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Making Sense of Dynamic PSA Results: A Hybrid Approach

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A dynamic PSA in form of an integrated deterministic probabilistic safety analysis (IDPSA) combines the enhanced realism of a deterministic safety analysis (DSA) with the advantages of a probabilistic safety analysis (PSA). The GRS software tool MCDET (*M*onte *C*arlo *D*ynamic *E*vent *T*ree) for dynamic PSA allows to analyse and quantify the influence of aleatory and epistemic uncertainties on the behaviour of dynamic systems over time. It can be used both to identify unforeseen accident sequences as well as to quantify the dependencies between different end state scenarios and the respective uncertain input parameter(s).
The effects of the high-dimensional parameter space induced by variations of the system state and the timing of events are simulated and represented using a Monte Carlo approach in combination with the dynamic event tree simulation. This results in large samples of event trees and time-dependent scenarios requiring state-of-the-art methods of data analysis for analysing the huge amount of data generated.
This paper introduces how data analysis and machine learning can be used together with domain knowledge to extract and condense the relevant information, to estimate safety margins and to determine the most significant discrete and continuous parameters. Furthermore, it is outlined how various techniques can be combined in an example application of an accident during mid-loop operation in the ADAMO project (Application of *A*dvanced *D*ynamic PSA Methods for *A*ssessing the Effectiveness of Human Actions for Accidents in *Mi*d-Loop *O*peration). It also illustrates how interactive data visualization can be used to understand system processes and component interactions leading to the time series of dependent variables derived in an IDPSA.

Keywords: Probabilistic safety analysis (PSA), IDPSA, dynamic PSA, machine learning, mid-loop operation.

1. Introduction

This paper provides an example of the combined use of machine learning and domain knowledge in the result processing of an IDPSA. The dynamic PSA method *MCDET (M*onte *C*arlo *D*ynamic *E*vent *T*ree*)* has been developed for performing an IDPSA (Kloos and Peschke 2015, Peschke 2018).

MCDET is a combination of Monte Carlo simulation and the dynamic event tree (DET) method which can be applied for analysing and quantifying the influence of uncertainties, both aleatory and epistemic, on the behaviour of dynamic systems over time. This particularly involves random timing and random ordering of events and their effects on the progression of a dynamic process. In addition to *MCDET,* the *Crew Module (*Wenzel et al. 2020*)* has been developed to model and simulate time dependent human action sequences which may depend on system states and stochastic influences.

After this introduction, a short description of the analytical steps performed during the calculation of the IDPSA results is given in Section 2. In Section 3, the event and the corresponding action model of the accident scenario are outlined. This IDPSA example has been performed as part of a research project called ADAMO (Application of Advanced Dynamic PSA Methods for Assessing the Effectiveness of Human Actions for Accidents in Mid-Loop Operation) funded by the Swiss Nuclear Authority ENSI (*E*idgenössisches *N*uklear*s*icherheits*i*nspektorat) (Wenzel et al. 2020, Wenzel et al. 2021, Mateos Canals et al. 2022, Mateos Canals and Eraerds 2023) and covers a large range of analysis objectives detailed in Section 4. The variables used as input of the MCDET analysis as well as in the result processing are presented in Section 5. Section 6 provides details on how machine learning can be used for a fast grouping of the time series of variables in an IDPSA. In this context, it should be noted that the sheer number of these time series

makes a manual approach unfeasible. The derivation of failure implicants based on the groups of time series presented in Section 6 is shown in Section 7 using the example of those implicants that led to primary side design pressure. Finally, Section 8 presents how an additional software tool developed by GRS has been applied to understand the structure of the dynamic event tree and the parameter development of selected variables.

