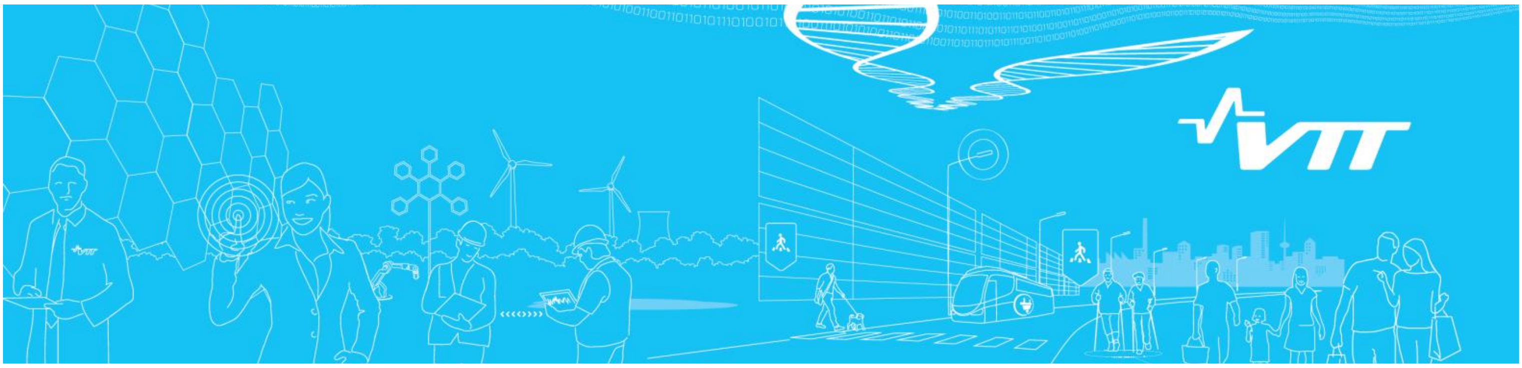

RESEARCH REPORT

VTT-R-00191-18

Level 2 PRA studies – Steam explosions and integration of PRA levels 1 and 2

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Summary

This report continues the development of simplified probabilistic risk analysis models of a boiling water reactor plant. Previously developed level 1 and level 2 models are extended and integrated so that it is possible to list most important event tree sequences, initiating events and basic events with regard to radioactive releases. A special focus is on the computation of emergency core cooling system recovery probability based on level 1 results. Some possibilities for the improvement of FinPSA level 2 software tool are identified concerning tight integration of PRA levels 1 and 2. The example model can later be utilised in further studies, demonstrations, training and FinPSA testing.

To handle separately different types of uncertainties in dynamic containment event trees, a method with two-phase uncertainty analysis has been outlined. The method would enable explicit modelling of dynamic dependencies and production of proper uncertainty distributions as a result at the same time, whereas with normal one-phase uncertainty analysis it is difficult to do both.

Ex-vessel steam explosions are also discussed in the report. Probabilistic modelling of steam explosions is very challenging because uncertainties related to the phenomenon are very high. Pressure impulses of explosions can be calculated quite well using deterministic software tools, but the probability that an explosion occurs in the first place cannot be properly estimated based on current knowledge. Currently, it is a good idea to use conservative probabilities in PRA. It could be studied if explosion triggering probabilities could be estimated based on some physical parameters calculated by deterministic software tools.

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Contents

1. Introduction

Level 2 probabilistic risk analysis (PRA) studies nuclear power plant accident progression after core damage, and frequency, size and composition of radioactive releases [1]. Severe accident phenomena, e.g. hydrogen explosions, and timings of events, such as cooling system recovery, play an important role in such analyses. Information on severe accident progression provided by deterministic analyses is crucial to the construction of proper level 2 PRA. Integrated deterministic and probabilistic safety analysis (IDPSA) aims to bring the two types of analysis closer and improve their co-operation.

This report continues the development of simplified boiling water reactor (BWR) plant PRA models [2-4]. Level 1 PRA model from [3] is integrated with the level 2 model from [2]. The level 2 model is extended to cover five plant damage states. The integration of the PRA levels is made tight so that level 1 information is used in level 2 modelling, and the contributions of level 1 events are seen in level 2 results [5]. Special focus is on modelling the recovery of an emergence core cooling system.

Steam explosions [6] are one severe accident phenomenon that can lead to the rupture of the reactor containment. Steam explosions can occur when core melt gets in contact with water, for example when core melt spills from the pressure vessel to the lower part of a flooded containment. A steam explosion is a very complex phenomenon which is difficult to model realistically in deterministic and probabilistic analyses. Some attempts have been made, such as [7-10]. This report discusses the probabilistic modelling and what would be needed to make it more realistic.

2. Ex-vessel steam explosions

A steam explosion [6] can occur when core melt gets in contact with water and vaporizes it rapidly. It may occur inside or outside the pressure vessel. Explosions outside the vessel (ex-vessel explosions) are considered more likely and dangerous. Therefore, only ex-vessel explosions are discussed in this report. An ex-vessel steam explosion may occur when the pressure vessel is broken and core melt spills to the lower part of the containment which is flooded with water.

A steam explosion is a very complex physical phenomenon involving several different phases including premixing, triggering, propagation, and expansion and energy release. The details of the phenomenon are presented for example in [8]. They are not repeated in this report.

2.1 Previous studies

Probabilistic modelling of an ex-vessel steam explosion requires the estimation of the probability that an explosion occurs and the probability that the explosion breaks the containment if it occurs. In [8], the modelling for BWR was performed in the following way:

- It was conservatively assumed that steam explosion is triggered with certainty in high pressure, and with probability 0.5 in low pressure, assuming that core melt spills to the lower drywell (LDW) that contains enough water.

- An uncertainty distribution was given for the pressure impulse of the explosion. The distribution was varied depending on the pressure (high or low) and how much core melt was ejected to the LDW (more than 50% of the core inventory or less than 50% of the core inventory). The distributions are presented in Figure 1. In the figure, LP refers to low pressure, HP refers to high pressure, 1 means that much melt is ejected to the LDW and 2 means that little melt is ejected to the LDW. The distributions were loosely based on pressure impulses presented in literature [11].

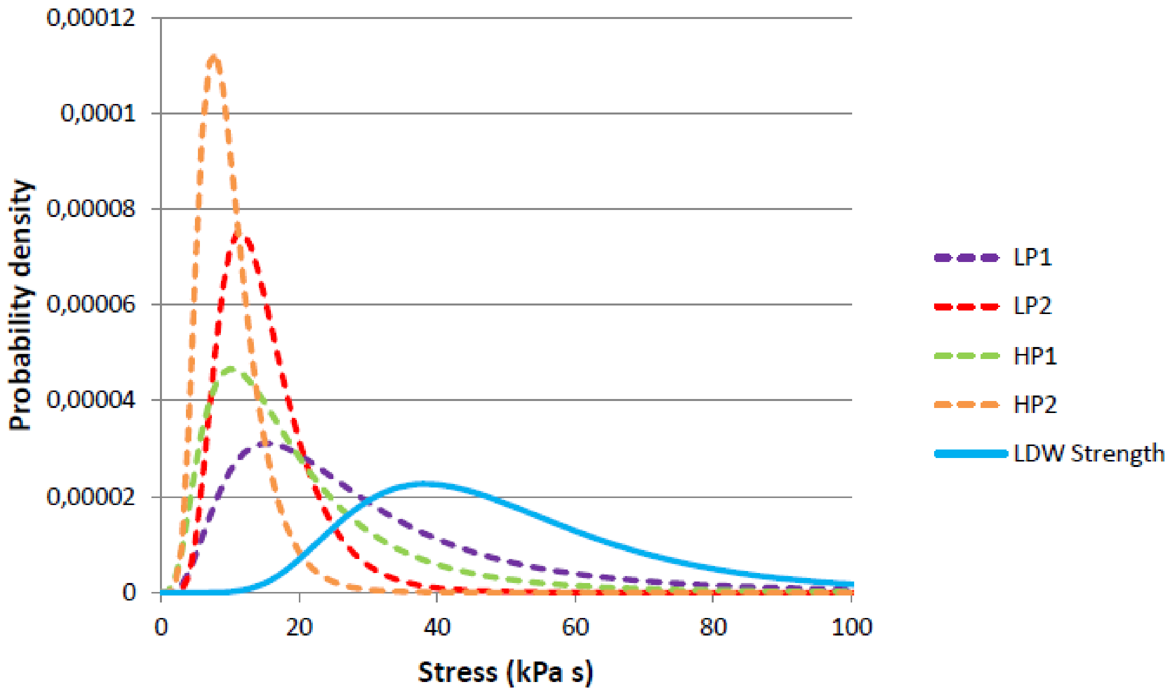

Figure 1: Distributions used to determine whether LDW fails due to pressure impulse caused by ex-vessel steam explosion.

