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A Framework of Streamlined Simulation of Thermal-hydraulic Code for Dynamic Probabilistic Safety Assessment

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1. Introduction

The safety assessment of nuclear power plants is crucial for public safety. Probabilistic Safety Assessment (PSA) is widely used for this purpose. [1] Nuclear power plants operate through the function of various systems. As observed in the Fukushima accidents, nuclear accidents can result in radiation leaks, causing long-term damage to surrounding areas and ecosystems. [2] Therefore, identifying and evaluating the potential risks of nuclear power plants is essential. PSA serves as an important tool to achieve these objectives. It systematically evaluates the risks associated with various accident scenarios in nuclear power plants and develops strategies to improve safety. Dynamic PSA, unlike static PSA, incorporates the dynamic characteristics of systems that change over time, allowing for a more realistic and accurate assessment. [3] By considering the actual operating conditions where system states evolve over time, Dynamic PSA provides a more reliable safety evaluation.

However, Dynamic PSA requires simulating the dynamic changes of failure state, various accident scenarios, and interactions of multiple parameters, which increases computational load and simulation time. [4] Efficiently reducing the simulation time of Dynamic PSA is an important task for performing safety assessments of nuclear power plants efficiently and accurately.

The objective of this study is to develop the algorithm and framework that can efficiently reduce the simulation time of Dynamic PSA. This study seeks to develop an algorithm and that reduces simulation time by integrating the `Restart` function of MAAP 5.05 [5] with Deep learning-based Searching Algorithm for Informative Limit Surface/States/Scenarios (Deep-SAILS). [6] The developed algorithm will be tested under the Station Black Out (SBO) scenario, and its performance will be compared and analyzed against existing methods without applying the developed algorithm. By achieving this, the study aims to facilitate faster and more accurate safety evaluations of nuclear power plants.

This paper is structured as follows. Chapter 2 details the implementation of the proposed algorithm and framework. Chapter 3 presents the case study about SBO accident and results. Chapter 4 offers conclusions and future work.

2. Optimized and Accelerated Simulation Algorithm

The proposed algorithm optimizes and accelerates simulations by utilizing the 'Restart' function of MAAP 5.05 and Deep-SAILS to store and use branch point information. This is illustrated in Fig. 1.

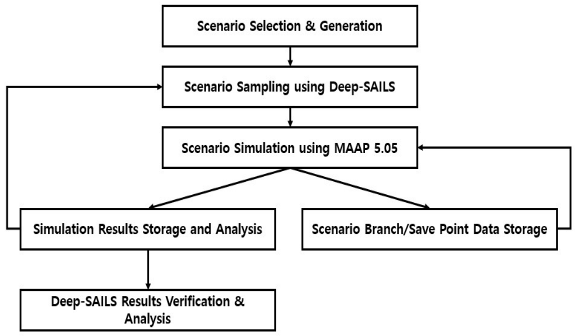

Fig. 1. Overall framework of optimized and accelerated simulation algorithm

Deep-SAILS is an iterative process of locating the Limit Surface (LS) that is a boundary between the regions of success and failure scenarios using the metamodel. [7] MAAP 5.05 is a software for simulating thermohydraulic behavior in nuclear power plant accident scenarios to assess system safety. It includes a 'Restart' function that allows storing information at desired points for reuse at the same points.

The first step in the algorithm is the scenario selection and generation. In first step, initial incidents and subsequent mitigation measures are set according to accident scenarios such as Station Black Out (SBO) and Loss of Coolant Accident (LOCA). The second step involves scenario sampling using Deep-SAILS. Scenarios near the Limit Surface (LS) are primarily sampled. In the third step, the sampled scenarios are simulated using the MAAP 5.05 code.

After the third step, the process proceeds to two distinct fourth steps: Scenario Branch/Save Point Storage, Simulation Results Storage and Analysis. In a scenario, a branch point refers to the end point of a parameter or the point where a component fails to run, leading to different branches. Branch points are defined as the points where events diverge in the event tree.

In the scenario branch/save point data storage step, data saved at each branch point during the scenario simulation is labeled and stored in a database. These saved files are used to accelerate simulations in subsequent iterations when duplicate branch points are encountered in sampled scenarios. In the simulation results storage and analysis step, the results of simulations for each iteration are stored and analyzed. These stored and analyzed results are used for scenario sampling in the next iteration of Deep-SAILS. If the terminate condition of Deep-SAILS is met, the proposed algorithm and Deep-SAILS are concluded, and the process moves to the final step, Deep-SAILS results verification and analysis, to analyze the Deep-SAILS results.

