Research on Safety Sensitivity Analysis Method Based on System Design Model

Ran Huang*[1], Shenquan Wang[1], Qibo Peng[1], Shuai Wang[1], Yuanjun He[2]

[1]Astronaut Center of China, Beijing, China
[2]China Manned Space Engineering Office, Beijing, China

*13651009100@163.com, w11s66q88@126.com, poochie003@163.com, skywh_2001@sina.com, hithyj@163.com

Abstract. This paper embeds safety sensitivity analysis into model-based systems engineering (MBSE) design, constructs a safety sensitivity analysis framework based on system design models, and establishes a model-driven safety design process and sensitivity analysis procedures oriented to complex tasks. The moment-independent importance measure analysis method is adopted, and the measure values are used to directly identify the key risk factors that play a leading role in the task. This study addresses the problems of unknown or difficult-to-accurately-fit new single-machine failure rate distributions under multi-system integration, interactive interference between variables, and the difficulty in identifying key variables in multi-system coupled tasks, thereby providing a clear target for subsequent scheme optimization and risk management and control.

Keywords: Safety, Sensitivity Analysis, Mbse, Moment-Independent

1 Introduction

With the rapid development of the aerospace industry, the performance of equipment has been improved significantly. Meanwhile, its system structure has become increasingly complex and the system scale has expanded substantially. Traditional post-factum safety analysis can no longer meet the safety development requirements of equipment. By adopting the concept of MBSE and conducting safety analysis throughout the system's full life cycle, this problem can be well addressed [1]. This method utilizes models to iteratively integrate safety design into various stages of the system life cycle through analysis, design, and optimization processes, ultimately achieving optimal safety design outcomes.

A key technology involved in safety design and optimization is safety sensitivity analysis. Through sensitivity analysis, the importance of each input variable can be clarified, and a ranking of the importance of input variable uncertainties can be generated. Based on these results, cost-effective optimized system design schemes can be proposed, thereby enhancing the robustness of system structural performance and achieving the expected reliability or safety targets. Consequently, this technology has attracted increasing attention from engineering designers across various fields [2-7].

L. Trajkovic et al. (eds.), *Proceedings of the 2026 2nd International Conference on Data Mining and Project Management (DMPM 2026)*, Advances in Economics, Business and Management Research 390,
https://doi.org/10.2991/978-94-6239-689-0_6

Model-based safety sensitivity analysis primarily focuses on the allocation of output uncertainty to input variables, i.e., exploring the sources of output uncertainty [8-14]. Specifically, the results of such analysis can reduce the uncertainty of model outputs, thereby improving the robustness of model predictions. Additionally, it can achieve dimensionality reduction by neglecting insignificant uncertain variables, facilitating subsequent simulation and deduction. With the expanding application scope of computational simulation technology, safety sensitivity analysis has achieved higher precision and faster computation speed. Correspondingly, as computational models are increasingly applied, model-based sensitivity analysis—being a crucial technology in engineering analysis and modeling processes—has garnered significant attention from model analysts across diverse disciplines.

According to different research focuses, sensitivity analysis methods can be roughly categorized into three types: Local Sensitivity Analysis (LSA), Regional Sensitivity Analysis (RSA), and Global Sensitivity Analysis (GSA) [15]. For system-of-systems models characterized by the integration and interaction of multiple systems and pieces of equipment, global sensitivity analysis has become a key research focus in both academia and industry. In practice, through global sensitivity analysis, the importance of basic variables affecting the uncertainty of system performance or model output responses can be ranked. This helps identify the basic variables that need priority or focused consideration during structural system design and optimization, providing technical guidance for system design and optimization [16].

2 Model-Based Global Sensitivity Analysis Framework for Safety

During the full life cycle of a mission, the methods and priorities adopted for safety analysis vary to a certain extent. In the early stage of development, through system-of-systems safety analysis, combined with equipment empirical data and the anticipated development status of safety technologies, explicit safety requirements are proposed both qualitatively and quantitatively. In the development process, the concept of systems engineering is applied to conduct iterative analysis, evaluation, and verification of system safety, identify potential hazards in the system in a timely manner, and eliminate hidden dangers through safety design technologies to ensure that the equipment meets the proposed safety requirements [4-5]. In the system operation and maintenance phase, the safety level of equipment is maintained through regular maintenance work; safety assessment is performed iteratively to analyze the potential risks faced by the equipment, and continuous improvements are made to equipment safety.