- An uncertainty distribution was also given for the LDW strength and it is also presented in Figure 1.
- The probability of containment failure was calculated based on the distributions of the pressure impulse and the LDW strength. The probabilities are presented in Table 1.

Table 1: Conditional probability of explosion impulse exceeding strength of LDW walls given vessel failure, explosion trigger and enough water in LDW.

	Much melt ejected (case 1, late or no ECCS recovery)	Little melt ejected (case 2, early ECCS recovery)
RCS depressurized (case LP)	0.207	0.021
RCS not depressurized (case HP)	0.091	0.003

- Steam explosion was considered possible only if the LDW contained enough water, which depended on the success of the flooding function and the time of the vessel breach.
- The amount of core melt ejected to the LDW depended on the core meltdown and several factors affecting it.

Steam explosions have also been studied by deterministic MC3D computer code in [8-9]. MC3D is primarily used to estimate the pressure impulses of ex-vessel steam explosions. In the studies, calculated pressure impulses were significantly larger than those used in the previously presented study [8] and generally found in literature [11]. On the other hand, in the studies, there were difficulties to find scenarios where explosion is actually triggered. This could imply that the conservative explosion triggering probabilities used in the previously presented study [8] could be much too conservative. However, it is not known how reliably the explosion triggering probability can be judged based on MC3D analyses. Based on the analyses, it also seems to make difference how the pressure vessel is ruptured, i.e. explosions were triggered only for cases were the pressure vessel leaks from the centre. It was however suspected that the model could be incorrect for the side breaks of the vessel.

In [12], a probability distribution was calculated for steam explosion pressure impulses in a pressurized water reactor (PWR) plant. Steam explosions were simulated using deterministic JASMINE software. Uncertainty distributions were specified for input parameters including melt jet inlet diameter, velocity, initial melt temperature, water pool depth and melt droplet diameter during premixing. Latin hypercube sampling was used to generate computation cases based on the uncertainty distributions. That way uncertainties were propagated through deterministic calculations to produce the uncertainty distribution for the pressure impulses. It was assumed that an explosion is triggered at the time of the first peak of the premixed mass, but the timing was also varied in alternative computation cases. It was claimed that the triggering probability is included in the resulting pressure impulse distribution. We assume that explosion was not triggered in some computation cases, and the probability that an explosion is not triggered comes from the portion of those cases.

Grishchenko et al. have performed extensive steam explosion analyses using TEXAS-V software and a surrogate model [13, 14]. The surrogate model is a simplified model that is based on artificial neural networks and a database of TEXAS-V results. The surrogate model produces approximately same results as TEXAS-V and enables a large number of simulations to perform comprehensive sensitivity and uncertainty analyses. Grishchenko et al. studied the effects of explosion triggering times, and they found that the behaviour of pressure impulses as a function of the triggering time is chaotic. The produced pressure impulses changed a lot even with a tiny change in the triggering time.

2.2 Possibilities to improve probabilistic modelling

Based on the previous steam explosion studies, it is evident that there is room for improvement in both deterministic and probabilistic modelling of steam explosions. Concerning probabilistic modelling, uncertainties are high for most of the parameters involved.

The explosion triggering probabilities are the most questionable parameters in the previous studies. It seems that triggering probabilities cannot be estimated realistically currently because deterministic computer codes are not reliable enough, sensitivity of triggering to parameter changes is great, and uncertainties related to the triggering phenomena are high. Plenty of development work and analyses are needed before well-justified probabilities can be estimated. Currently, it is better to use conservative values in the PRA models. However, the conservativeness of the values has to be acknowledged.

To estimate more realistic explosion triggering probability, a comprehensive and realistic set of calculation cases should be analysed using a deterministic computer code, like in [12]. However, since there is significant uncertainty on the correctness of the computer code itself, for each computation case, a triggering probability should be estimated instead of only examining whether explosion was triggered in the deterministic calculation. Possibly, the triggering probability of a case could be judged based on physical variables, e.g. explosivity curve produced by MC3D. The overall triggering probability could then be calculated as the average of the triggering probabilities of different cases. A method to estimate the triggering probability based on the explosivity curve should however be developed first. It can be difficult because the triggering time is highly uncertain, and even with high explosivity an explosion does not occur without a trigger.

Estimation of pressure impulse distributions would require many more deterministic analyses than performed in the previous studies [8-9]. Those previous studies also focused mainly on the maximum values whereas complete distributions would be needed. With a sufficiently reliable computer code and a comprehensive and realistic set of calculation cases, the pressure impulse distribution could be approximated in a straightforward manner. Reference [12] provides a good example for the selection of computation cases and propagation of uncertainties through deterministic analyses. The use of a surrogate model, like in [13], can be beneficial when a large number of cases needs to be calculated. If deterministic analyses cannot be performed reliably enough, an alternative is to use an uncertainty distribution that covers different values found in the literature and gives more weight on larger values.

To estimate the actual containment failure probability in the case of a steam explosion, the best option would be to apply structural reliability analysis. The classical approach is to somehow estimate two probability distributions: the explosion load (pressure impulse) and the resistance of the structure to loads of different sizes. The probability that the structure fails is then the probability that the load exceeds the resistance. In the general case, resistance may depend on the load, there may be several failure modes, failure probability may be time-dependent (taking into account the ageing of structures, corrosion, etc.), and there may be several (or an infinite number of) positions where the structure may fail. In this case, the probability density function is multidimensional: each component of the random vector involved represents a resistance random variable or a load random variable acting on the system. Integration is usually then carried out by numerical approximation methods, of which Monte Carlo simulation is the most popular. Structural reliability analysis in general is explained in [15] and [16], and the impact of explosive loads on structures is treated in [17].

In the light of previous analyses [9-10], it also seems to make a difference how the core melt spills from the pressure vessel to the containment, which depends on how the pressure vessel leaks. Pressure vessel failures could be divided into different cases for which separate steam explosion analyses could be performed, such as in [10]. However, probabilities should then also be estimated for different vessel leak cases. Structural reliability analysis methods could be used for that. If it would not be possible to do this, the worst leak case could be assumed to simplify the analysis.

In [10], it was concluded that loss of coolant accident (LOCA) and station blackout scenarios were quite similar from the steam explosion analysis point of view. In general, severe accident progression, at least on containment event tree level, is very similar for several different plant damage states. Therefore, it seems that there is no reason to put much effort on the analysis of multiple plant damage states, since probabilistic steam explosion modelling can be assumed to be similar for different plant damage states. The focus should be more on the analysis of different cases with regard to pressure conditions, vessel failure, flooding time and amount of core melt.

Probability estimation of steam explosions could be improved upon in several ways, given sufficiently reliable steam explosion analysis computer code and time to perform enough computations. One is based on calculating numerical probabilities in hypercubes, motivated by the wish to reduce uncertainties surrounding the probability of steam explosions and explosion strength. In it, we consider a range of initial condition variables, most notably related to melt ejection mode [14] and pool characteristics; call the space formed by these variables the parameter space. This parameter space is divided into hypercubes by partitioning the possible range of each initial condition variable to a suitable number of intervals. For each such hypercube, a number of Monte Carlo experiments is conducted by selecting the initial condition variables randomly within the hypercube, and then performing a simulation with a steam explosion code (such as MC3D) to determine whether a steam explosion takes place, and if it does, what is its strength. The (numerical) probability of a steam explosion in the hypercube is the number of cases when the explosion occurred divided by all trials in that hypercube. The probability distribution of explosion load in the hypercube is formed based on the explosion loads in the positive cases. The conditional containment failure probability can be calculated based on the explosion load distribution, e.g. using load vs. strength approach. The steam explosion probability and the conditional containment failure probability would then be tabulated in a table, indexed by the intervals of the individual variables in the hypercube.

When assessing an accident sequence in a level 2 analysis, probability distribution over the hypercubes of the parameter space is determined, e.g. with help of deterministic analyses. Then, the steam explosion probability and the conditional containment failure probability can be calculated based on the probability table and the distribution of hypercubes.

Modelling of steam explosions in level 2 PRA can be performed in several ways:

1. Containment failure probability in a containment event tree sequence can be estimated outside the PRA model based on the deterministic analyses, and a single probability (with uncertainty distribution) can be brought to the PRA model. This probability may have been estimated, for example, by the “hypercube method” introduced in the previous paragraphs.

