Automatic Accident Sequences Generation for Dynamic PSA

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Abstract: Probabilistic safety assessment (PSA) is a crucial tool for evaluating and managing risks in complex systems, traditionally utilizing a static, structured approach based on event trees (ETs) and fault trees. Static-based PSA has limitations when modeling realistic, time-dependent scenarios and their interactions. To address this, the dynamic event tree (DET) method has been developed to accurately assess risks by simulating dynamic scenarios, often incorporating thermal-hydraulic code simulations to identify success and failure sequences. Conducting a risk analysis using DET to improve the accuracy of consequence analysis of the system state or operator action time significantly increases the number of ET branches, which may make interpretation and understanding challenging for analysts. In this study, we proposed an algorithm that automatically generates accident sequences based on a specified number of branching points. The algorithm also improves the accuracy of the result analysis by using optimized simulations to search the limit surface, which defines the boundary between success and failure regions. In the proposed algorithm, the alpha shape method is employed to identify candidate branching points, effectively covering most success scenarios in high-dimensional simulation spaces. To demonstrate the algorithm's applicability, we present a case study of a loss of coolant accident (LOCA), which includes dynamic features with LOCA break sizes and operator recovery times for two operator tasks.

Keywords: Probabilistic Safety Assessment, Dynamic Event Tree, Alpha Shape, Loss of Coolant Accident

1. INTRODUCTION

In recent decades, probabilistic safety assessment (PSA) has been widely applied in many fields such as the nuclear industry and aerospace [1]. PSA is a static-based, comprehensive, and structured approach where a combination of event tree (ET) and fault tree (FT) are used to identify failure scenarios and evaluate the risk of complex systems using Boolean logic [2, 3]. PSA is supported with deterministic safety analysis using thermal-hydraulic safety analysis code to strengthen the modeling of accident scenarios which typically involve complex interactions among physical processes, safety systems, and operator actions [4]. Each methodology has played a sufficient role in presenting the possibility and consequence of risk assessment through integrated deterministic-probabilistic safety assessment. However, as types of nuclear facilities diversify, particularly with the advent of small modular reactors and new technologies such as passive systems and digital instrumentation control and automation systems, and as the scope of safety evaluations expands spatially and temporally for checking safety requirements or safety goals, the need for optimal evaluation through realistic scenario analysis is increasing. Improving the realism of accident progression modeling is one of the key PSA technical challenges [5].

From the perspective of traditional PSA, there are some key limitations, such as that physical, temporal, and spatial dependencies are only loosely considered [6]. Other limitations of traditional approaches include challenges in the representation of changes in the order of events, difficulty for capturing the effects of event timing, and accounting for epistemic uncertainties [7]. These limitations have driven the development of dynamic probabilistic safety assessment (DPSA) or simulation-based PSA as a more robust and realistic approach to safety evaluation. DPSA integrates time-dependent probabilistic analysis with system dynamics, allowing for the assessment of safety more comprehensively. This approach considers the temporal evaluation of system states and their interactions with stochastic processes, thereby providing a more accurate representation of potential failure scenarios. The foundation of DPSA lies in its ability to model the behavior of complex systems over time, incorporating both deterministic and probabilistic elements.

Early DPSA research focused on the application of dynamic reliability analysis methods such as Monte Carlo simulation and Markov chains. These techniques enabled the modeling of time-dependent behaviors and the assessment of system reliability over a specified period. For instance, Monten Carlo simulation was utilized to explore numerous possible system trajectories and identify critical failure paths in nuclear power plants [8] Similarly, Markov chain models have been employed to represent the probabilistic transitions between different system states, capturing the dynamic nature of operational and failure processes [9]. Recent advancements in DPSA have seen the incorporation of more sophisticated modeling frameworks, such as dynamic event tree (DET) and Petri nets. DET extends traditional ET analysis by allowing for the branching of system states based on both deterministic and stochastic events over time. This method provides a powerful tool for analyzing complex, time-dependent scenarios and understanding the interactions between different system components [10]. On the other hand, Petri nets offer a graphical and mathematical modeling approach that is particularly useful for representing concurrent and asynchronous events in systems [11]. In addition, dynamic integrated consequence evaluation (DICE) was developed as a notable advancement in DPSA methodology [12]. DICE facilitates the integration of real-time data and advanced computational techniques to dynamically update safety assessments as new information becomes available. DICE consists of a scheduler that supports the exchange of information between modules, including a physical module for thermal-hydraulic simulations, a diagnosis module for specifying branching points for safety systems, and a reliability module for providing system availability. This approach emphasizes compliance with traditional PSA methodologies while providing enhanced capabilities for investigating unforeseen scenarios [12].

