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Topical Review

Reliability of valves in nuclear power plant: a review of full life-cycle frameworks and evolution toward physics-data fusion

Zhuo-Cheng Sun, Tong An, Zhao-Le Qian, Fang-Na Xiang, Zhang-Yong Jin, An-Qi Guan, Zhi-Jiang Jin and Jin-Yuan Qian*

Institute of Advanced Equipment, Zhejiang University, Hangzhou, People's Republic of China

E-mail: qianjy@zju.edu.cn

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Abstract
Valves constitute the largest population of active components in the 'Defense in Depth' philosophy of nuclear power plants (NPPs), and their reliability is crucial for nuclear safety. Operational experience and numerous studies indicate that valves remain a critical weak link, yet existing academic reviews are often limited to a single failure mechanism or the operation & maintenance (O&M) phase. To address the lack of a systematic perspective centered on this critical component, this paper constructs a full life-cycle reliability framework, systematically reviewing the current status and progress of NPP valve reliability research from four interrelated pillars: (1) reliability-oriented design and optimization; (2) key failure modes and mechanism analysis; (3) reliability assessment and life prediction; (4) condition monitoring and intelligent O&M. Complementing prior reviews limited to specific phases, this paper utilizes the proposed full life-cycle framework to analyze the profound paradigm shift in NPP valve reliability research—transitioning from static, isolated, physics-dominated analysis toward dynamic, systematic, deep physics-data fusion. We identify four core contradictions hindering this evolution: the conflict between small samples and data-greedy methods, complex physics and simplified models, mechatronic systems and single components, and the black-box nature of models versus the need for explainability. To address these challenges, we provide a forward-looking perspective focused on deepening physics-data fusion, coupling

* Author to whom any correspondence should be addressed.

component-level remaining useful life with system-level probabilistic risk assessment, and exploring solutions for model trustworthiness and uncertainty quantification.

Keywords: nuclear power plant, valves, reliability, full life-cycle, physics-data fusion

Abbreviations

NPP	Nuclear power plant
LOCA	Loss-of-coolant accident
MOV	Motor-operated valve
AOV	Air-operated valve
PORV	Power-operated relief valve
SOV	Solenoid-operated valve
CFD	Computational fluid dynamics
FEA	Finite element analysis
PBM	Physics-based method
DDM	Data-driven method
PINN	Physics-informed neural network
FIV	Flow-induced vibration
FAC	Flow-accelerated corrosion
RUL	Remaining useful life
PRA	Probabilistic risk assessment
UQ	Uncertainty quantification
O&M	Operation and maintenance
CBM	Condition-based maintenance
PdM	Predictive maintenance
LTO	Long-term operation

1. Introduction

As a clean and efficient energy source, nuclear power represents a key pathway to achieving global carbon neutrality. However, its sustainable development hinges on the cornerstone of extreme safety. The safe operation of NPPs relies on the fundamental safety principle of 'Defense in Depth' [1]. This concept was explicitly articulated by the International Nuclear Safety Advisory Group (INSAG) in its seminal report, INSAG-10. Its core principle is to establish multiple, independent physical barriers and levels of protection. The goal is to ensure that radioactive materials remain contained, despite single or multiple equipment failures. Following this foundational philosophy, the International Atomic Energy Agency (IAEA) further provided a concrete assessment methodology in its Safety Reports Series No. 46 [2], used to evaluate the comprehensiveness of DiD in existing NPPs. This method systematically verifies whether the five levels of protection effectively ensure that the fundamental safety functions (FSFs)—namely, controlling reactivity, removing heat, and confining radioactive material—can be achieved under all plant conditions. The interrelationship between these physical barriers and the five levels of protection is illustrated in figure 1, while the flow-chart logic for applying this strategy is shown in figure 2.

Valves constitute the largest population of active components used to implement this Defense in Depth philosophy. They are the final control elements that execute the FSFs. Different valves are positioned at key points across the physical barriers to control reactivity (FSF1), remove heat (FSF2), and maintain confinement (FSF3). Figure 3 provides a simplified schematic of a typical nuclear power system, highlighting the locations of these key valves. Table 1 offers a detailed breakdown, linking these valves (e.g. PORVs, SIS valves, MSIVs) directly to the specific DiD levels and FSFs they support.

To engineer and validate this safety philosophy, the nuclear industry must rely on a systematic and rigorous reliability analysis methodology. Standards such as ANSI/IEEE Std 352–1987 [4] provide the foundational principles for reliability analysis of safety systems, including tools like failure mode and effects analysis (FMEA) and fault tree analysis (FTA). For physical implementation, the American Society of Mechanical Engineers (ASME) codes serve as a global benchmark. ASME BPVC Section III [5] provides the 'code of law' for component construction, ASME B16.34 [6] establishes the standard for valve pressure-temperature ratings, materials, and dimensions, while ASME QME-1 [7] specifies qualification standards for active mechanical equipment and the ASME OM Code [8] dictates in-service testing requirements.

This regulatory baseline serves as a global benchmark, resonated in international standards such as France's RCC-M code [9] and China's system, which includes NNSA regulations (e.g. HAF 102 [10], HAF 003 [11]) and NEA technical specifications (e.g. the NB/T 20 010 series [12]). Together, these standards establish the comprehensive baseline for life-cycle reliability. Standards for NPP valves in various countries are shown in table 2.

While these standards provide the baseline, engineering practice and decades of operational experience (OpEx) have revealed significant challenges. Authoritative reports from the U.S. Nuclear Regulatory Commission (NRC), often stemming from generic safety issues, provide compelling evidence that valves (such as PORVs [13], check valves [14], and MOVs [15]) are a critical and persistent weak link in plant reliability.

These reports, through in-depth data analysis (as shown in table 3 and figure 4), identified key failure modes such as internal leakage, control degradation, and Common-Cause Failures (CCFs). Crucially, this deep understanding of failure data has driven a successful analysis-feedback-improvement loop within the industry. Indeed, a recent NRC-commissioned study INL/RPT-23-73956 [16] revealed that while the demand frequency for certain valves has shown a statistically significant increase over the last decade, their failure probability has demonstrated a statistically significant decrease (see figure 5). This achievement—decreasing failure rates despite increasing demands—powerfully demonstrates the success of systematically learning from OpEx.

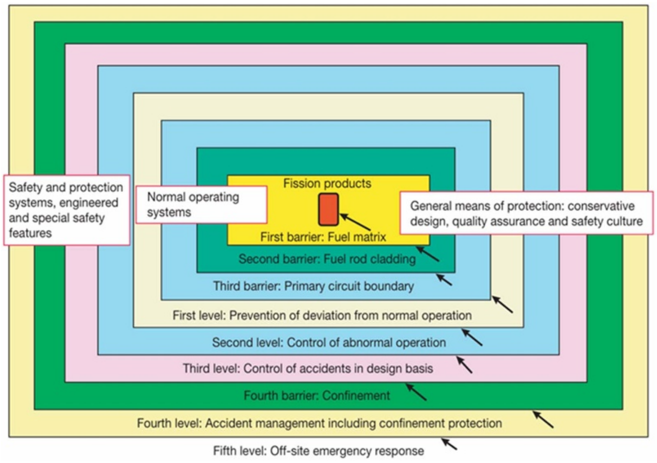

Figure 1. Interrelationship between physical barriers and levels of protection in Defense in Depth [3].

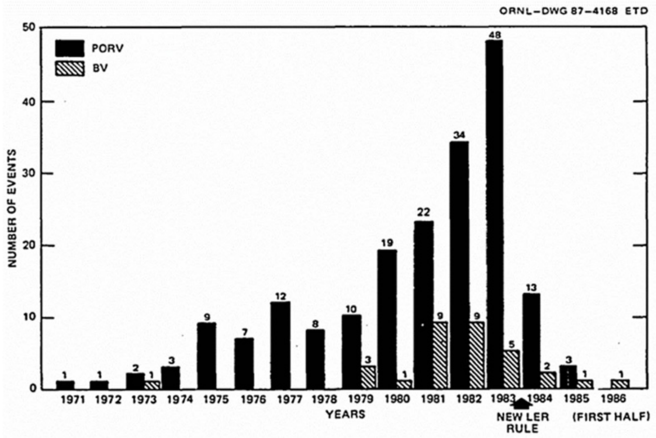

Figure 3. Reported PORV failure events 1971–1986 [13]. *Note*: PORV: power-operated relief valve; BV: block valve.

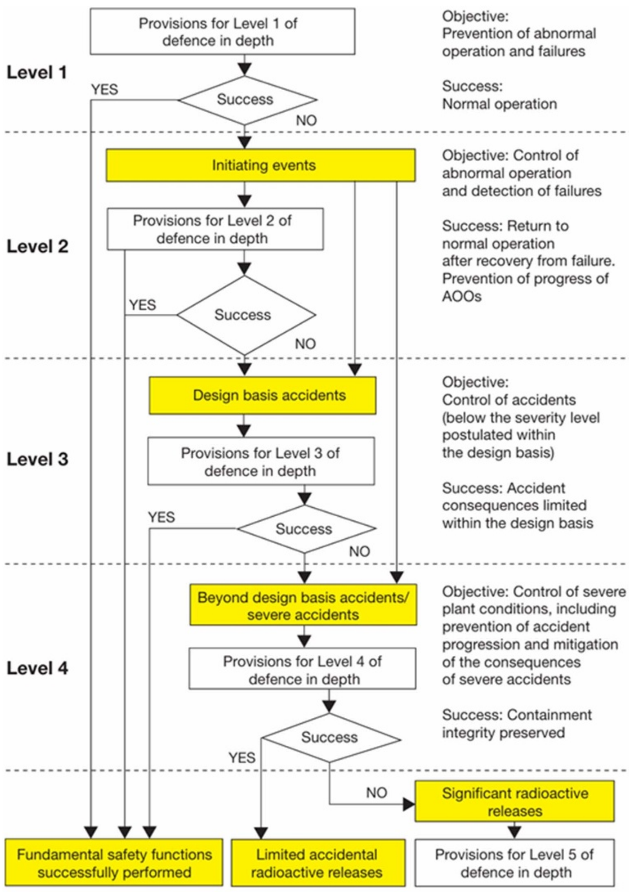

Figure 2. Flow chart for defense in depth [2].

Valves

PORV: power-operated relief valve; MSSV: main steam safety valve; MSRV: main steam relief valve; PSV: spring-loaded safety valve; VDA: Vapeur D'échappement à l'Atmosphère; SDV: steam dump valve; MSIV: main steam isolation valve; MOV: motor-operated valve; GV: gate valve; CV: check valve

Systems/components

PRT: pressurizer relief tank; CVCS: chemical and volume control system; ACC: accumulator; SIS: safety injection system; AFW: auxiliary feedwater system

In recent years, scholars have also reviewed valve reliability from various perspectives, but these reviews are often focused on a single aspect of the life cycle. Regarding failure mechanisms, Gao *et al* [19] conducted a comprehensive review of cavitation erosion in NPP pumps and valves, focusing on the transient dynamics and material properties related to this single physical failure mode. Regarding assessment methods, Rezaeianjouybari and Shang [20] reviewed the broad application of deep learning (DL) in prognostics and health management (PHM). Their work detailed how DL models can solve the RUL prediction and fault diagnosis challenges for critical mechanical components, such as valves. This provides a theoretical framework for the DDMs discussed in Chapter 4 of this review. Building on this, Ayodeji *et al* [21] provided a critical review of DL applications in nuclear safety assessment, addressing the key challenges of model reliability and the black-box problem by focusing on the need for explainability. Regarding O&M and diagnostics, Zhang *et al* [22] offered a comprehensive review of valve health diagnosis and assessment, focusing on fault diagnosis, condition monitoring, and RUL prediction techniques for intelligent maintenance—topics closely related to Chapters 4 and 5 of this paper.

While these reviews [19–22] have laid a solid foundation by detailing specific mechanisms or algorithms, a critical challenge remains in methodological integration. Specifically, current research lacks established pathways to translate deterministic physical behaviors (e.g. microscopic damage accumulation) into the probabilistic parameters required for system-level risk assessment (e.g. dynamic failure rates). This rigorous separation limits the extent to which theoretical failure mechanisms can inform practical reliability engineering. Therefore, distinct from previous studies, this review

Table 1. Role of critical nuclear power plant valves in defense-in-depth (DiD) and fundamental safety functions (FSF).

Typical valve	Circuit	Physical barrier	Key level of defense (DiD)	Associated specific function
Pressurizer PORV/PSV	Circuit 1 (RCS)	3rd physical Barrier	Level 2 (control of abnormal operation) Level 3 (control of DBA) level 4 (severe accident mitigation)	FSF(2): provides heat removal via 'Feed and Bleed' operation FSF(3): maintains pressure boundary integrity by preventing overpressure
Safety injection system (SIS) Valves (MOV/Check Valve)	Circuit 1 (RCS)	3rd physical barrier	Level 3 (executes safety injection during LOCA)	FSF(2): injects emergency cooling water into the core during a LOCA FSF(3): provides isolation to maintain pressure boundary during normal operation
Chemical & volume control (CVCS) valves (control/isolation valve)	Circuit 1 (RCS)	3rd physical barrier	Level 1 (controls boron concentration and inventory)	FSF(1): controls reactor power by adjusting boric acid concentration (boration) FSF(3): maintains pressure boundary integrity (isolation function)
Accumulator (ACC) squib valve/isolation valve	Circuit 1 (RCS)	3rd physical barrier	Level 3 (control of design basis accidents—LOCA)	FSF(1): assists in reactivity control via borated water injection. FSF(2): rapidly injects large volumes of borated water into the core during Large Break LOCA (passive safety)
Atmospheric steam dump valves(VDA/SDV)	Circuit 2 (main steam)	Secondary Circuit boundary	Level 2/3 (controlled cooldown during loss of offsite power.)	FSF(2): provides decay heat removal by discharging steam to the atmosphere when the main condenser is unavailable (Loss of ultimate heat sink). FSF(3): prevents secondary overpressure to maintain SG tube integrity.
Main steam safety valve (MSSV/MSRV)	Circuit 2 (main steam)	Secondary circuit boundary	Level 3: overpressure protection during transients.	FSF(2): acts as a passive backup for heat removal if VDA fails. FSF(3): maintains pressure boundary integrity by preventing secondary side overpressure.
Main steam isolation valve (MSIV)	Circuit 2 (main steam)	Secondary circuit boundary	Level 3 (isolates main steam line break or SGTR accidents)	FSF(2): prevents reactor overcooling by isolating steam flow during a steam line break FSF(3): isolates containment and prevents radioactive release during a steam generator tube rupture (SGTR)
Auxiliary feedwater (AFW) valves (MOV/control valve)	Circuit 2 (feedwater)	Not a barrier, but acts to protect the barriers	Level 2/3 (primary means of heat removal during transients)	FSF(2): provides decay heat removal by supplying emergency water to steam generators when main feedwater is lost
Essential service water (ESW) valves (butterfly/check valve)	Circuit 3 (cooling water)	Not a barrier, but ensures the ultimate heat sink	Level 3 (provides cooling to safety-grade equipment)	FSF(2): provides cooling to essential safety equipment (e.g. safety pumps, diesel generators), ensuring the ultimate heat sink

Table 2. Standards for nuclear power plant valves in various countries.

Country/region	Key organization/institution	Standard designation	Standard full name
USA	American National Standards Institute (ANSI)/Institute of Electrical and Electronics Engineers (IEEE)	ANSI/IEEE Std 352–1987	IEEE Standard Guide for General Principles of Reliability Analysis of Power Generating Station Safety Systems
	American Society of Mechanical Engineers (ASME)	ASME BPVC Section III	ASME Boiler and Pressure Vessel Code, Section III: Rules for Construction of Nuclear Facility Components
		ASME B16.34	Valves—flanged, threaded, and welding end
		ASME QME-1	Qualification of active mechanical equipment used in nuclear power plants
		ASME OM Code	Code for operation and maintenance of nuclear power plants
Europe	International Organization for Standardization (ISO)	EN ISO 19 443 [17]	Quality management systems—specific requirements for the application of ISO 9001:2015 by organizations in the supply chain of the nuclear energy sector supplying products and services important to nuclear safe[1]ty (ITNS)
France	Afcen	RCC-M	Règles de Conception et de Construction des Matériels Mécaniques des Îlots Nucléaires PWR
Germany	KTA	KTA 1401 [18]	General requirements for quality assurance
China	National Nuclear Safety Administration (NNSA)	HAF 102	Safety regulations for design of nuclear power plants
		HAF 003	Safety regulations for quality assurance of nuclear power plants
	National Energy Administration (NEA)	NB/T 20 010.1-2010	General specifications for design and manufacture of valves for conventional island and auxiliary facilities of nuclear power plant

Table 3. Failure modes for PORV mechanical/controls/BVs [13]. Bold values indicate the subtotals for each respective failure category.

