A Framework of Quantification for Dynamic Probabilistic Safety Assessment

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1. Introduction

Static probabilistic safety assessment (PSA) has been widely used to quantify risk in nuclear power plants. Dynamic PSA has also been proposed to complement static PSA. Dynamic PSA is a study that analyzes time variables that are conservatively assumed in static PSA [1], and results are obtained by simulating a nuclear power plant using system code [2]. Because it utilizes time variables, dynamic PSA has been conducted as a phenomena-oriented study instead of quantification such as core damage frequency [3]. Even when quantification is performed, results are approximated, and assumptions are made about time variables in the quantification [4]. Dynamic PSA plays the role of complementing static PSA by suggesting more realistic conservative assumptions applied in static PSA, or by complementing and verifying static PSA. Therefore, in this paper, we propose a dynamic PSA, a quantification framework that utilizes time variables.

2. Methods

2.1 Concept of Quantification

Summation of success probability and failure probability of an event or component is 1. That means there are 2 kinds of possible state of the component or events we consider. At this point, we divide possible failure state over time. The state of a component could be divided success and failure and then the failure state is divided over time. For example, we can consider a running failure event of emergency diesel generator (EDG) and the failure state is split over running failure time as shown in Figure 1. Thus, summation of every probability of failure state is 1 and they can represent running failure probabilities over time.

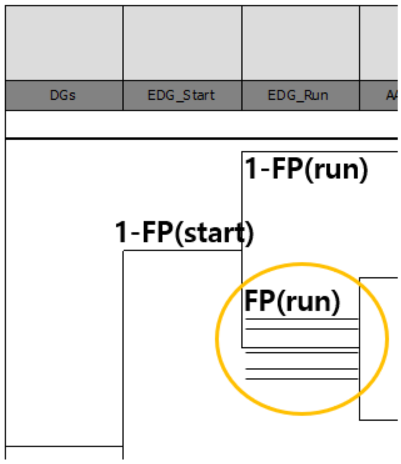

Figure 1 Quantification scheme for DPSA using AIMS-PSA

$$F(time_{run}) = F(run) * F(time)$$

when
$F(run) = failure\ probability\ of\ running$
$F(time) = divided\ failure\ probability\ of\ running\ time$

As above equations, a 2-hour running failure probability of EDG can be represented by

$$F(2h_{run}) = F(run) * F(2h)$$

Moreover, below equations show the concept of quantification of this paper briefly.

$$F(run) + S(run) = 1$$
$$\sum F(time) = 1$$
$$\sum \{F(run) * F(time)\} + S(run) = 1$$

when
$S(run) = success\ probability\ of\ running$

2.2 Dynamic PSA and their results

Before describing the detailed quantification method, we should mention how we can get dynamic PSA result for the quantification. We use Deep-SAILS algorithm that is an optimization algorithm searching a limit surface [5]. With the algorithm, a bunch of NPP simulations using a system code MAAP 5 are calculated 6], and the criteria of core damage or not is found effectively. In that process, we can set time variable to the input variable in the simulation. Thus, scenarios of the simulation consist of time variety are decided as core damage or not. With these scenario information, conditional core damage probability is deduced.

2.3 Process

Below sequential explanations show detailed methodology of the framework.

I. Calculate of reliability data over time.

This step describes how to draw reliability data over time. Main significance of this step is reasonable outcome. Thus, we consider an industry-average performance data as basis data of reliability [7]. From the data, there is information about failure time. For example, EDG has total 327 failures during running, and the failures are sorted by 172 failures before 1 hour and 155 failures after 1 hour. Using the information, with random sampling, we can deduce failure distribution over time as shown in Figure 2. As the example, the reliability distribution over time can be drawn with reasonable experimental data.

II. Divide variable sections over time data.

In this step, we decide the fineness of input data. That means how many bins in the reliability data distribution you will consider.

III. Calculate the probability of sections.

With the reliability distribution over time, we do integration following the sections (bins).

IV. Calculate the probability of scenarios – expending the result of simulations.

Every scenario we considered consists of a combination of events. Thus, every event has their own reliability distribution, and every bin of the distribution over time is granted probability. Using them, the scenarios could be quantified as mentioned in *2.1 concept of quantification*. Of course, including limit surface, every scenario in the domain should be considered.

V. Calculate the probability of sequences.

Conjugating the simulation results, the core damage scenarios are considered to deduce CCDP of the sequence.

