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Dynamic Risk Assessment Framework to Support Decision-Making for Nuclear Safety

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Probabilistic safety assessment (PSA) is widely used in the risk assessment field of nuclear power plants (NPPs) using static event trees (ETs) and fault trees. Traditional PSA evaluates NPP safety by analysing representative scenarios with conservative assumptions in complex cases. Over the past several decades, research has been performed to evaluate realistic risk assessments considering dynamic characteristics. This is expected to help understand the differences between traditional PSA and dynamic PSA. However, to date, there have been no dynamic PSA applications that have influenced regulatory decision-making, partly due to the complexity of modelling and simulating dynamic accident scenarios. Moreover, dynamic PSA requires time-dependent reliability functions not only for system components but also for human actions to evaluate dynamic risk. For these reasons, this work proposes a novel dynamic PSA methodology, a dynamic risk assessment through automatic accident sequence generation using optimized simulations of NPPs (DRAGON). DRAGON consists of three main components: (i) an optimized simulation algorithm to reduce the number of required simulations, (ii) an automatic accident sequence generation method to present the results in an interpretable manner while controlling the scenario coverage and accident sequence complexity using alpha shape algorithm, and (iii) a time-dependent human reliability evaluation framework to assess dynamic risk quantitatively. The integration of three elements enables decision-makers to determine the desired level of scenario coverage, the complexity of the generated accident sequences, and evaluate the resulting dynamic risk, thereby supporting adaptive decision-making for nuclear safety. DRAGON was demonstrated with a case study for station blackout with dynamic scenarios including the timing of portable facility installation. The results showed that DRAGON can effectively support decision-making to select the accident sequences for dynamic scenarios.

Keywords: Dynamic Probabilistic Safety Assessment, Decision-Making, Station Blackout, Dynamic Scenario, Automatic Accident Sequence Generation, Alpha Shape method

1. Introduction

Probabilistic safety assessment (PSA) is a standard framework for quantifying the risk of nuclear power plants (NPPs). PSA is commonly performed using conventional event trees (ETs) and fault trees (FTs) to evaluate accident sequences and system reliability. Because it is impractical to explicitly simulate the full range of beyond-design-basis accident progressions, static PSA typically assesses plant safety by selecting representative scenarios based on conservative assumptions and predefined success criteria. This approach has been widely used in regulatory and industrial practice. However, it has structural limitations in capturing the time-varying physical behavior of the plant and its interaction with operator actions during accident progression.

Dynamic PSA (DPSA) has been studied to address these limitations. DPSA explicitly considers time dependence and state evolution during accidents. It couples probabilistic modeling with physics-based simulators (e.g., thermal-hydraulic system codes) to represent accident progression mechanistically. It also creates branches based on event timing and plant conditions. As a result, DPSA can reflect time-critical decisions such as recovery actions and external support (e.g., employment of portable equipment). For these reasons, DPSA has been viewed as a promising alternative for evaluating realistic risk.

Despite its potential, DPSA has seen limited use in regulatory decision-making because dynamic scenarios increase both modelling complexity and computational cost. The results depend not only on whether actions succeed or fail, but also on when they occur and under what plant conditions. DPSA also requires time-dependent reliability models for component operation and human actions under evolving conditions. Accordingly, prior work has found it difficult to simultaneously reduce computational burden, preserve interpretable accident-sequence representations, and integrate time-dependent human reliability analysis (HRA) within a unified framework.

To address these challenges, this study proposes an algorithm, Dynamic Risk Assessment through automatic accident sequence Generation using Optimized simulations for NPPs or DRAGON. DRAGON performs dynamic risk assessment by automatically generating accident sequences from optimized simulations. The methodology consists of three components. First, an optimized simulation algorithm reduces the number of required simulations by selectively evaluating informative scenarios. Second, an alpha-shape-based algorithm identifies branching points and automatically generates accident sequences, while allowing users to control the trade-off between scenario coverage and sequence complexity. Third, a time-dependent HRA framework is incorporated to quantify dynamic risk by capturing how the timing, delays, and success likelihood of human actions affect outcomes. By integrating these components, DRAGON enables decision-makers to evaluate the desired coverage, the complexity of generated sequences, and the resulting risk, thereby supporting adaptive decision-making for nuclear safety.