Failure parts	Failure modes	Totals
PORV mechanical	Leakage—internal	62
	Leakage—external	3
	Fail to open	12
	Fail to close	7
	Other	17
	Subtotal	**101**
PORV controls	Fail to open	6
	Fail to close	2
	Spurious opening	11
	Control degraded	52
	Other	20
	Subtotal	**91**
BVs	Leakage—external	12
	Fail to open	2
	Fail to close	12
	Spurious opening	3
	Other	3
	Subtotal	**32**

Note: PORV: Power-operated relief valve; BV: block valve.

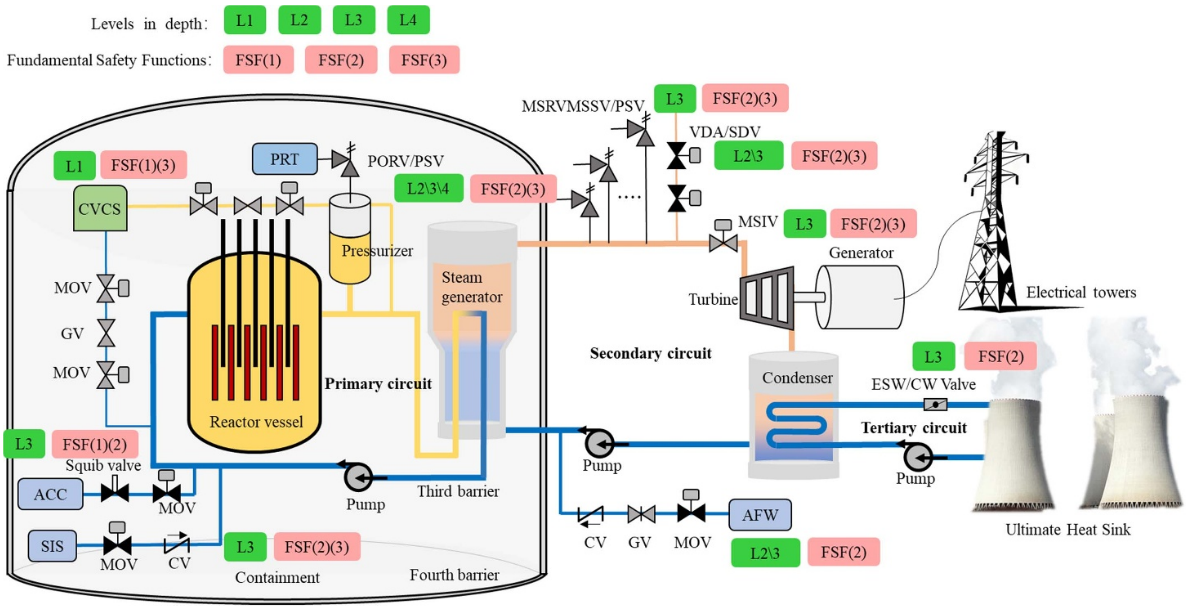

Figure 4. Nuclear system and typical valves in nuclear loops.

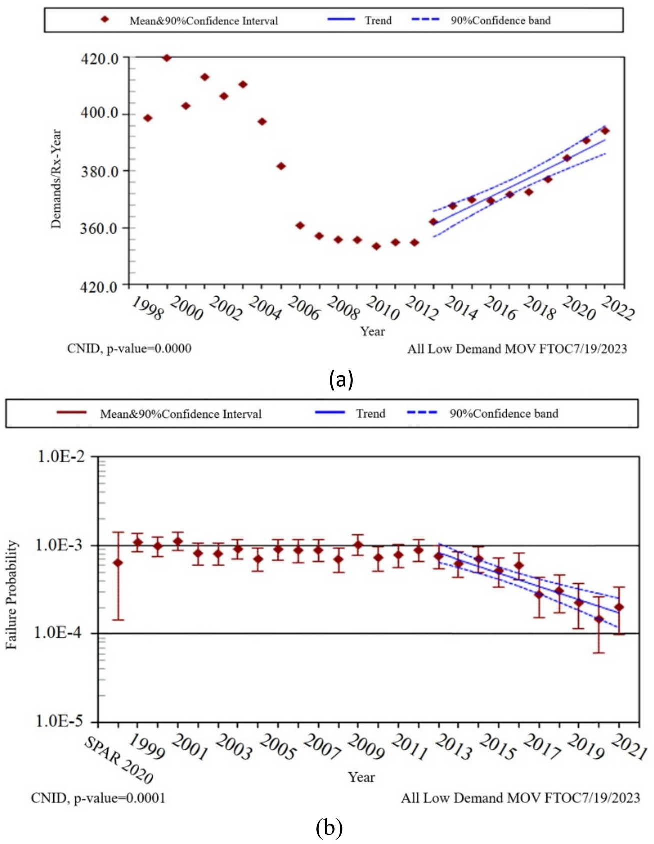

Figure 5. (a) Failure probability estimate trend for low-demand MOV FTOC, (b) frequency of FTOC demands for low-demands MOVs [16].

addresses this limitation by constructing a full life-cycle integrated framework.

This review posits that a complete reliability research loop should consist of four pillars: (1) reliability-oriented design, to mitigate failure at the source and achieve proactive reliability; (2) failure mechanism analysis, to understand failure laws and provide a physical basis for reactive correction and proactive prevention; (3) reliability assessment and life prediction, to quantify the health status and failure probability of valves during operation; and (4) condition monitoring and intelligent O&M, to transition from reactive maintenance to PdM and ensure procedural reliability.

As emphasized by the core logic of this review, valve reliability is not an isolated design metric but rather a dynamic attribute that spans its entire life cycle—from design and manufacturing to operation and decommissioning. These research phases are interdependent, yet their effective integration requires robust interface methodologies to connect the deterministic and probabilistic domains. Consequently, this paper aims to address this methodological fragmentation by systematically reviewing key technologies across the four stages. Special attention is given to how emerging tools like physics-data fusion and UQ can serve as the connection between these stages. By doing so, we strive to foster a more integrated understanding of NPP valve reliability research. Finally, the paper provides an outlook on future trends.

2. Reliability-oriented design and optimization

Valve design is the first step in determining equipment reliability. In the demanding field of nuclear power, valves must not only operate stably under normal conditions but also ensure functionality under extreme conditions, placing high demands on design and analysis methods. This chapter reviews the key technological evolutions in reliability-oriented valve design and optimization. This chapter will revisit traditional simulation methods represented by FEA and CFD, which are the cornerstones for understanding valve flow, dynamics, and structural characteristics. Subsequently, the discussion extends to the in-depth application of these methods in specific, complex nuclear power conditions. However, the high computational cost of traditional simulation methods renders them inadequate for multi-parameter, multi-objective global optimization. Therefore, this chapter will focus on sorting the cutting-edge methods that have emerged to overcome this challenge. These methods represent a technological shift from simulation-driven validation to data-driven optimization. The chapter will detail high-efficiency analysis and design methods, including surrogate models, more robust ensemble models, and the latest PINNs.

2.1. Structural parameter analysis and design validation

A valve's key structural parameters (e.g. plug shape, spring stiffness) fundamentally determine its flow, dynamic, and structural characteristics, making them the origin of reliability design. Traditionally, researchers have relied on FEA for design validation and parameter analysis. However, with the growing demand for efficient, multi-objective optimization, design methods are transitioning from a reliance on high-cost simulation to the adoption of high-efficiency, data-driven models.

Overall, FEA methods, particularly CFD, are the mainstream approach for valve design and analysis today. Scholars utilize simulation technology to assess the impact of key parameters on valve performance during the design phase, primarily focusing on two core performance areas:

First is the assessment of structural parameters on flow performance and flow-induced noise. This is the most extensive area of research. Scholars use CFD to deeply investigate the influence of plug shape, opening, or flow path structure on the internal flow field, flow characteristics, and noise sources. For instance, the studies by Qian, *et al* [23], and Bairagi *et al* [24] focus on the macroscopic impact of key parameters on the flow coefficient. In contrast, Sun *et al* [25], Asim *et al* [26], and Jin *et al* [27] delve deeper into the flow field details, turbulent kinetic energy, and cavitation characteristics within multi-stage or cage valves, aiming to provide a basis for noise reduction and anti-erosion optimization. As illustrated in figure 6, these CFD analyses visualize the intricate flow details. For instance, the pressure contours within a multi-stage trim clearly show the step-by-step pressure drop across each row and pinpoint the critical low-pressure zones prone to cavitation. Building on this, Wang *et al* [28] went a step further, designing an innovative valve plug to actively suppress fluid oscillations, thereby solving abnormal actuator shutdowns.

Second is the analysis of dynamic characteristics. Compared to conventional control valves, the reliability of rapid-opening/closing devices like safety valves is more dependent on their transient response. Therefore, scholars (e.g. Ye *et al* [29]) have focused on analyzing the impact of key parameters, such as spring stiffness and adjustment ring, on the opening/closing dynamics of safety valves. Zang *et al* [30] utilized dynamic mesh techniques to extend the analysis to the full fluid-structure-motion process of pilot valves,

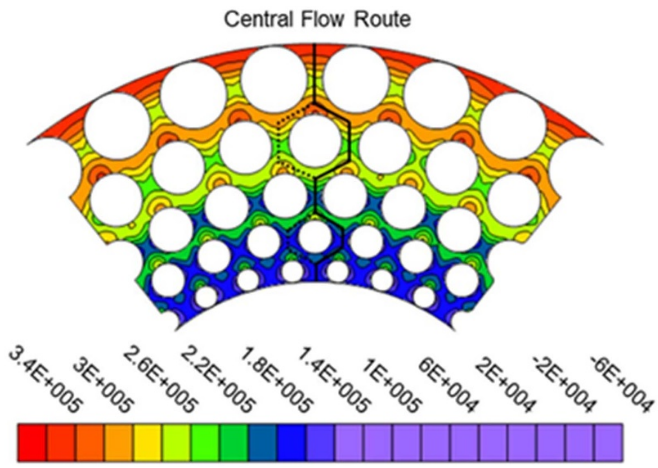

Figure 6. Static gauge pressure (Pa) variations within the top disk of the trim at 100% valve [26].

assessing the influence of inlet diameter on their response speed.

Whether for regular operating conditions or preliminary explorations of special conditions—such as Tiberga *et al* [31]'s work on freezer valves for molten salt fast reactors—the aforementioned studies fully demonstrate the immense value of FEA in replacing high-cost experiments and guiding design validation.

However, the limitations of this traditional simulation-driven validation paradigm are also evident: when faced with complex, multi-parameter, multi-objective optimization problems, the high computational cost required by FEA (especially CFD and transient analysis) becomes a significant bottleneck. Traditional simulation is more often used for design validation or single-parameter scans rather than efficient global design optimization, which underscores the development of data-driven, high-efficiency optimization methods.

2.2. Response analysis under complex operating condition

Beyond parameter optimization in the design phase, another critical application of FEA methods is to assess valve responses under complex or extreme (e.g. accident) conditions and to explore potential failure mechanisms. This is a prerequisite for the reliability and safety assessment of NPP valves.

2.2.1. Complex flow regimes. Valves in actual operation often face complex flow states such as multi-phase flow, choked flow, or internal leakage. Elucidating the flow phenomena and physical mechanisms under these extreme states is a prerequisite for reliability assessment.

Against this backdrop, scholars first dedicated efforts to reproducing and revealing complex fluid phenomena. For example, Yang *et al* [32], by simulating a triple-eccentric butterfly valve, successfully revealed the spatial correlation between vortices and choked flow.

Building on the mastery of complex flow mechanisms, a more critical step is to evaluate the fluid's reaction force on the valve structure. Yang *et al* [33] employed the fluid-structure interaction method to deeply investigate the dynamic response of a control valve under high pressure differentials. The study clearly identified vortex shedding in the throttling zone as the direct cause of structural vibration and successfully pinpointed stability risks at specific openings.

This line of research is focused not on designing valves, but on understanding their physical behavior under specific conditions like choking or leakage. It not only validates the capability of simulation models in predicting complex phenomena but also provides a physical foundation for the failure mechanism analysis discussed in Chapter 3, as well as for the fault diagnostics and operational control strategies in Chapter 5.

2.2.2. Coupled-field analysis. Nuclear power operating conditions (especially startup/shutdown or accidents) are typified by high temperatures, high pressures, and severe thermal transients, posing a stringent test for a valve's structural integrity. In analyzing such extreme conditions, ensuring the quality of the basic FEM itself is crucial. Analysis of a single physical field is insufficient to simulate these conditions, necessitating a shift toward thermal–fluid–solid multi-field coupled analysis, which is a key tool for NPP valve reliability assessment.

Scholars (e.g. Zhang *et al* [34], and Li *et al* [35]) have addressed this challenge through coupled-field simulations of relief valves or feedwater valves. They reached an important conclusion for NPP valve reliability assessment. First, thermal stress is the main component of coupled stress. Second, thermal load—rather than pressure load—is often the primary cause of stress overload accidents. This critical finding is compellingly visualized in figure 7. The analysis of the feedwater valve shows that the stress under mechanical load alone (labeled 'No thermal loads') is minimal. However, during thermal transients, the stress intensity spikes dramatically (e.g. to 514 MPa at 50 s) due to the severe temperature gradient across the valve body wall, before slowly decreasing as the temperature gradient dissipates.

This conclusion clearly redefines the focus of NPP valve reliability analysis: safety assessments must compare the coupled stress against the allowable stress intensity. A simple static pressure analysis, such as that used for conventional industrial valves, is far from sufficient for NPP valves.

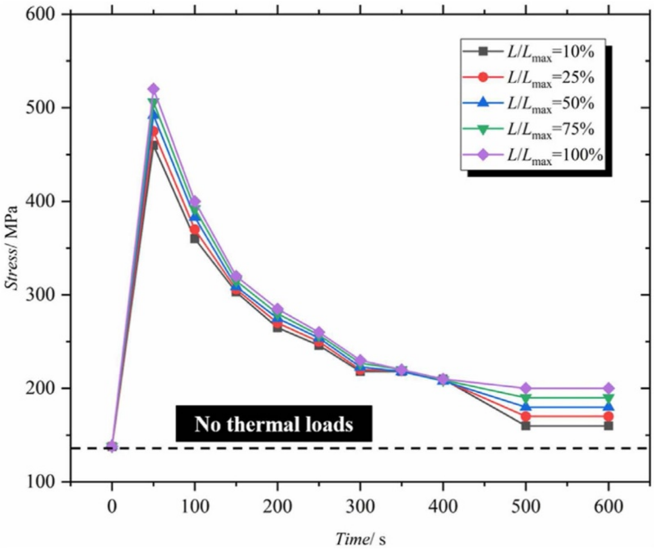

Figure 7. The maximum stress intensity changes of the valve body with time under different openings [35].

2.3. High-efficiency optimization methods based on surrogate models

To overcome the optimization bottleneck of high computational costs in traditional methods (as discussed in 2.1), data-driven approaches represented by surrogate models are gaining widespread application and research. The core idea of a surrogate model is to build an extremely low-cost mathematical model (e.g. Kriging, polynomial chaos expansion (PCE), support vector regression) by learning from a small number of high-fidelity FEA results. This model approximates and replaces the high-cost FEA model, which is crucial for global optimization, reliability analysis, or UQ that requires thousands of iterations.

This high-efficiency optimization concept has been widely validated and applied in valve design. For instance:

In wear prediction, Yan *et al* [36] used a Kriging surrogate model to successfully replace costly CFD-DPM simulations, achieving rapid prediction of erosion rates on sealing surfaces.

In acoustic optimization, Xie *et al* [37] employed a Kriging model to analyze the transient flow-field noise of spring-loaded relief valves, predicting noise directivity based on key structural parameters.

In structural and sealing design, Zong *et al* [38] used a PCE model to optimize the sealing performance of a nuclear relief valve, increasing its sealing stress by 24.42%.

