Transactions of the Korean Nuclear Society Spring Meeting
Jeju, Korea, May 7-8, 2026

DynaScen Framework for Dynamic PSA: Development and Comparative Analysis with Static PSA for Station Blackout

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***Keywords: Dynamic PSA; Monte Carlo Simulation; Meta model; Station Blackout; CCDP**

1. Introduction

Probabilistic Safety Assessment (PSA) systematically identifies potential accident scenarios in nuclear power plants and quantitatively assesses the frequency and consequences of each scenario. It has been utilized in various fields, including plant design, operation, and regulation, for decades. However, conventional PSA is inherently static, assessing risks based on assumptions about various system and operator actions, such as failure or operational timing. Therefore, static PSA tends to conservatively assume a significant number of scenarios, resulting in conservatively assessed results. Furthermore, assessing realistic scenarios is not only more effective in utilizing risk information, but is also essential for accurately assessing advanced reactors with very low core damage probabilities, such as small modular reactors and Gen 4 reactors.

In this context, dynamic PSA has been proposed as a method to complement the limitations of conventional static PSA, and various related studies are underway. Representative methods include event tree-based continuous event tree and discrete event tree methodologies, sampling-based methods like Monte Carlo sampling (MCS) and adaptive sampling, and state-space-based methods like Markov/CCMT, dynamic fault tree, and Petri-nets. Recently, AI (artificial intelligent) and surrogate-based methodologies have emerged, driven by improved AI performance. These methodologies are being developed to enable faster computation, improved accuracy, and more effective simulation count management [1-3]. However, most existing tools remain computationally intensive or lack a direct interface with conventional static PSA structures, limiting their practical adoption in industrial and regulatory applications.

This study proposes the DynaScen framework for performing dynamic PSA based on the MCS method. Using the proposed method, a case study was conducted for an station black out (SBO) scenario at a large nuclear power plant, comparing static and dynamic PSA. Section 2 presents the DynaScen framework, Section 3 describes the case study and its results, and Sections 4 and 5 present the discussion and conclusions, respectively.

2. DynaScen Framework

DynaScen is a MCS-based dynamic PSA framework that integrates stochastic dynamic scenario generation, input generation for thermal-hydraulic (T/H) code simulation, and meta model- (or rule-based) assisted classification to produce conditional core damage probability (CCDP) estimates and associated uncertainty quantification. The framework takes two primary inputs—a plant PSA model (event tree and fault tree) and a dynamic scenario parameter file in CSV format—and produces a structured output containing per-sequence CCDP values, uncertainty bounds, and a side-by-side comparison with static PSA results. As depicted in Figure 1, the workflow is organized into three sequential modules: (A) dynamic scenario modeling and sampling, (B) classification of core damage/no core damage (CD/NCD), and (C) summarization of results. This modular architecture allows each component to be independently updated or extended, for example by retraining the meta model for a new initiating event or incorporating additional parameter definitions, without restructuring the overall framework.

2.1. Module A: Dynamic Scenario Modeling and Sampling

Module A generates the dynamic scenario and creates the T/H code inputs required for each sampled simulation. At the core of this module is a dynamic modeling component equipped with trigger logic, which defines the various conditions (especially temporal conditions) under which component failures, system actuations, or operator actions are initiated during the accident progression. Unlike static PSA, where system states are treated as fixed at predetermined time points considering procedures and system availability, this trigger mechanism allows the model to capture state transitions that occur as the accident evolves in time.

Parameter relationships are explicitly represented at three levels within the module through triggers. Intra-system dependencies capture correlations among components within a single system, inter-system dependencies account for functional or support-system linkages across different safety systems, and common cause failure (CCF) parameters model the probability of simultaneous failures among redundant trains sharing a common root cause. These three layers collectively define a joint parameter space from which N scenarios are generated through stochastic sampling. Each dynamic scenario sample corresponds to a unique combination of component states, failure timings, and CCF occurrences, and is automatically translated into a MAAP5 input deck, yielding N T/H input files ready for execution or surrogate-based evaluation.

2.2. Module B: Classification of CD/NCD

Module B determines the binary outcome—core damage (CD) or no core damage (NCD)—for each of the N sampled scenarios. To balance classification fidelity with computational tractability, the module employs a two-track architecture that operates in parallel, as shown in Figure 1.

