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Topical Review

Modeling of complex electromechanical systems based on state-space, graph network and intelligent algorithms: a review

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Abstract
Focusing on complex systems with large-scale and fault coupling characteristics, this study summarizes the reliability modeling and assessment methods for complex systems in the operational stage over the past few decades. Due to the distributed layout and heterogeneous design, the complex system offers unprecedented opportunities for improvement of reliability. However, the inherent complexity of systems which stem from increasing scalability, high-dimensional spaces and strongly coupled interactions have also posed great challenges to the accurate modeling and assessment of complex systems. This paper aims to systematically examine existing methodologies and emerging frontiers in complex system reliability assessment, discuss the problems of multi-field interactions, multi-state characteristics and multi-failure coupling relationships, and provide an overview of the advantages and limitations of prevailing evaluation approaches. Furthermore, some promising research directions are proposed, including integrated modeling frameworks, advanced physics-data fusion, and extended engineering applications.

Keywords: complex systems, reliability modeling, reliability assessment, system analysis

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1. Introduction

With the advancement of manufacturing, information and intelligent technologies, the complexity of engineering systems has increased significantly. The fourth industrial revolution has witnessed the evolution of industrial products from simple mechanical products to integrated complex systems with both physical and cyber connections. Complex systems usually integrate computing, communication and control systems to realize real-time perception, dynamic control and health service. This kind of system exhibits characteristics such as modularity, hierarchy, and nonlinearity [1–3]. Effective reliability modeling and assessment serve as the prerequisites for safe operation and successful application; however, reliability analysis can be a sophisticated and formidable task for these large-scale and multi-layer complex systems. On the one hand, the mechanisms of structural, functional and informational interactions and the fault handling strategy are unclear or even unknown due to the complexity of systems. On the other hand, the fault coupling and transmission between components, collaboration and rescheduling between layers, and performance degradation and functional failure interaction make the reliability modeling difficult. How to comprehensively characterize the fault relationship among the components, layers and systems is urgent for its reliability modeling and assessment. In fact, reliability is a critical consideration spanning the entire life cycle of complex electromechanical systems (CMESs), encompassing design, manufacturing, assembly, and operational stages. In this manuscript, we mainly pay attention to the reliability modeling and evaluation of CMESs in the operational stage.

Traditional reliability modeling focuses on building the reliability relationship between components and systems, in which the reliability data of critical components plays a more important role in reliability evaluation [4, 5]. However, it is difficult to describe the detailed degradation of fault, communicational effect and their interactions with each other in complex system. Not to mention considering fault reconstruction or fault-tolerant controls issues. In addition, it is not easy to obtain reliability data considering the mutual influence between components, layers and cyber-physical space through current reliability tests. For example, the operation of aircraft depends on the proper control of its three axes (toll, pitch and yaw) shown on figure 1. The pitch (roll or yaw) control of the surface control relies on the operation of actuators. The performance of actuators is based on its components such as servo valve and cylinder or motor and pump. Hence, the reliability assessment for large-scale complex systems needs to be conducted based on hierarchical architecture.

In the functional stratification of aircraft control systems shown in figure 1, only the bottom level (component) could utilize the traditional reliability model to evaluate its reliability. At the actuator level, due to the heterogeneous redundant actuator design, the actuators drive the sub-surface whose reliability could be calculated by dynamic reliability method. On the surface level, the distributed redundancy and fault-tolerant sub-surfaces design provides many faults tolerant resources, in which the reliability assessment should be considered the fault tolerant and mutual functional substitution. In the manipulate level, functional coupling of manipulation gives more possibility of improving flight quality. The reliability evaluation should characterize the flight performance. At the aircraft level, the system reliability is based on three-axis reliable operation. Therefore, reliability modeling and assessment of complex systems is multi-threaded system engineering.

In order to simplify the description, reliability modeling and assessment of complex systems could adopt pyramid-shape configuration shown in figure 2, in which the system is decomposed into three layers (component level, sub-system level and system level).

Within this hierarchical inference framework, intra-level functional interactions (e.g. dependencies among components) and inter-level couplings (e.g. subsystem-to-system relationships) are integrated systematically to quantify the comprehensive reliability for complex systems. The hierarchical structure inherent to complex systems gives rise to dual complexities in their reliability analysis. To be specific, due to the fault coupling between internal components, sometimes even a small number of component failures can cause a series of cascading failures, resulting in the collapse of the entire system. Given this, in existing research particular attention has been devoted to the analysis of fault patterns and the mechanism of fault propagation, namely, how to characterize the process from the failure of a single or several components to system-level collapse. On the other hand, system complexity may also enhance the adaptability of system to some extent, enabling it to adapt to and recover from disturbances. For instance, many complex systems are configured with similar or dissimilar redundancy structures, which effectively improve the fault-tolerant capability and total reliability of entire system, while simultaneously increasing the difficulty of reliability analysis. The prevailing reliability reasoning methods for complex systems include classical methods, Bayesian method, Markov chain-based methods, universal generating function (UGF) method, complex network theory method, Go method, etc. Among the diverse array of methodologies, classical reliability models tend to be static, which mainly focus on the fixed connections between components, while neglecting those dynamic factors such as environmental influences, external disturbances, changes of system structure and task, maintenance and repair, etc.

- Classical methods. This type of models mainly includes the reliability block diagram (RBD) [6–8], Fault Tree Analysis (FTA) [9–11], minimal cut sets (MCSs) [12], binary decision diagram (BDD) [13], multi-valued decision diagrams (MDDs) [14], and so on. Rooted in FTA, MCS-based methods have been a cornerstone of system-level reliability modeling for over 60 years. A minimal cut set represents a minimal subset of system components whose simultaneous failure guarantees the failure of the entire system. It requires that no proper subset of an MCS can induce system failure, ensuring computational efficiency. MCS methods enable quantitative calculation of system failure probability, and

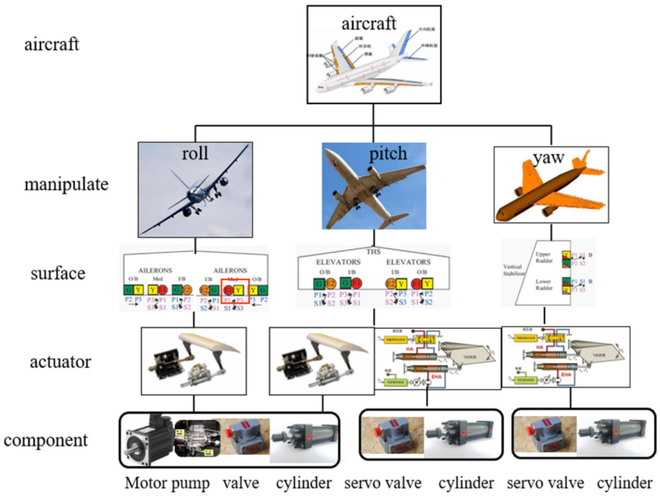

Figure 1. The hierarchical architecture of flight control system.

