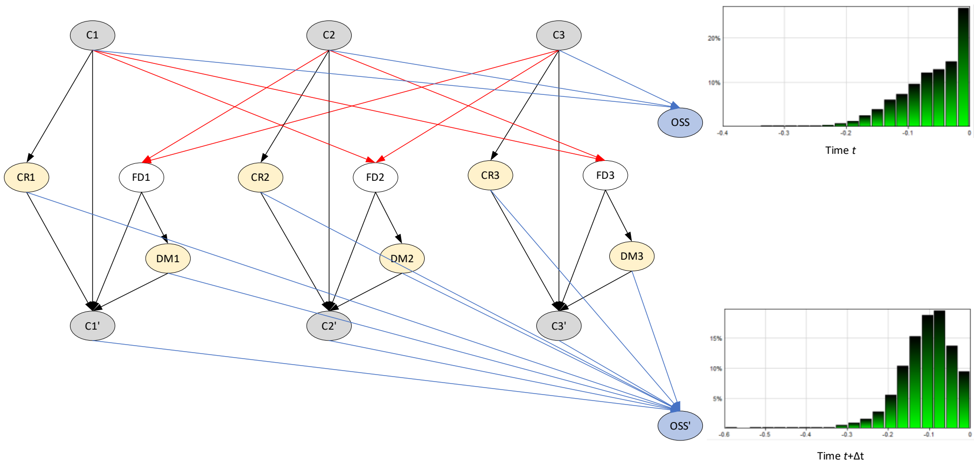


Figure 25 *OSS* evaluation model and results [33]

The mean value of OSS^* is selected to assess the impact of component degradation and various maintenance activities on the overall sustainability during the period. Figure 26 shows the mean values of the overall sustainability after delay period with six kinds of maintenance strategies. The maintenance strategies are varied by changing the conditional probability tables (CPTs) for various types of maintenance activities such as No Maintenance (NM) activities, Preventive Maintenance (PM) activities, Corrective Maintenance (CM) activities, and Decoupling Maintenance (DM) activities. The results show that the overall sustainability could be improved if the maintenance activities are implemented suitably according to specific cases.

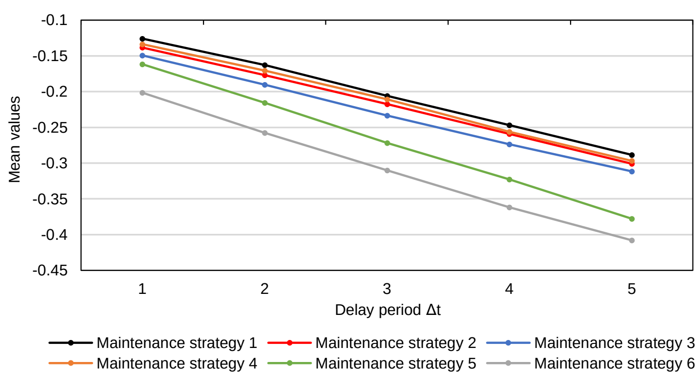


Figure 26 Mean values of OSS^* with various maintenance strategies

5.3 Main contributions

5.3.1 Contribution to Research Objective 1

The RO1 of this Ph.D. thesis is set to elucidate the definitions of terminologies related to failure dependence and clarify delimitations for various types of failure dependence. The contributions to RO1 are found in three articles:

Article I: Condition-based Maintenance for Systems with Dependencies: Related Concepts, Challenges and Opportunities

Article I introduces the definitions of terminologies related to maintenance of complex systems with dependences and highlighted the needs to explore the CAFs. This investigation provides potential directions to improve system performance and prevent CAFs by CBM.

Article II: Cascading failure analysis of multistate loading dependent systems with application in an overloading piping network

Article II categorizes the CAFs into two types. In this study, CAFs are classified as direct- and indirect- ones. The difference and similarities between two types of CAFs are listed in Table 7. A direct CAF occurs if the failure of a component or components directly induces damage to other ones or reduce their lifetime to some extent, while an indirect CAF often occurs due to loading dependence: The overall workload of the system is redistributed because some components exclude from normal operation. This work acts as a foundation for further classification of failure dependence in Article IV.

Table 7 Comparison between Direct and Indirect types of CAFs

Category		Direct	Indirect
Difference	Driving force	Sudden shock and damage	Loading dependence
	Effects on components in sequence	Failures or degradation	Failures, degradation or overloading components
Similarities	Trigger	One failure or failures	
	Stop condition	There are no more new failures	

Article IV: Condition-based maintenance for a multi-component system subject to heterogeneous failure dependences

Article IV clarifies the similarities and differences of two types of failure dependence: type I failure dependence exists in a context where a triggering event results in a direct damage, while type II failure dependence exists in a context where a triggering event redistributes the total working load on the overall system. This delimitation facilitates one to improve the overall understanding of complex systems, as well as the initiations and consequences of the failure dependence.

To summarize, the specific contributions concerning RO1 are listed as follows:

- Highlight the importance of considering system dependences and CAFs.
- Improve the overall understanding of complex systems, CAFs, and failure dependence.
- Clarify the definitions and classifications of CAFs and failure dependence.

5.3.2 Contribution to Research Objective 2

The RO2 is related to the reliability issues of complex systems with multi-state components considering overloads. The contributions to RO2include a reliability analysis model of a loading dependent system considering overloading state. The objective is achieved by two articles:

Article II: Cascading failure analysis of multistate loading dependent systems with application in an overloading piping network

Article II proposes a multi-state CASCADE model for analyzing the propagation process of failures in loading dependent systems considering overloading states and degradation of components. The multinomial distribution is applied to characterize the probabilities of numbers of failed-, overloading-, and working components, as shown in Equation (1). In addition, probability distributions of different stop scenarios of cascading process are derived, including the stop scenarios where the system fails, which lays the groundwork for the reliability analysis model of loading dependent systems. The contribution of this work lies in the investigation of CAFs in systems subject to type II failure dependence with involvement of overloading components and degradation of components. The studies could be extended to accomplish the reliability analysis model investigation.

$$P\left[X_1 = n_f, X_2 = n_o, X_3 = n_w\right] = C_n^{n_f} C_{n-n_f}^{n_o} p_f^{n_f} p_o^{n_o} p_w^{n_w} \tag{1}$$

Article III: Reliability analysis of a loading dependent system with cascading failures considering overloads

Article III develops a system reliability analysis model for loading dependent systems considering overloads based on the multi-state CASCADE model. By incorporating the interval time of each generation in the cascading process which follows an exponential distribution, as shown in Equation (2), the multi-state CASCADE model can be extended to characterize the duration of cascading process. A combination of analytical and simulation techniques is employed to investigate how various factors of failure dependence and cascading processes influence the system reliability. Such findings can improve the decision-makings of reliability prediction, system design, and maintenance optimization, especially in scenarios involving the CAFs triggered by type II failure dependence.

$$f_Y(t) = \mu e^{-\mu t} \tag{2}$$

To summarize, the specific contributions concerning RO2 are listed as follows:

- Propose a model to examine the cascading process of CAFs in loading dependent systems subject to type II failure dependence.
- Identify the probability distributions for evolving scenarios of the cascading process.
- Propose a model to analyze the reliability of the loading dependent system with CAFs subject to type II failure dependence.
- Evaluate the effects of variation of some influencing factors on system reliability.
- Highlight the overloading states and degradation of components in the models.
- Examine the proposed models in a practical case of piping network.
- Offer suggestions for engineers and maintenance crews from both a system design and managerial standpoint.

5.3.3 Contribution to Research Objective 3

The RO3 concerns maintenance issues of complex systems subject to failure dependences. This RO is addressed through Article IV and Article V.

Article IV: Condition-based maintenance for a multi-component system subject to heterogeneous failure dependences

Article IV develops a comprehensive framework for evaluating heterogeneous failure dependences and a maintenance optimization model by Markov processes for multi-component systems. In the proposed model, the degradation rate of the component changes when there is failure dependence, as denoted by the equation below. The degradation of components, the failure dependence, and the maintenance activities are all characterized and integrated in the Markov model. The proposed model demonstrates its effectiveness in managing the maintenance of complex multi-component systems, particularly those with heterogeneous failure dependences. By adopting the model, organizations can optimize the maintenance strategies by minimizing the maintenance costs while ensuring the system availability.

$$\lambda^{i}_{x_i,x_j} = \left(1 + D_{i,x_j}\right)\lambda_{x_i} \tag{3}$$

Article V: Sustainability evaluation of multi-component subsea systems considering failure dependence and maintenance activities

Article V develops a comprehensive framework for sustainability evaluation of the complex systems, considering the effect failure dependence and maintenances. In the proposed model, both the failure dependence and the maintenance activities to mitigate the failure dependence are considered. In addition, the impacts of maintenance activities on the sustainability are examined two distinct ways: 1) maintenance activities indirectly contribute to sustainability improvement by enhancing system performance; 2) maintenance activities themselves can directly result in sustainability changes. This study contributes to maintenance optimization of complex subsea systems for higher reliability and reasonable cost.

To summarize, the specific contributions concerning RO3 are listed as follows:

- Propose a framework to evaluate heterogeneous failure dependences.
- Present a generalized CBM model for complex systems with heterogeneous failure dependences.
- Discussed the effects of heterogeneous failure dependences on the system availability and maintenance costs.
- Verify the proposed models in practical cases of subsea transmission system.
- Delimitate and model a new type of maintenance, the Decoupling Maintenance (DM) activity, to eliminate the failure dependences among components.
- Explore the impact of various maintenance strategies on the overall sustainability of the system.
- Offer suggestions for engineers and maintenance crews from both a system design and managerial standpoint.

5.3.4 Contribution to Research Objective 4

The RO4 addresses the problem of proposing a sustainability evaluation framework for complex systems subject to failure dependence. This RO is achieved through Article V.

Article V: Sustainability evaluation of multi-component subsea systems considering failure dependence and maintenance activities

Article V develops an integrated framework using the Bayesian networks, which thoroughly examines the coupling effect of component degradation, failure dependence and maintenance management on the sustainability evaluation of the complex systems. The overall sustainability of the complex system is scored from three perspectives: Environmental, Economic, Social. The main steps to assess the sustainability are suggested in Table 8. This study contributes to sustainability evaluation of complex subsea systems, as well as provide valuable insights for decision-makers in seeking for sustainable maintenance practices.

Table 8 Suggested stepwise procedure of the sustainability

Step	Description
Step 1	System familiarization.
Step 2	Information acquisition and determination of nominal states of the components.
Step 3	Scoring the effects of the component performance on each sustainability indicator.
Step 4	Weighing the contribution of the sustainability indicators to the sustainability pillar.
Step 5	Determination of the importance of each sustainability pillar.
Step 6	Determination of the *OSS* by impacts of component performance.

To summarize, the specific contributions concerning RO4 are listed as follows:

- Provide an integrated framework, integrating the impact of component degradation, the failure dependences among components, and the maintenance activities on the overall sustainability.
- Explore the impact of various maintenance strategies on the overall sustainability of the system.
- Verify the proposed framework in a practical case of subsea transmission system.
- Provide managerial recommendations for maintenance crews.

Chapter 6

6 Conclusions and future work

6.1 Conclusions

The overall Research Objective of the Ph.D. thesis is to explore a comprehensive and efficient approach for the system performance analysis of complex systems, particularly focus on the effects of failure dependence. The overall Research Objective is structured into four specific objectives, which were addressed and elaborated through an international conference paper and four journal articles in Part II. The main conclusions are summarized as follows.

1. The differences and similarities between different types of failure dependences are clarified. This research may help the reader to increase the awareness of CAFs, improve the overall understanding of complex systems, and become familiar with the most adopted analytical models of failure dependence. Meanwhile, it is expected to serve as a reference for formulating measures to weaken failure dependence and prevent CAFs during system design, operation, and maintenance.
2. A multi-state CASCADE model is established to analyze the failure propagation process in loading dependent systems considering overloading state. The multinomial distribution is employed to characterize the probabilities of total numbers of failed components and overloading components. Besides, the probability distributions of various stop scenarios of cascading process are derived. Subsequently, MATLAB numerical analysis is executed to assess the influencing factors of the probability distributions, the occurrence of various stop scenarios, and the cumulative cascading time of the cascade process. The presented multi-state CASCADE model and reliability analysis model prove valuable for enhancing the design and maintenance of loading dependent systems.
3. A comprehensive framework for evaluating the heterogeneous failure dependences in multi-component systems is proposed, and a general CBM model to optimize the maintenance strategies of such system is developed by Markov model. Moreover, the numerical results are conduct and a case study consisting in a parallel subsea transmission system is examined to optimize the maintenance strategies. The findings demonstrate that the proposed framework and model are capable of optimizing maintenance strategies by maximizing system availability and minimizing maintenance costs.
4. An integrated framework is proposed to thoroughly examine the coupling effect of component degradation, failure dependence and maintenance management on the sustainability evaluation of the complex systems. The framework is examined based on a DBN model and applied in a case study of the subsea transmission system. Through the case study, the influence of failure dependences and the influence of maintenance strategies on the overall sustainability are illustrated. The research is expected to guide maintenance optimization of complex subsea systems for higher reliability and reasonable cost.

In summary, this paper significantly contributes to comprehension of the influence of failure dependence on the system performance of complex systems. The methodologies and models proposed in this study offer several advantages: 1) Provide accurate understanding of failure dependences and holistic analysis of system performance; 2) Furnish practical guidance for the design, operation, and maintenance of complex systems, aiming to enhance the overall system performance. While these contributions are noteworthy, there remain certain unresolved issues in this research that requires further exploration, which are stated in the following subsection.

6.2 Future work

This section introduces open questions and suggestions for future research in the realms of approaches and models, maintenance strategies, various dependences, and verification techniques.

6.2.1 Approaches and models

While the current model in this Ph.D. work adequately fulfills the fundamental requirements for evaluating the system performance of complex systems with failure dependences, there remains a necessity for further enhancement of the approaches and models. For example, simplification of the system in the models raises certain gap between research and reality. Some assumptions of the models exhibit certain restrictiveness, as systems in more complicated configurations have not been considered. Additionally, as systems become increasingly complex, the failure dependences between components experience exponential growth, stimulating the need for enhanced efficiency in the proposed models.

6.2.2 Maintenance strategies

This thesis focuses on the maintenance activities related to complex systems with failure dependences, and there are three potential aspects for further investigation. Firstly, the consideration of additional factors in maintenance activities is stimulated, encompassing aspects such as repair time, repair delay, inspection intervals, proof testing, test coverage, and test schedules etc. Secondly, it is worthwhile to discuss more detailed maintenance activities aimed at mitigating failure dependences and decoupling the dependent components. The discussion could involve exploration of the cost and efficiency associated with various decoupling maintenance activities. Additionally, comparisons with alternative maintenance models, such as Opportunistic Maintenance or Age-based Maintenance, could be conducted to identify optimal maintenance policies.

6.2.3 Various dependences

This thesis places a spotlight on sole type of failure dependence within the complex systems. However, a system could be subject to combinations of several types of dependences, and their effects on the system performance can be interacted. It is suggested to consider the combination of failure dependence and other types of dependences that exist within the system, such as structural dependence, economic dependences, resource dependences, etc.

6.2.4 Verification techniques

This Ph.D. thesis needs more verification, such as the incorporation of Monte Carlo simulations or empirical data. To enhance the credibility of the research, Monte Carlo simulations could be conducted to assess the robustness of the proposed models. Additionally, accurate modeling of system performance analysis hinges on the availability of high-quality data. This verification process can be facilitated by obtaining data from industries or conducting experiments tailored to the specific cases under examination.

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Part II

Articles

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I

Article I

Zhao, Yixin; Liu, Yiliu. Condition-based maintenance for systems with dependencies: A review on related concepted, challenges and opportunities. *Proceedings of the 31st European Safety and Reliability Conference* (ESREL), Sep 19-23, 2021, Angers, France.

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Condition-based Maintenance for Systems with Dependencies: Related Concepts, Challenges and Opportunities

Yixin Zhao
Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Norway. E-mail: yixinz@stud.ntnu.no

Yiliu Liu
Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Norway. E-mail: yiliu.liu@ntnu.no

Abstract: Many critical systems with dependencies do not collapse immediately due to single-point failures but are more vulnerable to the cascading effects of these failures. Condition-based maintenance (CBM) has been found useful not only in improving availability of technical system but also in reducing the risks related to unexpected breakdowns, including those events related to dependencies, such as cascading failures. The serious disasters created by such failures and increased requirements for CBM policy due to dependencies urges a comprehensive study on current research and future challenges. In this study, a systematic literature review on the implementations of CBM in the systems with dependencies is conducted. Relevant papers are deliberately selected and analyzed in the VOSviewer program, to identify co-occurrences of keywords and so to illustrate basic concepts of CBM. Specifically, considering various types of dependencies, challenges, research advancements and research perspectives are identified. Opportunities of CBM for improving availability and reducing risks of dependent systems are finally explored.

Keywords: Condition-based Maintenance, maintenance procedure, dependent systems, cascading failure, risk analysis, Risk-informed Condition-based Maintenance.

1. Introduction

In an intelligent manufacturing process under Industry 4.0 (Lee et al. 2014), variety of equipment and programs work together to form a complicated and interdependent system. This change is largely reflected in the fields of mechanical manufacturing and electrical engineering. Condition-based maintenance (CBM) is considered as a preparatory strategy before a system fails, compared to other traditional maintenance solutions (Kwon et al. 2016). It can detect the current deterioration and predict behavior patterns, so as to determine when and how maintenance is conducted to keep satisfying system performance while saving cost.

CBM has been noted as a booming field, with some reviews from different perspectives providing a general understanding of its development. Reviews on condition monitoring and Diagnostics (Peng and Chu 2004; Martin 1994) could be found since 1990s. Jardine (2006) summarized the research in diagnostics and prognostics when implementing CBM and discussed the techniques applied for data fusion from multiple sensors. Sakib (2018) focused on the contributions with different methods in Predictive Maintenance (PdM) and CBM and proposed a brief discussion on the challenges. Keizer (2017) reviewed multi-component systems subject to different dependencies and provide real-life examples for each type. With bibliometric tool, Quatrini (2020) gave an extensive literature review on CBM, encompassing over 4000 contributions and made reflection on specific implementation strategies, inspection, replacement and Prognostics. Bibliometric indicators (Mohammed et al. 2019) were also utilized to determine the most influential author, country, organization and the most productive research in CBM field.

Obviously, CBM has received increasing attention recently, but the research perspective of existing contributions is still relatively traditional. A current trend is to implement CBM to more complex system (Keizer, Flapper, and Teunter 2017) but some special dependencies have still not received enough attention yet. In addition, the dependencies between components within the system are still not defined unequivocally. Another reason for having a focus on system dependency is that risk factor remains not

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well considered in addition to traditional maintenance activities within contemporary dependent systems. Dependencies within such system may easily trigger cascading accidents, which threatens the surrounding environment and the life safety of operators. This paper mainly analyzes the application of CBM in systems with dependency and reviews the goal of CBM especially including reducing risk. Furthermore, a more comprehensive understanding of research perspectives that need to be improved in CBM could be obtained.

The rest of the paper is organized as follows. In Section 2, some CBM related concepts are presented. The related work about procedure of CBM, types of systems with dependency and expected benefits of CBM are respectively discussed in Section 3, 4 and 5. Section 6 proposes research perspectives and potential challenges.

2. Related concepts

Related studies in the last 30 years are analyzed because research about CBM has emerged since 1990s (Mohammed et al. 2019). By defining search terms and restricting timespan, we have collected 1074 papers in total in the Web of Science database (WoS). The key terms we choose for searching include "Condition-based Maintenance", "Predictive Maintenance" and "Condition Based Predictive Maintenance. In order to avoid false screening, we use search logic word "and" between the first two topic terms and add search logic word "or" before the last topic terms.

VOSviewer as a software tool is used here to construct maps in which keywords could be connected by co-authorship, co-occurrence, citation, or co-citation links based on network data (Eck and Waltman 2020). For the obtained 1074 papers, bibliographic data including authors, abstracts and references of selected papers are exported from WoS. When creating the map, note that synonymous words may split weight of occurrence due to different writing of the same concept. To avoid redundancy, repeating expressions are filtered out and replaced by one definite expression. Minimum number of occurrences of a keyword is set as 20, with 27 keywords satisfying this threshold.

Co-occurrence network is visualized to present the existence frequency of keywords and their relationships in this research field. The map of Fig. 1 refers to a relationship of main terms used in papers related to CBM policies. From a holistic point of view, the two dominant keywords are "Predictive Maintenance" and "Condition-based Maintenance". For example, the total link strength and common occurrences for the two items are respectively 604, 318 and 338, 142. The total link strength indicates the total strength of the links between an item with other items, which to some extent explains the weight of the item. With "Condition-based Maintenance" as the center, the most closely related keywords form a cluster. In this cluster, condition monitoring is important foundation to collect information when taking maintenance actions, and two main principles related to CBM program are prognostics and diagnostics. Also, CBM cluster in Fig. 1 maps the main links with some following terms: preventive maintenance, optimization, machine learning, neural network, replacement and degradation.

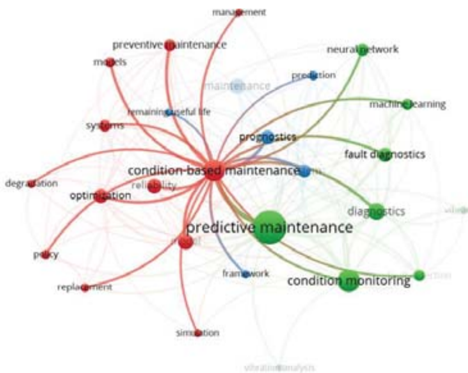

Fig. 1. Co-occurrence of related concepts in CBM

We highlight their definitions in the following part. The concept of condition-based maintenance was firstly proposed in late 1940s by the Rio Grande Railway Company (Prajapati, Bechtel, and Ganesan 2012) and there also emerges variety of definitions as application backgrounds change. According to *EN 13306*, **Condition-based maintenance** is preventive maintenance which includes assessment of physical conditions, analysis and the possible ensuing maintenance actions. **Predictive maintenance** is condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item. **Condition monitoring** focuses on the assessment on a continuous or periodic basis of the system condition (Kobbacy and Murthy 2008), and is intended to measure at predetermined intervals the characteristics and parameters of the physical actual state of an item. Besides, diagnostics and prognostics are two main aspects in CBM actions. **Diagnostics** is a detection procedure for fault recognition, fault localization, identification of root causes when it occurs and determining the current health state of the system (Jimenez et al. 2020). **Prognostics** is dedicated to estimate the remaining useful life (RUL) and risk before a failure or more faults occur given current machine conditions and historical data. After the distinctions of keywords with approximate concepts, we classify the relevant literatures in different ways: based on procedure of CBM, based on dependent types of systems, and based on the goals of maintenance.

3. Procedure of CBM

Three key steps of the CBM program should be firstly specified (see Figure 2):

1. Data acquisition, to collect data related to system.

2. Data processing, including data selection (data examination, data cleaning) and data analysis.

3. Maintenance decision making, to provide the optimal solution for system maintenance.

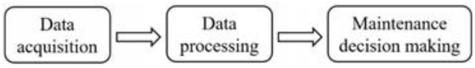

Fig. 2. Three steps in CBM (Jardine, Lin, and Banjevic 2006)

3.1. *Data acquisition*

Data acquisition is the first and necessary step in a CBM process. In CBM practices, two types of data, the event data and condition monitoring data, are often required to be obtained concurrently (Jardine, Lin, and Banjevic 2006).

Event data is the basis for familiarity with system structure, operating information, potential faults, normally including installation, breakdown, overhaul, minor repair, preventive maintenance, etc. Event data is of equal importance with monitoring data, which it is usually underestimated due to that human manipulation is often involved in this process. Condition monitoring data such as vibration data, acoustic data, or environment data including temperature, pressure, moisture, humidity is collected by a variety of sensors. With the development of sensor technology, their accuracy and storage capacity have been greatly improved, which also ensures that the accuracy of monitoring data is improved.

3.2. *Data processing*

When referring to larger and more sophisticated systems with dependencies, a deeper investigation on large amount of data will be certainly necessary.

Data selection still remains as one promising area. It is crucial even for contemporary CBM field mainly because that either event data or conditioning data might involve errors. For event data, human operations such as collecting data and inputting data are prone to human error. For monitoring data, errors can exist because sensors are not fully accurate.

Handling of missing data is also crucial aspect especially for modern CBM implementation (Jardine, Lin, and Banjevic 2006). For incomplete or missing data, dedicated approach is needed for its compensation. To achieve that, Jardine (2006) proposed to utilize the expectation-maximization (EM) algorithm to deal with the missing data. Furthermore, Zuashkiani et al. (2009) described the methodology to estimate the parameters with time-dependent covariates based on expert's beliefs and experience.

Data analysis is known for building, based on data, a mathematical model that properly describes the underlying mechanism of a fault or a failure. A time-dependent proportional hazards model is typically used for analyzing both event and condition monitoring data together. Data for proportional hazards model construction comprise installation data, failure or replacement data, condition data and maintenance data (Jardine, Lin, and Banjevic 2006).

3.3. *Maintenance decision making*

Techniques support for maintenance decision making in CBM is divided into two main categories: diagnostics and prognostics (Jardine, Lin, and Banjevic 2006). The necessity of diagnostics lies in the detection of some unexpected faults in actual applications, which cannot be identified 100% by prediction, while prognostics facilitates preventing failures, preparing for troubleshooting, and saving on additional maintenance costs. Diagnostics helps to improve prognostics by providing more accurate data for the similar type of failure. Prognostics can be regarded as a supplementary tool to optimize maintenance decision making support during diagnostics. Three types of approaches are often put forward in CBM: physics-based approaches (Mehdigholi, Rafsanjani, and Mehdi 2012; Luo et al. 2008), data-driven approaches (Javed, Gouriveau, and Zerhouni 2017), and hybrid prognostics approaches (Qian, Yan, and Gao 2017; Zhang, Kang, and Pecht 2009).

Maintenance decision optimization is usually based on reliability and cost, with parameters such as the products' degradation patterns. Among that RUL estimation plays an important role in maintenance decision making process. To describe fault propagation and predict RUL, model-based methods artificial intelligent approaches and data-driven models are widely adopted (Jardine, Lin, and Banjevic 2006). More available historic data, more accurate estimation results could be achieved (Olesen and Shaker 2021). Suitable models for reflecting dependent degradation phenomena are also required (Tian et al. 2011; Shi and Zeng 2016). A clearer definition of parameters in degradation models for case study helps the estimation to be more consistent with the actual situation to a large extent. To address this problem, one particular objective of related contributions recently is to demonstrate how dependencies between different components in complex systems influence the optimal CBM policy for the system as a whole (Keizer, Flapper, and Teunter 2017).

4. CBM for system with different dependencies

There generally exist economic, structural or evolution dependencies within a multi-component system (Dekker, Wildeman, and Schouten 1997), which cannot be neglected in maintenance decisions to avoid high cost and extra downtime.

4.1. *CBM for system with economic dependency*

Economic dependency exists in systems where inspection or maintenance cost differs when multiple components are inspected and maintained simultaneously or separately (Dekker, Wildeman, and Schouten 1997). The review article of Dekker et al. (1997) gave a good overview of multi-component systems with economic dependence, including stationary and dynamic models. Tian et al. (2011) developed a numerical algorithm for exact cost evaluation and applied it into the multi-component system where economic dependency exists to obtain optimal CBM policy considering proportional hazards model. By a artificial neural network, an optimal CBM policy was also proposed by the same authors to address the economic dependencies among multiple wind turbines in wind farms (Tian et al. 2011). These works provide reference to solve the maintenance decision-making related to economic dependently multi-component systems, while there still to be further investigated about CBM in systems containing various types of components instead of same components. Studies mentioned above do not distinguish between positive and negative economic dependency. When cost could be saved via jointly maintenance, it is called positive economic dependence (PED), whereas negative economic dependence (NED) occurs when it cost more to maintain several components simultaneously than separately (Nguyen, Do, and Grall 2015). However, NED has not yet been deeply investigated in the current CBM study, which could be underlined in future works. When the system subjected to economic dependency, priorities should be placed on cost when making decisions.

4.2. *CBM for system with structural dependency*

Structural dependency exists when some components structurally form a part or a system. To carry out maintenance process for a failed component in such system, working components should also be involved simultaneously (Dekker, Wildeman, and Schouten 1997) or at least dismantled (Nguyen, Do, and Grall 2015). Structural dependencies are mainly represented by two ways, technical dependency or performance dependency. Considering technical dependencies, failure or maintenance of some components can either prohibit maintenance on other components or influence the operation on other components alternatively. Most of the studies focus on performance dependency, mainly including series, parallel relationship and redundancy components. In some circumstances, series and parallel relationship coexist in the same system (Wang et al. 2009; Mercier and Pham 2012; Liu et al. 2014). The series structure means that maintenance on one component requires the entire system to be stopped. Such issues are often investigated accompanied by other types of dependencies (Keizer, Flapper, and Teunter 2017) such as economic dependency and may result in high cost for downtime yet also provide other components opportunities for maintenance correspondingly. It is worth noting that even if the system with a parallel configuration is still running, it would be affected and gradually degrade, eventually causing downtime costs at both component and system level. Redundancy is also an important factor utilized to avoid sudden failures in maintenance activities (Keizer, Teunter, and Veldman 2016), which is often largely overlooked when construct the system model.

4.3. *CBM for system with evolution dependency*

Evolution dependency often occurs when the failure or degradation of one component directly or indirectly facilitates decreasing reliability and availability of the remaining components. It describes some similar situation where stochastic dependence was traditionally used, e.g. degradation or failure related dependence, but we choose the term of evolution for this category, since at least economic dependency, also can be stochastic. Another argument is that in this paper propagation of failures is considered, which can lead to a sequence of events, and when one event occurs, the occurrence of the subsequent event can be deterministic.

Evolution dependency can be direct or indirect. The previous one occurs if the degradation and failure of a component directly induce to the damage of other components or influence the lifetime distribution of other ones to some extent (Dekker, Wildeman, and Schouten 1997). Shi et al. (2016) presented a dynamic opportunistic CBM strategy considering trade-off between RUL and the set-up cost. In his research, real-time RUL prediction is carried out considering such dependency of the components, namely the impact of real-time degradation states of certain components on the RUL of other components. The indirect evolution dependency often occurs by load sharing (Keizer, Flapper, and Teunter 2017). For this case, the system will continue to operate, but the failed component puts higher demands on the output of the remaining components. Therefore, the load on working parts increases and aggravates the deterioration of the whole system. To illustrate two types of evolution dependencies, a system comprising five components in a mixed (series and parallel) structure is introduced, as shown in Fig.3. If the component 1 fails, it can be regarded as an *initiative event*. For the consequence of direct failure propagation, a cascading effect exerts on the components 2 and 4. The system will still operate at this moment because components 3 and 5 are still available. However, as the system continues running, the excessive load accelerates the degradation of components 3 and 5. So for this system, there exist direct evolution dependencies between component 1 and component 2&4, as well as indirect evolution dependencies between component 1 and component 3&5.

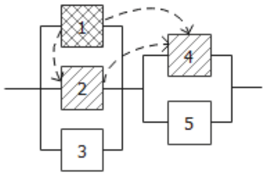

Fig. 3. System structures with evolution dependency

When the failure of certain components can be cascaded, it is necessary to consider the effects of evolution dependency when we predict RULs of other components and update maintenance plan for the whole system.

5. Expected benefits of CBM to systems with dependencies

5.1. *Higher productivity*

When a system is subjected to failures especially the dependent failure modes, the productivity would be reduced due to system performance degradation and possible downtime and maintenance time. Whether existing research focuses on perfect maintenance (Ahmad and Kamaruddin 2012; Dieulle et al. 2003) or imperfect maintenance (Wang et al. 2011; Yang et al. 2019; Fan et al. 2011), and whether the target system is a single-unit component system (Yang et al. 2019) or multi-component systems, improving system productivity is the primary goal of maintenance. Implementing CBM helps develop productivity via improving system availability, extending component life expectancy and reducing system downtime. To evaluate the expected productivity, Van et al. (Van and Berenguer 2012) assumed a very large interval of time to do the simulations, namely the long-run expected productivity. Long-run expected productivity is of great importance because given productivity level in industrial engineering is jointly determined according to the system capacity and customer requirements within a certain running time. Therefore, it is necessary to seek for an optimal maintenance strategy to restore the system capacity to required productivity level during operation, instead of taking perfect maintenance measures for the system.

5.2. *Lower cost*

The goal of reducing maintenance costs is reflected in almost every CBM case study, especially in systems with economic dependencies. To develop the maintenance cost model, several cost functions have been proposed (Alaswad and Xiang 2017), involving some variables: inspection cost, maintenance cost, replacement cost, cost rate, downtime cost rate, as well as two parameters that influence the maintenance cost, inter-inspection interval and preventive replacement threshold. Before maintenance is carried out, decisions should be made whether preventive maintenance or corrective replacement is required, which affects the values of the variables mentioned above. It depends on the inspection results. Obviously, the inspection cost also depends on the inspection types. When the system subjected to continuous monitoring (Tian et al. 2011), maintenance activities can be carried out only when necessary, but there also lies high inspection cost. On the other hand, some systems such as the underground infrastructures cannot be applicable for continuous monitoring and could only be inspected periodically. In addition, regular inspections may also not be cost-effective when the inspection process is expensive. Under this circumstance, the next inspection interval is determined based on the system status after maintenance and deterioration trend, which is known as non-periodic inspection (Flage et al. 2012).