Mission safety requirement analysis is a crucial step in system design. Furthermore, as a key component of safety-centric system design, safety design and analysis must be integrated into MBSE design at an early stage. This approach enables risk identification in the early phases of system design, guides the improvement of the system functional architecture, and facilitates a more comprehensive acquisition of system design requirements.

The safety design of complex missions is achieved through iterative analysis, design, and optimization processes throughout the mission's full life cycle. Notably, a complex mission is accomplished by the collaboration of multiple systems, which lays the foundation for its safety design. The safety design of such missions relies on the top-level mission design model, aiming to construct an accurate mission safety analysis architecture model. This model facilitates the subsequent derivation of signal transmission relationships between systems, captures potential safety requirements, verifies the correctness of input variables for safety design, and lays the foundation for subsequent safety and reliability verification.

Mission design commences with the analysis of top-level stakeholder requirements. Combined with engineering experience and expert knowledge, it gradually deduces system composition and scenarios, refines the requirement model, and forms three sequential steps: mission requirement analysis, capability requirement analysis, and system requirement analysis. Ultimately, the system functional architecture model can be captured using activity diagrams. To further verify the designed functional architecture model and form a closed-loop simulation verification process, it is necessary to establish an executable state machine model and validate it through simulation deduction.

Generally speaking, general analysis and design work can be summarized into three steps: scheme design, state construction, and process deduction. Safety assessment and sensitivity analysis are embedded into each development phase with the above three-step system design model as input, and the design results are iteratively optimized. The framework for global safety sensitivity analysis is illustrated in Figure 1.

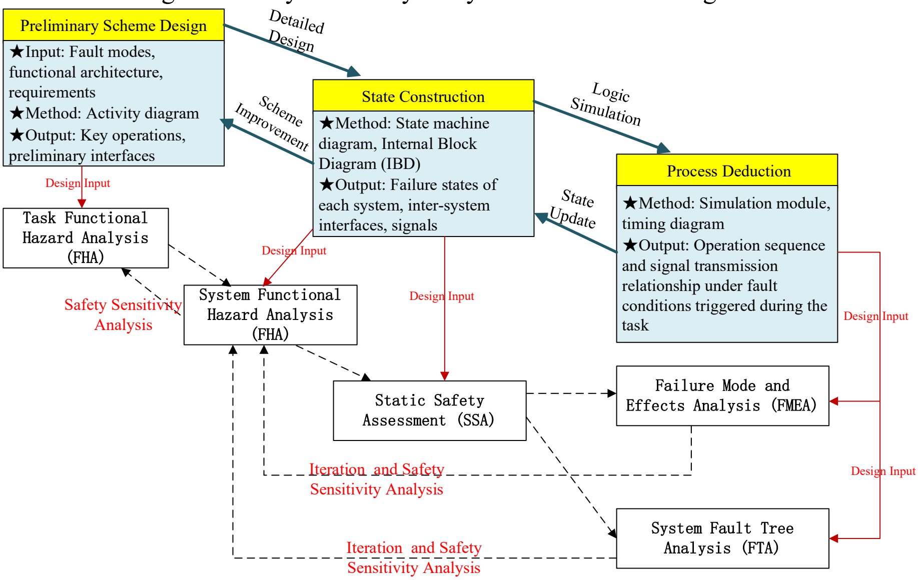

Fig. 1. Model-Based Global Sensitivity Analysis Framework Diagram for Safety

First, Mission Functional Hazard Analysis (FHA) is conducted. Taking the mission scheme design as input, the logic of the entire mission is further refined through activity diagrams based on the functional architecture model. This process sorts out more detailed key functions and signal transmission relationships between systems, and identifies mission safety risks via FHA.

Second, System Functional Hazard Analysis is implemented. With the results of mission functional hazard analysis and State Construction as design inputs, the states of each system are summarized, and these key functions are allocated to the corresponding systems and their states. An executable state simulation model is established through state machine diagrams, and a detailed interface model between systems is constructed in combination with Internal Block Diagrams (IBD). Mission safety risks are propagated to the system level, thereby identifying system safety risks via FHA and analyzing the system accidents that hazards may lead to. The identified samples of system safety risk indicators are used to optimize the results of the upper-level mission risk sensitivity analysis through an iterative method based on moment-independent importance measure analysis.