The proposed algorithm is demonstrated using a station blackout (SBO) case study that includes dynamic scenarios in which the timing of portable equipment operating affects accident consequences. The case study shows that DRAGON can efficiently analyze risk information under limited computational resources, TH simulation results into accident sequences, and quantify risk while accounting for time-dependent human reliability.

This paper is organized as follows. Section 2 describes the DRAGON framework. Section 3 presents the SBO case study, including the results. Section 4 concludes the paper and discusses future work.

2. Methodology

This study uses the DRAGON procedure, which combines limit-surface (LS) exploration via optimized simulations with automatic accident-sequence generation from simulation results, to simultaneously reduce the computational and interpretability burdens that arise in DPSA.

Figure 1 summarizes the DRAGON workflow. The left panel presents the top-level process: defining the analysis scope (Step 1), developing simulation models (Step 2), simulating dynamic accident scenarios using an LS-searching strategy (Step 3), generating dynamic accident sequences from optimized simulation data (Step 4), and evaluating dynamic risk (Step 5). The right panel of Figure 1 details the internal procedure of Step 4, referred to as the automatic dynamic accident sequence generation algorithm. Overall, the workflow is designed to mitigate enormous computational burden of DPSA while producing interpretable branching structures that can be mapped to a dynamic event tree (DET).

2.1. *Defining the scope of analysis*

In Step 1, the algorithm fixes the analysis scope to determine what is evaluated, how far the analysis extends, and which criteria are used. Specifically, we define the initiating event types and ranges, the systems and components included in the analysis, and the operator actions to be modelled. We also specify the uncertain variables that constitute the dynamic scenario space and their ranges, together with the success/failure classification based on a safety variable threshold.

2.2. *Developing simulation models for process, components, and operator actions*

In Step 2, the scope and criteria from Step 1 are implemented in executable simulation models. This includes (i) TH simulation models, (ii) system/component action models, and (iii) operator-action models including required time. Modelling of operator response and time-sensitive actions can be supported by established time-aware HRA approaches.

2.3. *Developing simulation models for process, components, and operator actions*

The objective of Step 3 is to identify the success–failure boundary efficiently without simulating the full scenario space. We use a LS searching strategy, deep neural network-based searching algorithm of informative LSs and states (Deep-SAILS) that prioritizes scenarios near the LS and iteratively runs thermal-hydraulic (TH) simulations for those informative scenarios. The remaining regions are complemented with surrogate-based prediction, reducing a large number of simulations. The inputs to Step 3 are the scenario variables and ranges, the success/failure criterion, and the simulator from Step 2. The outputs are scenario consequence about NPP safety variable (e.g., peak cladding temperature).

2.4. *Generating dynamic accident sequences from optimized simulation data*

Step 4 is the core step highlighted in Figure 1. Its purpose is to convert the high-dimensional optimized simulation results obtained in Step 3 into interpretable accident sequences. This is performed using the automatic dynamic accident sequence generation algorithm shown in the right panel of Figure 1.

Figure 2 is a conceptual illustration of the alpha shape construction process. Alpha shapes capture the shape of point sets in two or higher dimensions, and the alpha parameter, α controls the boundary detail. Alpha shapes can be derived from Delaunay triangulation, where α determines which simplices are retained to form the final boundary representation. Using this mechanism, the algorithm applies alpha shapes to the set of success scenarios to approximate the outer boundary of the success region and to enable systematic tuning of how tightly that region is enclosed.

The algorithm then checks whether the current α satisfies a coverage condition. Coverage is defined as the fraction of success scenarios captured by the scenario space relative to all success scenarios. If the coverage requirement is not met, α is reduced and the alpha-shape

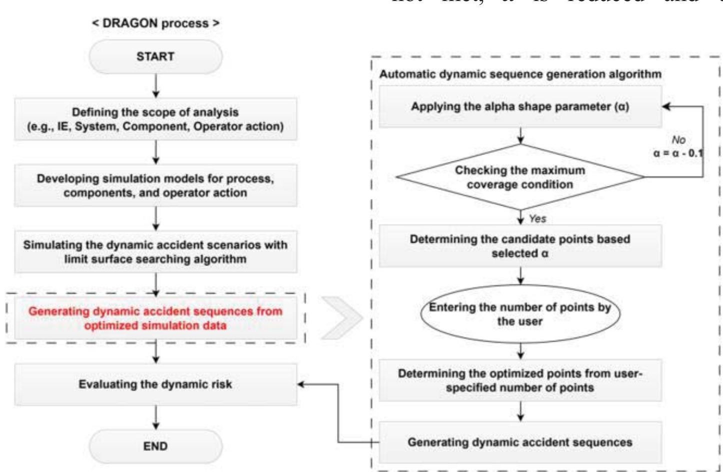

Figure 1. Overall workflow of DRAGON and the automatic dynamic accident sequence generation algorithm.

construction is repeated until the requirement is satisfied.