3. Case Study

In this study, the performance of the Optimized and Accelerated Simulation Algorithm is evaluated using the SBO accident case for a nuclear power plant.

3.1 Scenario Selection & Generation

In the SBO accident scenario, the outcome is determined by the Peak Cladding Temperature (PCT) resulting from cladding overheating. For the light water reactor OPR1000 used in the case study, the failure criterion for PCT is set at 1255K. [8] If the PCT exceeds 1255K, the scenario is classified as a Core Damage (CD) scenario, whereas if the PCT is below 1255K, it is classified as an OK scenario without core damage.

The initial event is set as Loss of Off-site Power. Subsequently, a delay time is provided until the AAC-DG (Alternative AC-Diesel Generator) starts to run. This delay time represents the period during which both AC and DC power are unavailable. If the delay time is 4 hours or less, the EDG (Emergency Diesel Generator) and TDP (Turbine Driven Pump) start to run from the beginning of the delay time, removing decay heat through auxiliary feedwater. Once the delay time ends, the EDG and TDP fail to run. If the delay time exceeds 4 hours, the EDG and TDP start to run from the beginning of the delay time, removing decay heat through auxiliary feedwater. However, they fail to run once the delay time reaches 4 hours. In case the AAC-DG fails to start or run, another delay time is provided until the MDG (Mobile Diesel Generator) starts to run. During the operation of the MDG and AAC-DG, it is assumed that the MDP (Motor Driven Pump) operates to remove decay heat.

Based on the defined scenario, dynamic scenarios were generated. In the dynamic scenarios, a total of four parameters were considered. The parameters included the first delay time before the AAC-DG and MDP start to run, the run time of the AAC-DG and MDP, the second delay time before the MDG and MDP start to run after the AAC-DG and MDP fail to run, and the run time of the MDG and MDP. The uncertainty domain for these parameters was set from 0 to 24 hours, with a resolution of 1 hour, resulting in cases at 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, and 24 hours. The goal is to determine whether each scenario results in CD or OK. The total number of scenarios is 390,625.

3.2 Scenario Sampling

In the Deep-SAILS integrated with the proposed algorithm, automatic sampling occurs, and as iterations progress, the number of sampled scenarios per iteration gradually decreases. For the hyperparameter, the initial number of sampled scenarios, N is set to 200. When the number of sampled scenarios in an iteration drops below the terminate condition, Deep-SAILS and the algorithm perform the final simulation step. The terminate condition is set to 0.9. If the number of sampled scenarios in an iteration falls to 20 or fewer, Deep-SAILS conducts the final simulation.

3.3 Scenario Simulation

In the scenario sampling step, the sampled scenarios are automatically simulated by integrating Deep-SAILS with the MAAP 5.05.

3.4.1 Simulation Results Storage and Analysis

The results of the scenarios simulated in MAAP 5.05 are stored in a database. These simulation results influence scenario sampling in the next iteration. If the iteration meets the terminate condition and is the final iteration, this step is followed by the Deep-SAILS results storage and analysis step, where the overall results are analyzed.

3.4.2 Simulation Branch/Save Point Data Storage

During scenario simulations using MAAP 5.05, files containing information about the scenario branch points are stored in a database. These saved files are used to accelerate scenario simulations by reusing the saved files at duplicate branch points. In this case study, 7,504 save data files were generated, occupying a total of 112.37GB.

3.5 Deep-SAILS Results Verification and Analysis

The results for the above scenarios were obtained by fixing the first delay time at 4, 8, and 12 hours, and then varying the time parameters of the following three variables: the run time of the MDG and MDP, the second delay time before the AAC-DG and MDP start to run after the MDG and MDP fail to run, and the run time of the AAC-DG and MDP. This approach aimed to identify the LS that separates the CD and OK regions in three dimensions.

Fig. 3 shows a 3D graph of dynamic scenarios with the first delay time fixed at 4, 8, and 12 hours, with the proposed algorithm applied. In the graph, the simulated sampled scenarios are visualized as scatter plots, with blue dots representing scenarios with OK outcomes and red dots representing scenarios with CD outcomes.