2. Containment failure probability in a containment event tree sequence can be calculated in the PRA model. The results of deterministic analyses could be incorporated in the model as a table representing different input parameter cases and corresponding containment failure probabilities (or triggering probabilities and pressure impulses); also here the “hypercube method” presented in the previous paragraphs could be used. The input parameters would have probability distributions, and values for them could be drawn on each simulation cycle of Monte Carlo simulation. The containment failure probability would be obtained from the table based on the drawn input parameter values. This approach requires a suitable PRA tool, like FinPSA level 2 [18], and it was used in a simplified manner with only four input parameter cases in [8].

3. Separate containment event tree sequences can be created for different steam explosion cases, e.g. based on melt ejection mode and pool characteristic as presented in [14]. Containment failure probabilities in different sequences can be estimated in the PRA model or outside the PRA model as described in the previous alternatives.

The best alternative for modelling is not obvious. Alternatives 2 and 3 can make the model complicated. On the other hand, they enable modelling of dependencies between phenomena, such as that the LDW pool characteristics affect also ex-vessel debris coolability. Alternative 2 enables modelling of input parameters as continuous variables, and more detailed modelling of dependencies than alternative 3. Alternative 3 could easily be used to calculate importance values for different scenarios related to input parameters. However, with alternative 3, the event tree could grow very large.

3. Dynamic containment event trees

The level 2 modelling in FinPSA software tool [18] is based on dynamic containment event trees (CETs) and containment event tree programming language (CETL). The CETL language is used to define functions to calculate conditional probabilities of event tree branches, timings of the accident progression and amounts of releases. A CETL function is defined for each branch of a dynamic containment event tree, and a CET also contains an initial conditions section, where the plant damage state, source term computation routine, and some probability and process variable values are defined. In addition, the model contains a global “common section”, where some global variables and functions can be defined. CETL programming is very flexible. At any branch, new value can be set or calculated for any global variable, and that way accident progression can be modelled dynamically. Binning rules can also be defined to divide the end points of the CET into release categories.

To account for uncertainties related to variable values, it is possible to specify probability distributions for parameters and perform Monte Carlo simulations. At each simulation cycle, a value is sampled from each specified distribution, and based on that, numerical conditional probabilities are calculated for all the branches, and values are calculated for all variables at each end point of the CET. After the simulations, statistical analyses are performed to calculate frequency and variable value distributions for each end point and release category among other statistical results and correlation analyses. It is also possible to just calculate point values of the CET based on the mean values of distributions.

4. Boiling water reactor plant model

This chapter continues the development of simplified boiling water reactor (BWR) plant PRA models [2-4]. Level 1 PRA model from [3] is integrated with the level 2 model from [2]. The level 2 model is extended to cover five plant damage states. The integration of the PRA levels is made tight so that level 1 information is used in level 2 modelling, and the contributions of level 1 events are seen in level 2 results [5]. Specifically, level 1 minimal cut set information is used to determine the probability of emergency core cooling recovery in different cases in level 2.

4.1 Level 1

The level 1 part of the model contains four event trees:

- Large LOCA (Figure 2)
- Loss of main feedwater (Figure 3)
- Loss of offsite power (Figure 4)
- General transient (Figure 5)

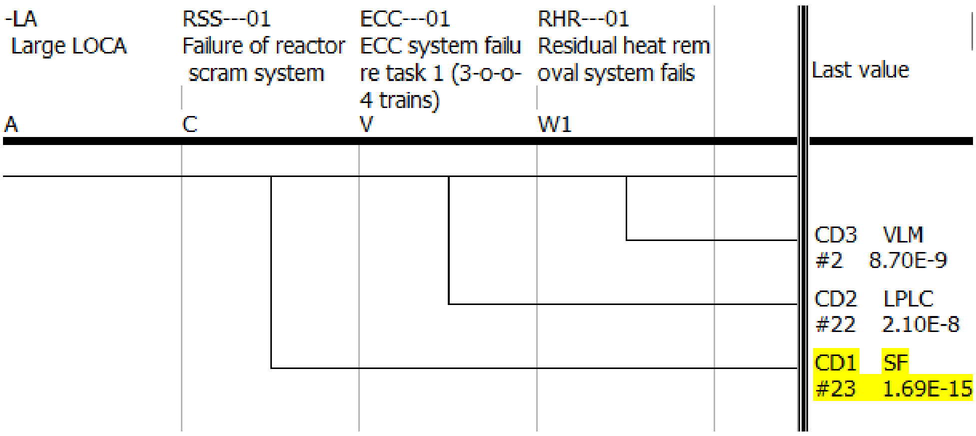

Figure 2: Event tree for large LOCA.

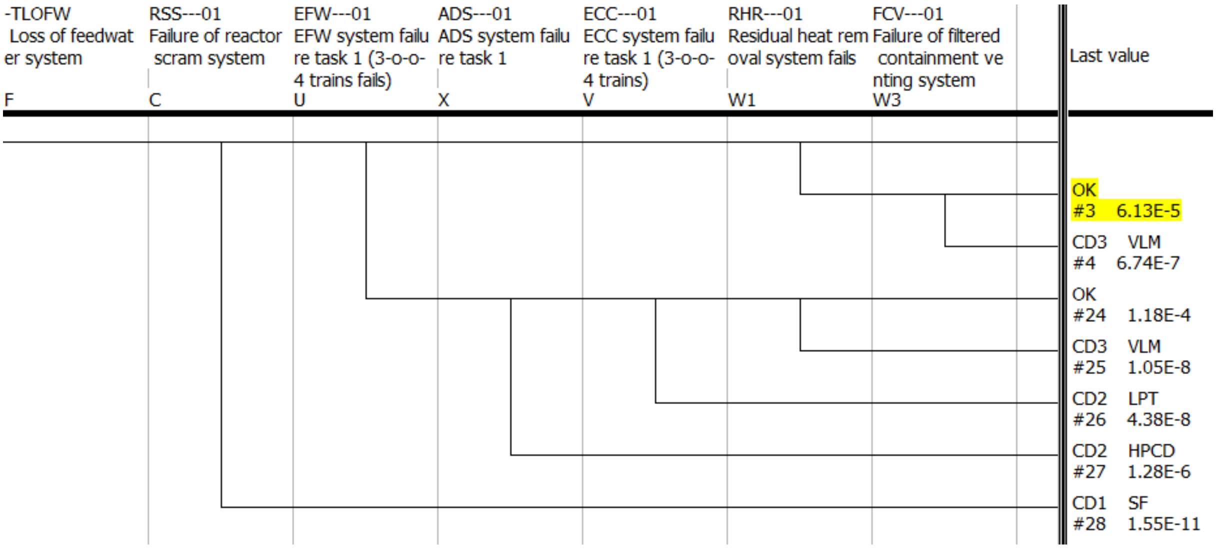

Figure 3: Event tree for loss of main feedwater.

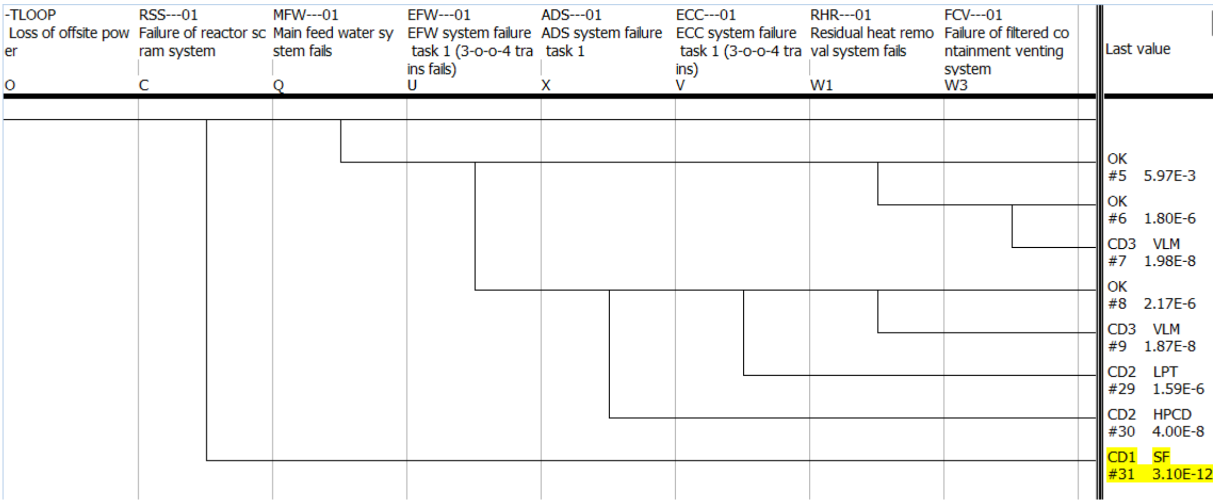

Figure 4: Event tree for loss of offsite power.