5.3. *Acceptable level of risk*

To start with, the definition of risk should be specified: risk consist of probability of failure and consequence of failure, as well as the cost particularly in the CBM area. It is well known that safety barriers are embedded in many manufacturing engineering systems to ensure smooth and, more importantly, safe operation of the system. The safety and risk level of the system should never be ignored, otherwise, once suffered a fault which can cause an accident, not only the productivity will be reduced, but also the safety of the entire system and the environment (e.g., nearby units and operators) will be threatened. In practical applications, risk acceptability can be combined with the requirements of maintenance and cost.

Potter et al. (2015) proposed the Reliability Centered Maintenance (RCM) framework to ensure asset availability and reliability for the aviation industry. RCM has been implemented in various fields such as medical devices, petrol station, railway systems. Based on RCM, an emerging framework namely risk-based maintenance (RBM) was developed, which could also be considered as a complement of CBM (Leoni et al. 2019). Risk assessment and maintenance measures are adopted in RBM scheduling (Cullum et al. 2018), endowing this method with applicability, innovation and comprehensiveness and compensates for the limitations of RCM. Khan et al. (2003) presented methodology for risk-based maintenance as shown in Fig.4. Dawotola et al. (2012) also proposed the RBM optimization process consisting of six steps for petroleum pipeline system: (1) probability of failure estimation, (2) determination of consequences of failure, (3) estimation of risk of failure, (4) calculation of risk reduction, (5) calculation of total cost, and (6) determination of cost-optimal inspection frequency. Their contributions based on risk analysis provided reference to minimize the consequences related to safety and environment of a system outage but focused too much on risk reduction so as to neglected to improve the most basic requirements of the system -- productivity and availability.

Even if the research about RBM flourish in recent years, more comprehensive investigation, with better balance between risk and reliability appears still challenging. In a recent study (Yeter, Garbatov, and Soares 2020), the most cost-effective inspection and maintenance policy is found for wind farms and a novel framework that maximizes the inspections benefits for a multi-unit system is developed. Nevertheless, the dependencies within this multi-component system are still weak since that the difference between offshore wind farms studied is relatively low.

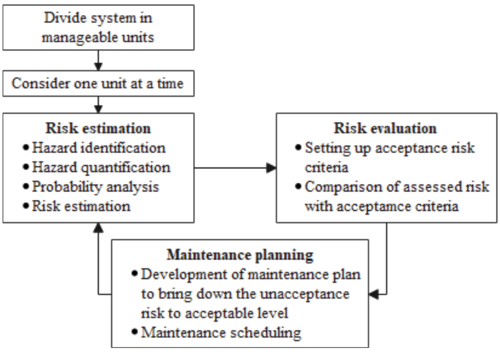

Fig. 4. Architecture of RBM methodology

6. Research perspectives and final discussion

6.1. *Research perspectives*

The above results show that CBM implementation still comes with some research perspectives to be solved. It is noteworthy that three aspects display challenges within dependent systems.

- *Maintenance optimization for systems with dependencies*

To optimize maintenance process, dependencies within systems need to be defined more specifically. On the one hand, types of dependency could impose influence on possible maintenance activities. For example, preventive maintenance should be performed at a relatively early stage for systems with serial configurations, and at a later stage for systems with redundancy. On the other hand, it appears still immature to define interactions among components, with most studies highlighting the effects of solely single type of dependency and neglecting the joint effects of other types, not to mention considering special dependencies like NED. Further, as systems become more complex, new dependencies are emerging. For now, the case that maintenance of one component also requiring maintenance of other components, namely grouping maintenance, is still rare in CBM research. At this point, it is necessary to balance the implementation time and method of maintenance measures to optimize maintenance planning. Therefore, new degradation model and maintenance model incorporating detailed dependencies need to be deeply investigated.

- *CBM for systems where cascading failures occur*

Cascading failures calls for more attention in maintenance activities especially in dependent systems. In interdependent systems or systems with functional redundancies, five correlations among cascading failures comprise competition, inhibit, trigger, acceleration, and accumulation (Chen et al. 2015). In fact, researchers have been making efforts to study how to mitigate the cascading development of accidents in these five phases. As a typical domino risk prevention and control measure, safety barriers are installed to avoid whole system bankrupt due to a single component failure (Liu 2020). Cascading failures highlights the practical relevance, due to that if one of the components is detected to be faulty, it is also helpful to inspect and maintain the other component that may fail due to the initial failure. In terms of risk assessment, cascading failures also play an important role, because the propagation of failures has a great impact on the probability of accidents and the severity of consequences. So far, the quantification of the probability and consequences of failure propagation still remains an urgent problem to be addressed. The last thing to be clear is that cascading failures may not occur in systems with dependencies, but there must be dependencies in systems where cascading failures occur.

- *Combination of CBM with risk analysis*

CBM is expected to be capable of optimizing maintenance to better obtain the anticipated benefits by introducing risk analysis. Though the importance of productivity and cost management has already been clearly highlighted in CBM, it has been hardly to meet the expected requirements of maintenance activities for some systems in Industry 4.0. When it comes to cascading failures in a complex system, risk remains as an unavoidable factor that is difficult to implement in traditional CBM. While in another maintenance policy, RBM as discussed before, risk level of a system is regarded as the basic criteria. We notice that CBM and RBM have addressed their respective fields and performed well, but the negative impact of system outages or failures will only be minimized from an economic perspective both risks and cost-effectiveness are considered in maintenance activities. We hereon extend CBM as multiple-objective decision-making maintenance activities with considering risks, by including the new concept Risk-informed Condition-based Maintenance (RICBM) more specifically. RICBM requires that the probability and consequence of events, as well as the productivity and maintenance cost should be considered comprehensively when carrying out maintenance management. In other words, the RICBM program represents a further development of the work in CBM and RBM policies.

6.2. *Final discussion*

In this paper, a short review of CBM for dependent systems is presented. We summarize CBM related papers according to the process of its implementation and mainly review characteristics of systems subject to three types of dependencies (economic, structural, and evolution). We also notice that many researchers are going after improving productivity, cost minimization, and acceptable level of risk in CBM. Based on this, we highlight some recommendations for CBM investigation. System dependencies and cascading failures triggered by that are supposed to be addressed in future. Also, a new, more comprehensive maintenance policy, Risk-informed Condition-based Maintenance (RICBM), is introduced and requires further research.

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II

Article II

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Cascading failure analysis of multistate loading dependent systems with application in an overloading piping network

Yixin Zhao [a], Baoping Cai [b], Henry Hooi-Siang Kang [c], Yiliu Liu [a,*]

[a] Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Trondheim, Norway
[b] College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, Shandong, China
[c] Institute for Vehicle System & Engineering (IVeSE), Universiti Teknologi Malaysia, Johor Bahru, Malaysia

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ABSTRACT

Many production and safeguard systems consisting of multiple components are susceptible to the cascading failures, where one possibility is that the failure of a component leads to more workloads of other components. Such loading dependence can result in failure propagation, make the systems more vulnerable and maintenance decision-makings more difficult. In this study, we develop a model for analyzing the propagation process of failures in loading dependent systems considering overloading states and degradation of components. The multinomial distribution is applied to characterize the probabilities of total numbers of failed- and overloading components, and probability distributions of different stop scenarios of cascading process are derived. A practical case in piping network is investigated to illustrate the analysis procedure, and to compare the effectiveness of the proposed model with those of the existing methods. Numerical analyses are conducted for evaluating the factors influencing the probability distributions of total number of failed- and overloading components, as well as the occurrence frequencies of different stop scenarios. It is expected that design and maintenance of loading dependent systems can be optimized with the support of this new cascading analysis approach.

Notation

n	Total number of components in a system
j	Cascading generation $j = 0,1,2,\ldots$
d	Initial disturbance amount
L^{max}	Maximum workload on a component
L^{min}	Minimum workload on a component
l_i	Initial workload on component i
l_f	The additional load from a failed component
l_o	The additional load from an overloading component
l_j	Loading increments from all the failed and overloading component in the jth generation
l_{ij}	Workload on component i in the jth generation
C^{max}	Maximum capacity of a component
C^{min}	Minimum capacity of a component
c_0	Initial capacity of component i
c_d	Capacity decrement of functioning component in every generation
c_j	Capacity of every component in the jth generation
r_{ij}	The workload-capacity ratio of component i in the jth generation
r^*	The overloading threshold for a component
p_f	The probability for a component to fail
p_o	The probability for a component to overload
p_w	The probability for a component to work normally
$\Phi(x)$	The saturation function representing the probability
n_{fj}	Number of failed components in the jth generation
n_{oj}	Number of overloading components in the jth generation
n_{wj}	Number of working components in the jth generation
s_j	The case of how many components are in each state in the jth generation
u	The total number of the failed components
v	The total number of the overloading components
t	Cascading time, and $t = 0$ when the cascading process starts
$R(t)$	The probability that the system is still working until time t
T_j	The duration of cascading process from the start to the jth generation
$F^{(J+1)}(t)$	The probability distribution function that all components fail in generation J at time t

* Corresponding author.
E-mail address: yiliu.liu@ntnu.no (Y. Liu).

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1. Introduction

Technologies bring more capabilities as well as more complexities to production, transportation, storage, and safeguard systems, which are currently composed of interacted subsystems and components. In a complex system, when one component fails, the failure may propagate, meaning to cause failures of other components. Each failed component further weakens system performance. We call this phenomenon as a cascading failure (CAF). CAF has been recognized as one of the usual causes resulting in the catastrophes of many modern technical systems [1], such as power grids system [2,3], industrial communication networks, railway networks [4], chemical clusters [5] and other complex network systems [6,7]. Typical events triggered by CAFs are blackout in American in 1996 [8] and massive blackout occurred in Italy [9] in 2003, seriously shocks the normal functions of the society. The Fukushima nuclear accident generated by a tsunami and started by earthquake in 2011 and The Amazon Web Services outage in 2012 are also classical CAFs examples [6,10]. These CAF events occur because technical systems are composed of multiple components structurally or functionally dependent with each other. Loading dependent system is one of the typical systems with dependence, where all components share the overall workload on the system.

Performance of a component always depends on its capacity and workload. In most cases, when the workload on a component is much higher than its capacity, a failure occurs. Then, the overall load on the system is re-distributed to the remaining functioning components whose workloads become higher, and these components become more vulnerable to failures. Such a re-distribution of workloads thus initiates a cascading process. For a loading dependent system, e.g., a wind farm, an energy station with several chargers, a piping network, and a medical center relying on several key devices, its performance can be related to the number of functioning components. If a cascading process starts, performance of such a system will degrade with less functioning components. For an individual component, an increasing workload can result in an immediate failure or an overloading state [11,12]. In the latter situation, the increased workload does not exceed the capacity of the component but is higher than the normal. Another non-negligible factor is the natural degradation of components in a loading dependent system, which has been studied in some research [13,14]. The degradation of components consists of their independent natural degradation and the degradation initiated by the conditions of other components [15], namely the capacity loss of components in our work. The performance of such an overloading component due to additional loads and capacity loss can thus be expected to deteriorate, and such degradation can shorten the lifetime of this component and affect the associated maintenance planning. For a loading dependent system, appropriate understanding on the overloading problems can be helpful to avoid the system-level failure or serious accidents.

Several models can be found for analyzing CAFs, such as the sand pile model [16,17], the ORNL-PSerc-Alask (OPA) model [18], the CASCADE model [8,19], the branching process model [20,21], and the topological models from the complex network theory [22,23], etc. Moon et al. [24] have proposed a load-dependent cascading failure model to evaluate the resilience of small devices' network to strategies for node removal by adopting the principle of sandpile process. Qi et al. [25] have estimated the joint distribution of two types of cascading outages with multi-type branching processes and tested with data generated by the AC OPA cascading simulations on the IEEE 118-bus system. Some methods based on the CASCADE model can be found in [16,26] for solving the self-organizing issue during cascading overload failures. The cascading process in a loading dependent system was first investigated by the CASCADE model [8,18], following an extended quasi-binomial distribution. The classical CASCADE model calculates probabilistic cascading failure for the weakening of the system as the basic cascade proceeds due to loads transformation [18]. The branching process model [21], as approximation of the CASCADE model, describes the total number of failed components as a Poisson random variable. However, the aforementioned cascading overload failure still refers to a failure mode induced by overloads, which is distinct from the notion overloading state as we proposed. To our best knowledge, most previous work focuses on direct failure spreading while ignoring the overloading phenomenon and components degradation.

Some practical challenges motivate the extension of the existing models on the issue of lacking the discussion about the overloading phenomenon and components degradation. For example, some pipes operating at higher pressures than expected might impose additional loads on other pipes in the same network. This kind of overloading state may occur due to their own degradation or other environmental factors and lead to loads transformation. The loading dependence induced by overloading components is thought to exert influence on the failure cascading process, though it is not as noticeable as that caused by failed components. The additional loads from overloading components and the natural degradation of components will undoubtedly promote component degradation and affect the evolution of the cascading process. The component reliability and system performance will be overestimated if the influence of this type of loading dependence and components own degradation on the failure cascading process is discarded. If the state of a component or system is overestimated when performing maintenance activities, delayed or inadequate maintenance may follow. In such cases, a more precise, realistic model that accounts for overloading components and component degradation supports maintenance decision makers in making more appropriate decisions.

Therefore, a more practical method is needed for analyzing the performance of loading dependent system subjected to CAFs affected by overloading components. In this new model, we consider the situation that components degrade gradually and may become overloading. Whenever a component is overloaded, it might have a negative effect on the other functioning components in the loading dependent system. It is expected that the extended model can reflect the cascading process more practically and detect more information such as the effect of overloading phenomenon and components degradation which are ignored in the existing classical CASCADE models.

The remainder of this paper is organized as follows. In Section 2, we describe the states transition mechanism in loading dependent systems and the algorithm of the classical CASCADE modeling, based on which some assumptions and algorithm of the CASCADE model are proposed. The model considering overloading components and three stop scenarios for cascading process are illustrated in Section 3. To illustrate the differences between the proposed model and classical model, an example of a piping system is provided in Section 4. In Section 5, we examine the variables affecting probability distributions of total number of failed and overloading components by discussing numerical results. Conclusions and future research directions are summarized in Section 6.

2. *Cascading failures and analysis models*

2.1. *Loading dependence as a cascading mechanism*

CAFs occur when the failure or degradation of one component weakens reliability and availability of the remaining components [27]. In this study, we classify CAFs as direct- and indirect- ones. The

Table 1
Comparison between Direct and Indirect Types of CAFs.

Category		Direct	Indirect
Difference	Driving force	Sudden shock and damage	Loading dependence
	Effects on components in sequence	Failures or degradation	Failures, degradation or overloading components
Similarities	Trigger	One failure or failures	
	Stop condition	There are no more new failures	

difference and similarities between two types of CAFs are listed in Table 1. A direct CAF occurs if the failure of a component or components directly induces damage to other ones or reduce their lifetime to some extent, while an indirect CAF often occurs due to loading dependence: The overall workload of the system is redistributed because some components exclude from normal operation. The loading dependence is resulted from the activities of loading balancing or loading sharing. Loading balancing is the practice of equally spreading the workload across distributed system nodes to optimize resource efficiency and task response time, which avoids a situation that some nodes are substantially loaded while others are idle or performing little work [28]. Loading sharing system is the practice of spreading the workload in a way that some loads are sent to one node in the system while the remainder is routed to others [28]. Loading dependent systems suffer from indirect CAFs.

2.2. CASCADE models

2.2.1. Classical CASCADE model

In this section, we present the mechanism of the classical nonstandard CASCADE model in loading dependent systems and the failure mechanisms of cascading process. This model is the basis inspired by which we extend our model. In current research related to classical CASCADE model, states Working and Failed are characterized for a component in a loading dependent system. When the workload is higher than the failure threshold, a failure occurs. Load redistribution then further facilitates the cascading process until that no new failures occur. Some assumptions are made in this classical CASCADE model:

1) The total number of components n in the system is finite.
2) All components in the system are identical, exchangeable and nonrepairable.
3) Each component in the system has two states: Working and Failed.

The classical CASCADE model is proceeding as the following steps:

Step 0. All components are normally working initially with random loads uniformly distributed in $[L^{min}, L^{max}]$.
Step 1. An initial outside disturbance to all components triggers the initial event followed by failure propagation. The initial failure is set as a trigger in generation 0 of a CAF.
Step 2. Check states for each component. If the load of component i exceeds L^{max}, then component i is failed. Otherwise, the component is working. Suppose that there are n_{fj} failed components in the jth generation. If $n_{fj} = 0$, there is no more new failures in the jth generation, and the cascading process stops. The stop condition of cascading process is that all components fail or the loads of the unfailed components are less than L^{max}.
Step 3. Additional loads due to failed components in this generation are allocated according to the number of failed components and added to working components in next generation.
Step 4. Go to the next generation and iterate from step 2.

This cascading mechanism is shown in Fig. 1. According to the CASCADE algorithm, the failure cascading process is triggered by an outside disturbance and stops in the jth generation if there are no more new failures in generation $j+1$. This cascading process can stop when a) all components fail (cascading process stops, system fails); or b) the load of the unfailed component is less than the failure threshold (cascading process stops, system does not fail).

The classical CASCADE model is a tractable tool to capture the basic failure cascading process driven by loading dependence. However, the effect of some practical issues such as other states of components and components degradation on cascading property should be considered more. This encourages us to extend and improve the current classical models to tackle more practical problems. In practices, some components are functioning in the overloading state, which is often undervalued since the overloading components only seem to reduce the efficiency of the system. For example, the cascading process of a loading dependent piping network may vary if we consider not only the failures but also the overloading state of the pipelines, compared to the cascading process considering only the failures. Moreover, what about the impact on the cascading process when the inherent degradation of pipelines is also considered? This is also a subject we need focus on since most components may degrade naturally in reality, which should not be neglected. These practical problems will be addressed in the following sections.

2.2.2. Multi-state cascade model

In this section, we provide the mechanism of multi-state CASCADE model considering overloading components in loading dependent systems and the failure mechanisms of cascading process. For a component in a loading dependent system, it can actually have three states or performance levels: Normally Working, Overloading and Failed. The performance level can be determined by the ratio of workload to capacity r. When the workload is very highly, namely the ratio to capacity exceeds the failure threshold, a failure occurs. When the workload is higher than normal value, but the load/capacity ratio is still below the failure threshold, we regard the component is at an overloading state. We can also have a certain value of the load/capacity ratio as the overloading threshold, indicating that if the ratio is lower than this value, the component is Normally Working. In both Normally Working and Overloading states, a component is functioning, but it is inclined to fail when it is overloading. We use Functioning to denote the states of Overloading and Normally Working for short in this study. The failed and overloading components allocate loads to the functioning components during cascading process. Note that the overloading components also allocate loads to themselves. Here we do not consider maintenance, and the component state is generally getting worse. The states transition during cascading process are illustrated by Fig. 2.

Consider a technical system, some assumptions for our model are shown as below

1) The total number of components n in the system is finite.

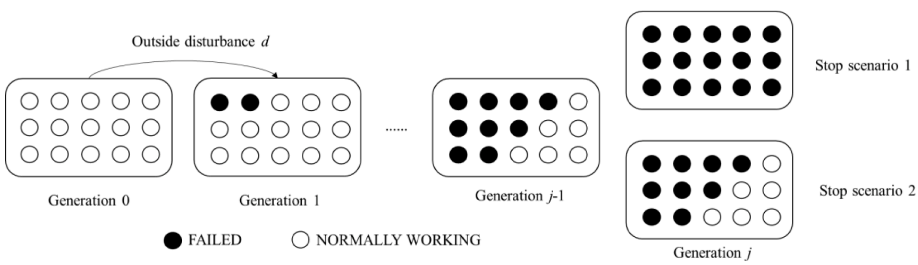


Fig. 1. Failure cascading process and stop scenarios of classical CASCADE model.

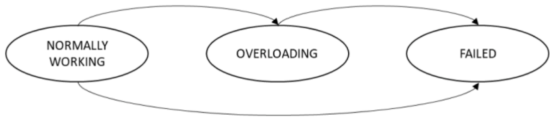


Fig. 2. States transition of components.

2) All components in the system are identical, exchangeable and nonrepairable.
3) Each component in the system has three states: Working, Overloading and Failed.
4) The capacity of every functioning component degrades naturally as the cascading failure propagate. The value of capacity decrement in every generation is c_d.

We can set that the workload on components lies in $[L^{min}, L^{max}]$, the capacity lies in $[C^{min}, C^{max}]$, and the initial disturbance D lies in $[D^{min}, D^{max}]$. When illustrating these parameters with a case of piping network, the workload can correspond to the flow rate through a pipeline, and the capacity is related with the failure limit and the expectation flow rate. An unexpected rise in flow rate is triggered by change of client requirement or work schedule, to lead to an initial disturbance. Furthermore, abrupt temperature fluctuations from the surroundings might affect workload via provoking an initial disturbance. These undesirable alterations should be observed since they are the driving force behind the start of the CAFs. The values of L^{min}, C^{min} and D^{min} are generally 0 in practice, but the values of L^{max}, C^{max} and D^{max} are not fixed. It is convenient for calculation to normalize the loads l and capacity c in [0, 1]. Based on the normalization of loads and capacity, if the initial disturbance $d \geq 1$, all components fail, and the cascading process stops immediately. If the initial disturbance $d = 0$, every component is working well and there is no failure to start the failure cascading process. Hence the following discussions assume that the range of d is normalized in (0, 1).

The nonstandard CASCADE model [8,19,20] and Modified Normalized CASCADE model [29] have been introduced for assigning workloads and initial disturbance to the components. Inspired by the existing CASCADE models, we reflect the cascading process in a similar way. To illustrate overloading state and capacity degradation, we introduce the quasi-multinomial distribution to model the three states of components. The extended multi-state CASCADE is modeled as the following steps:

Step 0. All components are normally working initially with capacity $c_0 = 1$ and random loads l_i that are uniformly distributed in [0, 1].

Step 1. An initial outside disturbance d to all components triggers the initial event followed by failure propagation. The initial failure is set as a trigger in generation 0 of a CAF.

Step 2. Check states for each component. The performance level is represented by ratio of workload to capacity l/c. If the ratio r_i of component $i < r^*$, then component i is working well. When the ratio r_i of component i exceeds 1, the workload of the component will be more than its capacity could endure, so the component fails. Otherwise, the component is overloading. Suppose that there are n_{fj} failed components and n_{oj} overloading components in the jth generation. If $n_{fj} = 0$, there is no more new failures in the jth generation, and the cascading process stops. We define the stop condition of cascading process that if no new failures occur in one generation, the failure cascading process stops here, regardless of whether there would be more failures occur in subsequent generations.

Step 3. The capacity of every functioning component decreases due to natural degradation, so we have the capacity of the component in the jth generation $c_j = c_0 - j \cdot c_d$ and the load/capacity ratio of the component $r_{ij} = \frac{l_{ij}}{c_j}$. The additional load due to each failure in this generation on every functioning component in next generation is l_f. The additional load on every functioning component in next generation due to each overloading component in this generation is l_o. It is natural that l_o is considered smaller than l_f. Additional loads $l_j = n_{fj} l_f + n_{oj} l_o$ are allocated according to the number of failed and overloading components and added to every functioning component. Each functioning component is assigned an additional load value of l_j.

Step 4. Go to the next generation and iterate from step 2.

This cascading mechanism is shown in Fig. 3. According to the CASCADE algorithm, if and only if there are no more new failed components in generation $j + 1$, the cascading process stops in the jth generation. This is the only criterion for determining if the cascading process stops, regardless of whether there are still functioning components in the system currently. We consider it as a *new cascading process* if the remaining components tend to fail after a period and there would be *new generation 0*. We shall clarify that the stop condition of cascading process is differentiated from the stop condition of system. The former one is determined by whether new failures occur at a certain generation, whereas the latter one is determined by the system reliability. In conclusion, the cascading process stops when all components fail, but not all components fail when the cascading process stops. Following the explanation of the stop condition of cascading process, we can characterize three stop scenarios (scenarios of how the system works) when the cascading process terminates as follows. This cascading process can stop when a) all components fail (cascading process stops, system fails); or b) the load/capacity ratio of the functioning component is less than the failure threshold (cascading process stops, system does not fail). These two cases could be classified into three scenarios. In stop scenario 1, all components and the system already failed; in stop scenario 2, there exist some overloading components; in stop scenario 3, the load/capacity ratio of the functioning component is less than r^* and all components work normally.

3. Quantitative analysis with the multi-state CASCADE model

3.1. Total number of components in different states

To start the cascade, initial disturbance d is assigned to each component. If there are components failed, the failure cascading process starts, followed by that the number of failed components increases and the functioning components decreases generally. The numbers of failed components, overloading components and normally working components are n_f, n_o, n_w and $n_f + n_o + n_w \leq n$. It is natural that $n > 0$ and n_{fj}, n_{oj}, n_{wj} for $j = 0, 1, \ldots$ are restricted to nonnegative integers. The state of the component follows a multinomial distribution $X \sim PN(\mathrm{N}: p_f, p_o, p_w)$, determined by outside initial disturbance, additional loads from failed and overloading components, and overloading threshold of components. In each generation, the probability that there are n_{fj} components failed, n_{oj} components overloading and n_{wj} components normally working is

$$P\left[X_1 = n_f,\ X_2 = n_o, X_3 = n_w\right] = C_n^{n_f} C_{n-n_f}^{n_o} p_f^{n_f} p_o^{n_o} p_w^{n_w} \tag{1}$$

where $p_f \geq 0,\ p_o \geq 0, p_w \geq 0, p_f + p_o + p_w = 1$.

The probability of the total number of components in different states might be derived as follows:

In generation 0, before the initial disturbance applied, the probabilities that the component in different states depend solely on the random loads l_i. Then we could obtain $p_f = 0,\ p_o = 1 - r^*,\ p_w = r^*$. In generation 0, the cascading process has not been started yet since all components are functioning.

After the initial disturbance d is applied in generation 1, the load of component i is $l_i + d$. But the capacity of each component is still c_0 since the cascading process just started from this generation. After the cascading process begins, the capacity of components gradually

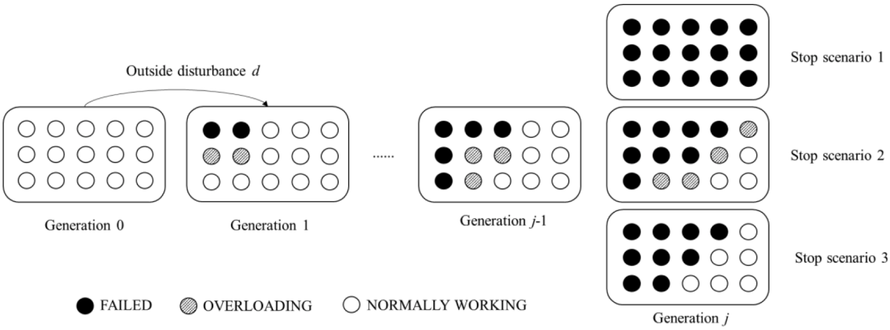


Fig. 3. Failure cascading process and stop scenarios of multi-state CASCADE model.

declines. Similar to the load redistribution principle, the component capacity loss at this generation (generation 1) will be reflected in the next generation (generation 2). For generation 1, if the load/capacity ratio of a component exceeds 1, the component fails, we have $l_i \le 1$ and $1 < \frac{l_i+d}{c_0}$, and the probability that the component fails is the probability that l_i satisfies the constraints of the previous two equations. So, we could obtain the interval of l_i: $c_0 - d < l_i \le 1$, and further we could easily achieve $p_f = 1 - c_0 + d$. The same holds applicable for the other two probabilities. According to our definition, if the load/capacity ratio of a component lies in $[r^*, 1]$, this component is overloading, which could be represented by $r^* < \frac{l_i+d}{c_0} < 1$. Hence, we obtain the probability that the component in overloading state is $p_o = c_0(1 - r^*)$. When $\frac{l_i+d}{c_0} < r^*$, the component works well, and the probability is $p_w = c_0 r^* - d$. The three probabilities are respectively $p_f = d,\ p_o = 1 - r^*,\ p_w = r^* - d$ in generation 1 based on that the initially capacity is normalized as $c_0 = 1$.

In the jth generation, the cascading process has already gone through some generations, the total number of failed components and the total number of overloading components could be calculated. Let $s_j = (n_{fj}, n_{oj}, n_{wj})$, $S_j = (N_{fj}, N_{oj}, N_{wj})$ for $j = 0, 1, \ldots$ and write

$$u_j = n_{f0} + n_{f1} + \cdots + n_{fj} \text{ and } v_j = n_{oj} \tag{2}$$

for $j = 0, 1, \cdots$.

Each functioning component suffers additional loads $ul_f + vl_o$ from failed and overloading components and total loads $l_i + d + ul_f + vl_o$. With the same principle for calculation of probability of components in different states in generation 1, we have $l_i \le 1$ and $1 < (l_i + d + ul_f + vl_o)/c_j$ for the case that the component fails, and the probability that the component fails is the probability that l_i satisfies the previous two constraint equations. So, we could obtain the interval of l_i: $c_j - (d + ul_f + vl_o) < l_i \le 1$, and further we could get $p_f = 1 - c_j + d + ul_f + vl_o$.

$$P[U=u, V=v] = \begin{cases} C_n^u C_{n-u}^v \varphi(d)\varphi\left(1 - c_j + d + ul_f + vl_o\right)^{u-1} \varphi\left(c_j(1-r^*)\right)^v \varphi\left(c_j r^* - \left(d + ul_f + vl_o\right)\right)^{n-u-v}, & u = 0, 1, \ldots, n-1 \\ 1 - \sum_{u=0}^{u=n-1} P(U = u,\ V = v), & u = n \end{cases} \tag{5}$$

The same holds applicable for the other two probabilities. Likewise, we could obtain the constraint equations of other two states after some generations: when $r^* < (l_i + d + ul_f + vl_o)/c_j < 1$, the component is overloading and the probability is $p_o = c_j(1 - r^*)$. When $(l_i + d + ul_f + vl_o)/c_j < r^*$, the component works well, and the probability is $p_w = c_j r^* - (d + ul_f + vl_o)$.

Note that the total number of overloading components v_j is not sum of n_{oj} in previous generations for $j = 0, 1, \ldots$ since the overloading components may fail in a cascading process. If we calculate the total number of overloading components by summing up the overloading components in all generations, the total number of failed components partially overlaps the total number of overloading components. We only use the number of the overloading components in latest generation to represent the total number of overloading components. Generalize the derivation and apply this distribution to normalized load-dependent case and we can obtain the distribution of the total number of failed components and overloading components. An extended quasi-multinomial distribution is applied as following on basis of extended quasi-binominal distribution introduced by Consul [19,30]. The quasi-binomial distribution is a small "perturbation" of the binomial distribution, whose mass probability function could be defined by $P(X = k) = C_n^k p(p + k\phi)^{k-1}(1 - p - k\phi)^{n-k}$. When extended to quasi-multinomial distribution, we also strictly follows the format of the distribution, as shown in Eq. (3).

$$P[U=u, V=v] = \begin{cases} C_n^u C_{n-u}^v \varphi(d)\varphi(p_f)^{u-1}\varphi(p_o)^v \varphi(p_w)^{n-u-v}, & u = 0, 1, \ldots, n-1 \\ 1 - \sum_{u=0}^{u=n-1} P(U=u, V=v), & u = n \end{cases} \tag{3}$$

In Eq. (3), $\varphi(x)$ is a saturation function representing the probability

$$p = \varphi(x) = \begin{cases} 0, & x < 0 \\ x, & 0 \le x \le 1 \\ 1, & x > 1 \end{cases} \tag{4}$$

We have Eq. (5) to calculate the distributions of the total number of components in different states.

When we consider the accident risk, the number of failures is more of interest than number of overloading components. The equation to denote the distributions of the total number of failed components is Eq. (6).

$$P[U=u]=\begin{cases}C_n^u\varphi(d)\varphi(p_f)^{u-1}\varphi(1-p_f)^{n-u}, & u=0,1,\dots,n-1\\ 1-\sum_{u=0}^{n-1}P(U=u), & u=n\end{cases}\tag{6}$$

In this CASCADE model, the system reliability could be calculated as Eq. (7) when considering the cascading time t, which could be discussed in further research.

$$\begin{aligned}R(t)&=1-\sum_{j=0}^{n-1}P(U_j=n,\ T_j<t)\\&=1-\sum_{J=0}^{n-1}F^{(J+1)}(t)\cdot P[u=n]\end{aligned}\tag{7}$$

where $R(t)$ is the probability that the system is still working until time t. T_j is duration of cascading process from the start to generation J. $F^{(J+1)}(t)$ is the probability distribution function that all components fail in generation J at time t. This equation is independent of the number of overloading components, as only failed components are typically included when investigating system reliability.

