Modeling Operator Actions in Integrated Deterministic-Probabilistic Safety Assessment

Vinh N. Dang and Durga Rao Karanki,
Paul Scherrer Institute, Villigen PSI, Switzerland

Abstract: The Dynamic Event Tree (DET) framework is one of the main approaches for coupling simulations of physical models and stochastic processes. In applications related to nuclear power plant safety, the physical models include plant transient models while some of the principal stochastic events of interest relate to equipment failures and operator responses. The number and/or timing of these failures affect accident sequence outcomes; conversely, the plant state and its dynamic evolution may affect the distributions of the stochastic events. The capability to explicitly model these dynamic interactions motivates the application of DETs. In DET modeling, the operator response time is discretized. This paper presents the analysis of Medium Break Loss of Coolant Accidents (MLOCAs) accident scenarios. The results show the impact of the alternative discretizations of the operator response times for the actions in this scenario on the estimated core damage frequency. It concludes with recommendations on a discretization approach that balances the representation of the sequence dynamics while avoiding excessive conservatism in the risk estimates.

Keywords: Dynamic PSA, Dynamic Event Trees, Operator Modeling.

1. INTRODUCTION

The Dynamic Event Tree (DET) framework is one of the main approaches for coupling simulations of physical models and stochastic processes. In applications related to nuclear power plant safety, the physical models include plant transient models while some of the principal stochastic events of interest relate to equipment failures and operator responses. The number and/or timing of these failures affect accident sequence outcomes; conversely, the plant state and its dynamic evolution may affect the distributions of the stochastic events. The capability to explicitly model these dynamic interactions motivates the application of DETs.

The DET used in this work is a discrete DET (DDET) implementation of the framework. In DDETs, a particular challenge is the modelling of stochastic variables that are continuous. In a nuclear Probabilistic Safety Assessment (PSA) context, processes with random durations are such variables; they include the time to operator actions, the lifetime of power back-up batteries, or the time to power recovery. In contrast to a stochastic demand failure event that lead to a probabilistic branching event when the component or system is demanded, DET branches cannot be generated for each of the possible durations of a stochastic process. The stochastic process durations can be discretized. In this case, the number of discretization intervals and the bounds of the intervals need to be specified. For each process with a stochastic duration, branches representing the intervals of the durations are generated within a single DET. An alternative approach, applied in the MCDET (Monte Carlo DET) tool [1], is to apply a Monte Carlo sampling of the stochastic durations and perform a DET simulation for each MC sample. This avoids the discretization problem but requires the simulation of an ensemble of DETs. The work presented in this paper addresses the application of the discretization approach for stochastic durations, focusing on the modeling of operator actions.

To examine how the discretization of the operator response time affects the calculated risk and to develop recommendations for this discretization, a case study analysis of a Medium Break Loss of Coolant Accident (MLOCA) is performed. The model of the plant and its systems is based on the decommissioned Zion NPP, which has been used previously in the SM2A project of the OECD NEA Committee on the Safety of Nuclear Installations (CSNI) [2, 3] and in various follow-on studies [4].

With the overall aim to demonstrate methodological issues and solutions, the system or equipment failure models that are included have been selected for illustration and are not comprehensive; also, additional failure data has been assumed, selecting representative values for demonstration purposes. As a result of these assumptions, the core damage frequency (CDF) results obtained are not intended to and do not represent the risk for an actual plant. The ADS DET scheduler [5] was applied in the case study – specifically, ADS-TRACE is used [6, 7], in which the plant response is modeled with the TRACE NPP simulation code.

The scope and the features of the model of operator response are described in Section 2. While the operator response model remains the same, the number of discretization intervals and of the interval bounds are varied. In this paper, each combination of the selected number of intervals and interval bounds for the operator time response is referred to as a discretization model. Section 3 describes the MLOCA scenario, the accident sequence model, and the failure data used in the case study. In addition, the quantification of the DET results is presented. The CDF results for the MLOCA scenarios analyzed are presented and discussed in Section 4. The paper concludes with a summary of recommendations for a discretization model of operator actions in DDETs.

2. THE OPERATOR RESPONSE MODEL

In classical PSA, assessing the probability of failure of operator actions reduces to whether an operator action is performed within the available time; a lower bound for the available time (time windows) is estimated with plant simulations in which assumptions are made concerning the performance of equipment and preceding operator actions are taken. In contrast, in DETs or dynamic PSA, the question is to model what operator actions are taken and when. Time windows are not estimated for operator actions; instead, sequence outcomes are determined by simulating in the DET the evolution of the system response as a result of by the hardware and operator action events that have occurred.