2. Steps of the Analysis

The following steps have been found useful in analysing the complex time dependent results of an IDPSA:

- **Definition of analysis objectives:** Definition of the questions to be answered by the IDPSA.
- **Feature engineering:** Modelling the input of a dynamic PSA requires first to identify the relevant discrete and continuous uncertainties, and second, to understand how a desired system behaviour (e.g., manual opening of a high-pressure letdown system) can be implemented in a deterministic simulation code.
  The necessary simulation variables are stored in the MCDET output. However, these output variables may not necessarily be the most effective features for understanding the impact of uncertainties on the resulting system end states. Feature engineering involves combining the available output variables into the most meaningful features to address the analysis objectives.
- **Feature selection:** Typically, not all available output variables provide useful information to achieve the analysis objectives. In addition to feature engineering, feature selection is necessary to identify the most relevant features. Care must be taken to identify the causal relationships between the different output variables. Features should be engineered and selected to be as independent and orthogonal as possible.
- **Definition of result groups:** Once the analysis objectives are defined and feature engineering and selection are completed, machine learning methods can be employed to gain initial insights into the most relevant groupings of time series provided in the IDPSA output. A result group is characterized by a specific set of parameter values or parameter ranges that predominantly lead to one of the defined end states. To ensure the effectiveness of this initial grouping, only the most relevant and independent features should be utilized. Given the large number of parameters and time series involved, employing machine learning for this grouping significantly reduces the time required to achieve the analysis objectives.
- **Definition of failure implicants:** The term *implicant* refers to a set of feature values or ranges of feature values that result in one of the defined end states (cut sets in classic PSA). Identifying these implicants relies significantly on domain knowledge about the system's behaviour. Domain knowledge facilitates the use of features that exhibit causal correlations with other features and enables the translation of an implicant into a coherent narrative explaining how the failure state is achieved.
- **Investigation of unclear results**: In some instances, an initial analysis may identify sets of parameter values or ranges that correspond to more than one end state. In such cases, more detailed investigations into the system's behaviour are necessary to fully understand the driving forces that leads to the end state. These situations often provide opportunities to gain new insights into the system's behaviour.
- **Investigation of 'counter-intuitive' results:** In certain cases, clear implicants can be identified, however, these implicants may contradict intuitive expectations. In such scenarios, more detailed studies are required to resolve the apparent discrepancies.
- **Focus on specific analytical objectives:** Analysis objectives often emphasize particular areas of interest. During the final stages of the analysis, sequences related to these focal points can be examined in more depth.

3. Event and Action Model

The scenario under investigation involves a German PWR operating in a mid-loop configuration, specifically in the phase designated as "cold subcritical / primary system pressure-tight closed" (C) and is based on the study presented in (Babst, 2003). During this phase, the primary system is filled to three-quarters of the primary loop diame-

ter, and the residual heat removal (RHR) system utilizing three out of four available lines is responsible for evacuating the decay heat generated by the reactor core. At this stage, the accumulators and the emergency injection pumps are not operational. However, one steam generator remains filled and available as a backup heat evacuation feature via the secondary side, should the need arise.

The postulated initiating event is the "Failure of the RHR system triggered by a spurious actuation of the reactor protection system (RPS)". The above-mentioned start and boundary conditions are expected to significantly reduce automatic interventions from various subsystems, thereby increasing the reliance on operator actions to manage the situation. Specifically, the RPS action is activated due to a spurious breach of the emergency cooling criteria, leading to the interruption of the RHR system's heat removal mode and its replacement with safety injection mode. In response, the three available RHR pumps, along with three out of four extra borating system pumps (EBP), start injecting coolant into the primary system with zero feed pressures of 12 bar and 150 bar, respectively. Without intervention from the operators, the evacuation of decay heat is disrupted, and the pressure in the primary system (PPCS) increases exponentially.

To assess the operator response to this event, an operator action model has been developed. This model includes all potential actions and measures that the plant personnel can take to mitigate the consequences of the event. The operator action model presented in this study is based on a human problem solving process model, which serves as a framework for understanding the sequence of actions that operators may undertake in response to an abnormal situation. Specifically, this human problem solving model based on the distinct phases developed by Fassmann et al. (Fassmann, 2004) provides the basis for this approach.

In this example event, the operator's problem solving process is initiated by realizing the failure of the RHR system. During this **Initiation Phase**, the operators detect the loss of RHR and begin to collect visual information to assess the situation and to reflect the appropriate response. In the subsequent **Diagnosis Phase** (i.e. Problem Solving Phase**)**, the operators are faced with the decision to either apply a knowledge-based or rule-based approach to diagnose the event and to specify the necessary actions. If no suitable procedure can be identified by the operators, the model incorporates the possibility of revisiting the manual for recovery procedures. If still no procedure is clear, the event follows its course until safety components come into play (see below). Otherwise, the operators proceed to the **Execution Phase**.