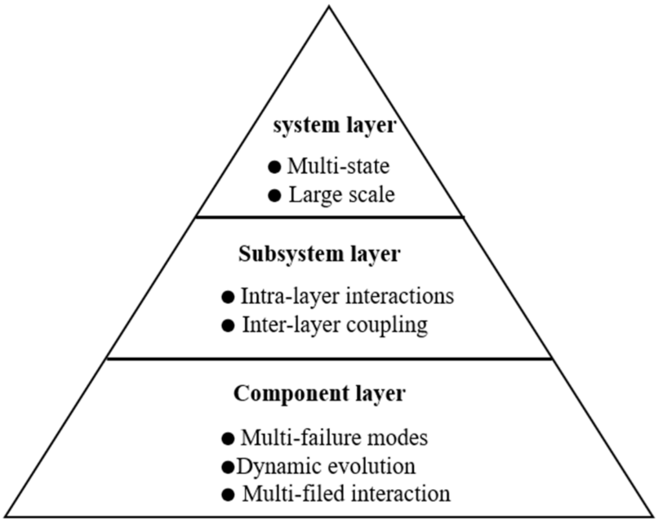

Figure 2. The pyramid-shape reliability calculation of complex system.

algorithms generated from MCS methods (e.g. BDD-based methods and MDD-based methods) can handle large-scale complex systems by pruning non-minimal combinations.

In reliability modeling of complex systems, BDD and MDD are advanced graphical tools widely employed to enhance the efficiency and accuracy of reliability analysis. Extensively utilized in FTA and probabilistic risk assessment, BDD is a directed acyclic graph that provides a compact and canonical representation of Boolean functions. It decomposes system logic into binary branches (e.g. component operational or failed), enabling exact computation of system reliability metrics, calculation of MCSs and system failure probability. MDDs extend BDDs by accommodating multi-state systems, where components and systems can assume more than two states (e.g. fully operational, degraded, failed). Compared with BDD, MDD retain the canonical properties while supporting discrete multi-valued logic. As a result, MDD is capable of modeling multi-state components and dependencies between failure modes, which broadens its applicability in engineering systems with higher complexity.

Generally speaking, all the above methods have the features of simple principles, clear steps, and strong feasibility. Although when dealing with large-scale complex systems, classical methods can have huge computational burden and less flexibility, they are still of high significance and instructive meaning to system analysis, thus can be regarded as the foundation of many innovative reliability modeling methods for complex systems.

- Bayesian methods. Bayesian methods [15–17] rooted in probability theory and statistical inference, have provided a powerful framework for reliability analysis of complex systems, particularly in scenarios involving uncertainty, multi-component interactions, and limited data. Compared with classical approaches, the prominent advantage of Bayesian method lies in its capability in multi-source information fusion and flexibility in uncertainty analysis. By integrating prior knowledge with observed evidence, including reliability experiment data, historical life data, simulation data, as well as expert and empirical information, Bayesian methods leverage prior distributions and likelihood functions to derive posterior distributions of reliability parameters, enabling iterative learning as new data become available. As a result, the Bayesian method effectively reduces the dependence of classical methods on mass experimental data, and by this measure, Bayesian method can save the time and cost of reliability experiment to a large extent. Nevertheless, the performance of Bayesian method is significantly affected by the selection of prior distributions, which limits its application in practical engineering.
- Fiducial method. This method, also known as the inverse probability method, can directly derive the confidence interval of system reliability by constructing the confidence distribution of parameters with the observations of samples. It does not require a predetermined distribution, which avoids the problem of prior distribution selection in Bayesian method to some extent [18]. However, the construction of fiducial distributions relies on specific structural equations, and the model assumptions often require rigorous proof. Moreover, the high-dimensional parameter spaces of complex systems also lead to difficulties in constructing fiducial distributions, in many cases the fiducial distributions can only be obtained approximately via numerical methods (e.g. Bootstrap or MCMC). Furthermore, fiducial methods are less flexible in modeling interdependencies among component failures or common-cause failures, thus most existing studies still adopt independent assumptions. Consequently, compared with Bayesian and other probability-based approaches, the fiducial method currently exhibits narrower applicability, but it offers a new solution to small-sample and high-uncertainty problems, and also demonstrates potential in the reliability analysis of redundant systems.

Existing literature has reviewed several critical issues regarding the reliability analysis of complex systems, such as the characteristics of complex systems, prevailing modeling and assessing tools, as well as the development history and application scenarios of specific methods. For instance, Ladyman *et al* [2] reviewed various attempts to characterize a complex system and listed the necessary conditions as a characterization of complexity, implying that a complex system is a whole greater than the sum of its parts. In literature [3], Zhao and Xing highlighted some of the common complexity attributes shared by complex systems including interaction, dependency, and inherent dynamics, which collectively introduce significant challenges to the reliability evaluation of complex systems. Luo *et al* [19] presented a review of reliability assessment methods for complex systems, paying special attention to existing research on the systems with multi-state, multi-failure modes and repairable requirements. Regarding specific methods, Yi *et al* [20] reviewed the application of goal oriented (GO) method on the reliability assessment of complex systems, introducing the development history and application scenario, fundamentals and basic theory, as well as future directions. Meluso *et al* [21] did a literature review on the modeling of complex engineered system, proposed a new framework of complex system integrated utilities model. Naghshbandi *et al* [22] reviewed the literature on resilience study of complex engineering and engineered systems, introducing six methods for uncertainty and interconnectedness processing.

The reviews and literature mentioned above focus more on the fundamental principles, development history and the application scenarios of specific analysis methodologies. In contrast, this paper aims to concentrate on several topics including (1) principal challenges in complex system reliability analysis, (2) inherent difficulties in the reliability modeling of CMESs as well as representative prevailing assessment approaches, and (3) emerging research directions in this field. In this context, this paper is organized as follows. In section 2, the characteristics of complex systems and corresponding challenges are introduced, including multi-layer interactions, multi-state characteristics and multi-failure modes coupling. Section 3 conducts a comprehensive investigation of reliability modeling approaches for CMESs. In this part, particular attention has been paid to three classes of prevailing approaches, including state-space based modeling methods (such as Markov process-based approaches and UGF-based approaches), graph-based modeling methods (such as GO method, complex network theory-based method and Bayesian network-based method), and intelligent algorithm-based approaches that have risen to prominence in recent research. This section also incorporates a review of advanced reliability computation strategies for complex systems, concluding with a brief comparison of their respective advantages and limitations. From the perspective of addressing methodological limitations and emerging technological requirements, section 4 identifies existing gaps in current studies and attempts to propose potential directions for further investigation. The paper concludes in section 5.

2. Characteristics of complex systems and challenges of reliability modeling

Generally, complex systems have some characteristics including high dimensionality, multi-layer interactions, multi-state characteristics, coupling relationships and interactions between multi-failure modes, and dynamic and interdependent failure behaviors. Their reliability analysis faces challenges such as scalability barriers and computational complexity, data scarcity and uncertain quantification, data heterogeneity, scientific formulation of reliability metrics, physical interpretability, as well as cross-disciplinary integration and validation. Figure 3 gives their characteristics and challenges.

2.1. Characteristics of complex systems

Modern complex systems exhibit several intrinsic characteristics that fundamentally differentiate them from conventional systems.