3.2. Distributions of stop scenarios

In the previous subsection, the probability that there are n_{fj} components failed, n_{oj} components overloading and n_{wj} components normally working in the jth generation is

$$P[X_{1j}=n_{fj},\ X_{2j}=n_{oj},X_{3j}=n_{wj}]\ =C_n^{n_{fj}}C_{n-n_{fj}}^{n_{oj}}p_f^{n_{fj}}p_o^{n_{oj}}p_w^{n_{wj}}\tag{8}$$

However, in the cascading process, the sojourn probability of components in different states is not constant as the failure propagates and loads are reallocated. Since the workload of components is mounting due to loading dependent and the capacity of components is decreasing due to natural degradation gradually, the probability of the number of components in different states should be recalculated after each generation according to the loading increments. It is convenient to use equations of $\alpha_j=\varphi(p_{fj}),\ \beta_j=\varphi(p_{oj}),\ \gamma_j=\varphi(p_{wj})$ for calculating in the subsection.

In generation 0, $p_{f0}=0,\ p_{o0}=1-r^*,\ p_{w0}=r^*$, and we could obtain $\alpha_j=0,\ \beta_j=1-r^*,\ \gamma_j=r^*$ for $j=0$.

In generation 1, with the initial workloads given as described in step 0 and the initial disturbance applied as in step 1, the CASCADE algorithm starts. In step 2, for a loading dependent system considering decreasing capacity, the probability that the initial disturbance triggers one component fails or overloads in generation 1 is $\alpha_1=\varphi(1-c_0+d)$, $\beta_1=\varphi(c_0(1-r^*))$, $\gamma_1=\varphi(c_0r^*-d)$, and could be written as $\alpha_1=\varphi(d)$, $\beta_1=\varphi(1-r^*)$, $\gamma_1=\varphi(r^*-d)$ since $c_0=1$. The probability that there are n_{f0} failed components and n_{o0} overloading components is

$$\begin{aligned}P(S_0=s_0)&=P[X_1=n_{f0},\ X_2=n_{o0},X_3=n_{w0}]\\&=C_n^{n_{f0}}C_{n-n_{f0}}^{n_{o0}}\alpha_0^{m_{f0}}\beta_0^{m_{o0}}\gamma_0^{(n-n_{f0}-n_{o0})}\end{aligned}\tag{9}$$

In the jth generation, the capacity of each functioning component decreases due to natural degradation after several generations, and the additional loads are accumulated and added to each functioning component as cascading process proceeds. Additional loads from failed components in generation j-1 to the functioning components in the jth generation is $n_{f(j-1)}l_f$. Additional loads from overloading components in generation j-1 to the functioning components in the jth generation is $n_{o(j-1)}l_d$. The additional loads from failed and overloading components could be assigned to the functioning components including itself in generation $j+1$.

$$l_j=n_{f(j-1)}l_f+n_{o(j-1)}l_o\tag{10}$$

For loading dependent system considering capacity decrement of the components, we have

$$\begin{aligned}\alpha_j&=\varphi\left(\frac{1-d-u_{(j-2)}l_f-v_{(j-2)}l_d-c_j+l_j}{1-d-u_{(j-2)}l_f-v_{(j-2)}l_d}\right),\\ \beta_j&=\varphi\left(\frac{c_j(1-r^*)}{1-d-u_{(j-2)}l_f-v_{(j-2)}l_d}\right),\\ \gamma_j&=\varphi\left(\frac{c_jr^*-l_j}{1-d-u_{(j-2)}l_f-v_{(j-2)}l_d}\right)\end{aligned}\tag{11}$$

for $j=2,3,\dots$, and $u_{-1}=0,\ v_{-1}=0$.

The probability that the number of failed components and overloading components in every generation follows $(s_0,\ s_1,\dots s_j)$ until the jth generation is given by Eq. (12).

$$P[S_j=s_j,\dots,S_0=s_0]=\frac{n!}{n_{f0}!n_{o0}!n_{w0}!}\alpha_0^{n_{f0}}\beta_0^{n_{o0}}\gamma_0^{n_{w0}}\frac{(n-u_0)!}{n_{f1}!n_{o1}!n_{w1}!}\alpha_1^{n_{f1}}\beta_1^{n_{o1}}\gamma_1^{n_{w1}}\cdots\frac{(n-u_{(j-1)})!}{n_{fj}!n_{oj}!n_{wj}!}\alpha_j^{n_{fj}}\beta_j^{n_{oj}}\gamma_j^{n_{wj}}\tag{12}$$

Suppose that cascading process stops in the jth generation and $d+u_{(j-1)}l_f+v_{(j-1)}l_d\geq c_j$, then all components fail in the jth generation. Cascading process stops according to stop scenario 1. In this case

$$P[S_{j+1}=s_{j+1}|S_j=s_j,\dots,S_0=s_0]=1\tag{13}$$

for $n_{f(j+1)}=0$.

Suppose that cascading process stops in the jth generation and $d+u_{(j-1)}l_f+v_{(j-1)}l_d<c_j$, meaning to satisfy the stop scenarios 2 or 3. In addition, the loads of functioning components are uniformly distributed in $[d+u_{(j-1)}l_f+v_{(j-1)}l_d,\ c_j]$ conditioned on $n-u_j$ not have failed in generation $j+1$. The probability that there are $n_{o(j+1)}$ overloading components and $n_{w(j+1)}$ normally working components is given by Eq. (14).

$$P[S_{j+1}=s_{j+1}|S_j=s_j,\cdots,S_0=s_0]=C_{n-u_j}^{n_{o(j+1)}}\beta_{j+1}^{n_{o(j+1)}}\gamma_{j+1}^{n_{w(j+1)}}\tag{14}$$

Table 2
Load of components in an example of classical CASCADE model.

j	1	2	3	4	5	Loading increments to next generation	Notes
0	0.75	0.5	0.45	0.25	0.9	/	Initial workloads
1	0.95	0.7	0.65	0.45	1.1	0.1	Initial disturbance d added; 5 fails
2	1.05	0.8	0.75	0.55	/	0.1	1 fails
3	/	0.9	0.85	0.65	/	0	No new failure occurs, and the cascading process stops

Multiplying Eqs. (12) and (14) we could obtain Eq. (15) to verify the distribution for the stop scenarios.

$$P\left[S_{j+1}=s_{j+1},\cdots,S_0=s_0\right]=\frac{n!}{n_{f0}!n_{o0}!n_{w0}!}\alpha_0^{n_{f0}}\beta_0^{n_{o0}}\gamma_0^{n_{w0}}\frac{(n-u_0)!}{n_{f1}!n_{o1}!n_{w1}!}\alpha_1^{n_{f1}}\beta_1^{n_{o1}}\gamma_1^{n_{w1}}\cdots\frac{\left(n-u_{(j-1)}\right)!}{n_{fj}!n_{oj}!n_{wj}!}\alpha_j^{n_{fj}}\beta_j^{n_{oj}}\gamma_j^{n_{wj}}\cdot C_{n-u_j}^{n_{f(j+1)}}\beta_{j+1}^{n_{o(j+1)}}\gamma_{j+1}^{n_{w(j+1)}} \tag{15}$$

In case cascading process stops according to stop scenario 1, all components fail in the jth generation. In the case cascading process stops with stop scenario 2, some components (or all functioning components) are overloading in the jth generation, and the number of failed components in generation $j+1$ is 0. In case cascading process stops according to stop scenario 3, there are still $n-u_j$ components normally working well in the jth generation, and the number of failed components in generation $j+1$ is also 0.

4. A practical case with model comparison

In this section, we apply both the classical CASCADE model and the proposed multi-state CASCADE model to a generic petrochemical piping network for comparing their effectiveness in the analysis of cascading failures due to loading dependence. We consider a part of a piping network system consisting of 5 gas pipes. Each pipe is designed with a failure limit of 20 m/s and expectation flow rate 16 m/s. Fouling would emerge inside the pipe as the pipe transfers gas, increasing the pressure, reducing the gasses throughput, and lowering system operation efficiency, which is the process we called natural degradation. The volume of gas transported in the pipes is the indicator of working load, and the capacity of the pipe is determined by the degree of fouling. If one pipe stops functioning due to exogenous disturbance, sudden changes in temperature for example, other pipes share the workload of the failed pipe.

It is possible to use the classical CASCADE model to study the cascading failure in such a system. According to the classical CASCADE model, the components fail or normally working during the cascading process without degradation. We normalize the workloads and capacity to [0, 1]. The initial loads of components are randomly valued in [0, 1]. Assume that the initial disturbance $d=0.2$, loading increments from failed components $l_f=0.1$ without losing generality. Table 2 and Fig 4 show the changes of the workloads of all components and the cascading process. The loading increments in this model depends on the number of the failed components, the load of which exceeds 1. The failure cascading process ends in the third generation with components 1 and 5 failed, and the system is still working.

The classical CASCADE model investigates the loading dependence due to malfunction of some pipes. The congestion due to filth accumulation, which is inevitable during system operation, also require additional gas on the remaining functioning pipes. The extra gas speed up fouling of functioning pipes and let them undergo accelerated degradation. When the gas is transferred in the pipe at a rate more than the expectation flow rate 16 m/s but under the failure limit of 20 m/s, we think the pipe is overloading since the workload exceeds its expectation capacity. We could consider that there is the overloading threshold $r^*=0.8$. In one specific circumstance, we can assume that the value of overloading threshold is constant. However, when the component degrades, it stores less capacity, hence a lower workload will overload the component with the same overload threshold. Some pipes become overloading with excessive workloads, and their performance suffers severely, which is why overloading components need to be addressed in the proposed model. Based on the assumption about the initial loads, initial disturbance, and loading increments from failed components when using classical CASCADE model, the loading increments from overloading components l_o is set to be 0.05 without losing generality. In addition, assume that the capacity decrement of functioning component in every generation $c_d=0.01$. The load/capacity ratio r of components and cascading process are listed and performed in Table 3 and Fig 5. The loading increments in this model depends on the number of the failed components and overloading components. The capacity of the functioning components decreases in every generation. Using this model, load/capacity ratio r is utilized to determine states of components. When the failure cascading process stops in the fourth generation, all components fail, and the system fails.

From the example, we can see that the system and the pipes function in radically different states under the same circumstances. The cascading process of classical CASCADE model ends in the third generation, but the system continues to function. The cascading process of the proposed multi-state CASCADE model stops in the fourth generation, and all components fail. Furthermore, we can see that the load/capacity ratio values in Table 3 are generally bigger than those in Table 2 (if we consider the component capacity in the example in Table 3 to be constant at 1). This implies that the components in multi-state CASCADE model operates in somewhat worse state than those in classical CASCADE model. The primary difference between the two conclusions is that the degradation of components and the effects of overloading components are considered, which is more compatible with how the system works in engineering industry. In practice, if we neglect components degradation and the influence of overloading components, we may overestimate the performance of components and the system, negatively affecting maintenance decision making.

5. Model parameter analysis

The model proposed can be used to analyze the cascading process in a large complex system with loading dependence. These systems can be wind plants, power systems, piping networks, key medical devices, road systems, etc., where the system performance is related to the number of functioning components. To investigate the usefulness of this CASCADE model in the optimization of controllable variables in design and operation, this section examines several examples of the effects with varying parameters of CASCADE distribution on failures and stop scenarios of a general loading dependent system.

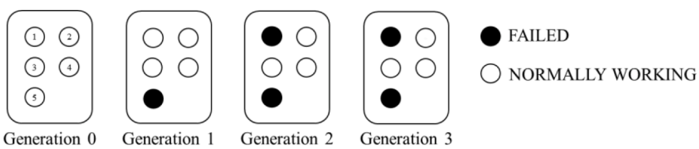


Fig. 4. Failure cascading process of a piping system using classical CASCADE model.

Table 3
Load/capacity ratio of components in an example of multi-state CASCADE model.

j	1	2	3	4	5	Loading increments to next generation	Capacity of the functioning components	Notes
0	0.75	0.5	0.45	0.25	0.9	/	1	Initial workloads/ Initial capacity
1	0.96	0.71	0.66	0.45	1.11	0.15	0.99	Initial disturbance d added; 5 fails
2	1.12	0.87	0.82	0.61	/	0.2	0.98	1 fails
3	/	1.08	1.03	0.82	/	0.25	0.97	2 and 3 fail
4	/	/	/	1.09	/	0.15	0.96	4 fails; the system fails; the cascading process stops

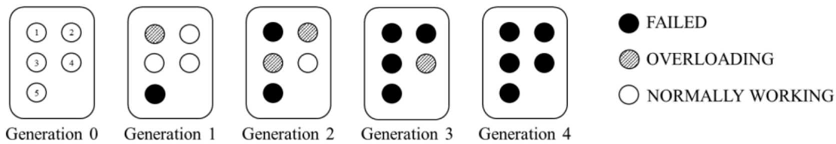


Fig. 5. Failure cascading process of a piping system using multi-state CASCADE model.

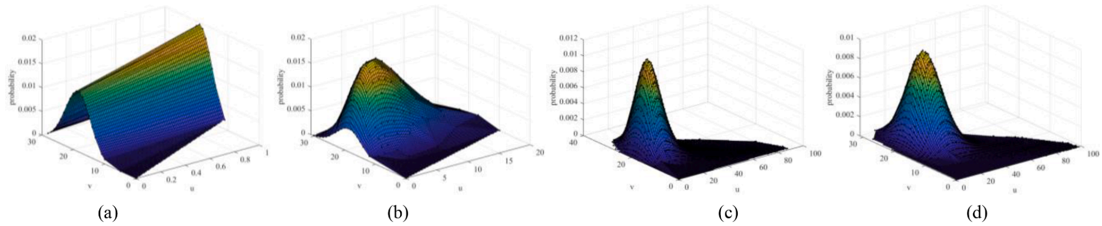


Fig. 6. Total number of failed and overloading components with different d. (a) $d = 0.001$. (b) $d = 0.01$. (c) $d = 0.05$. (d) $d = 0.1$.

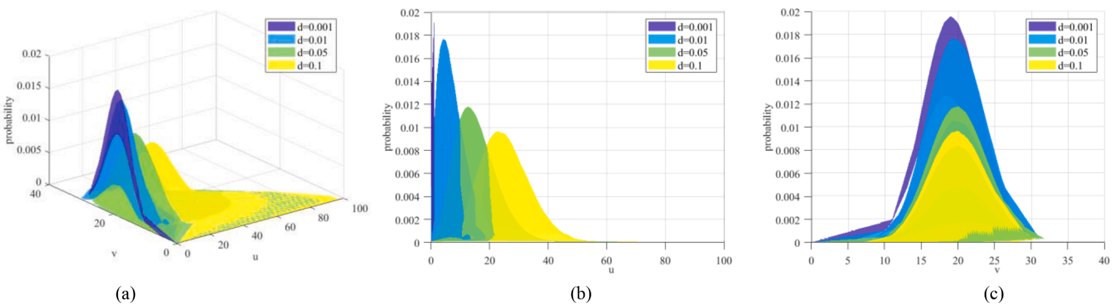


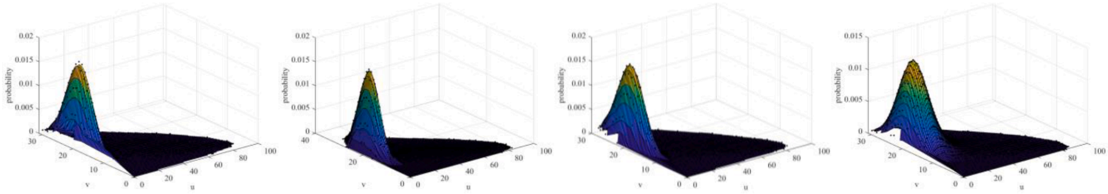
Fig. 7. Integration of probability distributions with different d. (a) Three-dimensional profile. (b) p-u profile. (c) p-v profile.

5.1. Effect of initial disturbance

This subsection illustrates the change of CASCADE distribution as the initial disturbance varies by comparing the probabilities of total numbers of failed and overloading components. We consider a system in which the number of components $n = 100$. Without losing generality, we firstly assume that the overloading threshold of a component is $r^* = 0.8$, the loading increments from failed and overloading components are respectively $l_f = 0.005$, and $l_o = 0.001$. The changes of probability distributions of total numbers of failed and overloading components are observed with different initial disturbance $d = 0.001, 0.01, 0.05, 0.1$.

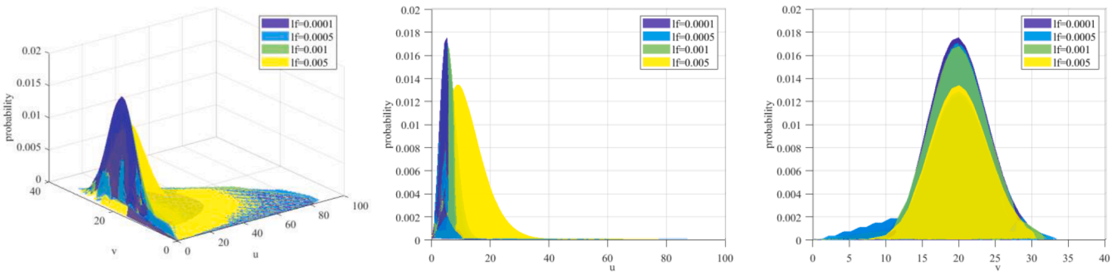
The probability distributions of total numbers of failed and overloading components are calculated and shown in Figs. 6 and 7. The nodes on the surfaces in Fig. 6 denotes the probabilities of total numbers of failed and overloading components of numerical results. When the initial disturbance increases, the workloads of components tend to exceed the failure threshold, which is the reason the value of u grows up. For $d = 0.001$, the initial disturbance value is relatively small, causing only a small number of failures. The low number of failed components also results in fewer additional loads to drive the cascade process. The cascading process ends quickly when there are still some functioning components, and the system is still operating (stop scenario 2). The short cascading process leads to that only few nodes can be observed to compose a surface in Fig. 6(a), which is more like a folded plane. As d increases, the number of obtained nodes in Fig. 6(b), (c) and (d) gradually rises, the surface becomes smoother and shows obvious peaks. This peak represents the highest probability of a scenario with a certain total number of failed components and a certain total number of overloading components in this case. The phenomenon that all components fail emerges in Fig. 6(d), indicating that stop scenario 3 occurs.

Fig. 7 integrates the five surface to illustrate the variation tendency better. Fig. 7(a) illustrates the trend of a lower overall probability



(a) (b) (c) (d)

Fig. 8. Total number of failed and overloading components with different l_f. (a) l_f =0.0001. (b) l_f =0.0005. (c) l_f =0.001. (d) l_f =0.005.

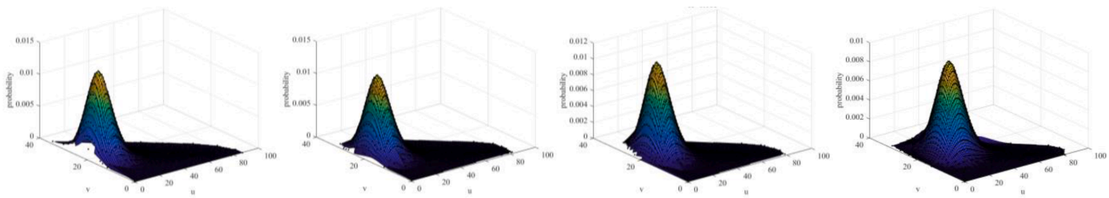


(a) (b) (c)

Fig. 9. Integration of probability distributions with different l_f. (a) Three-dimensional profile. (b) *p-u* profile. (c) *p-v* profile.

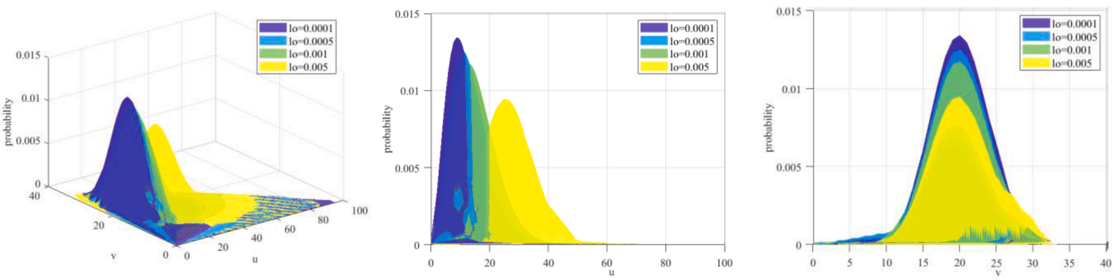
distribution of total numbers of failed and overloading components. Fig. 7(b) verifies the conclusion that there is a critical value of u that maximizes the probability. As d increases, this peak value of probability gradually decreases. In addition, the probability distribution range corresponding to u gradually shifts to the direction that u becomes larger when d becomes larger. It could also be observed from Fig. 7(c) that for different d, the number of overloading components is basically concentrated from 15 to 25, and the probability peak decreases gradually as d increases. Besides, the peaks of probabilities for u and v both show approximate power law behavior near the peak value.

Overall, when the initial disturbance value is small, the number of failed components is small, but the maximum probability of its occurrence is large. When the initial disturbance value is large, more components fail, but the maximum probability of its occurrence is small. The initial disturbance can be sudden shock or short-term increase in flow. Since the initial disturbance is an external factor, it is difficult to be controlled in system design, but we can still obtain some managerial implications, such as avoiding disturbances that can directly trigger



(a) (b) (c) (d)

Fig. 10. Total number of failed and overloading components with different l_o. (a) l_o =0.0001. (b) l_o =0.0005. (c) l_o =0.001. (d) l_o =0.005.



(a) (b) (c)

Fig. 11. Integration of probability distributions with different l_o. (a) Three-dimensional profile. (b) *p-u* profile. (c) *p-v* profile.

failure of components. In practices, such efforts can lead to high cost to ensure that none of the components in the system fail. In addition, it is unwise to ignore outside disturbances due to the low probability of occurrence that many components fail. When the system can accept a certain range of number of failed components, we can get an acceptable external disturbance value accordingly. In a bridge system, for example, the value of a sudden increase in traffic caused by holiday trips can be limited to an acceptable range to ensure long-term good operation of the system. During inspection, if the external disturbance is lower than this value, we do not need take more actions.

5.2. Effect of loading increments

To compare the effects of two kinds of loading increments, we use different values of l_f and l_o for different configurations in this subsection. To match the configurations with reality, l_o cannot exceed l_f. For the case that $n = 100$, we set $d = 0.05$, $r^* = 0.8$. Firstly, we evaluate the loading increments l_f as: 0.0001, 0.0005, 0.001, and 0.005 when fixing $l_o = 0.0001$. Then, we set $l_f = 0.005$, and observe different loading increments l_o as 0.0001, 0.0005, 0.001, and 0.005.

Figs. 8 and 10 respectively describe the probability distributions of total numbers of failed and overloading components under different settings of parameters l_f and l_o. It can be found that such changes have little influence on the shape of the surface. From integration results in Figs. 9 and 11, surfaces cannot be easily differentiated when l_f and l_o varying from 0.0001 to 0.001, while the surface apparently changes when l_f and l_o assumed to be 0.005. A reasonable explanation can be provided that when the loading increments are small, the effect of their changes on the probability distributions could be ignored, but when it reaches to a certain value, it still can affect the probability distributions of total numbers of failed and overloading components. This conclusion recommends that more attention should be paid to the timely maintenances of overloading components in practice. It is also worth mentioning that the probability distributions range of the number of overloading components is almost same as in the previous section.

Actually, the values of two kinds of loading increments could be impacted by management or strategies. Given that an initial failure has already been triggered, we try to avoid subsequent failures by developing a more rational strategy for workload distribution, that is, to manage how much workload should be reallocated to which component during system operating. Generally, the loading increments are not fixed in the design period, hence the measures to manage workload distribution would be preferred. Taking a road system as an example, when a road section cannot be used or gets blocked due to overloading, other roads will bear more traffic and pedestrian flow, or in other words, bear additional workloads. This kind of additional workloads can be adjusted by taking current limiting and reasonable diverting measures.

5.3. Effect of overloading threshold

The overloading state of components has been introduced in the proposed extended multi-state CASCADE model, accompanying with the new parameter overloading threshold considered to distinguish the state of overloading components from normally working components. Here we discuss the influence of this new parameter. Consider that the overloading threshold r^* varies from 0.6 to 0.9 as shown in Figs. 12 and 13, in which $n = 100$, $d = 0.05$, $l_f = 0.005$, $l_o = 0.001$.

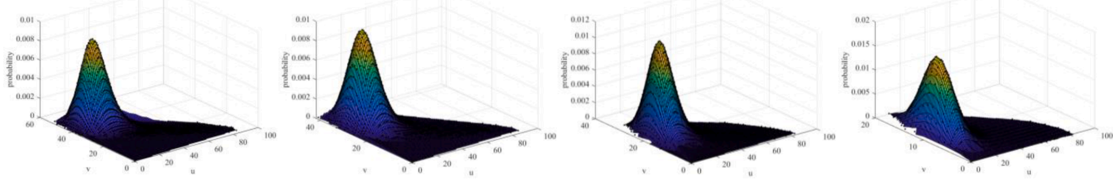
The shape and trend of each surface are still consistent with our previous discussion: each surface has an obvious peak, and the approximate power function law appears near the peak. In addition to this, the similarities and differences of the surfaces deserve more discussions. In Fig. 12, the probability distributions of total numbers of failed and overloading components, as well as the shape and trend of the surfaces are roughly same. The curved surfaces in Fig. 13 gradually shifts in the direction of v decreasing, as the overloading threshold increases. Different from the previous discussions, the distribution range of the number of failed components are almost same in this example, concentrated in 0 to 20, and the probability peaks when the overloading threshold r^* is 0.9. The results indicate that change of the overloading threshold mainly affect the probability distribution range of the number of overloading components but can barely affect that of failed components. It should be noted that even though the probability distribution range of the number of failed components is slightly affected by the overloading threshold, the maximum probability value ascends as the overloading threshold value increases, which demonstrates that as the overloading threshold value increases, it would be easier for components to fail.

The above results can provide references for practical system engineering design and operation. In a loading dependent system where the overloading components also influence the failure propagation, the overloading threshold should be a moderate value, neither not too high to make failures occurring easily, nor too low to prompt too many overloading components. The practical overloading threshold is a critical value beyond which the component operates in poor conditions and requires maintenance action. It could be controlled through providing different expectation values of safety margin in design. For a component designed with a failure limit of 200 MPa and normally working under its design expectation stress, it is overloading below the failure limit but in excess of the design expectation stress. Its threshold is 0.8 when expectation stress set to be 160 MPa and is 0.7 when expectation stress set to be 140 MPa. Apart from design in practical, some guidance could be provided during operation. For a repairable loading dependent system, periodical inspections and imperfect repair could be carried out during operation to restore the performance of overloading components under the threshold.

5.4. Stop scenarios and occurrences

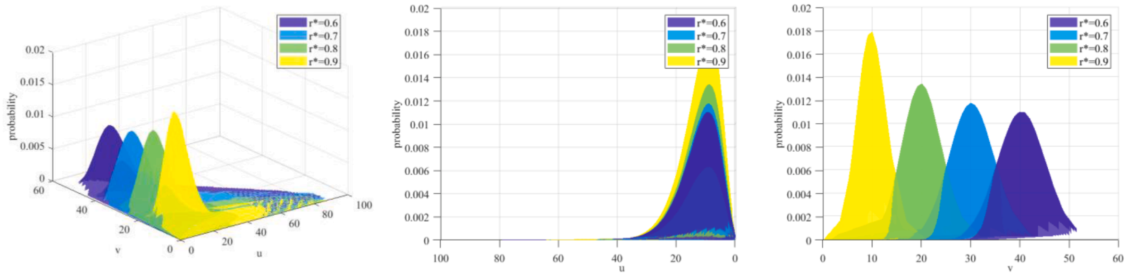
In the previous analysis, we only consider the probability distributions of the total number of failed and overloading components in the meantime when the cascading process is not stopped yet. We now explore the stop scenarios of the cascading process and their possibilities of occurrences.

It has been summarized in previous examples that the initial disturbance d has a relatively large impact on the number of failures, and the number of failures largely determines how the system operates when



(a) (b) (c) (d)

Fig. 12. Total number of failed and overloading components with different r^*. (a) r^*=0.6. (b) r^* =0.7. (c) r^* =0.8. (d) r^* =0.9.



(a) (b) (c)

Fig. 13. Integration of probability distributions with different r^*. (a) Three-dimensional profile. (b) *p-u* profile. (c) *p-v* profile.

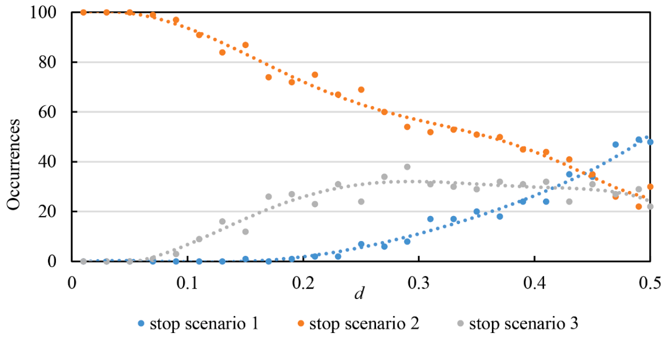


Fig. 14. Occurrences of three stop scenarios.

the cascading process stops, which is the so-called stop scenarios. Besides, the case that all components fail only occurs in Fig. 6(d), denoting that stop scenario 3 only happen in this configuration. Therefore, only the initial disturbance d is changed to conduct the investigation in this section.

Suppose $n = 100$, $r^* = 0.8$, $l_f = 0.005$, $l_o = 0.001$, and we perform 100 numerical calculations respectively for each d from 0.005 to 0.5 and examine how many times every stop scenario occurs. According to classification of stop scenarios in Section 2.2.2, there are three kinds of stop scenarios that may occur when the cascading process stops for each d. The dots in the results plotted in Fig. 14 show the occurrences times for three stop scenarios per 100 calculations for each d, denoting their possibilities of occurrences for each d. The sum of occurrences times of three stop scenarios is thus 100 for each d. The findings could be briefly summarized as follows: The cascading process of the system basically stops according to the stop scenario 2 if there is no sufficient initial disturbance. As the initial disturbance is larger, stop scenarios 1 and 3 are more likely to appear. More specifically, if the initial disturbance is small, the system is generally still working and there exist some overloading components when the cascading process terminates. When the cascading process stops, the possibility of the system being in one of two other stop scenarios grows as the initial disturbance increases: the system fails (stop scenario 1), or the system is running with all the remaining components working normally (stop scenario 3).

The difference between stop scenarios 1 and 3 is that the mounting trend of the occurrences of stop scenario 3 emerges earlier than that of stop scenario 1, which indicates that stop scenario 1 occurs with a larger initial disturbance. The occurrence times of stop scenario 1 ascends at a gradually increasing rate, while the occurrence times of stop scenario 3 initially rises rapidly, then tends to stabilize, and even shows a slight downward trend at the end of the trendline. Since the system stops running only when the stop scenario 1 occurs, the trendline of stop scenario 1 also reflects the failure probability variation of the system.

6. Conclusion remarks and future works

In this paper, we have developed a novel probabilistic model, multistate CASCADE, with the extended quasi-multinomial distribution, for loading dependent systems with CAFs where the cascading process could be affected by overloading components. Three cascading process stop scenarios are identified and interpreted. The contribution of this work lies in the involvement of overloading components and degradation of components, extending the existing studies. The results of the practical case indicate that the performance of components and the system would be overestimated if we neglect components degradation and the influence of overloading components. The proposed model can provide a more accurate characterization of the cascading process of the multistate loading dependent systems. Consequently, we can help maintenance crew and managers to make more reasonable maintenance policies. The more precise information regarding the performance of components and the system serves as the backbone to improve the decision-making process when people consider maintenance optimization for a loading dependent system with CAFs. For example, the interval between maintenance activities can be shortened to ensure that proper maintenance actions are performed on time, or that overloading components can be also considered when taking maintenance actions.

In addition, numerical examples are given to illustrate the proposed model by analyzing the influencing factors of the probability distributions of total numbers of failed and overloading components. The findings in the numerical cases have shown that the initial disturbance and loading increments affects the probability distributions. More failures may occur as the initial disturbance and loading increments increase, but the maximum values of probability distributions decrease. A novel finding is that the overloading threshold affects the probability distribution range of number of overloading components rather not the failed components. For stop scenarios of cascading process, system always operates when there are still normally working and overloading components (stop scenario 2) if the initial disturbance is quite small. As the initial disturbance increases, the cascading process tends to stop in scenarios 1 and 3.

The proposed model will encounter some issues which may be worth to investigate in the future. Firstly, since our proposed model is still limited in the multi-component system in simple configuration, further investigations on multi-state CASCADE model for *k*-out-of-*n* system and engineering application are stimulated. Secondly, it may demonstrate the necessity and practical significance of the model more intuitively to apply a practical example with maintenance activities included. Thirdly, a comparison with other models, such as modeling the situation of three states and a finite number of components by a Markov chain with transition probabilities, is suggested in our future work.