One approach to determining what operator actions are taken and when they are taken is to simulate the evolution of the internal (or cognitive) state of operating crew or operators as they detect plant alarms and apply procedures and trained rules to collect and process plant information to assess the plant state and the decision criteria in the procedures to select the actions to perform. Such an approach is implemented, for example, in the ADS-IDAC model [8]. The work presented here represents the operator response at a higher level, with less detail.

2.1 Scope and basic structure of the operator model

In the following, the operating crew will be referred to as the "operator", not distinguishing that several operators work together and communicate to come to a decision and perform an action. The action on the plant is referred to as an operator action, consistent with the usual PSA terminology.

In this model, the basic unit of analysis is the crew's (operator's) response to a cue. When a plant alarm occurs, the operator performs a situation assessment to select a response action, which he then implements (executes). The duration of this process from cue to the completion of the action can be divided into two main parts: 1) Tdec from the cue to the decision (response selection), and 2) Texec from the decision to the completion of the execution. This basic model is represented in Figure 1a, from which it can be seen that other aspects of the model include addressing whether the cue is detected and whether the implementation of the action is successful. Additionally, the action will not be successful if either errors occur during the execution of the actions or if the hardware fails on demand.

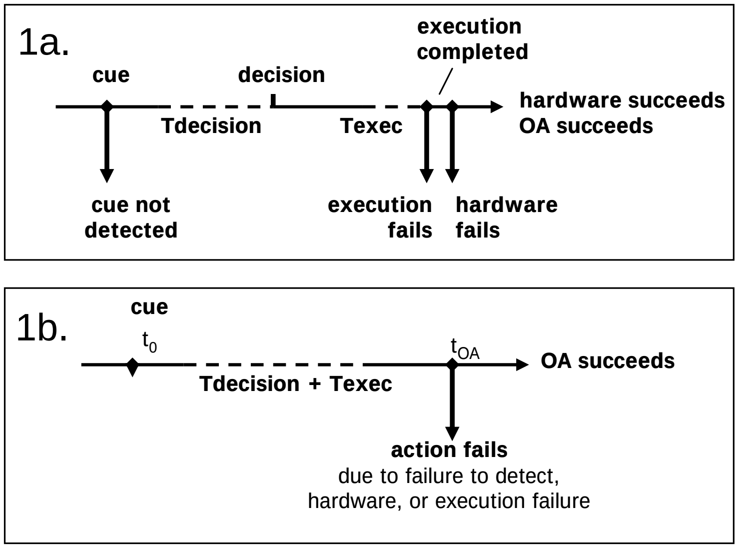

Figure 1: Conceptual model for the operator response

2.2 Inputs of the operator model

For each operator action to be modeled in the DET, the required inputs are:

- Cue (e.g. plant alarm)
- Probability of non-detection
- Duration of decision process
- Duration of execution
- Probability of execution failure
- Action (effect on the plant)

The generation of the cue in the physical model is the trigger for the operator model. The failure to detect the cue can be treated as a stochastic (binary) event; the probability of non-detection can be modeled dynamically, i.e. dependent on other plant parameters. For both the decision process and execution tasks, distributions of the durations need to be specified. The successful execution of the operator action is also a stochastic (binary) event; in general, the failure of any of the subtasks needed to complete the operator action is modeled with an overall (total) probability for the failure of execution.

This simplified model comprises two binary stochastic events and two processes with stochastic durations. From the point of view of the plant-crew interactions or of the coupled plant model and stochastic model, the operator response model can effectively reduced, as shown in Figure 1b. The binary events can be combined because if either of these fail, no operator action occurs and the evolution of the plant response is unperturbed. With regard to the timing of the response, the durations of the decision process and of the execution process can also be combined; the timing of the decision has no direct effect on the plant response so that their sum represents when the operator action takes place.

2.3 Discretization of time response

The implementation of this operator response model in a DDET requires an additional modeling step. The time response part of the model, which represents the overall duration of decision and execution, must be discretized. This discretization needs to satisfy three basic requirements: 1) minimization of the number of discretization intervals, in order to limit the size of the tree and the associated computational resources; 2) some representation of the low and middle ranges of the distribution, correspondonding to the early and median crew response times; and 3) an adequate representation of the high range (longer durations). Time responses in the low-middle range are of interest because they are representative, comprising the mass of the probability distribution; moreover, the effect of these responses on the subsequent evolution of the scenario and its outcomes may be significant. The longer durations would be expected to correspond fall in the range of time windows that are normally estimated for a classical HRA.

Figure 2 illlustrates the DDET branches in a timeline-view when the operator model, shown earlier in Figure 1B, is discretized. If a plant cue occurs at t0, discrete branches are generated for the completion of the operator action at t1, t2, ... and tn. At these times, the simulation of the plant evolution along the top line branches; in the lower branch, the operator action takes place. Beyond tn on the upper timeline, no operator action has taken place.

