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Dynamic containment event tree modelling techniques and uncertainty analysis

Tyrväinen, Tero; Karanta, Ilkka

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Authors: Tero Tyrväinen, Ilkka Karanta

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Summary

VTT has developed a probabilistic risk analysis (PRA) model of a generic boiling water reactor nuclear power plant for PRA levels 1 and 2. The model can be used in research, training, education and demonstration. In this report, some refinements to the level 2 (severe accidents) part of the model are described. Particularly, dynamic modelling of timings of depressurization, emergency feedwater system recovery, emergency core cooling system recovery and lower drywell flooding is implemented.

Different techniques to model emergency core cooling system recovery time and its effects are presented in a simplified case study. The techniques are evaluated concerning uncertainty analysis.

A two-phase method of uncertainty analysis is presented. The purpose is to separate the treatment of aleatoric and epistemic uncertainties, to get rid of certain issues and inconsistencies in more traditional one-phase uncertainty analysis. The method is demonstrated by the emergency core cooling system case study. A drawback of the two-phase uncertainty analysis is that it is computationally very demanding. Therefore, it is proposed that first limited dynamic models would be constructed and analysed by the two-phase procedure; this would give input to a simplified full-scope model, allowing one-phase uncertainty analysis.

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Written by	Reviewed by	Accepted by
Tero Tyrväinen Research Scientist	Kim Björkman Research Scientist	Eila Lehmus Research Team Leader

VTT's contact address
Box 1000, FI-02044 VTT, Finland

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Contents

1. Introduction

Level 2 probabilistic risk assessment (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.

In the previous research report [2], a simplified boiling water reactor (BWR) plant PRA model including levels 1 and 2 was developed based on earlier models [3-5]. This report continues the development of the level 2 part of the model, and particularly focuses on modelling techniques and uncertainty analysis. A two-phase uncertainty analysis procedure, outlined in the previous report, is presented and implemented in limited case studies. Modelling of core cooling system recovery time is studied. The core cooling system case is used to demonstrate dynamic containment event tree modelling and the benefits of the two-phase uncertainty analysis.

Section 2 briefly describes dynamic containment event trees of FinPSA [6]. Section 3 discusses modelling techniques and uncertainty analysis. Core cooling system recovery time modelling is studied with a simple example model in Section 4, and dynamic modelling of high pressure melting case is studied more comprehensively in Section 5. Section 6 concludes the study.

2. Dynamic containment event trees

The level 2 modelling in the FinPSA software tool [6] is based on dynamic containment event trees (CETs) and containment event tree programming language (CETL). CETL 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, a 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 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.

3. Modelling techniques and uncertainty analysis

The level 2 modelling in the previous BWR model [2] has been performed using 'probabilities first' approach, which means that the occurrence of each branch in a CET on a given simulation cycle 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 of 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: timings of events and other process parameters do not have an impact on accident sequence probabilities, except in the case where different timings are divided into separate branches in the event tree. Furthermore, it does not fully utilise the capabilities of the dynamic CETs of FinPSA, i.e. computation of probabilities is static, not dynamic.

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 [7]. 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 [8]. 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 that there are two types of uncertainties.

Uncertainties can be divided into two categories: aleatoric and epistemic [9-14]. Aleatoric uncertainty represents uncertainty resulting from inherent randomness, e.g. it is known that the toss of a coin can result in heads or tails based on chance. Characteristic of aleatoric uncertainty is that it can usually be reliably quantified, and in this sense, the amount of uncertainty is known: for example, the probability of a perfect coin arriving at tails after a toss is 0.5. 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 chance 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 our lack of knowledge about a system or 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 known exactly, there can be significant uncertainties about them.

Another way to characterize the difference between aleatoric and epistemic uncertainty is as follows [11]. Consider a class of objects which we wish to assess; for example, the class might be the core meltdown process, and its objects are the individual meltdowns that might happen. Some variables related to the class are uncertain, but whatever their values, they affect all the members of the class in the same way; for example, the probability that a valve in the emergency core cooling system works affects each core meltdown in the same way. Such variables possess epistemic uncertainty. On the other hand, there are variables whose values vary by each object independently of the other objects; for example, the reactivity of the molten fuel as a function of time varies in each meltdown, depending e.g. on the geometry of the corium. Such variables possess aleatoric uncertainty.

When aleatoric and epistemic uncertainties are handled uniformly, the resulting uncertainty distributions are often difficult to interpret. Separation of epistemic and aleatoric uncertainties

has been found necessary in many probabilistic analyses [9, 12-18], including dynamic event tree analyses [10, 19, 20] and level 2 PRA [21, 22]. The separation is particularly important when calculating the frequency of an accident sequence. The frequency itself should represent the aleatoric uncertainty related to the occurrence of the accident sequence, and the uncertainty distribution of the frequency should represent the epistemic uncertainty. This means that the frequency should not be conditional to the realisations of aleatoric uncertainties. Instead, the whole range of possible realisations of aleatoric uncertainties should be evaluated in the computation of each point in the uncertainty distribution of the frequency.

If epistemic and aleatoric uncertainties are not separated, uncertainty may be significantly overestimated because in this case also aleatoric uncertainties affect it. Aleatoric uncertainty is sometimes also called variability, and it can be claimed that it is not real uncertainty, since it is related to known behaviour of the system. Aleatoric uncertainty cannot be reduced, but epistemic uncertainty can. Therefore, it is desirable to measure the epistemic uncertainty related to risk, rather than total uncertainty.

One solution to improve the handling of uncertainties is to perform the uncertainty analysis in two phases [9, 10], as outlined in Figure 1. In this method, there are N simulation cycle blocks containing M simulation cycles. For the simulation results of one simulation cycle block, statistical analysis is performed to calculate average frequency and average release fractions for each accident sequence (along with some other results). Then, statistical analysis is 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 show the effects of epistemic uncertainties only. Statistical analysis can also be performed over both simulation loops to calculate uncertainty distributions that show the combined effects of both epistemic and aleatoric uncertainties. However, these distributions should not be calculated for frequencies.
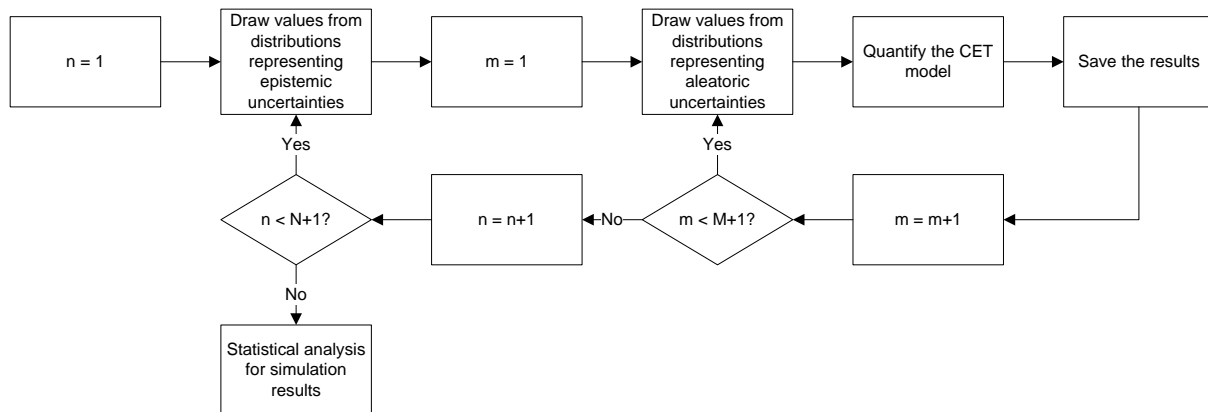
Figure 1: An outline for the progression of two-phase uncertainty analysis.