The primary track is a meta model interfacing module, in which a deep learning classifier trained on a representative subset of MAAP5 simulation results predicts the CD/NCD outcome for each scenario without executing the full T/H code [3]. This enables classification of up to 1E8 scenarios within minutes, a throughput that is orders of magnitude beyond what direct MAAP5 execution could achieve. The meta model is trained on M selected samples drawn from the N scenario space, where the training set encompasses both CD and NCD cases at a distribution sufficient to capture the decision boundary. The secondary track applies a rule-based module that evaluates scenarios against physics-based deterministic criteria derived from engineering judgment and simulation databases, providing a complementary approach for cases where the meta model may produce optimistic assessments or where explainable accident sequences are required.

The outputs of the two tracks—CD_MM / NCD_MM from the meta model and CD_RB / NCD_RB from the rule-based module—are recorded separately and subsequently reconciled by Module C. It is acknowledged that both tracks carry inherent classification uncertainty: the meta model introduces stochastic prediction error, while rule-based criteria embed modeling approximations (which tend to be relatively conservative). This uncertainty is most consequential in low-CCDP regimes, where the misclassification of even a single scenario can produce a non-negligible shift in the aggregate CCDP estimate.

2.3. Module C: Summarization of Results

Module C aggregates the binary classification labels from Module B into interpretable risk metrics and delivers the final output of the DynaScen framework. The core function of this module is a mapping step in which each of the N classified dynamic scenarios is matched to its corresponding sequence in the static PSA event tree. This mapping is a distinctive feature of DynaScen relative to conventional dynamic PSA tools such as MCDET, and it enables direct quantitative comparison between dynamic and static analysis results within the familiar event tree structure. Discrepancies between dynamic and static sequence outcomes constitute dynamic insights—evidence of timing effects, parameter dependencies, or CCF interactions that the static model does not capture.

Following the mapping step, the module combines CD and NCD counts classified by Module B, derived through T/H simulations, or already defined in the static PSA across all scenarios to compute per-sequence and overall CCDP values. Uncertainty in these estimates is quantified statistically by propagating both sampling variability and meta model classification error through the aggregation process, yielding confidence intervals alongside each point estimate. The final output is delivered as a Results CSV file containing per-sequence CCDP values, uncertainty bounds, dynamic-versus-static comparisons, and scenario metadata, providing a consolidated basis for dynamic insight extraction, model verification, and uncertainty quantification.

3. Case Study: Comparative Analysis of Static PSA and Dynamic PSA

3.1. Case Study Configuration

To demonstrate the capabilities of the DynaScen framework, a case study was conducted using a SBO initiating event based on a conventional pressurized water reactor (PWR) PSA model. Two cases were defined to serve distinct analytical objectives, as summarized in Table 1.

Case 1 (Base model without adjusted failure probability) retains the original component failure probabilities from the plant PSA model and runs 1E8 simulated scenarios. The primary objective of this case is to compute a realistic CCDP estimate under nominal modeling assumptions, providing a baseline for comparison with the static PSA result directly.

Case 2 (Base model with adjusted failure probability) artificially elevates selected failure probabilities to increase the frequency of CD scenarios within the sampled population. With 10^7 simulations, this case is designed not for realistic CCDP estimation but for the systematic identification of dynamic insights—specifically, sequences where the dynamic model produces significantly different CD/NCD outcomes compared to the static event tree.

3.2. Results
3.2.1 CCDP Results

The CCDP results for both cases are summarized in Table 2 and compared against the static PSA reference values.

For Case 1, the static PSA model yields a CCDP of 2.75E-6, while the static result reproduced within DynaScen is 2.59E-6, confirming internal consistency of the framework. The dynamic Rule-based result is 2.63E-6, representing a 4% decrease relative to the static DynaScen value. The dynamic Meta Model result, however, is 7.22E-6, a 163% increase relative to the static baseline. This divergence highlights the sensitivity of CCDP estimates in the low-probability regime to meta model classification behavior, as discussed further in Section 4.

For Case 2, the elevated failure probabilities yield a static CCDP of 0.733 from DynaScen. The dynamic Rule-based result is 0.656 (an 11% decrease) and the dynamic Meta Model result is 0.646 (a 12% decrease), both indicating that dynamic modeling identifies risk-beneficial timing effects that the static model conservatively neglects.

3.2.2 Dynamic Insights: CD to NCD (Risk Benefit Sequences)

A key output of Case 2 is the identification of sequences classified as CD in the static PSA but reclassified as NCD by the dynamic analysis, representing cases where static modeling is overly conservative. The Rule-based track identified 30% of static CD scenarios as dynamically NCD, while the Meta Model track identified 35%. Four representative sequences are described below.