CRediT authorship contribution statement

Yixin Zhao: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Baoping Cai:** Writing – review & editing, Validation, Methodology. **Henry Hooi-Siang Kang:** Writing – review & editing. **Yiliu Liu:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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III

Article III

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SPECIAL ISSUE ARTICLE

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Reliability analysis of a loading dependent system with cascading failures considering overloads

Yixin Zhao | Tianqi Sun | Yiliu Liu

Department of Mechanical and Industrial Engineering Faculty of Engineering, Norwegian University of Science and Technology, Trondheim, Norway

Correspondence
Yiliu Liu, Department of Mechanical and Industrial Engineering Faculty of Engineering, Norwegian University of Science and Technology, Trondheim, Norway.
Email: yiliu.liu@ntnu.no

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Abstract

In many production facilities, multiple components have to work together to share the overall workload on the entire system, leading to loading dependence and higher vulnerability to cascading failures. Additionally, overloading of one component can expedite the failures of others, exemplifying another form of loading dependence. In this study, we develop a system reliability analysis model for loading dependent systems considering overloads based on the Multi-state CASCADE model. By incorporating a time variable, the tailor-made model is able to characterize the duration of each generation in the cascading process, along with the cumulative time of the whole cascading process until the system collapse. A combination of analytical and simulation techniques is then employed to investigate how various potential influencing factors of loading dependence and cascading processes influence the system reliability. The results demonstrate that the effectiveness of proposed method in estimating the system reliability of the loading dependent system considering overloads. Such findings can improve the decision-makings of reliability prediction, system design, and maintenance optimization, especially in scenarios involving the loading dependent with cascading failures.

KEYWORDS

cascading failures, cascading time, multi-state CASCADE model, overloading, system reliability

1 | INTRODUCTION

Modern production systems become increasingly complicated with more interconnected devices and components. Interactions and dependences between various components can increase the likelihood of failures. When one component fails, the failure might propagate and cause failures of other components. This phenomenon is known as a cascading failure (CAF). CAFs are the major threat to electric power transmission systems,[1,2] transportation systems,[3] healthcare infrastructure systems,[4] safety instrumented systems,[5] chemical industry clusters,[6,7] and other complex network systems.[8–10] For example, the 2003 blackout in the Northeastern United States was initially triggered by the tripping of multiple power transmission lines, and finally led to considerable traffic congestion and communication breakdowns due to dependencies between various systems.[11] Another typical event triggered by CAFs is the domino accident that took place in Mexico in 1984.[12] This event led to a chain reaction, resulting in 12 to 20 subsequent accidents, and this catastrophic sequence of events claimed the lives of 650 people. Concerning the damages brought by CAFs, it is essential to consider the mechanism and consequence of potential CAFs in system design, system reliability analysis and maintenance optimization.

CAFs can be attributed to the structural or functional dependence among various components within a complex system. One of the prime examples of systems exhibiting such dependencies is a loading dependent system, in which all components collectively share the overall workload of the entire system.[13] CAFs have been found common in loading dependent systems.[14–16] Keizer et al.[14] explored a parallel and redundant system that experiences failure dependence due to load sharing and economic dependence. The study varies the extent of load sharing and the degradation process to uncover crucial insights into the optimal maintenance strategy. Brown et al.[15] proposed an innovative spatial model aimed at assessing the reliability of load-sharing systems, accounting for spatial dependence and proximity effects, which is suitable for systems, whether they can provide distance-related information or not. Sharifi et al.[16] presented a novel matrix-based approach for the multi-state and load-sharing components to calculate the system inspection cost. These contributions have served as inspiration for researchers to focus on the loading dependence mechanism and CAFs.

For a loading dependent system, degradation of components and the systems due to overloading "nodes" are very common, which nevertheless is not well studied in current research. Evaluation of the overloading state of components needs to be generalized. In a loading dependent system, "overloading" typically refers to a scenario where a component experiences the operational workloads surpassing its intended or specified capacity. The overloading state of a component may be caused by a sudden outside disturbance or by additional workloads allocated from other components during the cascading process, or by capacity decrement due to component degradation. These overloading components are frequently overlooked in comparison to outright failures, because they still continue to be functioning or at least partly functioning. However, despite not presenting as severe a risk as complete failures, these overloads can pose hazards and require costly maintenance or replacement of the associated components if not addressed promptly. Besides, overloading components may allocate loads to the others, and reduce the performance of more components, accelerate their deterioration, or even result in substantial failures. The following two examples can illustrate such situations. In a power system, if a transformer is overloading, it can lead to overheating or potential damage. Other transformers in the system are therefore required to share more workloads, possibly approaching or exceeding their expected capacity. In terms of a traffic network, if there is a traffic jam on a major road, causing an "overloading" major road, vehicles are then forced to pass through other roads, which triggers an increase in traffic flow on other roads and an intensification of congestion. These examples also demonstrate that the study of CAFs for loading dependent systems, considering overloading components, remains worthy to be investigated.

To address the above issue concerning overloading components, an extended multi-state CASCADE Model[13] has been developed based on some studies of classical CASCADE models.[17–19] Such a model[13] involves discussions on three types of stop scenarios of the cascading process. It reflects the cascading process mechanism more practically and provides a reference for cascading probability analysis of loading dependent systems subjected to CAFs affected by overloading components. However, some special scenarios need to be further explored, including the cascading scenarios where the cascading process stops and the system fails. Such a study is crucial for analyzing system reliability. Further investigations of the previous model on system reliability analysis are thus stimulated.

Reliability describes the ability of a system to sustain its regular operation in a specific period without failures. System reliability analysis can offer important information to guide design, operation, and maintenance strategies. There has been an uprising interest in the research of reliability analysis for loading dependent systems in recent years.[2,20–24] Some researches consider the internal degradation of the components in loading dependent systems. For example, Duan et al.[2] developed a novel cascading failure model to uncover the influence of route-choosing behavior on traffic network reliability with consideration of overload failures. Zhao et al.[20] explored a framework for modeling and analyzing the reliability of load-sharing systems consisting of identical components. Some other works include both the internal degradation and external shocks simultaneously. For example, Guo et al.[21] proposed an analytical model to compute the reliability with local load-sharing effect and shock processes for consecutive k-out-of-n: F systems. Nezakati et al.[24] investigated the conditional distribution considering the soft and hard failures, and developed a reliability model for the load sharing k-out-of-n system. Despite the varying approaches, the contributions outlined above collectively emphasize the importance of reliability analysis for loading dependent systems and their relevance to a wide range of complex systems. This has motivated us to enhance the multi-state CASCADE model to incorporate a system reliability perspective.

In the analysis of system reliability, it is essential to consider the failure scenarios and the duration for such a scenario to occur. For a loading dependent system with CAFs, the time for the system to fail can be naturally assumed to be closely related with the duration of the cascading process. The duration for a cascading process to proceed could be referred to as cascading time. The previously proposed model solely accounted for varying evolving scenarios of the cascading process, without considering the time for each generation or the time for the overall duration, let alone emphasizing the time at which system failure occurs during the cascading process. In the new model, we consider that there is a period for each generation in the cascading process. The cascading time of each generation, the duration of the whole cascading process, and the probability that the loading dependent system fails are also calculated. By integrating the cascading time and failure probability, the system reliability is expected to be estimated. Some discussions about reliability analysis of a loading dependent system considering overloads are given with case studies.

The rest of the paper is organized as follows. In Section 2, detailed descriptions of the theoretical basis and our previous works are presented. The method to consider cascading period and the system reliability function is discussed in Section 3. Section 4 illustrates the reliability analysis results by the case study, and conclusions are presented in Section 5.

2 | MULTI-STATE CASCADE MODEL WITH CASCADING TIME

This section provides the theoretical basis of this study by illustrating the multi-state CASCADE model briefly. The mechanism of multi-state CASCADE model considering overloading components in loading dependent systems and the cascading scenarios of cascading process are performed in our previous contribution.[13] In this model, the components in a loading dependent system have three states or performance levels: Normally Working, Overloading and Failed, which can be determined by the ratio of load to capacity, denoted as load/capacity ratio for abbreviation. The capacity of components decreases when the cascading failures propagate, due to the naturally degradation of components. The load on components depends on the initial workload, the sudden outside disturbance, and additional loads from overloading and failed components. The initial workload refers to the load that a component bears during its normal operation before encountering a sudden disturbance. The sudden outside disturbance can be a suddenly environmental change, such as temperature and pressure, etc., or manifest as unexpected damage, such as pollution or strikes. Additional loads arise due to overloads or the failures of other components with loading dependence. In a loading dependent system, when some components fail, they become incapable of handling the expected workloads, and additional loads are assigned to the components that are still functioning. Considering the actual situation, overloading components cannot bear all the expected workloads well, and also in turn allocate additional loads to the components that are still functioning. Therefore, this article considers the intermediate state between the Normally Working and Failed, defining as the Overloading state.

The introduction of a new state can bring challenges in modeling since it is difficult to achieve a classification that perfectly aligns with real-world situations. In addition, the cost required for detailed differentiation of component states when the model is applied in practice is also substantial. According to existing research,[13] despite the fact that overloading components exert certain influence on the cascading process, their impact on the probability distribution of the number of failed components and system reliability is less pronounced when compared to failed components. Therefore, although the value of the additional loads depends on the actual state of the component, it is of little significance to determine the additional loads based on the specific actual states of the overloading component. This study simplifies the additional loads into two types: those from failed components and those from overloading components.

This model acts as the foundation for our subsequent reliability analysis. According to the steps of the multi-state CASCADE model, a new algorithm that accounts for cascading time is structured as the following steps:

Step 0. All components are normally working initially.

Step 1. An initial outside disturbance d to all components triggers the initial event.

Step 2. Check states for each component i. If the load/capacity ratio of component is less than r^*, then it is working well. When the load/capacity ratio exceeds 1, the component fails. Otherwise, the component is overloading. Suppose that there are n_{fj} failed components and noj overloading components in the jth generation.

Step 3. The capacity of functioning components decreases due to natural degradation. The additional loads due to each failure and each overloading component in this generation on every functioning component in next generation are respectively.

Step 4. l_f and l_o. Additional loads $l_j = n_{fj}\, l_f + n_{oj} l_o$ are allocated and added to every functioning component. In this step, the new state of each component could be obtained according to the ratio of new workload and new capacity.

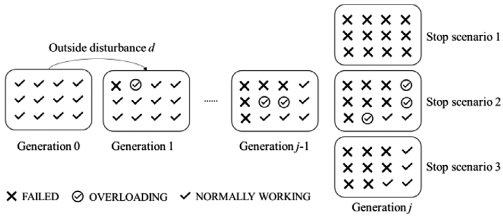

FIGURE 1 Cascading process of multi-state CASCADE model.

Step 5. Record the cascading time for every generation. Assume that the interval time of each generation in the cascading process is Y_j.

Step 6. If $n_{fj} = 0$, there is no more new failures in the jth generation, and the cascading process stops. Then the total cascading time from the start until the cascading process stops can be calculated by accumulation. Otherwise, the cascading process proceeds, then go to the next generation and iterate from step 2.

In this multi-state CASCADE model, some assumptions are made as below:

1. The system contains a finite number of components, denoted as n.
2. Every component within the system is identical, exchangeable, and nonrepairable.
3. The initial capacity of the components $c_0 = 1$, and their random loads l_i are uniformly distributed in $[0, 1]$.
4. As the cascading process proceeds, the capacity of each functioning component naturally decreases. The reduction in capacity for each generation is denoted as c_d.
5. The cascading process starts when there is a failure at time $T_0 = 0$.

This cascading process is shown in Figure 1. According to the above algorithm, the cascading process stops in the jth generation if and only if when there are no subsequent failed components in the generation j+1. If the remaining components tend to fail after a period, we consider it as a new cascading process with a new generation 0. When the cascading process ends, this does not imply that all components fail. However, when all the components fail in the jth generation of the cascading process, the system fails, and the cascading process stops in the jth generation since there are no new failures in the generation j+1.

There are plenty of cascading scenarios for the cascading process to proceed. When the cascading process stops, there are three types of scenarios, denoted as stop scenarios:

·Stop scenario 1: All components fail (cascading process stops, the system fails);
·Stop scenario 2: The load/capacity ratio of the functioning component is less than the failure threshold, and there exist some overloading components (cascading process stops, the system does not fail);
·Stop scenario 3: The load/capacity ratio of the functioning component is less than r^*, and all components work normally (cascading process stops, the system does not fail).

Based on the multi-state CASCADE model proposed in Ref.,[13] the probability that the number of failed components and overloading components in every generation follows $(s_0,\ s_1, \ldots s_j)$ until the jth generation is given by Equation (1).

$$P\left[S_j = s_j, \cdots, S_0 = s_0\right] = \frac{n!}{n_{f0}!n_{o0}!n_{w0}!}\alpha_0^{n_{f0}}\beta_0^{n_{o0}}\gamma_0^{n_{w0}}\frac{(n-u_0)!}{n_{f1}!n_{o1}!n_{w1}!}\alpha_1^{n_{f1}}\beta_1^{n_{o1}}\gamma_1^{n_{w1}}\cdots\frac{\left(n-u_{(j-1)}\right)!}{n_{fj}!n_{oj}!n_{wj}!}\alpha_j^{n_{fj}}\beta_j^{n_{oj}}\gamma_j^{n_{wj}} \tag{1}$$

In Equation (1), $n_{fj},\ n_{oj},\ n_{wj}$ are respectively the numbers of failed components, overloading components and normally working components in the jth generation. u_j is the total number of the failed components until the jth generation. v_j is the number of overloading components in the jth generation. α, β, and γ are the indices used to abbreviate the probability of components in different states. More illustrations about the indices and this equation could be referred to Ref.[13]

Suppose that cascading process stops and all components fail in the jth generation, it could be obtained that $n_{f(j+1)} = 0$, then $0 = n_{f(j+1)} = n_{f(j+2)} = \ldots$. Besides, since $u_j = n$ in this stop scenario, there are no more subsequent failures in following generations. In this case, we have

$$P\left[S_{j+1} = s_{j+1} \mid S_j = s_j, \dots, S_0 = s_0\right] = 1 \tag{2}$$

for $n_{f(j+1)} = 0$.

By multiplying Equation (1) with Equation (2), we could derive Equation (3) to verify the distribution associated with the stop scenario 1.

$$P\left[S_{j+1} = s_{j+1}, \cdots, S_0 = s_0\right] = \frac{n!}{n_{f0}!n_{o0}!n_{w0}!}\alpha_0^{n_{f0}}\beta_0^{n_{o0}}\gamma_0^{n_{w0}}\frac{(n-u_0)!}{n_{f1}!n_{o1}!n_{w1}!}\alpha_1^{n_{f1}}\beta_1^{n_{o1}}\gamma_1^{n_{w1}}\cdots\frac{\left(n-u_{(j-1)}\right)!}{n_{fj}!n_{oj}!n_{wj}!}\alpha_j^{n_{fj}}\beta_j^{n_{oj}}\gamma_j^{n_{wj}} \tag{3}$$

The probability distribution of cascading scenarios, represented by $(s_0,\ s_1, \dots s_{j+1})$, is provided by the multi-state CASCADE model. Using this model, the probability distribution of overall scenarios where the cascading process stops in the jth generation could be identified. Furthermore, with the inclusion of cascading time, the system reliability analysis could then be conducted.

3 | SYSTEM RELIABILITY ANALYSIS

This section provides the reliability analysis of a loading dependent system based on the multi-state CASCADE model. As distinguished before, the criterion to determine if the cascading process stops in the jth generation is whether there are new failed components in the generation j+1. The criterion to determine if the system fails is whether all the components fail. The situations in which the cascading process ends following stop scenario 1 are examined to assess system reliability.

Since the cascading process can evolve in various ways, there are several scenarios where the cascading process stops and the system fails in the jth generation. It is necessary to determine the probability of each scenario resulting in system failure in the jth generation. The overall system failure probability is accomplished by summing the probabilities of all the scenarios resulting in system failure in the jth generation. Equation (3) represents one cascading scenario of the cascading process, which follows $(s_0,\ s_1, \dots s_j)$. By summing all the cascading scenarios where the cascading process ends and the system fails in the jth generation, we can obtain Equation (4). The cascading scenarios encompass situations where there are varying number of failed and overloading components for each generation. The equation represents the probability distribution of S_j, as shown the probability that the cascading process ends and the system fails at the jth generation, no matter how the cascading process proceeds before the jth generation. The probability distribution of S_j is crucial to evaluate the system reliability when the cascading process proceeds to the jth generation.

$$\begin{aligned} P\left[S_j = s_j\right] = &\sum_{n_{f0}=1}^{n-j}\ \sum_{n_{o0}=0}^{n-n_{f0}-j}\ \sum_{n_{f1}=1}^{n-u_0-(j-1)}\ \sum_{n_{o1}=0}^{n-u_1-(j-1)}\cdots\sum_{n_{f(j-1)}=1}^{n-u_{(j-2)}-1}\ \sum_{n_{o(j-1)}=0}^{n-u_{(j-1)}-1} \\ &\times\frac{n!}{n_{f0}!n_{o0}!n_{w0}!}\alpha_0^{n_{f0}}\beta_0^{n_{o0}}\gamma_0^{n_{w0}}\frac{(n-u_0)!}{n_{f1}!n_{o1}!n_{w1}!}\alpha_1^{n_{f1}}\beta_1^{n_{o1}}\gamma_1^{n_{w1}}\cdot\cdot\frac{\left(n-u_{(j-1)}\right)!}{n_{fj}!n_{oj}!n_{wj}!}\alpha_j^{n_{fj}}\beta_j^{n_{oj}}\gamma_j^{n_{wj}} \end{aligned} \tag{4}$$

The probability that the cascading process stops in the Jth generation is

$$P(j = J) = P\left(u_J = n, n_{fJ} \neq 0\right) + P\left(u_J < n, n_{fJ} \geq 1, n_{f(J+1)} = 0\right) \tag{5}$$

In Equation (5), $P(u_J = n, n_{fJ} \neq 0)$ implies the probability of the stop scenario 1. $u_J = n$ implies the event that the total number of failed components until the Jth generation is n, which means that all the components fail until the generation J. $n_{fJ} \neq 0$ implies the event that the number of failed components in the Jth generation is not 0, which means that there are still new failures in the Jth generation. In addition, $u_J < n, n_{fJ} \geq 1$, and $n_{f(J+1)} = 0$ separately implies the event that the total number of failed components until the Jth generation is less than n, the event that there are at least one failed component in the Jth generation, and the event that there are no new failed components in the generation J+1. These restrictions exhibit a scenario that the cascading process stops, but the system does not fail in the Jth generation, whose probability could be denoted by $P(u_J < n, n_{fJ} \geq 1,\ \ n_{f(J+1)} = 0)$.

Therefore, the probability that the system fails and cascading process stops in the Jth generation is

$$P\left(j = J,\ u_J = n\right) = P\left(u_J = n, n_{fJ} \neq 0\right) \tag{6}$$

Since the cascading time is further considered in the model, and the cascading time is closely related to the generation j of the cascading process, the index J where the cascading process stops is the key factor to analyze the system reliability. The cascading events occur at time $\{T_0, T_1, \ldots T_j\}$, and T_j is duration of cascading process from the start to the jth generation $T_j = T_{j-1} + Y_j$. Assume that the cascading time Y_j for every generation follows an exponential distribution[19] with probability density function

$$f_{\mathrm{Y}}\left(t\right) = \mu \mathrm{e}^{-\mu t} \tag{7}$$

for $\mu > 0$, where μ is the rate parameter, which could be changed to control the cascading time distribution.

Then the cumulative probability distribution function that all components fail in the Jth generation at time t could be denoted as

$$F_{\mathrm{Y}}{}^{(J+1)}\left(t\right) = 1 - \mathrm{e}^{-\mu t} \tag{8}$$

The system reliability can be represented as the probability that the system is still working until time t, and could then be evaluated using the following equation

$$R\left(t\right) = 1 - \sum_{j=0}^{n-1} P(U_j = n,\ T_j < t) = 1 - \sum_{J=0}^{n-1} F_{Y}{}^{(J+1)}\left(t\right) \cdot P\left(J = j, u_J = n\right) \tag{9}$$

where $P(U_j = n, T_j < t)$ represents the probability that the system fails before time t. Through the integration of the Equations (4), (8), and (9), the system reliability over time could be obtained.

This model could be more general to extend the assumption of system failure. For instance, it can encompass scenarios where the system fails if a specific number of components fail, as in the case of a k-out-of-n system where the system fails when k components out of n fail. The only difference shown by the model for a k-out-of-n system is the stop scenario 1 where the cascading process stops if the total number of failed components is no less than k.

In this case, the probability that the system fails and cascading process stops in the Jth generation is

$$P\left(j = J, u_J \geq k\right) = P\left(u_J \geq k, n_{fJ} \geq 1,\ \ n_{f(J+1)} = 0\right) \tag{10}$$

The system reliability for a k-out-of-n system can be represented as Equation (11). Through the integration of the Equations (4), (8), and (11), the reliability for the k-out-of-n system over time could be obtained.

$$R\left(t\right) = 1 - \sum_{j=0}^{k-1} P(U_j \geq k, T_j < t) = 1 - \sum_{J=0}^{k-1} F_{Y}{}^{(J+1)}\left(t\right) \cdot P\left(u_J \geq k, n_{fJ} \geq 1,\ \ n_{f(J+1)} = 0\right) \tag{11}$$

The above outputs improved the multi-state CASCADE model by inducing cascading time and offers failure probability estimation of the loading system considering different cascading scenarios. The improved model can be used to assess the system condition, optimize system design and maintenance activities to increase reliability. The following section will provide some numerical examples for further illustration.

4 | NUMERICAL EXAMPLES

To provide guidance on system design and operation, the effects of variation of some parameters on system reliability are examined in this section. Numerical examples are studied with coding in MATLAB. These case studies are mostly sensitivity analysis, meaning that when one parameter is analyzed, the other parameters remain constant.

Table 1 shows the parameter benchmark. In this study, load redistribution is the main driving force of the cascading process. The parameters c_0 and c_d imply the properties of the components themselves and the natural degradation, which

TABLE 1 Parameter benchmark of the examples.

Parameter	d	c_0	c_d	n	l_f	l_o	r^*	μ
Value	0.3	1	0.05	100	0.05	0.01	0.8	0.2

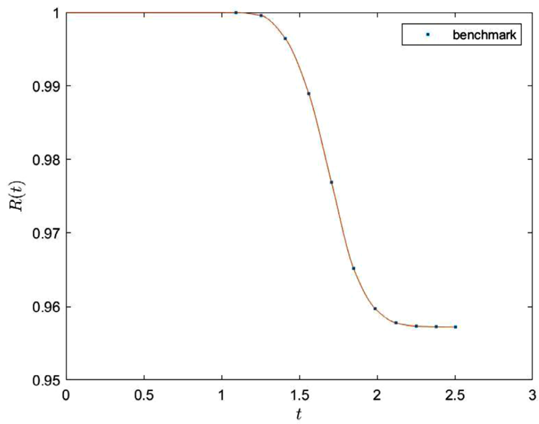

FIGURE 2 System reliability over time as a benchmark.

are relatively independent of the load redistribution mechanism. Therefore, the case studies do not delve into the impact of c_0 and c_d on the system reliability. Values of the other parameters are drawn from our previous work.[13] For example, the total number of the components is fixed as 100, and the overloading threshold is set as 0.8 in the benchmark. However, since the focus of this study is on studying the stop scenario 1 and system reliability, the values that increase the likelihood of stop scenario 1 occurring are favored. Therefore, the values of initial disturbance and the loading increments in this numerical example are set much larger than that in previous example.[13]

Based on the benchmark, a reliability curve is drawn to show the main properties of the reliability over time, as shown in Figure 2.

In overall, the system reliability experiences a minor decline at the start, a sharp drop in the middle phase, and another slight decrease towards the end of the curve. Towards the end, there seems to be a trend for the curve to remain constant. Such a curve can be explained as follows: At the onset of the cascading process, the probability of system failure is determined by adding the initial disturbance to the initial workload of components. As a result, there is a very low likelihood of all components failing simultaneously in the beginning, meaning that the system reliability is close to 1. As the cascading process proceeds, more generations of the cascading process imply more additional workloads on the functioning (overloading and normally working) components, and such load redistribution causes more components to fail, leading to a rapid decline in the system reliability. The total number of generations J remains stable for a given initial disturbance d in the scenario where the cascading process stops and the system fails. Consequently, as the cascading process slows down, and the reliability curve approaches its tail, the system reliability gradually reaches a stable value, which could be abbreviated as the minimum stable system reliability in our study.

According to Figure 2, it is also found that the curve stops at a specific time, instead of extending further. This is because that the curve only demonstrates the system reliability within a single cascading process that terminates at a specific time due to various cascading scenarios. As mentioned before, we only consider one cascading process until it stops. If the remaining components tend to fail after a period, we mark it as a new cascading process, which is not included in this model. This clarifies why the curve comes to a halt at a specific time, rather than advancing continuously. The duration of cascading process stopping in stop scenario 1 could also be employed to help to evaluate system reliability, because the system is generally expected to maintain normal operation for longer period.

System reliability, as defined, can be assessed using two primary metrics: the probability of system failure and the operating time before failures. These aspects can be described in terms of the duration cascading process stopping in stop scenario 1 and the minimum stable system reliability. This prompts us to emphasize these two aspects when performing sensitivity analysis.

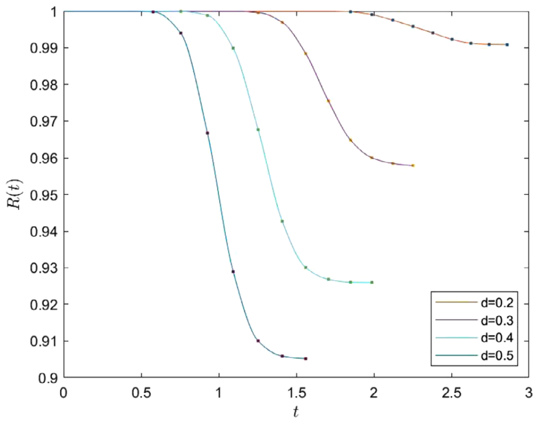

FIGURE 3 System reliability with different initial disturbance.

4.1 | Effect of initial disturbance

This subsection illustrates the change of system reliability with different initial disturbances. According to the previous work, stop scenario 1 was reported to occur only when there is a sufficient initial disturbance of at least 0.2. Besides, the analysis of system reliability is performed when the system fails under stop scenario 1, which can occur with different initial disturbances valued at $d = 0.2, 0.3, 0.4, 0.5$.

Figure 3 presents the variations in system reliability with various initial disturbances. Through a detailed comparison of these four curves, some findings could be obtained. The system reliability is lower when the initial disturbance value is larger at the same timepoint. Besides, the minimum stable system reliability is also lower when the initial disturbance value is larger. The explanation is provided as follows: As the initial disturbance increases, the workloads of more components tend to surpass the failure threshold, resulting in lower system reliability. Apart from the system reliability, it is also found that the cascading process stops and the system fails in shorter time when the initial disturbance value is larger.

The results emphasize the importance of controlling the initial disturbance to improve the system reliability and provide some managerial implications. In practice, it is costly to strive for an extremely high system reliability approaching a value of 1. However, it is equally unwise to ignore the impact of disturbances. Thus, we can determine an acceptable range for external disturbance when the system can tolerate a certain level of reliability. An example from the solar panel system could be taken to demonstrates that how the proposed model serves as an effective tool in system reliability prediction and maintenance optimization. The solar panel system is a loading dependent system with CAFs, where the performance of the panel is affected by a variety of external disturbances, including light intensity, temperature, and contaminants. In terms of the external disturbance contaminants, the pursuit of maintaining 100% power output can result in high cleaning and maintenance costs. On the contrary, by employing the proposed model, the system reliability under varying initial disturbances can be estimated. The estimation results, when combined with system design specifications and standards, allows for the determination of an acceptable range of system reliability. Subsequently, maintenance strategies for regular solar panel cleaning can be customized to minimize costs while ensuring that the system can tolerate a certain degree of surface contamination without causing a significant decline in system reliability.

4.2 | Effect of total number of components

The proposed model is now used to examine the cascading process and system reliability changes in various systems with different total number of components. Figure 4 displays the changes in system reliability observed when altering the total numbers of components $n = 50, 100, 150, 200$.

Figure 4 illustrates a similar trend of all the curves, which is consistent with the trend of the curves in the last subsection. When comparing the four curves, it is observed that as n increases, the system reliability curves shift toward the right. Specifically, the curves begin to decline at a later time and reach the halt point at a later time as well. Additionally, for larger

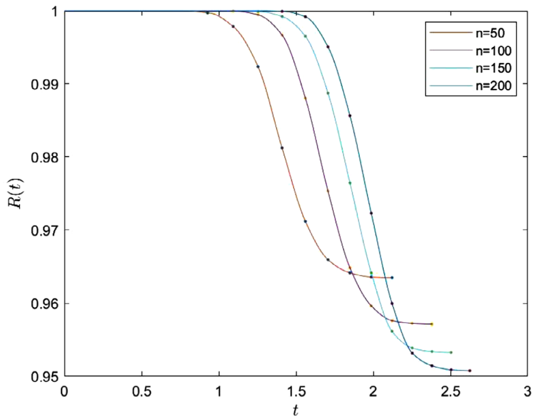

FIGURE 4 System reliability with different total number of components.

values of n, the system reliability displays a lower value once it stabilizes and reaches the endpoint. In brief, an increased number of components in a system lead to lower minimum system reliability and an extended cascading process. This implies that when there are more components within a system, the likelihood of system failure increases, but the time it takes for the system to eventually fail is longer. The aforementioned findings can be explained by that when there are more components in a system, it takes more time for all the components to fail and also takes more time for a cascading process to end in stop scenario 1. In a system with more components, a longer cascading process implies more possibilities for the process to proceed, resulting in an increased likelihood of system failure and lower system reliability.

Such findings also can remind engineers that during the design phase of a system with CAFs, reducing the number of components to a suitable range may improve the minimum stable system reliability and assist in sustaining the system operation within an acceptable timeframe. In term of the operation phase, some suggestions can be provided: when time is limited, priority is given to maintaining systems with fewer components, while when the primary aim is to improve system reliability, it is advisable to allocate more maintenance resources to systems with more components.

4.3 | Effect of loading increments

In this subsection, we utilize varying values of l_f and l_o for different configurations to compare the impacts of two types of loading increments. The loading increments are the additional loads from the failed or overloading components to the remaining functioning components, representing the dependence among components. Based on the assumption that the initial workload of the component lies in $[0, 1]$, the values of l_f and l_o also lie in $[0, 1]$, and the value of l_o must not surpass l_f to align the configurations with reality. In this example, we firstly set $l_o = 0.01$, and set different loading increments l_f as: 0.03, 0.05, 0.07, and 0.09. Then, we set different loading increments l_o as 0.01, 0.02, 0.03, and 0.04 for $l_f = 0.05$.

The changes of system reliability under two types of loading increments are respectively depicted in Figures 5 and 6. It is noteworthy that the curves closely overlap during the previous part of the cascading process, and discernible differences only as the process nears its tails. The results show that the loading increments have a stronger influence on the system reliability as the cascading process proceeds. The reason for this finding can be attributed to the following. At every generation, the two kinds of load increments are added to the functioning components, resulting in increased cumulative loads as the cascading process proceeds over time. Furthermore, the dissimilarity in cumulative loads induced by distinct load increments becomes more apparent, amplifying the variance in their effect on the system reliability. Besides, As shown in Figures 5 and 6, higher values of loading increments result in reduced system reliability. Higher loading increments lead to increased additional loads on functioning components, and lead to a higher likelihood of their failures. This ultimately leads to lower system reliability. This outcome implies that the loading increment has a certain degree of impact on the system reliability, but the extent of this influence is observable only when it is considerably large.

Another finding is that the impact on the system reliability due to failed components and that due to overloading components are similar to a certain extent. According to the proposed model, both kinds of loading increments are assigned to

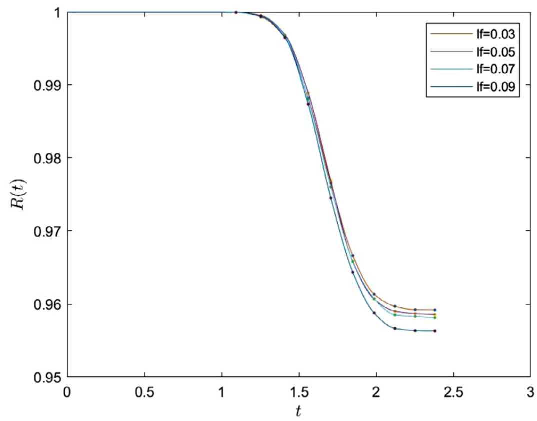

FIGURE 5 System reliability with different loading increment from failed components.