The two-phase uncertainty analysis results in uncertainty distributions that reflect only epistemic uncertainties related to the input parameters. Aleatoric uncertainties are completely evaluated inside simulation cycle blocks and the results of one simulation block are 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 is computationally more demanding than normal one-phase uncertainty analysis. The analysis contains NM simulation cycles in total. The number of simulation cycles inside one block (M) needs to be sufficiently large so that results can be produced for each accident sequence. Suitable number of simulations depends significantly on the model.

If ordinary Monte Carlo simulation methods were used and 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 tens of thousands to obtain statistically reliable simulation results. The needed number of simulations can be affected by modelling decisions. Reasonable handling of rare event sequences is crucial to keep the number of needed simulations moderate. If very little or not at all data is produced about some event sequence, the model needs to be modified if the event sequence is considered relevant. It can, for example, mean addition of a new branch in the event tree. In principle, handling of rare event sequences should not be a problem in event trees.

The number of simulation cycle blocks needs to also be sufficiently large so that proper uncertainty distributions can be produced (at least hundreds). Some approximate methods have been developed to reduce the required number of simulation cycles [10, 12, 20]. Their applicability to FinPSA level 2 could be studied. Use of intelligent sampling and simulation techniques could also be studied in this context to reduce the number of required simulations [23-26].

In previous models, such as the BWR model [2], no division to epistemic and aleatoric uncertainties has been made. For example, there is only one uncertainty distribution for emergency core cooling system recovery time in a 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 recovery time and deviation parameter that would represent epistemic uncertainty on the core cooling recovery. The separation of the uncertainties makes the modelling more complicated and challenging. In some cases, simplifications may be sufficient, such as treating all the uncertainty of a variable as epistemic. On the other hand, in some cases the portion of aleatoric uncertainty is significant and it should not be treated as epistemic; such is the case of the emergency core cooling system recovery time.

4. Modelling emergency core cooling system recovery time

This section studies different ways to model emergency core cooling system (ECCS) recovery time and its effects. Different modelling techniques are evaluated with regard to uncertainty analysis.

4.1 The previous BWR models

In the previous BWR models [2, 7], the ECCS recovery is modelled with two branches: successful recovery and no recovery. In the original model [7], the recovery time was drawn from a distribution, and time available for recovery was drawn from a distribution as well. If the recovery time was larger than the available time, the 'no recovery' branch had probability 1. Respectively, if the recovery time was smaller than the available time, the 'successful recovery' branch had probability 1. This way of modelling is valid, if the aim is only to determine the mean frequencies of accident sequences. Proper uncertainty analysis cannot be performed this way due to the reasons discussed in Section 3 concerning the physical parameters first approach. It is also inefficient to evaluate only one value from each distribution in one simulation cycle.

In the latest model [2], the ECCS recovery is modelled with the same two branches, but the recovery probability is drawn from a distribution instead of using the recovery time. This way proper uncertainty analysis can be performed. If the recovery is successful, the recovery time is drawn from a distribution, but it is only used to determine the end time for core melting, which further affects other accident timings and source term calculation.

From the results of [2], it can be noticed that the recovery time does not affect core meltdown fraction and ex-vessel accident phenomena in the previous models, except that the core meltdown fraction is set to 1 if the recovery is not successful. If the recovery is successful, the core meltdown fraction is drawn from a distribution. However, in reality, the core meltdown

fraction is highly dependent on the ECCS recovery time as the ECCS recovery is typically able to stop the meltdown. Therefore, the model could be improved by modelling this dependence. The previous modelling decision has been inherited from an old BWR model developed by Okkonen [27]. The old model is significantly more complicated than the example model in [2]. It models thermohydraulic conditions in the reactor core and containment explicitly by physical equations. However, the core meltdown fraction has been modelled in a very simple way due to lack of knowledge of the melting phenomenon.

4.2   One branch covering all timings

To model the dependence between ECCS recovery time and core meltdown fraction, a simple event tree model has been developed. The event tree is presented in Figure 2, and the CETL scripts after the figure. First, the mean and error factor of ECCS recovery time distribution are drawn from uncertainty distributions. The recovery time distribution is a rough lognormal approximation of the distribution used in [7] for high pressure case. It should be noticed that the high pressure core cooling system is called ECCS here, but in Section 5, only the low pressure core cooling system is called ECCS.
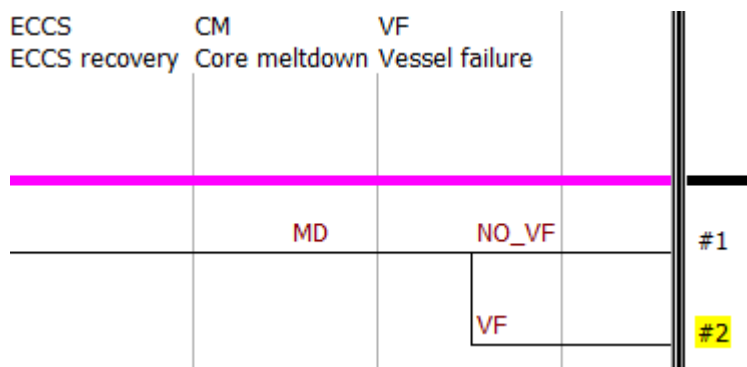

Figure 2: Emergency core cooling system recovery event tree.

Initial section

```
real M, EF, ECCSRecT, CoreMDF, MelStT, FuMelT

source ECCSRecT, MelStT, CoreMDF, FuMelT

routine init
  M = raneven(1000, 3000)
  EF = raneven(5, 30)
  ECCSRecT = ranlogn(M,EF)
return

routine finish

return

CUTFREQ = 0
```

CM

```
real x1, x2, x3, MM, S, D

routine init
```

```
  MM = raneven(3000,4000)
  S = raneven(150,250)
  x1 = rannorm (MM,S)
  x2 = raneven(-3000,3000)
  x3 = raneven(9000,14000)
  D = raneven(0.5,1.5)
return

function nil MD
  MelStT = x1
  FuMelT = x1+x3+x2
  CoreMDF = (ECCSRecT-MelStT)/(FuMelT-MelStT)
  if CoreMDF > 1 then CoreMDF = 1
  if CoreMDF < 0 then CoreMDF = 0
  CoreMDF = pow(CoreMDF,D)
return nil
```

VF

```
real p

normal RCSdebF = (0.3,0.1)

routine init

return

$------------------------------------------------------

function real NO_VF

$ No vessel melt-through if not enough melt
p = 1-cumul(RCSdebF, CoreMDF)
if CoreMDF <= 0 then p = 1

return p

$------------------------------------------------------

function nil VF

return nil
```

In the CM section, the core meltdown fraction is calculated based on the ECCS recovery time. Hypothetical melting start time and end time (assuming that the ECCS recovery is not successful) are drawn from distributions. Core meltdown fraction is calculated using the following formula:

$$CoreMDF = \left(\frac{\text{ECCSRecT} - \text{MelStT}}{\text{FuMelT} - \text{MelStT}}\right)^{D},$$

where FuMelT is the hypothetical melting end time, MelStT is hypothetical melting start time, and D is a factor that is assumed evenly distributed between 0.5 and 1.5. The formula is used

only if the ECCS recovery occurs during the melting. If the recovery occurs before the melting, the core meltdown fraction is assumed to be 0. This is a rough model that assumes that core melting is approximately linear as a function of time, and that the ECCS recovery stops the melting immediately. This formula is used purely for the demonstration of modelling techniques and is not based on any real data or physical considerations beyond the approximate linearity assumption. In reality, core meltdown is an extremely complicated phenomenon that is very challenging to model accurately [28]. NKS-395 [22] presents a core meltdown fraction curve (Figure 3.55 in [22]) that is close to linear, but evidently that is not always the case. A more realistic model could be developed by varying the ECCS recovery time in a set of deterministic analyses similar to those performed in [7], but the accuracy of the model is not relevant for the evaluation of modelling techniques.

In the VF section, the vessel failure probability is modelled as depending only on the core meltdown fraction. The amount of core melt needed for the vessel failure is approximated as a normal distribution in the same way as in [7]. CETL function CUMUL is used to determine the probability that the core meltdown fraction exceeds the limit value (RCSdepF), and this probability is used as the vessel failure probability.