(1) **High dimensionality**

Complex systems such as aerospace systems and power grids often comprise thousands of interconnected components with nonlinear interactions. As the size of system increases, traditional combination-based reliability models struggle to handle the exponentially growing computational demands. For instance, simulating cascading failures in a network system requires solving high-dimensional state-space equations, which can lead to prohibitive computational costs. While approximation techniques like Monte Carlo simulation and surrogate modeling can obtain numerical solutions by sacrificing accuracy to some extent, there still exist a trade-off between accuracy and efficiency remaining unresolved.

(2) **Multi-layer interactions**

Multi-layer interactive mechanisms arise from the integration of heterogeneous subsystems including mechanical, electronic, and communicational components. Besides physical connections, information connections and power connections such as the control bus and power links also exist in complex systems, and as a consequence the reliability of entire system is inevitably affected by the reliability level of corresponding connections. These coupling interactions lead to the bilateral dependencies between component failures, and the propagation of local failure cross functional boundaries. Moreover, modern complex systems often exhibit nonlinear interactions between components, thus small perturbations may trigger cascading failures through amplification effects.

(3) **Multi-state characteristics**

Many previous studies adopt a general assumption that the systems only have success-failure binary states. However, as a result of stochastic failures and complex characteristics of internal components, complex systems can have multiple performance levels, and these different levels must be taken into consideration in reliability analysis. From the perspective of practical application, the failure of complex system is a

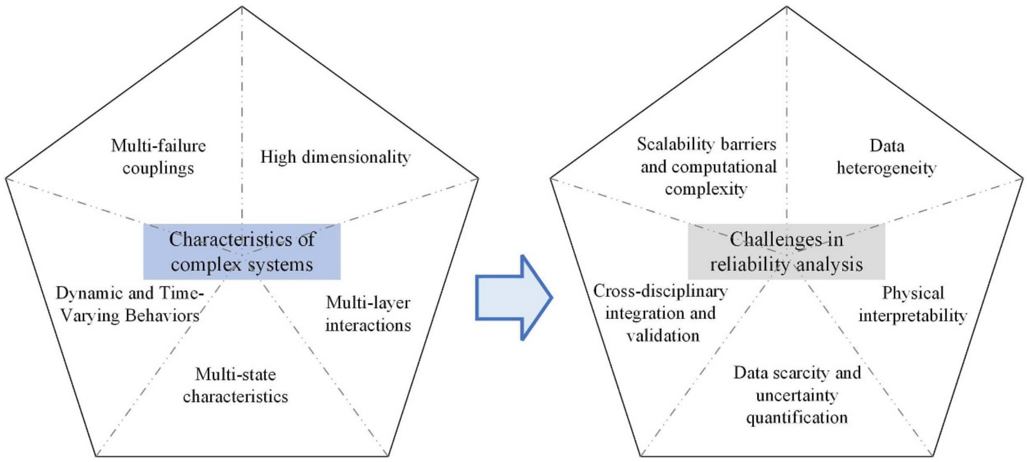

Figure 3. Characteristics of complex systems and challenges of reliability assessment.

long-term degradation process, thus apart from normal operation and complete failure, the system may also have intermediate states. Systems with multiple performance levels are known as multi-state systems. In this kind of system, from perfect operation to complete failure, the performance level of components or entire system are usually divided into multiple ranges, and each range is defined as a state of performance. The main characteristic of a complex multi-state system is the multiple system performance states presented during operation. It should be noted that the multi-state characteristics of a complex system are independent of the number of states of internal components. Specifically, a complex system completely composed of binary components can also be a multi-state system. Compared with binary-state systems, considering multiple performance states will further increase the complexity and difficulty of reliability analysis, especially when the system consists of a large and diverse range of components.

(4) **Coupling relationships and interactions between multi-failure modes**

From the perspective of practical engineering, in complex systems there may exist multiple failure modes simultaneously, and these diverse failure modes can be both interrelated and strongly coupled in many cases. Recent research has found that in complex systems, there is a phenomenon of correlation between the failure events of multiple components, and ignoring this correlation can lead to significant deviations of evaluation results. Some literatures refer to this type of dependent failure between multiple components such as common cause failure (CCF), or common mold failure. It is caused by a certain 'source' such as the occurrence of a special condition, featuring the simultaneous failure of two or even more components. Specifically, this 'source' can be both external or internal, including the occurrence of an extreme environmental condition, a sudden change of external load, an error in maintenance, or a defect hidden in the process of system design. It should be noted that when the CCF is caused by internal factors, in most cases there will be a failure propagation phenomenon in the system, increasing the probability of joint failure of multiple components with functional or topological correlations. As a common form of dependent failure, CCF can have a significant impact on the reliability assessment result of complex systems, thus has attracted much attention in the past decades. For instance, CMESs may exhibit hybrid failure modes including mechanical wear, software fault, and human-induced operational errors. Over-simplifying these multi-coupled failure modes can lead to underestimated risks.

(5) **Dynamic and interdependent failure behaviors**

In addition to the coupling between different failure modes, characteristics including phased missions, cascading effects, standby configurations, and competing failures transcends the conventional independent failure assumptions, imposing even more formidable challenges on the reliability analysis of complex systems. For systems with phased-mission and standby configurations, the change of system mission and structure introduce time-dependent failure behaviors of system. To be specific, phased mission systems introduce time-varying reliability requirements, where system functionality and critical components differ across operational phases, demanding dynamic probabilistic modeling to address phase-dependent stress conditions and cross-phase failure propagation. Standby techniques—including cold, warm, and hot standby redundancies—create nuanced failure dependencies, where dormant components exhibit distinct failure rates during idle periods and switching mechanisms introduce new failure modes such as imperfect detection or delayed activation. Meanwhile, cascading failures arise when localized component failures trigger disproportionate systemic collapse through network interdependencies, as observed in power grids and transportation infrastructure, necessitating graph-theoretic approaches and percolation theory to quantify propagation thresholds. Competing failures manifest when mutually exclusive failure processes (e.g. overstress versus wear-out mechanisms) interact, requiring coupled degradation modeling and stochastic process frameworks like competing risks theory.

2.2. Emerging challenges in reliability modeling

Complex system characteristics aforementioned have also introduced several challenges to reliability analysis, including scale barriers and computational complexity, data scarcity and uncertain quantification, data heterogeneity, scientific formulation of reliability metrics, physical interpretability, as well as cross-disciplinary integration and validation.

(1) **Scale barriers and computational complexity**

Reliability analysis of complex systems is confronted with scale barriers stemming from the exponential growth of computational demands with system dimensionality. Governed by the state space explosion principle, a system with n internal components can have 2^n states, and this number may be even higher if multi-state characteristics are taken into consideration. This combinatorial complexity renders exact solutions through conventional methods like Markov chain analysis or Monte Carlo simulation increasingly intractable, particularly for modern cyber-physical systems integrating hundreds and even more interacting elements. Furthermore, this challenge intensifies when addressing multi-failure modes and cross-scale interaction issues that require simultaneous resolution of multiple types of coupled equations. While emerging techniques like hierarchical abstraction and network decomposition demonstrate promise in reducing computational complexity, they may also introduce new tradeoffs between fidelity and computational tractability.