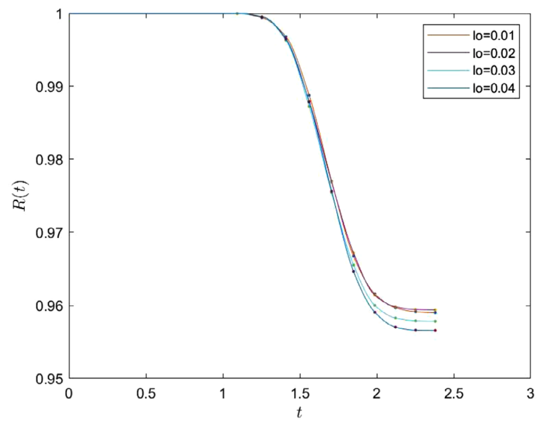

FIGURE 6 System reliability with different loading increment from overloading components.

the remaining functioning components in the same way. This distribution way ensures that the influence of these loading increments on the component should be comparable.

Based on such findings, firstly, management need to attempt to avoid subsequent failures by developing a more reasonable workload allocation strategy. Taking a pipeline system as an example, when a pipeline ruptures or becomes blocked, other pipelines will bear more flow, in other words, additional workload. This extra workload can be adjusted through valve regulation and reasonable diversion measures. Besides, given the roughly equal impact of both loading increments changes on system reliability, the strategy with higher cost-effectiveness can be chosen by comparing the costs associated with controlling the two kinds of loading increments.

4.4 | Effect of overloading threshold

By setting that the overloading threshold r^* varies from 0.5 to 0.9, the changes of system reliability are observed as shown in Figure 7.

According to Figure 7, we can observe that as the overloading threshold increases or decreases, the system reliability curve changes, but not in a systematic manner. In other words, we cannot make a definitive conclusion that the overload threshold has a significant impact on the system reliability. This finding aligns with our prior research result, where we

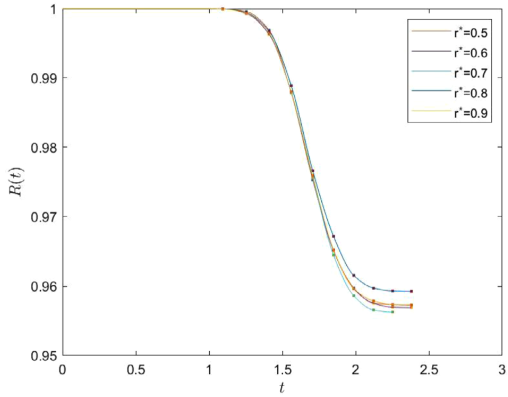

FIGURE 7 System reliability with different overloading threshold.

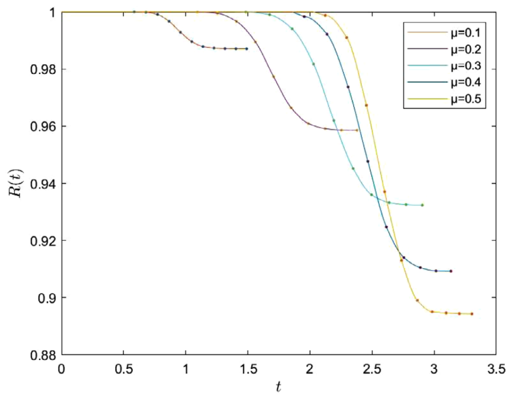

FIGURE 8 System reliability with different cascading time.

discovered that altering the overloading threshold mainly influences the probability distribution range of the number of overloading components, but has minimal impact on the probability distribution range of failed components, which is closely linked to system reliability.

4.5 | Effect of cascading time

The developmental features of the cascading process may vary for distinct systems, environments, and failure modes. In various cascading scenarios, alternative probability distributions may be considered. This paper assumes that the exponential probability distribution governs the cascading time taken for the development of each generation in the system cascading process. To investigate the effect of cascading time, an example is given by changing the rate parameter μ of the probability density function. Set that the value of rate parameter μ varies from 0.1 to 0.5, and the changes of system reliability are observed as shown in Figure 8.

Figure 8 displays how system reliability changes with different cascading time. As the value of μ increases, it can be observed that the system reliability curves shift towards the right. This implies that in situations where μ is high, the evolving of the cascading process takes more time. Besides, the minimum stable system reliability decreases when μ is high. In mathematical terms, μ represents the scale parameter of the exponential distribution. As μ increases, the value of $f_Y(t)$ near the origin also increases, signifying that the time needed for each generation at the start of the cascading process increases. Consequently, with an increase in the μ value, the initial cascading process requires more time to proceed,

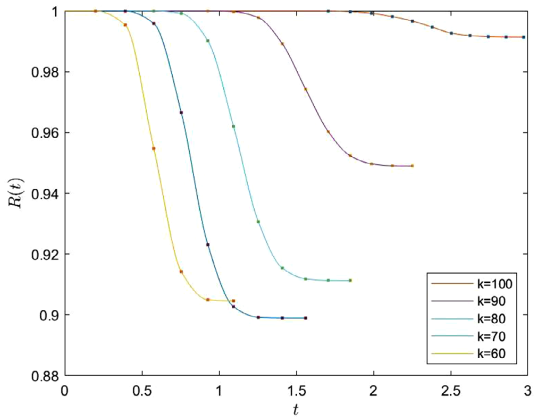

FIGURE 9 System reliability with different parameter k in a k-out-of-n system.

causing the corresponding system reliability curve to display its decline at a later period. This, in turn, contributes to an extended total duration for the development of the whole cascading process. In addition, as μ increases, the value of $f_Y(t)$ far away from the origin decreases, implying that as the cascading process proceeds, the time needed for each generation, and the time for causing the failed components, decreases, resulting in a faster rate for system degradation. This also accounts for the phenomenon that a higher value of μ leads to a more significant slope in the declining section of the system reliability curve.

This finding offers insights for system design and management. Regarding system design, simplifying the internal components and avoiding a tightly-packed layout can be effective in reducing cascading time. In terms of management, systems with higher rate parameters and fast-developing cascading processes should undergo more frequent inspections and maintenance activities. Moreover, systems with different rate parameters have distinct reliability curves, leading to different results in risk assessments. These dissimilar outcomes are crucial references for managers when making decisions.

4.6 | Effect of parameter *k* in a k-out-of-n system

The above subsections discuss the reliability analysis for the system where system failure occurs only when all components fail. In this part, the value of k is changed from 60 to 100 to display the reliability variations of the k-out-of-n system consisting of 100 components in total.

From Figure 9, when the value of k decreases, the system reliability curves shift toward the left. Initially, the minimum stable system reliability experiences a gradual decline, but it increases when $k = 60$. Following is the explanation for this phenomenon. When k decreases, it signifies that a smaller number of failed components can lead to system failure. Firstly, the system will therefore fail in a shorter period, reducing the duration of the cascading process and causing the reliability curves to shift leftward. Secondly, the system becomes more prone to failures, meaning the probability of system failure increases, thereby decreasing the minimum stable system reliability. However, when k decreases to a certain extent, the system fails very quickly, increasing the value of system reliability. According to the definition of system reliability, it depends on the combined influence of the probability of system failure and the operating time before failures. Therefore, in this case, even though the probability of system failure increases, its impact on system reliability is not as significant as the effect of the duration for the system to fail, leading to an increase in the minimum system reliability value instead.

5 | CONCLUSION AND FUTURE WORKS

In this paper, we have proposed a new reliability index for evaluating the system reliability of a loading dependent system considering overloading state based on the multi-state CASCADE model. Cascading time is well considered in such a method. The numerical example is conducted to examine the system reliability model and demonstrate the impacts of different factors on the cascading process and the system reliability: Alterations in the initial disturbance, the total number of components, the cascading time distribution, and the parameter k in a k-out-of-n system all significantly influence both the system reliability and the duration of the cascading process. On the other hand, the variation of the loading increments only exhibits an influence on the system reliability when the cascading process approaches its end due to influence accumulation. Notably, neither the system reliability nor the duration of the cascading process remains unaffected by the overloading thresholds of the components. These findings can help maintenance crews and managers make more informed decisions in terms of system design and operational management when considering cascade time and reliability.

Some relevant topics are worth examining in future studies. Firstly, given that the model we propose are mainly used for the multi-component systems with simple structures, further investigations for complex systems such as series-parallel system or parallel-series system in engineering applications are encouraged. In addition, from a comprehensive point of view, the system may still operate after the cascading process end. Therefore, the system reliability analysis could be examined after the first cascading process ends. Thirdly, since the environmental factors are dynamic and may cause multiple outside disturbances, this model can be extended to allow a series of outside disturbances which happen at different time points before the system fails. The extended model will consider the probabilities of more cascading scenarios. These cascading scenarios are categorized based on different numbers of outside disturbances, and are subsequently subdivided into two types, the scenario where the cascading process ends before the arrival of the last disturbance, as well as the scenario where the cascading process ends after the last disturbance has arrived. All scenarios will be examined and the probabilities of cascading scenarios where the system fails are accumulated to provide a final calculation of system reliability.

NOMENCLATURE

c_0	initial capacity of the component
c_{d}	capacity decrement of the functioning components during each generation
c_{j}	capacity of the component in the jth generation
d	the value of the initial disturbance
j	generation of the cascading process, $j = 0,1,2,\ldots.$
J	the generation that the cascading process stops
k	the number of components out of the total number of components that need to be functioning for the entire system to function.
l_{f}	the loading increment from a failed component
l_{i}	the initial workload on component i
l_{j}	the loading increments from all the failed and overloading component in the jth generation
l_{o}	the loading increment from an overloading component
n	total number of the components in a system
n_{fj}	number of the failed components in the jth generation
n_{oj}	number of the overloading components in the jth generation
n_{wj}	number of the working components in the jth generation
r^*	overloading threshold of the component
$R(t)$	the system reliability with time t
s_{j}	the case that there are n_{fj} failed components, n_{oj} overloading components, and n_{wj} normally working components in the jth generation
t	cascading time, and $t = 0$ when the cascading process starts
T_{j}	the time interval from the initiation of the cascading process to the jth generation
u	total number of the failed components
v	total number of the overloading components
Y_{j}	the cascading time for generation j
α, β, γ	the indices used to abbreviate the probability of components in three different states
μ	rate parameter of the exponential distribution characterizing the cascading time

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Yixin Zhao https://orcid.org/0000-0003-0309-3882

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AUTHOR BIOGRAPHIES

Yixin Zhao received the BEng degree in safety engineering from Zhengzhou University, Zhengzhou, China in 2017 and received the MEng degree in safety technology and engineering from South China University of Technology, Guangzhou, China in 2020. She is currently working toward the Ph.D. degree in Norwegian University of Science and Technology, Trondheim, Norway. Her research interests include cascading failures, reliability engineering and maintenance optimization.

Tianqi Sun has a BEng degree in Safety Engineering from China University of Petroleum (East China) and received a MEng degree in Research Group of Reliability, Availability, Maintainability and Safety from Norwegian University of Science and Technology, Trondheim, Norway. He is currently working toward the Ph.D. degree with Research Group of Reliability, Availability, Maintainability and Safety, Norwegian University of Science and Technology. His research focus on the reliability engineering and maintenance models.

Yiliu Liu (Member, IEEE), received the PhD degree in Management Science and Engineering from Tianjin University, Tianjin, China in 2010. He currently works as a professor with Research Group of Reliability, Availability, Maintainability and Safety, Norwegian University of Science and Technology, Trondheim, Norway. He has published more than 100 papers and coauthored some scientific books. His interests are product reliability engineering and warranty analysis, cascading failures and barrier theory, system analysis for reliability and resilience, prognostics and maintenance optimization. Prof. Liu serves as co-chair in Norway of *IEEE Reliability Society Norway-Sweden Joint Section*.

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IV

Article IV

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Condition-based maintenance for a multi-component system subject to heterogeneous failure dependences

Yixin Zhao [a,b], Valerio Cozzani [b], Tianqi Sun [a], Jørn Vatn [a], Yiliu Liu [a,*]

[a] Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Trondheim, Norway
[b] LISES–Laboratory of Industrial Safety and Environmental Sustainability - Department of Civil, Chemical, Environmental and Materials Engineering, University of Bologna, Bologna, Italy

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ABSTRACT

Many industrial facilities consisting of multiple components are prone to failure interactions and degradation interactions. In such systems, these interactions are frequently characterized by failure dependences that may accelerate the degradation of components. Due to system layout and functional interactions, not all components have the same failure dependence. In the general context of complex failure dependences in dependent multi-component systems, heterogeneous failure dependences further complicate the maintenance activities during operation. The present study developed a comprehensive framework for evaluating heterogeneous failure dependences and a maintenance optimization model by Markov processes for multi-component systems. The proposed method is applied to a practical case consisting in a parallel subsea transmission system to illustrate the effects of heterogeneous failure dependences. The results show that the heterogeneous failure dependences framework and the maintenance model guide the optimization of maintenance strategies to maximize the system availability and minimize the maintenance cost.

1. Introduction

Modern industrial systems usually consist of several components that need to operate simultaneously to accomplish the overall mission. As the systems become more complex with more interactions among the components, it is essential to pay close attention to the failure dependences existing between them. Failure dependences exist in such systems, meaning that the failure of one component may have influence on the failures of the other components, usually increasing their failure probabilities. The malfunction or degradation of the first component is defined as the triggering event of a failure cascading process. The failed component is defined as the triggering component. In some cases, failure dependence may not manifest as an immediate termination of component functions, but as a gradual degradation in the performance of those components. Thus, the failure dependences can be classified as [1,2]:

- Type I failure dependence: A triggering event results in direct damage. In such a context, a component could fail due to a combined effect of its normally inherent degradation, and the shock from the failures of other components.
- Type II failure dependence: A triggering event redistributes the total working load on the overall system. In such a context, a component could fail due to a combined effect of its normally inherent degradation, and the accelerated degradation caused by the failures or malfunctions of other components.

These two types of failure dependences can take place within the same system [3]. Thus, it is necessary to consider both in reliability analysis and maintenance.

In reliability analysis, degradation models are generally developed based on the performance data of a system or component over time to predict how it will degrade in the future. By considering failure dependence in degradation models, it is possible to have a better understanding on the underlying mechanisms of degradations and failures in complex systems. This can lead to more accurate models reflecting the reality. Therefore, numerous studies have been conducted so far integrating failure dependence in degradation models for reliability analysis and maintenance optimization. These models are roughly divided into three categories: multivariate joint distribution-based models, copula-based models, and degradation rate interaction (DRI) models [4,5]. Multivariate joint distribution-based models use joint probability distribution to present the dependence of degradation paths [6,7].

* Corresponding author
E-mail address: yiliu.liu@ntnu.no (Y. Liu).

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Notation

n	Total number of components in a system
k	The number of degradation states of components before failure
x_i	The degradation state of component i
$x_i(t)$	The degradation state of component i at time t
χ	The state space of the n components system, which is taken to be $\{X_0,\ X_1,\dots X_{k^n}\}$
a	The threshold for minor preventive maintenance activity
b	The threshold for major corrective maintenance activity
N_{IMR}	The total number of inspections, maintenances and repairs
s	The number of inspections, maintenances and repairs
$P_{x_i}(t)$	The probability that the component i is in state x_i at time t
$P_{X_i}(t)$	The probability that the entire system is in state X_i at time t
$P(t)$	The sojourn probability of the Markov process at time t.
λ_{x_i}	The degradation rate of component i from state x_i to state x_i $+1$ without failure dependence
$\lambda^i_{x_i,x_j}$	The degradation rate of component i from state x_i to state x_i $+ 1$ when there exists failure dependence between it and another component j whose state is x_j
γ_{ij}	Cascading intensity from component j to component i
φ_j	Degradation level of component j
β_j	Correction coefficient
ϕ_{x_j}	Influencing level from component j
D_{i,x_j}	The failure dependence from component j on component i when component j is in state x_j
$\mathbb{A}$	The transition matrix denoting the transition rates of the entire system
$\mathbb{B}$	The probability matrix of different states after inspection, maintenance and repair actions
$\mathbb{D}$	The matrix of failure dependences among components
t^-	The time immediately before inspection
t^+	The time right after inspection, maintenance and repair actions
T_s	The time when the sth inspections, maintenances and repairs are conducted
X_F	The failed state of the component or the entire system
$\overline{A_s}$	The unavailability of the system
A_S	The availability of the system
c_{in}	The inspection cost of the system for each time
$c_{\mathrm{m1},i}$	The cost of each minor preventive maintenance activity on component i
$c_{\mathrm{m2},i}$	The cost of each major corrective maintenance activity on component i
c_{p}	The planned downtime cost per inspection
c_{u}	The unplanned downtime cost of the system
C_S	The average life-time cost

Abbreviation

DMDM	Degradation model for dependent multi-component system
FD	Failure dependence model
CBM	Condition-based maintenance
CTMC	Continuous-time Markovian chain
IMRs	Inspections, maintenances and repairs
PM	Minor preventive maintenance
CM	Major corrective maintenance
MTTF	Mean time to failure
MTBI	Mean time between inspections
OREDA	Offshore and Onshore Reliability Data

Copula-based method models the dependence between components in the combination of multivariate dependence with univariate marginals [8–10]. These two approaches have one common property that they use a multivariate distribution or copula to describe the joint aging process. Different from the above two methods, the DRI models manifest the degradation process of one component affected by the degradation of other components, which is more in accordance with the actual degradation of a dependent multi-component system [4]. The DRI model was firstly proposed by Bian and Gebraeel [11] to analyze the stochastic degradation process and prognostics of a multi-component system. Hafsa et al. [12] defined a degradation effect coefficient and presented a stochastic methodology by modeling the DRI effects of multi-component interaction in the remaining useful life (RUL) calculation. Considering Based the influence of degradation interaction and uncertainty, Shao et al. [13] contributed a multi-stage model-based framework to better describe the degradation acceleration process and evaluate the system RUL.

Given that the degradation status can be observed or measured, condition-based maintenance (CBM) is applied to many technical systems to keep system reliability while reducing maintenance cost. The Markov chain has been used for modeling the interactions between degradation processes and maintenance activities [14–18]. In these studies, a continuous-time Markovian chain (CTMC) is generally adopted to describe the system degradation behavior and the transitions between states. There are plenty of studies applying CTMC to model the degradation process and maintenance policies of a multi-state system, providing approximate analytical solutions for availability and cost [15, 19-21]. However, CBM for a multi-component system with failure dependences is generally more complicated [22]. Several previous studies on CBM strategies for multi-component system with failure dependence using the CTMC model were carried out by Liang et al. [15,23,24], where the failure dependence is modeled as the accelerated deterioration, and CBMs is optimized in considering multiple dependent deterioration path. Inspired by the above, we intend to build the CBM model by CTMC to present the normal degradation process and accelerated degradation process.

To the best of our knowledge, most of the current modeling approaches consider a two-component system or an n components system with identical failure dependence. For example, the chemical cluster is a system with n components mainly subject to Type I failure dependence, and a road network is a system with n components only subject to Type II failure dependence. However, such approaches are no longer completely aligned with reality, since the failure dependences in a multi-component system are more complex and heterogeneous [4]. Heterogeneous failure dependences occur in the situation where at least two types of non-identical failure dependence exist in a multi-component system. Therefore, a flexible framework to model the heterogeneous failure dependences in the context of maintenance optimization is desired for designing more reasonable CBM policies. In this paper, we focus on modeling the heterogeneous failure dependence within a multi-component system. Compared to alternative modeling approaches applied only in a two-component system, or in a multi-component system with identical components, the presenting work targets a multi-component system with non-identical components. In contrast to the current approaches, heterogeneous failure dependences modeling accounts better for the variety of interactions and dependences among non-identical components in a system. Such work is expected to predict the system behavior more precisely, which helps identify critical components and failure modes that are often overlooked in simpler models. In detail, the degradation model for dependent multi-component system (DMDM) is proposed based on two basic principles: (1) the general degradation process of independent component is depicted by a discrete

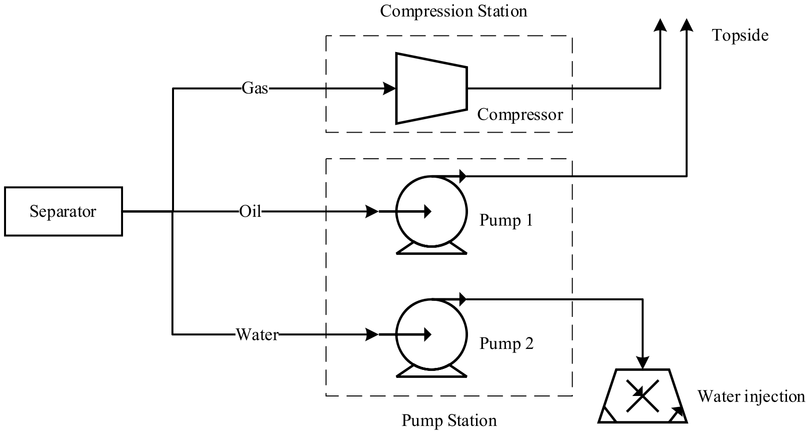


Fig. 1. Scheme of the transmission system considered in the motivating case

state space; (2) the failure dependences among components are characterized and quantified by proposing the failure dependence (FD) model.

Then, we will specify the CBM policy for multi-component systems accordingly. The maintenance policies are depicted considering preventive maintenance (PM) and corrective maintenance (CM). The major contributions of this study are outlined below:

(1) A new mechanism to model the heterogeneity of failure dependences for the degradation process in a multi-component system.
(2) A novel CBM strategy-making method for the multi-component system with heterogeneous failure dependences.
(3) Managerial implications on optimizing maintenances with a case study on a parallel subsea transmission system after the separator.

The rest of this paper is structured as follows. To start, we present a description of the motivating example about the subsea transmission system in Section 2. The degradation models for independent components and the dependent multi-component system are described in Section 3. In Section 4, the maintenance policies are interpreted by the Markov chain. Section 5 applies the overall approach to the practical case study of a three-component system maintenance. Finally, suggested future work and conclusions occur in Section 6.

2. Motivating example and problem description

In our study, we consider that load redistribution and failure-induced damage mainly lead to failure and degradation dependences. In the load redistribution mode, redistributed load determines the strength of failure dependence. In the failure-induce damage mode, the distance between components and safety barrier measures influence failure dependence.

In order to illustrate the problem, we introduce the transmission system of a subsea separation system that is developed to enhance oil recovery, using a horizontal gravity separator to separate bulk water from the hydrocarbon stream. A scheme of the system is reported in Fig. 1. Three pipes transporting gas, oil and water after the outlet of separator [25] are directed to the pump station and compression station, which are located near the separation station. The transmission part of the subsea system, which encompasses the compression station and pump station, can be regarded as a dependent system. In the following, we will refer to this system as the transmission system for the sake of brevity. One compressor and two pumps are installed in parallel in the simplified transmission system model. Wet gas is compressed by a compressor routed to the topside platform. Then, the separated oil and water are respectively pumped following the topside direction or reinjected into a reservoir via the water injection.

The service life of the compressor and pump are generally designed for 5-10 years without any intervention [26] and they are expected to serve 30-50 years with inspections, maintenances and repairs (IMRs) [27]. During their long service lifetime, these devices deteriorate stochastically, and the degradation process may be accelerated by the malfunction or degradation of the other components. The compressor and the two pumps normally transport different substances at the desired power under ideal conditions. In practice, however, devices degrade naturally, resulting in a variety of failure modes such as low output, leakage, vibration, overheating, spurious stop, etc. Some of the failures affect not only their own production efficiency, but also the degradation rates of other devices in the system. For example, the separator cannot separate the three substances completely, and the mutual doping of substances will aggravate the degradation of the compressor and pumps. Similarly, if a component such as compressor malfunctions, but somehow the system cannot be inspected and repaired timely, and it still needs to continue working, gas will enter the pipeline that transports oil or water, and the doping of the gas will compound the damage to the pumps, which is what we call failure dependence. This type of failure dependence can be considered as load redistribution. Another example is that the vibration and overheating of one pump may have a direct impact on the operation and aging process of another pump within a certain distance in the pump station. This kind of failure dependence is related to the safety distance, and the safety barrier measures. Hence, we can find that the compressor and pumps are subject to gradual degradation failure and two types of failure dependences.

Condition of the transmission system is assessed through periodic inspections. Two types of maintenances can be implemented according to the inspection results. The first is minor preventive maintenance which could lower the accumulated damage to a certain level, such as anti-corrosion coating, de-rusting and cleaning. The second type is major corrective maintenance including overhaul and preventive replacement that components are perfectly overhauled or replaced, and their states are reset to “as-good-as-new” state.

IMRs are considered very costly when the accessibility of the item to be maintained is low, such as this system operating in deep water[27]. It is beneficial to conduct a reasonable maintenance strategy for reducing IMRs costs while keeping the system performance acceptable. With the motivating example, a comprehensive approach is proposed to optimize

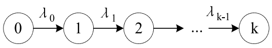


Fig. 2. State transition diagram of individual component

the maintenance activities for dependent multi-component systems. The overall approach developed in this paper can be summarized as follows:

Step 1 Describe the degradation process of the system without failure dependence.
Step 2 Identify the system structure and factors influencing the failure dependence.
Step 3 Evaluate the failure dependences between components based on system and environmental conditions.
Step 4 Describe the degradation process of the system with failure dependence.
Step 5 Construct a CBM model.
Step 6 Calculate the system availability and maintenance cost.
Step 7 Find the optimal maintenance threshold for maintenance activities.

The proposed approach is detailed and discussed in the following sections.

3. Degradation models for a dependent multi-component system

3.1. Independent general degradation model

An independent general degradation model with a general degradation path is developed firstly in Fig. 2 to reflect the inherent independent degradation of components in a dependent system. This model serves as the foundation of DMDM when degradation dependences are taken into account in a dependent multi-component system.

We start with a fully functioning state $x = 0$ at time t=0 and observe the component until failure. State $x = k$ represents the failed state of component i as an absorbing state. Between $x = 0$ and $x = k$ there are $k-1$ intermediate states. Let $P_x(t)$ be the probability that the component is in state x at time t. We could obtain a time dependent probability vector $P(t) = [P_0(t), P_1(t), \ldots, P_k(t)]$, denoting the sojourn probability of the Markov process at time t. The initial state probability $P(0) = [1, 0, \ldots, 0]$, and the sum of state probabilities is equal to 1 at any time.

Let $\mathbb{A}$ be a $k \times k$ matrix where the element $a_{x,y}$ denotes the transition rates from state x to state y for all $x \neq y$ and $x, y \in \{0, 1, 2, \ldots, k\}$. State 0 is the brand-new state. For this simple independent degradation model, we assume that the degradation process proceeds all states chronologically from 0 to k. The degradation rate could be represented by λ_x from state x to state x+1. Then the state equation may be written according to Kolmogorov forward equations[28] in matrix terms as

$$P(t) \cdot \mathbb{A} = \dot{P}(t) \tag{1}$$

from which it follows

$$\dot{P}_y(t) = \sum_{x=0}^{k} a_{x,y} P_x(t) \tag{2}$$

If $P_x(t)$ tends to a constant value when $t \to \infty$, then

$$\lim_{t \to \infty} \dot{P}_y(t) = 0 \tag{3}$$

The steady state probabilities $\boldsymbol{P} = [P_0, P_1, \cdots, P_k]$ must therefore satisfy the matrix equation

$$\boldsymbol{P} \cdot \mathbb{A} = \boldsymbol{0} \tag{4}$$

More basic illustrations and details about how to develop the Markov models are reported in the literature[28].

3.2. Failure dependence model

If the degradation rate of a component is impacted by other degrading or failed components, the state transition can be shown in Fig. 3. The state of two-component system is expressed as $X = (x_1, \ x_2)^T$, and so is the state of the n components system $X = (x_1, \ x_2, \ldots \ x_n)^T$, where $x_i \in \{0, 1, 2, \ldots, k\}$ could characterize the degradation state of component i in this system. Each component has $k+1$ states, and the state in which the component is depends on how degraded it is in comparison to the failed state. As a result, components in the same state may exhibit varying degrees of degradation. This means that although there may be some components in the same degradation state, they could have distinct levels of degradation. The degradation of the two-component system could be illustrated by $\{X_0, \ X_1, \ldots \ X_{(k+1)^2}\}$ since there are states for each component and $(k+1)^2$ states for the whole system. Similarly, the degradation of the n components system is governed by the state space , which is taken to be $\{X_0, \ X_1, \cdots \ X_{(k+1)^n}\}$ since there are $k+1$ states for each component and $(k+1)^n$ states for the n components system in total. State $X_0 = (0, 0, \cdots, 0)^T$ is the brand-new

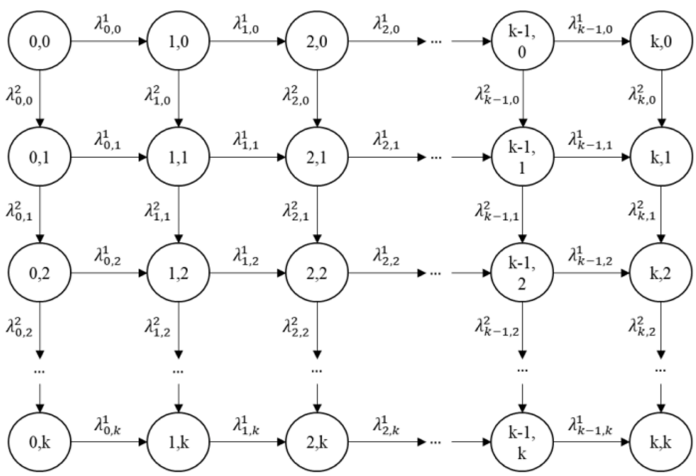


Fig. 3. State transition diagram of a two-component system with failure dependence

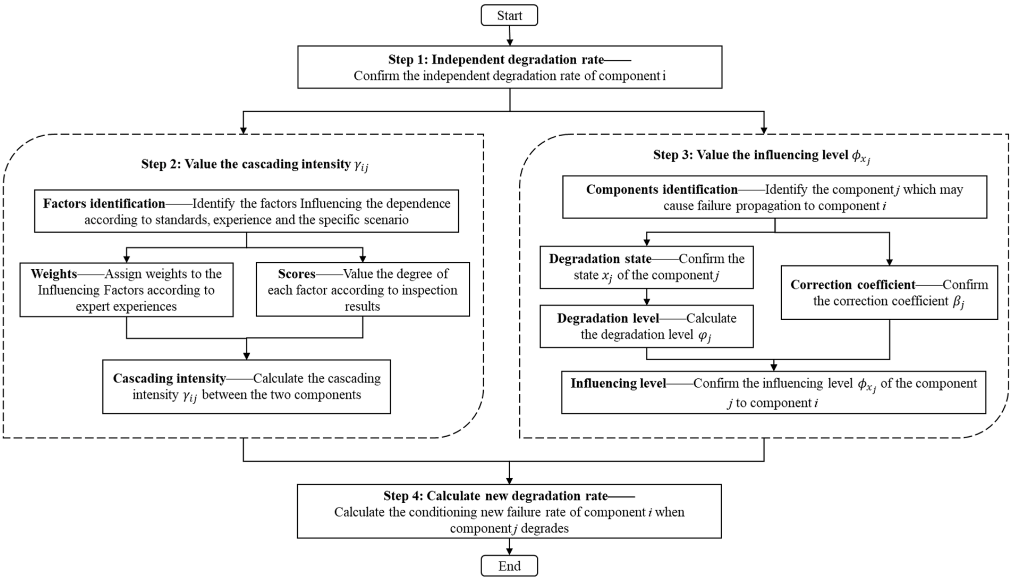


Fig. 4. Flowchart of new degradation rate identification considering failure dependence

state. State $X_{(k+1)^n} = (k, k, \cdots, k)^T$ is an absorbing state.

Now we start with $X = (0,0)^T$ at time t=0 in Fig. 3. State $X = (k,k)^T$ represents the failed state of the two-component system as an absorbing state. The transition rates in this state transition diagram are illustrated as follows. The $(k+1)^2 \times (k+1)^2$ matrix now represents the transition rates from state (x_1, x_2) to next state. $\lambda^1_{x_1,x_2}$ is the degradation rate of component 1 from state x_1 to state $x_1 + 1$ when there exists failure dependence between it and another component 2 whose state is x_2. Similarly, in an n components system, the $(k+1)^n \times (k+1)^n$ matrix represents the transition rates from state $(x_1, x_2, \cdots, x_i, \cdots, x_n)$ to next state. $\lambda^i_{x_1,x_2,\cdots,x_i,\cdots,x_n}$ is the degradation rate of component i from state x_i to state $x_i + 1$ when there exists failure dependence between it and other components whose states are $(x_1, x_2, \cdots, x_n)$. Observe that events of multiple transitions are not included in the state transition diagram, such as a transition between state (x_i, x_j) and $(x_i + 1, x_j + 1)$, since it is assumed to be impossible for all the components in a system to degrade simultaneously during a short time interval from the point of practical.