The model was simulated 10000 times. The mean probability of vessel failure was 0.062. Proper uncertainty curve was not produced for the probability because aleatoric and epistemic uncertainties were mixed in the analysis. Uncertainty analysis requires the two-phase procedure presented in Section 3.

The model was also implemented in Excel where it was possible to perform the two-phase analysis. Variables representing aleatoric uncertainties were simulated 200 times in each simulation block (M in Figure 1), and variables representing epistemic uncertainties where simulated 100 times (N in Figure 1). Variables representing epistemic uncertainties were M, EF, MM, S, x3 and D, and variables representing aleatoric uncertainties were ECCSRecT, x1 and x2. The mean vessel failure probability was calculated for each of 100 simulation blocks, and an uncertainty distribution was drawn for the vessel failure probability based on those 100 points. The cumulative uncertainty distribution is presented in Figure 3. The mean failure probability was 0.060, approximately same as calculated in FinPSA. From the uncertainty curve, it can also be seen that e.g. 95th percentile value is around 0.11. Figure 4 illustrates how the vessel failure probability depends on the mean ECCS recovery time (variable M, the data set is different from Figure 3).
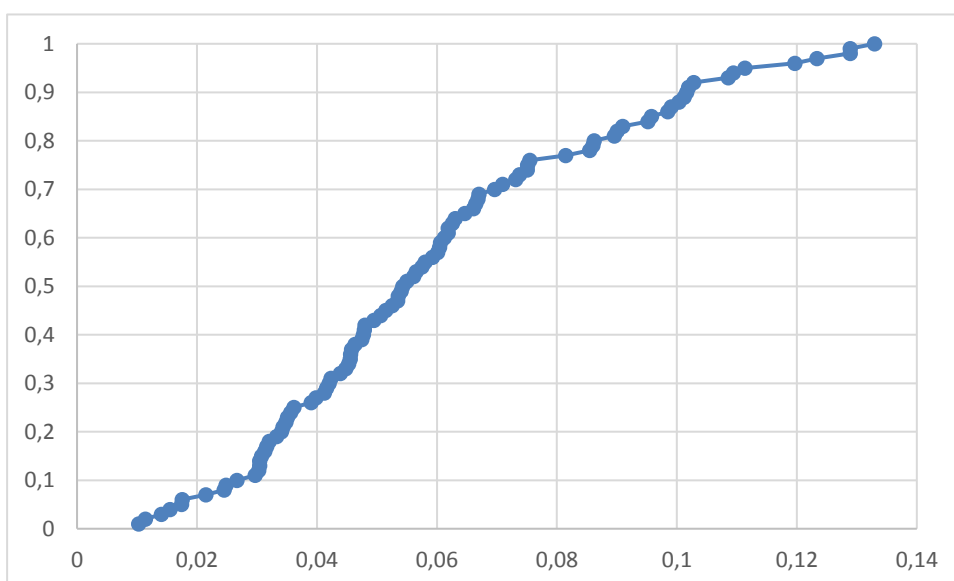
Figure 3: Cumulative distribution of the vessel failure probability.
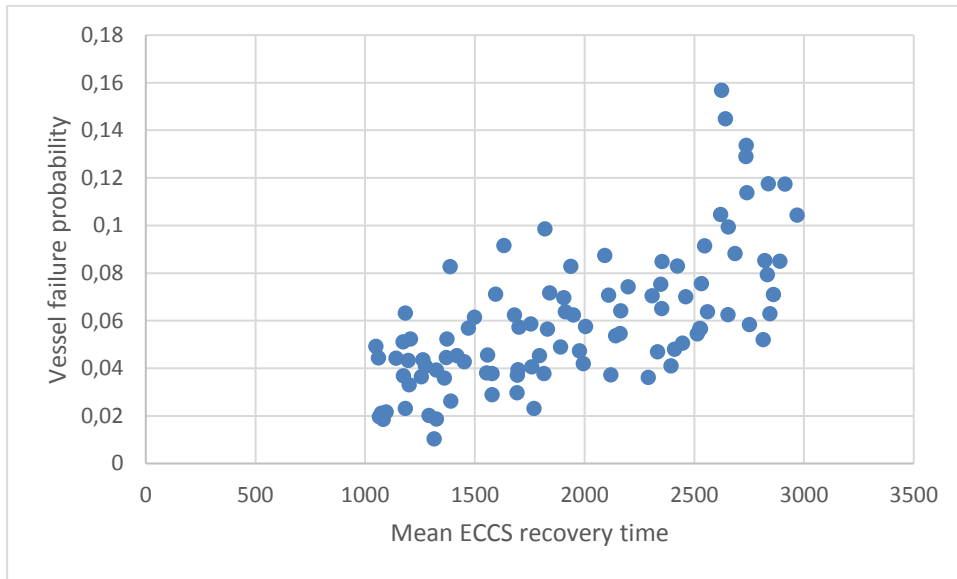
Figure 4: Scatter plot between the mean ECCS recovery time and the vessel failure probability.

4.3 Division to early and late recovery

With the previous example model, FinPSA calculated the vessel failure probability to be 0 approximately in 88% of the simulation cycles, even though those scenarios with late ECCS recovery are the most interesting cases. To focus more on the scenarios with late recovery, the event tree model is developed so that scenarios with early recovery and late recovery are analysed in separate accident sequences. The new event tree is presented in Figure 5. In this model, recovery is assumed to be late if it occurs after 2000 s. The limit value was selected because the earliest possible melting starting time is close to 2000 s. It can be noticed that late recovery defined this way does not automatically lead to vessel failure, but early recovery means that vessel failure is avoided. The new CETL scripts are presented after the figure. The CM and VF sections are the same as in the previous section.

Figure 5: Event tree with division to early and late ECCS recovery.

Initial section

```
real ECCSRecT, CoreMDF, MelStT, FuMelT

source ECCSRecT, MelStT, CoreMDF, FuMelT

routine init
```

```
return

routine finish

return

CUTFREQ = 0
```

ECCS

```
real M, EF, xe, RT, rn

LOGNOR RTD = (2000,17.5)

routine init
  M = raneven(1000, 3000)
  EF = raneven(5, 30)
  RTD = LOGNOR(M,EF)
  xe = 1-cumul(RTD,2000)
  rn = 1-random()*xe
  RT = icumul(RTD,rn)
return

function nil EARLY
  ECCSRecT = 1000
return nil

function real LATE
  ECCSRecT = RT
return xe
```
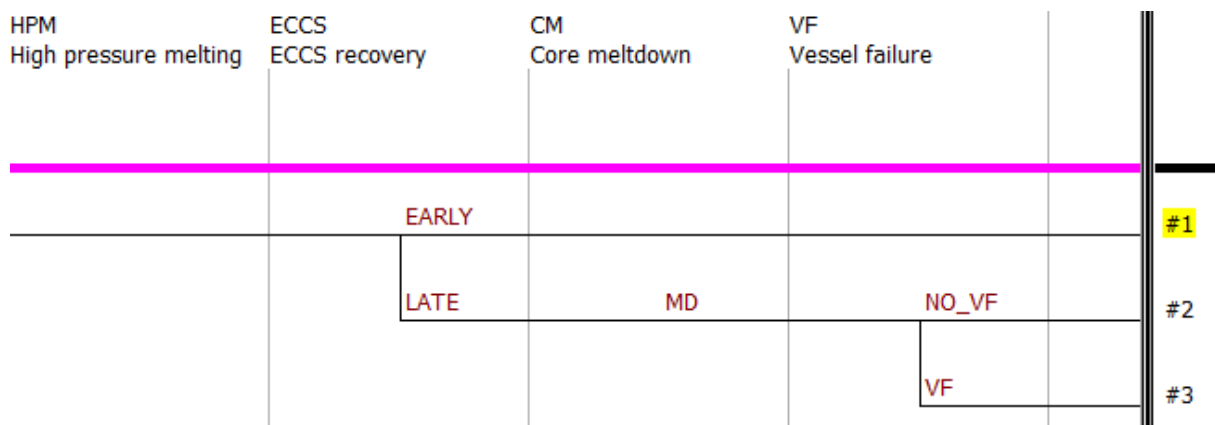
The probability of late recovery is now calculated using the CUMUL function, which returns here the probability that the recovery time is smaller than 2000 s. The time of late recovery time is drawn only from the part of the recovery time distribution (RTD) where 2000 s is exceeded, i.e. a random number between 1-xe and 1 is drawn and the corresponding recovery time is calculated using the ICUMUL function. In the case of early recovery, the actual time is not interesting, so the recovery time is just set to 1000 s.