The application of DPSA has expanded beyond traditional industries to include areas such as autonomous systems, cyber-physical systems, and infrastructure resilience. For example, in the field of autonomous systems, DPSA has been used to evaluate the safety of self-driving vehicles by modeling the interactions between the vehicles, their environment, and other road users [13]. In the realm of cyber-physical systems, DPSA helps in assessing the resilience of critical infrastructures against cyber-attacks and physical disturbances [14]. Despite the significant progress made in DPSA research, several challenges remain. One of the primary challenges is the computational complexity associated with modeling and analyzing large-scale dynamic systems. The need for high-fidelity models and extensive simulations can lead to significant computational resource requirements. The integration of human factors and organizational behaviors into DPSA models also presents another layer of complexity, as these elements are inherently difficult to quantify and predict. To address some of these challenges, recent studies have also explored the use of machine learning and artificial intelligence to improve the accuracy and efficiency of DPSA, further expanding its applicability and robustness [15,16]. Also, a human reliability evaluation method to quantify variability regarding operator action timing, which is for the application of DPSA [17].

However, there is still a pressing need to improve the efficiency and accuracy of DPSA methodologies. One of the key unresolved challenges is to analyze the optimized simulations such that dynamic event tree analyses can be performed quickly and accurately. This should enable decision-makers to interpret and understand the results with high precision and speed, facilitating more effective and timely safety interventions. The integration of advanced algorithms and computational techniques in DPSA remains a crucial area of ongoing research, aimed at enhancing the robustness and reliability of nuclear safety assessment. In this paper, an algorithm for automatically generating the dynamic accident sequences in the concept of the DET is proposed to analyze the optimized simulations on high-dimensional spaces. In the proposed algorithm, the alpha shape method was adopted to represent the candidate points that can encompass most of success scenarios from multi-dimensional optimized simulation results by capturing the geometric and topological properties of a point set. Once the candidate points are determined from the alpha shape, the optimal points that include the most success scenarios based on a user-specified number of points can be identified. Then, the DET can be automatically generated from the optimal points in the dynamic accident sequences. To demonstrate the applicability of the proposed algorithm, a case study for loss of coolant accident (LOCA) with dynamic features for LOCA break size and action time for two operator tasks.

2. METHOD

In this section, the steps for generating the DET using optimized simulation results from the high-dimensional spaces are focused on an automatic accident sequences generation algorithm in Figure 1.

