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A Comparative Analysis of Dynamic and Conventional PSA Methods with Unified Success Criteria and Key Insights

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1. Introduction

Probabilistic safety assessment (PSA) has long served as a method for evaluating nuclear power plant safety. In recent years, however, dynamic PSA has gained attention for its ability to incorporate time-dependent operator actions and evolving plant conditions, prompting comparisons with the conventional PSA approach. Dynamic and conventional PSA are sometimes depicted as fundamentally different. Some have claimed that conventional PSA simplifies time-dependent operator actions and evolving plant conditions [1]. Nevertheless, adjustments to success criteria and event trees can capture the same time-dependent behaviors within a conventional framework.

In this paper, we examine scenario cases from the dynamic PSA references, focusing on how scenario was modeled and identifying the key differences from a conventional PSA method. We then propose a method for integrating those identified differences into a conventional PSA framework, with a logic-based analysis. Ultimately, offers a more in-depth perspective on both methods, showing that a refined conventional PSA can produce results comparable to those from dynamic modeling. By comparing their outcomes, we explore whether dynamic PSA yields different results or if a conventional PSA can still provide similarly detailed insights, thereby we can clarify the nature of any differences.

2. Methods and Results

2.1 SLOCA Case

In this scenario, we consider a small break loss of coolant accident (SLOCA) involving a 2-inch cold leg break over a 3600 second time. We focus on high-pressure safety injection (HPSI) initiation time and atmospheric dump valve (ADV) delay time as primary failure modes, based on prior references [2,3]. To capture the scenario's time-dependent behavior, we divide the HPSI initiation time into 10-minute intervals up to 50 minutes, checking how each change affects the possibility of core damage (CD). At the same time, we monitor the ADV delay to determine if and when CD may occur. Using MARS-KS code to analyze these relationships and monitor the peak cladding temperature (PCT) under each condition [4]. We then produce the event tree shown in Figure 1.

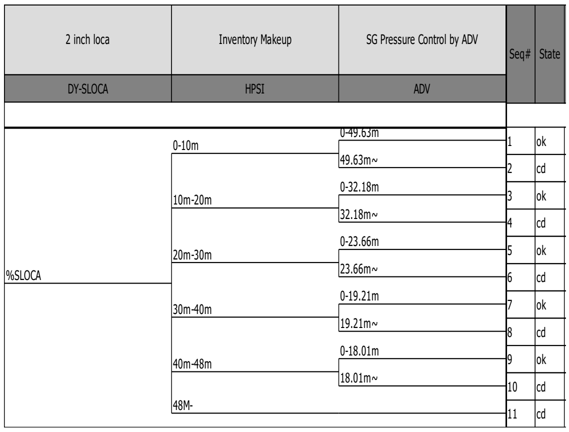

Fig. 1. Example of SLOCA Event tree.

In this case, often construct a dynamic event tree by dividing the analysis into discrete time intervals and generating multiple branches for each failure mode. It is noted that, although some researchers call this method dynamic PSA, the referenced approach essentially models failure modes in discrete divisions rather than fully capturing continuous time-dependent behavior. In our study, we will use this methodology as an example case, so we call it the dynamic PSA approach.

To quantify this scenario, it is necessary to assign probabilities to each failure mode. In a dynamic PSA, HPSI initiation and ADV delay times are treated as time-dependent parameters, requiring an appropriate probability distribution for each timing modeling. We set lognormal distributions for both variables, following from References [2, 5]. Table 1 provides the mean and standard deviation for HPSI initiation and ADV delay, ensuring that the time-based characteristics of each failure mode are represented in the model.

(1) $$f(t) = \frac{1}{t\sigma\sqrt{2\pi}} exp\left(-\frac{(lnt-\mu)^2}{2\sigma^2}\right),\ t > 0$$

Table I: Distribution variables of each system.

System	ln-scale Std. Dev (σ)	ln-scale Mean (μ)
HPSI	0.3403	3.3761
ADV	0.3850	3.6395

Then, we define the probability distribution function (PDF) for both HPSI and ADV as shown in Equation (1). By integrating these PDF, we set up the branch probabilities for each failure mode. Using the dynamic PSA approach for this case, we obtained a conditional core damage probability (CCDP) of 3.688E-4.

2.2 Modified Conventional PSA

Usually, in conventional PSA as shown in Figure 2 the event tree is simplify expressed using binary success criteria. Many dynamic references say that the conventional model is conservative because they do not account for time-dependent components.

In this example case, the key difference arises from the success criteria in the previous case, we subdivided the failure modes into the event tree to model a more detailed set of success criteria. By using the modified conventional model, we can integrate time-dependent characteristics into the analysis. If we incorporate these success criteria into the conventional model, it's possible to account for accurate quantification using a conventional PSA approach.