It can be noticed that instead of limit value 2000 s the real melting start time could be used if it was drawn already in the ECCS section, but it would not change the vessel failure probability. It would only change the probabilities of sequences 1 and 2.

The model was again simulated 10000 times. The mean probability of vessel failure was 0.060, approximately the same as before. The division to early and late recovery did not change the problem with uncertainty analysis. The probability of late recovery was correctly simulated only based on realizations of epistemic uncertainties (the mean recovery time and the error factor), but the vessel failure probability calculation still involved aleatoric uncertainties.

The model was again also implemented in Excel, and a two-phase uncertainty analysis was performed. Results similar to those presented in the previous section were produced. The main difference was that now there was more data with late recovery times, making the results more accurate. A smaller number of simulations related to aleatoric uncertainties (M in Figure 1) would have produced results with the same accuracy as in the previous section.

4.4 Early recovery, late recovery or recovery during core melting

Another model was implemented where the late ECCS recovery was divided into two branches: recovery during the core melting and recovery after the core melting. The new event tree is presented in Figure 6. In this model, the recovery is late if it occurs after 21000, which is approximately the latest possible end time for core melting. The recovery is assumed to occur during core melting if it occurs between 2000 s and 21000 s (these limit values only determine which recovery times are evaluated in the middle branch and do not affect the total vessel failure probability). Late recovery automatically leads to vessel failure. The CETL scripts of the ECCS section are presented after the figure. The scripts of other sections are the same as in the previous model version (see section 4.2 for CM and VF, and section 4.3 for initial section).
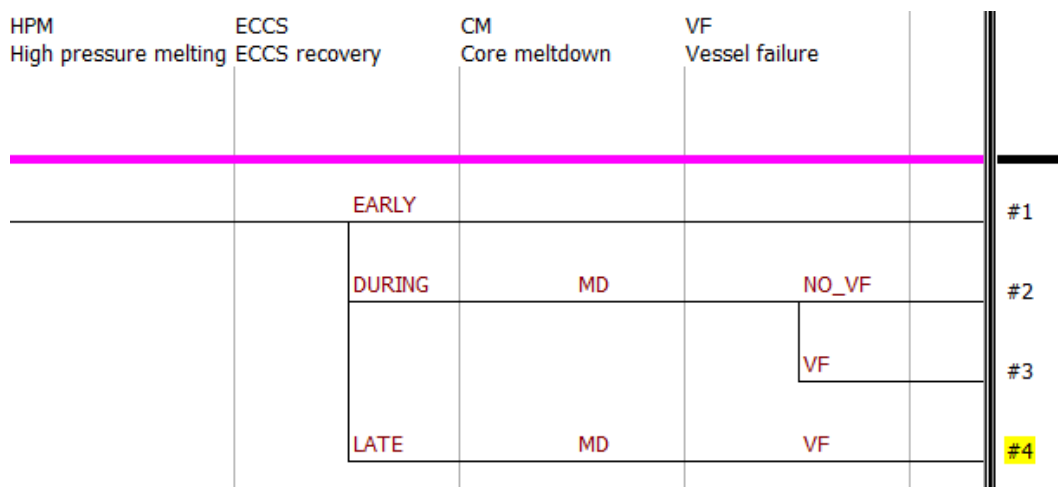
Figure 6: Event tree with three branches for the ECCS recovery.

ECCS

```
real M, EF, xe1, RT, rn, xe2

LOGNOR RTD = (2000,17.5)

routine init
  M = raneven(1000,3000)
  EF = raneven(5, 30)
  RTD = LOGNOR(M,EF)

  xe1 = 1-cumul(RTD,2000)
  xe2 = 1-cumul(RTD,21000)
  xe1 = xe1-xe2

  rn = 1-xe2-random()*xe1
  RT = icumul(RTD,rn)
return

function nil EARLY
  ECCSRecT = 1000
return nil

function real LATE
  ECCSRecT = 1E5
```

```
return xe2

function real DURING
  ECCSRecT = RT
return xe1
```

Variables xe1 and xe2 are the probabilities of recovery during core melting and late recovery. They are calculated from the recovery time distribution (RTD) using the CUMUL function. The recovery time for branch DURING is calculated by drawing a random number between 1-xe1-xe2 and 1-xe2 and calculating the corresponding recovery time from the distribution using the ICUMUL function. In the case of late recovery, the actual time is not interesting so the recovery time is just set to 100000 s.

The model was again simulated 10000 times. The mean probability of sequence 3 was 0.048 and the mean probability of sequence 4 was 0.012, which means that the mean probability of vessel failure was again 0.060. An improvement compared with the previous models was that the uncertainty analysis was performed correctly for sequence 4, because aleatoric uncertainties did not play any role in the computation of its probability. The uncertainty distribution is presented in Figure 7. However, for sequence 3, the uncertainty analysis still involved aleatoric uncertainty.
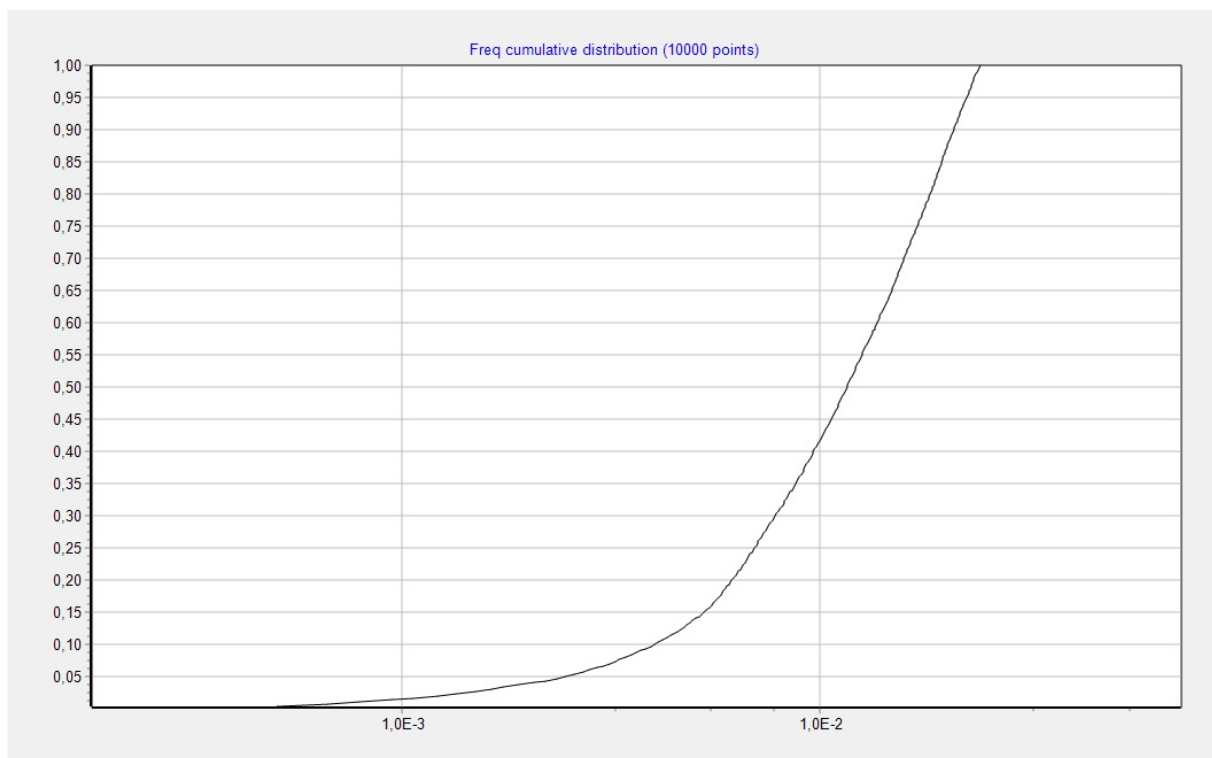
Figure 7: Cumulative distribution of the probability of sequence 4.