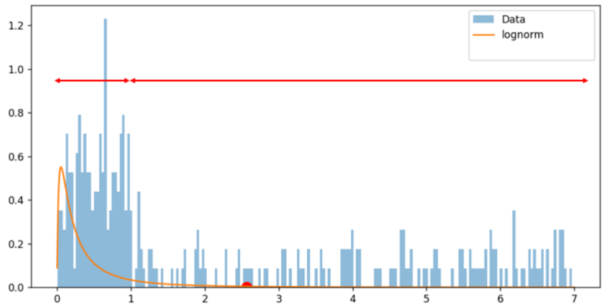

Figure 2 Reliability data over time using random sampling.

3. Case study

3.1 Scenario analysis and simulation

An initiating event we considered is station black out (SBO). Loss of offsite power occurs, and EDG starts to run but it cannot contribute to enter shutdown cooling condition. Thus, turbine-driven auxiliary feed water pump (AF-TDP) supplies feed water to steam generator. For the 2 components, we considered running failure for accident mitigation scenarios. Thus, different running failure time is applied to different scenario. To mitigate the initiating event, offsite power should be restored. Thus, we consider the time of offsite power recovery.

An alternative AC diesel generator (AAC-DG), mobile DG are not considered in this case. With the AF-TDP, air-dump valve in steam generator operation does not have any variation. It simulated with identified logic. For the simulations, MAAP 5 is adopted.

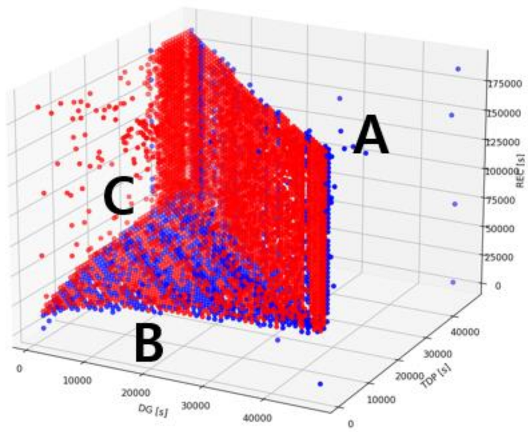

Figure 3 Simulation results with Deep-SAILS

With the algorithm, system code calculations are done with 5.63 % efficiency. That means the entire domain has 114,868 scenarios, and we found the limit surface with 6,473 scenario simulations. As shown in Figure 3, the simulation represents the success criteria of the sequences.

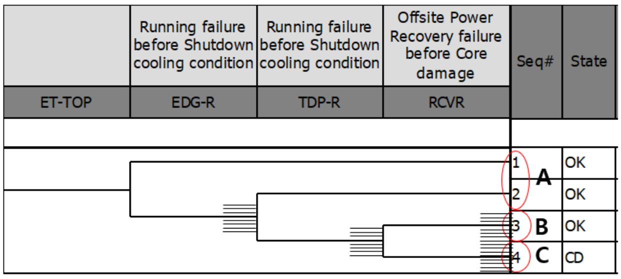

Figure 4 Accident sequences within SBO

The event tree in Figure 4 explains the area of domain into the sequences. The sequence to core damage is matched with the area C. The area A means OK scenarios regardless of recovery time. Lastly, the area B shows OK scenarios with suitable offsite recovery time.

3.2 Quantification

To deduce CCDP, we employed reliability data from reference [8]. In detail, offsite recovery data is from experimental data. That means how long does it take in history. With the procedure represented in *2.3 Process*, the quantification of SBO taking into account running failure time is deduced.

3.3 Result

CCDP of SBO is 7.26E-06. Because we only considered EDG, AF-TDP, and offsite recovery, the CCDP might be overestimated. However, like Table 1, comparison with static PSA was done. The ratio of dynamic CCDP and static CCDP is 1.2 %. and it shows static PSA is quite conservative.

Table 1 Conditional core damage probabilities

	Dynamic PSA	Static PSA
CCDP	7.26E-06	5.98E-04

4. Conclusions

In this paper, we show how to quantify the dynamic PSA and derive the CCDP of SBO using reasonable reliability data along with an algorithm to find the limit surface. This means that we have attempted to quantify the time variable that is difficult to apply, and since it is based on experimental data from an existing operating nuclear power plant, it can be applied to more complex initiating events and sequences in the future. It is hoped that this will make dynamic PSA more widely used, and that it will also be used to complement and validate static PSA.

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