

## **APPLICATION OF TIME-DEPENDENT DYNAMIC ACCIDENT SEQUENCE GENERATION METHOD TO MACST EQUIPMENT USING OPTIMIZED SIMULATIONS**

Wooseok Jo, Junyong Bae, Seung Jun Lee\*

<sup>1</sup> *Ulsan National Institute of Science and Technology: UNIST-gil 50, Ulsan, Republic of Korea, 44919, and  
cws5528@unist.ac.kr*

*Corresponding author: sjlee420@unist.ac.kr*

### **EXTENDED ABSTRACT**

Probabilistic Safety Assessment (PSA) is a critical methodology for evaluating nuclear power plant (NPP) safety by modeling accident sequences and estimated associated risks. Traditional event tree (ET)-based PSA methods employ binary success/failure criteria to model accident scenarios, but they struggle to account for the time-dependent progression of dynamic variables, system interactions, and operator actions [1]. Although dynamic event tree (DET) methods have been introduced to overcome these limitations by allowing accident sequences to develop based on time-dependent system and operator responses, DET-based analyses often result in a massive number of branches, making it difficult to interpret accident sequences and requiring significant computational resources.

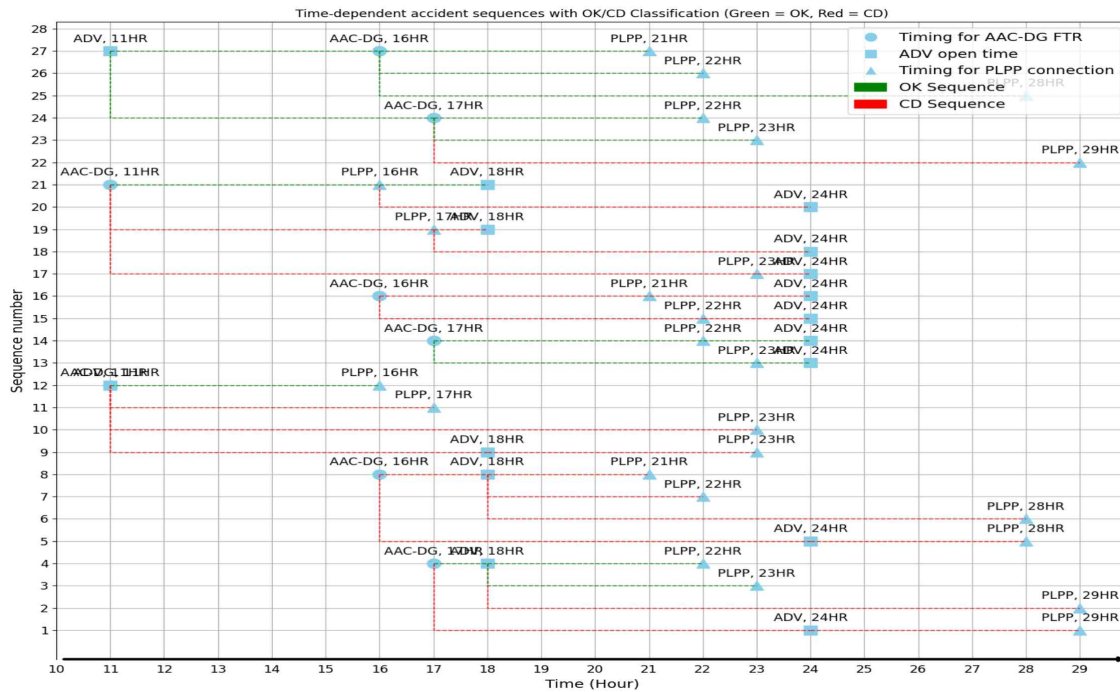
To address these challenges, a time-dependent accident sequence generation method was proposed with optimized simulations to reduce the high computational cost and accident sequence generation method to automatically generate dynamic accident sequences to facilitate the analysis for dynamic scenarios. The proposed method employs a limit surface searching algorithm coupled with a thermal-hydraulic system code to optimize a massive number of simulations for dynamic PSA [2]. This algorithm efficiently identifies the boundary (i.e., limit surface, LS) between success and failure scenarios through intensive simulations of scenarios proximate to the LS with iterative process.

