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Dynamic Risk Assessment with Optimized Simulations and Automatic Sequence Generation

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1. Introduction

Probabilistic Safety Assessment (PSA) is widely used to evaluate the risks associated with complex engineering systems like nuclear power plant (NPP) and is essential for periodic safety review of operating NPP and licensing of new NPP. PSA is a static-based comprehensive approach that employs event tree (ET) and fault tree to develop accident sequence model in PSA of NPPs. However, it has limitations to easily capture time-depedent and dynamic behaviors such as system interactions, component failure timing, and operator actions.

Recognizing the importance of realistic PSA for risk-informed applications, several studies have explored the use of dynamic event tree (DET) methodologies to enhance realistic risk understanding [1,2]. DET is an extension of the ET. Instead of relying on static branching, it dynamically generates branches to reflect the dynamic characteristics. Nevertheless, this approach can lead to the generation of a significantly large number of branches. It is impractical to simulate all possible dynamic scenarios with safety analysis code and to interpret the vast number of scenarios generated.

This study uses a optimized simulations and automatic accident sequence generation method. The former can address the computational burden to simulate all dynamic scenarios by efficiently a limit surface located between success and failure domain. Also, the latter can improve the interpretability of dynamic scenarios by automatically analyzing the optimized simulation data and controlling DET branches with minimizing the loss of scenarios.

For generated dynamic scenarios with station blackout (SBO), a case study was conducted with proposed method. From the generated accident sequences, conditional core damage probability (CCDP) was evaluated with time reliability functions for dynamic simulation parameters. The result was compared with the CCDP of static PSA.

This paper describes the proposed method with optimized simulations and automatic accident sequence generation in Section 2, a case study in Section 3, and the conclusion in Section 4.

2. Optimized Simulations and Automatic Accident Sequence Generation

2.1 Optimized Simulations

To address the computational burden associated with simulating extensive scenarios as one of the practical challenges in dynamic PSA, the co-author's previous research introduced a Deep learning-based Searching Algorithm for Informative Limit Surface/States/Scenarios (Deep-SAILS) [3]. As depicted in left side of Fig. 1, the limit surface (LS) defines as a boundary between the regions of success and failure scenarios with black dotted line. The blue circles and red crosses correspond to success and failure scenarios, respectively. Since the success or failure scenarios can be reasonably inferred using LS, identifying its location can be help to minimize the number of simulations.

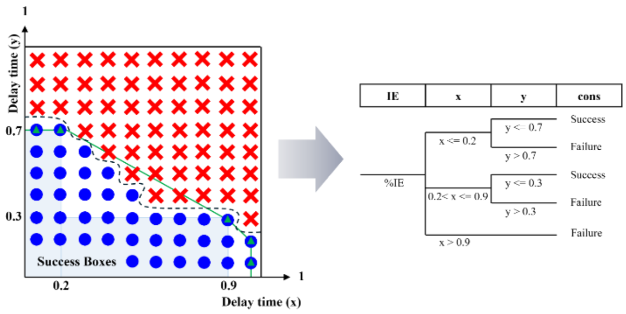

Fig. 1. Example of generating the dynamic accident sequences with optimized simulations and automatic generation algorithm

Deep-SAILS has an iterative process for identifying the limit surface (LS) using the metamodel, as illustrated in Fig. 2. The algorithm start with simulating the extreme scenarios with highest and lowest dynamic parameter values. Then, a deep learning metamodel is trained using simulated ones. After that, the algorithm samples the scenarios to be simulated. It is performed by first identifying informative (i.e., near the LS) scenarios based on the predicted result and uncertainty of each scenario and second randomly sampling the scenarios among the suspected scenarios. When sampled scenarios have already been simulated, then the algorithm wraps up and stops. If not, the algorithm repeats above processes. Please refer to [3] for more detailed information about the algorithm.

Even though Deep-SAILS can minimize the number of simulations by intensively simulating the scenarios proximate to the LS, comprehending the LS in high-dimensional space can be impractical. So, the LS should be converted into more comprehensible form by analyzing the optimized simulation results.

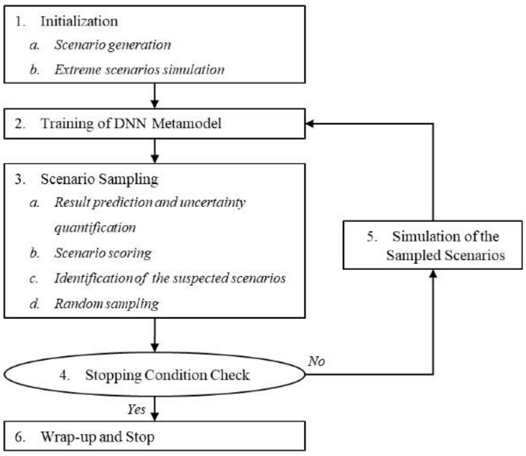

Fig. 2. Deep-SAILS algorithm

2.2 Automatic Accident Sequence Generation

To automatically analyze optimized simulation results with LS and convert it to comprehensible form (DET in this study), automatic accident sequence generation algorithm was proposed, as illustrated in Fig. 3 [4]. This algorithm utilizes an alpha shape method, which is useful to capture the shape of a point set in high-dimensional space and dynamically control the shape complexity through alpha shape parameter (α), to analyze the optimized simulation results.