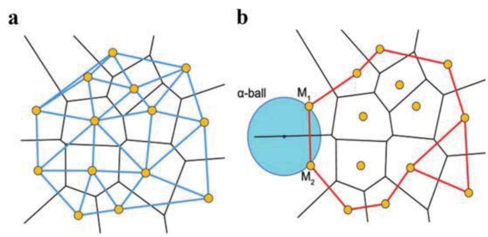

Figure 2. Conceptual illustration of alpha-shape construction using Delaunay triangulation

Figure 3 is an example how alpha shapes are applied to the success region together with the LS. In Figure 3, the algorithm identifies intersection/contact points of the success/failure regions and representing points that means candidate branching points (purple circles) Then, these points are used to form bounded success regions/boxes (purple boxes) intended to include success scenarios.

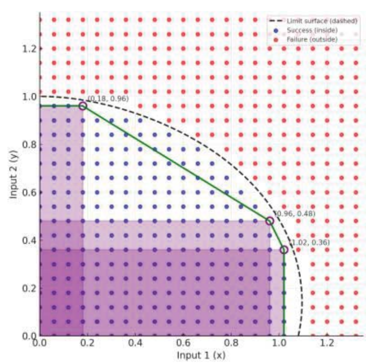

Figure 3. Example of alpha shape method application to success scenarios

Finally, given the user-specified k , the algorithm evaluates combinations of the candidate points and selects an optimized set of branching points. The selection criterion is to maximize coverage under the complexity k. The optimized branching points correspond to specific thresholds along the axis defined in the scenario space. Using these optimized points as branching criteria, the algorithm generates the final dynamic accident sequences, which can be directly mapped to the DET form.

2.5. *Evaluating the dynamic risk*

In Step 5, the generated accident sequences are used to quantify risk. The inputs include the accident sequences and probabilistic/reliability information such as component reliability and initiating-event frequencies. The outputs are risk metrics that can include sequence-wise contributions, overall risk values. This sequence-based quantification is consistent with DET informed risk modelling practices.

3. Case study

The case study demonstrates how DRAGON structures a large dynamic scenario space into interpretable accident sequences and quantifies dynamic risk under limited computational resources. The target plant response involves post-Fukushima coping actions using fixed and portable equipment.

Figure 4 shows the static ET for the SBO scenario considered in this case study. In Figure 4, the turbine-driven pump (TDP) and offsite power recovery are assumed to fail, while the main steam safety valve is assumed to succeed. Using failure probabilities from NUREG/CR-6928 and human error probabilities (HEPs) estimated with the THERP method, the conditional core damage probability (CCDP) of Sequence 10 is calculated as 6.619×10^{-5}.

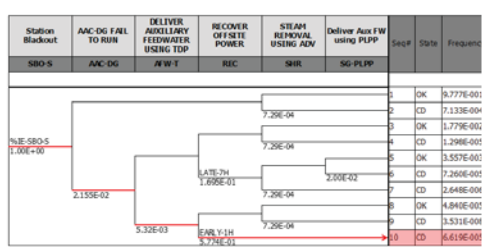

Figure 4. Static ET of SBO in the case study

In this case study, Sequence 10 from the static ET is re-evaluated using the proposed algorithm to obtain a more realistic, timing-aware representation. In Sequence 10, if the AAC-DG fails, the auxiliary feedwater system is actuated; if offsite power recovery subsequently fails, the sequence progresses to core damage. The analysis then assesses that additional component action affects the CCDP of Sequence 10.