(2) **Data scarcity and uncertainty quantification**

Existing reliability models, especially data-driven methods, significantly depend on high-quality failure datasets, yet such data are often limited for ultra-reliable complex systems. In such scenarios, traditional data-driven approaches, which rely on large datasets for robust parameter estimation and model validation, often suffer from high uncertainty, overfitting, or poor generalizability. For complex systems, the inherent nonlinearity, high dimensionality, and interdependencies within complex systems further exacerbate these difficulties, as limited observations may fail to capture critical dynamics or rare events. Moreover, epistemic uncertainty and aleatory uncertainty widely exist in physics-based models [23, 24] and data-driven approaches, and these uncertain factors can even exponentially propagate in coupled complex systems. In recent years, small-sample scenarios have stimulated the advancement in Bayesian methods and physics-informed machine learning (PIML). While these methods demonstrate moderate effectiveness in handling data scarcity issues, they may also increase the epistemic uncertainty within the decision-making framework. As far as we are concerned, how to distinguish between the aleatory and epistemic uncertainties within reliability models and improve model accuracy as much as possible by considering uncertainty factors, still remains a persistent issue.

(3) **Data heterogeneity**

In recent years, some researchers have attempted to comprehensively utilize failure data, status monitoring data, laboratory testing data, and virtual data generated based on advanced virtual models such as digital twins to achieve the reliability modeling and evaluation of complex systems. Even in data from the same source, heterogeneity can also arise from multiple sensor types (e.g. vibration, thermal, pressure sensors, etc), temporal inconsistencies (e.g. asynchronous sampling rates or irregular maintenance intervals) and spatial variability (e.g. distributed subsystems operating under localized environmental stresses). In this multi-source and multi-dimensional data fusion process (as given in figure 4), data heterogeneity presents a dual challenge: while the volume of total data obviously increases, how to achieve effective data fusion by balancing information amount and confidence level, still needs further studies.

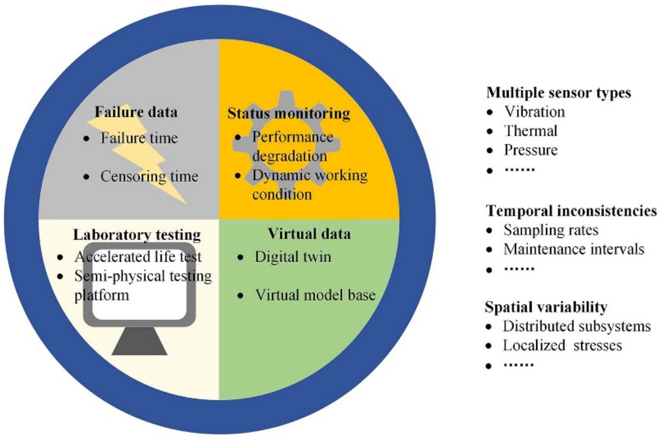

Figure 4. Data heterogeneity in complex systems.

(4) **Scientific formulation of reliability metrics**

The scientific formulation of reliability metrics for systems subject to interdependent failure mechanisms poses a fundamental challenge in reliability engineering and risk assessment. Unlike traditional reliability models that treat failure modes as independent events, real-world systems often exhibit complex interdependencies where the occurrence of one failure can trigger or amplify others through cascading effects, shared stressors, or functional coupling. This interdependence complicates probabilistic modeling, as conventional metrics (e.g. mean time between failures) may underestimate systemic risks due to unaccounted correlations. Rigorous quantification requires advanced methodologies, such as dynamic Bayesian networks (DBNs), copula theory, or stochastic Petri nets, to capture temporal, spatial, and logical dependencies among failure modes. Furthermore, the trade-off between model fidelity and computational tractability necessitates careful calibration, particularly when empirical data on joint failure distributions are sparse. Addressing this challenge is critical for high-consequence systems—such as power grids, aerospace structures, and networked infrastructure—where neglecting interdependencies may lead to catastrophic underestimation of failure probabilities. Future research directions include integrating physics-based degradation models with data-driven dependency analysis and developing scalable uncertainty propagation techniques for multi-failure scenarios.

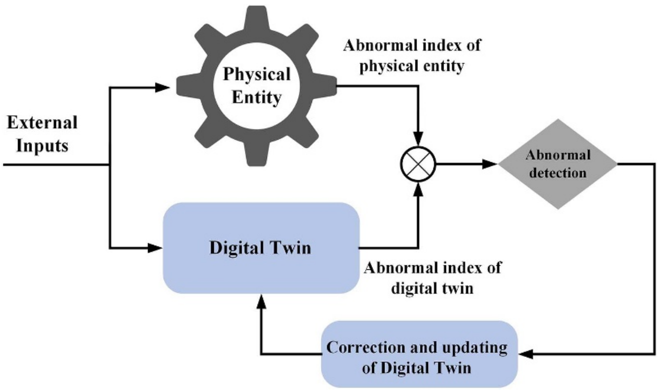

Figure 5. Scheme of physics-informed digital twin.

(5) **Physical interpretability**

A critical challenge in reliability modeling and analysis of complex systems lies in addressing the constraints of physical interpretability. While data-driven approaches (e.g. deep learning) demonstrate superior predictive performance, their 'black-box' nature can conflict with the requirement for clear failure mechanisms and causal interpretability. Practical engineering application may have stricter demand for validation against domain-specific physical laws (e.g. the propagation mechanism of crack). For example, a neural network-based method can have pretty high efficiency in reliability calculation and failure prediction, but its engineering application can be limited if it cannot attribute corresponding risk to specific material defects or stress effects. Conversely, physics-based models (e.g. finite element analysis) often preserve excellent interpretability but lack sufficient adaptability to heterogeneous data. As a result, it is still a tough task to balance the physical interpretability and flexibility of reliability assessment methods.

(6) **Cross-disciplinary integration and validation**

Modern complex systems usually integrate heterogeneous sub-systems, as a consequence its reliability assessment often demands cross-disciplinary expert knowledge and theoretical approaches. An integrated reliability model fully considers various limitations in practical application, features outstanding comprehensiveness and thus is more in line with practical application demands. However, in many cases the experimental validation of such integrated models is almost impossible due to limitations in feasibility, such as inducing cascading failures in large facilities, economic impracticalities, and safety-critical operational requirements particularly for high-cost systems (e.g. aircraft flight control systems) for which full-scale destructive testing is prohibitive. While emerging tools like physics-informed digital twins (of which the scheme is given in figure 5) and integrated cyber-physical simulation platforms offer potential solutions, their capability to characterize multi-domain coupling effects and early-stage behaviors under dynamic working conditions remains to be further quantified and validated.

3. Reliability modeling methods of CMESs

The key to the reliability assessment of complex systems is establishing a reasonable and effective model to characterize the evolution process of system performance. Based on the composition characteristics and key factors affecting its reliability, this part pays special attention to the CMESs, then provides an overview of corresponding reliability modeling and assessment approaches.

3.1. State-space-based reliability modeling methods of CMESs

CMESs can be regarded as a system of interconnected multiple mechanical and electronic components. Over the recent decades, CMESs have been widely adopted in engineering applications, e.g. high-speed railway systems [25, 26], and their reliability assessment has become a challenging and widely concerned problem [27–29]. As to the reliability modeling and assessment of CMES, early studies mainly focus on how to characterize the logical relationship between component failures and system failure. To this end, tools such as RBD [6], FTA [9] and Petri Net [30–32] were widely adopted, and the reliability of entire complex system was also evaluated from the perspective of functional properties.