However, the selection of a single surrogate model is challenging, and its robustness can be limited. The study by Wang *et al* [39] revealed this issue: when optimizing a butterfly valve, Kriging was found to have severely insufficient accuracy for the flow resistance coefficient, necessitating a switch to RSM. To solve this, a clear trend is the development of Ensemble Surrogates. The work by Zong *et al* [40] is a typical example; they used an advanced ensemble model-ensemble of adaptive hybrid functions (E-AHF) to optimize the flame-extinguishing capability of an explosion-proof safety valve and to improve the discharge capacity and dynamic stability of a main steam safety valve. Advanced ensemble methods like E-AHF (Song *et al* [41]) fuse the advantages of multiple single models through adaptive weighting, achieving more robust and accurate predictions.

Building on this core ensemble concept, the field's modeling strategy is advancing in two other directions:

Multi-fidelity modeling has emerged as one direction in the pursuit of higher computational efficiency. This approach

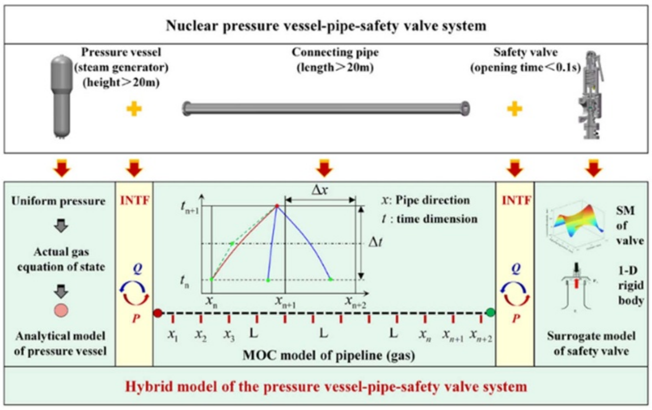

Figure 8. Overall scheme of the multi-fidelity model [42].

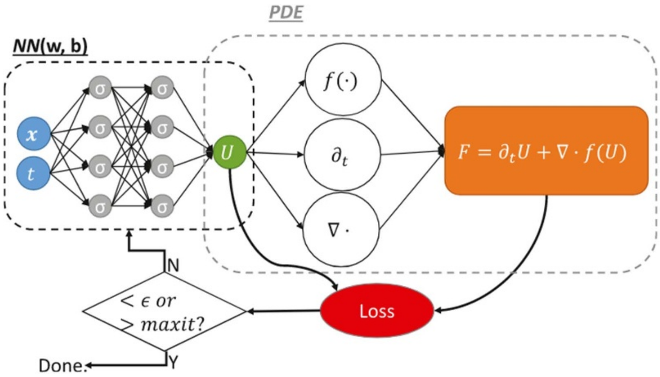

Figure 9. Schematic of PINN for the Euler equations [44].

no longer relies on a single high-cost FEA/CFD but instead integrates models of different fidelities (e.g. coarse 3D mesh, 2D simplified model, 1D method of characteristics (MOC)). Song *et al* [42], in modeling a pressurizer-vessel-pipe-safety-valve (PVPSV) system, combined analytical methods, the MOC, and surrogate models, significantly boosting system-level simulation efficiency while maintaining accuracy. The architecture of such a multi-fidelity hybrid model is shown in figure 8. To model the entire PVPSV system, the approach integrates different modeling techniques based on their suitability: a simple analytical model for the pressure vessel, the efficient MOC method for the long connecting pipe, and a data-driven Surrogate model for the geometrically complex safety valve.

Physics-data deep fusion constitutes the second, more prominent direction, aimed at resolving the consistency gap between simulation models and physical reality.

Under this strategy, one path is model updating, which uses physical measurement data to correct the virtual simulation model. For example, Xue *et al* [43] used measured seismic response data to successfully update an initial FEM, enabling it to more accurately identify structural parameters. This approach bridges the gap between physical testing and virtual simulation.

A more cutting-edge fusion path is the PINN. A PINN is essentially a surrogate model, but its novelty lies in embedding physical laws (like PDEs) directly into the neural network's loss function. This forces the model to adhere to physical laws during training, offering a potential solution to the challenge of training with small datasets. Although direct applications of PINNs to valves are still rare, their success in related fields like nuclear engineering piping (Wang *et al* [44]), incompressible two-phase flow (Buhendwa *et al* [45]) and high-speed flow (Mao *et al* [46]) demonstrates application prospects for application in the complex coupled-field analysis of NPP valves. To illustrate the fundamental architecture of PINNs, figure 9. (From Mao *et al* [46]) presents a typical schematic for solving high-speed flows governed by Euler equations. The framework consists of two interconnected pathways sharing the same hyper-parameters: an uninformed neural network that approximates the state variables U (e.g. density, velocity, pressure) from spatiotemporal inputs (x,t), and a physics-informed pathway that utilizes automatic differentiation to compute the partial derivatives required by the governing equations-PDEs. Crucially, the core logic lies in the construction of the composite loss function, which explicitly aggregates both the data mismatch loss and the physical residual loss. By minimizing this total loss, the network is forced to satisfy the physical conservation laws during the training process, thereby ensuring physical consistency even with sparse training data.

2.4. Summary

This chapter reviewed reliability-oriented design and analysis methods for NPP valves. While classic FEA methods remain a mainstream choice, their limitations in the face of demands for high-efficiency optimization and extreme-condition safety are increasingly apparent, catalyzing a series of more advanced analysis methods and design philosophies. The research clearly reveals several trends:

On the design optimization level, a shift from high-cost simulation-driven validation to data-driven high-efficiency optimization, represented by surrogate models.

On the condition response level, a focus shift from conventional flow analysis to multi-field coupled assessment under extreme conditions, identifying thermal stress as a key factor in structural failure.

On the modeling philosophy level, a trend beyond single components toward piping system multi-fidelity modeling, and an exploration of physics-data deep fusion.

In summary, Chapter 2 explored how to prevent failure through forward design. However, even with perfect design, valves inevitably degrade in harsh service environments. Therefore, it is essential to deeply understand their failure modes and mechanisms, which is the core content of Chapter 3.

3. Key failure modes and mechanism analysis

While Chapter 2 explored forward design methods for preventing failure, the reliability of valves—as critical dynamic components in high-temperature, high-pressure, high-radiation, and corrosive media—depends not just on initial design but also on their degradation processes throughout the life cycle. Therefore, this chapter adopts a reverse analysis perspective to systematically review the key failure modes and physical mechanisms that nuclear valves face during actual operation.

A deep understanding of these failure mechanisms—particularly fatigue, creep, corrosion, wear, and stiction, which are closely related to aging management—can directly guide reverse design optimization and developing scientific in-service inspection and maintenance strategies. This chapter will focus on three dimensions: pressure boundary integrity, flow path degradation, and functional failure.

3.1. Pressure boundary integrity: fatigue, creep, and fracture mechanisms

As pressure-bearing components in piping systems, the most severe failure mode for valves is the loss of structural integrity—the cracking or even rupture of the pressure boundary (e.g. body, bonnet, stem). In nuclear conditions, this failure is rarely caused by a single load but is rather a coupled-damage result of mechanical vibration, thermal transients, high-temperature environments, and corrosive media.

Research into NPP valve structural failure mechanisms is well-developed, with reviews and case studies collectively revealing that structural failure is not from a single load but a coupled result of drivers + accelerators + origins.

First, FIV and thermal cycles/transients are identified as the two core drivers.

In terms of dynamic loads, authoritative reviews (e.D, Yang *et al* [47]) have formed a conclusion that FIV is the primary driver of fatigue failure, with Haile *et al* [48] further adding that two-phase flow (steam-water mix) drastically worsens FIV. This conclusion is fully corroborated by specific case studies: Zeng *et al* [49]'s research reproduced the fretting-fatigue (a mechanism noted by Cai *et al* [50]) caused by FIV and successfully predicted the crack initiation sites. Tamura *et al* [51]'s study showed how FIV can induce flow-acoustic resonance, leading to high-cycle fatigue. Beyond internal FIV, external dynamic loads like earthquakes are also key drivers. Related studies (e.g. Chen *et al* [52], Dai *et al* [53], Meng *et al* [54]) have used FEA and shake-table tests to systematically verify the structural integrity and functional reliability of valves (especially safety valve springs) under seismic loads.

In terms of thermal loads, thermal transients during startup/shutdown and drastic temperature changes during accidents (e.g. cold safety injection) are another key driver. Benyamina *et al* [55] used large eddy simulation (LES) to reveal the intense temperature fluctuations caused by cold/hot fluid mixing at T-junctions, considered a direct cause of thermal fatigue cracks. A notorious industry example confirming this mechanism is the Farley Unit 2 incident (1987). In this event, unisolable leaks through the check valves caused severe thermal stratification and cycling in the safety injection piping. The interaction between the cold injection water and the hot reactor coolant led to a 120° circumferential fatigue

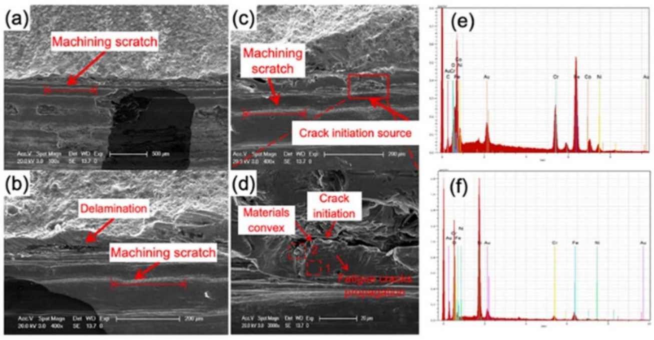

Figure 10. (a) and (b) SEM micro-morphology of the fracture surface, (c) crack initiation source and fatigue crack propagation, (d) the magnified view of figure (c), (e) EDS analysis at test point 1 in the crack initiation zone, (f) EDS analysis at test point 2 in the crack initiation zone [61].

crack, directly validating the lethality of the thermal striping mechanism described above. At high temperatures (>450 °C), as reviews by Zhao *et al* [56] and Gong *et al* [57] emphasize, creep–fatigue interaction replaces simple fatigue as the *dominant* failure mode for components like main steam valves or Gen-IV reactor valves. Gong *et al* [57] further noted that notches (geometric discontinuities) are the origins for creep damage, making them a focus of high-temperature integrity assessments. Zhao *et al* [58]'s FEA analysis also confirmed that the creep effects in relief valves during severe accident thermal shock *must* be included in assessments.

Second, corrosive environments and manufacturing defects act as key accelerators and origins.

Larrosa *et al* [59]'s review highlighted the corrosion-fatigue mechanism in light-water reactor environments, where corrosion significantly *accelerates* crack initiation and propagation.

If corrosion provides acceleration, manufacturing defects provide the origin. The failure analysis cases by Cheng *et al* [60], and Lu *et al* [61] offer strong proof: inclusions, pores, and other defects are often the starting points for fatigue cracks. As shown in the micrograph in figure 10, the visual evidence clearly reveals a fatigue crack originating directly from a sub-surface non-metallic inclusion, which acts as the origin or stress-riser for the coupled failure. To mitigate these material-based challenges, especially for Gen-IV high-temperature creep strength, scholars have focused on microstructural control in advanced materials (e.g. ODS steels), as detailed in reviews by Chen *et al* [62] and Zinkle *et al*.

The aforementioned research paints a clear picture: failure results from the interplay of 'FIV/thermal cycles (drivers) + complex environments (accelerators) + manufacturing defects (origins)'. This body of research collectively shows that NPP valve aging management must shift from single-fatigue analysis to a comprehensive damage tolerance assessment, one that accounts for the interaction of FIV, corrosion and creep, while fully considering the impacts of stress concentrations (notches) and manufacturing defects.

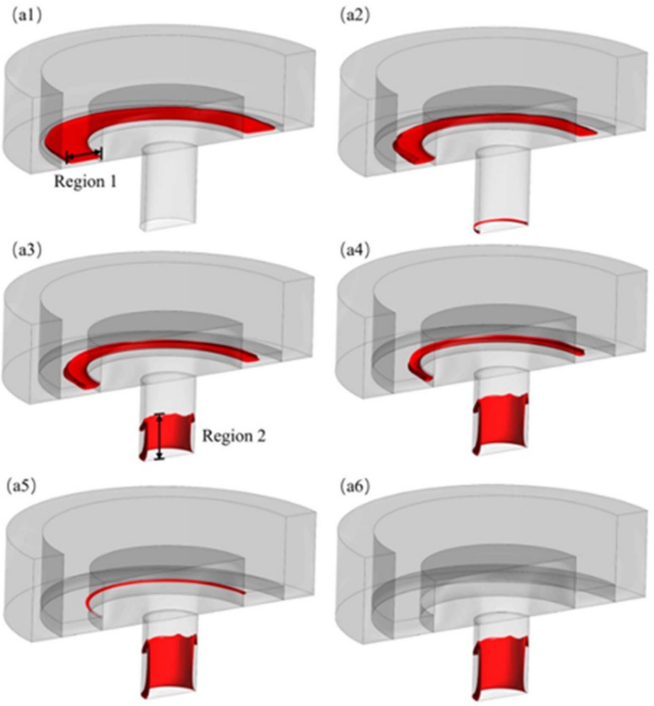

Figure 11. The vapor phase contour distribution at different valve openings: (a1) 0.6 mm, (a2) 0.8 mm, (a3) 0.9 mm, (a4) 1.0 mm, (a5) 1.2 mm, (a6) 1.5 mm [69].

3.2. Flow path degradation: cavitation, erosion, and corrosion

While structural failures (section 3.1) are often fatal, flow-induced wear is the most prevalent and primary progressive aging mechanism in valves. Authoritative reviews (e.g. Bhowmik and Sabharwall [64], Gao *et al* [19], Wang *et al* [65]) have reached a conclusion that cavitation, flashing, particle erosion, and corrosion are the key failure modes leading to performance degradation. The physical basis of these phenomena (such as the bubble dynamics described by Arndt [66]) dictates their direct destructive impact. The stripping of material from surfaces like the valve plug and seat, caused by phase changes or particle impact, leads to internal leakage, flow characteristic deviation, and vibration, severely threatening system safety.

Facing this severe engineering problem, research has shifted from qualitative failure description to quantitative prediction and precise localization. The value of this paradigm shift is three-fold:

First, precise localization of damage hotspots. Typified by the research of Liu *et al* [67], Liu *et al* [68], and Li *et al* [69] (i.e. the CFD applications mentioned in Chapter 2), scholars have used CFD coupled with cavitation models, validated by experiments, to accurately pinpoint damage zones, such as the leading and trailing edges of a butterfly valve disc. Figure 11 illustrates this precise localization. The CFD simulation successfully reproduces the complex physical process of the cavitation zone migrating from the gap (Region 1) to the nozzle (Region 2) as the valve opening increases.

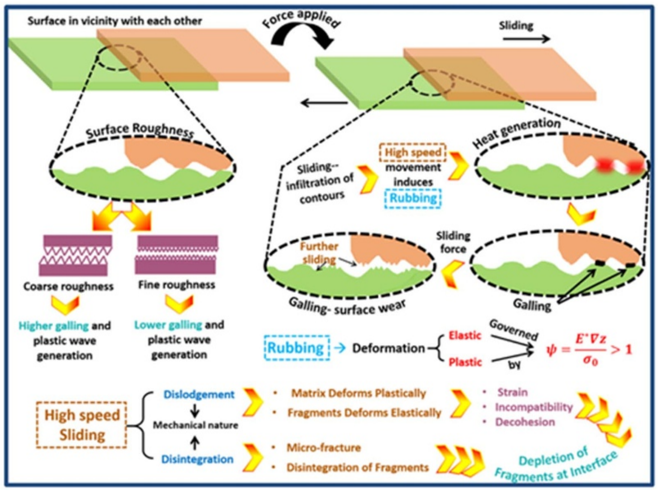

Figure 12. Comprehensive understanding of the various galling mechanism [76].