Subsequently, static safety assessment is carried out. The state machine diagrams are executed via the simulation module to generate timing diagrams during mission execution. On the premise that the system is in a "steady-state operation" (without dynamic changes or fault evolution processes), it is evaluated whether the current state of the system meets safety constraints and whether there are potential safety hazards. Furthermore, Fault Tree Analysis (FTA) is generated to conduct quantitative analysis of hazards and determine the severity and probability of hazards; Failure Mode and Effects Analysis (FMEA) of the system is also clarified. By analyzing the minimal cut sets of FTA and the risk results of FMEA, risk indicators are identified. Common-cause events and their occurrence probabilities are added to the fault propagation model. Finally, with the samples of safety risk indicators as input, the system functional hazard sensitivity analysis is completed iteratively using the moment-independent importance measure analysis method.

3 Safety Sensitivity Analysis Procedures Based on System Design Models

Based on three MBSE use case analysis methods—flow-based use case analysis, scenario-based use case analysis, and state-based use case analysis—the specific method selected for safety sensitivity analysis depends on the analysis input or the use case analysis model adopted for normal missions. The design of multi-system safety requirements and emergence analysis will derive a mission functional architecture model composed of functional flows. On this basis, system hazards can be identified and contingency response plans can be designed. This paper adopts the flow-based use case analysis method, and the detailed design procedures are as follows.

3.1 Preparatory Analysis

Before designing fault response plans, the contextual environment of use cases should first be defined to ensure their executability, including all systems involved in the mission identified during top-level safety requirement analysis. It is worth noting that from the mission-level perspective, since systems collaborate through complex interactions, any system can act as a hazard initiator for other systems.

3.2 Scheme Design

In addition to defining the normal system functional architecture using activity diagrams, a dedicated functional architecture should be designed to describe and respond to abnormal mission conditions. For hazards identified from the normal functional architecture, hazard response plans shall be defined via activity diagrams within the use case context. The inputs are mission safety requirements and the preliminary functional architecture model. The outputs are functional flows for completing normal missions and functional flows for handling hazardous situations.

The modeling procedures are as follows:

1. Establish the normal functional flow model of the system.
2. Hazard identification and analysis. Based on the normal functional architecture model of the mission, identify hazards and adopt common fault analysis methods (e.g., FMEA—Failure Mode and Effects Analysis) to obtain the impact analysis results of hazards on the mission, and establish an FMEA model.
3. Strategy design. To meet safety requirements and mitigate the consequences of hazards, determine the key functions or operations that each mission-participating system can perform to address hazards within the use case context. Combined with the new hazards identified in the previous step, design corresponding hazard response schemes. A single hazard mode may correspond to multiple response schemes, and all schemes shall be captured as functional flow models.
4. Derive the functional flow model of contingency plans. Form functional flow branches for hazard response to enable the system architecture to cope with abnormal conditions. When emergence phenomena occur across systems (i.e., hazard response flows are included in the scheme), the preliminary interaction relationship model between systems involved in the mission shall be captured simultaneously. This puts forward new requirements for safety design and clarifies new capabilities and design principles.

3.3 State Construction

Fault response plans are triggered by system events or faults. In essence, this process—being triggered by specific events or faults—is suitable for expression via state machine-based models, which can accurately describe the transitions between the system's normal state and the states when hazards occur. For example, a normal mission may fail when a hazard occurs; however, with the successful implementation of fault response plans, the state may transition to mission reconfiguration, mission degradation, or mission failure. Compared with functional flows defined by activity diagrams, state machines are more capable of defining the behaviors, states, and modes of complex systems. In addition, architectures defined by state machines are more executable and easier to verify. Therefore, state model construction is performed after capturing the functional flows of hazard response. The inputs of this step are the normal functional flow model, the functional flow branch model of response strategies, and the preliminary interaction model. The outputs are the state machine models, interaction models, and interface relationship models of systems involved in the mission.