Nevertheless, these physics-based reliability modeling methods usually neglected the topological relationship within system structure. Moreover, traditional network-based methods usually adopt single-layer assumptions, namely within the model only the physical connective relationships (such as mechanical connections) are taken into consideration. In fact, besides physical connections, information connections and power connections such as the control bus and power links also exist in CMESs, and as a consequence the reliability of entire system is inevitably affected by the reliability level of corresponding connections. To compensate for these deficiencies, numerous multi-layer network-based approaches were proposed. For instance, Liang *et al* [33] introduced an approach for the reliability and imprecision sensitivity analysis of CMESs by incorporating the Bayesian network, probability box, and pinching method. Feehally *et al* [34] developed a reduced-order mechanical drivetrain model to analyze the interactions within the network constructed from an aircraft electrical system. Jin *et al* [35] proposed a novel method integrating the fault tree technique with a Bayesian network to analyze the reliability of an electromechanical braking system. Xu *et al* [36] presented a physics-guided hierarchical network to identify the fault root cause within a CMES and performed a system reliability analysis utilizing a Wasserstein Generative Adversarial Networks and Long Short-Term Memory approach. Du *et al* [37] employed an FTA-based neural network approach to analyze the reliability allocation of remanufactured machine tools. Lin *et al* abstracted a CMES as a single-layer network by regarding components and their interactions as nodes and edges, which are then evaluated for reliability using an interval-valued intuitionistic hesitant fuzzy method [27]. In these methods, both functional and topological properties are incorporated to achieve comprehensive modeling and analysis of system reliability.

To cope with the complexity of CMESs induced by multiple system states, researchers have adopted a large variety of methods including structural function method, Markov process-based method, Monte Carlo simulation method and UGF method, etc. In recent years, due to its flexibility in modeling, the series–parallel and expansion methods have been widely applied to the reliability assessment of complex mechanical system [38–40], but it turns out to be computationally intensive and less efficient when dealing with large-scale systems with multiple failure modes [41]. Undeniably, structural function methods can conduct quantitative reliability assessment of multi-state systems, but when dealing with complex systems it can be very hard and time-consuming to obtain the minimum path set and minimum cut set. Due to relatively low efficiency, the application of structural function method to the reliability assessment of highly complex systems is rather limited, so the following part mainly introduces the other three methods.

(1) **Markov process-based method**

Markov process, established based on the Markov chain model first proposed in 1907, has been widely applied to degradation modeling and reliability analysis [42, 43]. It can be roughly divided into two types: those based on classical Markov state transition models and those based on semi-Markov state transition models. The former further segment the binary functional states with multiple granularities, establishing the transition of differential equations between different states to achieve multi state reliability modeling. The latter introduces kernel matrix functions, constructs embedded Markov chains without exponential distribution constraints by introducing kernel matrix functions, further improving the reliability evaluation accuracy of multi-state complex systems. As a commonly utilized flexible tool of degradation modeling, a large variety of Markov-based methods have been applied to the reliability analysis of complex systems, and the example of a discrete-time hidden Markov model (HMM) is given in figure 6. As given in figure 6, in a discrete-time HMM model, the system evolves through a finite set of discrete states $\{X_1, X_2, \cdots X_T\}$ over time, following the Markov property. However, the states themselves are not directly observable, instead reflected by the observation sequence $\{O_1, O_2, \cdots O_T\}$. When the system is in state X_i, there is a specific probability that the observation of system at this time step will be O_j. Li *et al* [44] proposed an improved based on wind turbines and established a reliability evaluation model for multiple health states. Su *et al* [45] presented a new reliability model for complex multistate systems with shared performance to evaluate the reliability of complex systems. On the basis of HMM and a graphical review technology network, Dong *et al* [46] proposed a new reliability evaluation method for multistate systems to describe the change in system health status. For instance, considering the fluctuation of degradation trajectory, Feng *et al* [47] used an improved HMM to capture the performance degradation process approximately and applied it to the reliability analysis of a computer numerical control (CNC) machine tool.

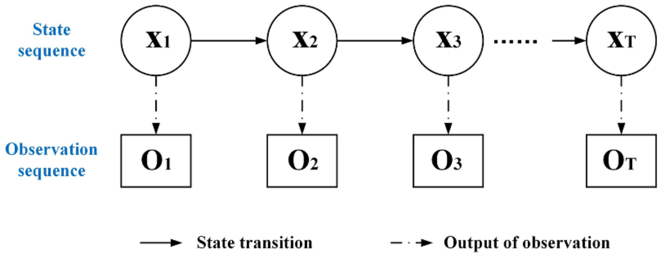

Figure 6. A discrete-time hidden Markov model.

Xiong *et al* [48] established an innovative multi-performance, multi-sequence HMM model to characterize the correlation of internal hidden states and several critical performance indices, achieving the reliability assessment of a CNC machine tool.

(2) **UGF-based method**

The UGF, which is first proposed by Gnedenko and Ushakov [49] and extended by Lisnianski and Levitin [50], serves as a bridge between discrete and continuous mathematics. The UFG method can clearly express the relationship between the state probability of components and the state probability of system, and obtain the system-level UGF from the component-level UFGs through simple calculations. As a commonly used tool for reliability analysis, UGF method reduces the complexity of reliability analysis by defining UGFs for separate components, and aggregating them through various aggregation operators in terms of the configuration coupling relationships [52]. In this way, it avoids the direct calculation of large-scale multi-state complex models, has fast calculation speed and thus effectively improves computational efficiency. In the past decades, UGF methods have been widely applied to the reliability analysis of a great variety of complex systems [53–55].

Considering the multiple subsystems and various failure modes existing in complex mechanical systems, Liu *et al* [38] proposed an adaptive decomposition-synchronous-coordination approach method to perform complex mechanical systems operational reliability assessment (CSORA), validating the superiority of proposed method in non-linear function approximation and applying it to the operational reliability assessment of aircraft braking system effectively. In their studies [56], CSORA is defined as the ability of a system to generate expected outputs during operation, taking into account the interdependence between systems, components, environment, organization, and human factors.

In recent decade, there have been numerous studies simultaneously taking physical and informatic relationships, topology connections and multi-state characteristics into consideration. For instance, Xia *et al* [51] characterized the CMES as a multi-layer and multi-state network, developed the multi-state models of internal minimum maintenance units, incorporated them with UGFs and built the system reliability model by incorporating cascading failure models. The reliability modeling process based on UGFs is given in figure 7. In this literature, three cases of high-speed train systems were used to verify the effectiveness of proposed method, and the researchers

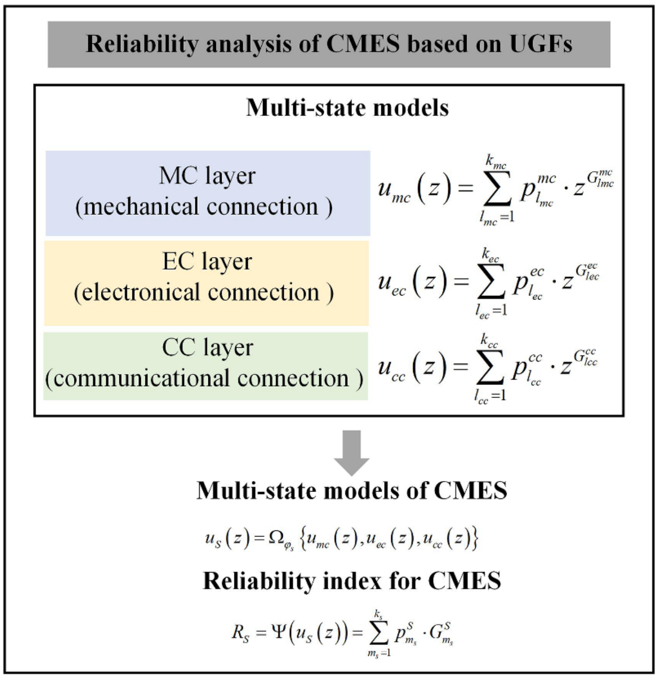

Figure 7. Reliability analysis process based on UGFs [51].