SBO-R/S-15-CD! Sequence involves failure of the auxiliary feedwater system (AFWS) after sustained operation of 10 hours or more. The dynamic analysis shows that if the steam dump system (SDS) opens and safety injection (SI) succeeds, core damage is avoided even when the feed-and-bleed (CSS F&B) function fails. The static model does not credit this timing-dependent recovery pathway, leading to a conservative CD classification. (see Figure 2)

SBO-S-18-CD! Sequence involves late power recovery. The dynamic analysis demonstrates that if AFWS operates for 15 hours or more before failing, core damage is avoided even when power recovery is delayed beyond 9 hours. This timing interaction between AFWS mission time and recovery window is not captured in the static event tree structure. (see Figure 2)

SBO-S-19-CD! and SBO-S/R-20-CD! Sequences involve RCP seal LOCA and PSV stuck-open events. The dynamic analysis shows that if SI injection and recirculation succeed continuously, core damage is avoided despite the presence of these additional failure modes. The static model treats these as unconditional CD sequences once the initiating failures occur. (see Figure 2)

TSLOCA-3-CD! Sequence (Total Steam Line LOCA) demonstrates that if SI injection and recirculation succeed, core damage is avoided even when AFWS fails or SDS opening is delayed by up to 31 hours. The extended timing window available for SDS actuation is a dynamic insight that the static model does not represent. (see Figure 3)

3.2.3 Dynamic Insights: NCD to CD (Optimistic Sequences)

Case 2 also identifies sequences where the static PSA classifies a scenario as NCD but the dynamic analysis reclassifies it as CD, revealing cases where the static model is unconservatively optimistic. The Rule-based track identified 0.41% of static NCD scenarios as dynamically CD, and the Meta Model track identified 0.88%.

Two principal sources of optimism were identified. First, the static PSA applies relatively optimistic Human Error Probabilities (HEPs) for operator actions such as MACST operation and offsite power recovery, whereas DynaScen applies HEPs derived from empirical data, resulting in a higher effective failure probability for these actions in the dynamic model. Second, the static PSA assumes that the turbine-driven pump (TDP) of the AFWS operates for a fixed duration following an EDG failure, whereas DynaScen applies a more realistic model in which TDP is considered failed if AAC/MACST-based recovery does not occur within 4 hours. These two modeling differences collectively account for the majority of the NCD-to-CD reclassifications observed in the dynamic analysis. (see Figure 4)

4. Discussion

The present study proposed a Monte Carlo simulation-based Dynamic PSA framework integrating a trained meta model for rapid scenario classification, and demonstrated its application to a Station Blackout initiating event, yielding dynamic insights that are structurally inaccessible to conventional static event tree analysis, including timing-dependent system interactions and a quantitative basis for verifying CCF modeling assumptions. The mapping functionality to existing static PSA event tree sequences is particularly noteworthy, as it enables direct comparison between static and dynamic results within a familiar analytical structure, lowering the barrier to practical adoption. Nevertheless, the framework relies on predefined scenario sampling prior to thermal-hydraulic simulation, which partially limits its capacity to fully reflect plant dynamic responses driven by actual operator action cues, procedure entry conditions, and state-dependent system availability. Also, at very low CCDP values approaching 10^{-6}, the required sample count escalates sharply beyond 10^7, and individual sequences may be represented by as few as one to three samples, introducing substantial statistical uncertainty that the meta model's inherent classification error further compounds. Extension to additional initiating events beyond SBO will require dedicated thermal-hydraulic modeling and retraining efforts, and conclusions regarding dynamic insights and CCDP estimates remain sensitive to modeling assumptions, underscoring the need for systematic sensitivity analysis in future applications.

5. Conclusions

This paper presented a meta model-based Dynamic PSA framework for SBO scenarios that achieves classification of up to 10^8 simulated cases within minutes, enabling statistically tractable estimation of CCDP and its uncertainty that would otherwise be computationally prohibitive with direct thermal-hydraulic code runs. The framework successfully extracted dynamic insights absent from static PSA, and its event tree mapping capability provides a practical bridge for validating and augmenting existing plant-level PSA models. While current limitations—including predefined scenario structure, statistical instability at low CCDP, and meta model classification uncertainty—constrain immediate industrial and regulatory applicability, these represent well-defined targets for future refinement. Broader applicability to multi-unit configurations, external hazard scenarios, and additional initiating events is anticipated through incremental modeling extensions. The results collectively suggest that meta model-assisted Dynamic PSA demonstrates strong potential as a computationally efficient complement to conventional static PSA in the nuclear safety assessment workflow.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF), funded by the Ministry of Science and ICT (No.RS-2022-00143695)