Within the **Execution Phase**, the operators may attempt to bypass the emergency cooling criteria and reset multiple RPS signals. If any of these actions fails, no further actions are pursued. The operators may or may not reset the EBS pump RPS signal and manually switch off the EBS pumps. The next step involves the check of the primary system pressure, which affects the subsequent actions. If the primary pressure exceeds 35 bar the operators will open the high-pressure letdown (HPLD) station to decrease the pressure before restarting the RHR system. Conversely, if the primary pressure is less than 35 bar the operators will directly restart the RHR and open the low-pressure letdown (LPLD) station. If these actions are not successful additional recovery means are available and the model accounts for these contingencies.

Several components could play a critical role in mitigating the event during the transient. These components include:

- The **pressurizer (PRZ) valves** consist of one relief valve (RV) and two safety valves (SV1, SV2), required at pressures of 164, 169, and 175 bar, respectively.
- The **EBS check valves (EBSV)** located on each available EBS loop (three in total). These valves limit EBS injection to 150 bar.
- The **main steam valves (MSV)** include one relief control valve (RCV) and one safety valve (SV), which are required at pressure levels of 2 bar and 87 bar, respectively, if the residual heat is removed via the secondary side.
- The **emergency feedwater pump (EFWP)** would be automatically engaged if the level in the steam generator drops to 5 m.

This structured approach to operator decision-making within the OAM ensures that all potential responses are systematically analysed and incorporated into the model to simulate the

operator's problem solving process in response to the initiating event.

For carrying out the IDPSA, MCDET was first coupled to the MCDET Crew Module to generate the time distributions for the involved human actions and second to GRS's thermal-hydraulic simulation code ATHLET (Wielenberg et al., 2019). 100 DETs have been generated in the ADAMO project, comprising 11775 time series for the various variables defined in the MCDET input. A clear analytical approach such as that presented in Section 2 is therefore a sensitive means for maximising the insights gained from the IDPSA.

4. Objectives of the Analysis

The specific analysis objectives in the described example are related to the operator's measures in the mitigation process. The analysis aims to provide the following results:

- Statements on the effectiveness of manual measures.
- Identification of critical points in the sequence of actions.

In addition, statements regarding the main implicants for the four resulting system state categories listed in Table 1 should be derived, as well as an understanding of the main influence factors on the time at which the first three system state categories are reached and the remaining time (safety margin) between the last operator action and the entry time of these system states.

Table 1. Resulting system state categories as defined in Section 4

Category	Explanation	Definition
1	Primary side design pressure (PPCS)	$p_{PCS} > 228$ bar
2	Secondary side design pressure (PS)	$p_S > 116$ bar
3	Core damage, high surface temperature	T > 1200 °C
4	Timeout, t = 50,000 s reached without exceeding other thresholds	None of the other categories

5. Variable Definition

In total, 143 simulator variables are defined in the MCDET input for this IDPSA. As detailed in Section 2, the aim is to simulate the operator measures that could be carried out in the regarded mid-loop accident scenario. To simulate the manual switch off of the EBS pumps or the commission of the RHR, HPLD and LPLD stations, several ATHLET simulator variables need to be adjusted at precise times. For instance, activating the manual operation of the RHR requires the modification of a total of twelve simulator signals. Additionally, system failures are modelled by introducing variables to represent the availability of various valves and pumps as well as the valve cross-sections at their times of failure. Aleatory variables are included in the input to account for uncertainties regarding the timing of human actions and system failure events. Three main target variables are used in the full IDPSA analysis:

- Main end state categories (primary side design pressure, secondary side design pressure, core damage, timeout).
- Time when the end state was reached.
- Period between the last operator action and the time when the different end states are reached.

5.1. *Feature engineering and selection*

Feature engineering and selection has led to the analysis features defined in Table 2. For each of these features, an additional time variable is defined indicating when the corresponding system change is initiated by adjusting the necessary simulation parameters. These time variables are indicated by the prefix "t_" preceding the corresponding variable name.