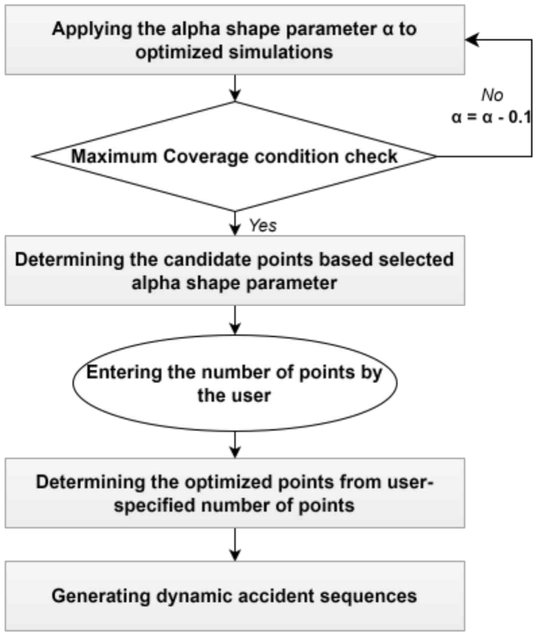

Figure 1. Flowchart of an automatic accident sequences generation algorithm

First, the alpha shape parameter α is applied to optimized simulation results in the high-dimensional spaces for analyzing the optimized simulation results. The alpha shape method has been used to capture the shape of a set of points in two dimensions or higher dimensions, defining the shape of a point set by connecting the points based on a given radius alpha shape parameter α [18]. Also, it can effectively detect and analyze complex shapes in high-dimensional data by allowing for the adjustment of the granularity of the shape, making it useful for defining the boundary of high-dimensional point sets. In the process of applying the alpha shape method, the circles (or shperes in higher dimensions) of radius alpha shape parmeter α around the points are firstly drawn. And, the points whose circles overlap are connected by creating edges between them. All the edges are combined to form a polygon (or polytope in higher dimensions). In this process, the value of the alpha shape parameter α determines the granularity of the shape meaning that a smaller alpha value results in a more detailed outline while a larger alpha value produces a smoother outline. Then, the points existing on the outline are filtered out when the hyper cuboid generated from each point is overlapped or included in the other hyper cuboids generated by other points. The remains are determined as the candidate points.

Second, the maximum coverage condition is checked whether it is satisfied or not when the candidate points are determined in the first step. Here, the maximum coverage condition is defined as how many success scenarios can be covered by the candidate points among the entire success scenarios in the optimized simulations, and the maximum coverage can be calculated as the number of success scenarios existing in the hyper cuboids generated from all candidate points divided by the number of success scenarios in the optimized simulations. If the condition is not satisfied, the first and second steps are iterated while lowering the alpha shape parameter α by 0.1 until the condition is satisfied.

Once the parameter α satisfying the maximum coverage condition is determined, the points selected with the corresponding parameter α are determined and stored as final candidate points. And then, the user enters how many out of all the candidate points to consider.

Next, by considering hypercuboids generated from all combinations that can be made by the number of points entered between all candidate points, the optimal case with the largest number of success scenarios is selected and the corresponding points are determined as the optimal points. As shown in Figure 2, when there are candidate points that satisfy the maximum coverage condition through the alpha shape method for the limit surface bolded in black searched through optimized simulations in two dimension spaces, the point that includes the most success scenarios existing in the identified success box is selected as the optimal point if only one branching point is considered.

Finally, an accident sequences are generated in the form of DET based on the value of each axis of the selected optimal point.

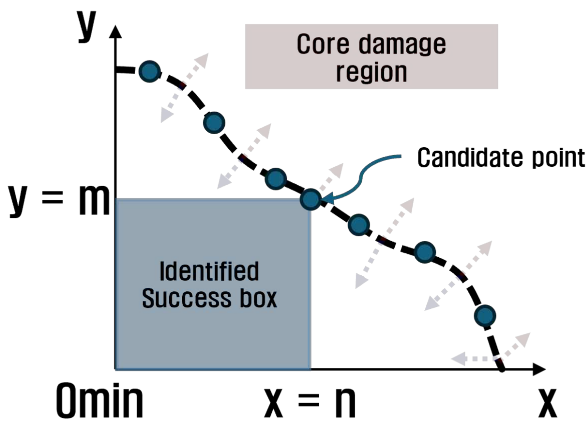

Figure 2. Concept to find success box from the candidate points with optimized simulations

3. CASE STUDY: LOCA

To demonstrate the applicability of the proposed method and its effectiveness, the proposed algorithm was applied to LOCA scenarios. In this case study, three dynamic variables were considered as following:

- the break size for LOCA
- the operator recovery time due to the failure of the safety injection actuation signal (SIAS) generation
- the operator recovery time due to the failure of the recirculation actuation signal (RAS) generation

When an LOCA occurs, the pressure in the reactor coolant system (RCS) is lowered and the reactor is eventually tripped, after which the SIAS is generated by the low-pressure signal of the pressurizer. Then, the safety injection pumps are operated by the SIAS to inject makeup water from the refueling water tank into the RCS. However, if the SIAS does not generate automatically, the operator should manually actuate the SIAS from the main control room. Subsequently, if the supply of makeup water is depleted from the refueling water tank, the suction source of the pump automatically switches from the refueling water tank to the sump by a RAS, continuously injecting coolant to perform long-term cooling. However, similarly, if the RAS does not generate automatically, the operator should manually actuate the RAS for long-term cooling. These two operator tasks were selected because they are considered in all small break LOCA, medium break LOCA, and large break LOCA scenarios, which are classified by break size in the traditional PSA.