However, comprehending the LS with more than three-dimensional space can be intricate. Therefore, the predicted scenarios with LS from above algorithm should be converted into more understandable form such as DET or other comprehensible forms. To settle this issue, automatic accident sequence generation method is applied [3]. In this method, the alpha shape method is adopted to analyze the optimized simulation data. The automatic generation algorithm analyzes success scenario data from optimized simulations and identifies the branching points that froms multiple boxes containing only success scenarios. Before applying alpha shape to success scenario data, conservative data preprocessing was applied, whereby if scenarios with better performance were estimated as failures while scenarios with poorer performance were estimated as successes, such cases were conservatively processed as failures. These boxes are optimally determined the number of the branching points specified by the user, and the regions partitioned by determined boxes can be converted into DETs. But, DETs have limitations to represent the time-dependent accident sequences since there are some mismatched dynamic scenarios over event headings in DETs, and the mismatched scenarios may be included in one region to construct the DET. So, the other comprehensible forms are needed to visualize the time-dependent accident scenarios.

For this, this study proposes a new method to generate the time-dependent accident sequences using branching points determined above automatic generation algorithm. The branching point means specific scenario when each simulation variable occur over time. So, dynamic scenario domains are splitted based on each value relevant to factors in branching points, and the branching points are subdivided. Then, subdivided branching points are depicted based on the each value relevant to simulation variables in time series.

To demonstrate the applicability of the the proposed method, the case study was conducted to a station blackout scenraio involving the multi-barrier accident coping strategy (MACST) equipment. The possible dynamic scenarios are predefined with generating a total of 14,400 scenarios through three dynamic variables; Running time for alternate AC–diesel generator (AAC-DG), delay time for atomspheric dump valve (ADV) open and potable low–pressure pump (PLPP) deployment. From the optimized simulations, a LS can be identified only 1,096 simulations among 14,400 scenarios. From the LS, the 4,087 and 10,313 scenarios are predicted as success and failure scenarios, respectively. Then, automatic generation algorithm

analyzed 13 branching points, which covers about 80.188% out of a total success scenarios. To visualize the time-dependent accident sequences using these points, 3 branching points were selected: (17, 24, 6), (11, 18, 5), and (16, 11, 12), corresponding to the (AAC-DG running time, Delay time for ADV open, Delay time for PLPP deployment). There points were optimally determined by considering all possible combinations of three out of a total of 13 branching points and identifying the combination that yielded the highest coverage. The resulting coverage corresponds to 59.46% of the total success scenarios. Among these variables, the PLPP variable is dependent for AAC-DG variable, whereas the ADV variable is independent for other variables. These points are further subdivided based on the specific values of the associated simulation variables.



**FIGURE 1. Time-Dependent Accident Sequences for AAC-DG Running Time, ADV Open Time, PLPP Deployment Time**

Fig. 1 shows the visualized results of the time-dependent accident sequences for subdivided branching points with AAC-DG running time, ADV open time, PLPP deployment time. The circle, rectangle, and triangle shapes represent AAC-DG running time, ADV open time, and PLPP delay time, respectively. The green and red lines indicate success and failure (i.e., core damage in this case study), respectively. From this result, three event ordering sequences can be identified. From 1 to 12 sequences, the events are ordered as AAC-DG running time, ADV open time, PLPP delay time while, from 13 to 21 sequences, the events are ordered as AAC-DG running time, PLPP delay time, ADV open time. In addition, from 22 to 27 sequences, the events are ordered as ADV open time, AAC-DG running time, PLPP delay time. In case of first event order, it can be known that the success criterias for delay time of PLPP deployment are in 16 hours when AAC-DG running time and ADV open time are 11 hours from sequence 12 or in 23 hours when AAC-DG running time is 17 hours and ADV open time is 18 hours from sequence 4.

We believe this novel method can serve to analyze the time-dependent scenarios for dynamic PSA. Further study will be conducted to validate the proposed method for more realistic accident scenarios

## ACKNOWLEDGMENTS

This work was supported by National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. RS-2022-00144328) and Korea Institute of Energy Technology Evaluation and Planning(KETEP) grant funded by the Korea government(MOTIE)(RS-2024-00403194, Next-Generation Nuclear Technology Creation IP-R&D Talent (Human Resources) Development Project)

**REFERENCES**

- [1] S. HOGENBOOM, T. PARHIZKAR, JE VINNEM, “Temporal decision-making factors in risk analyses of dynamic positioning operations,” *Reliability Engineering & System Safety*, **207**, 107347 (2021).
- [2] J. BAE, J.W. PARK, and S.J. LEE, “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 (2022).
- [3] W.S. JO, et al, “Optimized Simulation-Driven Automatic Generation of Dynamic Accident Sequences for LOCA Scenarios,” *Transactions of the Korean Nuclear Society Autumn Meeting*, Changwon, Korea, October 24-25 (2024).