The model was again also implemented in Excel, and a two-phase uncertainty analysis was performed. Results similar to those presented in the previous section were produced. The results were more accurate than in the previous section, because the probability of late recovery was calculated accurately for each of 100 simulation cycles concerning epistemic uncertainties, and there were slightly more simulation data where the recovery occurred during the core melting. It would be possible to increase the accuracy even more by separating the recovery during core melting into multiple branches. However, concerning a full scope level 2 PRA model, the number of branches has to be considered carefully to keep the size of the model reasonable. Likely, a better idea would be to increase the number of simulation cycles for aleatoric uncertainties (M in Figure 1).

4.5   Uncertainty distribution of conditional vessel failure probability

The two-phase uncertainty analysis can be avoided if a distribution is directly assigned to the conditional vessel failure probability in the case that the ECCS recovery occurs during core melting, because the probability calculated in one simulation cycle is then not conditional on realisations of aleatoric uncertainties. The dependence to the mean ECCS recovery time can still be modelled, because the uncertainty of the mean value is epistemic. The distribution can be estimated based on the previous results. The mean conditional vessel failure probability in sequence 3 varies approximately between 0.2 and 0.34 depending on the mean ECCS recovery time. A lognormal distribution with error factor 1.5 is used in the VF section:

```
real p, MP

routine init
  MP = 0.2+0.14*(M-1000)/2000
  p = 1-ranlogn(MP, 1.5)
  if p < 0 then p = 0
return


$----------------------------------------------------


function real NO_VF
  VFail = false
return p


$----------------------------------------------------


function nil VF
  VFail = true
return nil
```

A binner specifying a release category covering sequences 3 and 4 was also added to the model.

With these modifications, normal one-phase uncertainty analysis was sufficient to produce a distribution for the vessel failure probability. The distribution is presented in Figure 8.
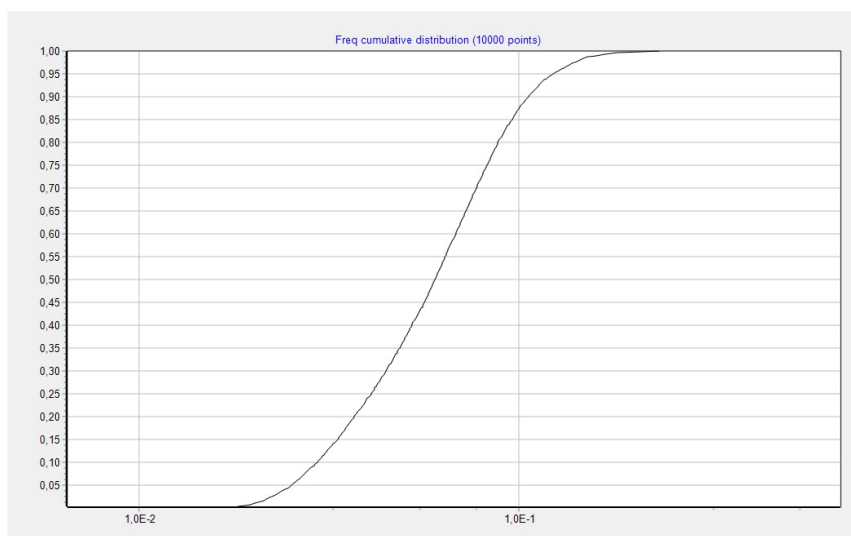
Figure 8: Cumulative distribution of the vessel failure probability produced by FinPSA.

This new version of the model does not include all the dependencies that the model in the previous section did. The vessel failure probability also depended on meltdown timing parameters, deviation parameters and the D parameter in the core meltdown fraction model, but these dependencies are now neglected. If it is not practical to use more accurate way of modelling like in the previous section, this type of simplification should be acceptable, especially if it is made in conservative manner.

4.6 Problems with one-phase uncertainty analysis

A problem with one-phase uncertainty analysis not separating epistemic and aleatoric uncertainties is that modelling decisions can affect results significantly. Aleatoric uncertainties can be modelled in several different ways resulting with different uncertainty distributions. Vessel failure probability distributions of models from sections 4.2-4.4 calculated by one-phase Monte Carlo simulation are presented in Figures 9-11. The probability distribution of the model of section 4.4 was calculated by adding a binner that sums the probabilities of sequences 3 and 4 in each simulation cycle. The distributions are totally different even though the same problem was modelled in each case, and the only difference was the division of ECCS recovery scenarios into event tree branches.

Figure 9: Total uncertainty distribution of vessel failure probability from the model of section 4.2.

Figure 10: Total uncertainty distribution of vessel failure probability from the model of section 4.3.
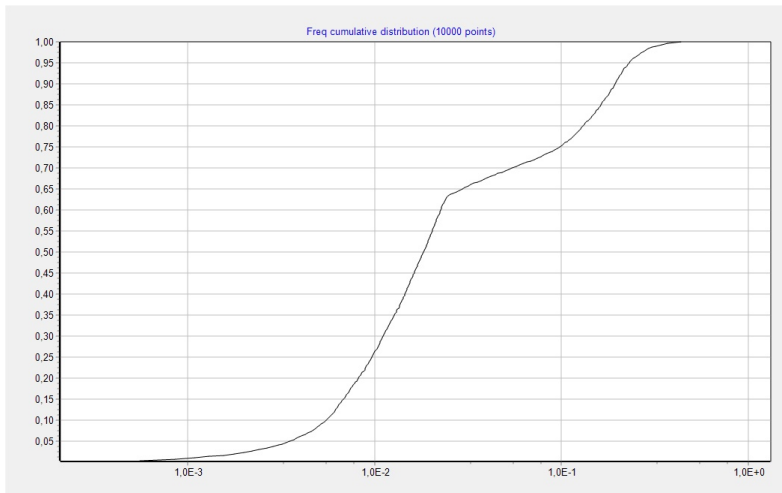
Figure 11: Total uncertainty distribution of vessel failure probability from the model of section 4.4.