We initially examine the failure dependence between two components i and j, and then expand the failure dependence model to conclude n components. For failure dependence between two components i and j, when component j degrades, the degradation rate of component i increased, and the calculation procedure of new degradation rate for component i could be demonstrated by the flowchart in Fig. 4. The new degradation rate for component i from state x_i to state x_i +1 and influenced by degradation of component j is expressed by

$$\lambda^i_{x_i,x_j} = \left(1 + \gamma_{ij}\phi_{x_j}\right)\lambda_{x_i}, \ \forall i \neq j \tag{5}$$

where γ_{ij} is the cascading intensity between components i and j, representing the possibility that failures or degradations are cascaded to components i from component j; ϕ_{x_j} is the influencing level from component j, whose value is determined by the degradation degree of component j compared to its failed state. Detailed explanations about the parameters are provided in the following:

(1) Cascading intensity γ_{ij}

The cascading intensity[29,30] between components is determined based on system layout, material backup, safety redundancy, and other practical constraints. According to industrial standards, expert experience, and practical scenarios, it is possible to obtain γ_{ij}, which characterizes the influence of component j on component i in a probabilistic manner, and the same goes for the influence of component i on component j. Furthermore, the value of cascading intensity is supposed to be between 0 and 1. When γ_{ij} is closer to 0, the degradation of component j has little influence on the degradation of component i. When γ_{ij} is closer to 1, the failure dependence between components is quite strong.

The value of cascading intensity depends on the importance of influencing factors and the situation of each factor in the given circumstances. A simple example is given here to illustrate how to determine γ_{ij}. Assume that there are three factors determining the cascading intensity between two pipelines: distance, load redistribution, and safety barrier. These three factors basically encompass the two types of failure dependences outlined previously, as well as the safety measures to mitigate them. More specifically, the distance between components is an essential factor influencing Type I failure dependence. Similarly, load redistribution is the dominant factor in Type II failure dependence. We assign weights for them based on historical data and expert experience: 0.4, 0.2, and 0.4. The value of distance degree could be scored simply as $1-(d/D)$, where d is the real distance between two pipelines and D is the safe distance. Thus, the distance degree could be 2/5 if their horizontal clearance is 30mm but the required horizontal clearance is 50mm. For load redistribution, if two pipelines are both required to transfer fluid at 70% capacity, and one pipeline would suffer 10% more when another pipeline fail, we can score the factor load redistribution between the two pipelines at 1/7. We can score the third factor based on whether a safety barrier is in place or not and what is its availability. If there is no safety barrier, the score is set as 1, and the score decreases as the availability and reliability of safety barrier improved. Here we assume there are thermal-protective coating surrounding the pipelines, but its reliability is on the decline, and we can provide a score of 0.7 after evaluation. The examination aforementioned can reach the conclusion that the overall cascade intensity between two pipelines is $0.4 \times 2/5 + 0.2 \times 1/7 +$

$0.4 \times 0.7 = 0.4686$. However, this study intends to develop a universal model to provide some guidance to quantify the failure dependence. Therefore, the methods to assign weighs and score influencing factors are not highly emphasized in our methodology.

(1) Influencing level ϕ_{x_j}

The influencing level ϕ_{x_j} denotes the loading increment or shock from degrading or failed inducing component *j* to the induced component *i*. It is considered to be determined by the degradation degree of component *j*:

$$\phi_{x_j} = \varphi_j \beta_j \tag{6}$$

where φ_j is the degradation degree of inducing component *j*, which depends solely on its degradation level compared to the failed state. Since the components degrade overtime and may be repaired after maintenance actions, the value of φ_j varies over time.

$$\varphi_j = x_j / k \tag{7}$$

Technical errors or environmental factors can negatively impact the accuracy of engineering data, resulting in obtained data that may not be in accordance with real data. In order to minimize such errors, we introduce a correction coefficient β_j considering that the effect of component degradation degree on other components is not strictly distributed due to unstable factors. Introducing correction coefficients enables adjustments of the influencing level model to better reflect the actual situation based on historical or experimental data. The range of correction coefficient should be [0, 1] empirically. Normally linear regression could be used to estimate the value of β_j based on historical data or experimental data. We assume the correction coefficient is uniformly distributed in [0, 1] in our study.

3.3. Dependent multi-component degradation model

For the degradation process in a system composed of *n* components, the state transition influenced by degradation of all the other components could be expressed by a Markov model step by step. Since there are n^2 correlations denoting the cascading intensity in the *n* components system, the cascading intensity among components could be expressed by a matrix $\boldsymbol{\gamma} = \{\gamma_{ij}\}_{n\times n}$. In addition, $\boldsymbol{\phi} = (\varphi_1\beta_1,\ \varphi_2\beta_2,\ \cdots,\ \varphi_k\beta_k)^T$ is a vector of influencing level for all the components $j \neq i$. We can use an $n \times n$ matrix $\mathbb{D}$ to denote the failure dependences among components

$$\mathbb{D} = \begin{pmatrix} \mathbb{D}_1 \\ \mathbb{D}_2 \\ \vdots \\ \mathbb{D}_n \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \boldsymbol{D}_{1,2} & \cdots & \boldsymbol{D}_{1,n-1} & \boldsymbol{D}_{1,n} \\ \boldsymbol{D}_{2,1} & \mathbf{0} & & \boldsymbol{D}_{2,n-1} & \boldsymbol{D}_{2,n} \\ \vdots & & \ddots & \vdots & \\ \boldsymbol{D}_{n,1} & \boldsymbol{D}_{n,2} & \cdots & \boldsymbol{D}_{n,n-1} & \mathbf{0} \end{pmatrix} \tag{8}$$

where $\mathbb{D}_i$ is the matrix of failure dependences from other components to component *i* following the selection of component *i* as the target component, which is component 1. As the identification numbers of the components do not carry any significance, any component in the system can be designated as component 1. For this reason, in the section of our study that follows, we presume that component 1 and the identification numbers of the other components have been determined to simplify the issue. **0** is the null matrix whose order is corresponding by the dimensions of blocks $\boldsymbol{D}_{i,j}$, indicating that the component suffers no failure dependence from itself. This also means that $D_{i,x_i} = 0$ for any component *i*. $\boldsymbol{D}_{i,j} = (D_{i,x_j=0},\ D_{i,x_j=1},\ \cdots,\ D_{i,x_j=k})$ denoting the failure dependence from component *j* on component *i*. Furthermore, the element in the submatrix $D_{i,x_j} = \gamma_{ij}\phi_{x_j}$ is vector to represent the failure dependence from component *j* on component *i* when component *j* is in state x_j. After the qualification of the correlations among components, the new transition rates of the component could be updated as below.

$$\lambda^i_{x_i,x_j} = \left(1 + D_{i,x_j}\right)\lambda_{x_i} \tag{9}$$

$$\lambda^j_{x_i,x_j} = \left(1 + D_{j,x_i}\right)\lambda_{x_j} \tag{10}$$

where $\lambda^i_{x_i,x_j}$ is the degradation rate of component *i* from state x_i to state $x_i + 1$ when there exists failure dependence between it and another component *j* whose state is x_j, and $\lambda^j_{x_i,x_j}$ is the degradation rate of component *j* from state x_j to state $x_j + 1$ when there exists failure dependence between it and another component *i* whose state is x_i.

The states of the system $(x_1,\ x_2,\ \cdots,\ x_n)$, from (0,…,0) to (*k*,…,*k*), are divided into $(k+1)^{(n-1)}$ subsets, where only the component 1 (any component could be chosen as component 1) degrades and other components remain the constant states in every subset $\{(0,x_2,\cdots,\ x_n),(1,x_2,\cdots,\ x_n),\cdots,\ (k,x_2,\cdots,\ x_n)\}$. Consequently, the matrix could be expressed as a $(k+1)^{(n-1)} \times (k+1)^{(n-1)}$ matrix as follows.

$$\mathbb{A} = \begin{pmatrix} \mathbb{A}_n^{\mathbf{0}} & \boldsymbol{A}_n^{\mathbf{0}} & & & & \\ & \mathbb{A}_n^{\mathbf{1}} & \boldsymbol{A}_n^{\mathbf{1}} & & & \\ & & \mathbb{A}_n^{\mathbf{2}} & & & \\ & & & \ddots & & \\ & & & & \mathbb{A}_n^{\boldsymbol{k-1}} & \boldsymbol{A}_n^{\boldsymbol{k-1}} \\ & & & & & \mathbb{A}_n^{\boldsymbol{k}} \end{pmatrix} \tag{11}$$

The blocks $\mathbb{A}_n^{x_n}$ are the sub matrixes of the whole matrix $\mathbb{A}$, denoting the transition rates of the system where the state of component *n* keeps constant x_n; The blocks $\boldsymbol{A}_n^{x_n}$ are also the sub matrixes of the whole matrix $\mathbb{A}$, denoting the transition rates of the system where only the component *n* degrades from state x_n to state $x_n + 1$. The other blocks are null, and their orders are corresponding by the dimensions of blocks and $\boldsymbol{A}_n^{x_n}$. The blocks $\mathbb{A}_n^{x_n}$ could also be further represented by smaller sub matrixes and $\boldsymbol{A}_{n-1}^{x_{n-1}}$ using the same recursive way from $\mathbb{A}$ to and $\boldsymbol{A}_n^{x_n}$. The same applies to the general sub matrixes $\mathbb{A}_i^{x_i}$. With the recursive method, the general blocks $\mathbb{A}_i^{x_i}$ could also be further represented by smaller sub matrixes and $\boldsymbol{A}_j^{x_j}$ as below. The blocks $\mathbb{A}_i^{x_i}$ are the sub matrixes denoting the transition rates of the system where the state of component *i* keeps constant x_i; The blocks $\boldsymbol{A}_j^{x_j}$ are the sub matrixes denoting the transition rates of the system where only the component *j* degrades from state x_j to state $x_j + 1$. The other blocks are null, and their orders are corresponding by the dimensions of blocks and $\boldsymbol{A}_j^{x_j}$.

$$\mathbb{A}_i^{x_i} = \begin{pmatrix} \mathbb{A}_{\mathbf{i-1}}^{\mathbf{0}} & \boldsymbol{A}_{\mathbf{i-1}}^{\mathbf{0}} & & & & \\ & \mathbb{A}_{\mathbf{i-1}}^{\mathbf{1}} & \boldsymbol{A}_{\mathbf{i-1}}^{\mathbf{1}} & & & \\ & & \mathbb{A}_{\mathbf{i-1}}^{\mathbf{2}} & & & \\ & & & \ddots & & \\ & & & & \mathbb{A}_{\mathbf{i-1}}^{\mathbf{k-1}} & \boldsymbol{A}_{\mathbf{i-1}}^{\mathbf{k-1}} \\ & & & & & \mathbb{A}_{\mathbf{i-1}}^{\mathbf{k}} \end{pmatrix} \tag{12}$$

$$\boldsymbol{A}_j^{x_j} = \begin{pmatrix} \boldsymbol{A}^j_{x_2,\cdots,0,x_{j+1},\cdots,x_n} & & & \\ & \boldsymbol{A}^j_{x_2,\cdots,1,x_{j+1},\cdots,x_n} & & \\ & & \ddots & \\ & & & \boldsymbol{A}^j_{x_2,\cdots,k,x_{j+1},\cdots,x_n} \end{pmatrix} \tag{13}$$

for $j = 2, 3, \cdots, n$.

where the elements $\boldsymbol{A}^j_{x_2,\cdots,x_j,\ \cdots x_n}$ in $\boldsymbol{A}_j^{x_j}$ are also sub matrixes, as shown in equation (14), denoting the transition rates of the system where only the component j degrades from state x_j to state x_j+1 when other components are at state $(x_1, \cdots, x_n)$ for $j \neq 1$. For example, $\boldsymbol{A}^j_{x_2,\cdots,0,x_{j+1},\cdots,x_n}$ refers to the transition rates of the system where only the component j degrades from state 0 to state 1 when other components are at state $(x_1, \cdots, x_n)$ for $j \neq 1$.

$$\boldsymbol{A}^j_{x_2,\cdots,x_j,\ \cdots x_n} = \begin{pmatrix} \lambda^j_{0,\ x_2,\cdots,x_j,\ \cdots x_n} & & & \\ & \lambda^j_{1,\ x_2,\cdots,x_j,\ \cdots x_n} & & \\ & & \ddots & \\ & & & \lambda^j_{k,\ x_2,\cdots,x_j,\ \cdots x_n} \end{pmatrix} \tag{14}$$

As mentioned before, the whole matrix $\mathbb{A}$ is recursed to the blocks $\mathbb{A}_n^{x_n}$, and further recursed to the blocks for $i = 3, \cdots,\ n-1$. The recursive process stops when i equals 3, and at this point we have

$$\mathbb{A}_3^{x_3} = \begin{pmatrix} \mathbb{A}_{0,\ x_3,\cdots,\ x_n} & \boldsymbol{A}^2_{0,\ x_3,\cdots,\ x_n} & & & & \\ & \mathbb{A}_{1,\ x_3,\cdots,\ x_n} & \boldsymbol{A}^2_{1,\ x_3,\cdots,\ x_n} & & & \\ & & \mathbb{A}_{2,\ x_3,\cdots,\ x_n} & & & \\ & & & \ddots & & \\ & & & & \mathbb{A}_{k-1,\ x_3,\cdots,\ x_n} & \boldsymbol{A}^2_{k-1,\ x_3,\cdots,\ x_n} \\ & & & & & \mathbb{A}_{k,\ x_3,\cdots,\ x_n} \end{pmatrix} \tag{15}$$

The block $\boldsymbol{A}^j_{x_2,\cdots x_j,\ \cdots x_n}$ could be obtained by equation (14). The block $\mathbb{A}_{\ x_2,\cdots,\ x_n}$ is the submatrix denoting the transition rates of components 1 when other components are at state $(x_2, \cdots, x_n)$.

$$\mathbb{A}_{x_2,\cdots,x_n} = \begin{pmatrix} -\sum_{j=1}^{n}\lambda^j_{0,x_2,\cdots,x_n} & \lambda^1_{0,x_2,\cdots,x_n} & & & \\ & -\sum_{j=1}^{n}\lambda^j_{1,x_2,\cdots,x_n} & & & \\ & & \ddots & & \\ & & & -\sum_{j=1}^{n}\lambda^j_{k-1,x_2,\cdots,x_n} & \lambda^1_{k-1,x_2,\cdots,x_n} \\ & & & & -\sum_{j=2}^{n}\lambda^j_{k,x_2,\cdots,x_n} \end{pmatrix} \tag{16}$$

where $\lambda^1_{x_1,x_2,\cdots,x_n}$ is transition rate of the component 1 from state from state x_1 to state x_1+1 when there exist failure dependences between it and other components whose state are $(x_2, \cdots, x_n)$

$$\lambda^1_{x_1,x_2,\cdots,x_n} = \lambda_{x_1} \cdot \prod_{j=1}^{n}\left(1 + D_{1,x_j}\right) \tag{17}$$

and $\lambda^j_{\ x_1,\cdots,x_n}$ is transition rate of the component j from state from state x_j to state x_j+1 when there exist failure dependences between it and other components whose state are $(x_1, \cdots, x_n)$ for $j \neq 1$.

$$\lambda^j_{x_1,\cdots,x_n} = \lambda_{x_j} \cdot \prod_{i=1}^{n}\left(1 + D_{j,x_i}\right) \tag{18}$$

In this situation we let $P_{x_i}(t)$ be the probability that the component i is in state x_i at time t and $P_{X_i}(t)$ be the probability that the entire system is in state X_i at time t. The vector $\boldsymbol{P}(t) = [P_{X_0}(t), P_{X_1}(t), \cdots, P_{\ X_{k^n-1}}(t)]$ denotes the time dependent state probability, and the initial state probability $\boldsymbol{P}(0) = [1, 0, \ldots, 0]$.

4. Modeling and formulation of condition-based maintenances

In this section we describe the general maintenance policies for multi-component systems with heterogeneous failure dependences. We consider a system with n components. The system state transition process is modeled with a Markov model. In the model, the following assumptions are introduced:

- The states of components are revealed upon periodic inspections.
- The maintenance policies are based on the detected state of system.
- At inspection, a maintenance action can begin without any delay.
- The inspection and repair time could be ignored compared to its long service lifetime.

4.1. Inspections and maintenances

Regular inspections are conducted for many passive items such as valves, pipelines, vessels, and pumps in the process industry. As assumed above, the inspection interval is $(s-1)\tau \leq t \leq s\tau$ for $s = 1, 2, \cdots, N_{IMR}$, where τ is a constant value independent of the component state and the time. Suppose every inspection for the system could reveal the states of all components. The inspections durations are assumed to be neglected and the state of components are revealed immediately. The inspection intervals are recounted after each inspection, maintenance, or repair in the overall lifecycle of the system, and could be modeled as $[0, T_1]$, $[T_1, T_2]$, $\cdots$, $[T_{N_{IMR}-1}, T_{N_{IMR}}]$ If the states of components are found to reach the thresholds of maintenance measures, then a corresponding maintenance task will be carried out timely. The time immediately before inspection is denoted by t^- and the time right after IMRs is denoted by t^+ When the state of the system when $t = T_s^-$ is given, the maintenance activities for the system could be then decided. Note that CBM is a maintenance strategy that involves monitoring the actual condition of systems in order to determine the maintenance activities. Based upon the maintenance policy, the possible maintenance actions and the state of the system just after IMRs are assumed to depend on the state of the system when $t = T_s^-$, but independent of all transitions of the system before T_s The effect of IMRs at time $t = T_s$ could be illustrated by

$$Pr\left(X\left(T_s^+\right) = X_j \middle| X\left(T_s^-\right) = X_i\right) = b_{X_i,X_j}, \quad \text{for all } X_i, X_j \in \boldsymbol{\chi} \tag{19}$$

where b_{X_i,X_j} is the probability that the system is in state X_j after IMRs, given that it was in state X_i before inspection.

Considering the aforementioned inspection strategies, several maintenance strategies are proposed. PM and CM are implemented according to the inspection results. The maintenance strategies are illustrated in the Fig. 5.

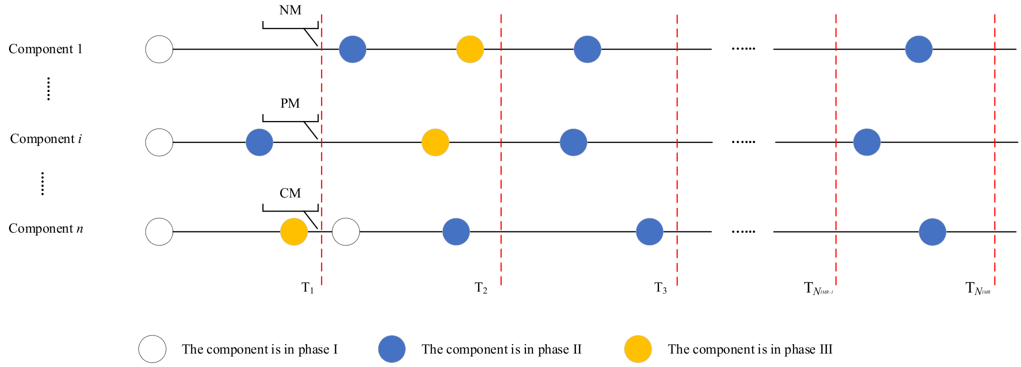


Fig. 5. Illustration of maintenance policies

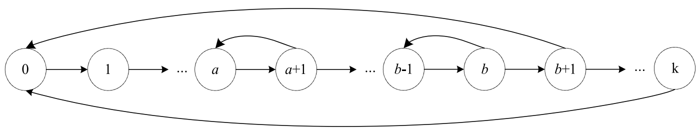


Fig. 6. Markov model of an individual component

For an independent component, the maintenance policy is classified into three phases.

In phase I ($x \le a$), the component is in an acceptable state, and no maintenance activities (NM) are required.

In phase II ($a+\ 1 \le x \le b$), the component is operating in a degrading state, and PM will be performed to improve the component condition by one state.

In phase III ($b+1 \le x \le k$), CM is needed to restore the component to an as good as new state.

After applying the maintenance actions, the state transitions could be denoted by degradation transitions, repair transitions, and combinations of those, as seen in Fig. 6. Assume that the components have constant transition rate between two states.

Let $\mathbb{B}$ describes the corresponding maintenance transition matrix of the system, then

$$\boldsymbol{P}(T_s^+) = \boldsymbol{P}(T_s^-)\cdot\mathbb{B} \tag{20}$$

The corresponding maintenance matrix $\mathbb{B}$ is expressed by the sub matrixes

$$\mathbb{B} = \begin{pmatrix} \mathbb{B}_{\mathbf{n}}^{\mathbf{I}} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbb{B}_{\mathbf{n}}^{\mathbf{a}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbb{B}_{\mathbf{n}}^{\mathbf{a+1}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbb{B}_{\mathbf{n}}^{II} & \mathbf{0} \\ \mathbb{B}_{\mathbf{n}}^{III} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{21}$$

The blocks $\mathbb{B}_n^I$ and $\mathbb{B}_n^{\mathbf{a}}$ are the sub matrixes, separately denote the maintenance transition of the system where the component n is in phase I or in state a. The explanation for other sub matrixes in equation (21) can be obtained similarly. These sub matrixes could be generalized and recursively defined using equation (22)

$$\mathbb{B}_i^{x_i} = \begin{pmatrix} \mathbf{B}_{\mathbf{i-1}}^{\mathbf{I}} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_{\mathbf{i-1}}^{\mathbf{a}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_{\mathbf{i-1}}^{\mathbf{a+1}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{B}_{\mathbf{i-1}}^{II} & \mathbf{0} \\ \mathbf{B}_{\mathbf{i-1}}^{III} & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{22}$$

The blocks **0** are null, and their orders are corresponding by the dimensions of sub matrixes.

Recurse the matrix until reaching the matrix of component 2.

$$\mathbb{B}_{\mathbf{2}}^{x_2} = \begin{pmatrix} 1 & & & & & & & & & \\ & \ddots & & & & & & & & \\ & & 1 & & & & & & & \\ & & & 1 & & & & & & \\ & & & 1 & 0 & & & & & \\ & & & & & \ddots & & & & \\ & & & & & & 0 & & & \\ & & & & & & 1 & 0 & & \\ 1 & & & & & & & & 0 & \\ \vdots & & & & & & & & & \ddots \\ 1 & & & & & & & & & & 0 \end{pmatrix} \tag{23}$$

Since the process has no steady state and could be divided into several time units on a given finite time horizon, the time-dependent state probability vector $\boldsymbol{P}(t)$ at time t could be then given by

$$\boldsymbol{P}(t) = \boldsymbol{P}(0)\cdot\left(\prod_{s=1}^{s=N_{IMR}} \exp(\mathbb{A}(T_s - T_{s-1})\cdot\mathbb{B}\right)\cdot \exp(\mathbb{A}(t - T_{N_{IMR}})) \tag{24}$$

Table 1
Parameter setting of the subsea system considered in the case-study.

Parameter	Value (/year)		Parameter	Value (€)		Parameter	Value (€)
	Compressor	Pumps		Compressor	Pumps		
λ_0	0.046	0.104	c_{m1}	1.93×10^6	2.41×10^6	c_{in}	1.21×10^6
λ_1	0.021	0.105	c_{m2}	2.89×10^6	3.86×10^6	c_p	7.23×10^5
λ_2	0.041	0.056				c_u	6.51×10^7

4.2. System availability analysis

In this subsection, the developed state probabilities formulas are applied to quantify the system availability, which refers to the percentage of time that the system remains operational under normal circumstances in order to perform its intended function. Suppose that the system is not available only when it fails, the mean value of the system failure probability over a period of time could then be used to represent the unavailability of the system

$$\overline{A_s} = \frac{1}{T}\int_0^T P_{X_F}(t)dt \tag{25}$$

where X_F denotes that the component or the entire system is in the failed states immediately at time t. $P_{X_F}(t)$ represents the probability that the entire system is in the failed states at time t. Based on the identification of all the failed states and the probabilities that the system is in various states at time t included in vector $\boldsymbol{P}(t)$, $P_{X_F}(t)$ could be calculated by summing up all the probabilities that the entire system is in the failed state at time t.

The availability of the system is the probability of being operational given by

$$A_S = 1 - \overline{A_s} \tag{26}$$

The model in this subsection is proposed to seek for the optimal value of the maintenance threshold to increase the system availability to an acceptable level.

4.3. Maintenance cost

Here we consider that the maintenance cost consists of the inspection cost, the downtime cost, and the repair cost.

Suppose that the inspection cost is c_{in} for each time. The downtime cost contains the planned downtime cost c_p caused by the scheduled maintenance activities and the unplanned downtime cost c_u induced by unexpected failures.

The cumulative maintenance cost between two inspections in the time interval $(T_{s-1}, T_s]$ accounts for the maintenance cost at time $t = T_s$. The repair cost is supposed to includes $c_{m1,i}$ and $c_{m2,i}$ respectively for maintenance activities PM and CM to component i. Therefore, the cumulative maintenance cost for the system in $(T_{s-1}, T_s]$ is

$$\begin{aligned} C((T_{s-1},T_s]) &= \sum_{i=1}^{n}\left[c_{m1,i}Pr(a+1\le x_i(T_s)\le b)+c_{m2,i}Pr(b+1\le x_i(T_s)\le k)\right] \\ &= \sum_{i=1}^{n}\left[c_{m1,i}P_{a+1\le x_i\le b}(T_s)+c_{m2,i}P_{b+1\le x_i\le k}(T_s)\right] \end{aligned} \tag{27}$$

where $x_i(t)$ is the degradation state of component i at time t.

The average life-time cost during the period T could be given by

$$C_S = \left[c_{in}N_{IMR} + c_pN_{IMR} + \sum_{s=1}^{N_{IMR}} C((T_{s-1},T_s])\right] \Big/ T + c_u\overline{A_s} \tag{28}$$

The model in this subsection is proposed to seek for the optimal value of the maintenance threshold to minimize the maintenance cost.

Table 2
Parameter setting of the failure dependences.

Parameter	Value	Parameter	Value
γ_{12}	0.34	ϕ_0	0
γ_{13}	0.24	ϕ_1	1/3
γ_{23}	0.66	ϕ_2	2/3
γ_{21}	0.44	ϕ_3	1
γ_{31}	0.34		
γ_{32}	0.56		

5. Case-Study: assessment of the motivating example

The motivating example of a subsea transmission system is explored to illustrate the advantages of the proposed maintenance policies. To reveal the hidden failures, inspections are performed regularly to examine the system to confirm compliance with the performance requirements. The parameter setting of the degradation, inspection and maintenance are provided Table 1. The failure rates values are obtained from the existing literature[25,31] and from the application of the Cox model [32], using the data derived from OREDA database[33]. The service life and repair cost were obtained from the article[34] and thesis [27].

We assume that there are only four states for each component: normally operating, moderately degraded, severely degraded, and failed. The initial state probability . The states of the system $X = (x_1, x_2, x_3)$ from (0, 0, 0) to (3, 3, 3), are divided into 4^2 subsets: (0,0,0), (1,0,0), (2,0,0), (3,0,0); (0,1,0), (1,1,0), (2,1,0) (3,1,0); …; (0,3,0), (1,3,0), (2,3,0), (3,3,0); ……; (0,0,3), (1,0,3), (2,0,3), (3,0,3); (0,1,3), (1,1,3), (2,1,3), (3,1,3); …; (0,3,3), (1,3,3), (2,3,3), (3,3,3).

As illustrated before, three key factors are generally considered to impact on the failure dependences between components: load redistribution, distance, and safety barrier. In this system, weights of the factors are assigned according to experts' experience: distance (2), load redistribution (5), and safety barrier (3). Here load redistribution denotes the material transfer and doping. After expert experience, the parameters of the failure dependences could be evaluated as Table 2 based on the method proposed in Subsection 3.2. Since the states of all the components are expressed as $x_i \in \{0, 1, 2, 3\}$, the degradation level of the components could be estimated as $\varphi_j \in \{0, 1/3, 2/3, 1\}$. It is plausible to conclude that $\boldsymbol{\phi} = (\phi_0, \phi_1, \phi_1, \phi_3)^T = (0, 1/3, 2/3, 1)^T$ is the vector of influencing level for all the components when correction coefficient β_j is assumed to be 1. To address the necessity of considering failure dependence, we also set all the parameters in Table 2 as 0 or other values to imitate the scenario when failure dependence is neglected or varied in this example. With modifying the values in the table after assessing the failure dependences of differing levels, the proposed model could be applied to computing the system under various conditions.

Based on the data from Table 2, we could obtain a 3×3 matrix $\mathbb{D}$ to denote the failure dependences among components

$$\mathbb{D} = \begin{pmatrix} \boldsymbol{E} & \boldsymbol{D}_{1,2} & \boldsymbol{D}_{1,3} \\ \boldsymbol{D}_{2,1} & \boldsymbol{E} & \boldsymbol{D}_{2,3} \\ \boldsymbol{D}_{3,1} & \boldsymbol{D}_{3,2} & \boldsymbol{E} \end{pmatrix} \tag{29}$$

Taking the failure dependence from component 2 on component 1 as a simple example to illustrate the calculation of failure dependences, we have $\boldsymbol{D}_{1,2} = (D_{1,x_2=0}, D_{1,x_2=1}, \cdots, D_{1,x_2=3}) = (0, 0.103, 0.207, 0.31)$ if the correction coefficient β_2 is supposed to be 1. The same calculation method can be applied to other submatrices of failure dependences. With the confirmation of failure dependences among components, the DMDM could be denoted by the transition matrix $\mathbb{A}$. The transition matrix $\mathbb{A}$ could be expressed as a $4^2 \times 4^2$ matrix

$$\mathbb{A} = \begin{pmatrix} \mathbf{A}_3^0 & \mathbf{A}_3^0 & & \\ & \mathbf{A}_3^1 & \mathbf{A}_3^1 & \\ & & \mathbf{A}_3^2 & \mathbf{A}_3^2 \\ & & & \mathbf{A}_3^3 \end{pmatrix} \tag{30}$$

$$\mathbb{A}_3^{x_3} = \begin{pmatrix} \mathbb{A}_{0,x_3} & \boldsymbol{A}^2_{0,x_3} & & \\ & \mathbb{A}_{1,x_3} & \boldsymbol{A}^2_{1,x_3} & \\ & & \mathbb{A}_{2,x_3} & \boldsymbol{A}^2_{2,x_3} \\ & & & \mathbb{A}_{3,x_3} \end{pmatrix} \tag{31}$$

for $x_3 = 0, 1, 2, 3$.

$$\boldsymbol{A}_3^{x_3} = \begin{pmatrix} \boldsymbol{A}^3_{x_2,x_3} & & & \\ & \boldsymbol{A}^3_{x_2,x_3} & & \\ & & \boldsymbol{A}^3_{x_2,x_3} & \\ & & & \boldsymbol{A}^3_{x_2,x_3} \end{pmatrix} \tag{32}$$

for $x_3 = 0, 1, 2$.

$$\boldsymbol{A}_2^{x_2} = \begin{pmatrix} \boldsymbol{A}^2_{x_2,x_3} & & & \\ & \boldsymbol{A}^2_{x_2,x_3} & & \\ & & \boldsymbol{A}^2_{x_2,x_3} & \\ & & & \boldsymbol{A}^2_{x_2,x_3} \end{pmatrix} \tag{33}$$

for $x_2 = 0, 1, 2$.

where the blocks $\mathbb{A}_{x_2,\,x_3}$ and $\boldsymbol{A}^j{}_{x_2,\,x_3}$ are as follows

$$\mathbb{A}_{x_2,\,x_3} = \begin{pmatrix} -\sum_{i=1}^{3}\lambda^i_{0,\,x_2,\,x_3} & \lambda^1_{0,\,x_2,\,x_3} & & \\ & -\sum_{i=1}^{3}\lambda^i_{1,\,x_2,\,x_3} & \lambda^1_{1,\,x_2,\,x_3} & \\ & & -\sum_{i=1}^{3}\lambda^i_{2,\,x_2,\,x_3} & \lambda^1_{2,\,x_2,\,x_3} \\ & & & -\sum_{i=2}^{3}\lambda^i_{3,\,x_2,\,x_3} \end{pmatrix} \tag{34}$$

$$\boldsymbol{A}^j{}_{x_2,\,x_3} = \begin{pmatrix} \lambda^j_{0,\,x_2,\,x_3} & & & \\ & \lambda^j_{1,\,x_2,\,x_3} & & \\ & & \lambda^j_{2,\,x_2,\,x_3} & \\ & & & \lambda^j_{3,\,x_2,\,x_3} \end{pmatrix} \tag{35}$$

for $j = 2, 3$.

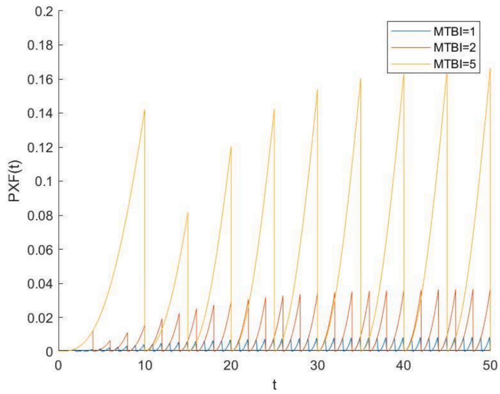


Fig. 7. Failure probabilities for different MTBI

The matrix $\mathbb{B}$ could be expressed as a $4^2 \times 4^2$ matrix.

$$\mathbb{B} = \begin{pmatrix} \mathbf{B}_3^0 & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_3^1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_3^2 & \mathbf{0} & \mathbf{0} \\ \mathbf{B}_3^3 & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix} \tag{36}$$

$$\mathbb{B}_3^{x_3} = \begin{pmatrix} \mathbf{B}_2^0 & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2^1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{B}_2^2 & \mathbf{0} & \mathbf{0} \\ \mathbf{B}_2^3 & \mathbf{0} & \mathbf{0} & \mathbf{0} \end{pmatrix},\ \mathbb{B}_2^{x_2} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} \tag{37}$$

$\mathbb{B}_3^{x_3}$ and represents the maintenance matrix when components 3 or 2 are respectively in the state x_3 or x_2.