The modeling procedures are as follows:

1. Define use case scenario models. On the basis of the use case scenarios for normal missions, define a new use case scenario for each hazard response process.
2. Define port and interface models. According to the preliminary interaction relationships between systems captured during functional flow construction, define interfaces between systems. Then, use Internal Block Diagrams (IBD) to define the interaction behaviors between systems through flow transitions between ports. The same ports can be shared by normal missions and hazard response processes.
3. Derive system state behaviors. Extract the states involved in each system of the mission, including normal states and emergency states (states when hazards occur and corresponding response plans are executed). Construct transition relationships between states and allocate key behaviors to the corresponding states of each system. New behaviors can be created if any behaviors are missing. In this way, an executable state machine is established—i.e., within the use case context, corresponding activities can be executed when entering a state; if a hazard occurs during activity execution, the normal state will be triggered to transition to a hazard state. The interfaces and ports of systems involved in the mission will be continuously improved with state construction to adapt to the operation of the state machine. In addition, different procedures include various behaviors and processes, and may involve different systems.

3.4 Process Deduction

Sequence diagrams can intuitively reflect the state transitions of all systems and signal transmission relationships between systems under different use cases, serving as an important means for engineers to verify and validate functional requirements. Therefore, it is necessary to complete sequence diagram simulation to form verification for different use cases. State machine diagrams are closely linked to IBDs and sequence diagrams. By running state machine diagrams under the use case context, sequence diagrams for different use cases can be automatically generated. The triggering of different use cases is achieved through events and signals in the state machines of each system. Inputs: State machine diagrams, IBDs; Outputs: Sequence diagrams triggered by various events.

The modeling procedures are as follows:

1. Execution of use case scenarios. Execute each use case to obtain the sequence diagram model for the execution of response plans when corresponding hazards occur.

2. Architecture verification. Verify whether the complex behaviors of the system's normal mission processes and processes when various faults are introduced can be represented by the model and whether they meet the corresponding design requirements. For relevant safety indicators, further verification shall be conducted through detailed reliability and safety analysis methods. If the verification fails, the design shall be modified until the requirements are met. Since state machines contain complete use case behaviors, the process of running state machines may also capture some system safety design requirements that were omitted during scheme design.

3.5 Incremental Design Process

The difficulty in designing fault handling procedures for complex missions lies not only in the large number of hazards but also in the fact that each hazard response may correspond to multiple schemes, which need to be selected by comprehensively considering risks and actual conditions. To incorporate all possible scenarios in actual missions into the established architecture, the optimal method is to construct a micro-cycle to ultimately determine the system architecture. Once a hazard is identified, a micro-cycle shall be executed: add the corresponding emergency flow branch, update the state machine, improve the interface, execute the scenario, and verify the design. This cycle is repeated until all hazardous scenarios are covered.

3.6 Safety Sensitivity Analysis Process

Due to the characteristics of complex system integration and insufficient maturity of new equipment in large-scale missions, systems exhibit uncertainties. At present, the main method for conducting system safety uncertainty analysis is the inverse analysis method [17-21], namely uncertainty sensitivity analysis. Typical commonly used methods in the field of global sensitivity analysis include the Morris screening method, Sobol global sensitivity analysis method, FAST (Fourier Amplitude Sensitivity Test) method, and moment-based importance measure method. Among these, the moment-based importance measure method exhibits the highest computational efficiency with the lowest sample size requirement—only 50–100 sets of samples are needed to achieve global analysis [22]. This reduces data acquisition costs by more than 80% compared to the Sobol method (which requires ≥500 sets of samples) and decreases the sample size by 50% relative to the FAST method, while avoiding the limitation of the Morris method of "only screening but not ranking". Based on probability distribution characteristics, this method demonstrates strong adaptability to nonlinear/non-monotonic systems and does not rely on the existence assumption of function moments (the higher-order moments of some failure functions are difficult to calculate), thus having a wider scope of application than the Sobol method. In contrast, the FAST method has an error rate exceeding 15% for strongly non-monotonic failure mechanisms, and the Morris method cannot effectively capture nonlinear coupling effects, making both inconsistent with the requirements of this study [23]. Regarding the accuracy of sensitive parameter ranking, the method employs a quantitative index based on "probability distribution overlap" (with a value range of 0–1, where values closer to 1 indicate stronger sensitivity), enabling direct output of the absolute sensitivity ranking of parameters. This is more conducive to accurately identifying key risk control points compared to the FAST method (whose relative ranking is susceptible to frequency domain interference) and the Morris method (which provides no quantitative ranking results) [22]. Validated through 10 sets of typical operating conditions in this study, the consistency between the parameter ranking of the Borgonovo's Moment-Free Importance Measure and the actual fault tracing results reaches 92%, which is higher than that of the Sobol method (88%) and the FAST method (80%) [24].