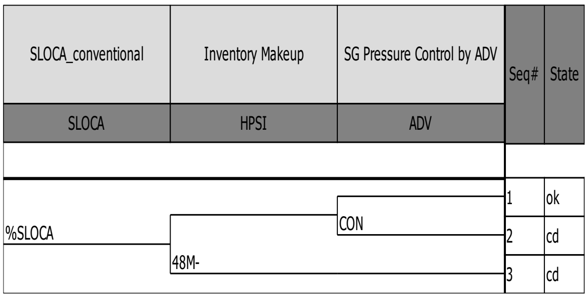

Fig. 2. Conventional event tree model.

To logically adapt the success criteria from our previous example, we fitted the parameter from each TH simulation. We aim to define a continuous success boundary rather than a discrete boundary. To determine the best-fit function, we used the root mean squared error (RMSE) methodology by considering linear, quadratic, exponential, and logarithmic functions. Based on the RMSE results, we selected the logarithmic function and determined the parameters a and b in Equation (2) accordingly. In this equation, x represents the HPSI initiation time and y represents the ADV delay time.

(2) $$y = a - b \times ln(x)$$

(3) $$Pr\big(Y > f(x)\big) = \iint_{y>f(x)} f_x(x) \times f_y(y)dxdy$$

$$f_x(x) = PDF\ of\ HPSI\ initiation$$
$$f_y(y) = PDF\ of\ ADV\ delay$$
$$f(x) = Success\ Boundary\ function$$

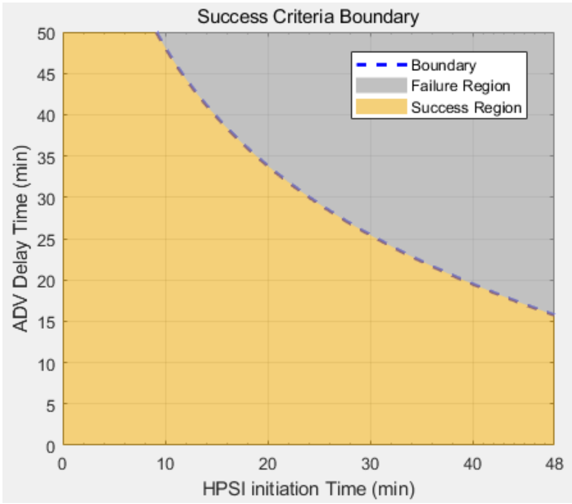

Fig. 3. Success/ Failure boundary.

We derived the success boundary curve using Equation (2) and visualized it in Figure 3. As shown in Figure 3, the above region boundary (gray) represents the failure region, while the below region boundary (yellow) represents the success region. We defined a continuous boundary function for this process. After defining a continuous boundary function, we multiply the PDF for HPSI and ADV in Equation (3). We then integrate the region above the success criteria to get the failure probability. This failure probability is reflected in the fault tree for sequence 2 in Figure 2 and the probability for sequence 3 in Figure 2 reflects that sequence 11 in Figure 1. Finally, Equation (3) yields approximately 0.626, and when this value is incorporated into the conventional PSA framework, the calculated CCDP is 3.725E-4.

Table II: CCDP Comparison.

Method	Approach	CCDP
Example case	Discrete	3.688E-4
Conventional	Continuous	3.725E-4

3. Conclusions

From a methodological point, this case shows the differences between the example case and conventional PSA approaches arise from how the success criteria are defined and applied. In example case, requires extensive thermal-hydraulic simulations to capture time-dependent behavior, while a conventional approach can model the same scenario with less computational effort. Detailed time-dependent success criteria are incorporated into the conventional model and the resulting conditional core damage probability closely aligns with that first method. Our study provides insights into how to segment and model success criteria for a case with dynamic characteristics and incorporate existing models, suggesting that under certain conditions a conventional PSA can yield insights similar to those from a dynamic PSA.

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REFERENCES

[1] Hakobyan. A, et al, "Dynamic generation of accident progression event trees." Nuclear Engineering and Design 238.12, 3457-3467, 2008.

[2] Jo. W. and Lee. S. J, "Human reliability evaluation method covering operator action timing for dynamic probabilistic safety assessment." Reliability Engineering & System Safety 241, 109686, 2024.

[3] Park, J. W. and Lee, S. J, "Simulation optimization framework for dynamic probabilistic safety assessment." Reliability Engineering & System Safety 220, 108316, 2022.

[4] Korea Institute of Nuclear Safety, "MARS Code Manual Volume II: Input Requirements. Korea Institute of Nuclear Safety." KINS/RR-1822, Vol. 2 Rev.1, 2022.

[5] Cho. J. et al, "Realistic estimation of human error probability through Monte Carlo thermal hydraulic simulation." Reliability Engineering & System Safety 193: 106673, 2020.