3.1. Optimized Simulations

To simulate the dynamic accident sequences using the previously proposed optimized simulation research [15], boundary conditions for three dynamic variables were assumed, and a simulation model considering the dynamic variables selected was developed. Boundary conditions for the LOCA break size considered a total of 31 conditions, ranging from 0.5 inch and 1 inch to 30 inch at intervals of 1 inch. For the two operator tasks a total of 41 scenarios each were considered, at intervals of 180 seconds from 0 seconds to 7200 seconds. For the boundary conditions of the two operator tasks, a conservative assumption of twice the available time considered in the traditional PSA for two operator tasks was made. These dynamic conditions result in a total of 52,111 scenarios being considered in this case study.

The simulation model was developed with consideration of the LOCA break size, SIAS recovery action, and RAS recovery action. In this case study, the modular accident analysis program version 5 (MAAP5) was used. And, a novel limit surface/states searching algorithm using deep neural networks and Monte Carlo dropout for NPP safety assessment was adopted to optimize the massive number of simulations [15]. This approach demonstrated the potential of combining machine learning techniques with DPSA methods to enhance model accuracy and reduce computational requirements. Figure 3 shows the simulation results using optimized simulation for dynamic variables. The left side shows the results of running simulations using MAAP5, which identifies the limit surface between success and failure scenarios through optimized simulations with a minimal number of simulations. The right side plots all the predicted scenarios based on the limit surface. In the simulation results, the blue points mean the success scenario, while the red points indicate failure scenarios. In other words, the red points mean scenarios where core damage occurs within the allowable time. Consequently, by simulating only 2,119 scenarios out of a total of 52,111 scenarios, all scenarios can be determined with only about 4% of the total number of simulations.

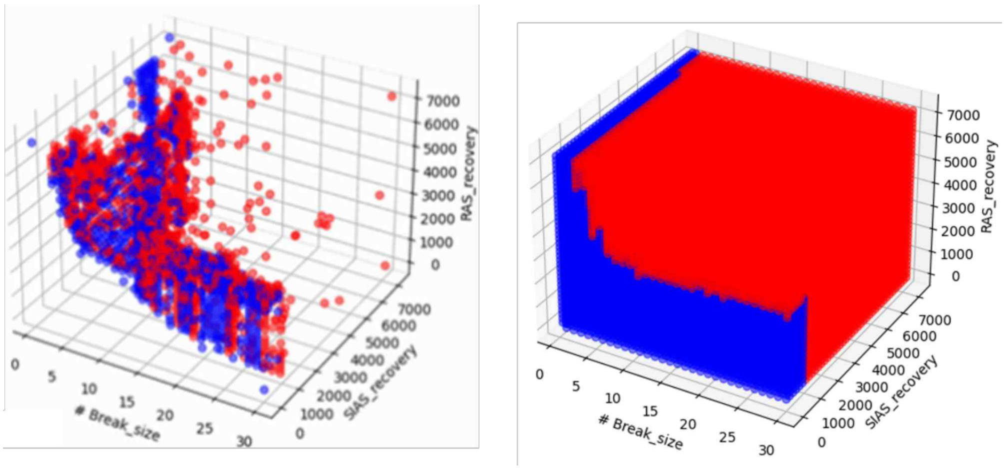

Figure 3. Simulation results of actual data (left) and predicted data (right) using optimized simulations with dynamic variables

3.2. Automatic Dynamic Sequences Generation

From the optimized simulation result, the automatic dynamic sequences generation algorithm was conducted. Before applying the alpha shape, data preprocessing and normalization were performed for optimized simulation results. To determine the appropriate alpha value that satisfies the conditions for maximum coverage, the alpha parameter was started from a 1.0 value. The results of this iterative process are shown in Table 1. Out of a total of 52,111 scenarios, there were 11,453 success scenarios. When the alpha values were 1.0, the number of success scenarios identified was 11,333, resulting in a coverage of 98.95%. In the process of selecting candidate points, those with overlapping cuboids were removed. As a result, a total of 18 points were selected as candidate points as shown in Figure 4.