Table 1 summarizes the selected component parameters, discretization. The SBO scenario space is defined using three time-related control parameters associated with coping equipment and operator actions: (i) alternative AC-diesel generator (AAC-DG) running time, (ii) atmosphere dump valves (ADVs) opening time, and (iii) portable low-pressure pump (PLPP) delay time for injection, each discretized from 0 to 24 h, yielding a total of 15,625 scenarios. In this setting, the PLPP injection action is feasible only after adequate steam generator depressurization via ADV opening within a required time window.

Table 1. Dynamic parameters and discretization of the parameter for the SBO case

Parameters	Unit	Discretization
AAC-DG running time	hour	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24 (25)
ADVs opening time	hour	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24 (25)
PLPP delay time	hour	0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24 (25)

TH system code is used to simulate each scenario, and success/failure is determined by a thermal safety criterion over the mission time. In this study, failure is defined by exceeding a PCT threshold (1478 K) within the 72 h mission time, while other cases are classified as success. The success/failure labelling supports both LS identification and subsequent sequence generation.

Directly simulating all 15,625 scenarios is computationally expensive. Instead, DRAGON uses an optimized simulation that reduce the burden on informative scenarios near the success–failure boundary. Figure 5 presents the optimized simulation results, including the approximated LS between success and failure and predicted consequence of total scenarios. As a result, only 1,096 simulations (about 7.01% of the full scenario set) are executed to characterize the boundary region while enabling prediction over the remaining unsimulated scenarios.

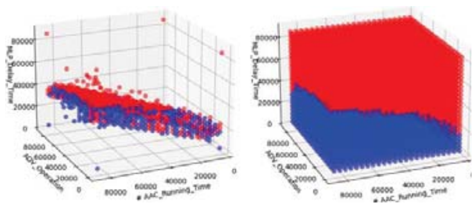

Figure 5. Optimized simulation results for the SBO case study: limit surface (left) and predicted consequence of total scenarios (right)

Using the predicted consequence of total scenarios, DRAGON generates accident sequence automatically. First, an alpha-shape boundary is constructed for the success scenarios, and the α is systematically reduced in 0.1 from 1.0 to meet a user-specified minimum coverage target. For each α, DRAGON forms candidate success boxes that aim to include as many success cases as possible while avoiding failure consequence. Coverage is evaluated as the fraction of total success scenarios captured by these boxes. Figure 6 reports the sensitivity results, 0.8 alpha shape parameter with 18 representing points, across visualizes the representing points (green points) and associated success boxes (blue regions). In this case study, the desired coverage is 80%, and the selected alpha parameter is 0.8 and achieves 80.40% coverage (3,684 out of 4,582 success scenarios).

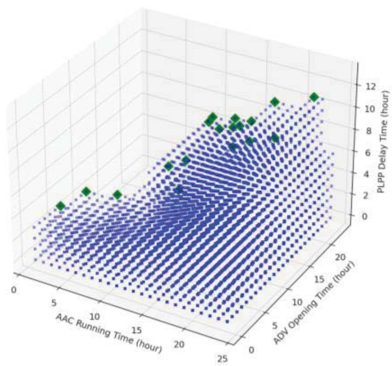

Figure 6. Sensitivity results to identify the alpha parameter satisfying the desired coverage

Second, DRAGON selects the branching points among representing points and constructs optimal boxes. Figure 7 illustrates the optimal boxes used to select three branching points from the 18 representing points. With this selection, the DET achieves 59.80% coverage (2,740 of 4,582 success scenarios), whereas using all 18 representing points attains the target coverage of 80.40%.

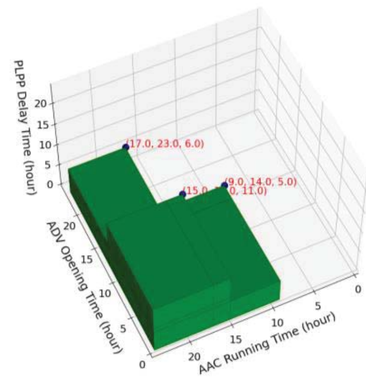

Figure 7. Optimal boxes constructed with 3 branching points among 18 representing points

To quantify risk, DRAGON generates a DET using three optimal branching points selected from the representative point set. The DET then evaluates CCDP using Sequence 10 in figure 4, while reflecting temporal effects.