There is also another way to calculate the uncertainty distributions of the models of sections 4.2 and 4.3. It is to remove those simulation cycles where the probability is 0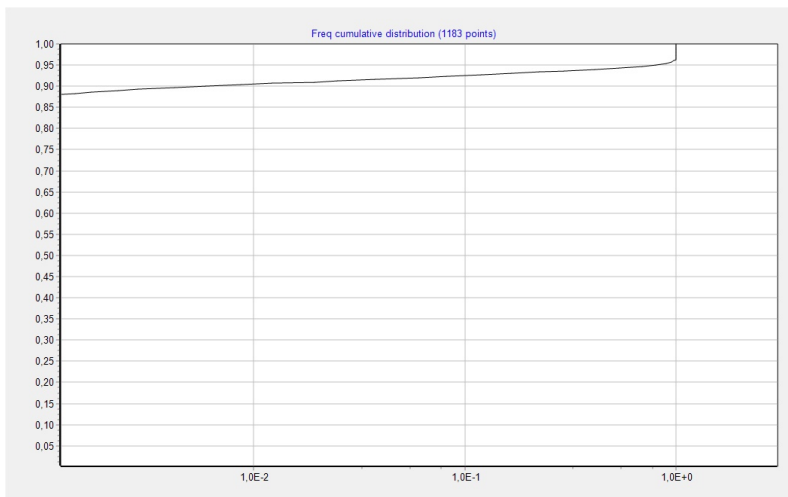, and scale the probabilities of other simulation cycles with the portion of the simulation cycles with non-zero probability. FinPSA calculates release category frequencies/probabilities this way. Therefore, binners were also added to the models of sections 4.2 and 4.3, even though they include only one sequence for vessel failure. The alternative uncertainty distributions are presented in Figures 12 and 13. These distributions are closer to each other and the distribution presented in Figure 11, though not exactly similar. Still, the interpretation of these distributions is problematic. In Figure 12, the right tail is clearly incorrect and gives an underestimation of highest possible vessel failure probabilities (see Figure 3 for comparison). In some other case, this type of underestimation could be more significant. The scaling procedure does not treat epistemic uncertainties correctly. Firstly, in some cases, the probability could really be 0 (not in this example). Secondly, the scaling procedure scales all non-zero values with the same portion, and does not take into account that the occurrence of 0 probability in a simulation cycle is more likely with specific realisations of epistemic uncertainties, and higher probabilities are more likely with other realisations of epistemic uncertainties. For example, it could be that specific realisations of epistemic uncertainties would not return probability 0 in any case, which means that the scaling of the related output probabilities would clearly be wrong.
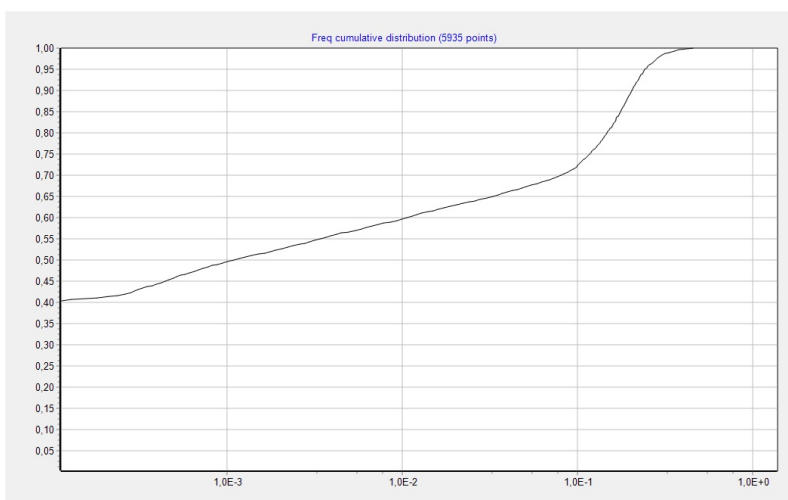

Figure 12: Alternative total uncertainty distribution of vessel failure probability from the model of section 4.2.

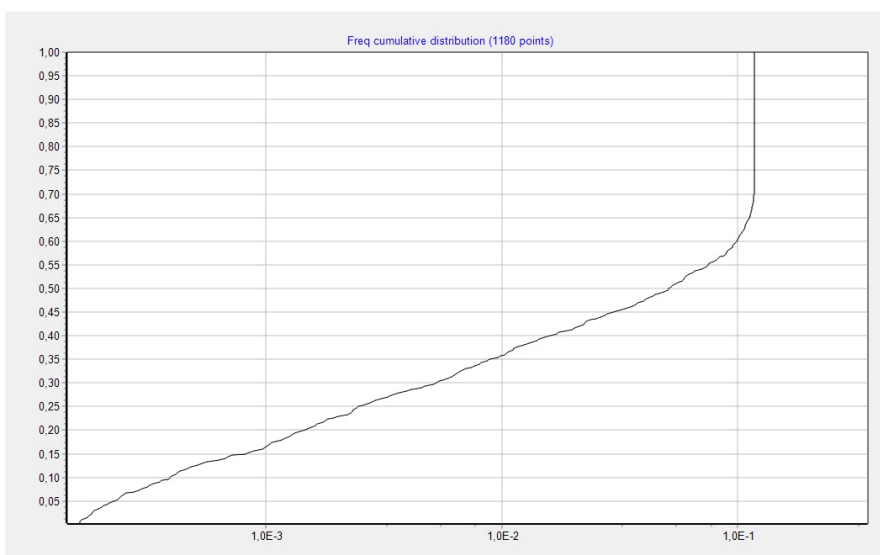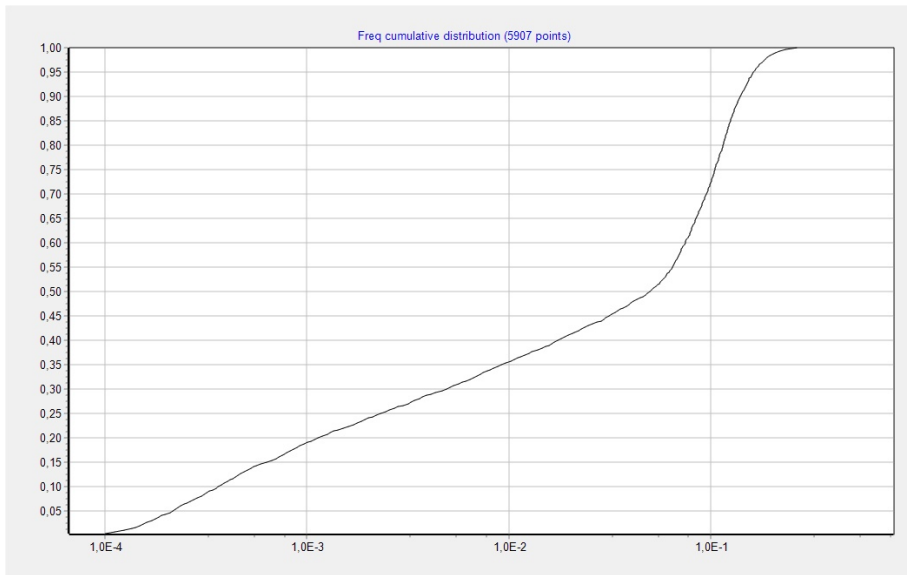*Figure 13: Alternative total uncertainty distribution of vessel failure probability from the model of section 4.3.*

When aleatoric uncertainties are not treated separately, the resulting uncertainty distributions can be very sensitive to the modelling choices, whereas the two-phase uncertainty analysis produces approximately same distribution regardless of how aleatoric uncertainties are modelled. This does not mean that one-phase uncertainty analysis is totally useless. By improving the modelling of aleatoric uncertainties, e.g. by adding more event tree branches, the resulting uncertainty distribution can be made to reflect the aleatoric uncertainties less. By adding enough event tree branches for each aleatoric variable, the resulting uncertainty distribution could be made to represent almost exclusively epistemic uncertainties. In summary, it is a matter of modelling choices how aleatoric uncertainties are seen in the results. To conduct the uncertainty analysis in a consistent manner, either aleatoric uncertainties need to be handled carefully, or two-phase uncertainty analysis needs to be used.

4.7 Conclusions on the example models

The previous examples illustrated the role of a timing of an event in probabilistic CET analysis. The ECCS recovery was used as the example case, but the general principles and conclusions drawn are quite generally applicable to different timing modelling cases. Timings of events, such as depressurisation, ECCS recovery and lower drywell flooding, can significantly affect accident progression. The analysis can be made most accurate and dynamic if the timing information is included explicitly in the computation of sequence frequencies. However, to perform proper uncertainty analysis, the separation of epistemic and aleatoric uncertainties with a two-phase procedure is needed.

A drawback of the two-phase uncertainty analysis is that it requires a significantly larger number of simulation cycles than normal one-phase uncertainty analysis. With a large and complex model, it can mean that a very limited number of simulations can be performed resulting in low accuracy, or alternatively calculations last for days. It might be practical to make some simplifications so that one-phase uncertainty analysis can be performed and produces sufficiently accurate results. Section 4.5 presented an example on how to make such simplification. However, the results of a two-phase uncertainty analysis were the basis for the simplification. Hence, even if a full scope level 2 model would be implemented so that one-phase uncertainty analysis would be sufficient, it could be beneficial to perform some supporting analyses using two-phase uncertainty analysis to provide input data for the full scope analysis.