The whole degradation transition matrix $\mathbb{A}$ and the whole maintenance transition matrix could be obtained after splicing the matrices. The state probability vector $\boldsymbol{P}(t)$ could then be calculated by equation (24). The time dependent failure probabilities $P_{X_F}(t)$ are obtained by summing the probabilities of different failure states of the system.

The maintenance cost for an independent component in $(T_{s-1}, T_s]$ is

$$\begin{aligned} C((T_{s-1}, T_s]) &= c_{m1,comp}P_{x_1=2}(T_s) + c_{m2,comp}P_{x_1=3}(T_s) \\ &\quad + \sum_{i=2}^{3}\left[c_{m1,pump}P_{x_i=2}(T_s) + c_{m2,pump}P_{x_i=3}(T_s)\right] \end{aligned} \tag{38}$$

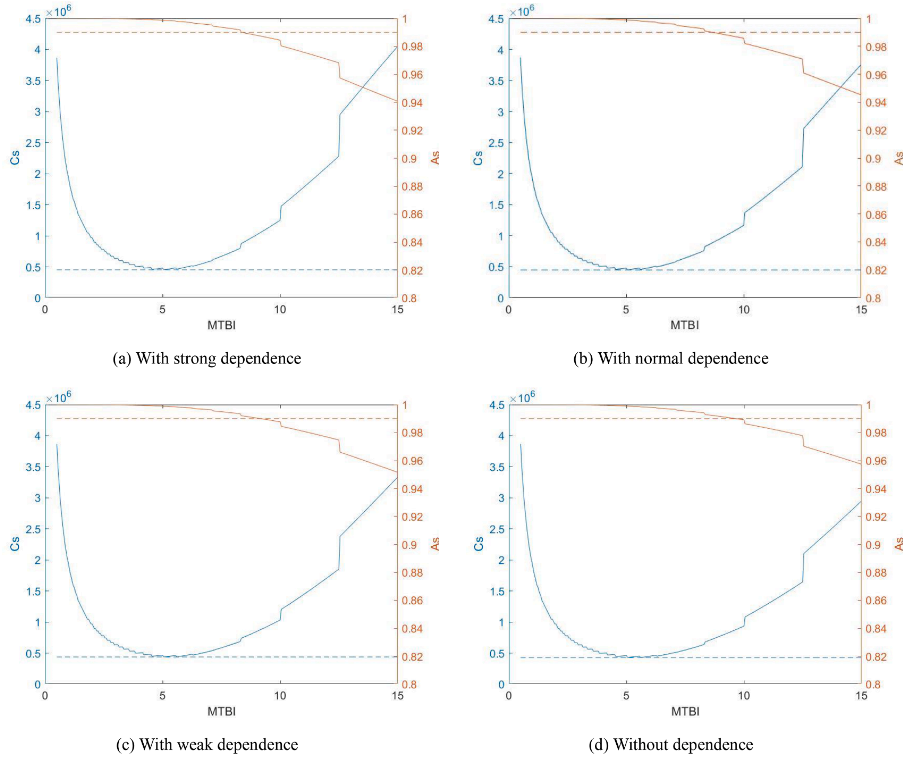
where the $c_{m1,comp}$ and $c_{m2,comp}$ are respectively the PM and CM for a compressor, $c_{m1,pump}$ and $c_{m2,comp}$ are respectively the PM and CM for a pump.

For this kind of system, the availability of the system and its average life-time cost could be obtained by equations (28) and (38).

5.1. Failure probabilities

The time dependent failure probabilities could be found by CTMC simulation. To evaluate the effect of mean time between inspections (MTBI) on the system conditions, observe the difference of $P_{X_F}(t)$ curves in the log-run horizon by testing various MTBI ($MTBI = 1\ year; 2\ years; 5\ years.$). The results are shown in Fig. 7.

It can be found that the failure probability increases with time and decreases suddenly at the IMRs timepoints under varying MTBI. This is because the system and its components degrade over time. When



(a) With strong dependence (b) With normal dependence (c) With weak dependence (d) Without dependence

Fig. 8. Availability and average life-time cost of the transition system under different MTBI

approaching the IMRs timepoints, the failure probability peaks in this interval of time. However, after the IMRs timepoints, the status of the system and its components could be noticeably improved, and the system failure probability is close to zero, indicating a peak value at the IMRs timepoints. Another finding can be obtained by comparing the failure probability curves under different MTBI. It is obvious that with smaller MTBI, the maximum values of failure probabilities are expected to be lower. On the contrary, the maximum values of failure probabilities tend to be higher when the MTBI increases, which means that the system tends to be less reliable. In this regard, the reliability and availability of the system can be improved by reducing the value of MTBI, that is, shortening the IMRs interval. However, a lower MTBI is not always preferable. The following subsections will go through how to achieve the optimum MTBI value in practical applications.

5.2. Maintenance strategies with various failure dependences

Fig. 8 shows the availability and average life-time cost of the transition system under the condition of with various failure dependence respectively. The actual failure dependence in Table 2 is denoted as normal dependence. The failure dependences of the system under other circumstances are also accounted for: The strong dependence is set when all the γ take the maximum value (0.66) in Table 2; the case that all the γ take the minimum value (0.24) in Table 2 is weak dependence; there is no dependence when all the γ take the value of 0.

The figures show that the availability of the system decreases with the increase of MTBI. One interesting observation is that these curves are not smooth, but rather contain distinct breaking lines. It is found by examining these fold points that they are always located at certain MTBI values that enable the IMRs number to be an integer. For the A_s-MTBI curves, the smaller the MTBI is, the larger number of inspections and maintenance activities are needed, the higher the availability reached, and vice versa. This trend is consistent with the conclusion of the previous subsection. At each fold point, the IMRs frequency drops by one, which leads to a sudden increase in system failure probability and steady state probability of failure, resulting in a sudden decrease in system availability. Besides, the curves C_s-MTBI show a similar trend that the average life-time cost falls initially and subsequently climbs as MTBI grows, indicating that there is a point to minimize the cost. A reasonable explanation is that when the MTBI is relatively small, more inspections and maintenance are undertaken, which may lower the failure probability of system and the unexpected downtime cost, also may impose considerable IMRs costs. However, when the MTBI is greatly increased, the IMRs costs can be accordingly decreased; but the system unavailability rises, inevitably leading to more production loss due to unplanned downtime. Similarly, before the cost reaches the lowest value, the variation of IMRs cost dominates the trend of C_s-MTBI curves. As MTBI increases, the amount of IMRs may drop by one, causing the immediate drop of total IMRs cost and the average life-time cost. After the lowest value, the variation of unexpected downtime cost dominates the trend of C_s-MTBI curves. Hence the effect of drop amount of IMRs on the unexpected downtime cost is stronger than the effect on the IMRs cost. As the amount of IMRs drops, the failure probability increases suddenly, as well as the downtime cost, which is strongly proportional to it.

In practical engineering applications, an acceptable availability threshold is generally determined since it is too costly to pursue extensive system availability. In this case the average life-time cost should be minimized while ensuring system availability over 0.99. The optimum of the maintenance policy could be achieved by adjusting the parameter MTBI. From the figures of Fig. 8, the minimal cost appears in the range of

Table 3
Results for the transition system with various failure dependence.

	Availability When A_s is 0.99	When MTBI=15	Average life-time cost When C_s is minimized	When MTBI=15
With strong dependence	(8.35, 0.99)	(15, 0.9408)	(4.55, 454525)	(15, 4047150)
With normal dependence	(8.65, 0.99)	(15, 0.9452)	(5.05, 448474)	(15, 3755460)
With weak dependence	(9.15, 0.99)	(15, 0.9516)	(5.6, 438202)	(15, 3333170)
Without dependence	(9.65, 0.99)	(15, 0.9574)	(5.6, 428870)	(15, 2948640)

system availability greater than 0.99, thus the point of this minimal value could be considered as the ideal option of the maintenance strategy.

Notable distinctions between the findings with various failure dependence could also be observed. Table 3 displays the comparison of the results. In terms of the impact of MTBI on system availability, the availability of the system with stronger failure dependence is generally lower than that of the system with weaker failure dependence and that of the system without failure dependence. The thresholds of MTBI for system availability under 0.99 increases as system failure dependence weakens: 8.35 (strong), 8.65 (normal), 9.15 (weak), 9.65 (without). This means that when there is stronger failure dependence, the system should be inspected and maintained more regularly to keep its availability. From a financial standpoint, the minimal average life-time cost considering strong, normal, and weak failure dependence are respectively 454525€, 448474€, and 438202€, higher than the minimal average life-time cost without failure dependence (428870€). This also supports a similar result that a higher investment is required when stronger failure dependence is considered. The comparison of these graphs reveals the necessity of highlighting the failure dependence of complex systems while implementing CBM.

5.3. Maintenance strategies for various initial costs input

In the following, the variation of some cost parameters setting on the average life-time cost is investigated and the other parameters remain unchanged. By resetting the inspection cost $c_{in} = [1.21 \times 10^5, 1.21 \times 10^6, 1.21 \times 10^7]$, the planned downtime cost $c_p = [7.23 \times 10^4, 7.23 \times 10^5, 7.23 \times 10^6]$, the unplanned downtime cost $c_u = [6.51 \times 10^6, 6.51 \times 10^7, 6.51 \times 10^8]$, the influence of costs input on the average life-time cost is explored in Fig. 9. The A_s-MTBI curves are not depicted in this figure because the costs input hardly imposes effect on availability of the system.

Fig. 9 shows that the average life-time cost basically increases as the three kinds of cost increase. However, the impact of inspection cost and the planned downtime cost are most prominent when the MTBI value is small, whereas the impact of unplanned downtime cost is most pronounced when the MTBI value is high. This finding can serve as a guideline for adjusting the cost in accordance with the existing maintenance strategy. For example, when the MTBI is small and the amount of IMRs is high, the inspection cost can be appropriately decreased to control the average life-time cost. When the value of MTBI is high and the amount of IMRs is low, the unplanned downtime cost is preferred to be lowered by implementing some safety measures to minimize the average life-time cost.

6. Conclusions

Focusing on the heterogeneous failure dependences of component degradation process in a multi-component system, this paper proposed a framework to quantify the failure dependences between components and optimized the policy of condition-based maintenance. By taking the reasonable system availability and minimal average life-time cost in the long-run as the objectives, the Markov process is implemented to with varying MTBI. The impact of the heterogeneous failure dependences on the system maintenance strategies were discussed examining a practical subsea transmission system. The practical implementation of the proposed model in a case study demonstrates its effectiveness and potential for widespread adoption in managing complex multi-component systems, particularly those with heterogeneous failure dependences. The combination of theoretical modeling and its application in a practical case study validates the usefulness of the proposed model. The results of the practical case indicate that the system tends to be more reliable with smaller MTBI. Furthermore, the availability of the system would be overestimated and the annual IMRs costs would be underestimated if we neglect the influence of heterogeneous failure dependences. For various values of MTBI, the inspection cost and planned downtime cost have significant effect on the average life-time cost for low MTBI values, while the impact of unplanned downtime cost is prominent for high MTBI values.

The paper presents managerial actions as references for the decision makers on when to implement the maintenance strategies for complex multi-component system with heterogeneous failure dependences. Based on the finding that a certain system with higher failure dependence is more likely to experience unavailability, one implication could be to address the dependence or to increase the frequency of inspections and maintenance checks. In addition, the system can be assessed to identify the different MTBI ranges and determine the optimal type of cost that maintenance crews could manage to improve the system availability. By optimizing condition-based maintenance strategies,

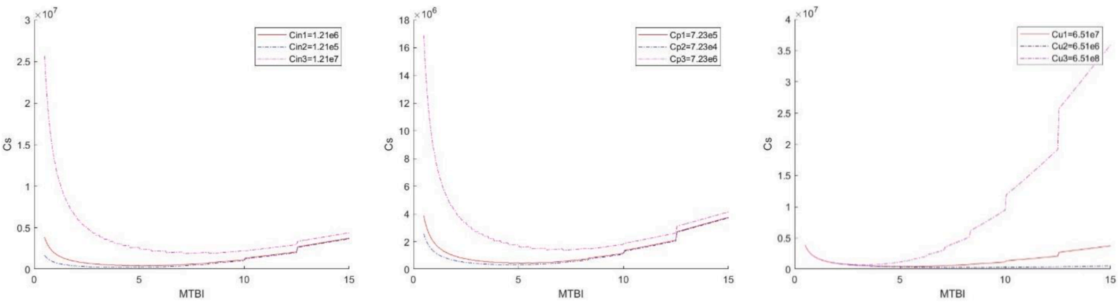


Fig. 9. Maintenance cost for different initial costs input.

organizations can minimize their maintenance costs while ensuring the system remains highly available.

Some other perspectives may be worth to investigating in future work. Firstly, the applicability of the given method may be further verified by applying the proposed model to the maintenance strategies of systems in other configurations. In addition, comparisons with other maintenance models, such as Age-based Maintenance or Opportunistic Maintenance, could be investigated to seek for the optimal maintenance policies for such complex systems.

CRediT authorship contribution statement

Yixin Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Valerio Cozzani:** Writing – review & editing, Supervision, Methodology. **Tianqi Sun:** Software, Conceptualization. **Jørn Vatn:** Supervision, Conceptualization. **Yiliu Liu:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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V

Article V

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Research paper

Sustainability evaluation of multi-component subsea transmission system considering failure dependence and maintenance activities

Yixin Zhao [a], Baoping Cai [b], Tao Zeng [c], Zhengbing He [d], Yiliu Liu [a,*]

[a] Department of Mechanical and Industrial Engineering, Norwegian University of Science and Technology, Trondheim, Norway
[b] College of Mechanical and Electronic Engineering, China University of Petroleum, Qingdao, Shandong, China
[c] China Academy of Safety Science and Technology, Beijing, China
[d] Senseable City Lab, Massachusetts Institute of Technology, Cambridge, MA, USA

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ABSTRACT

Technical systems operating in the subsea context are often with multiple components under complex failure dependences. Due to the hostile subsea environments, it is challenging to perform efficient maintenance for such systems to ensure their operational reliability while keeping the maintenance activities sustainably. A general approach has not been established yet for assessing impacts of failure dependences, effectiveness of maintenance activities, and sustainability. This paper innovatively develops an integrated framework using the Bayesian networks, which thoroughly examines the coupling effect of component degradation, failure dependence and maintenance management on the sustainability evaluation of the complex systems. The impact of different maintenance strategies and the impact of different failure dependences on the overall sustainability are explored to apply the proposed model. The case study verifies the necessity of considering failure dependence and the feasibility of the proposed sustainability evaluation model, as well as provides solutions for optimizing maintenance strategies from a sustainable perspective. The findings of this study contribute to maintenance optimization of complex subsea systems for higher reliability and reasonable cost, as well as provide valuable insights for decision-makers in seeking for sustainable maintenance practices.

1. Introduction

In some complex multi-component engineering systems like subsea production systems, some components tend to be functionally or structurally interdependent on each other, whose states could be influenced by others. Subsea production systems encompass various components, such as wells, pipelines, manifolds, separators, Christmas trees, and pumps (Cheliyan et al., 2018). Among these components, the failure dependences may exist to speed up their degradation. If the failure of one component may impact the failures of the other components, it is termed as a cascading failure (CAF). In complex systems where CAFs may occur among specific components, these components are referred to as dependent components or coupling components, and there exists failure dependence among them (Zhao et al., 2023a). The term *couple* represents the action to connect two items together. The term *coupling components* thus refer to components within a system that are interconnected with failure dependence which can amplify the impact of CAFs. Due to such failure dependence, the malfunction of one component may trigger CAF events, lead to system failures, damage long-term economic viability, amplify the environmental risks, and thus result in severe sustainability issues. Sustainability aims to ensure that technical systems are designed and operated in a way that fulfills current requirements while preserving the capacity of future generations to meet their own (Development, 1987). In the engineering sense, sustainability refers to the ability of the system to maintain a long-term process continuously over time, considering the incorporation of environmental, social, and economic aspects. To attain economic growth, subsea industrial engineering is experiencing rapid growth, resulting in more and more complicated systems to meet the human needs. However, this growth also brings challenges linked to social and environmental concerns, namely the sustainability issues highlighted above. More complicated multi-component systems are more susceptible to the failure dependences, leading to increased risks, higher economic losses, and more serious environmental pollution, which are all manifestations of reduced sustainability from various aspects. In this context, the operation and expansion of subsea production systems subject to failure dependences also pose hazards to the marine ecosystem from the aspect

* Corresponding author.
E-mail address: yiliu.liu@ntnu.no (Y. Liu).

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Abbreviations

CAF	Cascading failure	DBN	Dynamic Bayesian network
RUL	Remaining useful life	BN	Bayesian network
CBM	Condition-based maintenance	NM	No Maintenance
LCSA	Life-cycle sustainability assessment	PM	Preventive maintenance
HCM	Hierarchical Component Model	CM	Corrective maintenance
SDG	Sustainable Development Goal	SI	Sustainability indicator
3D	Three-dimensional	SP	Sustainability pillar
FE	Finite element	OSS	Overall sustainability score
RC	Reinforced concrete	OREDA	Offshore and Onshore Reliability Data
DM	Decoupling Maintenance	QRA	Quantitative risk analysis
		CPT	Conditional probability table
		StdDev	Standard Deviation

of sustainability, especially as the systems gradually grow in both scale and complexity.

To mitigate the failure dependences and improve the overall sustainability, some specific maintenance activities could be taken to decouple the components. However, both such maintenance activities and the conventional maintenance practices for subsea components present a set of unique challenges due to the hostile subsea environments such as high pressure and low temperature, corrosive seawater, and the constant exposure to the wastes. Moreover, the maintenance itself is placed as an essential element within the paradigm of sustainable development (Ghaleb et al., 2022), and may also have an impact on the sustainability. Given the fact that the failures such as leakage, collapse, erosion, the accelerated degradation due to failure dependences, as well as the challenging maintenance activities could all significantly impact sustainability, the mitigation of failure dependences and the evaluation of sustainability for subsea systems considering maintenance activities becomes imperative tasks.

The shock or the loading dependence could be the factors that result in failure dependences and couple the components (Zhao et al., 2023b). For subsea systems, since maintenance interventions are extremely challenging, costly and time-consuming (Cheliyan et al., 2018), the damage from the failure dependences potentially is amplified. Some studies have been conducted for reliability analysis and maintenance optimization in consideration of failure dependence (Sheu et al., 2015; Gao et al., 2015; Zhang et al., 2022; Chang et al., 2024; Schafer et al., 2018). Cai et al. (2021) introduced an innovative modeling approach to predict the remaining useful life (RUL) of multilevel subsea systems with consideration of CAF based on the position importance and function importance. Shao et al. (2022) contributed a multi-stage model-based RUL estimation approach for the subsea Christmas tree considering component degradation interactions. To evaluate the reliability of subsea pipelines with dependent competition failure, Liu et al. (2023) developed a novel method for evaluating the system reliability and studied the interaction between the degradation failure and sudden failure. Sometimes the failure dependences in the systems are complex and heterogeneous. In this situation, Zhao et al. (2023a) proposed a framework for heterogeneous failure dependences in multi-component systems by Markov processes and developed a general Condition-based maintenance (CBM) model to optimize the maintenance strategies. These studies emphasize the necessity of considering the failure dependences within subsea systems when investigating the reliability analysis and maintenance strategies optimization. However, to the best of our knowledge, none of the previous research pointed out the specific maintenance activities that can help to decouple dependent components, in other words, to mitigate the failure dependences among components, even though the maintenance activities to mitigate the failure dependences show great efficiency in avoiding unexpected CAFs.

Considerable contributions have been made to models for estimating sustainability and strategies for enhancement (Shukor et al., 2022; Jaradat et al., 2023; Juhl et al., 2024). In terms of specific research questions, some studies consider the sustainability evaluation not only during system operation, but also associated with the maintenance interventions. Nezami et al. (2013) presented a fuzzy framework that incorporates an effective sustainability program to provide appropriate decision-makings for maintenance strategies among a set of maintenance alternatives. Zheng et al. (2019) presented a comprehensive four-step structure for pavement life-cycle sustainability assessment (LCSA), including the maintenance phase. On the basis of above studies, some works focus on the assessment of the impact of maintenance activities themselves on the asset sustainability. Ghaleb et al. (2022) proposed an approach for quantifying and measuring the impact of maintenance activities on overall sustainability, which shows suitability being implemented in a sustainability dashboard (user interface). Saihi et al. (2023) established a fourth-order Hierarchical Component Model (HCM) to evaluate the sustainable performance of maintenance practices, and conduct a model validation through a survey of the Oil & Gas industry. The trend of industrial engineering gradually expanding from land to ocean has also inspired more and more investigation (Virto, 2018; Kappenthuler et al., 2021; Frederiksen et al., 2021; Chen et al., 2023; Qiu et al., 2023) on the sustainability of the marine environments. Building on the frontiers of ocean science, Virto et al. (Virto, 2018) examined the framework for the most appropriate Sustainable Development Goal (SDG) 14 indicators and proposed the challenges and opportunities for future research. Kappenthuler et al. (2021) developed a material selection framework to analyze the long-term potential of five common metal types in marine construction and provided the evaluation of their durability, economics, sustainability and future availability. Qiu et al. (2023) developed a three-dimensional (3D) nonlinear finite element (FE) framework to systematically examine the time-dependent seismic resilience and sustainability of reinforced concrete (RC) bridges under aggressive marine environments. The above studies evaluated the sustainability of the system from different aspects, but they do not investigate the phenomenon of failure dependence even though the dependent systems are riskier. Particularly, for complex subsea systems, the coupling impact of components degradation, failure dependences and the maintenance activities on sustainability is complicated, and how to construct a comprehensive model to evaluate the overall sustainability of the system is still a challenging issue.

The above discussions lead to the following unresolved research issues: Lack of research on modeling the maintenance activity that can decouple dependent components and mitigate failure dependence; Absence of a sufficiently comprehensive framework that enables engineers to conduct a thorough assessment of the overall sustainability of a subsea system, considering the failure dependence and maintenance activities. Directing to these research issues, this paper proposed a novel framework to evaluate the system sustainability with consideration of failure dependence and maintenance activities, and subsequently applies this model to a subsea transmission system. The expected contribution of this study could be summarized below:

(1) Delimitate and model the new maintenance activity, called as Decoupling Maintenance (DM) activity, that is used to eliminate the failure dependences among components, in addition to the conventional maintenance activities.
(2) Provide a comprehensive methodology, integrating the impact of component degradation, the failure dependences among components, and the maintenance activities on the overall sustainability.
(3) Explore the impact of various maintenance strategies on the overall sustainability through application of the proposed methodology in a case study.

The rest of the work is outlined as follows. Section 2 provides an overview of the multi-component subsea transmission system and the integrated evaluation framework. The illustration of the degradation model and maintenance model are presented in Section 3. In Section 4, the sustainability evaluation model considering the impact of component performance and maintenance activities is constructed. In Section 5, a case study is conducted to demonstrate the practical application of the proposed methodology in the subsea transmission system. Section 6 discussed the influence of maintenance strategies and failure dependences on the overall sustainability following the case study. Section 7 outlines the conclusions of this paper and the direction of future work.

2. Integrated evaluation framework with a motivating example

Here we consider subsea transmission system, as illustrated in reference (Zhao et al., 2023a), suffering failure dependences and facing sustainability issues. Fig. 1 refers to (Zhao et al., 2023a; Grieb et al., 2008) and illustrates the subsea separation and transmission part. In this setup, a subsea separator is used to carry out the initial separation of well fluids into three distinct phases: gas, oil, and water. Following the outlet of the separator, three pipes convey the separated gas, oil, and water to a compressor and two pumps respectively. The components of the subsea production system responsible for transmission, including the compressor and two pumps, can be considered as a dependent system, referred to as the subsea transmission system. In this simplified model of the transmission system, there are one compressor and two pumps operating in parallel. The gas compressed by the compressor and the oil transported by the pump are both directed topside, while the separated water containing sand is pumped for potential release into the sea or for reinjection through the water injection process.

The compressor and pumps are used to transfer various substances at the desired power under ideal circumstances. However, these devices naturally undergo degradation, leading to various failure modes in practice, such as leakage, plugged, corrosion, vibration, overheating, spurious stop, etc. Some of these failures impact both their own operational efficiency and the degradation of other devices within the system. For instance, when a compressor fails, the intermingling of gas and liquid in the pumps exacerbates the degradation of the pumps. This kind of failure dependence has a relationship with the content of impurities contained. As another example, vibration and overheating of one pump may directly affect the operation and degradation of another pump. This type of failure dependence is associated with physical distance and safety barriers.

In this subsea transmission system, the component failure can easily trigger CAFs due to failure dependences and cause more severe accidents. Moreover, the inherent challenges in maintenance activities for subsea transmission system contribute to increased costs and resource demands. These factors collectively exert significant impacts on the subsea environment, the society, and the economy, thereby influencing the overall sustainability of the system.

To evaluate the sustainability of the subsea transmission system over time, we develop an innovative methodology incorporating the failure dependences and maintenance activities, which is depicted in Fig. 2. This integrated framework comprises three sub-models. Within this framework, the degradation model involves estimating the state of components and failure dependences among components using historical data and expert assessments. Furthermore, drawing from expert experience and maintenance records, it is possible to determine the traditional maintenance strategies and the formulation of a maintenance model, which helps to identify the impacts that the maintenance strategies can have on the components. It is important to highlight that the innovative DM activities are embedded in the maintenance model to mitigate the failure dependences. Finally, a universal sustainability model is employed to assess alterations in sustainability throughout the system operation and maintenance activities, enabling optimization of the decision-making scheme. It is worth noting that the degradation process and maintenance activities of components within systems are closely interconnected and mutually influential. The degradation process determines the state of components and thus influences the maintenance policies. Conversely, the maintenance activities changed both the component states and degradation process. This prompt introducing the integration merging the degradation and maintenance models, denoted as degradation-maintenance model for short. Furthermore, changes in either of these elements of degradation and maintenance activities can significantly affect the overall sustainability, thereby the degradation-maintenance model influences the sustainability evaluation model.

Given that this research issue involves dynamics of a system, the dynamic Bayesian network (DBN) can be reasonable method for capturing capture the dynamic behaviors of the system in a real ever-

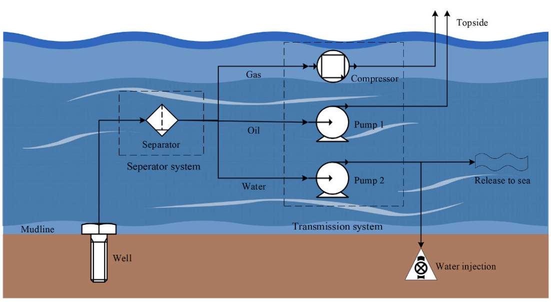


Fig. 1. Scheme of the subsea separator system and transmission system.

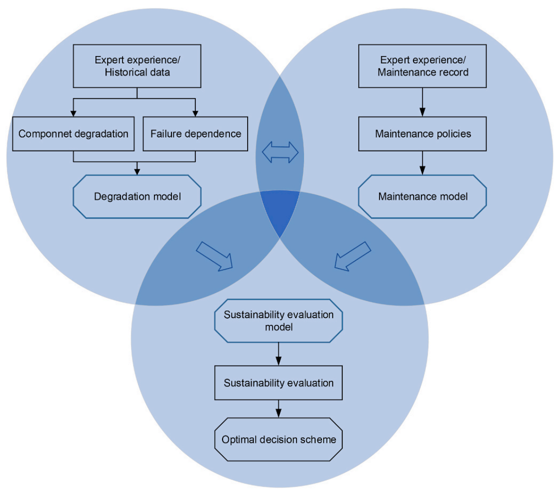


Fig. 2. The integrated framework of the proposed methodology.

changing environment (Wu et al., 2022). DBN can handle the uncertainty of complex systems, allowing engineers to better understand the evolution of the system over time and better formulate maintenance strategies. The advantage can be demonstrated in some existing studies. To predict the RUL of multilevel subsea systems with consideration of CAF, Cai et al. (2021) introduced the modeling using DBNs. Liu et al. (2023) developed a DBN-based modeling for evaluating the reliability of subsea pipelines considering the interaction between degradation failure and sudden failure. In our research, the DBN model addresses the components and the system at different time intervals. Comparisons of overall sustainability before and after required maintenance activities can therefore be studied. Specifically, the DBN is a model represented by a directed temporal acyclic graph. Nodes in the model represent stochastic variables, while the directed arcs correspond to the probabilistic conditional relationships among these variables. The DBN calculation is implemented through the software GeNIe. The GeNIe primarily serves the purpose of constructing, assessing, and visualizing probabilistic graphical models, with a particular focus on Bayesian networks (BNs) and DBNs (Ma et al., 2018). The GeNIe provides a free development environment for graphical decision-theoretic models to analyze the probabilistic relationships among various variables (Cheng et al., 2021), which is helpful to understand and handle the probabilistic events in complex systems.

3. Degradation-maintenance model

The degradation-maintenance model is illustrated in Fig. 3. Taking component 1 as an example to illustrate this model, the grey nodes labeled C1 and C1' denote its state of at time t and $t+\Delta t$. The nodes CR1 and DM1 in yellow represents the maintenance activities concerning the component and the maintenance activities to mitigate the failure dependences, respectively. The node FD1 denotes the overall failure dependence originating from other components towards component 1. The failure dependence relationship linking component 1 with each of the other components is visualized by the red arcs extending from their respective nodes to the node FD1.

The state of the n components system could be denoted by $X = (x_1, x_2, \dots x_n)^T$, where $x_i \in [0,1]$ characterizes the state of component i in this system. When $x_i = 0$, the component i is in the As-Good-As-New state, i.e., the component is brand new; while when $x_i = 1$, the component i is in Failed state. As the component degrades, its state value increases. Use a saturation function $\varphi(x)$ to restrict the state of the components in $[0,1]$

$$x_i = \varphi(x_i) = \begin{cases} 0, & x_i < 0 \\ x_i, & 0 \le x_i \le 1 \\ 1, & x_i > 1 \end{cases} \tag{1}$$

The components experience degradation and maintenance intervention over time. Let $x_i(t)$ represent the state of component i at time t. Then $x_i(t+\Delta t)$ is the state of component i at time $t+\Delta t$, where Δt is the period of component degradation and maintenance intervention, starting from the moment the component states are observed until completion of the maintenance, which could be abbreviated as *delay period*. The delay period may be affected by the following factors: maintenance type, component importance, failure impact, maintenance procedures and resource availability, etc. Overall, the delay period is generally determined based on balancing factors such as component availability, cost-effectiveness, and safety. Its specific scope varies based on specific application scenarios and component characteristics. The function to determine $x_i(t+\Delta t)$ refers to equation (2).

$$x_i(t+\Delta t) = \varphi(x_i(t) \bullet D_i + \eta) \tag{2}$$

where D_i is the failure dependences from other components on component i, implying that the state of a component can be affected by the degradation or failure of other components;

$$D_i = \prod_{j=1}^{n} (1 + x_j(t)) \tag{3}$$

and η is the state change of the component, representing the degradation and the maintenance effectiveness.

$$\eta = \begin{cases} \eta_D \Delta t, & \text{for NM} \\ \eta_{PM}, & \text{for PM} \\ \eta_{CM}, & \text{for CM} \end{cases} \tag{4}$$

In equation (4), η_D is the degradation decrement of component i during time unit. When there is no maintenance intervention, the state of component i only changes due to degradation and failure dependences. A value between 0 and 1 is assigned to state change rate due to degradation. If there is maintenance intervention during Δt, the state of component i changes due to maintenance intervention and failure dependences. Let η_{PM} and η_{CM} denote the maintenance effectiveness of Preventive Maintenance (PM) activities and Corrective Maintenance (CM) activities respectively, then a value between -1 and 0 is assigned to state change caused to each PM and CM activities. In this model, the η_D is assigned a positive value since it signifies the degradation of the component. On the other hand, η_{PM} and η_{CM} are assigned negative values because they denote the improvement of the component state, leading to a decrement in its state value. This model assume that the maintenance activities could eliminate the cumulative effect of both previous and current damage. Therefore, the degradation during the period of Δt is not considered in the equations related to the maintenance activities.