Collectively, these variables account for the effects of uncertainties related to human actions as well as those associated with system availabilities.

Table 2. Definition of the features for the ADAMO analysis

Feature	Explanation
RHR	# started RHR systems
LPLD	LPLD (0: not. opened/ 1: opened)
HPLD1	HPLD1 (0: not. opened/ 1: opened)
HPLD2	HPLD2 (0: not. opened/ 1: opened)
LPPI	Categorical variable depending on the low-pressure pump injection (LPPI). 0: = no LPPI

Feature	Explanation
	1: = LPPI from >=1 LPP but not for the full time
	2: LPPI from >= 1 LPP for the full time
	3: LPPI for the full time from all LPPs
PRZV	Denotes which PRZ valve fails last and if it fails in open or closed state.
	Value = 0: no failure
	Value < 0: open failure
	Value > 0: closed failure
	Abs(value) = 1: PRZ-RV fails last
	Abs(value) = 2: PRZ-SV1 fails last
	Abs(value) = 3: PRZ-SV2 fails last
#PRVC	#PRZ-RV cycles + #PRZ-SV1 cycles + #PRZ-SV2 cycles
MSV	Denotes which MS valve fails last and if it fails in open or closed state.
	Value = 0: no failure
	Value < 0: open failure
	Value > 0: closed failure
	Abs(value) = 1: MS-RCV fails last
	Abs(value) = 2: MS-SV fails last
EBSP	EBS pumps (on. 1/off: 0)
EBSV	EBS valves (avail.: 1/unavail.: 0)
EFWS	EFWP
	-1: failure
	0: not demanded
	1: available

6. Definition of Result Groups

As explained in Section 2, machine learning is used for binning the time sequences into several distinct result groups based on the values of three features defined in the previous section. These three features are RHR, PRZV and MSV and have been selected using importance measures, such as random forest importance (Breiman, 2001) and permutation feature importance, combined with domain knowledge. Domain knowledge has been used to decide which of those features with the best importance measure would provide sensible, physically explainable, and meaningful separations.

The results from the first categorization are presented in Table 3. Each row on the left side corresponds to a distinct result group and a predicted result category. Each row on the right side to an observed result category (see Table 1). The columns on the left side (*RHR, PRZV* and *MSV*) show the feature values for each result group, a star indicates that the selected time series don't depend on the feature. The columns on the right side provide information about the number of observed time series (#), the mean probability (mean p.) and the observed result category (cat.).

Table 3. Result groups of the generated time series, coloured by category (Table 1) as described in Section 6

RHR	*PRZV*	*MSV*	Time series		
			#	mean p.	cat.
0	3	*	483	6.7 E-05	1
			10	2.7 E-09	2
			10	9.4 E-06	4
0	0	2	319	5.2 E-06	2
0	1&2	2	348	4.8 E-06	2
*	< 0	*	3,380	1.3 E-02	3
			1,325	2.0 E-02	4
			6	1.6 E-07	2
3	0	< 2	2,042	5.6 E-01	4
0	0	< 2	2052	3.5 E-01	4
			381	4.3 E-03	3
0	1 & 2	< 2	954	1.7 E-02	4
			465	5.3 E-03	3

The first categorization already provides a good separation for some of the defined failure states; further analysis is needed to understand the causes behind the failure states of each observed time series. The probabilities presented in Table 3 should be interpreted with caution as it can be assumed that operators would likely initiate more attempts to commission the HPLP, LPLP, and RHR than accounted for in this study.

7. Search for Final State Implicants for Primary Pressure (PPCS) Exceeding Design Pressure

To distinguish the time series of the result group 1 belonging to category 1 (PPCS exceeding design pressure) from those belonging to other categories, the following additional features are used: *MSV*, *EFWS, EBSV*, *t_PRZV*, and, in the case of MS valve failure, the time difference between the failure of MS valve and the failure of a PRZ valve.