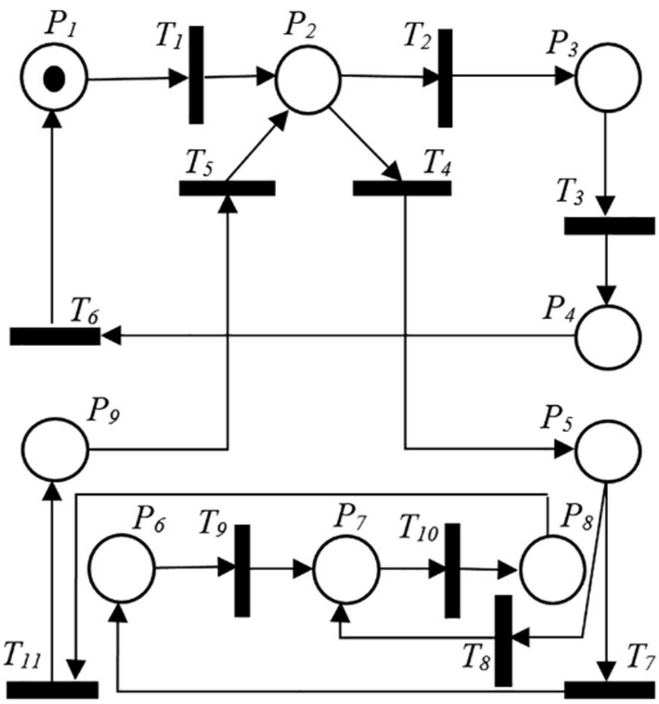

Figure 13. PN model for DFWCS system [92].

Second, quantitative attribution of key parameters. Building on these localization studies, research has converged to confirm that valve *opening* (throttling degree) and *pressure differential* are the two key operational parameters governing the damage rate. For example, Liu *et al* [68] and Zhao *et al* [70] used visualization experiments and numerical simulations, respectively, to quantitatively reveal the dominant effect of inlet pressure and opening angle on cavitation and erosion area.

Finally, extension of mechanism boundaries. This quantitative paradigm has even revealed wear mechanisms beyond traditional cognition. Sedghkerdar *et al* [71], using particle image velocimetry experiments, cleverly demonstrated that wear is not limited to cavitation and particle erosion; the high turbulent kinetic energy region downstream of a gate valve was highly correlated with FAC damage. This indicates that high turbulence itself is a destructive load that accelerates wear via mass transfer.

In summary, cavitation and erosion research is the most mature application of CFD in failure analysis. Its ultimate goal, however, is not just analysis but to feed-back to the forward design discussed in Chapter 2. It is precisely through this deep understanding of mechanisms and damage localization that scholars (e.g. Wang *et al* [72]) have been able to propose fundamental anti-wear structures, such as multi-stage throttle cages, to dissipate pressure drops and eliminate bubbles, thereby proactively enhancing valve reliability from the design stage.

3.3. Functional failure: leakage, stiction, and seizure

Functional failure refers to when the valve's pressure boundary is intact, but it fails to perform its required open, close, or throttling function. In a NPP, this failure poses a threat to system security, as it can lead to system over-pressurization or loss of key safety functions.

In-depth analysis of such failures indicates that their root cause often traces back to a core physical contradiction, precisely identified in Sotoodeh [73]'s authoritative review: the conflict between Sealing and Actuation in stem packing design.

On one hand, to prevent leakage, the packing must be highly compressed. This sharply increased static friction is the physical root of 'stiction'—the most common fault in control valves (as reviewed by Bacci Di Capaci and Scali [74]). Regarding its evolution, Wu *et al* [75] revealed that high-temperature stiction is driven by a competition between asperity creep, micro-welding, and oxide formation. Under high temperature and pressure, this friction can deteriorate into catastrophic seizure (a complete loss of movement). A historic lesson on this mechanism is the Three Mile Island Unit 2 (TMI-2) accident. In this event, the power-operated relief valve (PORV) failed to reseat after a pressure transient—essentially experiencing a 'stuck-open' seizure induced by mechanical binding. This functional failure, compounded by misleading control room indications (which showed the solenoid status rather than the actual stem position), escalated a minor transient into a severe LOCA. The primary physical mechanism driving this failure mode is galling (a 'cold-welding' mechanism reviewed by Kakulite & Kandasubramanian [76]), where micro-scale material transfer occurs between the stem/packing or plug/guide, causing the components to seize. The physical mechanism of various galling mechanisms are depicted in the schematic in figure 12. Also, Li *et al* [77] adds that unbalanced hydraulic forces can also exacerbate seizing risk.

On the other hand, the consequence of failures on the leakage side of this conflict is systemic and cascading. Multiple studies (e.g. Du *et al* [78], Kim *et al* [79], & Chen *et al* [80]) have confirmed that internal valve leakage, particularly when prolonged or exceeding critical thresholds, serve as a key root cause of severe secondary disasters in piping systems, such as water hammer and thermal stratification (which in turn causes the thermal fatigue discussed in 3.1). Because the consequences are so severe, research into leakage mechanisms and diagnostics is critical. For example, Qian and Hu [81]'s deep simulation (LES) of leakage acoustics provides a solid mechanistic basis for the acoustic leak detection techniques discussed in Chapter 5.

In conclusion, functional failure is not an isolated issue but a direct consequence of the mechanisms described in 3.1 (corrosion) and 3.2 (wear). The sealing-friction contradiction (Sotoodeh [73]) highlights the core challenge of valve reliability. The actuator (AOV/MOV) must always provide sufficient margin to overcome the dynamic increase in friction. This friction increase can be caused by aging, operating conditions, or improper maintenance (e.g. foreign object intrusion, as noted by Ezekoye *et al* [82]. This clearly indicates that aging management of the actuators themselves (AOV/MOV diagnostic testing) must be a top priority for functional reliability.

3.4. Summary

This chapter systematically reviewed the physical roots of valve failures:

(1) Pressure boundary integrity: Structural failure is rarely caused by a single load but emerges as a coupled result of drivers and mechanisms, often accelerated by environmental factors.
(2) Flow path degradation: Internal surface damage is dominated by fluid-dynamic mechanisms such as cavitation and particle erosion. Research in this domain has successfully transitioned from qualitative description to quantitative damage localization to guide anti-wear design.
(3) Functional failure: The inherent sealing-actuation design conflict creates significant tribological challenges. Specifically, stiction behaves as a dynamic evolution driven by time-dependent mechanisms, which can eventually escalate into galling and catastrophic seizure.

This research has shifted from post-mortem analysis to quantitative reproduction using CFD/FEM, laying the mechanistic groundwork for the diagnostics in Chapter 5. However, all mechanisms described—fatigue, creep, wear—are inherently stochastic and time-dependent. A qualitative description is insufficient for aging management; probabilistic methods must be introduced to quantify the failure probability. This is precisely the core topic of Chapter 4.

4. Reliability assessment and life prediction methods

The failure mechanisms analyzed in Chapter 3—ranging from thermal fatigue to tribological stiction—provide the deterministic physical basis for understanding valve degradation. However, in actual NPP operation, these physical processes are inherently stochastic due to variabilities in material properties, manufacturing tolerances, and fluctuating loads.

Consequently, reliability research must transition from qualitatively analyzing the 'physics of failure' to quantitatively evaluating the 'probability of failure'. A core engineering and safety question arises: how to *quantitatively assess* the reliability status (e.g. failure rate, failure probability) and scientifically predict the RUL of these valves?

Answering this question is key to transitioning from traditional time-based maintenance (TBM) to CBM and PdM. It is vital for ensuring NPP safety, optimizing spare parts, reducing O&M costs, and supporting decisions on operational lifetime extension.

To address this, the research community has followed two classic but diverging paths:

(1) PBMs, which offer unparalleled interpretability.
(2) DDMs, which excel at mining non-linear patterns.

However, this divergence also exposes their fundamental limitations: PBMs (4.1) are often overly complex and parameter-sensitive, while DDMs (4.2) face black-box and data-dependency challenges. To bridge the gap between physical interpretability and data-driven efficiency, a necessary research frontier—hybrid methods (4.3) represented by surrogate models and PINNs—is emerging.

Therefore, this chapter will follow this evolutionary path to review the methodologies for valve reliability assessment and life prediction.

4.1. Physics-based assessment methods (PBM)

PBMs rely on a deep understanding of failure mechanisms or system logic to build mathematical models. They offer the strongest physical interpretability and can be divided into component-level and system-level approaches.

4.1.1. Component-level: physical-of-failure analysis and UQ. These models aim to translate the specific physical degradation processes (Chapter 3) into mathematical expressions to predict component RUL.

In this path, scholars first apply classic physical laws. Taking the crack propagation from 3.1 as an example, Xu *et al* [83]'s work is a typical case, using the Paris Law as the state function, combined with particle filtering, to effectively predict the RUL of an *electric gate valve*. Similarly, Lee *et al* [84] proposed a probabilistic method for the leakage mechanism (3.3) to derive the probability density function of damage parameters for *reciprocating pump valves*.

However, a more severe challenge than model-building itself is quantifying and handling the inevitable uncertainty in these models like material properties and initial crack length. Baraldi *et al* [85]'s research directly targets this core problem. When assessing the fatigue degradation of a check valve, the study explicitly noted that ignoring cognitive uncertainty in model parameters leads to completely erroneous maintenance decisions. This probabilistic risk perspective is also reflected in the degradation assessment framework built by Lewandowski *et al* [86].

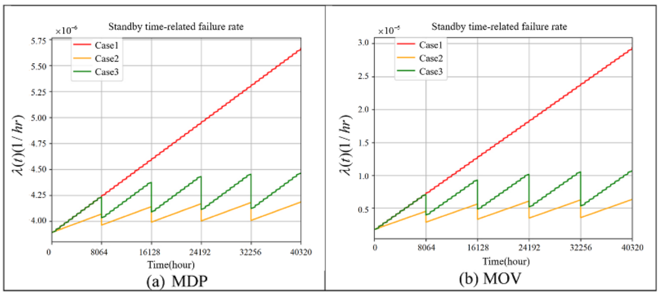

Figure 14. Standby time-related failure rate of components (a) MDP, (b) MOV [94].

In summary, the core advantage of PBMs is their physical interpretability. But, as demonstrated by the research (especially Baraldi), their fundamental weakness is equally evident: they are extremely complex and their results are highly sensitive to physical parameters that are difficult to acquire, posing significant challenges for practical application.

4.1.2. System-level: from static logic to dynamic risk assessment. These models scale up from the component (4.1.1) to the system level, establishing logical models to assess overall risk or identify critical components.

The foundational methodology of this field is classic FTA and FMEA, which remain indispensable for identifying system risks. For example, Chisholm *et al* [87] used FTA to quantify risks for a molten salt reactor freezer valve, identifying accidental unfreeze as a far higher risk than failure to unfreeze on demand. The studies by Subekti & Sunaryo [88] and Zubair [89] similarly used FTA to successfully pinpoint failure of main isolation valve to open as a key basic event.

However, classic tools are not perfect. On one hand, scholars (e.g. Zhu *et al* [90]) work to improve limitations in traditional FMEA (like information fusion). On the other hand, a more fundamental limitation is that FTA/Markov models struggle with complex dynamic, concurrent, and synchronous behaviors. This represents a critical gap, as high-level perspectives (Zio [91]) emphasize that ensuring enhanced safety in complex systems requires moving beyond static analysis toward dynamic risk assessment. To meet this challenge, more powerful formal tools like Petri nets (PNs) have emerged. The work by Kumar *et al* [92, 93] clearly demonstrates the superiority of PNs in analyzing complex dynamic systems like shutdown systems and digital feedwater control systems (including main steam safety valves). The formal structure of such a PN model is shown in figure 14. Unlike a static fault tree, the PN architecture uses places (e.g. P5: MSSV fails to open) and transitions (e.g. T7: Planned maintenance triggers) to explicitly model the complex, dynamic, and concurrent event sequences that characterize these safety systems.

But whether using FTA or PNs, the final accuracy depends on the failure rates of the underlying components like valves. Therefore, the most critical and cutting-edge evolution in this field has shifted toward providing PRA with more realistic, dynamic inputs. For key components like MOVs, the research by Parsaei *et al* [94] and Martorell *et al* [95] abandons the

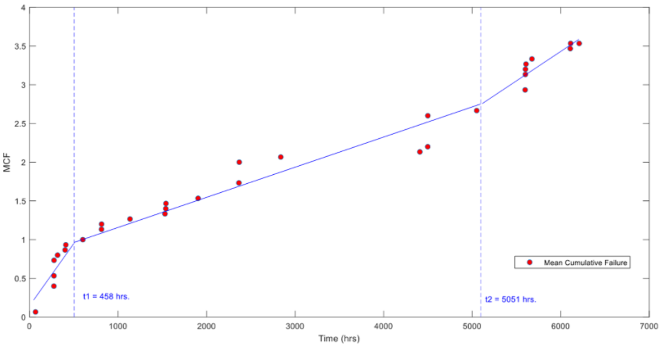

Figure 15. Representation of cumulative mean function plot [99].

outdated constant failure rate assumption, developing sophisticated unavailability models that dynamically reflect aging, surveillance test degradation, and imperfect maintenance. As visualized in figure 15, this refined approach starkly contrasts with the outdated constant failure rate assumption. The model (e.g. Case 3) shows the failure rate dynamically increasing with component age and periodically decreasing due to imperfect maintenance activities, providing a far more realistic input for PRA.

In summary, system-level formal modeling is the bedrock of risk assessment. But, as highlighted by Parsaei and Martorell, the accuracy of physical models is ultimately highly dependent on the failure rate data of basic events. Where does the data come from?—This is both the final obstacle of PBMs (4.1) and the core starting point for DDMs (4.2).

4.2. Data-driven assessment methods (DDM)

When physical models are difficult to build or parameters are unknown, DDMs become the core approach, focusing on extracting information from data. As noted in the introduction, this path is divided into two major categories based on the data type.

4.2.1. Statistical modeling and parameter estimation (sparse/event data). This first path focuses on the most typical data characteristic in nuclear power: sparse failure data (small data), alongside abundant event data (tests, maintenance).

This feature determines the core mission of this path: not real-time RUL prediction, but providing credible, dynamically updated reliability parameters (e.g. failure rates) for the system-level models (FTA/PRA) discussed in 4.1.2.

However, sparse data poses a severe statistical challenge. To address the small-sample problem, research inevitably turns to Bayesian inference. The Bayesian method is naturally adept at fusing prior information (e.g. generic data) with sparse, plant-specific data. For example, Maskin *et al* [96] applied Bayesian updating to improve PSA posterior data; He *et al* [97] used it to aggregate small-sample data for assessing long-dormant rupture valves; and Prakash and Pandey [98] used in-service data to update the life distribution of *pneumatic control valves*, providing justification for extending overhaul intervals.

Building on this, the research frontier is moving from static to dynamic parameter estimation to reflect the real-world impacts of aging and environment. For instance, Martón *et al* [99] proposed a three-step methodology utilizing segmented regression on Nelson–Aalen estimates to identify aging turning points in the failure rate of components like safety valves, while Wu *et al* [100] introduced a DSMIF method that continuously adjusts failure rates based on environmental changes. Figure 15 clearly visualizes this methodology. By applying joint point regression to the sparse historical failure data (red dots), the approach objectively identifies the critical break points (e.g. t1 and t2) where the failure rate behavior changes, thus distinguishing the random failure period from the onset of the wear-out period.

In summary, statistical modeling, represented by Bayesian inference and maximum likelihood estimation (MLE) (e.g. Martorell *et al* [101]), provides the data input for physical models (4.1) and practical O&M. They solve the PBM dependency on underlying data by providing dynamically updated parameter inputs.

4.2.2. ML/DL for RUL prediction (continuous monitoring data). In stark contrast to the sparse scenario (4.2.1), this second path leverages the richness of continuous monitoring data (e.g. acoustic, vibration, temperature) from sensors. Consequently, its core mission shifts from parameter estimation to direct RUL prediction.

The evolution of this path reflects an increasing depth of data mining:

Initially, scholars (e.g. Utah and Jung [102]) used traditional ML or DNNs to predict RUL for AC-powered SOVs, but this relies heavily on manual feature extraction (e.g. time/-frequency domain) from the raw signals.

However, manual features often fail to capture the temporal dependencies in non-linear degradation. To overcome this, advanced time-series models (e.g. temporal convolutional network (TCN), long short-term memory (LSTM)) emerged. Wang *et al* [103], for instance, emphasized that TCNs are far superior at capturing short-term changes in sensor data. Wang *et al* [104] also successfully used an LSTM-convolutional hybrid to predict the RUL of electric valves.

Despite solving the temporal problem, TCNs/LSTMs exposed the fundamental flaws of DDMs. As noted previously, these methods are data-greedy, and in the nuclear field—where high-quality, full-life-cycle, and failed-state data is scarce—this is a severe challenge.

