Optimized Simulation-Driven Automatic Generation of Dynamic Accident Sequences for LOCA Scenarios

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1. Introduction

As the scope of safety evaluations expands spatially and temporally for checking safety requirements or safety goals with the advent of small modular reactors and new technologies such as passive systems, digital instrumentation control, and automation systems, the need for optimal evaluation through realistic scenario analysis is increasing. Improving the realism of accident progression modeling is one of the key technical challenges for probabilistic safety assessment (PSA) [1].

From the perspective of conventional PSA, there is some key limitations, such as that physical, temporal, and spatial dependencies are loosely considered. Other limitations of conventional 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 [2]. These limitations have driven the development of dynamic probabilistic safety assessment (DPSA) or simulation-based PSA as a more robust and realistic approach for safety evaluation. DPSA integrates time-dependent probabilistic analysis with system dynamics, allowing for the assessment of safety more comprehensively. This approach may consider the temporal evaluation of system states and their interactions with stochastic processes, providing a more accurate representation of potential failure scenarios.

However, several challenges remain for DPSA applications to nuclear facilities despite of the significant progress made in DPSA research. 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 computation resource requirements. The integration of human factors and organizational behaviors into DPSA models also presents another layer of complexity. To address this issue, recent studies have also explored the use of machine learning and artificial intelligence to improve the accuracy and efficiency of DPSA simulation, further expanding its applicability and robustness [3,4]. Nevertheless, one of the key unresolved challenges is to analyze the optimized simulations such that dynamic event tree analyses can be performed flexibly and interpretably. This should enable decision-makers to interpret and understand the optimized simulations on high-dimensional space, facilitating more effective risk assessment. Therefore, this study proposes an algorithm for automatically generating the dynamic accident sequences in the concept of the dynamic event tree by analyzing the optimized simulations on high-dimensional spaces.

2. Automatic Dynamic Accident Sequences Generation Algorithm

In this section, alpha shapes used to analyze the high-dimensional optimized simulation results and the comprehensive algorithm to automatically generate the dynamic accident sequences with the concept of the dynamic event tree are described.

2.1 Alpha Shapes

The alpha shape method generalizes the convex hull by allowing the shape to be controlled through a parameter α, offering a more flexible and precise representation of the underlying structure of the data [5]. In addition, alpha shapes are derived from the Delaunay triangulation of a point set, with parameter α determining the level of detail. The small α values capture fine information and may result in a more fragmented shape, while the large α values produce smoother shapes that overlook finer details. Formally, the alpha shape of a set of points is constructed by selecting simplices (edges, triangles, or higher–dimensional counterparts) from the Delaunay triangulation whose circumcircle radius is less than or equal to $1/\alpha$. This filtering process eliminates simplices that do not contribute to the desired level of detail, thereby creating a shape that closely approximates the distribution and boundary of the points.

The computation of alpha shapes involves three main steps. First, the Delaunay triangulation is computed for the given set of points. Seconds, simplices whose circumcircle radius is smaller than the threshold defined by α are retained. Finally, the retained simplices are assembled to form the alpha shape.

2.2 The Algorithm

Figure 1 shows the algorithm for the automatic generation of dynamic accident sequences based on the alpha shape method. To automatically generate the dynamic accident sequences, the proposed algorithm is implemented based on the alpha shape method. All simulation variables used in optimized simulations are normalized before applying the alpha shape to the data point set. Then, the alpha shape is applied to optimized simulations in the high-dimensional space, and the resulting retained simplices are assembled to form the alpha shape. The points existing in the simplices are filtered out when the hypercuboids generated from points in the simplices are overlapped or included in the other hypercuboids generated from other points in the simplices. The selected points from the points in the simplices are determined as the candidate points in the first step.