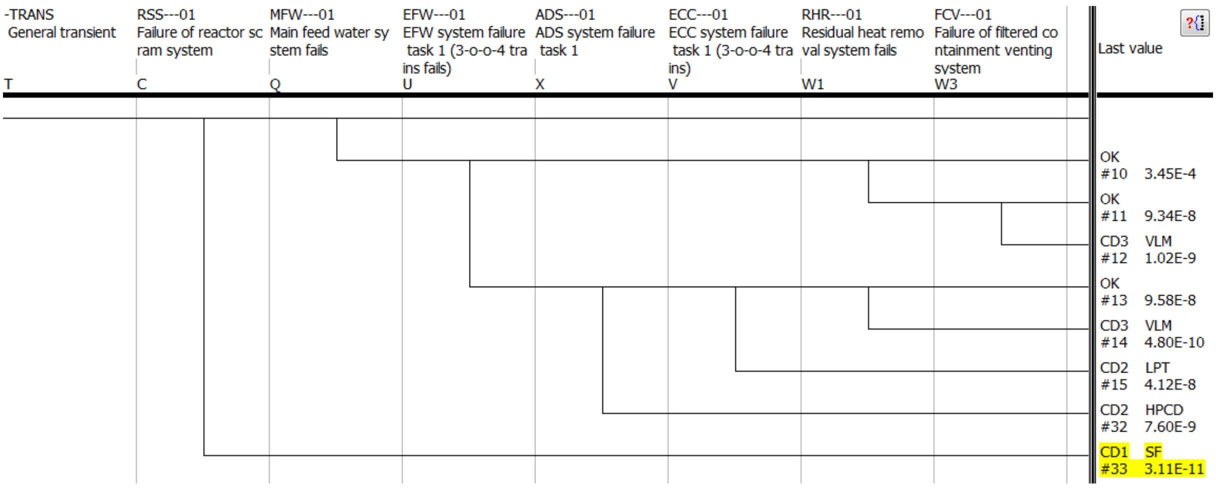

Figure 5: Event tree for general transient.

The main safety systems modelled are:

- Reactor scram system

- Main feedwater system
- Emergency feedwater system
- Depressurization system
- Emergency core cooling system (ECCS)
- Residual heat removal system
- Filtered containment venting system

The emergency feedwater system operates in high pressure, and the emergency core cooling system operates in low pressure. Support systems for the main safety systems include AC power system, DC power system, component cooling system, heating, ventilation and conditioning system, service water system, and two reactor protection systems (RPSs) serving different safety systems. Everything except reactor protection systems have been modelled in a simplified manner, because the model was originally developed for I&C system analysis [3].

For this study, uncertainty distributions were assigned to the frequencies of initiating events, the probabilities of most basic events, and the probabilities of common cause failures. All the distributions were lognormal, and error factors ranged between 2 and 200. Error factor is defined here as the 95th percentile value divided by the median. The parameter values were completely made up for this study. Generally, larger error factors were assigned to basic events with smaller probabilities and especially to I&C component failures. Similar basic events were placed into the same population, which means that their probabilities are same in uncertainty analysis.

4.2 Plant damage states

The model contains five plant damage states (PDSs):

- High pressure melting
- Low pressure melting due to LOCA
- Low pressure melting due to transient
- Melting due to scram failure
- Very late melting

Level 1 sequences are linked to PDSs via interface trees that directly correspond to the PDSs:

- High pressure core damage (HPCD)
- Low pressure LOCA (LPLC)
- Low pressure transient (LPT)
- Scram failure (SF)
- Very late melting (VLM)

The interface trees can be seen at the end points of the event trees presented in Figures 2-5. Each interface tree contains only one sequence which means that the level 1 sequences are practically directly linked to the PDSs.

4.3 Level 2

The model presented in [2], originating from [8], was the basis for the development of the level 2 part. The model in [2] contained one containment event tree which covered both high pressure and low pressure melting scenarios. In this report, high and low pressure cases are separated on PDS level. Hence, separate CETs are developed for low and high pressure. The structure of the high pressure melting CET is the same as in [2]. For low pressure melting due to LOCA, low pressure melting due to transient, and very late melting, the CET structure is similar except that the depressurization section is not included because the pressure is assumed to be low already. The CETs for high pressure melting and low pressure melting due to transient are presented in Figures 6-7.

The CETL modelling behind the CET sections has been discussed in [4] and is not repeated here.

For low pressure melting due to LOCA, it is assumed that the containment is not inert with much smaller probability. Lognormal distribution with mean value 0.01 and error factor 5 is used in this case, whereas mean probability 0.3 is used for transient. This means that the risk of hydrogen explosion is significantly smaller in the LOCA case.

For very late melting, the accident modelling is similar to the low pressure cases, which was also the case in [19]. However, timings were changed so that core melting starts around 100000 seconds (≈ 28 hours) after the initiating event, and other events occur correspondingly after that. The timings were set quite roughly without in-depth consideration, because the modelling of very late melting accident was not the main focus of the study. All containment failures in the very late melting CET lead to release category 'very late containment failure'.

The CET for melting due to scram failure contains only one sequence which assumes failure of containment isolation. The modelling decision is based on the model presented in [19]. The CET is presented in Figure 8.

Table 2 presents the release categories and containment failure modes of the model.

4.4 Emergency core cooling recovery

Emergency core cooling system recovery was modelled based on level 1 results. It was identified that core cooling failure can be caused by

- cooling system component (e.g. pump or valve) failures,
- power supply failures,
- heating, ventilation and conditioning (HVAC) system failures,
- demineralized water tank failure,
- reactor protection system failures,
- component cooling water system component failures,
- service water system component failures,
- condensation pool failure.

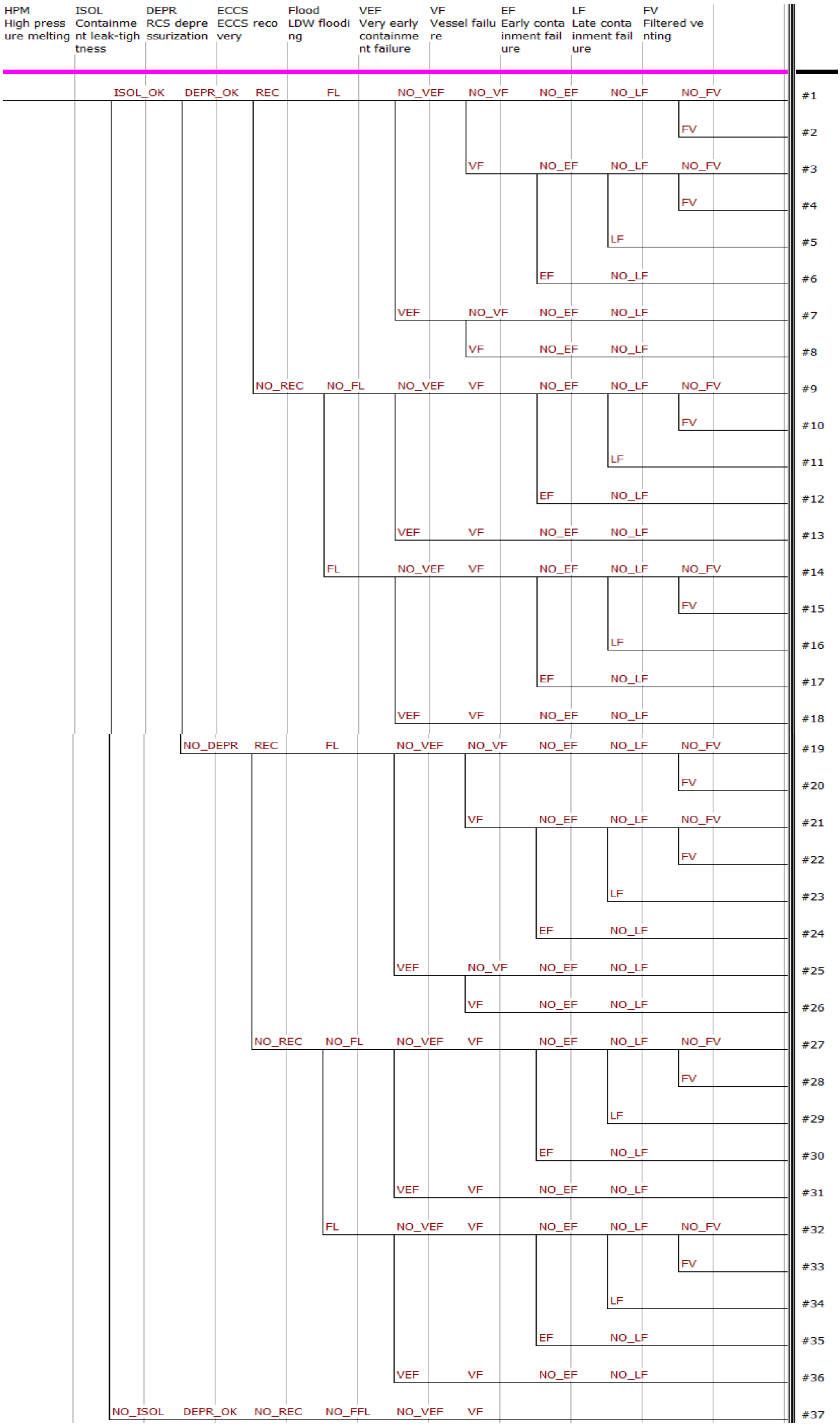

Figure 6: Containment event tree for high pressure melting.