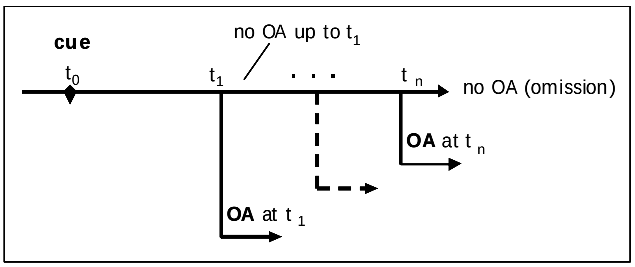

Figure 2: DDET branches for the operator model – timeline-view

In Figure 2,

$$t_1 = t_0 + T_{dec,1} + T_{exec}$$

$$t_n = t_0 + T_{dec,n} + T_{exec}$$

The same branches are shown in a logical (probabilistic) tree in Figure 3. From these figures, it can be seen that if n duration values are chosen to represent the time response for an operator action, the last interval represents the case that the operator action is not performed. Following the usual event tree notation, the lowest branch in the logical tree now corresponds to non-response, i.e. no operator action taking place. This branch represents the case that the time to response is larger than Tn as well as the failure to detect the cue, execution failures, and the failure of the hardware required for the operator action. All of these have the effect that the plant evolution is unperturbed.

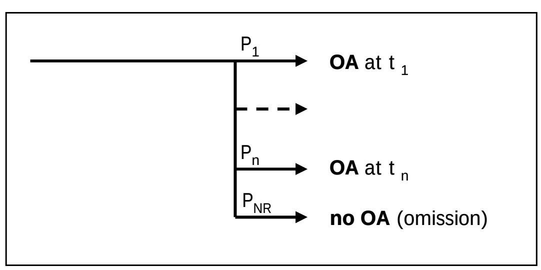

Figure 3: DDET branches for the operator model – logical view

In Figure 3,

$$P_1 = Pr(0 < T_{dec} < T_{dec,1}) = F_{dec}(T_{dec,1})$$

where F_{dec} is the cumulative probability distribution for T_{dec}

$$P_n = Pr(Tn\text{-}1 < Tdec < Tn) = F_{dec}(T_{dec,n}) - F_{dec}(T_{dec,n-1})$$

$$P_{NR} = Pr(\,T_{dec} > T_n) + P_{hardware} + P_{failure,\ detect} + P_{failure,\ exec}$$

The combinations of number of intervals and interval bounds for the operator time response examined in this work are shown in Table 1.

Table 1: Alternative discretization models for the operator time response (in percentiles)

Model	Interval bounds	Interval ranges						
A	5-50-95	0-5	5-50	50-95	>95			
B	50-95-99	0-50	50-95	95-99	>99			
C	50-95-99.9	0-50	50-95	95-99.9	>99.9			
D	50-95-99.99	0-50	50-95	95-99.99	>99.99			
E (Ref)	5-50-95-99-99.9-99.99	0-5	5-50	50-95	95-99	99-99.9	99.9-99.99	>99.99

For each of the interval ranges, the duration corresponding to the upper end of the range is used in the simulation. The last interval and its probability represents the event not taking place (non-response). In Model A, the discretization bounds were selected at the 5th, median, and 95th percentiles of the time response distribution. Such a model has been used in previous work [9, 10, 11]; it is particularly suitable when the aim is mainly qualitative. These percentiles can be viewed as corresponding to early, representative or median, and late responses. On the other hand, in a probabilistic context, such a model is quite pessimistic because it corresponds to a non-response probability of 0.05, excluding execution failure and hardware contributions.

Models B, C, and D drop the 5th percentile while the last interval bound is increased, to model the non-response probability with values of 0.01, 0.001, and 0.0001. Model E is used as a reference model; with seven branches per operator action, this model leads to large DETs if sequences include multiple operator actions and/or other processes with stochastic durations.

3. THE MLOCA SCENARIO AND MODEL DATA

The MLOCA scenario is initiated by a break with a break with an effective diameter between 2 and 8 inches. The accumulators are assumed to be available. For high pressure injection, the plant has two train of high head injection pumps and two trains of charging pumps. For low pressure injection there are two trains. When the refueling water storage tank is low, the crew should manually switch injection to draw from the sump in the recirculation phase.

In [6], the impact of the break size and the scenario dynamics due to the number of available low and high pressure pumps were previously examined. The break size was modeled in three ranges, 2.0-4.5”, 4.5-6.5”, and 6.5-8.0”, differentiating between a small MLOCA, and intermediate MLOCA, and a large MLOCA. For the purposes of this study, only the first two break size ranges are examined. These are sufficient to observe the differences in sequence outcomes due to the scenario dynamics.