To cope with this data-scarce reality, the current frontier (e.g. Li *et al* [105], Li *et al* [106]) has been forced to develop more complex hybrid neural networks (like Trans-TCN-GRU) to fuse simulation and real data for control valves, or just-in-time-learning (JITL) methods to handle diverse degradation modes in components like reciprocating compressor valves. Furthermore, advanced prognostic research, such as that by Gu *et al* [107], is moving toward generalized approaches that explicitly quantify and propagate multi-source uncertainty (e.g. measurement, model, and operational condition uncertainty) to improve the robustness of RUL predictions.

In summary, ML/DL-based RUL prediction shows powerful non-linear processing capability. However, its two fundamental flaws—being a black-box and data-greedy—make it difficult for it to independently shoulder the burden of reliability assessment in the high-safety, small-sample nuclear domain.

4.3. Physics/data-fused surrogate models and hybrid methods

As the previous sections revealed, PBMs (4.1) and DDMs (4.2) both have fundamental limitations. PBMs are interpretable but computationally expensive; DDMs are efficient but are black-box and data-greedy. As high-level reviews like Zhang *et al* [108] point out, this black-box nature is not just an academic flaw; it poses a fundamental challenge of AI systems. The lack of trustworthiness is unacceptable in safety-critical applications like nuclear power.

To bridge the massive gap between physical interpretability and data-driven efficiency, hybrid models have become a major frontier of development. This path is clearly diverging into two distinct but complementary strategies:

Strategy 1: Accelerate physics (PBM-based) this strategy uses data (4.2) to accelerate physics (4.1). This is the core value of surrogate models. Their main goal is to solve the computational bottleneck of high-fidelity simulations (FEM/CFD), making the dynamic PRA and UQ discussed in 4.1.2 engineering-feasible. For example, scholars (e.g. Lombardo *et al* [109], Kamkar and Abbasi [110]) use Kriging or ML models to *replace* costly MC simulations or time-domain simulators, enabling reliability analysis of reactors. A more advanced evolution is the multi-fidelity method (e.g. Zheng *et al* [111], Dhulipala *et al* [112]), which intelligently uses low-fidelity models to guide high-fidelity sampling in critical regions (like failure boundaries), efficiently estimating rare failure probabilities with minimal HF model calls.

Strategy 2: Constrain data (DDM-based) this strategy uses physics (4.1) to empower data (4.2). Its main goal is to solve the black-box and data-greedy flaws of DDMs (especially 4.2.2). This has catalyzed the deeper physics-enhanced machine learning PEML. As Lye *et al* [113]'s review summarizes, the mainstream trend in PEML is the PINN. The novelty of PINNs is that they embed physical laws (e.g. PDEs) directly into the neural network's loss function. This forces the network to obey physical laws. This characteristic offers a highly promising solution for the nuclear field's small-sample and high-trust requirements. Although its application to valve reliability is nascent, its success in adjacent fields shows clear feasibility: Wang *et al* [44] has used it to predict probabilistic fatigue in nuclear components, and Lai *et al* [114] proposed a multistage PINN framework, as visualized in figure 16. By integrating the derivative of the valve sizing equation into the loss function (shown as L_{phy}), this architecture explicitly constrains the relationship between valve displacement and flow capacity. This approach not only ensures physical consistency under small samples but also enables the model to interpretatively distinguish between fault types (e.g. sedimentation vs. leakage) by analyzing the deviations in the estimated flow coefficient curves.

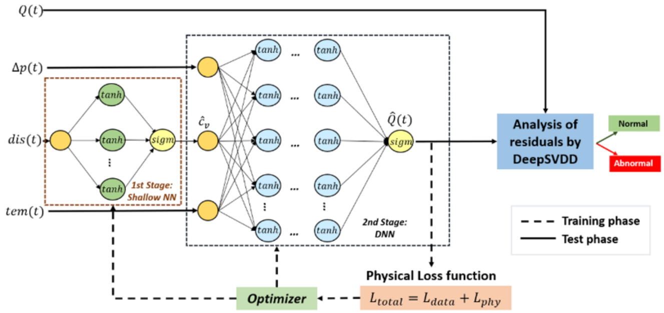

Figure 16. Proposed method for fault detection in regulating valves [114].

4.4. Summary

This chapter reviewed the methodologies for reliability assessment, revealing that the field is evolving along two distinct dimensions: (1) a methodological axis, transitioning from interpretable PBMs to efficient DDMs, and ultimately to trustworthy hybrid models; (2) a scope axis, expanding from component-level RUL prediction to system-level dynamic risk assessment.

At the component-level, the focus evolved from high-cost, interpretable PBMs (4.1.1, e.g. Paris Law) to efficient, non-linear DDM for RUL prediction (4.2.2, e.g. TCNs). The limitations of both—PBM complexity and DDM black-box nature—drove the development of component-level hybrid models (4.3). These hybrids act either as accelerators or, more importantly, as interpreters to solve the small-sample and trustworthiness challenges.

At the system-level, the focus evolved from managing static logic to capturing complex, dynamic behaviors. This shift, motivated by the need for dynamic risk assessment, advanced from PNs to sophisticated models incorporating dynamic, age-dependent failure rates. This level also relies on DDM to provide the critical (but sparse) failure data needed to feed these advanced PBMs.

To provide a clear comparison of the discussed methodologies, table 4 summarizes the key characteristics, pros, and cons of Physics-based, data-driven, and Hybrid methods.

In summary, the field faces persistent challenges of data scarcity and the need to balance interpretability with efficiency. Future research will inevitably focus on more robust hybrid models. This includes developing generalized RUL frameworks that manage multi-source uncertainty at the component level (Gu *et al* [107]) and exploring advanced intelligent algorithms, such as graph neural networks, to better model the complex, dynamic dependencies of the entire system (Wang and Geng [115]).

Table 4. Summary of methodologies for reliability assessment and life prediction (Chapter 4).

Section	Author (s)	Valve type	Core problem/goal	Specific model /method
4.1.1 PBM-component	Xu, R Y	Electric gate valve	Predict RUL based on physical crack growth laws	Paris law + PF
	Lee, J K	Reciprocating pump valves	Estimate PDF functions from leakage mechanisms	PDF of damage
	Baraldi, P	Check valve	Quantify epistemic uncertainty in physical degradation models	Epistemic uncertainty framework
	Lewandowski, R	Passive components (pipes)	Model gradual degradation mechanisms (FAC/SCC)	Condition-dependent PRA
4.1.2 PBM-system	Chisholm, B M	Molten salt reactor freezer valve	Quantify system-level risk for novel reactor components	FTA
	Deswandri	Main isolation valve	Pinpoint key failure events in a system	FTA
	Zubair, M	Control/isolation valve	Identify high-contribution failure events	FTA
	Zhu, J H	Nuclear reheat valve system	Address expert preference interdependence and psychological behavior	Hybrid FMEA IVPFN + WIVPFBM TODIM based on GRA
	Kumar, P	Shutdown systems, MSSV	Address dynamic, concurrent system behaviors in complex systems	Petri nets (PNs)
	Parsaei, S	MOVs	Model age-dependent unavailability considering test degradation	Age-dependent unavailability model
	Martorell, P	MOVs	Assess demand failure probability under degradation stress	Demand failure probability model
4.2.1 DDM-sparse	Martorell, S	MOVs	Estimate parameters for complex PBMs from sparse data	Maximum likelihood estimation (MLE)
	Prakash, G	Pneumatic control valves	Fuse prior knowledge with sparse plant data	Bayesian inference
	Maskin, M	Manual valve	Update component reliability parameters for PSA	Bayesian updating
	He, J	Squib valve	Aggregate small-sample data for high-reliability components	Bayesian inference
	Wu, Y	Spring-loaded safety valves	Incorporate environmental factors into failure rate prediction	DSMIF method
	Martón, I	Safety valves	Identify aging turning points from sparse historical data	Three-step methodology (joinpoint regression)
4.2.2 DDM continuous	Utah, M N	Solenoid valves	RUL prediction from raw signal features	Traditional ML & DNN
	Wang, H	Electric gate valves	Capture temporal dependencies for RUL prediction	Improved TCN
	Wang, H	Electric valves	Extract features from acoustic signals for prognosis	LSTM-convolutional hybrid
	Li, G	Control valves	Predict RUL under data-scarce conditions	Transformer-TCN-GRU
	Li, X	Reciprocating compressor valves	Handle diverse degradation modes for prognosis	Just-in-time learning (JITL)

(Continued.)

Table 4. (Continued.)

4.3.1 fusion	Lombardo, S S	Reactor (LBE-XADS)	Accelerate reliability analysis to overcome computational costs	Adaptive Kriging importance sampling (AK-IS)
	Zheng, X	Reactor (BWR)	Perform dynamic risk assessment efficiently	Multi-fidelity surrogate model (MF-SM)
	Chakroborty, P	TRISO nuclear fuel	Estimate rare failure probabilities	multi-fidelity surrogate model (MF-SM)
	Kamkar & Abbasi	Reactor (WWER)	Perform uncertainty quantification and sensitivity analysis	ML-based surrogate models
4.3.2 fusion	Lye, A	General review	Categorize physics-enhanced learning strategies	PIML, PGML review
	Wang, X	Nuclear piping (elbow)	Constrain neural networks with physical laws (fatigue/ratcheting)	pLMM framework (training LDNN)
	Lai, C	Regulating valves	Enhance diagnostic trustworthiness via physical constraints	PINN

Note: IVPFN: interval-valued Pythagorean fuzzy number; WIVPFBM: weighted interval-valued Pythagorean fuzzy Bonferroni mean; TODIM: interactive and multi-criteria decision making; GRA: gray relational analysis; DSMIF: dynamic stress-strength interference model with fuzziness; GRU: gated recurrent unit; PIML/PGML: physics-informed/guided machine learning; pLMM: probabilistic linear matching method; LDNN: LMM-driven neural network.

5. Condition monitoring and intelligent O&M

Having established the failure mechanisms (Chapter 3) and assessment methods (Chapter 4), this chapter focuses on the action phase: how to ensure sustained reliability through effective condition monitoring and intelligent O&M.

Considering that NPP valves are numerous and often located in inaccessible, high-radiation areas, traditional TBM is increasingly viewed as inefficient and prone to introducing maintenance-induced risks. Therefore, CBM and PdM are the necessary trend. This relies on advanced monitoring to detect early fault signatures and intelligent diagnostics to guide precise, efficient O&M decisions. This chapter will proceed in three parts: (5.1) monitoring techniques and system-level considerations; (5.2) advanced fault diagnosis methodologies; and (5.3) risk-based intelligent O&M decision-making. This section reviews the evolution of O&M strategies from corrective to PdM. A comprehensive classification of these strategies, along with their applicable scenarios and data requirements, is presented in table 5.

5.1. Condition monitoring and intelligent platforms

Effective condition monitoring is the first step toward intelligent O&M, aiming to capture deviations in operational status to provide early warnings for diagnostics.

For NPP valves, given their harsh conditions or inaccessibility, non-intrusive monitoring (e.g. acoustic emission (AE), vibration) is the preferred choice for CBM/PdM. Initial research in this area focused on using these signals for anomaly detection. For example, Xu *et al* [116], and Huang *et al* [117] both validated the feasibility of using AE signals combined with PCA or autoencoders for status detection. Liu *et al* [118], focusing on new NPP valves, explored using vibration and power signal features (like power spectral entropy) to predict fault critical points.

However, monitoring effectiveness depends not just on the sensor, but on the intelligence of the monitoring system. Thus, the current research trend has moved beyond simple threshold alarms toward integrated and intelligent monitoring platforms. This evolution is reflected in:

From passive to active: Kim *et al* [119] developed a self-diagnostic monitoring system for AOVs, which uses multi-algorithm integration and majority-voting to actively improve decision reliability.

From physical to virtual: Kim *et al* [120] took a different path, building a virtual diagnostic model for AOV assemblies, using a validated numerical model to achieve non-physical monitoring of aging status. As visualized in figure 17 (from Kim *et al*), the core of this virtual diagnostic approach is the validation of the numerical model. The figure demonstrates a high degree of agreement between the physical Experimental Diagnosis data (dashed line) and the numerical diagnosis simulation (solid line), thus proving the model's capability to serve as a reliable virtual sensor for aging monitoring.

From static to dynamic: To solve the fundamental problem of models becoming obsolete over time, Zhao *et al* [121], using SOVs as an example, emphasized the necessity of sequential parameter learning, proving that only dynamically updated models can ensure long-term accuracy.

In summary, the monitoring technologies and intelligent platforms discussed in 5.1 provide the data input and platform support for the precise fault diagnosis in 5.2.

Table 5. Summary of methodologies for condition monitoring and intelligent O&M (Chapter 5).

Section	Author (s)	Valve type	Core problem/goal	Input data/signal	Specific method
5.1 Monitoring	Xu, R	Electric valve	Detect anomalies via acoustic feature extraction	Acoustic emission (AE)	PCA
	Huang, X	Electric valve	Detect anomalies using unsupervised learning	Acoustic emission (AE)	VMD + autoencoder (AE)
	Liu, Z	New NPP valves	Predict fault critical points under small-sample conditions	Vibration & Power signals	Feature analysis (spectral entropy)
	Kim, W	AOVs	Improve diagnostic reliability using active monitoring	Process parameters (Pressure, Position)	Ensemble ML (LR, ANN, SVM) + Majority Vote
	Kim, J	AOV assemblies	Monitor aging status using validated virtual sensors	Experimental diagnostic data	Multibody dynamic numerical model
	Zhao, Y F	SOVs	Enhance accuracy by updating model parameters online	Flowrate/plunger position	Sequential Bayesian learning
5.2 Diagnosis	Liu, Z	Nuclear gate valve	Diagnose fault severity via energy characteristics	Vibration signals	EEMD + IMF energy analysis
	Gao, J	Electric gate valve (EGV)	Diagnose faults with optimized feature extraction	Vibration & acoustic emission (AE)	VMD + MDI-ISSA-RF
	Luo, J	Electric gate valve (EGV)	Detect internal leakage anomalies with high accuracy	Acoustic emission (AE)	Multi-Kernel SVM
	Huang, X	Electric gate valve (EGV)	Provide high-quality data for DL	Experimental fault data	Fault simulation testbed
	Huang, X	Electric gate valve (EGV)	Extract fault features under strong background noise	Acceleration signals	SBO-VMD + SVD + BGRU
	Huang, X	Electric gate valve (EGV)	Classify fault types and assess fault severity	Vibration & AE signals	CEEMDAN + Bi-LSTM
	Ai, X	Electric isolation valve	Diagnose concurrent (simultaneous) fault modes	Vibration, AE, current, valve position, flow	Two-layer: rule-based (FMEA) + VMD-FastICA-GRU
	Liu, Y K	Electric valve	Integrate fault detection and leak size estimation	Vibration (for detection) & acoustic (for sizing)	IPS-SVM + DBN
	An, Z	NPP valves	Enable online long-term fault prediction	Acoustic signals (long-term)	PCA-informer
5.2 Diagnosis	Lai, C	Regulating valve	Ensure physical consistency in data-driven diagnosis	Process parameters	PINN + DeepSVDD
	Cilliers, A C	PORV, AFW stop valve	Detect faults during transient operation	Plant measurement data vs simulator output	Expert system (based on PCTRAN simulator)
5.3 Decision	Ballesteros, A	General valves	Identify maintenance-induced risks statistically	NPP maintenance event data	Statistical analysis
	Yang, D W	Containment isolation valve (SIV)	Quantify human error probabilities in maintenance	Maintenance task steps	THERP HCR (HEP quantification)

(Continued.)

Table 5. (Continued.)

Section	Author (s)	Valve type	Core problem/goal	Input data/signal	Specific method
	Zhan, X L	Steam control-valve	Optimize periodic testing strategies to reduce operational risk	Field test data	Periodic test strategy optimization
	Martorell, S	General/safety components	Coordinate maintenance based on reliability, availability, risk	Reliability & Risk data	Risk-Informed (RAM) coordination
	Do, P	General degrading system	Quantify imperfect maintenance effectiveness to optimize proactive CBM policies	Continuous degradation monitoring data	Probabilistic improvement factor model
	Zhang, C	Multi-component system	Dynamic decision-making for opportunistic maintenance under load-sharing and imperfect repair	Real-time system state	Deep reinforcement learning

Note: VMD: variational mode decomposition; EEMD: ensemble empirical mode decomposition; IMF: intrinsic mode function; MDI: mutual dimensionless indicator; SBO: improved sparrow search algorithm (SBO is a variant abbrev.); GRU: gated recurrent unit; SAE: stacked autoencoder; DBN: deep belief network; THERP: technique for human error rate prediction; HCR: human cognitive reliability.