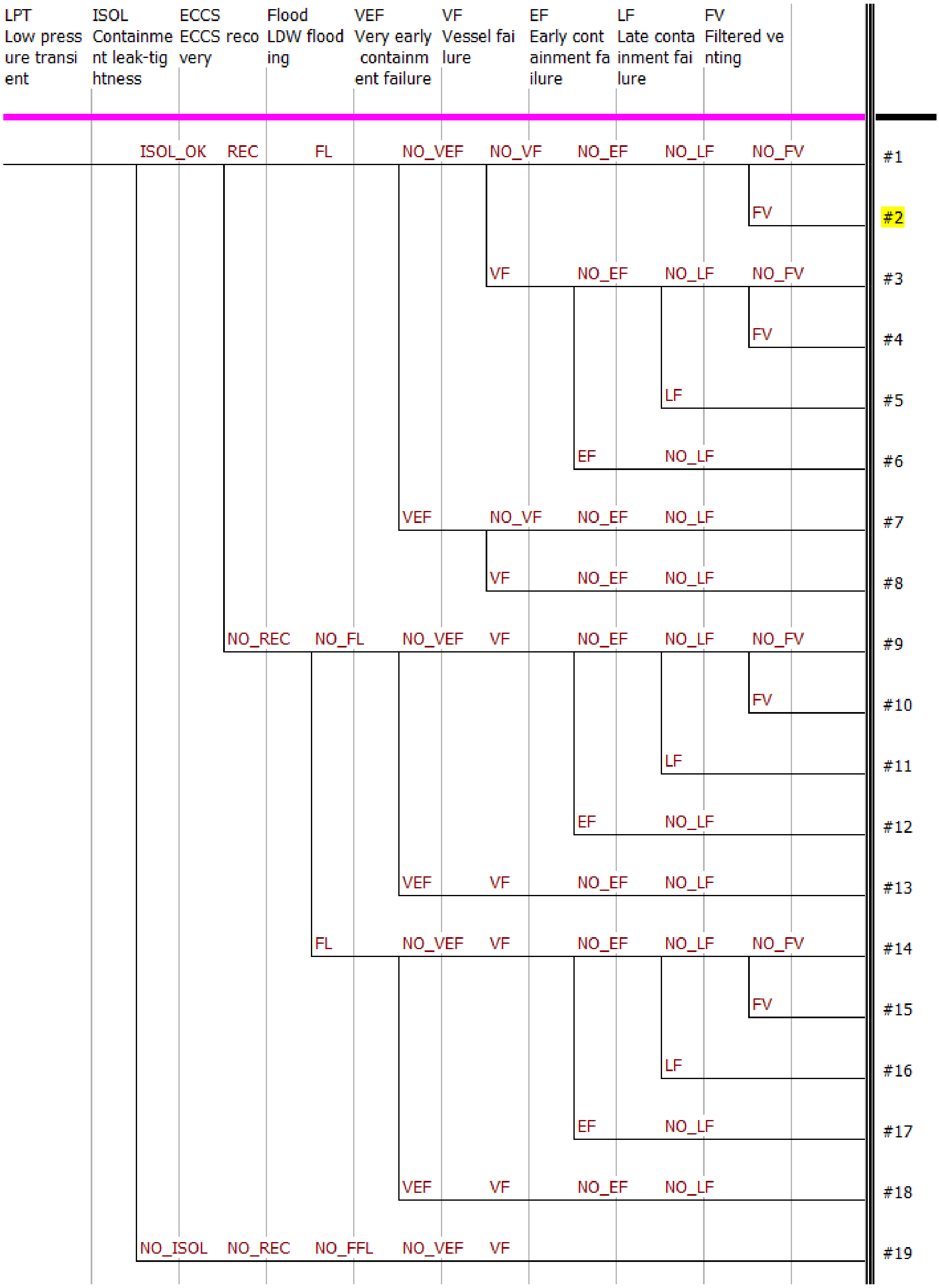

Figure 7: Containment event tree for low pressure melting due to transient.

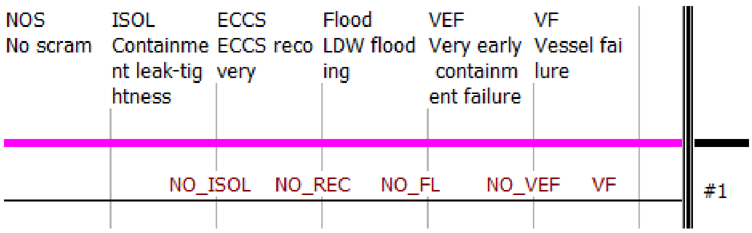

Figure 8: Containment event tree for melting due to scram failure.

Table 2: Containment failure categories and the corresponding failure modes used in the CET model.

Release category	Containment failure/vent mode
No containment failure of filtered venting (OK)	-
Isolation failure (ISOL)	1. Containment not leak-tight (ISOL)
Very early containment failure (VEF)	1. Containment over-pressurization (COP) 2. Hydrogen deflagration/detonation (H2) 3. Alpha-mode failure (ALPHA)
Early containment failure (EF)	1. Ex-vessel steam explosion (STEAM) 2. Failure of containment penetrations (PENE)
Late containment failure (LF)	1. Non-coolable ex-vessel debris causes basemat melt-through (BASE)
Very late containment failure (VLF)	1. All above containment failure modes combined with very late release time
Filtered venting (FV)	1. Very early venting (VEFV) 2. Early venting (EFV) 3. Late venting (LFV) 4. Very late venting (VLFV)

The recovery time depends on which components have failed. In the original model, power supply failure was assumed, and a recovery time distribution was specified for power supply [8]. The new model considers recovery times of different component types. However, since no repair time data was available, recovery probability distributions were assigned directly to different component types. Table 3 presents the mean recovery probabilities in different cases. The recovery probability distributions were lognormal and error factor 2 was used for each probability distribution. The probabilities vary depending on the pressure and time of the core melting. The probabilities were totally made up for this study except for power supply recovery failure probabilities which came from the previous studies [2, 8]. According to [8], there is less time for recovery in low pressure case. Therefore, smaller recovery probabilities were used in low pressure case. For very late melting, larger recovery probabilities were assumed than for normal low pressure case. Symbol '-' in the table means that no recovery probability was needed for the case, because the probability of the case was small or 0.

The recovery probability modelling was performed using CETL function BE_FV. BE_FV calculates Fussell-Vesely importance measure of a basic event, using the minimal cut sets of the PDS. The minimal cut sets of different PDSs were examined to identify which basic events or common cause failures caused the failure of the core cooling, and the basic events were categorised into the groups listed above. Only 100 most important minimal cut sets were examined in each case to find the most significant basic events. In the REC function (see Figures 6-7), BE_FV function is called for each basic event, and the probability of each group is calculated by summing the Fussell-Vesely values of the basic events belonging to the group. The recovery probability is calculated as a weighted sum of the probabilities presented in Table 3, where the weights are the probabilities calculated using BE_FV function.

In the case that depressurization is successful after high pressure melting, the emergency core cooling system recovery probability was assumed to be 0.99, even though the low pressure emergency core cooling system is not even used before core melting in that scenario.

Table 3: Mean probabilities of emergency core cooling system recovery depending on the failed components.

Components	High pressure	Low pressure	Very late melting
Cooling system components	0.2	0.05	0.1
Power supply	0.976	0.922	-
HVAC system	0.5	-	-
Demineralized water tank failure	0.1	-	-
Reactor protection system	0.999	0.99	0.995
Component cooling water system components	-	0.05	-
Service water system components	-	0.05	0.1
Condensation pool	-	-	0.05

The resulting mean recovery probabilities in different cases are presented in Table 4. The recovery fails most likely in the LOCA case, because pumps or valves of the emergency core cooling system are failed in a large portion of LOCA scenarios and their recovery in time was assumed unlikely. In other cases, power supply failures and reactor protection system failures dominate more and their repair in time is assumed likely.

Table 4: Mean probabilities for emergency core cooling system recovery for CET branches.