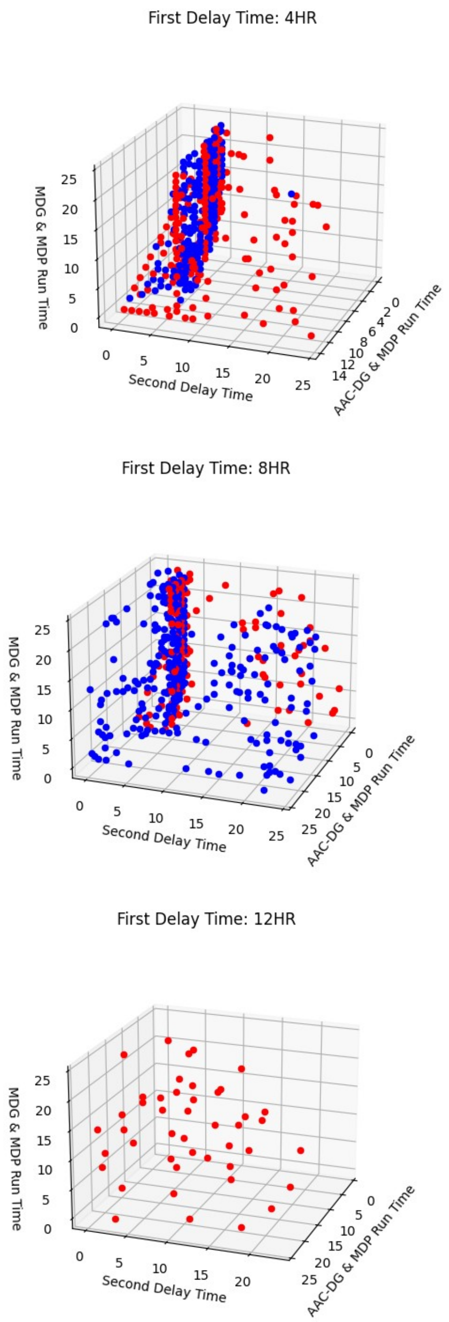

Fig. 3. Simulation results of the Deep-SAILS scenarios using the optimized and accelerated simulation algorithm (top: first delay time 4HR, middle: first delay time 8HR, bottom: first delay time 12HR).

This is an analysis of the results with and without the proposed algorithm. For the case where the first delay time is 4 hours, auxiliary feedwater of TDP continuously injects and removes decay heat. Consequently, scenarios where the second delay time exceeds 5 hours are classified as CD scenarios. Additionally, if the combined run time of AAC-DG & MDP and MDG & MDP is less than 10 hours, CD is observed. For the case where the first delay time is 8 hours, the first 4 hours involve decay heat removal by TDP, but TDP fails to run for the subsequent 4 hours, preventing decay heat removal. Hence, scenarios where the second delay time exceeds 4 hours are classified as CD scenarios. Moreover, if the combined run time of AAC-DG & MDP and MDG & MDP is less than 11 hours, CD is observed. For the case where the first delay time is 12 hours, all scenarios result in CD. It was analyzed that after TDP, powered by DC power of EDG, runs for 4 hours and then fails, decay heat is not removed for 8 hours, causing the PCT to exceed 1255K and leading to CD.

In the Deep-SAILS not integrated with the proposed algorithm, a total of 5,516 scenarios were sampled with 59 iterations occurring. This represents 1.412% of the total scenarios (390,625). The total time to complete all iterations of Deep-SAILS was 46 hours and 17 minutes, with each scenario simulation taking 0.503 minutes. In the Deep-SAILS integrated with the proposed algorithm, a total of 4,976 scenarios were sampled with 46 iterations occurring. This represents 1.273% of the total scenarios. The total time to complete all iterations of Deep-SAILS was 28 hours and 41 minutes, with each scenario simulation taking 0.357 minutes. The running time of Deep-SAILS not integrated with the proposed algorithm is 61.36% slower compared to the running time of Deep-SAILS integrated with the proposed algorithm.

4. Conclusion

This study proposes an algorithm that optimizes and accelerates scenario simulations by storing save data at scenario branch points and retrieving this data from the database when the same branch point occurs. The case study was conducted on approximately 400,000 scenarios of an SBO accident to compare the Deep-SAILS running time of the traditional methodology with the running time of Deep-SAILS using the proposed algorithm. The results showed that the running time of Deep-SAILS with the proposed algorithm was 61.03% shorter, resulting in a 38.01% increase in speed. These significant results suggest that the efficiency of the proposed algorithm would further improve and reduce more time when applied to a larger number of scenarios and iterations.

Future research will focus on processing a wider variety of scenarios and managing save files at internal branch points of scenarios. The current limitation of the proposed algorithm is its inability to handle simultaneous changes in multiple components. To address this, new methods and algorithms will be applied. In this study, approximately 400,000 scenarios resulted in a scenario save file database of 112.37GB. As simulations are conducted on more scenarios, there will be a need to manage frequently used save files efficiently.

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