Table 1. Alpha shape parameter selection and accuracy evaluation

Alpha values	# of identified success scenarios	Coverage (%)	# of whole success scenarios
1.0	11,333	98.95	11,453

Along with these 18 candidate points, the optimal points that include the maximum number of success scenarios based on the user-specified number of points were identified by calculating the combination of the candidate points. Figure 5 shows the results of finding the optimal points when the number of points is set to 2, 3 ,4 and 18. The figure (a) in Figure 5 visualizes the optimal points and the cuboid generated from these two points when the user-specified number of points is 2. Similarly, figure (b), (c), and (d) visualize the optimal points and the cuboids generated from them when the number of points is 3, 4, and 15, respectively. When examining the optimal points, the following points were determined: with 2 points (2, 5760, 7200) and (27, 900, 3060); and with 3 points (2, 5760, 7200, (5, 4860, 3780), and (27, 900, 3060); and with 4 points (2, 5760, 7200), (5, 4860, 3780), (15, 1620, 3060), (30, 700, 3060). The optimal points in 3 points include all the optimal points from the 2 points selection, whereas the optimal points in 4 points do not include some optimal points from 2 points and 3 points. This indicates that the success criteria for each system or human operator action can be evaluated differently depending on the number of optimal points, demonstrating the potential for various evaluations. Anyway, based on the determined optimal points, the DET was automatically generated. Figure 6 shows an example of the DET for (a) case in Figure 5.

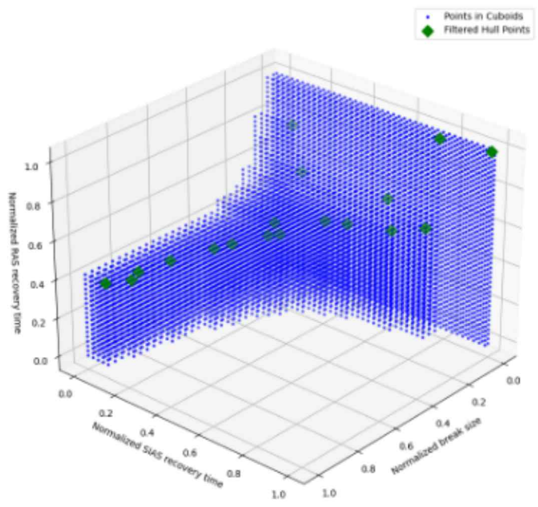

Figure 4. Identification of candidate points using alpha shape method

Table 2 presents the number of success scenarios identified, coverage, and whole success scenarios for each case. The results indicate that as the number of points increases, the number of identified success scenarios also increases, leading to higher coverage. These results are expected to support risk assessment within DPSA by providing decision-makers with information on DETs that have an appropriate level of coverage, which is both interpretable and understandable, promptly based on optimized simulation results.

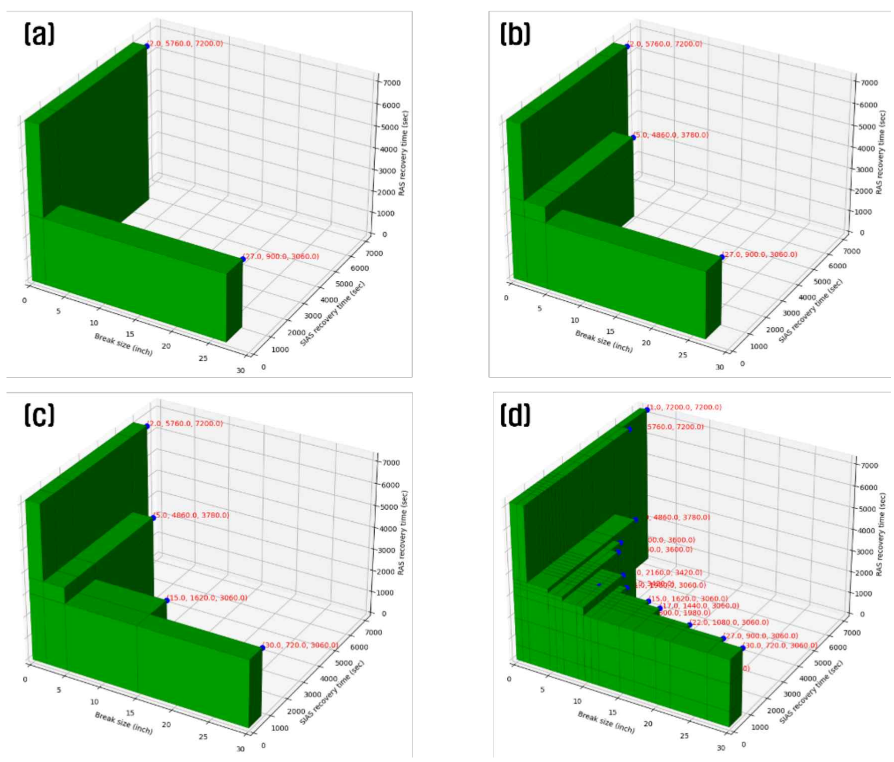

Figure 5. Optimal points and generated success cuboids for different user-specified points