Case	Recovery probability
High pressure melting and depressurization	0.99
High pressure melting and no depressurization	0.828
Low pressure melting due to LOCA	0.352
Low pressure melting due to transient	0.922
Very late melting	0.938

4.5 Results

Table 5 presents main results calculated over all CETs including the frequencies and release fractions for all release categories. The four values in the cells of the table are mean, 5th percentile, median and 95th percentile. Weighted total release fractions are weighted by the frequencies of different release categories.

Table 5: Summary of results.

Bin	Freq.	S_Xe	S_Cs	S_Ru
OK	8.32E-07	7.76E-11	0.00E+00	0.00E+00
	1.02E-07	3.35E-11	0.00E+00	0.00E+00
	4.16E-07	8.41E-11	0.00E+00	0.00E+00
	2.74E-06	1.00E-10	0.00E+00	0.00E+00
ISOL	2.93E-08	8.49E-01	2.55E-01	8.82E-03
	2.19E-09	5.27E-01	1.02E-01	1.57E-04
	1.24E-08	9.15E-01	2.43E-01	5.56E-03
	1.03E-07	1.00E+00	4.37E-01	2.86E-02
VEF	5.40E-07	7.72E-01	1.19E-01	4.00E-03
	4.36E-08	3.01E-01	1.89E-02	4.47E-05
	2.38E-07	8.63E-01	9.79E-02	1.43E-03
	1.98E-06	1.00E+00	2.97E-01	1.61E-02
EF	8.48E-08	7.90E-01	1.55E-01	5.58E-03
	5.70E-09	3.60E-01	3.46E-02	1.04E-04
	3.31E-08	8.84E-01	1.38E-01	2.51E-03
	3.15E-07	1.00E+00	3.38E-01	2.10E-02
LF	5.99E-08	8.02E-01	1.56E-01	4.54E-03
	4.12E-09	3.87E-01	3.87E-02	3.18E-05
	2.31E-08	8.89E-01	1.40E-01	1.85E-03
	2.24E-07	1.00E+00	3.16E-01	1.85E-02
FV	1.99E-06	7.75E-01	9.84E-04	2.89E-05
	2.51E-07	3.24E-01	1.48E-05	1.60E-08
	1.02E-06	8.45E-01	1.27E-04	1.71E-06
	6.81E-06	1.00E+00	3.97E-03	9.24E-05
VLF	1.95E-07	7.72E-01	1.29E-01	4.31E-03
	1.14E-08	1.93E-01	1.75E-02	1.02E-06
	6.84E-08	1.00E+00	1.07E-01	1.20E-03
	6.93E-07	1.00E+00	3.28E-01	1.95E-02
Weighted Total	3.73E-06	6.05E-01	3.31E-02	1.10E-03
	5.14E-07	2.63E-01	8.58E-03	3.52E-05
	1.93E-06	6.50E-01	2.73E-02	5.47E-04
	1.22E-05	8.18E-01	7.73E-02	4.10E-03

FinPSA calculates also contributions of level 1 sequences to different level 2 results. For example, the most important event tree sequences contributing to total Cesium releases are listed in Table 6 and the sequences can be found in the event trees presented in Figures 2-5. It can be seen that most of the Cesium release risk comes from the three level 1 sequences with the largest frequencies. The contribution of sequence i is calculated with the following formula:

$$C^{Cs}(i) = \frac{\sum_{k=1}^{n}\sum_{j=1}^{m} F_{i,j}(k) f_j(k) Cs_j(k)}{\sum_{k=1}^{n}\sum_{j=1}^{m} f_j(k) Cs_j(k)},$$

where n is the number of simulation cycles, m is the number of level 2 sequences, $F_{i,j}(k)$ is the conditional probability of level 1 sequence i given level 2 sequence j in k:th simulation cycle, $f_j(k)$ is the frequency of level 2 sequence j in k:th simulation cycle, and $Cs_j(k)$ is the amount of Cesium releases in level 2 sequence j in k:th simulation cycle.

Table 6: The most important level 1 sequences contributing to total Cesium releases.

Nr.	Sequence	Contribution (%)
1	29	51.56
2	27	26.02
3	4	17.87
4	26	2.04
5	15	0.87

Table 7 presents the most important basic events and initiating events contributing to total Cesium releases. Loss of main feedwater and loss of offsite power are the dominating initiating events. The contribution of event E is calculated with the following formula:

$$C^{Cs}(E) = \sum_{i=1}^{l} FV_i(E) \cdot C^{Cs}(i),$$

where l is the number of level 1 sequences, $FV_i(E)$ is Fussell-Vesely of event E in sequence i, and $C^{Cs}(i)$ is the contribution of sequence i to the Cesium releases.

Table 7: The most important level 1 events contributing to total Cesium releases.

Nr.	Event	Contribution (%)
1	Loss of offsite power (IE)	51.90
2	Loss of main feedwater (IE)	46.24
3	Gas turbine failure to start	36.73
4	Diesel generators CCF (all DGs fail to operate)	28.83
5	Failure of manual depressurization	24.16
6	Filtered containment venting failure	18.03
7	Gas turbine under maintenance	16.92

4.6 Sensitivity analysis

4.6.1 Ex-vessel steam explosions

As discussed in Section 2, uncertainties related to ex-vessel steam explosions are high. The explosion triggering probabilities used in the model are likely conservative:

- mean triggering probability is 0.99 in high pressure case,
- mean triggering probability is 0.5 in low pressure case.

However, containment failure probabilities that are conditional on the occurrence of steam explosion impulse exceeding the strength of LDW walls might not be conservative. They are based on pressure impulse curves presented in Figure 1. In some studies [8-9], significantly larger pressure impulses have been calculated. To study the sensitivity of the results to steam explosions, alternative analysis is performed using higher conditional containment failure probabilities presented in Table 8 (see Table 1 for comparison).

Table 8: Alternative conditional probabilities of explosion impulse exceeding strength of LDW walls.

	Much melt ejected (case 1, late or no ECCS recovery)	Little melt ejected (case 2, early ECCS recovery)
RCS depressurized (case LP)	1.0	0.2
RCS not depressurized (case HP)	0.5	0.1

The change in conditional containment failure probabilities increased significantly the frequency of an early containment failure (release category EF). The mean frequency increased from 8.48E-8 to 4.06E-7. This new frequency forms 42.6% of the large early release frequency (which is the sum of the frequencies of release categories VEF, EF and ISOL). This indicates that ex-vessel steam explosions have potential to be a major contributor to early release risk.

4.6.2 Basemat melt-through

The mean probability for basemat melt-through given that the ex-vessel debris is not coolable is 0.1 in the model. In some other models [14], this probability is assumed to be 1. Therefore, to study to sensitivity of the results to this assumption, the probability is set to 1 for alternative analysis. By this change, the frequency of late containment failure becomes ten times higher. Then 36% of the large release frequency comes from basemat melt-through.

4.7 Basic event contributions

A drawback in the use of BE_FV function to estimate the ECCS recovery probability (see Section 4.4) is currently that the contributions of level 1 basic events to level 2 results are not calculated correctly. For example, the failure of the emergency core cooling system in the case of ‘low pressure melting due to LOCA’ is caused by RPS failures with probability 0.32 and by failures of pumps and valves with probability 0.68. However, the recovery of the emergency core cooling is assumed much more likely if RPS failure has caused the failure of the ECCS. Computation of basic event contributions does not take this into account. Therefore, contributions of pump and valve failures to radioactive releases should be larger than what is calculated. At its root, this problem is one of model parsimony: we could solve it by inserting a new layer to the event tree (see below), but to keep the tree more compact we want instead to handle RPS failures and other component failures in the same event tree sequence. It would not be a problem to separate these two types of failures in different event tree branches, but when there are more failure categories, like in the high pressure melting case, the CETs would become too large.

An alternative version of the model where RPS failures were separated to different accident sequence was created. Modified event tree for large LOCA is presented in Figure 9. Minimal cut sets with RPS failures go to sequence 2 and minimal cut sets with other component failures go to sequence 1.