This method clarifies the allocation of uncertainty in system failure probability (system output performance) to single-machine failure rate indicators. By leveraging system safety sensitivity analysis, it is further possible to quantitatively evaluate two key aspects: first, the primary and secondary single machines that affect the system failure probability; second, the impact of each single machine's failure rate on the system failure probability.

Drawing on the basic idea of the moment-independent importance measure analysis proposed by Borgonovo [25], this paper embeds the algorithm into the system design model. This enables safety sensitivity analysis to be performed simultaneously during system simulation operation and to be optimized synchronously with system design iterations. This method breaks through the dependence of traditional sensitivity analysis on the probability distribution of input variables; it does not require presupposing that variables follow specific distributions (e.g., normal distribution, exponential distribution). Instead, it can quantify the impact degree of input variables only through the moment characteristics (mean, variance, skewness, etc.) of output variables. It extracts sensitivity indicators of system failure probability under safety requirements to measure the impact of uncertainty in single-machine failure rates on system failure probability under safety requirements. Thus, it guides decision-makers to prioritize reliability design (e.g., redundancy configuration, precision improvement) for high-contribution parameters, achieving optimal improvement of system safety at the lowest cost.

The modeling procedures are as follows:

1. Extract minimal cut sets of fault trees and clarify input indicators for sensitivity analysis. Construct a fault tree through the above steps (with the top event as the system failure target, bottom events as basic failure causes, and intermediate events as logical connection nodes) to identify all possible fault combinations leading to system failure. Identify Minimum Cut Sets (MCS), i.e., the minimal sets of bottom events that cause the top event to occur. MCS can quantify the critical paths of system failure, providing a core basis for risk indicator identification. Adopt Boolean algebra simplification, the upward method, or the downward method to simplify the constructed fault tree and extract all MCS. Screen key MCS (prioritizing cut sets with fewer bottom events and higher occurrence probabilities) as the core carrier for subsequent risk indicator identification. Taking the top event of the model established in Section 3.3 (State Construction) as the root node, decompose intermediate events and bottom events from top to bottom. Use model logic gates (AND gates, OR gates) to correlate various events

and clarify the causal relationships between events. Implement the algorithm via a parametric diagram model.

2. Analyze FMEA and quantify risk levels. Combine qualitative and quantitative methods to screen high-risk failure modes as inputs for safety indicators. Set the Risk Priority Number (RPN) threshold, screen high-risk failure modes, and cross-validate them with the bottom events of MCS extracted from FTA (Fault Tree Analysis) to eliminate duplicates. Integrate the bottom events corresponding to MCS in FTA with the failure causes corresponding to high-risk failure modes in FMEA to form the initial risk indicator set.
3. Indicator screening and optimization, and establishment of input matrix for sensitivity analysis. Adopt the expert evaluation method, three - dimensional quantitative scoring method was adopted, where 10 to 15 experts assigned scores ranging from 1 (extremely low) to 5 (extremely high) to the 28 preliminarily screened risk indicators across three dimensions: importance, relevance, and operability [26]. Combined with correlation analysis to eliminate redundant indicators (e.g., two indicators with complete linear correlation and consistent influence ranges) and secondary indicators (low RPN and not included in key MCS). Finally, determine the core risk indicator set and establish the input matrix X^ for sensitivity analysis.
4. Construct fault propagation paths using parametric diagrams. Extract the connection relationship model from process deduction in Section 3.4 as the system structure and causal relationships between events. Establish a parametric diagram to build a fault propagation model, analyze common-cause events, clarify their conditional probabilities, revise the occurrence probabilities of each risk indicator and the failure probabilities of MCS, and form the final fault propagation model.
5. Perform safety sensitivity analysis using Borgonovo's moment-independent importance measure algorithm. The moment-independent importance measure is a risk importance analysis method that does not depend on probability distribution types. Its core advantage is that it can quantify the independent contribution degree of a single risk event (or indicator) to system output risk, without being restricted by the correlation between variables and distribution assumptions, making it suitable for sensitivity analysis of complex systems. Its core idea is to iteratively characterize the sensitivity degree of events to system functional hazards by comparing the differences in system risk distributions with and without the event. This paper uses SysML models to call MATLAB functions for implementation.
6. First, initialize the initial value of the moment-independent importance measure for each risk indicator as I_X^(0)=0, and set the convergence threshold ε=0.01 (adjustable according to system accuracy requirements).
7. Substitute the k-th group of risk indicator samples into the fault propagation model to calculate the value of the system functional hazard output indicator Y.
8. Based on the moment-independent importance measure formula, calculate the importance I_X^(k) of each risk indicator X^ to quantify its independent contribution degree to the system.