The MLOCA scenario model used in this work is similar to that from [6, 7]. In the scenario automatic safety systems will trip the reactor and turbine and start to inject water into the reactor coolant system in order to compensate for the loss of coolant. For MLOCAs, high pressure injection systems are required initially. Next, the RCS pressure will drop, allowing the accumulators and, finally, the low pressure injection systems to inject. Two manual actions are often considered in MLOCAs: switching HPI or LPI to recirculation when the coolant reserve is low, and in scenarios in which HPI fails, a rapid cooldown to reduce pressure and allow LPI to inject. The nominal success sequence in MLOCA requires the availability of high pressure injection (HPI), accumulators, low pressure injection (LPI), and the recirculation. The following functions were assumed to be available and to operate when needed: reactor trip, turbine trip, the SI signals, containment spray, accumulators, and auxiliary feed water system.

3.1 Modeling of hardware failures

The MLOCA initiating frequencies are derived from NUREG-1829 [12]. The frequency for the range 2-4.5" is 2.59E-4 /yr while it is 7.56E-6 /yr for the 4.5-6" range. Note that the corresponding frequecy for the 6.5-8.0 range is 1.98E-6 /yr.

Representative failure data have been selected and derived from [13], [14], and [15]. For the safety injection pumps (HH, CH, and LPI), failures to start, failures to run, maintenance unavailability and common cause failures have been included. The required alignments of motor-operated valves and check valves are also included. In addition, AC power bus unavailability is also considered. These result in the conditional probabilities for the configurations of available HPI and LPI pumps shown in the third column of Table 2. For the contribution to recirculation failure due to equipment failures, the switchover only credits the available safety injection trains and models the demand failures associated with restarting the pump after the re-alignment of the suction source. The resulting conditional probabilities are shown in the last column in Table 2.

Table 2: Conditional probabilities for hardware failures

available HPI trains	available LPI trains	Conditional probability for (HPI, LPI)	Conditional probability for hardware failure of recirculation
4	2	~0.975	5.47E-4 /demand
	1	1.11E-2	3.03E-3
	0	5.50E-4	
3	2	1.29E-2	5.52E-4
	1	1.98E-4	3.05E-3
	0	7.46E-6	
2	2	5.48E-4	5.86E-4
	1	6.73E-6	3.08E-3
	0	3.06E-7	
1	2	2.83E-6	8.41E-4
	1	5.17E-8	3.75E-3
	0	1.69E-9	
0	-	2.45E-8	

3.2 Modeling of the operator action: switchover to recirculation

The operator action to switch the injection source for safety injection to the sump, referred to as the recirculation mode, occurs late in the MLOCA scenario. The cue for this action is a low level in the Refueling Water Storage Tank (RWST), specifically the low-low level alarm; the timing of the cue depends on the size of the break and the number of safety injection pumps in operation. The success of the switchover requires that the crew stops the operation of injection from the RWST, re-aligns injection to draw suction from the sump, and restarts injection without allowing the RWST to be completely empty.

As in [3, 5], it is assumed that the decision to perform the switchover is deliberate and not rushed. The need for the switchover is expected and the availability of water in the sump should be ensured. The resulting distribution of the decision process, i.e. the time to reach the decision, is assumed to follow a lognormal distribution with a median of 6 minutes (half the crews would be expected to reach the decision in 6 minutes), a 5th percentile of 3 minutes, and a 95th percentile of 12 minutes (19 of 20 crews would reach the decision within 12 minutes). The distribution is shown in Figure 4 in probability density and cumulative probability; in this figure, the values of the 5th percentile and median are plotted on the x-axis. A failure to detect the low-low level alarm is neglected. For the execution, a constant 6 minutes are assumed, although the actual duration may depend on the specific configuration for the recirculation. Because the sum of Tdecision and Texecution affects the scenario dynamics, it can be assumed that the Tdecision distribution includes the variability of the execution time among crews and depending on the task.

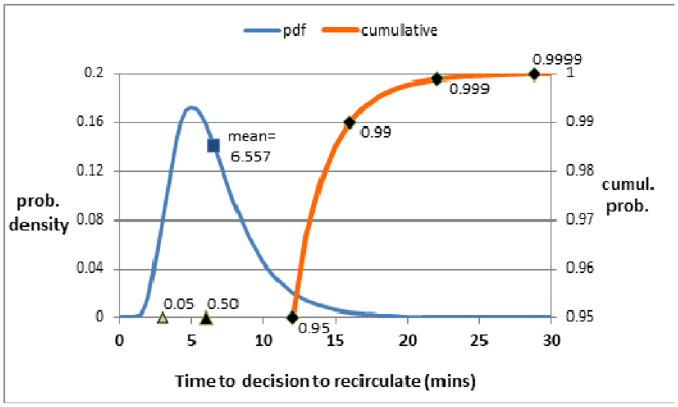

Figure 4: Distribution function for the time to the decision to recirculate (Tdec)

Applying the discretization models for these durations from Table 1, the modeled Tdec intervals are shown in Figure 5. The decision durations used in the DET model are the values at the right of each of the colored bars, in the upper figure (Fig. 5a). The right-most portion of the bar (in grey-white) represents the failure to reach a decision at all. The probabilities of the intervals are shown in the lower figure (Fig. 5b).