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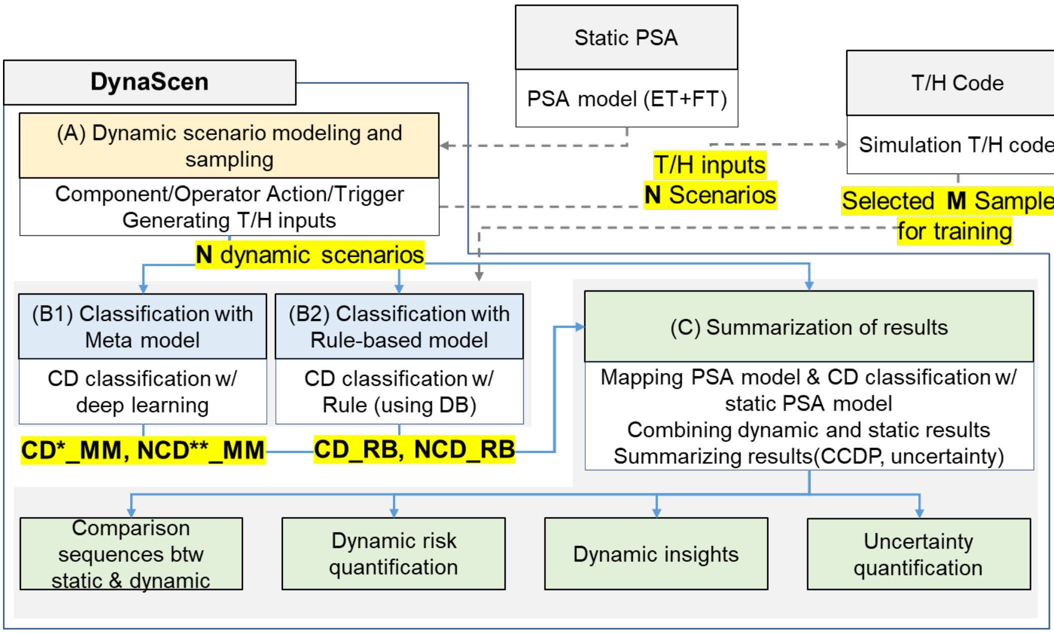

Figure 1. Overall architecture of the DynaScen framework

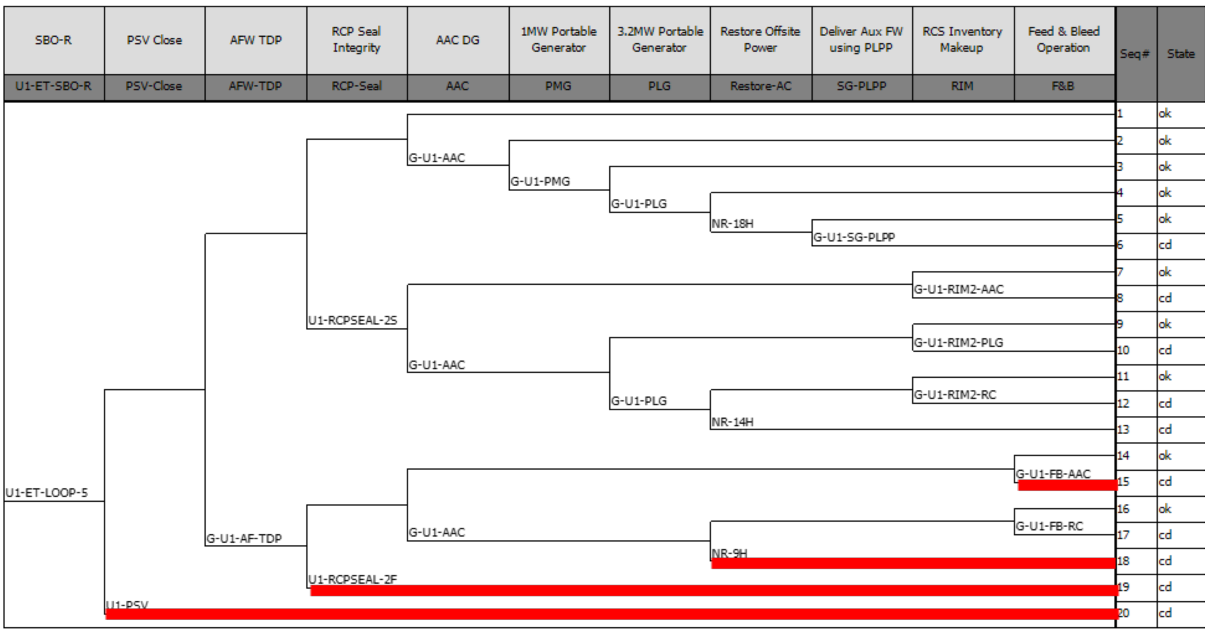

Figure 2. Representative CD-to-NCD scenarios detail for the SBO-R (also SBO-S)