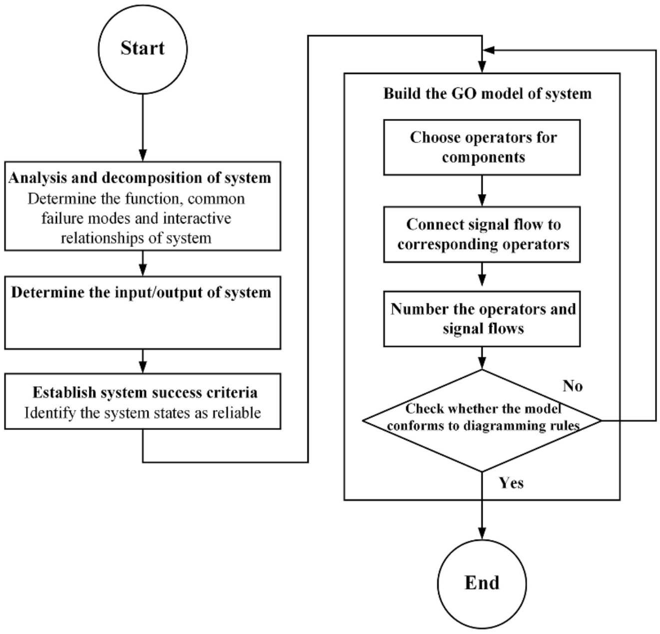

Figure 8. Modeling process based on GO-method.

believe the proposed framework can be further applied to other electromechanical systems.

3.2. Graph-based reliability modeling methods of CMESs

Apart from critical mechanical components, some complex electromechanical systems are composed of a large number of interconnected electronic devices and components, which are used for processing, transmitting and storing large amounts of information. These types of systems typically have a high degree of integration, which provides the possibility of rescheduling and fault tolerance through interaction and collaborative work. Taking the Avionics Full-Duplex Switched Ethernet (AFDX) of commercial aircraft as an example, a typical AFDX system consists of redundant buses, multi-flight management computers and integrated modular avionics.

It is obvious that AFDX is complex and intricate, including hardware, software and communication networks. For such systems, the connectivity of network also has significant influences on reliability, thus needs special consideration. On the one hand, in practical systems the frequent occurrence of time delays, interruption of communication lines, bit error and packet loss obviously increase the risk of systems. On the other hand, with the advancement of technology and expansion of application, the coverage and topological scale of communication network show an exponential growth trend, posing a series of 'curse of dimensionality' problems. Moreover, due to the vast number of nodes, in large-scale complex systems even an extremely low failure rate of single node can have a significant impact on the system connectivity. For such CMESs with more extensive hierarchical structures and severer communication problems, graph-based reliability modeling methods are commonly employed.

In the past few decades, researchers have utilized numerous graph-based approaches such as stochastic Petri net method, GO method, complex network theory, DBN method, etc. Given the limitations of traditional Petri net methods in characterizing the synchronization of various flows and batch behavior, a variety of improved models and algorithms have emerged in the past decades. For instance, Jyotish *et al* [57] proposed a batch deterministic and stochastic Petri nets algorithm to obtain the transition rate matrix of CTMC, establishing a three-phase evaluation framework for the reliability of safety-critical and control systems. In view of the generality and applicability of method, the following part mainly reviews the GO method, complex network theory method, and DBN-based method.

(1) **GO method**

In recent years, the GO method has been widely applied in the field of reliability. To achieve reliability modeling and evaluation, this method first converts the structural schematic of system into a GO graph model, then solves the model with GO-FLOW operations. The core tools of the GO method, the GO graph and GO-FLOW operation, endowed it with good flexibility and compatibility in the signal analysis of both software and hardware faults. A GO graph consists of operators and signal flows, and a basic GO graph model contains at most 17 types of operators, including function operators, logical operators, and auxiliary operators [20]. The modeling process based on GO method is given in figure 8. In order to compensate for the deficiencies of basic operators in handling redundant systems, closed-loop systems, multi-state systems and systems with CCF, researchers have established various new operators. For instance, for redundant systems, Yi *et al* established two operators to express the standby relationship [58], overcoming the limitations of unit property. Liu *et al* created three types of new operators and applied them comprehensively to the reliability modeling of three-state electronic units [59]. Considering that in basic GO models feedback loops are forbidden, Yi *et al* [60, 61] established a new operator to model the feedback loop in multiple-input closed-loop systems. For reparable systems with multiple failure modes, Yi *et al* derived the system-level reliability formula on the basis of Markov theory [62]. In terms of GO operation, apart from classical algorithms such as state-combination algorithms and probability formula algorithm, numerous special algorithms have been proposed to characterize the essential factors affecting the reliability analysis of complex systems. For example, to quantitatively solve the reliability of phased-mission systems with loop structure, Matsuoka [63] presented a GO-FLOW-based methodology and effectively applied it to the reliability analysis of boiling water reactor systems at startup stage. Ye *et al* [64, 65] combined GO method with Bayesian networks and established improved GO algorithms, further enhancing the capability of GO method for closed-loop system reliability modeling and analysis. Li *et al* [66] proposed a methodology combining cyclic Go model to corresponding cyclic Bayesian networks, showing good adaptation for complex closed-loop systems. In addition, some researchers have integrated GO method with other theoretical tools such as probability theory, grey theory and fuzzy theory, proposing a class of GO-FLOW methods and applying them to the reliability analysis of complex systems. For instance, Li *et al* [67] established a new GO-FLOW operator to simulate the load-sharing system with CCF, used an α-factor to characterize the relationship between the independent failure rate and CCF rate, then conducted reliability analysis by combining GO method and Markov process. In [68], Li *et al* combined GO method with GERT network, achieving effective reliability simulation of energy storage systems.

(2) **Complex network theory (CNT)-based method**

CNT, which was first proposed by Watts and Strogatz in 1998 [69], is a promising approach to fill these research gaps by characterizing the topological features. In the context of reliability engineering, CNT has been applied to evaluate the reliability of complex systems. For example, Beyza *et al* [70] analyzed the vulnerability of energy infrastructures, while Liu *et al* [71] evaluated and improved the topology of airline route networks. Lin *et al* [72] assessed the reliability of the chassis to carry the wheels of a high-speed train with CNT. Considering both node failure and edge failure scenarios, Zang and Fiondell [1] proposed a CNT-based reliability analysis approach for complex systems with dynamic structures, applied it to a train control system and identified the weak nodes and edges. In recent years, complex network models have also been applied to novel complex systems, such as unmanned aerial vehicle (UAV) swarms. For instance, for the vulnerability modeling and analysis of UAV swarm, Yang *et al* [73] took the communication-based and mission-based relationships into consideration comprehensively, proposing a two-layer multi-edge complex network model for UAV swarm.