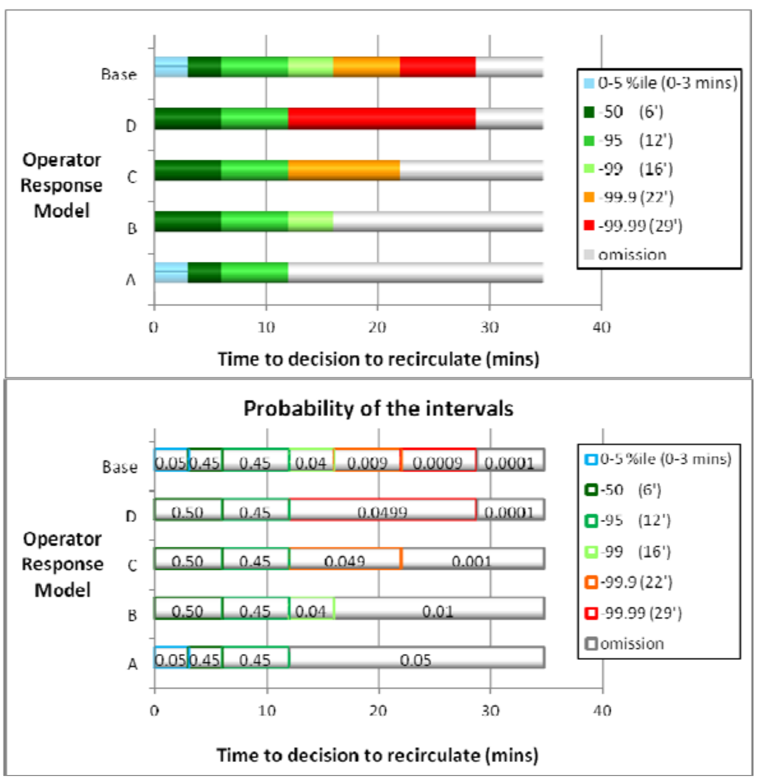

Figure 5: Discretization models for Tdec, the time to the decision, showing the intervals, their bounds (in minutes converted from percentiles), and the interval probabilities (lower figure)

Finally, an failure probability of 0.001 is used for the failure of the execution of the recirculation alignments.

3.3 Quantification

In the Zion PSA [11, 12] and other models, the failure of the switchover to recirculation is a dominant contributor to the CDF from MLOCA. In principle, the CDF is calculated by simulating the plant-operator response in the DET with the operator action to recirculate occurring at the times representing the intervals of the response distribution and summing the frequencies of the sequences that lead to failure. In practice, the dependencies among the frontline systems due to CCF and support system dependencies such as AC power introduce an additional difficulty for quantification. For instance, the failure probability for LPI is conditional on the preceding events due to the contribution of the support system failures to the HPI failures.

Consequently, in this work, the DDET is used to determine the sequence outcomes that result from the hardware failure events and the timing of the operator action (or its omission). The sequences and their outcomes are then modeled using a PSA. As a result, the conditional probabilities shown in Table 2 account for the support system dependencies as well as the unavailability of the trains for recirculation.

4. RESULTS

4.1 Comparison of time response models (discretization)

The Conditional Core Damage Probability (CCDP) and the CDF obtained using the different discretization models are shown in Table 3. The base model, with 7 discretization intervals, is the best estimate and is used as the reference value in this comparison. The CCDP multiplied by the initiating event frequency (the frequency of the break range) yields the CDF. The multiplier shown below the CDF is the ratio of the result obtained with the discretization model compared to the base or reference model.

Table 3: Summary of results

MLOCA break range		**Model A** “5-50-95”	**Model B** “50-95-99”	**Model C** “50-95-99.9”	**Model D** “50-95-99.99”	**Base model** “05-50-95-99-99.9-99.99”
2.0-4.5”	CCDP	5.34 E-2	1.24 E-2	3.20 E-3	2.27 E-3	2.27 E-3
	CDF	1.38 E-5	3.22 E-6	8.28 E-7	**5.89 E-7**	**5.89 E-7**
	Multiplier	23.5	5.5	1.4	**1.0**	
4.5-6.5”	CCDP	5.34 E-2	1.24 E-2	3.20 E-3	5.34 E-2	3.20 E-3
	CDF	4.04 E-7	9.39 E-8	**2.42 E-8**	4.04 E-7	**2.42 E-8**
	Multiplier	16.7	3.9	**1.0**	16.7	

For the 2.0-4.5” break range, the percentile selected for the largest interval bound, e.g. 99 in discretization model B, generally determines the degree of pessimism for the CDF. Discretization model D is shown to be the best model, yielding the same CDF as the base model. The CDF is increasingly pessimistic as this percentile is reduced from 99.99 (model D) to 95 (model A). In this case, the interval bound at the 5th percentile does not affect the obtained CDF because all time responses up to the median have the same, successful outcome.