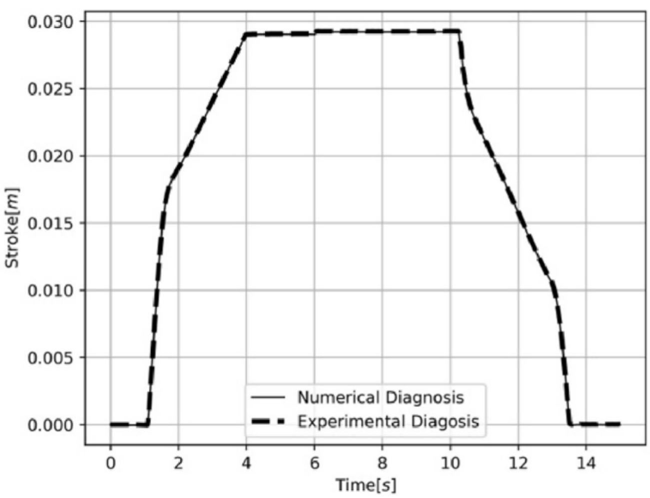

Figure 17. Comparison of stroke using test-based methodology in the dynamic diagnosis [120].

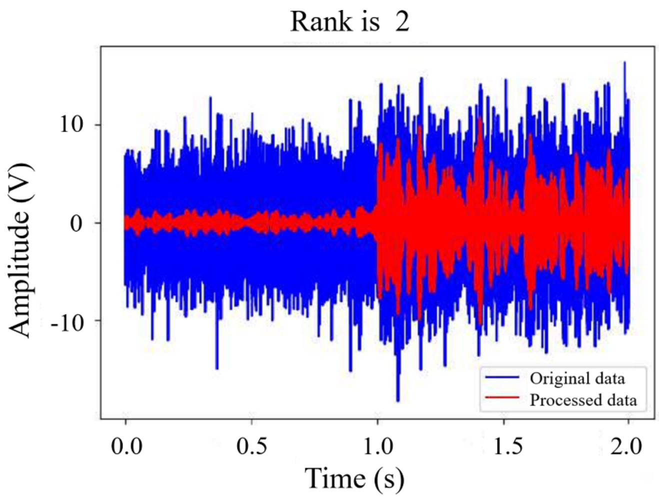

Figure 18. SVD denoising result display [126].

5.2. Fault diagnosis methodologies

While the primary objective of condition monitoring (section 5.1) is anomaly detection, the subsequent task of fault diagnosis focuses on characterizing the specific nature of the failure—identifying its type, location, and severity. The evolutionary path here is clear:

First, the manual features + machine learning classic paradigm. This paradigm relies on expert experience to first extract fault-sensitive features using signal processing (e.g. ensemble empirical mode decomposition (EEMD), variational mode decomposition (VMD)), which are then fed into a traditional classifier (e.g. random forest (RF), support vector machine (SVM)). For instance, Liu *et al* [122] and Gao *et al* [123] used the EEMD-RF and VMD-RF paradigms, respectively, to diagnose vibration signals. Luo *et al* [124] validated the effectiveness of multi-kernel SVM for internal leakage in electric motor-operated valves (MOVs). However, the classic paradigm is overly reliant on the manual feature extraction bottleneck.

Second, the automatic feature extraction DL mainstream paradigm. Thus, the mainstream trend has shifted to end-to-end DL (e.g. bidirectional gated recurrent unit (BGRU), bidirectional LSTM (Bi-LSTM)), which can automatically learn features. Supported by high-quality experimental data (such as the MOV fault simulation testbed built by Huang *et al* [125]), the DL paradigm is being applied to address complex field challenges:

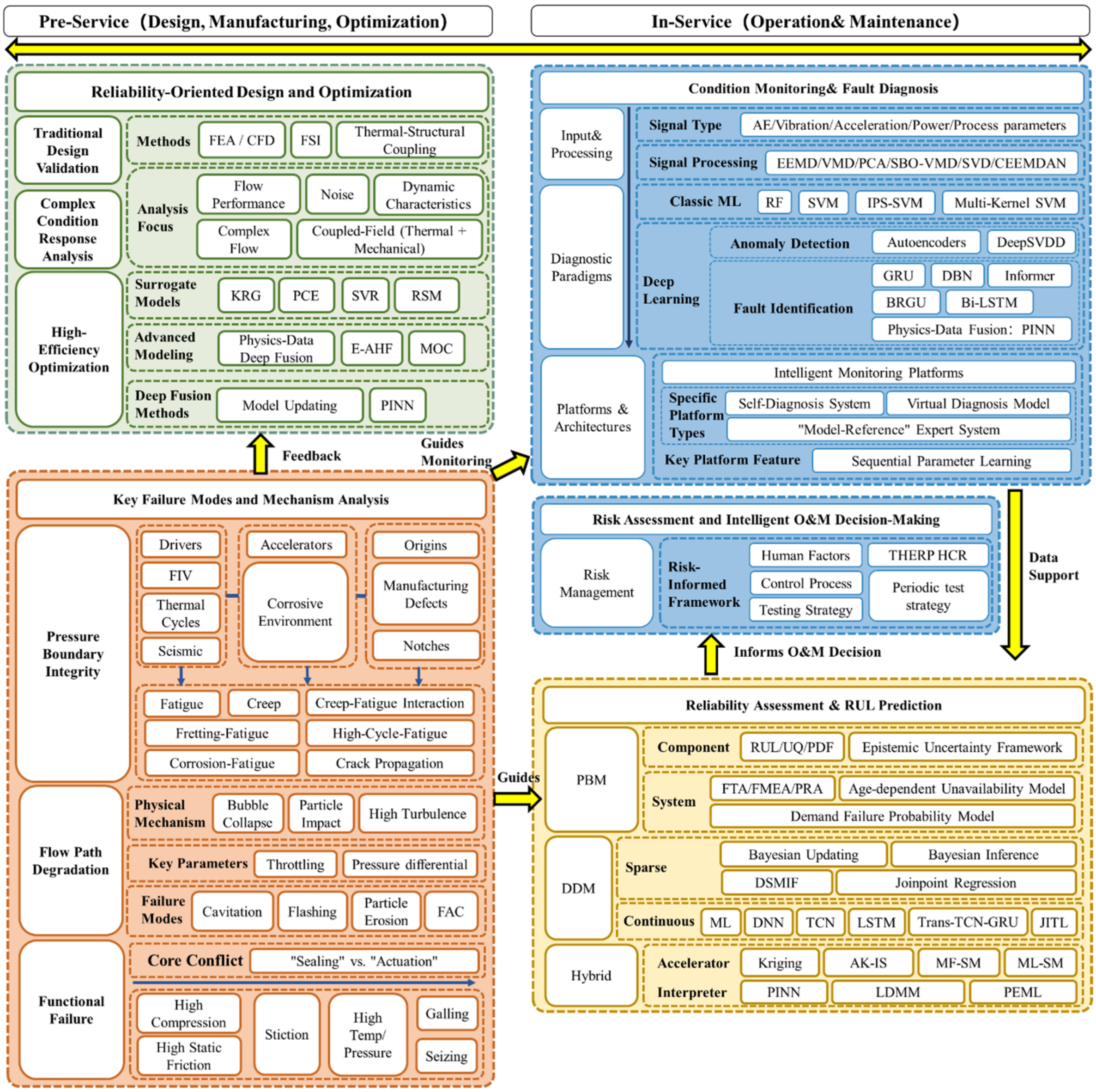

Figure 19. Full life-cycle reliability framework for NPP valves.

Dealing with strong noise: Huang *et al* [126] utilized VMD and SVD to filter out background noise (as shown in figure 18), and applied a BGRU network to classify the refined fault signals of MOVs.

Assessing fault severity: Huang *et al* [127] further used Bi-LSTM to achieve quantitative assessment of MOV fault severity.

Identifying concurrent & mixed faults: Ai *et al* [128] proposed a two-layer framework for concurrent faults. Similarly, Liu *et al* [129] proposed an integrated shallow-deep model (**IPS-SVM** + deep belief network (DBN)) to classify valve damage and estimate internal leakage size.

Achieving online prediction: An *et al* [130] explored online prediction, validating the informer model for long-term sequence forecasting of NPP valve acoustic signals. Finally, the physics-enhanced frontier paradigm. Despite its superior feature-learning capabilities, the DL paradigm's black-box nature (discussed in 4.2) remains a fundamental flaw in the high-safety nuclear domain. To resolve this trust crisis, the research frontier (echoing the fusion trend in 4.3) is turning to physics-enhanced diagnostic models. For example, Lai *et al* [114] proposed a multi-level PINN for control valve fault detection, innovatively integrating the valve flow equation into the loss function to ensure physical consistency. Similarly, Cilliers [131] (2018) validated the superiority of a model-reference expert system (based on the PCTRAN simulator) in diagnosing complex accidents.

In summary, valve fault diagnosis has evolved from the expert-dependent classic paradigm, to the data-dependent DL paradigm, and is now moving toward the data and physics co-driven, interpretable, and high-trust paradigm.

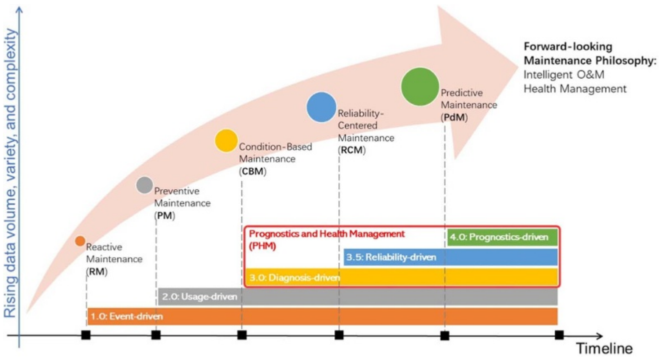

Figure 20. The development progress of maintenance strategies [138].

5.3. Risk assessment and intelligent O&M decision-making

After obtaining the valve's health status via monitoring (5.1) and diagnostics (5.2), the ultimate goal of intelligent O&M is to formulate an optimal maintenance decision.

However, maintenance activity itself is a high-risk event. Ballesteros *et al* [132]'s statistical analysis of NPP maintenance events sounded an alarm: ∼47% of reported events were directly related to periodic maintenance, and valves were the most affected components. The root causes pointed directly to improper maintenance execution and procedural deficiencies.

This critical insight redefines the core task of O&M decision-making: it addresses not only the optimal timing of maintenance but also the safety and efficiency of maintenance execution. Addressing this, research has diverged into two key control domains:

One is controlling human risk—quantifying and managing human factors. To address the improper execution problem, Yang and Liu [133] provided a quantitative method. By integrating the technique for human error rate prediction (THERP) and human cognitive reliability (HCR) models, the study calculated the human error probability (HEP) for each step of a containment isolation valve overhaul. The value of this work is its provision of a decision basis for high-risk step identification, personnel optimization, and standard operating procedure improvement.

The second is controlling process risk—optimizing testing and maintenance strategies. To address procedural deficiencies and inefficiency, Zhan *et al* [134]'s study offers a model for optimizing O&M strategies. By optimizing the periodic test control strategy for a steam control valve, field tests showed the new plan dramatically reduced load fluctuations and shortened test times. This demonstrates that the scope of intelligent O&M encompasses not only corrective maintenance execution but also the optimization of surveillance testing strategies, thereby achieving both safety and economic gains.

Furthermore, beyond optimizing maintenance schedules, quantifying the actual 'Maintenance Effectiveness' represents a critical frontier. As emphasized by the 'Maintenance Rule' (e.g. 10 CFR 50.65), maintenance activities in practice are often 'imperfect'—meaning they do not always restore components to an ideal 'as-good-as-new' state. Consequently, future O&M models must evolve from simple binary assumptions to quantitative assessments of restoration quality. For instance, Do *et al* [135] proposed probabilistic models using improvement factors to quantify the partial restoration of degrading systems, while Zhang *et al* [136] recently advanced this by integrating imperfect maintenance constraints into deep reinforcement learning (DRL) frameworks for dynamic decision-making. Incorporating such 'Imperfect Maintenance' theories is vital for accurately evaluating safety margins during the LTO and license renewal phases of NPPs.

In conclusion, the essence of intelligent O&M is a risk-based system engineering task. As Martorell *et al* [137] emphasized, the optimal strategy is not an isolated diagnose-repair loop, but a risk-informed coordination framework. This framework must dynamically coordinate the risk assessments (4.1), fault diagnostics (5.2), human factor analysis, and testing strategies to achieve a true balance between reliability, availability, maintainability (RAM), and risk.

6. Conclusion

This paper constructs a full life-cycle reliability framework, as visually summarized in figure 19. It systematically reviews the current status and progress of NPP valve reliability research from the perspective of four pillars: reliability-oriented design, key failure mechanisms, reliability assessment, and intelligent O&M. As discussed above, these four pillars are not independent but form a dynamic analysis-feedback-improvement closed loop. This is logically isomorphic to the industry's successful practice of learning from OpEx:

(1) **Failure feeds back to design:** A deep understanding of failure mechanisms (such as cavitation and corrosion) directly promotes the development of reliability-oriented design.
(2) **Mechanisms guide assessment and monitoring:** Research into physical phenomena provides a solid physical basis for assessment methods and condition monitoring techniques.
(3) **Data supports assessment:** Monitoring data from intelligent O&M serves as the 'fuel' for data-driven models and Bayesian statistics in reliability assessment and RUL prediction.
(4) **Assessment optimizes O&M:** The dynamic risk and health status provided by assessment are the prerequisites for risk-informed intelligent O&M to make optimal decisions.

NPP valve reliability research is undergoing a profound paradigm shift. It is moving from 'static, isolated, physics-dominated' analysis toward 'dynamic, systematic, deep physics-data fusion' reliability management. As Liu *et al* [138] pointed out in their review of intelligent reliability assurance for engineering systems (see figure 20), the entire engineering field is experiencing an intelligent paradigm evolution from traditional preventive maintenance to PdM centered on PHM. Research in the Nuclear power domain has indeed shown rapid growth in recent years.

However, this mainstream trend encounters unique challenges for the specific equipment of NPP valves, leading to a relative lag in application. The root of this lag is a fundamental conflict between the valves' service scenarios and the sweet spot of mainstream methods (especially intelligent methods).

Challenges and lag: The contradictions in NPP valve reliability assessment

Data conflict: The data requirement for intelligent methods represented by DL is large. As high-reliability, low-failure equipment, NPP valves' failure data is often incidental, unplanned, or even has never occurred. The data-greedy nature of mainstream intelligent algorithms is fundamentally incompatible with the data-scarce reality of high-reliability nuclear equipment.

Physical conflict: PBMs are typically based on simplified, single failure physics. Although these models have low data requirements, their accuracy is only medium [136]. Consequently, traditional simplified physical models fall short in capturing the strong non-linearities of multi-physics coupling behaviors under extreme accident conditions.

System conflict: As analyzed in Chapters 4 and 5 of this paper, a NPP valve is itself a complex mechatronic system. Its compound fault modes far exceed the single components targeted by mainstream PHM. The difficulty increases exponentially when migrating from single-fault types to compound faults.

Regulatory conflict: In the nuclear safety field, the high accuracy of a black-box model is unacceptable. Its assessment methods must be explainable and trustworthy. This sets an extremely high regulatory bar for the adoption of intelligent methods.

This series of conflicts collectively leads to the lag in the application of mainstream popular methods in the NPP valve domain.

Future outlook

To bridge the gap between academic algorithms and industrial application, future research must move beyond general methodology applications to address fundamental scientific challenges in reliability engineering.

Firstly, regarding the physics-data fusion discussed, current research often simplifies complex accident dynamics into steady-state problems. Future work should focus on solving the numerical stiffness inherent in transient multi-physics governing equations. Developing adaptive weighting strategies or transient-specific neural architectures will be crucial to extend reliability assessment from normal operations to extreme accident scenarios, ensuring that data-driven models remain robust under rapid state changes.