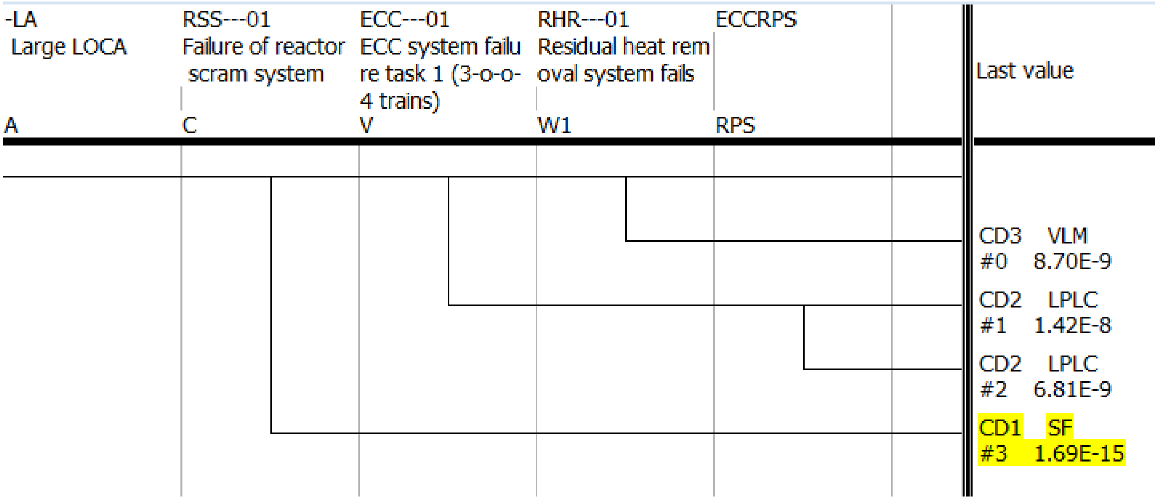

Figure 9: Modified event tree for large LOCA.

New section called RPSF was added to the CET for low pressure melting due to LOCA (Figure 10). In this section, it is asked whether the emergency core cooling system has failed due to RPS failure or other failures. Function SC_INCL [5] is used to calculate the probabilities of the branches in section RPSF (the function is called in branch functions COMF and RPSF). The probabilities are the portions (conditional probabilities) of event tree sequences 1 and 2. Due to SC_INCL function, only event tree sequence 1 is seen in the results of CET sequences 1-18, and only event tree sequence 2 is seen in the results of CET sequences 19-36. The emergency core cooling system recovery probability is also calculated as dependent on the result of RPSF section instead of using BE_FV function. When the modelling is performed this way, basic event contributions are calculated correctly.

Table 9 presents the most important basic events contributing to Cesium releases in the LOCA CET. Both contributions from the original model and contributions from the modified model are presented. The modified model gives the correct contribution values. It can be seen that the importance of software CCFs is overestimated significantly in the original model.

The modified model produced correct results because RPS failures were separated into different event tree sequence than other failures. Similar modelling style could also be applied to other PDSs. However, for example, for high pressure melting, four new event tree (or interface tree) sequences would be needed, because there are five different failure categories with different recovery probabilities. The CET would correspondingly grow four times larger so that it would include 181 sequences. The model would become very large.

It would be possible to fix the issue with BE_FV function by scaling the basic event contributions according to corresponding recovery probabilities. In the sequences where the ECC recovery is successful in the LOCA CET, RPS failure contributions would be scaled by

$$\frac{r_p}{p_p \cdot r_p + p_c \cdot r_c},$$

where r_p is recovery probability in case of RPS failure, p_p is the probability that ECCS failure was caused by RPS failure, p_c is the probability that ECCS failure was caused by other component failures and r_c is the recovery probability in case of other component failures. Respectively, in the sequences where the ECCS recovery fails, RPS failure contributions would be scaled by

$$\frac{1 - r_p}{p_p \cdot (1 - r_p) + p_c \cdot (1 - r_c)}.$$

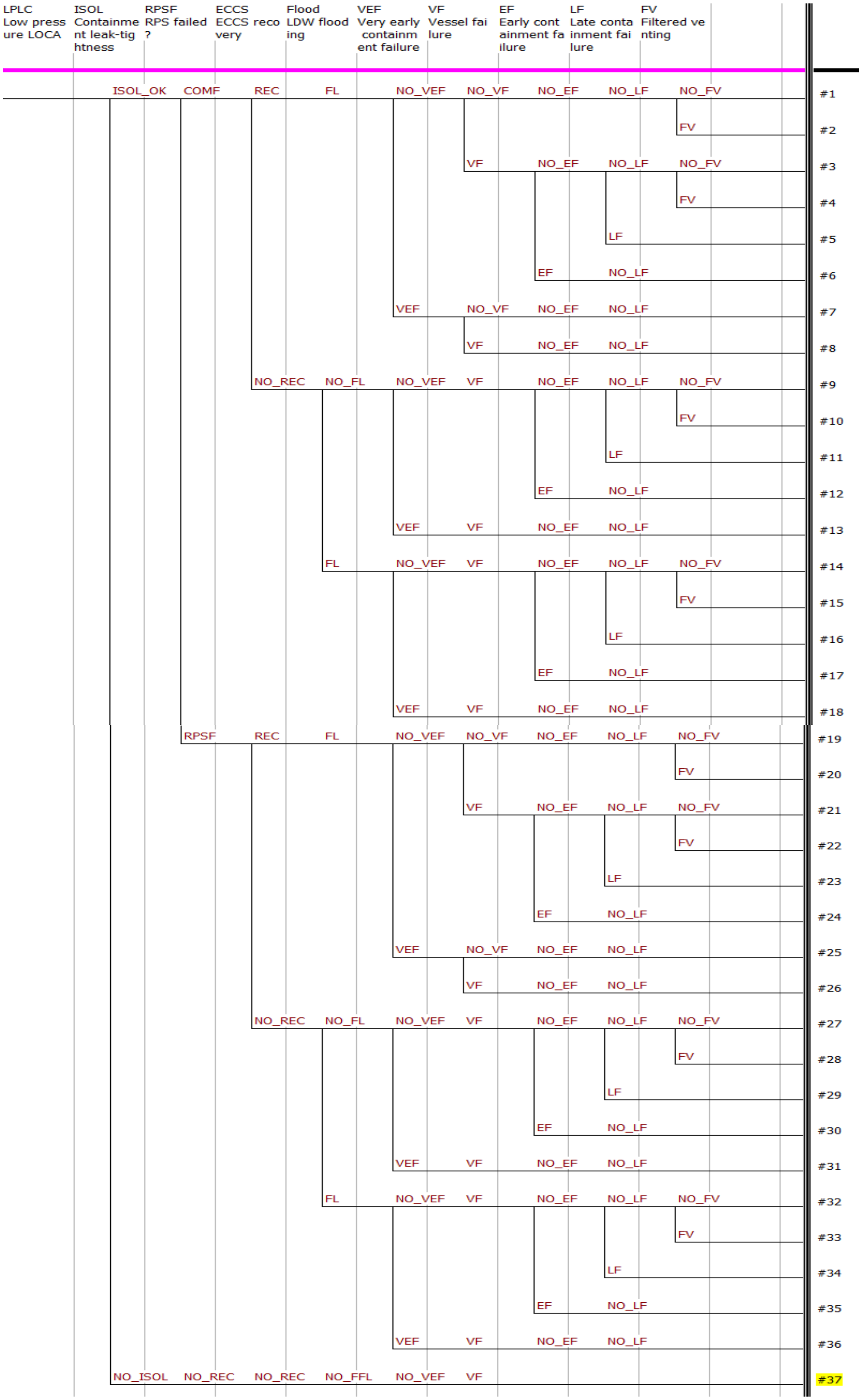

Figure 10: Modified CET for low pressure melting due to LOCA.

Table 9: The most important basic events contributing to Cesium releases in the LOCA case.

Event	**Contribution (%) in original model**	**Contribution (%) in modified model**
ECCS pumps CCF (all pumps stop operating)	30.78	39.39
Software CCF: spurious actuation of ECC2 (same results for 5 other software CCF events)	4.75	1.97
ECCS pumps CCF (pumps A, B and C stop operating) (same results for 3 other similar CCF events)	3.60	4.61
ECCS pump A stops operating (same results for 3 other pumps)	3.16	4.05
ECCS train A under maintenance (same results for 3 other trains)	2.75	3.52
ECCS pumps CCF (all pumps fail to start)	2.44	3.12
ECCS valves CCF (all valves fail to open)	2.43	3.10
SWS pumps CCF (all pumps fail to start)	2.14	2.74
CCW pumps CCF (all pumps fail to start)	2.14	2.74
SWS pumps CCF (all pumps stop operating)	1.79	2.28

The contributions of other component failures would be scaled correspondingly. This type of scaling function could possibly be implemented in CETL.

When there are many basic events in the results, it is also not practical to call BE_FV function for all of them. In this study, only basic events appearing in the 100 most important minimal cut sets were considered, which excluded quite many basic events and caused small errors in the emergency core cooling system recovery probability calculation. Use of BE_FV function many times also increases computation times significantly. It would be more practical if BE_FV type of function could be called for a group of basic events instead of one at a time. For example, computation of Fussell-Vesely for a particular system could be useful in level 2.