For the 4.5-6.5” break range, discretization model C is the best model. While the results are increasingly pessimistic from C to A, model D also overestimates the CDF and it does so significantly.

4.2 Discussion

In this section, the contributions to the CDF are analyzed to identify the underlying reasons for the results obtained. In the 2.0-4.5” break range, the sequences with the omission of recirculation (recirculation is not performed at all) dominate the CDF. In particular, the scenario with all 4 HP trains available, 2 LP trains available, and the omission of recirculation contributes 70% of the CDF of

5.89 E-7 (model D and base model). The second largest contributor is the scenario with 4 HP trains and no LP trains, in which recirculation is not available because the LP pumps are needed in piggy-back operation (all scenarios with 0 LP pumps are assigned to core damage). Because the omission of recirculation dominates the CDF, the probability assigned to omission is particularly important. It consists of the hardware failure of the equipment needed for recirculation, the execution failure of recirculation alignment tasks, and the probability assigned to the last range of the discretized time response; the last is shown as the right-most interval in Figure 5b.

It can be seen that the difference between model C and model D for the 2.0-4.5" break range is relatively small although the non-response component of the probability of the last interval is 1E-3 in model C and 1E-4 in model D. The hardware failure probability, on the order of 5E-4 in the dominant scenario (4HP, 2LP), and the execution failure probability of 1E-3, are significant contributions on the order of the non-response probability. As a result, the total probability of omission of recirculation considering all causes is 2.55E-3 in model C and 1.65E-3 in model D. The small difference in this total failure probability for recirculation explains the small difference between these models.

A summary of the CDF contributions for model C for the 2.0-4.5" break range is provided in Figure 6 (placed before References section). In the configurations (1 HP, 2 LP) and (1HP, 1 LP), highlighted in yellow, the operator action at the 99.9th percentile also leads to core damage. This interval represents the recirculation performed at 22+6 mins., which the DDET determines is "too late", as opposed to "not performed at all". The size of this interval (i.e. the interval between the 99.9th percentile and the next lower percentile used as an interval bound) determines the probability assigned to core damage. The values in Figure 6 show, however, that the conditional probability of these sequences is small relative to the scenarios with few HP and LP failures (several orders of magnitude smaller).

Although these relationships also hold for the 4.5-6.5" break range, the CDFs from models C and D differ by more than an order of magnitude. The reason is that, in this break range, the 99.99th percentile time response leads to core damage; moreover, this occurs also for the scenarios with high conditional probabilities, such as (4 HP, 2LP) (4HP, 1LP). The probability of a total omission of recirculation plays a role as before but the 95-99.99 interval for model D, with a conditional probability of 0.0499 is also assigned to core damage. The dominant contributors for this break range are shown in Table 4, for models C and D, with the "too late" sequences highlighted in yellow.

It should be noted that in the more limiting scenarios of the 4.5-6.5" break range, such as those with only 1 HP available, the median, 95th and 99th percentiles of the time response are also "too late" and lead to core damage. However, these scenarios have much smaller conditional probabilities so that their contribution to the CDF is practically negligible. For instance, the (1 HP, 2 LP) scenario, for which the median response time leads to CD, has a CDF contribution of 1.E-11.

4.3 Recommendations for the discretization of the operator time response

In general, the number of discretization intervals is limited due to the need to keep the overall size of the DET (the number of different scenarios to be computed) manageable. In general, the actual time windows are specific to the plant response to a given initiating event and to the available systems in the modeled accident sequences. The response time distributions are specific to the operator action of interest (they can also depend on the accident sequences). Nevertheless, some overall recommendations can be drawn from this case study.

1. The percentile selected for the largest interval bound should be selected so that the non-response probability is not overly pessimistic. This percentile determines the non-response probability so that selecting the 95th percentile for this bound is equivalent to assuming a non-response probability of 0.05 that is applied to all scenarios. This means that this percentile should be as high as possible. However, the percentile should be selected so that sequence is successful (does not lead to core damage) if the operator action is performed at this time. If the sequence leads to failure, the interval up to and including this bound is assigned to core damage.