Secondly, a methodological disconnect persists between continuous component-level degradation and discrete system-level risk assessment. Future frameworks should utilize mathematical interfaces, such as dynamic Bayesian networks or state-space integrated models, to map real-time degradation trajectories directly onto the dynamic failure probabilities of system fault trees. This integration is essential for constructing risk-informed digital twins that reflect the real-time safety margins of the entire plant.

Furthermore, to align with nuclear regulatory standards, model evaluation must evolve from pure data accuracy to physical verifiability. Research should establish rigorous frameworks where physical residual loss—such as errors in mass or energy conservation—is quantified as a standardized safety metric. Demonstrating that model predictions strictly adhere to physical laws, even when data is noisy, will provide the necessary evidence of trustworthiness for licensing.

Finally, to mitigate the rigorous dependency on large-scale historical fault data, transfer learning paradigms should be further explored. By pre-training diagnostic models on high-fidelity simulations or general industrial datasets, the industry can achieve effective fault diagnosis even with limited nuclear-specific samples. This approach offers a scientifically viable pathway to resolve the data scarcity issues inherent in high-reliability nuclear components.

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References

[1] International Nuclear Safety Advisory Group 1996 Defence in depth in nuclear safety *Report No. STI/PUB/1013* (International Atomic Energy Agency)
[2] International Atomic Energy Agency 2005 Assessment of defence in depth for nuclear power plants *Report No. STI/PUB/1218* (International Atomic Energy Agency)
[3] International Nuclear Safety Advisory Group 1999 Basic safety principles for nuclear power plants *75-INSAG-3 Rev 1 INSAG-12* (International Atomic Energy Agency)
[4] A Institute of Electrical and Electronics Engineers 1987 IEEE guide for general principles of reliability analysis of nuclear power generating station safety systems (ANSI/IEEE Std 352–1987)
[5] American Society of Mechanical Engineers 2023 ASME BPVC Section III: rules for construction of nuclear facility components
[6] American Society of Mechanical Engineers 2020 Valves—flanged, threaded, and welding end (ASME B16.34)
[7] American Society of Mechanical Engineers 2022 Qualification of active mechanical equipment used in nuclear facilities (ASME QME-1)
[8] American Society of Mechanical Engineers 2020 Code for operation and maintenance of nuclear power plants (ASME OM Code)
[9] AFCEN 2022 Design and construction rules for mechanical components of PWR nuclear islands (RCC-M)
[10] National Nuclear Safety Administration 2004 Safety regulations for quality assurance of nuclear power plants (HAF 102)

[11] National Nuclear Safety Administration 1991 Safety regulations for quality assurance of nuclear power plants (HAF 003)
[12] National Energy Administration 2010 Equipment for conventional island of nuclear power plant—valves—part 1: general requirements (NB/T 20010.1–2010)
[13] Murphy G A and Cletcher J W II. 1987. Operating experience review of failures of power operated relief valves and block valves in nuclear power plants *Report No. NUREG/CR-4692, ORNL/NOAC-233* (U.S. Nuclear Regulatory Commission)
[14] Wierman T E, Rasmuson D M and Stockton N B 2003 Common-cause failure event insights: motor-operated valves *Report No. NUREG/CR-6819* vol 2 (U.S. Nuclear Regulatory Commission)
[15] Casada D A and Todd M D 1993 A characterization of check valve degradation and failure experience in the nuclear power industry *Report No. NUREG/CR-5944, ORNL-6734* (U.S. Nuclear Regulatory Commission)
[16] Ma Z 2023. Enhanced component performance study: motor-operated valves 1998–2022 *Report No. INL/RPT-23-73956* (Idaho National Laboratory)
[17] International Organization for Standardization 2018 *Quality management systems—specific requirements for the application of ISO 9001:2015 by organizations in the supply chain of the nuclear energy sector supplying products and services important to nuclear safety (ITNS) (EN ISO 19443)* (International Organization for Standardization)
[18] Ausschuss K 2017 General requirements for quality assurance (KTA 1401)
[19] Gao G, Guo S and Li D 2024 A review of cavitation erosion on pumps and valves in nuclear power plants *Materials* **17** 1007
[20] Rezaeianjouybari B and Shang Y 2020 Deep learning for prognostics and health management: state of the art, challenges, and opportunities *Measurement* **163** 107929
[21] Ayodeji A, Amidu M A, Olatubosun S A, Addad Y and Ahmed H 2022 Deep learning for safety assessment of nuclear power reactors: reliability, explainability, and research opportunities *Prog. Nucl. Energy* **151** 104339
[22] Zhang S, Luo M, Qian H, Liu L, Yang H, Zhang Y, Liu X, Xie Z, Yang L and Zhang W 2023 A review of valve health diagnosis and assessment: insights for intelligence maintenance of natural gas pipeline valves in China *Eng. Fail. Anal.* **153** 107581
[23] Qian J-Y, Hou C-W, Mu J, Gao Z-X and Jin Z-J 2020 Valve core shapes analysis on flux through control valves in nuclear power plants *Nucl. Eng. Technol.* **52** 2173–82
[24] Bairagi A, He M and Chen M 2024 Numerical investigation of butterfly valve performance in variable valve sizes, positions and flow regimes *J. Nucl. Eng.* **5** 128–49
[25] Sun Y, Wu J, Xu J and Bai X 2022 Flow characteristics study of high-parameter multi-stage sleeve control valve *Processes* **10** 1504
[26] Asim T, Charlton M and Mishra R 2017 CFD based investigations for the design of severe service control valves used in energy systems *Energy Convers. Manage.* **153** 288–303
[27] Jin H Z, Tang K M, Liu X F and Wang C 2023 Numerical simulation and experimental study on internal depressurization flow characteristics of a multi-layer sleeve regulating valve *J. Appl. Fluid Mech.* **16** 877–90
[28] Wang S, Ji Z, Han F, Xie Y, Han J, Wang Y and Li C 2025 A control valve for fluid-load oscillation inhibiting and energy harvesting *Prog. Nucl. Energy* **186** 105820
[29] Ye Z-H, Li W-Q, Xu Y-X, Jin Z-J and Qian J-Y 2025 Effects of adjusting ring and spring stiffness on fluid dynamics of steam spring-loaded safety valve *Nucl. Eng. Technol.* **57** 103338
[30] Zang J-L, Yao H-Y, Zhang F-H, Liu Z-Y, Meng J, Zhu J-M, Wang Z-M and Qian J-Y 2022 Dynamic characteristics analysis of pilot valves with different inlet diameters installed on the main steam valve set *Case Stud. Therm. Eng.* **34** 102004
[31] Tiberga M, Shafer D, Lathouwers D, Rohde M and Kloosterman J L 2019 Preliminary investigation on the melting behavior of a freeze-valve for the Molten Salt Fast Reactor *Ann. Nucl. Energy* **132** 544–54
[32] Yang X, Lü Y, Xu L, Ma Y, Chen R and Zhao X 2024 Numerical investigation on cavitation erosion and evolution of choked flow in a tri-eccentric butterfly valve *Flow Meas. Instrum.* **100** 102725
[33] Yang L, Li S and Hou J 2025 Flow-induced vibration stability in pilot-operated control valves with nonlinear fluid–structure interaction analysis *Actuators* vol 14 (MDPI) p 372
[34] Zhang H, Zhao L, Peng S-E, Ru Q, Liu P and Wu J-M 2021 Thermal-fluid-structure analysis of fast pressure relief valve under severe nuclear accident *Nucl. Eng. Des.* **371** 110937
[35] Li W-Q, Zhao L, Yue Y, Wu J-Y, Jin Z-J and Qian J-Y 2022 Thermo-mechanical stress analysis of feed-water valves in nuclear power plants *Nucl. Eng. Technol.* **54** 849–59
[36] Yan L, Ma X, Miao X, Wang Y, Pang Y and Song X 2024 Numerical investigation and rapid prediction of the erosion rate of gate valve in gas-solid flow *Powder Technol.* **448** 120285
[37] Xie D, Jiang P, Zhao X, Zhang C, Shi M and Zong C 2025 Numerical modeling and characteristic analysis of the pneumatic noise of spring-loaded pressure relief valves *Nucl. Eng. Technol.* **57** 103760
[38] Zong C, Shi M, Li Q, Xue T, Song X, Li X and Chen D 2023 Sealing design optimization of nuclear pressure relief valves based on the polynomial chaos expansion surrogate model *Nucl. Eng. Technol.* **55** 1382–99
[39] Wang L, Zheng S, Liu X, Xie H and Dou J 2021 Flow resistance optimization of link lever butterfly valve based on combined surrogate model *Struct. Multidiscip. Optim.* **64** 4255–70
[40] Zong C, Shi M, Li Q, Liu F, Zhou W and Song X 2022 Design optimization of a nuclear main steam safety valve based on an E-AHF ensemble surrogate model *Nucl. Eng. Technol.* **54** 4181–94
[41] Song X, Lv L, Li J, Sun W and Zhang J 2018 An advanced and robust ensemble surrogate model: extended adaptive hybrid functions *J. Mech. Des.* **140** 041402
[42] Song X, Li Q, Liu F, Zhou W and Zong C 2023 Multi-fidelity modeling and analysis of a pressurized vessel-pipe-safety valve system based on MOC and surrogate modeling methods *Nucl. Eng. Technol.* **55** 3088–101
[43] Xue R, Yu S and Zhang X 2020 Identification of parameters in 2D-FEM of valve piping system within NPP utilizing seismic response *Comput. Mater. Continua* **65** 789–805
[44] Wang X, Chen H and Xuan F 2023 Physics-based neural network for probabilistic low cycle fatigue and ratcheting assessments of pressurized elbow pipe component *Int. J. Fatigue* **172** 107598
[45] Buhendwa A B, Adami S and Adams N A 2021 Inferring incompressible two-phase flow fields from the interface motion using physics-informed neural networks *Mach. Learn. Appl.* **4** 100029
[46] Mao Z, Jagtap A D and Karniadakis G E 2020 Physics-informed neural networks for high-speed flows *Comput. Methods Appl. Mech. Eng.* **360** 112789

[47] Yang L, Li S and Hou J 2025 A comprehensive review of flow-induced vibration and fatigue failure in the moving components of control valves *Machines* **13** 766
[48] Haile S G, Woschke E, Tibba G S and Pandey V 2022 Internal two-phase flow induced vibrations: a review *Cogent Eng.* **9** 2083472
[49] Zeng X, Xia H, Dong Y and Liu Z 2013 Analysis of fatigue life for main steam isolation valve in nuclear power plants *Int. Conf. on Nuclear Engineering* vol 55799 (American Society of Mechanical Engineers) pp V002T03A013
[50] Cai Z-B, Li Z-Y, Yin M-G, Zhu M-H and Zhou Z-R 2020 A review of fretting study on nuclear power equipment *Tribol. Int.* **144** 106095
[51] Tamura A, Okuyama K, Takahashi S and Ohtsuka M 2012 Development of numerical analysis method of flow-acoustic resonance in stub pipes of safety relief valves *J. Nucl. Sci. Technol.* **49** 793–803
[52] Yiwe C, Hong S, Dong W and Yan W 2022 Study on thermal stress and fatigue stress of nuclear high temperature and high pressure three-way valve *Advances in Machinery, Materials Science and Engineering Application: Proc. of the 8th Int. Conf. on Advances in Machinery, Materials Science and Engineering Application (MMSE 2022).Wuhan, China, both in-person and online. 23–24 July 2022* (IOS Press) pp 534–40
[53] Dai Y, Zhang H, Zhang H, Wei W and Liu R 2019 Failure analysis and experimental research on the structure of key parts of safety valves *MATEC Web of Conf.* vol 256 (EDP Sciences) p 02009
[54] Meng F, Zhang H, Dai Y, Zhang H, Wei W and Liu R 2020 Anti-seismic characteristics of safety valve and its spring failure prediction analysis *MATEC Web of Conf.* vol 306 (EDP Sciences) p 04004
[55] Benyamina M, Knyazkov P and Imine O 2017 Large eddy simulation of thermal turbulent mixing and reduction of temperature fluctuations with swirl in T-junction *J. Braz. Soc. Mech. Sci. Eng.* **39** 4985–99
[56] Zhao J, Qiu F and Xu C 2023 Review of creep-thermomechanical fatigue behavior of austenitic stainless steel *Crystals* **13** 70
[57] Gong J-G, Gong C, Xuan F-Z and Chen H 2019 Notch effect on structural strength of components at elevated temperature under creep, fatigue, and creep-fatigue loading conditions: phenomenon and mechanism *J. Press. Vessel Technol.* **141** 050801
[58] Zhao L, He J-R, Jiang W-J, Ru Q, Liu P, Wu J-M and Zhang H 2022 Structural operability and integrity analysis of the pressure relief valve under severe accident *Case Stud. Therm. Eng.* **37** 102301
[59] Larrosa N O, Akid R and Ainsworth R A 2018 Corrosion-fatigue: a review of damage tolerance models *Int. Mater. Rev.* **63** 283–308
[60] Cheng J, Fang K, Fei K, Wang Q, Li B and Farfán E B 2025 Failure analysis of CRDINiCr butterfly valves for nuclear power plant applications *Nucl. Technol.* **211** 584–97
[61] Lu X Y, Ding Q, Ni T W, Gong Y and Yang Z G 2025 Fatigue fracture failure of stainless steel valve rod for seawater gate valve in nuclear power plant *J. Fail. Anal. Prev.* **25** 1–14
[62] Chen S, Xie A, Lv X, Chen S, Yan C, Jiang H and Rong L 2023 Tailoring microstructure of austenitic stainless steel with improved performance for generation-IV fast reactor application: a review *Crystals* **13** 268
[63] Zinkle S J, Terrani K A and Snead L L 2016 Motivation for utilizing new high-performance advanced materials in nuclear energy systems *Curr. Opin. Solid State Mater. Sci.* **20** 401–10
[64] Bhowmik P K and Sabharwall P 2023 Sizing and selection of pressure relief valves for high-pressure thermal–hydraulic systems *Processes* **12** 21
[65] Wang H, Cai S and Zhang Z 2025 Erosion wear of high-pressure throttle valves: a review *Corrosion* **81** 826–47
[66] Arndt R E A 2002 Cavitation in vortical flows *Annu. Rev. Fluid Mech.* **34** 143–75
[67] Liu B, Zhao J and Qian J 2017 Numerical analysis of cavitation erosion and particle erosion in butterfly valve *Eng. Fail. Anal.* **80** 312–24
[68] Liu C B, Jiang S L and Zheng Y G 2012 Experimental and computational failure analysis of a valve in a nuclear power plant *Eng. Fail. Anal.* **22** 1–10
[69] Li Q, Zhang S, Wang M, Zong C, Li X and Song X 2023 Numerical and experimental analysis of cavitation characteristics in safety valves of the nuclear power second circuit using a modified cavitation model *Eng. Appl. Comput. Fluid Mech.* **17** 2251546
[70] Zhao J, Yin H, Tang Z and Ding C 2024 Numerical analysis of erosion characteristics of three eccentric butterfly valves based on CFD *Eur. Phys. J. Plus* **139** 766
[71] Sedghkerdar A, Erfaninia A and Nematollahi M 2020 2D PIV study of flow accelerated corrosion downstream a typical industrial gate valve *Prog. Nucl. Energy* **121** 103260
[72] Wang H, Zhu Z, Zhang M, Li J and Huo W 2021 Investigation on cavitating flow and parameter effects in a control valve with a perforated cage *Nucl. Eng. Technol.* **53** 2669–81
[73] Sotoodeh K 2021 A review of valve stem sealing to prevent leakage from the valve and its effect on valve operation *J. Fail. Anal. Prev.* **21** 9–16
[74] Di Capaci R B and Scali C 2018 Review and comparison of techniques of analysis of valve stiction: from modeling to smart diagnosis *Chem. Eng. Res. Des.* **130** 230–65
[75] Wu Y, Azzi M, Khelfaoui F, Vernhes L, Martinu L and Klemberg-Sapieha J 2024 Static friction measurement methodology for the assessment of performance of industrial valves at high temperatures: case study for a nickel-based alloy coating *Tribol. Int.* **192** 109237k
[76] Kakulite K K and Kandasubramanian B 2019 Rudiment of 'galling: tribological phenomenon'for engineering components in aggregate with the advancement in functioning of the anti-galling coatings *Surf. Interfaces* **17** 100383
[77] Li R, Sun Y, Wu X, Zhang P, Li D, Lin J, Xia Y and Sun Q 2023 Review of the research on and optimization of the flow force of hydraulic spool valves *Processes* **11** 2183
[78] Du Z, Liu M, Zhang Y, Liu W and Yan J 2022 Dynamic simulation and analysis of steam dump valve failure using secondary side model of PWR *Nucl. Eng. Des.* **396** 111886
[79] Kim S-H, Choi J-B, Park J-S, Choi Y-H and Lee J-H 2013 A coupled CFD-FEM analysis on the safety injection piping subjected to thermal stratification *Nucl. Eng. Technol.* **45** 237–48
[80] Chen C, Wang X, Wang M, Qi Y, Zhang J, Tian W, Qiu S and Su G H 2021 CFD simulation of thermal hydraulic phenomena in enclosed cavity of nuclear power plants *Ann. Nucl. Energy* **151** 107953
[81] Qian F and Hu M 2021 Numerical simulation of leakage flow field and acoustic characteristics for safety valve *MATEC Web of Conf.* vol 336 (EDP Sciences) p 01007
[82] Ezekoye L I, Rain M and Thygesen T E 2020 Check valves in nuclear power plants: ASME OM code requirements and industry compliance *Pressure Vessels and Piping Conf.* vol 83884 (American Society of Mechanical Engineers) p V008T08A018