(3) **DBN-based method**

The failure process of complex systems often exhibits dynamic characteristics in both failure time and failure sequence. In this case, traditional static Bayesian networks are unable to describe above dynamic characteristics and therefore cannot meet the demands of reliability analysis.

As one of the most effective tools for evaluating the dynamic influencing factors of systems, DBN has experienced rapid development after 2000 [74, 75] and widely utilized in the reliability analysis of dynamic complex systems. The existing DBN algorithms include discrete time Bayesian network (DTBN) and continuous time Bayesian network (CTBN). Among them, DTBN has been extensively studied and applied to the reliability analysis of dynamic networks with different failure distributions of components. By dividing the time into multiple non-overlapping intervals, DTBN obtain the marginal probability and conditional probability tables of each node approximately. However, it cannot be applied to non-time variables [17], and can be time-consuming when the number of nodes and time intervals increase sharply. In contrast, in CTBN the failure events follow a continuous distribution, and all the marginal probability and conditional probability are also presented in the form of functions. For some specific distributions, CTBN can obtain accurate reliability results by deriving the analytical probability functions directly, but for general probability density functions, the derivation of analytical solutions can be very complex and even impractical. On this condition, researchers have established various methods to approximate the conditional probability at each time instant. A class of generalized CTBN (GCTBN)-based methods is proposed, which models the failure process with both continuous-time temporal characteristics and static probability characteristics. For example, Li *et al* [76] proposed a GCTBN method with binary state marginal probability table and applied it to the reliability assessment of the communication network in the command-and-control systems.

3.3. Intelligent algorithm-based reliability modeling methods of CMESs

The past decade has witnessed the booming of massive intelligent algorithm-based methods in the reliability assessment of CMESs. Numerous artificial neural networks, machine learning, incremental learning and even transfer learning algorithms have been combined together or integrated with other prevailing reliability modeling tools, including but not limited to physical mechanism models, evidence theory, Bayesian theory, etc [77]. For instance, Surrogate modeling [78–80] emerges as a potential tool of reliability analysis. Early researches combined extreme theory with surrogate model, establishing extreme response surfaces for each failure model and proposing numerous response surface methods [81, 82]. Nevertheless, these methods are also faced with the problem of large computational burden and deficiencies in high

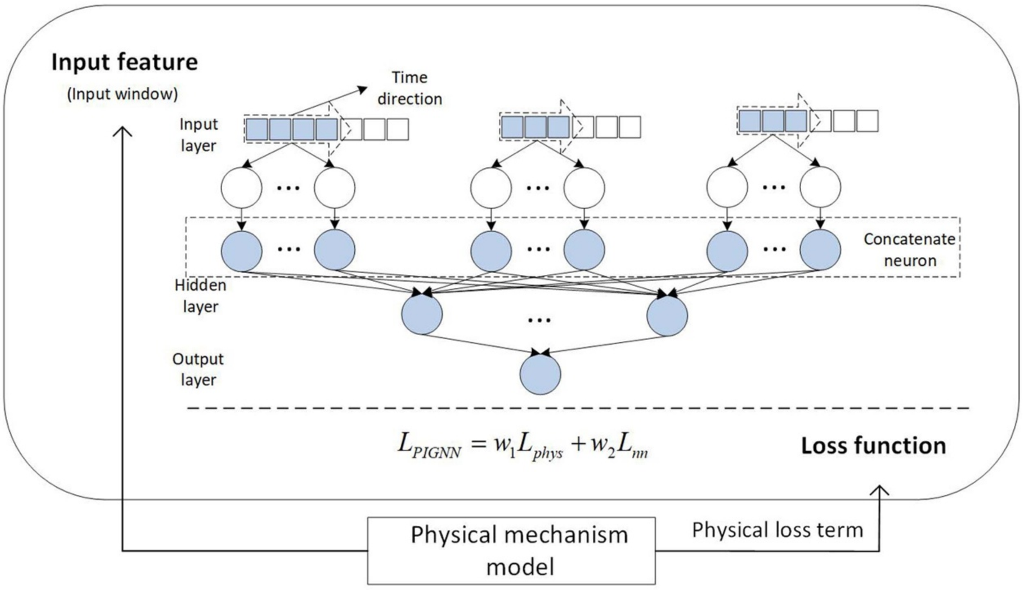

Figure 9. Principle of physics-informed neural network.

nonlinearity processing. Zhan and Xiao [83] proposed a novel active learning surrogate model for the reliability analysis of time- and space-dependent system, proposing a new stopping criterion to achieve the balance of accuracy and efficiency. The booming of surrogate model also promoted the development of new reliability concepts. For example, combining surrogate model, matrix theory, generate adversarial strategy and other mathematical tools, Teng *et al* [84, 85] proposed the concept of VGASM reliability evaluation for engineering structural systems, and established adaptive vectorial surrogate modeling framework for multi-objective reliability estimation. Apart from surrogate model-based approaches, Yeh *et al* [86] proposed a novel LSTM-BAT-MCS method to evaluate the time-dependent reliability of binary-state network, validating its effectiveness with three large-scale networks. Xu *et al* [87] integrated prior physical mechanism and machine learning models based on the Bayesian framework, presented a PIML method for complex system reliability analysis. Figure 9 gives an example of physics-informed neural network.

In many cases, intelligent algorithm-based methods have shown enhanced efficiency, high accuracy, outstanding capability in uncertainty handing and distinguished robustness. Nevertheless, compared with other reliability assessment approaches, some intelligent algorithm-based methods have inferior physical interpretability. How to enhance interpretability by effectively integrating physical information has become an important research interest in this field.

To sum up, the advantages and limitations of the above-mentioned reliability assessment methods are listed in table 1.

4. Future opportunities and directions

The reliability modeling and assessment of complex systems has emerged as a critical research frontier over recent decades, driven by its profound theoretical implications and practical significance across safety-critical industries. Despite substantial advancements, persistent methodological and computational obstacles continue to hinder the development of universally applicable frameworks. Many other possibilities also remain, and future research priorities can focus on addressing the following interconnected challenges as given in figure 10:

(1) **Integrated reliability modeling**
Modern complex systems inherently exhibit multidimensional interdependencies, including physical-informatic interactions, nonlinear topology couplings, multi-state operational dynamics, closed-loop structure (e.g. sensor-actuator feedback loops), redundancy configuration (similar or dissimilar redundancy), and multi-physics failure couplings (e.g. thermomechanical-electrochemical degradation couplings). Current analytical models often oversimplify these phenomena through decoupled assumptions or linear approximations, leading to fidelity gaps in failure mechanism characterization. A severe challenge still lies in formulating a unified mathematical framework that comprehensively integrates these attributes.