The algorithm firstly applies the alpha shape method to the scenarios in success domain with α of 1.0 and then alpha shape, that encloses the scenarios, is made as green line depicted in left side of Fig. 1. The alpha shape picks the candidate points, which overlaps between alpha shape and success scenarios, with triangular point. Each point forms the success box to cover only success scenarios. After that, in the next step, the maximum coverage condition is checked whether it is satisfied or not. If not, the algorithm is iterated while lowering the α by 0.1 until the maximum coverage condition is satisfied. Here, maximum coverage was defined as how many success scenarios among total success scenarios can be covered by the boxes generated by candidates. The condition can be specified by the user.

Once the maximum coverage meets, the candidate points selected with the correspoinding α are finally determind and stored in third step. At this stage, user can decide how many branching points to consider among the candidate points.

After that, the algorithm identifies optimized points that defines the optimal boxes (i.e., hyperrectangles), which include only success scenarios in the box as many as possible based on the user-specified number of points.

Finally, the optimal boxes can be easily converted into dynamic accident sequences as shown in the right side of Fig. 1. The dynamic accident sequences (i.e., DET) show increased as more branching points are considered, but at the cost of greater complexity. Therefore, this algorithm helps improve the interpretability of dynamic accident sequences by balancing coverage and complexity in dynamic accident sequences.

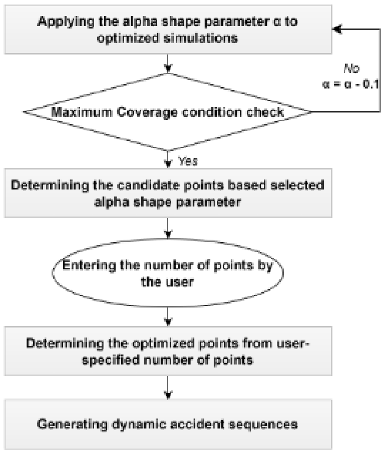

Fig. 3. Automatic accident sequence generation algorithm

3. Case Study

In this section, a case study was conducted for station blackout (SBO) with dynamic variables involving the multi-barrier accident copint strategy (MACST) facility, as a part of Post-Fukushima countermeasures.

3.1 Dynamic Scenarios

To generate dynamic scenarios, it is necessary to determine the initiating event and the dynamic variables to be considered. Also, the values of each variable should be specified for simulation. In this study, three dynamic variables for SBO were considered: Running time for alternate AC-diesel generator (AAC-DG), delay time for opening the atmospheric dump valve (ADV), and delay time for portable low-pressure pump (PLPP) deployment and installation as a MACST facility. In this case, PLPP can be used after depressurizing the internal pressure of the steam generator (SG) using ADVs because the operating pressure of PLPP is lower (20~30 kg/cm^2) than normal pressure of SG [5]. As shown in Table I, a total of 14,400 scenarios were generated with comprensive boundary condition for each parameter. In the dynamic scenarios, turbine-driven auxiliary feedwater pump and offsite recovery were assumed to fail unconditionally. In addition, main steam safety valve was assumed to be successful.

Fig. 4 shows the simplified ET for SBO in static PSA. In this study, sequence 10 was dynamically analyzed with above dynamic variable conditions.

Table I: Generated Dynamic Scenarios for SBO

Parameters	Values (hour)	Number of scenarios
AAC-DG running time	0, 1, 2, 3, 4, ..., 24	25
ADV open time	0, 1, 2, 3, 4, ..., 24	25
PLPP delay time	0, 1, 2, 3, 4, ..., 24	25
Total		**15,625**

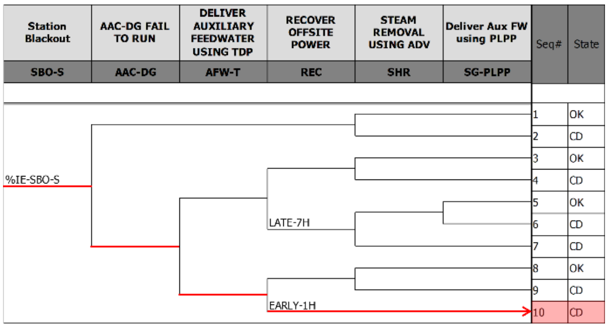

Fig. 4. Simplified ET for SBO in static PSA

3.2 Automatic Accident Sequence Generation with Optimized Simulations

For the generated dynamic scenarios, Deep-SAILS coupled with safety analysis code like MAAP5 was performed to optimized the simulations. Fig. 5 shows the LS (left) and predicted whole scenario consequence (right) derived from optimized simulations for dynamic scenarios. The blue and red dots represent success (i.e., No core damage) and failure (Core damage) scenarios, respectively. For failure criteria, a peak cladding temeprature was set at 1477 K.