After the candidate points are selected, it is checked whether the maximum coverage condition is satisfied or not in the second step. The maximum coverage is calculated as the number of success scenarios in the hypercuboids generated from all candidate points divided by the number of success scenarios in the optimized simulations. If the condition is not satisfied, the previous step with this step are iterated while lowering the parameter α by 0.1 until the maximum coverage condition is satisfied.

Once the alpha shape parameter α satisfying the maximum coverage condition has been determined, the points selected with the corresponding parameter α are finally determined and stored as candidate points in the third step. Then, the user enters how many points among the candidate points to consider.

From the user-specified number of points, the optimized points with the most optimal case including the most success scenario existing in the hypercuboids generated from the number of user-specified points among the candidate points by considering all possible combinations composed by the specified number of points.

Finally, the axis information of the optimized points is used to generate the dynamic accident sequences. The axis is the dynamic variables as a system, components, or operator action considered in the optimized simulations, and the axis information is the time or performance to simulate the dynamic scenarios. So, the axis information becomes the branching point of the dynamic sequences as it becomes the success criteria for each component and operator action.

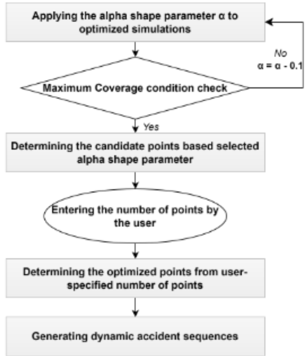

Fig. 1. Algorithm for automatic generation of dynamic accident sequences.

3. Case Study

3.1 Optimized Simulations

To demonstrate the practicality of the proposed algorithm, the dynamic scenarios with varying initiating event (IE) severity and operator actions has been generated. In this case study, several break sizes for loss of coolant accident (LOCA) were applied for dynamic variables related to IE severity. Also, safety injection actuation signal (SIAS) recovery due to SIAS generation failure and recirculation actuation signal (RAS) recovery due to RAS generation failure were adopted for the dynamic variables related to operator actions. From the combination of LOCA break sizes and action time for two operator tasks, a total number of 52,111 dynamic scenarios were generated. Based on the generated dynamic scenarios, a Deep learning-based Searching Algorithm for Informative Limit Surface/States/Scenarios (Deep-SAILS), which is an iterative process of locating the limit surface (LS) using the metamodel, was used to optimize the massive dynamic scenarios while minimizing the number of simulations [3]. For the parallel calculation of the system code from the algorithm, the Deep-SAILS was coupled with MAAP 5 (Modular Accident Analysis Program).

Figure 2 shows the LS and predicted whole scenarios derived from the optimized simulations for dynamic scenarios related to LOCA. The blue and red points represent the success (Non-core damage) and failure (core damage) scenarios, respectively. For the failure criterion for peak cladding temperature was set at 1477K [7].

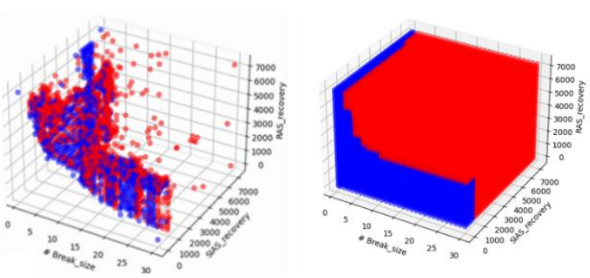

Fig. 2. LS (left) and predicted whole scenarios (right) derived

from the optimized simulations for dynamic scenarios related to LOCA.

3.2 Automatic Generation of Dynamic Accident Sequences

To generate the dynamic accident sequences by analyzing the optimized simulations, the proposed algorithm was applied to the optimized simulation results, as shown in Figure 2. First, to determine the candidate points based on the alpha shape parameter satisfying the maximum coverage condition, an iterative process was started from alpha shape parameter 1.0. Here, the maximum coverage condition was assumed as 95%.