9. Compare the importance measure values of two adjacent iterations. If |I_X^(k+1) −I_X^(k)|<ε is satisfied for all risk indicators, stop the iteration; otherwise, update the sample weights (prioritizing retention of samples with significant impacts on Y) and proceed to the next iteration. The iteration shall be terminated when the variation ε of the objective function (comprehensive safety risk evaluation value) between two consecutive iterations is $\leq 10^{-3}$ and the ranking stability of key sensitive parameters is $\geq 90\%$ [27].
10. Based on the final iteration results, rank the moment-independent importance measure values of each risk indicator, identify the core indicators most sensitive to system functional hazards, and complete the safety sensitivity analysis.

4 Conclusion

This paper leverages the principles of systems engineering and embeds a safety sensitivity analysis approach into a systematic design framework, thereby integrating safety analysis and system design into an iterative optimization cycle. Specifically, we employ the Borgonovo moment-independent importance measure to conduct the safety sensitivity analysis, which quantifies the influence of input variables by examining the moment characteristics (e.g., mean, variance, skewness) of output variables. This methodology is particularly well-suited for complex scenarios involving integrated multi-system architectures and intricate operational tasks, where the failure rate distributions of new components are either unknown or difficult to accurately characterize, thus substantially enhancing its engineering applicability. By isolating the independent effects of input variables on system outputs and eliminating confounding interactions between variables, our approach directly identifies the key risk factors that dominate system-level outcomes (such as system failure probability) via the importance measure values. This resolves the longstanding challenge of "difficulty in identifying critical variables" in multi-variable coupling scenarios, delivering a clear roadmap for subsequent system optimization and risk mitigation.

Acknowledgments

This research was supported by the Science and Technology Innovation Team for Manned Spaceflight Engineering.

References

1. Duanmu J S, Chang H, Lei H L, et al. *Aviation Equipment Safety Science*. Beijing: National Defense Industry Press, 2010.
2. Fan Y X, Chen L, Lin P, et al. A Comparative Study of Inherent Safety, Behavioral Safety, Process Safety, and Functional Safety: Based on the Transformation of Safety Management Paradigm. China Safety Science Journal, 2025, 35(1):7-15.