The LS can be identified by only simulating 1,096 scenarios among 15,625 scenarios, indicating about 7.01% efficiency. From LS, 4,582 success scenarios and 11,043 failure scenarios consequently identified.

The scenarios in success domain were analyzed with automatic accident sequence generation algorithm to deteremine the candidate points and generate the dynamic accident sequences based on the number of points. In this case study, the maximum coverage was set to be 80% and then 18 candidate points that covers about 80.40% with α of 0.8.

To generate dynamic accident sequences, 2 branching points were considered. These points cover about 50.41% among total success scenarios.

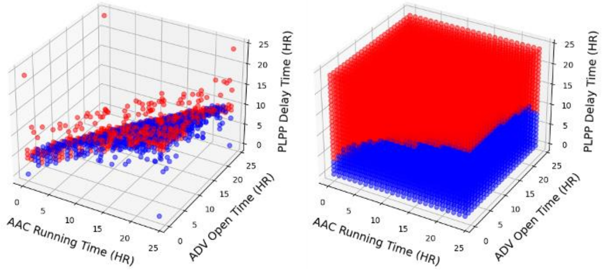

Fig. 5. LS (left) and whole scenarios (right) derived from Optimized simulations

To generate dynamic accident sequences, 2 branching points were considered. These points cover about 50.41% among total success scenarios. Fig. 6 shows DET generated from automatic accident sequence generation algorithm when 2 branching points were considered.

In the ET of static PSA, sequence 10 was conservatively assumed to lead to core damage, whereas in the DET, several sequences were identified as success depending on the AAC-DG running time, ADV open time, and PLPP delay time. The success sequences can be achieved, when the AAC-DG operates for 15~24 hours, if the ADV is opened within 12 hours and the PLPP is deployed and installed within 11hours after the AAC-DG failure or if the ADV is opened within 12~16 hours and the PLPP is completed within 5 hours after the AAC-DG failure. In addition, it was confirmed that core damage does not occur within mission time if the ADV is opened within 16 hours and the PLPP is completed within 5 hours when AAC-DG operates for 10~15 hours.

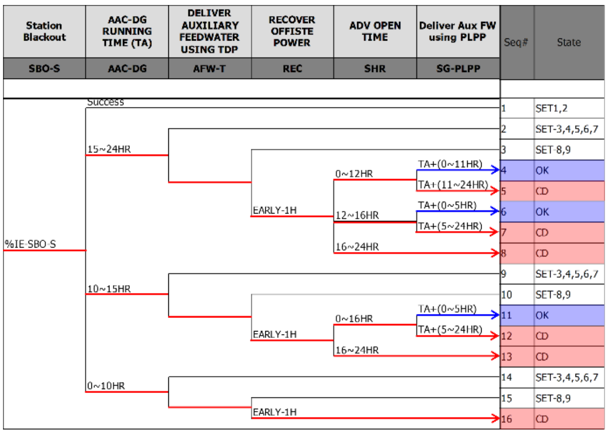

Fig. 6. DET generated with 2 branching points selected by automatic accident sequence generation algorithm

3.3 Dynamic Risk Assessment

To conduct dynamic risk assessment, the probability density functions (PDFs) of the uncertain times, which will be used for the risk quantification, are needed. The PDFs for times of ADV open and PLPP delay were approximated by lognormal distributions for operator actions. And, the PDF for times of AAC-DG fail-to-run was assumed to be exponential distribution. The PDF parameters related three dynamic variables used in the prsent analysis are summarized in Table II. λ is failure rate for exponential PDF, and μ and σ are independent parameters for lognormal PDF related to the analysis of the human actions. The data sources reviewed are in [6,7,8].

Table II: Assumed time distribution functions

Parameter	PDF
AAC-DG running time	Exponential PDF: $\lambda = 1.13e-03/hour$ [6]
ADV open time	Lognormal PDF: $\mu = 1.805, \sigma = 0.762$ [7]
PLPP delay time	Lognormal PDF: $\mu = 2.773, \sigma = 0.944$ [8]

Based on assumed time distribution funtions, CCDP for DET in Fig. 6 was quantified and compared with the CCDP from ET in static PSA. CCDP in static ET was quantified with assumed failure estimates.

Estimated CCDP in static ET was 6.619E-05, whereas CCDP estimated from DET was 2.779E-05. As a result, it was shown that the risk in dynamic PSA was reduced by approximately 58% compared to that in static PSA.

4. Conclusions

In this paper, LS searching algorithm to optimize the simulatiobs and automatic accident sequence generation alorithm were introduced for dynamic PSA, and a case study for SBO with three dynamic variables was performed. Also, CCDP was quantified with assumed time distributions for component and operator actions and compared with that in static PSA. It is believed that the novel method introduced in this paper can allow to dynamically making the decisions according to the required scenario coverage and acceptable complexity of dynamic accident sequences. In addition, it is expected to help in understanding the risk more realistically through dynamic risk assessment.

ACKNOWLEDGEMENTS

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