Figure 8 presents the DET generated by DRAGON and the corresponding CCDP values calculated for each DET branch. For the SBO case, the probabilistic inputs were set as follows. The initiating event was treated conditionally. Key component and recovery failure probabilities were taken from NUREG/CR-6928. In addition, branch probabilities were obtained from assumed time-dependent reliability functions, including a lognormal delay-time model.

In Figure 8, the sequences that are realistically subdivided from Sequence 10 of the static ET through the DPSA process are highlighted in blue and red. With these inputs, the DET with three branching points calculates a CCDP of 2.504×10^{-5}, which corresponds to a 62.18% reduction relative to the static ET CCDP of 6.619×10^{-5}.

Because the DET is constructed from optimized simulations rather than an exhaustive evaluation of all 15,625 scenarios, the CCDP reported here should be interpreted as an approximate dynamic risk estimate under the adopted coverage and branching settings. In the present SBO case, the three-branching-point DET covers 59.80% of the success scenarios, whereas the full set of 18 representing points achieves 80.40% coverage. Accordingly, some bias may remain in the CCDP estimate due to surrogate-based prediction and incomplete scenario coverage. This limitation should be interpreted together with the computational benefit of reducing direct TH simulations to 1,096 cases, corresponding to 7.01% of the full scenario set.

Among the DET branches, Sequence 23 contributes the largest share of CCDP. From a decision-making perspective, the branch-wise CCDP results can be used to identify the most risk-significant timing windows and to prioritize corresponding control actions. In the present SBO case, the dominant contribution of Sequence 23 indicates that the most effective near-term risk reduction measures are to maintain AAC-DG operation for longer than 9 h and to restore offsite power within 1 h. More generally, this information can be used to define response-time requirements, prioritize portable equipment deployment and operator actions, and compare alternative mitigation strategies within a risk-informed decision-making process.

4. Conclusion and Future works

This study developed DRAGON designed to simultaneously mitigate computational and interpretability burden in dynamic scenario analyses. DRAGON combines optimized simulations and an automatic dynamic accident sequence generation algorithm.

Using optimized simulation, the algorithm reduces the number of TH simulations for predicting consequence of the dynamic scenarios. In the case studies, only a small fraction of the full scenario space needed to be simulated (7.01% for the SBO case).

Beyond computational savings, DRAGON improves the usability of DPSA results by automatically generating DET. Using an alpha parameter of 0.8, the framework selects 3 branching points from 18 representative points and achieves 59.80% scenario coverage.

Finally, DRAGON quantifies dynamic risk more realistically than static PSA into the generated sequences. In the SBO case study, the static ET calculates a CCDP of 6.619×10^{-5}, whereas the DET produced a CCDP of 2.504×10^{-5} for the 3-branching point DET, corresponding to a 62.18% reduction. These results indicate that timing-aware modelling and sequence generation can re-calculate risk estimates and, therefore, influence safety conclusions and decision-making.

Future work will develop dynamic risk importance measures that are explicitly time- and

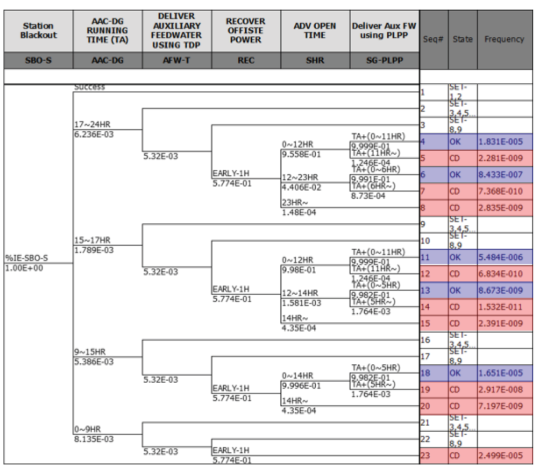

Figure 7. Generated DET and dynamic CCDP results for the SBO case study.

sequence-aware. These measures will quantify how the timing of operator actions and recovery affects CCDP across branches and time windows, enabling clear prioritization of dominant risk drivers under dynamic conditions.

In addition, DRAGON will be integrated into decision-making workflows through a risk-informed decision support system (RIDSS). RIDSS will translate DRAGON-generated sequences into decision-ready outputs to support evaluations of operational strategies, response-time requirements, and design changes in a traceable, performance-based manner.

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