In addition, this study also examines maintenance activities aiming at diminishing the failure dependences, i.e., Decoupling Maintenance (DM) activities. When such maintenance activities are implemented, the failure dependence is assumed to drop to 0, and the state of component i at time $t+\Delta t$ is

$$x_i(t+\Delta t) = \varphi(x_i(t) + \eta) \tag{5}$$

In conclusion, several types of maintenance activities are suggested, with the implementation of PM and CM activities aligned with the component states, as well as the implementation of DM activities aligned

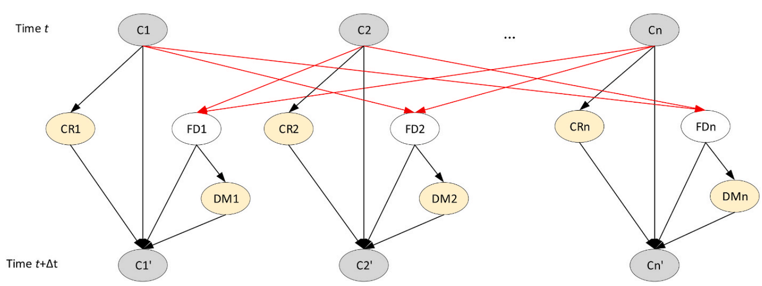


Fig. 3. DBN model for degradation process and maintenance activities considering CAFs.

with the failure dependences among components.

- No Maintenance (NM) activities: the state of the component is acceptable, which does not exceed the threshold for any maintenance activity ($x \le a$), and thus no maintenance intervention is required.
- Preventive Maintenance (PM) activities: The PM is imperfect maintenance and could only improve the component performance to a certain extent. Common PM activities for subsea systems include coating repair, cleaning, anti-rust treatment, etc.
- Corrective Maintenance (CM) activities: The CM is perfect maintenance, which restores the component to normally operating state. Typical CM activities for subsea systems involve replacements of broken pipelines or damaged key devices, etc.
- Decoupling Maintenance (DM) activities: The DM aims to decouple dependent components and is only related to the failure dependences among components. The failure dependence is assumed to be eliminated completely after DM activities. Examples of DM activities for subsea systems are physical isolation between equipment, redundant design, interlocking systems, etc.

4. Sustainability evaluation model

4.1. Evaluation of impacts of component performance on sustainability

The system performance determines not only the output efficiency, but also the pollution during its regular operation, and the pollution due to failures, i.e., the emissions, the wastes, and the noise. While the regular operation of the system constantly results in a certain amount of emission or pollution to the surrounding environment, its production will contribute positively to both society and the economy. To evaluate the impact of the component performance on the sustainability more comprehensively, the suggested procedure is provided as below (see Table 1).

Step 1. System familiarization.

The system should be well-defined, with clearly outlined physical boundaries and specific details regarding its operational requirements and relationship with sustainability. Operational familiarization includes the system structure, components functions and dependence among components. Environmental familiarization involves identification of all potential sustainability pillars and sustainability indicators that may contribute to each sustainability pillar.

Step 2. Information acquisition and determination of nominal states of the components.

States of the components are defined as $x_i \in [0, 1]$ in subsection 3.1. If the component is normally working, and no maintenance is required, it is supposed that the damage from the component performance to the sustainability is infinitely close to 0 and could be neglected. The state of component that falls below the threshold for maintenance activities could be then considered as the nominal state. Information about the nominal values of component states could be obtained from OREDA (SINTEF and NTNU, 2015), historical data, maintenance records, and other relevant sources.

Step 3. Scoring the effects of the component performance on each sustainability indicator.

Components below the maintenance threshold are assumed to be in a nominal state and have no effect on system sustainability indicators. Once a component surpasses this nominal state, the disparity between the component state and the nominal state can be utilized quantitatively to evaluate the effects of the component performance on sustainability indicators. Compared to the nominal states of the components, the effects of the component performance on each sustainability indicator could be denoted as

$$\sigma_{i\rightarrow SI_j} = \begin{cases} 0, & x_i < a \\ x_i - a, & x_i \ge a \end{cases} \tag{6}$$

The integrated effects of the component performance from all the components on each sustainability indicator can be then given by $\sum_{i=1}^{n}\varepsilon_{i\rightarrow SI_j}\sigma_{i\rightarrow SI_j}$, where $\varepsilon_{i\rightarrow SI_j}$ represents the relationship between the state of component i and the sustainability indicator SI_j, and

$$\sum_{i=1}^{n}\varepsilon_{i\rightarrow SI_j} = 1, \text{for } j = 1, 2, \ldots r \tag{7}$$

The scores of $\varepsilon_{i\rightarrow SI_j}$ can be derived from technical documentation, operational information, expert assessments, accident reports, and interviews with engineers. When the performance of the component declines, indicating an increase in the value of the component state, and such degradation negatively impacts the sustainability, $\varepsilon_{i\rightarrow SI_j}$ assumes a negative value within the range of -1 to 0. Conversely, when the component degradation positively affects the sustainability, $\varepsilon_{i\rightarrow SI_j}$ assumes a positive value within the range of 0–1.

Step 4. Weighing the contribution of the sustainability indicators to sustainability pillars.

Sustainability indicators and sustainability pillars are related concepts, but they serve different purposes. Sustainability indicators are the tools to assess how well the sustainability goals are achieved within these sustainability pillars. Sustainability pillars are the fundamental categories that represent the various aspects of sustainability. The most common sustainability pillars (Ghaleb et al., 2022) are Environmental, Social, Economic. Sustainability indicators are specific metrics used to evaluate the performance of a system in terms of sustainability. Examples include hazardous substances, carbon emissions, wastes, and noise regarding to the sustainability pillar Environmental. The sustainability indicators contributing to a sustainability pillar may have varying weights of influence. The contributing weight of sustainability indicator SI_j for the sustainability pillar SP_k is denoted as w_{jk}. Should there be no relation between sustainability indicator SI_j and the sustainability pillar SP_k, then $w_{jk} = 0$. The weights could be scaled in

Table 1
Suggested stepwise procedure of the sustainability evaluation concerning the impact component performance.

Step	Description
Step 1	System familiarization.
Step 2	Information acquisition and determination of nominal states of the components.
Step 3	Scoring the effects of the component performance on each sustainability indicator (SI).
Step 4	Weighing the contribution of the sustainability indicators to the sustainability pillar (SP).
Step 5	Determination of the importance of each sustainability pillar.
Step 6	Determination of the overall sustainability score (OSS) by impacts of component performance.

$$\sum_{j=1}^{r} w_{jk} = 1, \text{for } k = 1, 2, \ldots p \tag{8}$$

Step 5. Determination of the importance of each sustainability pillar.

The sustainability pillars provide a framework for conceptualizing the different sustainability indicators of systems. However, distinct systems may seek diverse sustainability objectives, leading to variations in the importance of sustainability pillars. To ensure alignment with the system distinctiveness and sustainability objectives, it is essential to assign weights to the sustainability pillars individually according to their importance to the overall sustainability when conducting sustainability evaluations. Suppose that there are p sustainability pillars in total, then

$$\sum_{k=1}^{p} I_k = 1 \tag{9}$$

Step 6. Determination of the overall sustainability score by impacts of component performance.

Finally, the overall sustainability can be calculated based on the obtained scores and weights, as shown in equation (10). While the influence of component performance on sustainability indicators and pillars may not perfectly align with the reality, it is still a reasonably accurate approximation for quantifying the *OSS*.

$$OSS = \sum_{k=1}^{p} I_k \bullet \left[\sum_{j=1}^{r} w_{jk} \bullet \left(\sum_{i=1}^{n} \varepsilon_{i \to SI_j} \sigma_{i \to SI_j} \right) \right] \tag{10}$$

Since equation (10) solely represents the influence of component performance on sustainability, which is, the evaluation of system sustainability prior to the execution of maintenance activities, it could be used to evaluate the system sustainability at time t. This system sustainability can be confined within a range from -1 to 1. A lower value of the *OSS* closer to -1 signifies a lower degree of acceptance for the system sustainability, and a higher *OSS* indicates an increased level of acceptability for the system sustainability. According to the sustainability evaluation framework we established, the value of *OSS* can comprehensively reflect the impact of component performance on sustainability from three aspects (environmental, social, and economic).

4.2. Evaluation of impacts of maintenance activities on sustainability

Maintenance activities can have a substantial impact on sustainability in two distinct ways: To start with, by enhancing system performance, maintenance activities indirectly contribute to improved system performance and thus improved the sustainability, which could be categorized to the discussion in the last subsection. However, maintenance activities themselves can directly result in sustainability changes. For example, Emissions arise from the transportation and deployment of old and new devices, as well as the maintenance crews. Replacement of failed components also contributes to resource wastage. This subsection examines the second type of effect.

Assign a correlation value ranging from 0 to 1 to map and assess the impact of each maintenance activity. Let $\sigma_{MSSi \to SI_j}$ represent the impact of maintenance activities for component i on sustainability indicator SI_j, and $\varepsilon_{MSSi \to SI_j}$ denote the relationship between the maintenance activities of component i and the sustainability indicator SI_j. In this case, the cumulative impact from all the maintenance activities on sustainability indicator SI_j could be denoted as $\sum_{i=1}^{n} \varepsilon_{MSSi \to SI_j} \sigma_{MSSi \to SI_j}$. Afterwards, the assessment of relationships among sustainability indicators, sustainability pillars, and the overall sustainability could adhere to the same steps that examines how component performance influences sustainability.

Every maintenance activity and component state change lead to the overall sustainability changes. The overall sustainability evaluation at time $t + \Delta t$ contains both of their effects. Since the impact of maintenance activities on sustainability is considered independent of the impact of component state change, their impact on sustainability indicators can be simply superimposed. Therefore, the overall sustainability score at time $t + \Delta t$ (*OSS**) can be calculated as below.

$$OSS^* = \sum_{k=1}^{p} I_k \bullet \left[\sum_{j=1}^{r} w_{jk} \bullet \left(\sum_{i=1}^{n} \left(\varepsilon_{i \to SI_j} \sigma_{i \to SI_j} + \varepsilon_{MSSi \to SI_j} \sigma_{MSSi \to SI_j} \right) \right) \right] \tag{11}$$

Compared with the *OSS* at time t, the overall sustainability at time $t + \Delta t$ considers the influence of maintenance activities as an independent factor. Consequently, the combination of the effects from component performance and the maintenance activities on sustainability can lead to an *OSS** value at time $t + \Delta t$ that falls beyond the range of $[-1, 1]$. Nonetheless, similarly with *OSS*, a higher *OSS* value still indicates an increased level of acceptability for system sustainability. Besides, the value of *OSS** can comprehensively reflect the impact of component performance and maintenance activities on sustainability from three aspects (environmental, social, and economic).

4.3. Process of overall sustainability evaluation

Fig. 4 shows the whole process to evaluate the overall sustainability. The blue nodes labeled *OSS* and *OSS** denote the overall sustainability score at time t and $t + \Delta t$. The *OSS* is calculated only relying on the states of the components at time t, while *OSS** calculation involves the effects of the component states at time $t + \Delta t$, as well as the effects of maintenance activities during the period Δt. At time t, the maintenance activities are not carried out, and the overall sustainability score depends only on the component states, denoted by the grey nodes. At time $t + \Delta t$, the overall sustainability score depends both on the component states and on the impact of maintenance activities for the component on the sustainability, which encompasses the impact of maintenance activities CR and the impact of maintenance activities DM. Based on the evaluation of the impact from maintenance activities and the impact of new component states at time $t + \Delta t$, the new overall sustainability score could be estimated.

5. Numerical analysis for the subsea transmission system

5.1. Degradation-maintenance model of the subsea transmission system

According to the proposed model, the state of component i is characterized by $x_i \in [0, 1]$. Assume that the state of component i follows a beta distribution $X \sim \text{Beta}(\alpha, \beta)$ to restrict the state values within the range of $[0, 1]$. The Beta distribution is widely used in statistical applications as a prior distribution for proportions in Bayesian analysis due to its analytical tractability, versatility (Fernández et al., 2012) and flexibility for modeling (Horn et al., 2019). In particular the beta distribution could be used to describe failure probability estimation in quantitative risk analysis (QRA) (Steijn et al., 2017) and denote failure rates of offshore components in reliability assessment (Horn et al., 2019), which demonstrates its relevance to our research. The beta distribution parameters could be adjusted for a more realistic representation to align the distribution shape with expert experience and empirical data (SINTEF and NTNU, 2015; O'Connor et al., 2016). Determine the probability distributions of the states for the compressor and two pumps as: $X_1 \sim \text{Beta}(1, 5)$, $X_2 \sim \text{Beta}(2, 4)$, $X_3 \sim \text{Beta}(2, 5)$. Their distributions are capable of being defined within the software GeNIe, and the screenshots depicting their representation in the software can be observed in Fig. 5. Fig. 5 illustrates the probability values associated with different states of distinct components at the initial time point t.

Each component exists in one of four states: normally operating

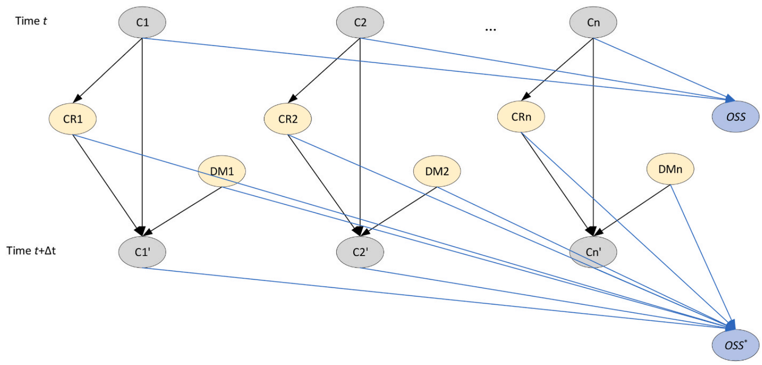
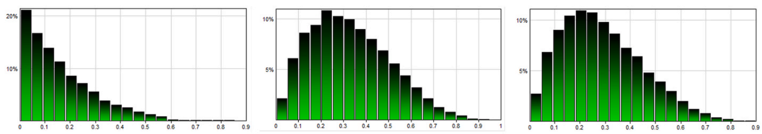


Fig. 4. DBN model for sustainability evaluation.



(a) Compressor (b) Pump 1 (c) Pump 2

Fig. 5. State distributions of the components at time t.

(state 0), moderately degraded (state 1), degraded (state 2), and failed (state 3). To scale the four states of component, the range of the value characterizing each state is set to be 0.25 : Normally Operating state falls within the interval of [0, 0.25); Moderately Degraded state lies in the interval of [0.25, 0.5) and so forth. During one time unit, the degradation decrement of the compressor is 0.01, and the degradation rates of the pumps is 0.05. If the component is degraded (state 2), PM is required to restore the component state to moderately degraded (state 1). Considering that PM solely restores the component to its prior state, and given that the gap between distinct states is 0.25, the assigned value for PM in this context is −0.25. This ensures that components undergoing PM revert to their previous state. If the component fails (state 3), CM is needed to take the component to the normally operating state (state 0). To handle the variety of CM activities, the CM activities are allocated a value of −0.75, guaranteeing that, following CM, the component falls within the Normally Operating state range [0, 0.25), regardless of its initial state. In this case, the state change rates due to degradation and the maintenance effectiveness could be valued as listed in Table 2.

In practical engineering, the implementation of maintenance activities relies not solely on the states of the components but also on factors like the urgency of the degradation or failures, the complexity of maintenance procedures, and the constraints of available maintenance resources. Consequently, there is not always a fixed, predetermined maintenance activities for a particular state of the component. The probabilities of choosing a specific maintenance activity for a particular component state are given according to the historical data, maintenance records and expert opinions. The historical data and maintenance records are documented by the industry. The expert opinions come from one engineer in the industry, one researcher in the safety institute, one professor in the university, and one PhD working on the maintenance management. According to their experience, the probabilities of various maintenance activities, considering the state of components are deliberated, gathered, and assessed. These probabilities can be considered as the prior probabilities and generalized into conditional probability tables (CPTs) when applied to DBNs, as shown in Table 3.

Similar to PM activities and CM activities, the prior probabilities of DM activities are also conditional. The probabilities carrying out the DM activities depend on the strength of failure dependence between components. Given the limited occurrence of DM maintenance activities addressing failure dependences in practical situations, the level of failure dependence is quantified by equation (3) and simply classified into Weak and Strong. Besides, the likelihood of undertaking corresponding maintenance activities for various components based on two levels is approximately equal, as inferred from maintenance records and expert opinions. From another perspective, reciprocal nature of failure dependence among components results in a more evenly distributed probability of performing DM maintenance activities for them. Table 4 shows the CPT for the DM maintenance policies.

Table 2
Parameters for the degradation decrement and maintenance effectiveness.

Parameters	Degradation decrement η_D		Maintenance effectiveness for PM η_{PM}	Maintenance effectiveness for CM η_{CM}
	Compressor	Pumps		
Values	0.01	0.05	−0.25	−0.75

5.2. *Sustainability evaluation model of the subsea transmission system*

The methodology to determine *OSS* is not focused in this study, so three sustainability-related pillars were assigned weights based on the BWM method applied in a case study (Ghaleb et al., 2022): Environmental (0.4); Social (0.2); and Economic (0.4). The sustainability pillars are specifically expressed by sustainability indicators. The sustainability indicators associated with each sustainability pillar does not have any contribution or connection on the other sustainability pillars. The contribution weights of sustainability indicators for each sustainability pillar should be given by experts. Table 5 lists the results of experts' estimation.

The effects of the component performance on each sustainability indicator and the impacts of maintenance activities on sustainability indicators are also evaluated through expert opinions, primarily derived

Table 3
CPT for the PM and CM maintenance policies.

Maintenance activities	Component 1				Component 2				Component3			
	State 0	State 1	State 2	State 3	State 0	State 1	State 2	State 3	State 0	State 1	State 2	State 3
NM	1	0.45	0	0	1	0.6	0	0	1	0.6	0	0
PM	0	0.55	0.6	0.1	0	0.4	0.7	0.1	0	0.4	0.7	0.1
CM	0	0	0.4	0.9	0	0	0.3	0.9	0	0	0.3	0.9

Table 4
CPT for the DM maintenance policies.

DM activities	Component 1		Component 2		Component 3	
	Weak	Strong	Weak	Strong	Weak	Strong
NO	1	0.4	1	0.4	1	0.4
YES	0	0.6	0	0.6	0	0.6

from the information contained within maintenance records. An example serves to highlight variations in the influence of maintenance activities on sustainability indicators. Maintenance activities such as replacement of components can significantly impact both SI-wastes and SI-downtime. An escalation in such maintenance activities leads to greater wastes and extended downtime, consequently diminishing sustainability. Consequently, the impact of these maintenance activities on sustainability indicators SI-wastes and SI-downtime can be quantitatively negative. On the other hand, maintenance activities centered on failure dependences among components, such as the installation of safety barriers, may result in some wastes but do not significantly impact component downtime. Therefore, the impact of DM activities on the sustainability indicator SI-downtime may register as a value that is either slightly negative and approaching zero, or it can be entirely directly ignored as 0 when quantified.

5.3. Overall sustainability scoring

After scoring all the values and weights, the overall sustainability score at time t and $t + \Delta t$ could be calculated using the software GeNIe. Suppose that the maintenance activities are completed in one time unit. Regarding to this case, the results of *OSS* and *OSS** are in distribution terms and shown in the right of Fig. 6.

As depicted in Fig. 6, prior to the implementation of the maintenance activities, the probability distribution of sustainability values lies to the left of 0, with a higher probability for values closer to 0. However, after experiencing component degradation and maintenance activities during the delay period Δt, the probability distribution of sustainability values shifts leftward, and some smaller sustainability values appear with a certain probability. This suggests that, even after the application of maintenance activities, the overall sustainability still exhibits a declining trend in general over time. Since GeNIe displays a handful of parameters of the distribution, more specific values of the results could be calculated and listed in Table 6. In Table 6, the StdDev is the abbreviation of Standard Deviation, which is used to measure the dispersion of a set of data. The maximum value indicates the peak level of overall sustainability acceptability, which is consistent for both *OSS* and *OSS**. Conversely, the minimum value and the mean value signify the lowest level and the average level of overall sustainability acceptability, and these two parameters may serve as estimates for overall sustainability. Therefore, we could also obtain a similar conclusion that

Table 6
Results for the *OSS* and *OSS** evaluation.

Values	StdDev	Maximum value	Minimum value	Mean value
OSS	0.0542	0	−0.3125	−0.0634
*OSS**	0.0765	0	−0.5687	−0.1259

Table 5
Contribution weights of SIs for each SP.

SPs	SIs							
	Energy consumption	Wastes	Noise	Accidents	Injury frequency	Resource usage costs	Productivity	Downtime
Environmental	0.6	0.25	0.15	–	–	–	–	–
Social	–	–	–	0.55	0.45	–	–	–
Economic	–	–	–	–	–	0.3	0.4	0.3

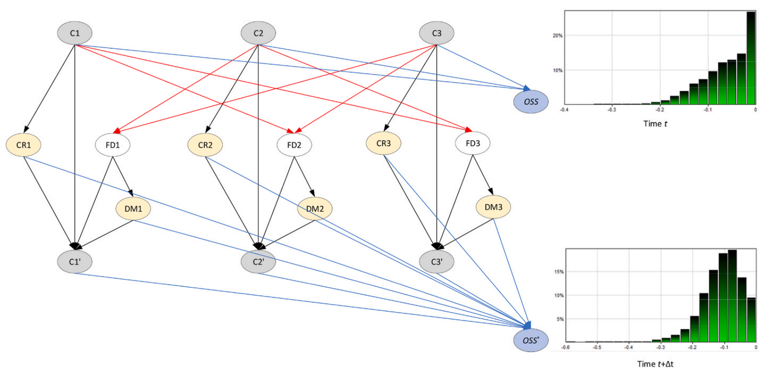


Fig. 6. *OSS* evaluation model and results.

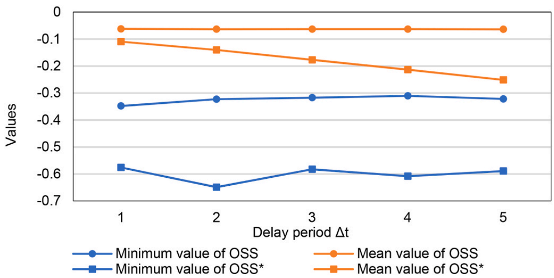


Fig. 7. *OSS* and *OSS** results with different delay period.

the overall sustainability declines by comparison of the results of these two parameters.

Then we assume that the duration of component degradation and maintenance interventions are extended, meaning that the value of delay period Δt is altered. The changes of the overall sustainability could be observed by comparing its mean values and minimum values. The results are shown in Fig. 7. From this figure, the mean values of *OSS* are almost stable on a horizontal line, while the minimum values of *OSS* exhibit minimal variation with changes in the delay period. This phenomenon can be easily comprehended since the value of *OSS* is independent of the delay period and the activities that occur during it. Hence, to assess the impact of component degradation and various maintenance activities on overall sustainability during the delay period, it is rational to exclusively consider the values of *OSS**. Regarding *OSS**, its minimum values experience fluctuations without obvious time-dependent pattern. However, the mean values of *OSS** demonstrate a consistent and steady decline as the delay period extends, making it a more suitable fundamental parameter for our analysis, compared to the minimum value. Furthermore, it is noteworthy that both the mean values and minimum values of *OSS** are considerably lower than their counterparts of *OSS*. This revalidates the previous conclusion that the overall sustainability diminishes following the delay period of component degradation and maintenance activities.

6. Results and discussion

6.1. Influence analysis of failure dependence

The numerical results of *OSS** with and without failure dependence could be compared by Fig. 8. The results show that the mean values of the overall sustainability with failure dependence are obviously smaller than that without failure dependence. The finding implies that the overall sustainability is in a less acceptable level when there is failure dependence. This phenomenon can be explained as follows: the failure dependence accelerates the component degradation, thereby amplifying the damage to the overall sustainability, ultimately causing the decline in the values of *OSS** to an even more unacceptable level. From Fig. 8, the corresponding changes in the overall sustainability are observed with varying the failure dependence. In reality, structural and functional failure dependences among components are very common and become more pronounced as system complexity grows. Consequently, neglecting the influence of failure dependences during system sustainability assessments can lead to overestimated outcomes than the actual values, potentially resulting in inappropriate maintenance strategies.

6.2. Influence analysis of maintenance strategies

The CPT of nodes can be flexibly changed in the DBN. Taking advantage of the feature, the overall sustainability can be reassessed under the assumption that various maintenance strategies are implemented. Subsequently, a maintenance decision can be determined according to the optimization of the reassessed sustainability, as mentioned in equation (11). The aforementioned maintenance strategy in the case study is denoted as maintenance strategy 1. Some other maintenance strategies are also considered. Fig. 9 shows the mean values of the overall sustainability after delay period with six kinds of maintenance decision. Compared to maintenance strategy 1, other maintenance strategies have varying alteration, as illustrated below.

- Maintenance strategy 2: Decreasing the probability of DM activities from 0.6 to 0.3 for all components;
- Maintenance strategy 3: Ignoring the DM activities (the probability of DM activities will be 0);
- Maintenance strategy 4: Using PM activities instead of CM activities (the probability of NM activities remains the same and the probability of PM activities will be $1 - \Pr(\mathrm{NM})$);
- Maintenance strategy 5: Using NM activities instead of PM activities (the probability of CM activities remains the same and the probability of NM activities will be $1 - \Pr(\mathrm{CM})$);
- Maintenance strategy 6: Ignoring all kinds of maintenance activities (the probability of NM activities will be 1, and the probability of DM activities will be 0).

As shown in Fig. 9, all the mean values of the overall sustainability considered other maintenance strategies are smaller than that considered maintenance strategy 1. The mean values of *OSS** show the biggest difference between the maintenance strategy 1 and maintenance strategy 6. It implies that the worst-case scenario for overall sustainability occurs when no maintenance interventions are implemented, and the component degradation is the sole factor causing a negative impact on overall sustainability. Despite the maintenance strategy itself having a somewhat adverse impact on sustainability, its beneficial consequences on the overall sustainability by improving the component performance far outweigh its inherent drawbacks. In addition, a more detailed discussion of maintenance strategies can reveal the different impacts that

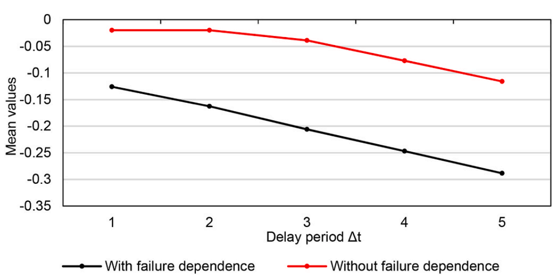


Fig. 8. Mean values of *OSS** with and without failure dependence.

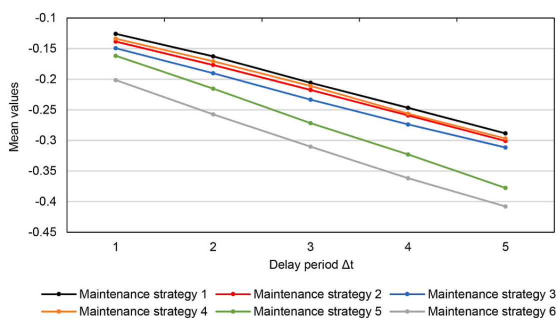


Fig. 9. Mean values of *OSS** with various maintenance strategies.

Table 7
CPT for the optimized PM and CM maintenance policies.

Maintenance activities	Component 1				Component 2				Component3			
	State 0	State 1	State 2	State 3	State 0	State 1	State 2	State 3	State 0	State 1	State 2	State 3
NM	1	0.4	0.05	0	1	0.35	0	0	1	0.35	0	0
PM	0	0.55	0.7	0.1	0	0.6	0.6	0.15	0	0.6	0.6	0.15
CM	0	0.05	0.25	0.9	0	0.05	0.4	0.85	0	0.05	0.4	0.85

Table 8
CPT for the optimized DM maintenance policies.

DM activities	Component 1		Component 2		Component 3	
	Weak	Strong	Weak	Strong	Weak	Strong
NO	1	0.3	1	0.3	1	0.3
YES	0	0.7	0	0.7	0	0.7

different maintenance strategies have on overall sustainability. Among them, maintenance strategies 2 and 3 focus on the alteration of DM maintenance activities, while maintenance strategies 4 and 5 focus on the alteration of PM and CM maintenance activities. Compared the maintenance strategies 1, 2 and 3, as the probability of implementing DM activities becomes smaller (0.7 to 0.3 to 0), the mean value of the overall sustainability is lower, while the reduction is not substantial. This implies that the DM activities have a modest capacity to enhance the overall sustainability, though their impact is not particularly pronounced. Therefore, in engineering practice, the DM activities could be considered when the budget and maintenance resources are sufficient. In terms of the maintenance strategies 1, 4, the differences between their numerical results are also not obvious, denoting that if all the maintenance activities are taken with CM, the overall sustainability could remain a pretty good level. However, if the moderate degradation or degradation are ignored to a large extent, and no maintenance activities are taken, which is maintenance strategy 5, the overall sustainability is largely decreased. Another observation is that as the delay period increases, the mean value of overall sustainability in the case of maintenance strategy 5 diminishes more rapidly than that in the case of maintenance strategy 1, in other words, the difference between them becomes larger. This could be attributed to the assumption that some components with moderate degradation or degradation are not maintained when considering only CM activities. With longer delay times, the degradation of these components intensifies. When components degrade severely, their hostile effect on the sustainability largely surpasses the possible negative impact of maintenance activities on the sustainability. Moreover, as the degree of component degradation increases, its hostile effect escalates at a faster rate, leading to a more rapid decline in the overall sustainability with longer delay period.

The above discussions involve the maintenance strategies under extreme circumstances and can serve as reference for investigating the influence of various maintenance activities on the overall sustainability.

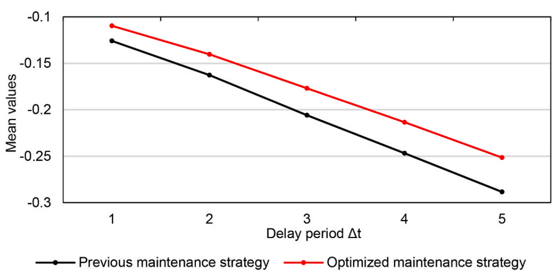


Fig. 10. Mean values of *OSS**under previous and optimized maintenance strategy.

To further consider the optimization of maintenance strategies based on the case study, altering the parameters of maintenance activities within the CPTs may yield diverse simulation results, revealing more effective maintenance strategies. An example of optimized maintenance strategy is provided, whose details are listed in Tables 7 and 8.

Fig. 10 shows the comparison of the sustainability evaluation under previous maintenance strategy and the optimized maintenance strategy. As shown in Fig. 10, the mean values of *OSS** under optimized maintenance strategy are always higher than that under previous maintenance strategy, which implies that the optimized maintenance strategy notably enhances the overall sustainability. This case demonstrates that the proposed methodology could be used to optimize the maintenance strategies based on sustainability in practice. In practical applications, this model can be used to simulate the enhancement of system sustainability under different maintenance strategies before decision-making, which is achieved by changing the type and corresponding probability of maintenance activities, thereby determining the optimal maintenance strategy.

7. Conclusions and future work

In this paper, a comprehensive framework to evaluate the overall sustainability of the complex multi-component system considering the failure dependences among components and the maintenance activities is proposed. The maintenance activities to mitigate the failure dependences are innovatively taken into account. The framework is examined based on a DBN model and applied in a case study of the subsea transmission system. Through the case study, the influence of failure dependences and the influence of maintenance strategies on the overall sustainability are illustrated. The results show that the overall sustainability is declining over time even after maintenance activities because the maintenance activities themselves also cause certain damage to the sustainability. Another finding is the overestimated sustainability without consideration of failure dependence, highlighting the significance of considering the failure dependence. Following that, several various maintenance strategies are examined and show that the overall sustainability could be improved to more acceptable level if the maintenance activities are implemented suitably according to the specific situations.

This research addressed several issues, such as introducing a novel maintenance activity (DM), and formulating a sufficiently comprehensive framework to assess the influence of failure dependence and maintenance activities on the overall sustainability of the system. The proposed framework is flexible, allowing for the investigation of various scenarios, including different degrees of failure dependence and diverse maintenance activities, through the straightforward adjustment of the CPTs. However, this research still has specific limitations that necessitate further investigation, as outlined below.

Firstly, the characterization of failure dependences among components was oversimplified due to that the study focuses more on the evaluation of overall sustainability. In fact, the failure dependences are complex and heterogeneous. To propose a more realistic framework, it is imperative to develop a more precise failure dependence model. Directions for future work can involve more investigations on the degradation mechanism caused by failure dependences. In addition, this research examines the contrast in overall sustainability pre and post once maintenance activities. Nevertheless, in practice, the system operates for several decades, during which it will undergo multiple testing and maintenance activities. If the degradation of the system and more maintenance activities over a longer period are considered, the results obtained should be more comprehensive and informative. Therefore, the Bayesian networks are suggested to be extended with multiple changes over longer periods. Thirdly, a more effective maintenance strategy is identified through inputting various maintenance strategies into the proposed model and conducting multiple simulations to compare the outcomes. However, pinpointing the optimal maintenance strategy proves challenging. Therefore, the model can be further improved to achieve the most optimal maintenance strategy to maximize the overall sustainability of the system.

CRediT authorship contribution statement

Yixin Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Baoping Cai:** Supervision. **Tao Zeng:** Software, Conceptualization. **Zhengbing He:** Writing – review & editing. **Yiliu Liu:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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