[83] Xu R-Y, Wang H, Peng M-J and Liu Y-K 2022 An improved regularized particle filter for remaining useful life prediction in nuclear plant electric gate valves *Nucl. Eng. Technol.* **54** 2107–19

[84] Lee J K, Kim T Y, Kim H S, Chai J-B and Lee J W 2016 Estimation of probability density functions of damage parameter for valve leakage detection in reciprocating pump used in nuclear power plants *Nucl. Eng. Technol.* **48** 1280–90

[85] Baraldi P, Compare M and Zio E 2014 Uncertainty treatment in expert information systems for maintenance policy assessment *Appl. Soft Comput.* **22** 297–310

[86] Lewandowski R, Denning R, Aldemir T and Zhang J 2016 Implementation of condition-dependent probabilistic risk assessment using surveillance data on passive components *Ann. Nucl. Energy* **87** 696–706

[87] Chisholm B M, Krahn S L and Sowder A G 2020 A unique molten salt reactor feature–the freeze valve system: design, operating experience, and reliability *Nucl. Eng. Des.* **368** 110803

[88] Subekti M and Sunaryo G R 2018 Reliability analysis of RSG-GAS primary cooling system to support aging management program *J. Phys.: Conf. Ser.* **962** 012002

[89] Zubair M and Testoni R 2022 Investigation of loss of feedwater (LOFW) accident in the APR-1400 using fault tree analysis *Sci. Technol. Nucl. Install.* **2022** 4666161

[90] Zhu J, Shuai B, Wang R and Chin K-S 2019 Risk assessment for failure mode and effects analysis using the Bonferroni mean and TODIM method *Mathematics* **7** 536

[91] Zio E 2025 Advances in reliability analysis and risk assessment for enhanced safety *J. Reliab. Sci. Eng.* **1** 013002

[92] Kumar P, Singh L K, Chaudhari N and Kumar C 2020 Availability analysis of safety-critical and control systems of NPP using stochastic modeling *Ann. Nucl. Energy* **147** 107657

[93] Kumar P, Singh L K and Kumar C 2020 Performance evaluation of safety-critical systems of nuclear power plant systems *Nucl. Eng. Technol.* **52** 560–7

[94] Parsaei S, Pirouzmand A, Nematollahi M R, Ahmadi A and Hadad K 2024 Effect of test-caused degradation on the unavailability of standby safety components *Nucl. Eng. Technol.* **56** 526–35

[95] Martorell P, Martón I, Sánchez A I and Martorell S 2017 Unavailability model for demand-caused failures of safety components addressing degradation by demand-induced stress, maintenance effectiveness and test efficiency *Reliab. Eng. Syst. Saf.* **168** 18–27

[96] Maskin M, Hassan A, Brayon F C, Phongsakorn P T, Zakaria M F, Ramli Z and Mohamed F 2018 Quantification of initiating event frequencies and component reliability data in level 1 probabilistic safety assessment at Puspati TRIGA research reactor *Ann. Nucl. Energy* **121** 22–28

[97] He J, Bao T, Wu J, Shao G, Du D, Le X and Zhang Q 2018 Reliability assessment and data processing techniques of the squib valve in pressurized water NPPs *Nucl. Eng. Des.* **332** 59–69

[98] Prakash G and Pandey M D 2025 Reliability assessment and maintenance planning of air-operated control valves used in a nuclear power plant *Nucl. Eng. Des.* **445** 114472

[99] Martón I, Sánchez A I, Carlos S, Mullor R and Martorell S 2023 Prognosis of wear-out effect on of safety equipment reliability for nuclear power plants long-term safe operation *Reliab. Eng. Syst. Saf.* **233** 109121

[100] Wu Y, Liu T, Tong J and Wang C 2025 Mechanical equipment failure rate prediction method for nuclear power plants *Ann. Nucl. Energy* **222** 111596

[101] Martorell S, Martorell P, Sánchez A I, Mullor R, Martón I and Falsone G 2017 Parameter estimation of a reliability model of demand-caused and standby-related failures of safety components exposed to degradation by demand stress and ageing that undergo imperfect maintenance *Math. Probl. Eng.* **2017** 7042453

[102] Utah M N and Jung J C 2020 Fault state detection and remaining useful life prediction in AC powered solenoid operated valves based on traditional machine learning and deep neural networks *Nucl. Eng. Technol.* **52** 1998–2008

[103] Wang H, Peng M, Xu R, Ayodeji A and Xia H 2020 Remaining useful life prediction based on improved temporal convolutional network for nuclear power plant valves *Front. Energy Res.* **8** 584463

[104] Wang H, Peng M-J, Liu Y-K, Liu S-W, Xu R-Y and Saeed H 2020 Remaining useful life prediction techniques of electric valves for nuclear power plants with convolution kernel and LSTM *Sci. Technol. Nucl. Install.* **2020** 8349349

[105] Li G, Chen J, Tao Y, Li A and Zhang X 2024 Residual life prediction of pneumatic control valves based on Trans-TCN-GRU modeling *IEEE Access* **12** 191670–81

[106] Li X, Mba D, Lin T, Yang Y and Loukopoulos P 2021 Just-in-time learning based probabilistic gradient boosting tree for valve failure prognostics *Mech. Syst. Signal Process.* **150** 107253

[107] Gu H, Li Y, Jiang L and Luo Z 2025 A generalized approach for remaining useful life prediction considering the multi-source uncertainty of mechanical systems *J. Reliab. Sci. Eng.* **1** 025301

[108] Zhang X, Wang T, Ma L and Mahadevan S 2025 Reliability engineering, risk management, and trustworthiness assurance for AI systems *J. Reliab. Sci. Eng.* **1** 022001

[109] Lombardo S S, Cadini F and Cammi A 2019 Impact of uncertainties on the safety performances of the LBE-XADS concept nuclear reactor *Nucl. Eng. Des.* **341** 16–24

[110] Kamkar A and Abbasi M 2025 Sensitivity analysis and uncertainty quantification of neutron noise simulations in WWER-type reactors using machine learning-based surrogate models *Nucl. Eng. Des.* **433** 113881

[111] Zheng X, Tamaki H, Sugiyama T and Maruyama Y 2022 Dynamic probabilistic risk assessment of nuclear power plants using multi-fidelity simulations *Reliab. Eng. Syst. Saf.* **223** 108503

[112] Dhulipala S L, Shields M D, Chakroborty P, Jiang W, Spencer B W, Hales J D and Che Y 2022 Reliability estimation of an advanced nuclear fuel using coupled active learning, multifidelity modeling, and subset simulation *Reliab. Eng. Syst. Saf.* **226** 108693

[113] Lye A, Ong T K C, Xiao S and Chung K Y 2025 Physics-enhanced machine learning for probabilistic risk assessment in nuclear safety: an overview, recent developments, and perspectives *Ann. Nucl. Energy* **222** 111562

[114] Lai C, Ahmed I, Zio E, Li W, Zhang Y, Yao W and Chen J 2024 A multistage physics-informed neural network for fault detection in regulating valves of nuclear power plants *Energies* **17** 2647

[115] Wang S and Geng Y 2025 Modeling of complex electromechanical systems based on state-space, graph network and intelligent algorithms: a review *J. Reliab. Sci. Eng.* **1** 032002

[116] Xu R, Peng M and Wang H 2021 Study on the condition monitoring technology of electric valve based on principal component analysis *International Congress and Workshop on Industrial AI* (Springer) pp 141–51

[117] Huang X-Y, Xia H, Liu Y-K, Zio E and Yin W-Z 2025 Fault diagnosis of nuclear power plant electric gate valves based

on acoustic emission signals *Ann. Nucl. Energy* **221** 111519

[118] Liu Z, Liu J, Huang Y, Li T, Nie C, Xia Y, Zhang L, Tang Z and Zhang L 2022 Fault critical point prediction method of nuclear gate valve with small samples based on characteristic analysis of operation *Materials* **15** 757

[119] Kim W, Chai J and Kim I 2015 Development of a majority vote decision module for a self-diagnostic monitoring system for an air-operated valve system *Nucl. Eng. Technol.* **47** 624–32

[120] Kim J, Lee S H and Park K 2025 Numerical modelling of an air operated valve assembly for virtual diagnosis based on experimental diagnosis in nuclear power plants *Nucl. Eng. Technol.* **57** 103403

[121] Zhao Y, Vaddi P K, Pietrykowski M, Khafizov M and Smidts C 2023 An empirical study of the added value of the sequential learning of model parameters to industrial system health monitoring *Reliab. Eng. Syst. Saf.* **240** 109592

[122] Liu Z, Li T, Huang Y, Liu J, Nie C, Zhan L and Tang Z C 2022 Research on fault diagnosis of nuclear gate valve based on analysis of energy variation characteristics of vibration signal *2022 IEEE Int. Conf. on Prognostics and Health Management (ICPHM)* (IEEE) pp 198–202

[123] Gao J-R, Liu Y-K, Duan C-J, Ding P and Song J-Q 2024 Research on fault diagnosis of electric gate valve in nuclear power plant based on the VMD-MDI-ISSA-RF model *Ann. Nucl. Energy* **207** 110701

[124] Luo J, Wang H and Peng M 2021 Anomaly detection of electric gate valve based on multi-kernel support vector machine *Int. Conf. on Nuclear Engineering* vol 85277 (American Society of Mechanical Engineers) p V004T14A064

[125] Huang X-Y, Liu Y-K, Xia H and Shan L-F 2024 Research on fault simulation and fault diagnosis of electric gate valves in nuclear power plants *Ann. Nucl. Energy* **208** 110788

[126] Huang X-Y, Xia H, Yin W-Z, Liu Y-K and Miyombo M E 2023 Research on fault diagnosis method of electric gate valve under strong background noise *Ann. Nucl. Energy* **194** 110055

[127] Huang X-Y, Xia H, Liu Y-K and Miyombo M E 2023 Improved fault diagnosis method of electric gate valve in nuclear power plant *Ann. Nucl. Energy* **194** 109996

[128] Ai X, Liu Y, Shan L, Xie C and Zhou H 2024 A concurrent fault diagnosis method for electric isolation valves in nuclear power plants based on rule-based reasoning and data-driven methods *Prog. Nucl. Energy* **171** 105190

[129] Liu Y-K, Zhou W, Ayodeji A, Zhou X-Q, Peng M-J and Chao N 2021 A multi-layer approach to DN 50 electric valve fault diagnosis using shallow-deep intelligent models *Nucl. Eng. Technol.* **53** 148–63

[130] An Z *et al* 2022 A novel principal component analysis-informer model for fault prediction of nuclear valves *Machines* **10** 240

[131] Cilliers A C 2013 Benchmarking an expert fault detection and diagnostic system on the Three Mile Island accident event sequence *Ann. Nucl. Energy* **62** 326–32

[132] BAllesteros A, Sanda R, Maqua M and Stephan J-L 2017 Maintenance related events in nuclear power stations *Eksploat. Niezawodn.* **19** 26–30

[133] Yang D and Liu H 2017 Application of THERP HCR model for valve overhaul in nuclear power plant *AIP Conf. Proc.* **1839** 020045

[134] Zhan X L, Liu Y and Zeng B 2017 The optimization of valve control strategy for valve periodic test in nuclear power plant *Int. Symp. on Software Reliability, Industrial Safety, Cyber Security and Physical Protection for Nuclear Power Plant* (Springer Singapore) pp 58–64

[135] Do P, Voisin A, Levrat E and Iung B 2015 A proactive condition-based maintenance strategy with both perfect and imperfect maintenance actions *Reliab. Eng. Syst. Saf.* **133** 22–32

[136] Zhang C, Li Y-F and Coit D W 2022 Deep reinforcement learning for dynamic opportunistic maintenance of multi-component systems with load sharing *IEEE Trans. Reliab.* **72** 863–77

[137] Martorell S, Martón I, Sanchez A and Carlos S 2020 Harmonisation of surveillance requirements and maintenance in a context of ageing and obsolescence based on reliability, availability and risk information *Reliab. Eng. Syst. Saf.* **202** 106992

[138] Liu Z, Zhang Q, Liu Y, Lei Y and Zuo M 2025 Intelligent reliability assurance methodologies for engineering systems: advances and challenges *J. Reliab. Sci. Eng.* **1** 032004

Zhuo-Cheng Sun received a BS degree in Process Equipment and Control Engineering from Zhejiang University, Hangzhou, China. He is currently pursuing an MS degree with the Institute of Advanced Equipment, Zhejiang University, Hangzhou, China. His research interests include intelligent operation & maintenance (O&M) and performance testing of smart control valve equipment.

Tong An received a BS degree in Process Equipment and Control Engineering from Zhejiang University, Hangzhou, China. He is currently pursuing a PhD degree with the Institute of Advanced Equipment, Zhejiang University, Hangzhou, China. His research interests focus on the wear field of valve seal components.

Zhao-Le Qian received a BS degree in Process Equipment and Control Engineering from Zhejiang University of Technology, Hangzhou, China. He is currently pursuing a PhD degree with the Institute of Advanced Equipment, Zhejiang University, Hangzhou, China. His research interests focus on the innovative design of special control valves.

Fang-Na Xiang received a BS degree in Process Equipment and Control Engineering from Zhejiang University, Hangzhou, China. She is currently pursuing a PhD degree with the Institute of Advanced Equipment, Zhejiang University, Hangzhou, China. Her research interests include intelligent operation & maintenance (O&M) and performance testing of smart control valve equipment.

Zhang-Yong Jin received an MS degree in Mechanical Engineering from Zhejiang University, Hangzhou, China, in 2025. He is currently pursuing a PhD degree with the College of Energy Engineering, Zhejiang University, Hangzhou, China. His research interests include the design and control of special valves. He has published three academic papers as the first author and holds nine authorized invention patents.

An-Qi Guan received the B.S. degree in Process Equipment and Control Engineering from China University of Petroleum (East China) Qingdao, China. He is currently pursuing the Ph.D. degree with the Institute of Advanced Equipment, Zhejiang University, Hangzhou, China. His research interests include intelligent operation & maintenance (O&M) and fault diagnosis of smart control valve equipment.

Zhi-Jiang Jin is a Professor at the Institute of Advanced Equipment, College of Energy Engineering, Zhejiang University, China. He received a BSc degree in Chemical Process Equipment from East China University of Science and Technology, China in 1990, MSc and PhD degrees in Chemical Process Equipment from Zhejiang University, China in 1993 and 1997, respectively. His research interests include heat transfer, flow control, pipeline safety assessment and computational fluid dynamics. He has coauthored about 100 articles in international journals and conferences.

Jin-Yuan Qian is a Professor, PhD Supervisor, and a recipient of the National Science Fund for Excellent Young Scholars at the Institute of Advanced Equipment, College of Energy Engineering, Zhejiang University, China. He received a PhD degree from Zhejiang University, Hangzhou, China, in 2016. He conducted postdoctoral research at Lund University, Sweden, and Hefei General Machinery Research Institute. His research interests focus on the design theory, vibration reduction, and reliability technology of smart control valves. He has authored over 120 academic papers and holds more than 40 invention patents.