Table 4: Dominant contributors for the 4.5-6.5" break range

HP	LP	cond. prob. (HP, LP)	recirc. interval	probability OA branch	outcome	CCDP	CDF
4	2	~0.975	0-50	0.5			
			50-95	0.45			
			95-99.9	0.049			
			99.9-100 *	2.55 E-3	CD	2.55 E-3	**1.93 E-8**
	1	1.11 E-2	0-50	0.5			
			50-95	0.45			
			95-99.9	0.049			
			99.9-100 *	5.03 E-3	CD	5.03 E-3	**4.22 E-10**
	0	5.50 E-4	n/a		CD	5.50 E-4	**4.16 E-9**
Model C 50-95-99.9-no action							**2.38 E-8** 98% of total CDF of 2.42 E-8

HP	LP	cond. prob. (HP, LP)	recirc. interval	probability OA branch	outcome	CCDP	CDF
4	2	~0.975	0-50	0.5			
			50-95	0.45			
			95-99.99	0.049	CD	4.99 E-2	**3.77 E-7**
			99.99-100 *	1.65 E-3	CD	1.65 E-3	**1.25 E-8**
	1	1.11 E-2	0-50	0.5			
			50-95	0.45			
			95-99.99	0.049	CD	5.5 E-4	**4.19 E-9**
			99.99-100 *	4.13 E-3	CD	4.5 E-5	**3.46 E-10**
	0	5.50 E-4	n/a		CD	5.5 E-4	**4.16 E-9**
Model D 50-95-99.99-no action							**3.98 E-7** 98.5% of total CDF of 4.04 E-7

* For this interval, the branch probability includes the failures of hardware and execution.

2. An upper limit for the largest interval bound (the bound that delineates the time for the latest performance of the action from omission or non-response) is to select a percentile that results in a non-response probability on the order of the sum of the hardware and execution failure probabilities. The non-response (decision is not reached), failures in implementing the operator action, and the hardware contribution are all part of the same branch in the DET. If the non-response probability is selected to be significantly smaller than the execution failure and hardware failure contributions, the overall probability of the branch is not significantly reduced while the likelihood that the operator action actually performed at this percentile will lead to a core damage sequence will increase. In that case, the interval from the next lower percentile to the largest interval bound also contributes to core damage, which can cause a significant overestimation of the CDF.

3. In selecting the interval bounds, the notion is to extract the most information from a limited number of sequences. Consequently, the actual durations corresponding to the percentiles should also be taken into account.

5. CONCLUSION

This paper presents the analysis of Medium Break Loss of Coolant Accidents (MLOCAs) accident scenarios. The results show that alternative discretizations of the operator response times for recirculation lead to differences of between one and two orders of magnitude in the estimated core damage frequency from the analyzed MLOCA scenarios. The case study suggests a 4-range discretization with interval bounds at the median, 95th and 99.9th percentile. In general, the largest interval bound should lead to a non-response probability of the order of the execution failure probability. Selecting the median for the lowest interval bound means that the time performance of a representative crew is addressed, which is not the case in an HRA where the upper bound of performance is usually considered. The choice of the intermediate bound does not appear to be as critical. The 95th percentile decreases the likelihood that this interval, which spans from the median up to this bound and has a substantial mass of the distribution, is assigned to core damage.

Acknowledgements

This work has been performed in the frame of a joint project with PSI's Laboratory for Reactor Physics and Systems Behaviour (LRS). It was partly supported by swissnuclear, the nuclear energy section of the organisation of Swiss electricity grid operators.

HP	LP	cond. prob. of (HP,LP)	response time interval (%iles)	prob of interval (*+hw+exec)	outcome	CCDP seq	CDF seq	Total CDF
4	2	9.75E-1	0-50	0.5	s			8.28E-7
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	2.55E-3	cd	2.54E-3	6.60E-7	
	1	1.11E-2	0-50	0.5	s			
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	5.03E-3	cd	5.58E-5	1.45E-8	
	0	5.50E-4		1	cd	5.50E-4	1.42E-7	
3	2	1.29E-2	0-50	0.5	s			
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	2.55E-3	cd	3.29E-5	8.53E-9	
	1	1.98E-4	0-50	0.5	s			
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	5.05E-3	cd	9.99E-7	2.59E-10	
	0	7.46E-6		1	cd	7.46E-6	1.93E-9	
2	2	5.48E-4	0-50	0.5	s			
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	2.59E-3	cd	1.42E-6	3.67E-10	
	1	6.73E-6	0-50	0.5	s			
			50-95	0.45	s			
			95-99.9	0.049	s			
			99.9-100 *	5.08E-3	cd	3.42E-8	8.85E-12	
	0	3.06E-7		1	cd	3.06E-7	7.93E-11	
1	2	2.83E-6	0-50	0.5				
			50-95	0.45				
			95-99.9	0.049	cd	1.39E-7	3.59E-11	
			99.9-100 *	2.84E-3	cd	8.04E-9	2.08E-12	
	1	5.17E-8	0-50	0.5				
			50-95	0.45				
			95-99.9	0.049	cd	2.53E-9	6.56E-13	
			99.9-100 *	5.75E-3	cd	2.97E-10	7.70E-14	
	0	1.69E-9		1	cd	1.69E-9	4.38E-13	
0	n/a	2.45E-8		1	cd	2.45E-8	6.35E-12	