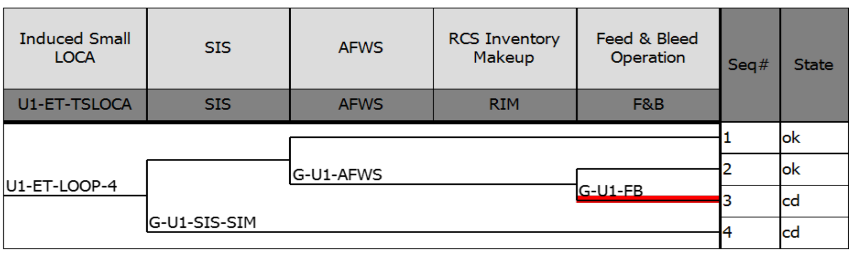

Figure 3. A representative CD-to-NCD scenario detail for the TSLOCA

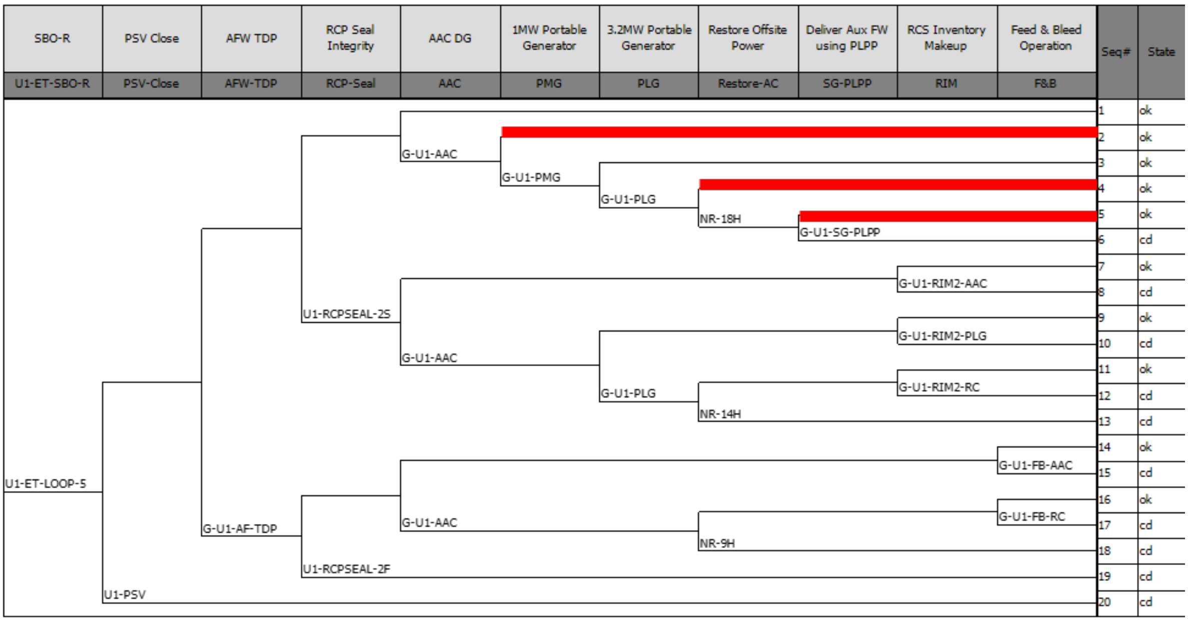

Figure 4. Representative NCD-to-CD scenarios detail for the SBO-R (also SBO-S)

Table 1. Summary of case study configurations

	Case 1	**Case 2**
Failure probability	Base (original)	Base + adjusted (elevated)
No. of simulations	$1{\times}10^{8}$	$1{\times}10^{7}$
Primary objective	Realistic CCDP estimation	Dynamic insight identification

Table 2. CCDP comparison between static PSA, dynamic Rule-based, and dynamic Meta Model results for both cases

	Static PSA	**Static in DynaScen**	**Dynamic (Rule)**	**Dynamic (MM)**
Case 1	2.75E-6	2.59E-6	2.63E-6 (-4%)	7.22E-6 (+163%)
Case 2	—	0.733	0.656 (-11%)	0.646 (-12%)