It could also have been possible to perform the probability calculations entirely using distribution functions. In that approach, a probability distribution would have been calculated for the core meltdown fraction on each simulation cycle based on the distributions of the ECCS recovery time, meltdown start time and hypothetical meltdown end time. Then, the vessel failure probability would have been calculated by comparing the core meltdown fraction distribution to the RCSdebF (reactor coolant system failure limit value) distribution. However, script compilation problems prevented trying that. There seems to be a bug in the assignment of a distribution to a DISTR variable. Distribution based probability computation would enable accurate uncertainty analysis with one phase only without simplifications like in section 5.5, but on the other hand, it is quite complicated and distribution functions are limited to basic operations (e.g. there is no power function). The number of operations allowed for distribution functions could be extended by utilizing transform formulae for functions of random variables (see, e.g., [29], Chapter 6). Also different probability distributions could be implemented, for example utilizing the information in [30].

5. High pressure melting analysis

A new version of the high pressure melting CET of the BWR model [2] has been prepared utilising dynamic modelling of timings of depressurisation, emergency feedwater system (EFWS) recovery, ECCS recovery and lower drywell (LDW) flooding. To perform uncertainty analysis for this new version, a two-phase procedure is needed. Since FinPSA does not currently include two-phase uncertainty analysis procedure, and the model is too large to be implemented in Excel or other tool with available resources, only one-phase uncertainty analysis is performed for the full CET to calculate the mean frequencies of accident sequences. In addition, a limited two-phase uncertainty analysis is performed for a small part of the CET in Excel.

The upper part of the CET is presented in Figure 14. Compared with [2], a new section for the EFWS recovery has been added (branches not shown in the figure because the high pressure part of the tree has been cut off). Some parts of the CET structure have also changed and some new CET functions have been introduced as presented in the following subsections. The most significant changes are in the CETL scripts. The source term model is the same as in the original model [7]. Table 1 presents the release categories and containment failure modes of the model. The plant damage state frequency is calculated by a level 1 model and an interface tree as in [2].

Table 1: 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)
Filtered venting (FV)	1. Very early venting (VEFV) 2. Early venting (EFV) 3. Late venting (LFV)
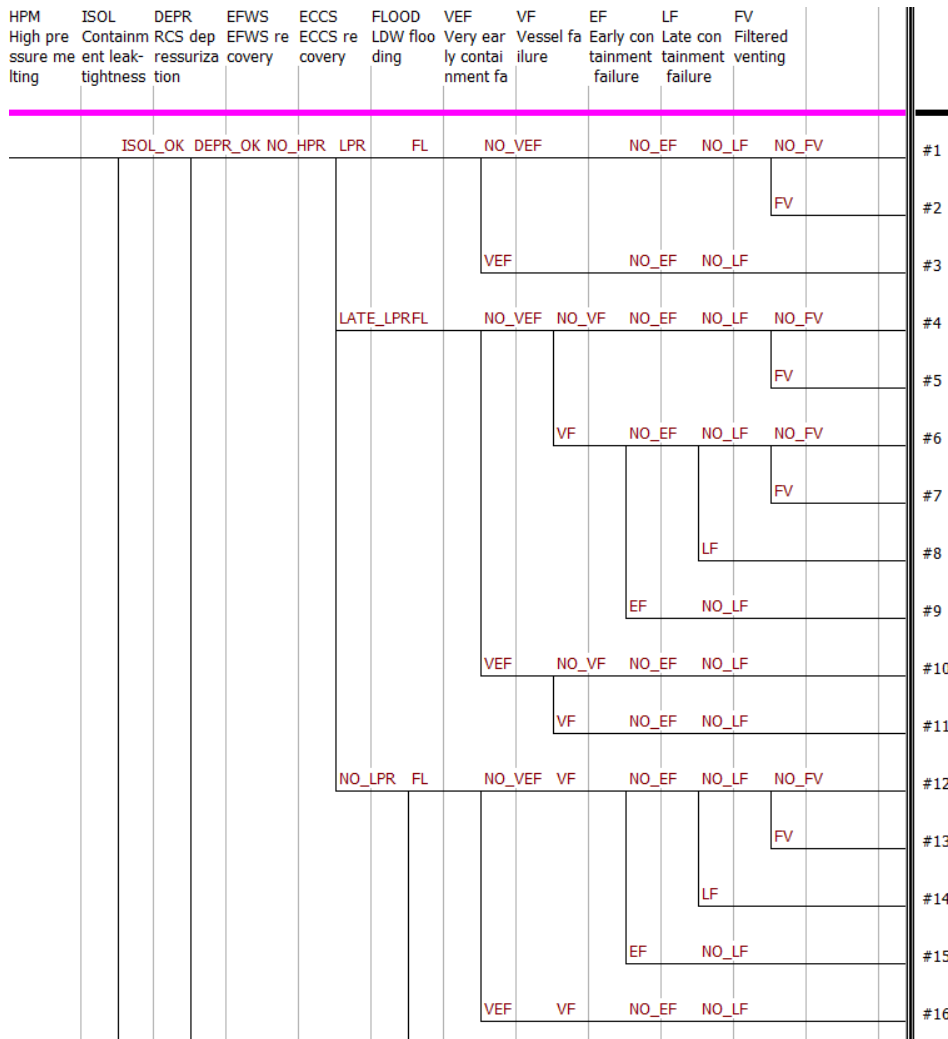
Figure 14: The upper part of the high pressure melting containment event tree.

5.1 Depressurisation

Three branches are used to model different depressurisation scenarios:

- DEPR_OK: depressurisation before meltdown

- DEPR_DM: depressurisation during meltdown

- NO_DEPR: no depressurisation during accident

The modelling is performed in the same way as for the ECCS recovery in Section 4.4. A lognormal distribution is used for the depressurisation time (depressurisation is assumed to occur instantaneously at this single time point with no delays). The mean value and error factor are drawn from distributions, and the probabilities of the branches are calculated from the lognormal distribution. On each simulation cycle, depressurisation time before meltdown and depressurisation time during meltdown are drawn from the distribution.

5.2 Emergency feedwater system recovery

The emergency feedwater system, which is used in the case of high pressure, is modelled in a section separate from the ECCS, whereas in the previous model [2], the cooling systems were modelled in the same section. The EFWS is modelled using two branches corresponding to the success and failure of recovery.

As in the previous model [2], level 1 results are utilised to determine what kind of failure caused the EFWS to fail in the first place. Different failure types that are considered are cooling system component failures (e.g. pumps and valves), power supply failures, heating ventilating and air conditioning (HVAC) system failures, demineralised water tank failure and reactor protection system failure. For each failure type, the conditional probability is calculated using Fussell-Vesely in the same way as in [2]. A lognormal recovery time distribution is also specified for each failure type, and the probability of successful recovery is calculated based on the distribution in each case. If depressurisation occurs during the meltdown, the success probability is the probability that the EFWS is recovered before the depressurisation, and therefore the depressurisation time is used in the calculation of the probability. The probability of successful recovery is a weighted sum of the success probabilities of the failure types weighted by the conditional probabilities of the failure types.

On each simulation cycle, for the success branch, a recovery time is drawn from the distributions. First, one failure type is drawn based on the conditional probabilities of the failure types given that the recovery is successful. Then, the recovery time is drawn from the recovery time distribution of that failure type.

5.3 Emergency core cooling system recovery

The low pressure ECCS recovery is modelled using three branches:

- LPR: recovery immediately after depressurisation

- LATE_LPR: recovery during meltdown, but not immediately after depressurisation

- NO_LPR: no recovery during accident

The probability of failure of immediate recovery is drawn from a lognormal distribution with mean value 0.02. In the case of immediate recovery, the recovery is set to 10 seconds after the depressurisation time. If immediate recovery fails, a lognormal distribution is used for the recovery time. The distribution is the same as the one used for the EFWS recovery in the case of power supply failure. However, the depressurisation time is added to the time obtained from the distribution. The probability that the recovery occurs during the meltdown is calculated based on the distribution, and a recovery time is drawn from the distribution on each simulation cycle.