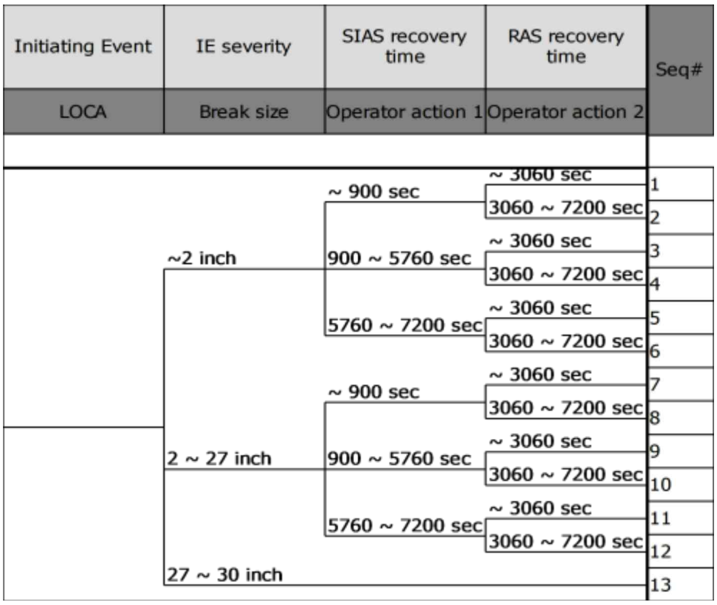

Figure 6. Examples of automatic dynamic sequences generation with the concept of the DET in the (a) case of the Figure 5

Table 2. Evaluation of identified success scenarios, accuracy, and computation time for different numbers of optimal points

# of user-specified points	# of identified success scenarios	Accuracy (%)	# of whole success scenarios
1	4,059	35.44	11,453
2	6,651	58.07	11,453
3	8,175	72.32	11,453
4	9,068	79.08	11,453
5	9,713	84.81	11,453
6	10,223	89.26	11,453
7	10,475	91.46	11,453
8	10,713	93.54	11,453
9	10,893	95.11	11,453
10	10,978	95.85	11,453
11	11,050	96.48	11,453
12	11,120	97.09	11,453
13	11,183	97.64	11,453
14	11,237	98.11	11,453
15	11,273	98.43	11,453
16	11,309	98.74	11,453
17	11,329	98.92	11,453
18	11,333	98.95	11,453

4. DISCUSSIONS AND CONCLUSION

The study presented in this paper explores the integration of an automatic DET generation algorithm within the DPSA framework. The proposed algorithm leverages alpha shapes to effectively analyze success and failure scenarios from high-dimensional optimized simulation results, thereby enhancing the precision and interpretability of dynamic accident sequences. The application of the alpha shape method demonstrated a significant improvement in capturing the geometric and topological properties of high-dimensional data. This approach allowed for a more accurate identification of candidate points that encompass success scenarios, ensuring that the DET generated are both comprehensive and reliable. The case study on LOCA scenarios, with dynamic variables including break size and operator recovery time for two operator tasks, highlighted the algorithm's capability to process complex data sets and provide meaningful insights into system behaviors under various conditions.

However, some discussion points remain regarding the application of the proposed method for DPSA. The first is that more case studies with high-dimension should be performed to better demonstrate the feasibility of the proposed method. In the present work, one case study with 3 dimensions for LOCA was performed due to limitations of the visualization and to act as a proof of concept.

The second point is the need for a comparative analysis with other methods that can be applied to generate DET in the optimized simulations. In this study, the alpha shape method was used to analyze the results, but it is necessary to compare these results with those obtained using employed algorithms such as Bruce force and greedy algorithms. This comparison will help to improve further validation of the effectiveness of the proposed algorithm.