5. Outline for two-phase uncertainty analysis

The level 2 modelling in the BWR model has been performed using ‘probabilities first’ approach, which means that the occurrence of each branch in a CET on a given simulation round is determined based on a probability parameter (or multiple probability parameters). The benefit of this approach is that it enables proper uncertainty analysis resulting in nice uncertainty curves that are easy to interpret. In the model, values for physical parameters used in source term calculations are determined based on the accident sequence. One could however argue that this modelling approach does not take very well into account the dynamic nature of severe accidents and does not fully utilise the capabilities of dynamic CETs of FinPSA.

An alternative modelling approach is ‘physical parameters first’ approach in which values for physical parameters are determined first (e.g. from uncertainty distribution) and the CET branch probabilities are determined based on the physical parameters, like in [8]. A drawback of that approach is that it is difficult calculate proper uncertainty distributions for release frequencies, i.e. the resulting distributions can be difficult to interpret or they might not be sensible at all [20]. On the other hand, the ‘physical parameters first’ approach gives better possibilities to model how accident scenarios vary depending on physical parameter values and to model dynamic dependencies related to severe accident phenomena. For better use of the ‘physical parameters first’ approach, it might be necessary to develop the FinPSA dynamic containment event tree modelling tool to take into account different types of uncertainties.

Uncertainties can be divided into aleatoric and epistemic uncertainties [21-23]. Aleatoric uncertainty is the uncertainty that is known, e.g. it is know that the toss of a coin can result in heads or tails based on a chance. In a level 2 model, branches and accident sequences of a CET represent possible realisations of aleatoric uncertainties, i.e. it is known that one sequence occurs given the PDS, but it is a matter of luck which one it is. The realisation of a specific value of a physical parameter, such as core meltdown fraction, is also subject to aleatoric uncertainty. Epistemic uncertainty is the uncertainty related to the knowledge about a phenomenon. For example, the probability of successful depressurisation is not known exactly; there is epistemic uncertainty about it. Other epistemic uncertainties appearing in level 2 are related to the probability distributions of physical parameters, such as core meltdown fraction; the mean values, levels of deviation and shapes of distributions are not know exactly, there can be significant uncertainties about them.

When aleatoric and epistemic uncertainties are handled in the same way, the resulting uncertainty distributions are difficult to interpret. For example, the frequency of an accident sequence is not subject to aleatoric uncertainty. Instead the occurrence of the accident sequence is subject to aleatoric uncertainty according to the frequency. If realisations of aleatoric uncertainties are used in the calculation the frequency on a simulation cycle, the resulting uncertainty distribution of the frequency is incorrect. The uncertainty distribution of the frequency should reflect only epistemic uncertainties of model parameters.

One solution to improve the handling of uncertainties would be to perform the uncertainty analysis in two phases [21, 22], as outlined in Figure 11. In this method, there would be N simulation cycle blocks containing M simulation cycles. For the simulation results of one simulation cycle block, statistical analysis would be performed to calculate average frequency and average release fractions for each accident sequence (along with some other results). Then, statistical analyses would be performed over the simulation cycle blocks based on their average results to produce uncertainty distributions for release frequencies, source variables and other collected variables. These distributions would show the effects of epistemic uncertainties only. Statistical analysis could also be performed over both simulation loops to calculate uncertainty distributions that would show the combined effects of both epistemic and aleatoric uncertainties. However, these distributions should not be calculated for frequencies.

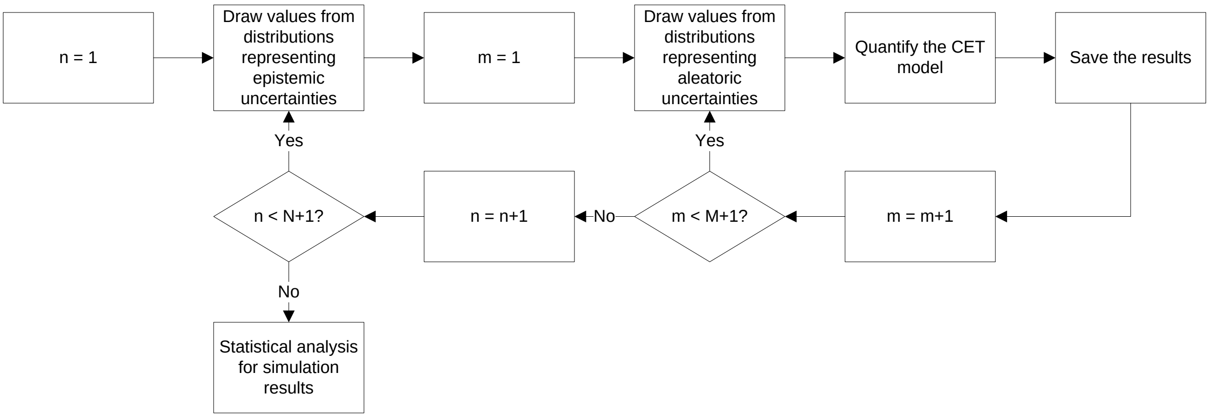

Figure 11: An outline for the progression of two-phase uncertainty analysis.

The two-phase uncertainty analysis would result in uncertainty distributions that would reflect only epistemic uncertainties related to the input parameters. Aleatoric uncertainties would be completely evaluated inside simulation cycle blocks and the results of one simulation block would be based on full range of possible occurrences of events and physical parameter values given specific values from distributions representing epistemic uncertainties.

The two-phase uncertainty analysis would be computationally more demanding than normal one-phase uncertainty analysis. The analysis would contain NM simulation cycles in total. The number of simulation cycles inside one block (M) should be sufficiently large so that results could be produced for each accident sequence. Suitable number of simulations would depend significantly on the model. If the model would contain some rare event sequences that would occur e.g. once in 1000 simulation cycles, then the number of simulations inside one block should be of that magnitude. The needed number of simulations can be affected by modelling decisions. Some special treatment for rare event sequences could be considered. The number of simulation cycle blocks should also be sufficiently large so that proper uncertainty distributions could be produced (at least hundreds). Some approximate methods have been developed to reduce the required number of simulation cycles [22, 23]. Their applicability to FinPSA level 2 could be studied.

In current models, such as the BWR model, no division to epistemic and aleatoric uncertainties has been made. For example, there is only one uncertainty distribution for core meltdown fraction in specific scenario. This uncertainty distribution covers both epistemic and aleatoric uncertainties. To make the analysis more correct, there should be separate uncertainty distributions for the mean core meltdown fraction and deviation parameter that would represent epistemic uncertainty on the core meltdown fraction. The separation of the uncertainties would make the modelling more complicated and challenging. In some cases, simplifications could be sufficient, such as treating all the uncertainty of a variable as epistemic, but only for variables that do not affect significantly the probabilities of CET branches.

6. Conclusions

This report has continued the development of simplified BWR plant PRA models. Previously developed level 1 and level 2 models were integrated and extended. The new model contains four level 1 event trees and five level 2 CETs. Uncertainty data was added to level 1, but otherwise the focus was on the extension of the level 2 part. Levels 1 and 2 were integrated so that it was possible to list most important event tree sequences, initiating events and basic events with regard to radioactive releases. The example model can later be utilised in further studies, demonstrations, training and FinPSA testing.

The computation of emergency core cooling system recovery probability based on level 1 results was studied. CETL function BE_FV (calculation of the Fussell-Vesely importance measure from minimal cut sets) was used for that. The resulting recovery probabilities varied significantly between PDSs. The probability parameters were however completely made up for this study, which means that the results might not be realistic. The purpose was just to demonstrate the modelling approach using BE_FV function. Some possibilities for the improvement of FinPSA level 2 were also identified. Contributions of level 1 basic events to level 2 results were not calculated correctly when BE_FV function was used. This problem could be solved by a suitable basic event contribution scaling function.

Ex-vessel steam explosions were also discussed in the report. Probabilistic modelling of steam explosions is very challenging because uncertainties related to the phenomenon, especially triggering of explosions, are very high. Pressure impulses of explosions can be calculated quite well using deterministic software tools, but the probability that an explosion occurs in the first place cannot be properly estimated based on current knowledge. Currently, it is a good idea to use conservative probabilities in PRA. It could be studied if explosion triggering probabilities could be estimated based on some physical parameters calculated by deterministic software tools, but plenty of development work and analyses are needed before well-justified probabilities can be estimated.

Sensitivity analysis results indicate that ex-vessel steam explosions have potential to be a major risk contributor. Therefore, more research activities should be dedicated to them. The same applies to basemat melt-through.

To handle separately different types of uncertainties in dynamic containment event trees, a method with two-phase uncertainty analysis was outlined. The method would enable explicit modelling of dynamic dependencies and production of proper uncertainty distributions as a result at the same time, whereas with normal one-phase uncertainty analysis it is difficult to do both. The study could be continued by developing software implementation of the two-phase uncertainty analysis and improving the modelling of dynamic dependencies related to physical parameters in the BWR model.

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