The implicants presented in Table 4 can be understood with the following event chain is assumed: Once PRZ-SV2 fails closed, the pressure begins to increase. In case of an early failure of PRZ-SV2, the design pressure is reached before the EFWP is demanded. The time threshold

after which a failure of PRZ-SV2 triggers a request for the EFWP depends on the states of MSV and EBSV. In case of an open failure of the MS-RCV, secondary coolant is more rapidly lost and the EFWP is demanded earlier. Depending on the PRZ-SV2 failure time, as well as the state of MSV and EBSV, the successful activation of the EFWP may or may not be sufficient to prevent the reach of design pressure.

The different failure implicants, along with the mean probability for each implicant across all DETs, are listed in Table 4 for $MSV < 2$. The definition of a failure implicant is chosen conservatively, meaning that a combination of feature values is assumed to lead to the damage final state unless contradictory observations are made. For example, in the case of failure implicant 2 in Table 4, a timeout event is observed for $t\_PRZV = 425$ min, indicating that, if the PRZ-SV2 fails after this time, the heat transfer between the primary and secondary sides is sufficiently effective to prevent reaching design pressure. For $MSV < 2$, all observed time series not included in the failure implicants listed in Table 4 result in a timeout. In contrast, a failure of the PRZ-SV2 at t = 375 min leads to design pressure, even though the EFWS was successfully initiated.

Table 4. Failure implicants for a PPCS exceeding the design pressure; variable description is given in Section 5

MSV	*EBSV*	*EFWS*	*t_PRZV* [min]	Mean Probability
0	0	-1/0	*	8.75 E-07
0	0	1	< 425	6.36 E-07
0	1	-1	*	4.99 E-05
-1	0	*	*	7.82 E-08
-1	1	-1	*	7.97 E-06
	0	-1/0	*	1.65 E-08
1	1	-1/0	*	7.36 E-06

* Variable does not influence the result

Translated into successful valve demand cycles, this means that if PRZ-SV2 fails after 84 cycles, it results in design pressure, whereas if the PRZ- SV2 fails after more than 224 cycles, it leads to a timeout. This is one cases in which the performed IDPSA leads to new knowledge about the importance of an uncertain aleatoric variable like the failure time/cycle of a valve. The provision of implicants or, in a second step, prime implicants can be used to generate IDPSA results in a convenient way to be used for enhancing an existing PSA model.

In the case of a failure of the MS-SV ($MSV = 2$), the key continuous variables are the time difference between the failure of the PRZ-SV2 and the failure of the MS-SV. If the PRZ-SV2 fails more than 30 min after the MS-SV, the secondary side design pressure is reached before the primary side design pressure. Conversely, if PRZ-SV2 fails less than 18 min after the MS-SV, the primary side design pressure is reached first.

Regarding the analysis objectives, it was found that among the different manual measures (RHR, HPLP1, HPLD2, LPLD), the observed correlation between high PPCS and the successful initiation of RHR is the least likely to occur under the null hypothesis of no correlation (p-value = 1.5 E-26), followed by LPLD (p-value = 1.5 E-13) and HPLD1 (p-value = 1.4 E-10). This can be interpreted as indicating that the initiation of RHR is the most effective manual measure to prevent reaching design pressure. To successfully commission the RHR without the need to start the HPLD first, the pressure control must be checked within approximately 65 min after the spurious signal activation. Otherwise, PPCS will already be too high when the corresponding actions are carried out.

Another important factor is the remaining time between the last operator action and the time when primary design pressure is reached. This time is influenced by continuous as well as categorical features. Permutation feature importance (PFI) is employed to compare the influence of different features. The PFI is a model inspection method that measures the contribution of each feature to the statistical performance of a fitted model by randomly shuffling the values of a single feature and observing the resulting degradation in model performance.

In contrary to the impurity-based random forest importance, the permutation feature importance does not exhibit a bias toward high-cardinality features and is therefore better suited for comparing the significance of different influence factors. A random forest regressor was used to generate a model for predicting the available time.