The last point is the need for additional analysis comparing the accident sequences considered in traditional PSA with the dynamic accident sequences generated by the proposed methods. This comparison should highlight the advantages of DPSA by demonstrating its ability to provide more realistic risk assessments through more realistic scenario analysis.

In the future work, the research should focus on further improving the efficiency and effectiveness of the algorithm, particularly in the context of larger and more complex scenarios. Additionally, by developing a user interface related associated with proposed method, we aim to enhance the accessibility of this methods within the DPSA framework.

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References

[1] A.K.Verma,S.Ajit,D.R.KarankiReliability and safety engineering, 43, Springer, London (2010)
[2] Hickman J.W. PRA procedures guide: a guide to the performance of probabilistic risk assessments for nuclear power plants 1983; NUREG/CR-2300.
[3] X.Zheng,et al.Dynamic probabilistic risk assessment of nuclear power plants using multi-fidelity simulations
[4] USNRC. Confirmatory thermal-hydraulic analysis to support specific successcriteria in the standardized plant analysis risk models—Surry and peachbottom, NUREG-1953; 2010.
[5] Siu N, Marksberry D, Cooper S, Coyne K, Stutzke M. PSA technology challengesrevealed by the Great East Japan Earthquake. In: PSAM topical conference inlight of the Fukushima Dai-Ichi Accident Tokyo, Japan; April 15–17, 2013.
[6] Andrea Alfonsi et al, Risk analysis virtual ENvironment for dynamic event tree-based analyses, Annals of Nuclear Energy, 2022.
[7] Aldemir, T., 2013. A survey of dynamic methodologies for probabilistic safetyassessment of nuclear power plants. Ann. Nucl. Energy 52, 113–124. https://doi.org/10.1016/j.anucene.2012.08.001.
[8] Aldemir, T., Miller, D. W., Kirschenbaum, J., & Samanta, P. (2006). Monte Carlo simulation for dynamic probabilistic risk assessment. *Reliability Engineering & System Safety*, 91(5), 569-580.

[9] Bento, L., Borges, M., & Thomas, P. (2008). A Markov chain model for dynamic reliability analysis. *International Journal of Reliability, Quality and Safety Engineering*, 15(1), 45-60.

[10] Martorell, S., Sanchez, A., & Carlos, S. (2008). Dynamic event tree analysis for dynamic probabilistic risk assessment of nuclear power plants. *Annals of Nuclear Energy*, 35(4), 514-522.

[11] Dotoli, M., Fanti, M. P., Mangini, A. M., & Ukovich, W. (2009). Petri net models for the management of dynamic systems with concurrent and asynchronous events. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 39(3), 640-653.

[12] Baek, S., & Heo, G. (2023). Development of dynamic integrated consequence evaluation (DICE) for dynamic event tree approaches: Numerical validation for a loss of coolant accident. *Reliability Engineering and System Safety*, 238, 109425.

[13] Tian, H., Yin, G., & Liu, H. (2018). Dynamic probabilistic risk assessment of autonomous vehicle operations. *IEEE Transactions on Intelligent Transportation Systems*, 19(5), 1536-1548.

[14] Kröger, W., & Zio, E. (2015). Vulnerability and risk analysis of critical infrastructures: bridging the gap between safety and security. *Reliability Engineering & System Safety*, 148, 251-256.

[15] Bae, J., Park, J. W., & Lee, S. J. (2022). Limit surface/states searching algorithm with a deep neural network and Monte Carlo dropout for nuclear power plant safety assessment. Applied Soft Computing, 124, 109007. https://doi.org/10.1016/j.asoc.2022.109007

[16] H. Kim, J. Cho, and J. Park, "Application of aDeep Learning Technique tothe Development of aFast Accident Scenario Identifier," *IEEE Access*, vol. 8, pp. 177363-177373, 2020. DOI: 10.1109/ACCESS.2020.3026104.

[17] W. Jo and S. J. Lee, “Human reliability evaluation method covering operator action timing for dynamic probabilistic safety assessment”, RELIABILITY ENGINEERING & SYSTEM SAFETY, v.241, pp.109686, 2024. 01 (DOI : 10.1016/j.ress.2023.109686)

[18] Edelsbrunner, H., Kirkpatrick, D., & Seidel, R. (1983). "On the shape of a set of points in the plane." IEEE Transactions on Information Theory, 29(4), 551-559.