Figure 6. Summary of the CDF contributions 2.0-4.5" break range, Model C

References

[1] 4. M. Kloos and J. Peschke, "*MCDET: A Probabilistic Dynamics Method Combining Monte Carlo Simulation with the Discrete Dynamic Event Tree Approach*," Nuclear Science and Eng. 153, pp.137-156 (2006).

[2] M.A. Zimmermann, V.N. Dang, J.-M. Lanore, P. Probst, J. Hortal, A. Amri, "*Insights from the SM2A pilot study towards quantification of a change of plant safety margin after a hypothetical power up-rate*", Proc. ANS Int. Topical meeting on Probabilistic Safety Assessment and Analysis (PSA 2011), Wilmington, NC, USA, 13-17 March 2011, CD-ROM.

[3] CSNI, "*Safety Margin Assessment and Application – Final report"*, CSNI/R(2011)3, Committee on the Safety of Nuclear Installations, OECD Nuclear Energy Agency, Paris, France, 2011.

[4] D.R. Karanki, V.N. Dang, T.W. Kim, "*Discrete Dynamic Event Tree Analysis of MLOCA using ADS-TRACE*", Int. Topical Meeting on Probabilistic Safety Assessment and Analysis 2011, Wilmington, NC, PSA 2011 1, pp.610-622 (2011).

[5] K.S. Hsueh, A. Mosleh, "*The Development and Application of the Accident Dynamic Simulator for Dynamic Probabilistic Risk Assessment of Nuclear Power Plants*", Reliability Engineering and System Safety, 52, pp.297-314 (1996)

[6] V.N. Dang, T.W. Kim, M.A. Zimmermann, A. Manera. "*Assessing Safety Margins: the impact of a power uprate on risk from Small and Medium LOCA scenarios*", Proc. 10th Int. Conf. on Probabilistic Safety Assessment and Management (PSAM10), Seattle, USA, 7-11 June 2010.

[7] D.R. Karanki, V.N. Dang, "*Quantified Dynamic Event Trees Vs PSA – A Comparison for MLOCA Risk*", ANS PSA 2013 International Topical Meeting on Probabilistic Safety Assessment and Analysis, Columbia, SC, USA, Sep 22-26, 2013, American Nuclear Society, 2013, CD-ROM.

[8] Y.H.J. Chang and A. Mosleh, "*Cognitive modeling and dynamic probabilistic simulation of operating crew response to complex system accidents. Part 1: Overview of the IDAC model*", Reliability Engineering and System Safety 92, pp 997-1013, (2007).

[9] K.A Coyne and A. Mosleh, "*Modeling nuclear plant operator knowledge and actions - the ads-idac simulation approach*", ANS PSA 2008 Topical Meeting-Challenges to PSA during the nuclear renaissance. Knoxville, Tennessee, 2008.

[10] D. Mercurio, V.N. Dang, "*Use of Dynamic Event Trees to Model Variability in Crew Time Performance*", 10th Int. Conference on Probabilistic Safety Assessment and Management (PSAM 2010), Volume 2, pp.1443-1454 (2010).

[11] J. LaChance, J. Cardoni, Y. Li, A. Mosleh, D. Aird, D. Helton, K. Coyne, "*Discrete Dynamic Probabilistic Risk Assessment Model Development and Application"*, Sandia Report SAND2012-9346, Sandia National Laboratories, Albuquerque NM, 2012.

[12] R. Tregoning, P. Scott, A. Csontos, *Estimating LOCA Frequencies Through the Elicitation Process*, NUREG-1829, vol. 1, U.S. Nuclear Regulatory Commission, Washington DC, USA, 2008.

[13] USNRC, "*Review and Evaluation of Zion Probabilistic Safety* Study", NUREG/CR-3300, U.S. Nuclear Regulatory Commission, Washington DC, USA, 1984.

[14] USNRC, "*Analysis of Core Damage Frequency: Zion Unit 1, Internal Events*", NUREG/CR-4550, EGG-2554, Vol. 7 (1990).

[15] IAEA, "*Component Reliability Data for Use in Probabilistic Safety Assessment*", IAEA-TECDOC-478, International Atomic Energy Agency, Vienna, Austria, 1988.