Table 1 shows the sensitivity analysis results to find out the appropriate alpha shape parameter satisfying the maximum coverage condition. It was shown that the maximum coverage condition of 95% was exceeded when the alpha shape parameter was 1.0. From the selected alpha shape parameter, a total of 18 points were determined as the candidate points. Based on these candidate points, the hypercuboids consisting only of success scenarios can be formed.

Table I: Sensitivity analysis to find out the appropriate alpha shape parameter

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

From the candidate points and success scenario cuboids, the optimized points were determined between the candidate points by considering all possible combinations generated by the user-specified number of points. Figure 3 shows the results of visualizing cuboids consisting only of success scenarios based on the number of optimized points specified by the user. The (a) in Figure 3 visualizes the cuboids considering 2 optimized points, (b) considering 3 optimized points, (c) considering 4 optimized points, and (d) considering 18 optimized points. With 2 optimized points, the available time for SIAS and RAS recovery action were, respectively, 5760 sec (96 min) and 7200 sec (120 min) when the break size is up to 2 inch. Whereas for the break size up to 26 inch, the available time for two actions were, respectively, 900 sec (15 min) and 3060 sec (51 min). The coverage was 58.07% with two optimized cuboids. With 4 optimized points, the available time for two operator actions were all 7200 sec (120 min) for the break size up to 1 inch. For the break size up to 4 inch, the available time for two operator actions were 5760 sec (96 min) and 4140 sec (69 min), respectively. For the break size up to 15 inch, the available time were 1620 sec (27 min) and 3060 sec (51 min), respectively. For the break size up to 30 inch, the available time were 720 sec (12 min) and 3060 sec (51 min), respectively. With 4 optimized cuboids, the coverage was 79.18%. In the remaining cases, the available time for two operator actions can be identified by the LOCA break size. In addition, it was found that the success criteria may vary because the optimal case with the greatest number of success scenarios is selected depending on the number of optimized points.

Based on the optimal cuboids generated by the optimized points, the dynamic accident sequences can be automatically generated in the concept of a dynamic event tree.

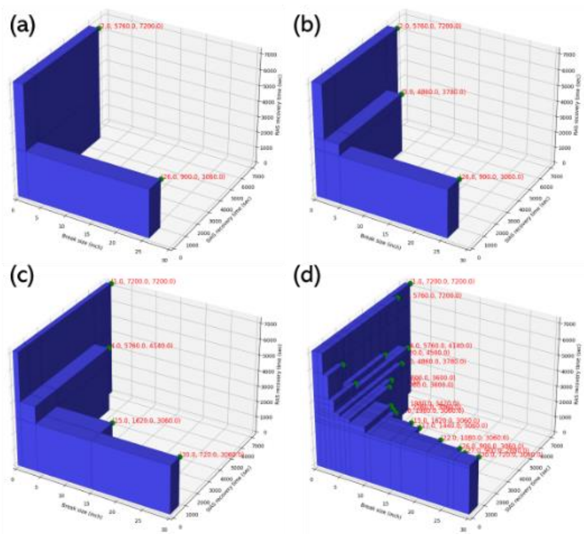

Fig. 3. Success scenario cuboids generated based on the number of optimized points (a): 2 points, (b): 3 points, (c): 4 points, (d): 18 points.

4. Conclusions

This study proposes an algorithm to automatically generate the dynamic accident sequences using optimized simulations. The case study was conducted on optimized simulation results with 3d simulation space along LOCA scenarios with dynamic variables to demonstrate the applicability of the proposed algorithm. The results showed that optimal cuboids were found based on a user-specified number of points among the number of the candidate points, and that coverage increased as the number of optimized points increased. In addition, the allowable time for the two operator tasks in each break size range varied depending on the number of optimized points, and the optimized points also varied. In conclusion, this study can visualize dynamic accident sequences according to the user's desired dynamic event tree complexity with high coverage. This is expected to help in the flexible and interpretable level of analysis for massive dynamic scenarios in dynamic PSA.

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