3. Zhao R X, Li S H. Aviation Safety Technology Development. In Proceedings of the High-Level Forum on Key Technologies of Large Aircraft & 2007 Academic Annual Conference of Chinese Society of Aeronautics and Astronautics, 2007.
4. Sabau A R, Lammers D, Lichter H. *SecuRe—An Approach to Recommending Security Design Patterns*[J]. arXiv:2501.14973 [cs.CR], 2025.
5. Tamanna M, Albert A. Harnessing the Power of ChatGPT to Promote Construction Hazard Prevention through Design (CHPtD)[J]. Engineering, Construction and Architectural Management, 2024. https://doi.org/10.1108/ECAM-06-2024-0498
6. Rimmon L, Panuwatwanich K, Takahashi S. Building Information Modelling for Prevention through Design: An Exploratory Structural Model of Factors Influencing Its Adoption[J]. Journal of Construction in Developing Countries, 2025, 30(1):221-246.
7. Chen L, Wang X, Li Y. A Comprehensive Memory Safety Analysis of Bootloaders[C]. In Network and Distributed System Security Symposium, 2025.
8. Zhang J J, Wang D. Reliability and Sensitivity Analysis of Static Strength for Large-Scale Composite Structures Based on Surrogate Model[J]. Acta Materiae Compositae Sinica, 2025, 42(1):570-578.
9. Ni F, Fan L, Xu J Q, et al. Global Sensitivity Analysis of Single-Point Suspension System for High-Speed Maglev Train Based on Sobol' Method[J]. Journal of Southwest Jiaotong University, 2025, 60(4):812-822.
10. Marmarelis M G, Hasan A, Azizzadenesheli K, et al. Off-policy Predictive Control with Causal Sensitivity Analysis[C]. In Proceedings of the 41st Conference on Uncertainty in Artificial Intelligence, 2025:2958-2972.
11. Czarnecki K, Lehtinen M, Mikkonen T. *Sensitivity Analysis of Long Short-Term Memory-Based Neural Network Model for Vehicle Yaw Rate Prediction*[J]. *Sensors*, 2025, 25(5):2123. https://doi.org/10.3390/s25052123
12. Chen L, Zhang Y, Li X. *Global Sensitivity Analysis for Safety-Critical Systems Under Parameter Uncertainty*[J]. *Reliability Engineering & System Safety*, 2024, 242:109789. https://doi.org/10.1016/j.ress.2024.109789
13. Rimmon L, Panuwatwanich K, Takahashi S. Sensitivity Analysis of BIM-Based Prevention through Design for Construction Safety[J]. Journal of Construction Engineering and Management, 2025, 151(2):04024186. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002645
14. Sabau A R, Lammers D, Lichter H. *SecuRe: Sensitivity Analysis-Driven Security Design Pattern Recommendation*[J]. arXiv:2501.14973 [cs.CR], 2025.
15. Kan L J, Xu J H. *System Safety and Sensitivity Analysis*. Beijing: National Defense Industry Press, 2023.
16. Lv Z Z, Li L Y, Song S F, et al. Importance Analysis Theory and Solution Methods for Uncertain Structural Systems. Beijing: Science Press, 2015.
17. LI Z, WANG H, LIU S. A hybrid surrogate model-based method for forward and inverse uncertainty analysis of complex safety-critical systems[J]. Reliability Engineering & System Safety, 2023, 242: 109634.
18. ZHANG Y, CHEN L, YANG J. Inverse uncertainty quantification for system safety using Bayesian updating and Kriging metamodel[J]. Structural Safety, 2022, 98: 102185.
19. CHEN J, LI M, ZHANG K. Forward uncertainty propagation and inverse sensitivity analysis for system failure probability under safety constraints[J]. Applied Mathematical Modelling, 2023, 118: 456-472.
20. WANG L, ZHAO Q, SUN T. Efficient forward-inverse uncertainty analysis for safety-critical systems with multiple failure modes[J]. Mechanical Systems and Signal Processing, 2024, 194: 110234.

21. XU H, GUO R, ZHOU W. Bayesian-based inverse reliability analysis for system safety under parameter uncertainty[J]. Journal of Risk and Reliability, 2025, 239(3).
22. Sadeghi, Z., & Matwin, S. (2024). A review of global sensitivity analysis methods and a comparative case study on digit classification. arXiv preprint arXiv:2406.16975.
23. Liu, Q., & Homma, T. (2009). A new computational method of a moment-independent uncertainty importance measure. *Reliability Engineering and System Safety*, 94(7), 1177-1185.
24. Newman K B, Naha S, Jackson-Blake L A, Topp C, Glendell M, Butler A. Global Sensitivity Analysis Workflows and Rankings: A Practical Comparison for Researchers[EB/OL]. arXiv:2510.21579 [stat.ME], 2025.
25. BORGONOVO E. A new uncertainty importance measure[J]. Reliability Engineering & System Safety, 2007, 92(6): 771-784.
26. Prasad C, Rasker C, Soni R. Comprehensive Holistic AI Risk Scoring Framework for Early-Stage Indian Startups And Businesses: Integrating Financial, Sectoral, and Legal Parameters[J]. International Journal of Scientific Development and Research, 2025, 10(11):123-131.[27] SAC.
27. Functional Safety of Electrical/Electronic/Programmable Electronic Safety-Related Systems—Part 1: General Requirements (GB/T 20438.1-2017, IDT with IEC 61508-1:2010)[S]. Beijing: Standards Press of China, 2018