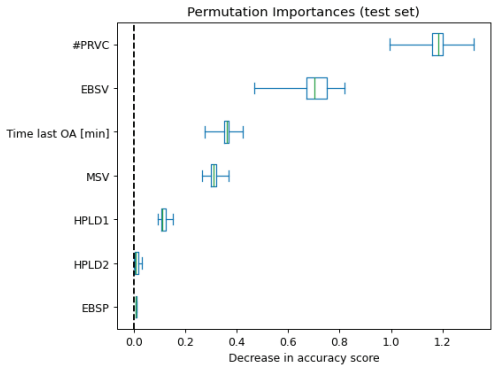

Fig. 1. Permutation feature importance for the prediction of the time period between the last operator action and the time PPCCL design pressure is reached.

The decrease in accuracy scores for the studied features is shown in Fig. 1. The number of PRZ valve cycles (*#PRVC*) before failure has the highest permutation feature importance, followed by the availability of the EBSVs. When the EBSVs are unavailable, the mean remaining time decreases from approximately 390 min to 300 min.

8. Use of Interactive Data Visualization

Occasionally, the observed results contradict intuition. In such cases, it is important to have a tool available to further investigate the event sequence and variable development for a given time series. To address this need, the MCDET EventTreeViewer has been developed. This is a Dash-based graphical user interface (GUI) that facilitates interactive investigation of generated DETs. Fig. 2 presents a snapshot of the MCDET EventTreeViewer.

9. Summary

Based on the example of an IDPSA for a mid-loop accident scenario induced by a spurious actuation of the RPS, the processing of the results based on machine learning and domain knowledge has been presented focussing on the potential end state category “primary side pressure exceeding design pressure”. The main influence factors for this end state category have been identified and different implicants and their probability distinguished. Since the main influence factors identified for the result scenario are system availabilities, an additional analysis has been conducted to understand the importance of various manual measures regarding the end state analysed.

In addition, the mean time between the last human action and the time when design pressure is reached has been determined together with the main influence factors for this time interval. Similar studies have been conducted in the frame of the ADAMO project for all categories listed in Table 1. One of the key findings of the study is

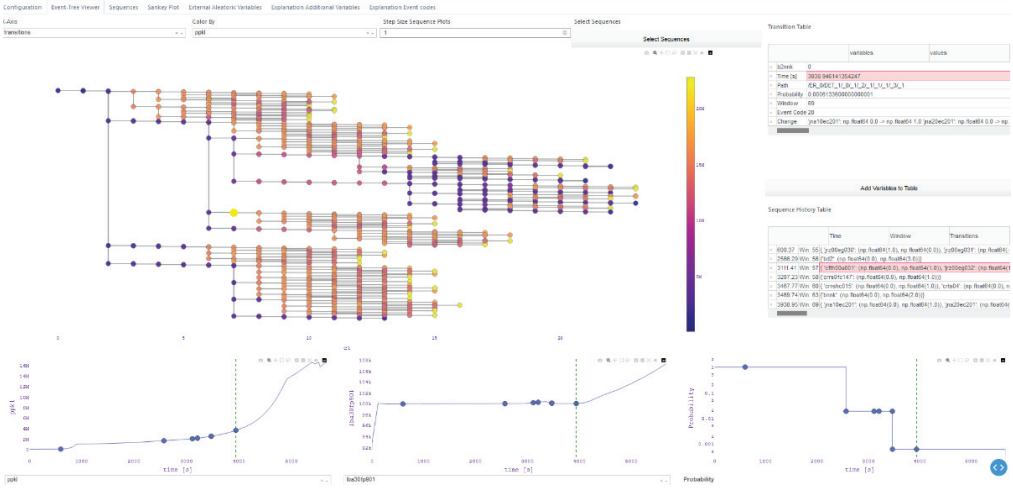

Fig. 2 Snapshot of the MCDET EventTreeViewer Dashboard, showing the structure of one of the ADAMO DETs and time series information up to the large yellow dot. It allows interactive investigation of a DET, inspection of variable changes at each knot of the DET and of the time series development for the observed simulation variables till each knot.

the identification of the time frame within which the check of the PPCS should be conducted to enable the direct commission of the RHR. The newly developed MCDET EventTreeViewer has helped understand counter-intuitive event sequences and is an important new tool for result processing.

It can be concluded that machine learning methods provide an important tool to simplify the result processing of an IDPSA but should be combined with domain knowledge to assure that the results remain meaningful.

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