(2) **Computational efficiency in high-dimensional spaces**
The dimensionality curse existed in reliability computation problems-manifested through ultra-large component networks (e.g. hundreds and even thousands of interdependent units), multi-state transition process (both in the levels of component, subsystem and entire system), and heterogeneous big data streams (e.g. extra-large-scale condition monitoring datasets)—exponentially amplify computational complexity. Conventional methods like Monte Carlo simulation or fault tree analysis become computationally intractable under such conditions. Emerging solutions involve machine learning-enhanced algorithms which develop surrogate models via deep

Table 1. Advantages and limitations of several methods in complex system reliability analysis.

Assessment method	Advantages	Limitations
Reliability block diagram (RBD)	• Simple and intuitive • Efficient for static and simple systems with independent components • Fast computation	• Limited ability to model dynamic dependencies of components and common-cause failures • Huge computational burden when for complex systems
Fault tree analysis (FTA)	• Effective for identifying root causes of system failures • Support qualitative and quantitative analysis	• Combinatorial explosion for large systems • Requires precise failure probability of components
Markovian process method	• Powerful for modeling dynamic systems with state transitions • Flexible in characterizing repair actions and component-level interactions	• State-space explosion for large systems • Limitations for non-Markovian systems • Computationally intensive
Universal generating function (UGF) method	• Efficient in multi-state system analysis • Reduced computational complexity	• Limited to systems with discrete performance levels • Requires predetermined performance distribution • Less intuitive in capturing complex dependencies
GO method	• Suitable for systems with signal-flow diagrams • Flexible to analysis of time-sequence and dependencies	• Large computational burden for large systems • Requires detailed logical analysis
Complex network theory method	• Ideal for interdependent network structures • Identify critical nodes	• Focus more on structural vulnerabilities instead of probabilistic failures • Limitations for modeling dynamic actions • Requires high-quality topological analysis
Bayesian network (BN) method	• Flexible in processing uncertainty and casual dependencies • Supporting probabilistic inference for incomplete data • Updating reliability metrics by incorporating real-time evidence	• Requires proper prior distributions • Computationally intensive for large systems
Intelligent algorithm methods	• Effective for high-dimensional, nonlinear systems with vast data • Robust in handling noisy or incomplete data	• Black-box nature with limited interpretability • Requires extensive training

neural networks to approximate complex limit state functions while preserving physical constraints; dimensionality reduction techniques which leverage manifold learning to project the complicated failure modes onto low-dimensional latent spaces without losing critical failure signatures; and edge-cloud collaborative computing which implement distributed reliability evaluation architectures that partition computational loads across edge devices and cloud platforms. Nevertheless, key challenges still persist in balancing algorithmic accuracy with computational tractability, particularly when handling rare-event probabilities or time-variable reliability analysis. How to utilize advanced computing tools such as machine learning technology to process massive amounts of data and accelerate computation speed, is another important direction.

(3) **Engineering applicability and validation**
While numerous reliability methodologies have been theoretically validated in literature, the application of existing methods to real-world engineering practice still faces systemic barriers. First of all, some existing models lack modular architectures to adapt to adjustable system reconfigurations (e.g. plug-and-play components in modular factories) or evolving operational profiles. In addition, many over parameterized models are derived from ideal laboratory conditions, thus often fail to account for field uncertainties like sensor noise, maintenance variability, and human operational errors, which affected the implementation feasibility of corresponding methods to a large extent. Last but not least, for many ultra-reliable and extra-large-scale complex systems, experimental

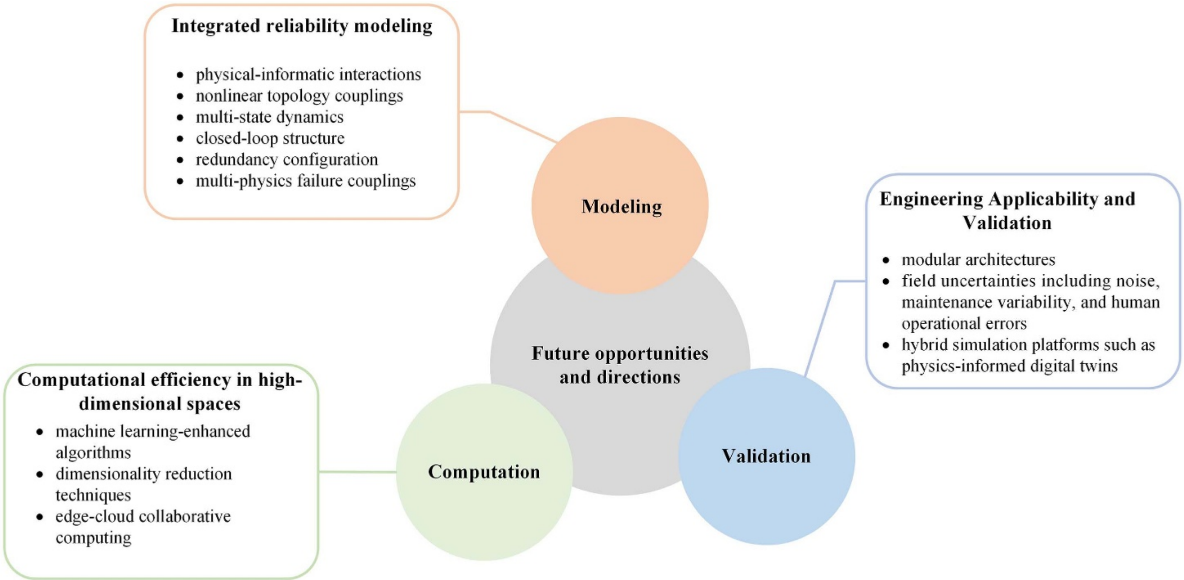

Figure 10. Future opportunities and directions in reliability assessment of complex systems.

verification remains economically prohibitive and even ethically constrained. To bridge this gap, efforts may be devoted to developing hybrid simulation platforms such as physics-informed digital twins, in order to conduct sufficient validation for reliability assessing approaches through strategically designed semi-physical experiments combining virtual and real facilities.

5. Conclusion

Inspired by the booming of studies on reliability modeling and assessment of complex systems, this paper provides an overview of corresponding challenges and difficulties, as well as numerous types of prevailing methods. To be specific, particular attention has been paid to two types of complex systems, CMESs and CEISs, since these two types of systems have a certain representativeness and the composition characteristics and critical factors affecting the reliability diverse to some extent. In the past decade, researchers have invested their efforts and proposed a series of innovative methods to better model the intricate functional, topological and informational interactions within complex systems, the complicated evolutionary process between multiple system states, as well as the possible coupling relationship between multiple failure modes. Regarding specific modeling and assessment approach, several types of prevailing methods are introduced briefly, including the Markov process-based methods, UGF-based methods, GO methods, complex network theory methods, DBN-based methods, as well as intelligent algorithm-based methods. In order to make full use of different types of information, improve computational efficiency while enhancing the physical interpretability, a growing number of existing methods no longer rely solely on a single tool, but often integrate multiple tools simultaneously. Nevertheless, we must admit that in order to further perform advances in the reliability modeling and assessment of complex systems, there are still a number of problems need to be considered in the following research, such as the exploration of comprehensive modeling framework, development of efficient computational methods utilizing advanced algorithms, filling the gap between theoretical research and practical application, and so on.

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