5.4 Lower drywell flooding

The modelling of the LDW flooding is similar to [2], except that a different flooding time distribution is used. Flooding is assumed always successful if the EFWS or ECCS is recovered. In the previous studies [2, 7], a very narrow flooding time distribution was used so that the flooding was always performed before the vessel failure if it was successful. Now, a lognormal distribution is used to cover the case of a late manual flooding.

5.5 Core meltdown

As in the previous studies [2, 7], the VEF section calls a function called MeltDown, which determines the melting start and end time, and core meltdown fraction. The core melting model used is similar to the one described in Section 4. However, the possibility of depressurisation during core melting and the two cooling systems complicate the computation. Table 2 presents core melting start time, end time and core meltdown fraction in different scenarios. Time is measured in seconds from initiating event. Some of the time estimates are roughly based on deterministic analyses performed in [7] and some are heuristic: physical (deterministic) modelling would be needed to obtain more accurate time estimates. In the table,

- S_{LP} is the meltdown start time in low pressure without cooling,

- R_{LP} is the ECCS recovery time,

- L_{LP} is the time it takes for the core to melt fully in low pressure without cooling,

- D is an uncertain parameter in the core meltdown model,

- T_D is the depressurisation time,

- S_{HP} is the meltdown start time in high pressure without cooling,

- R_{HP} is the EFWS recovery time,

- L_{HP} is the time it takes for the core to melt fully in high pressure without cooling.

Table 2: Core meltdown scenarios.

Depressurisation	EFWS recovery	ECCS recovery	Start time	End time	Core meltdown fraction
Early	-	Early	-	-	0
Early	-	During melting	S_{LP}	R_{LP}	$\left(\dfrac{R_{LP} - S_{LP}}{L_{LP}}\right)^D$
Early	-	-	S_{LP}	$S_{LP} + L_{LP}$	1
Between early and late melting start time	-	During melting	T_D	R_{LP}	$\left(\dfrac{R_{LP} - T_D}{L_{LP}}\right)^D$
Between early and late melting start time	-	-	T_D	$T_D + L_{LP}$	1
During melting	Early	During melting	T_D	R_{LP}	$\left(\dfrac{R_{LP} - T_D}{L_{LP}}\right)^D$
During melting	Early	-	T_D	$T_D + L_{LP}$	1
During melting	During melting	During melting	S_{HP}	R_{LP}	$\left(\dfrac{R_{HP} - S_{HP}}{L_{HP}} + \dfrac{R_{LP} - T_D}{L_{LP}}\right)^D$
During melting	During melting	-	S_{HP}	$T_D + L_{LP}\left(1 - \dfrac{R_{HP} - S_{HP}}{L_{HP}}\right)$	1
During melting	-	During melting	S_{HP}	R_{LP}	$\left(\dfrac{T_D - S_{HP}}{L_{HP}} + \dfrac{R_{LP} - T_D}{L_{LP}}\right)^D$
During melting	-	-	S_{HP}	$T_D + L_{LP}\left(1 - \dfrac{T_D - S_{HP}}{L_{HP}}\right)$	1
-	Early	-	-	-	0
-	During melting	-	S_{HP}	R_{HP}	$\left(\dfrac{R_{HP} - S_{HP}}{L_{HP}}\right)^D$
-	-	-	S_{HP}	$S_{HP} + L_{HP}$	1

Uncertainties related to high pressure melting timings are modelled in the same way as in Section 4. Normal distributions are used for the low pressure melting start time and duration.

5.6 Very early containment failure

The modelling of very early containment failure is similar to the previous model [2]. Modelling of recriticality however differs. The reactor is assumed to become recritical if core cooling is recovered within a critical time window. The starting time of the time window is evenly distributed between 50 s and 150 s after the start of meltdown. The duration of the critical time window is evenly distributed between 500 s and 1000 s.

In the previous model [2], very early containment failure was conservatively assumed possible even if the core cooling was recovered in time. In the new model, very early containment failure is possible only due to hydrogen explosion if the core cooling is recovered early.

5.7 Vessel failure

The vessel failure probability is calculated based on the core meltdown fraction in the same way as in Section 4.2. The vessel failure time is calculated based on the melting end time and a delay parameter, which is around 5000 s. In the case of a cooling system recovery during melting, a hypothetical melting end time assuming no cooling is used in the computation instead, which means that the delay after the end of core melting is longer.

A LDW flooding fraction (the proportion of the LDW that is filled with water compared to the maximum water level) is also calculated in the way that it was calculated in the original model [7]. It is assumed that the LDW is filled linearly so that the flooding fraction is

$$\frac{T_{VF} - T_{FS}}{T_{FE} - T_{FS}},$$

where T_{VF} is the vessel failure time, T_{FS} is the start time of LDW flooding, and T_{FE} is the end time of the flooding. If the flooding is over before the vessel failure, the fraction is 1, and if it has not been started, the fraction is 0.

Probabilities for melt flow modes concerning the injection of core melt to the LDW are drawn in the VF section. They are highly dependent on the core meltdown fraction as presented in Table 3. In the table, F_{CM} is the core meltdown fraction, P_{LF} is the probability of large flow, and P_{MF} is the probability of medium flow. The probabilities are completely made up, but they are based on the idea that the larger the core meltdown fraction the larger the probability of large flow. Compared with NKS-395 [22], which is the reference for the selection of the melt flow modes, the large flow is emphasised more. In NKS-395, all melt flow modes were assumed to be equally probable in the case of no core cooling (core meltdown fraction = 1) due to lack of data.

In the case of an alpha-mode steam explosion, the vessel is assumed to fail with certainty along with the containment, and no further considerations of ex-vessel phenomena are made.

5.8 Early containment failure

Possible causes of early containment failure are an ex-vessel steam explosion and a failure of containment penetrations. Both failure modes are modelled as dependent on the LDW flooding fraction. In addition, the probability of a steam explosion depends on the melt flow mode.

Containment failure probabilities due to a steam explosion are taken from NKS-395 [22] and they are presented in Table 4. Here, a single containment failure probability combines the probability that a steam explosion occurs and the probability of containment failure given that a steam explosion occurs. Lognormal uncertainty distributions are assigned to the probabilities, except for dripping flow. LDW pool is considered deep when the flooding

fraction is at least 0.7, and shallow when the flooding fraction is between 0.2 and 0.7. Same probabilities are used for high and low pressure cases.

Table 3: Probabilities of melt flow modes.

Core meltdown fraction	Large flow	Medium flow	Dripping flow
0.8 - 1.0	Uniform distribution between 0.8 and 1.0	$1 - P_{LF}$	0
0.3 - 0.8	Uniform distribution between $$0.3 + 0.3\frac{F_{CM} - 0.3}{0.5}$$ and $$0.7 + 0.3\frac{F_{CM} - 0.3}{0.5}$$	$1 - P_{LF}$	0
0.1 - 0.3	Uniform distribution between $$0.3\frac{F_{CM} - 0.1}{0.2}$$ and $$0.2 + 0.3\frac{F_{CM} - 0.1}{0.2}$$	Uniform distribution between $$0.3 + 0.2\frac{F_{CM} - 0.1}{0.2}$$ and $$0.5 + 0.2\frac{F_{CM} - 0.1}{0.2}$$	$1 - P_{LF} - P_{MF}$
0.0 - 0.1	0	Uniform distribution between $3F_{CM}$ and $0.2 + 3F_{CM}$	$1 - P_{MF}$

Table 4: Mean containment failure probabilities due to a steam explosion.

LDW flooding	Dripping flow	Medium flow	Large flow
Deep pool	0	0.0155	0.636
Shallow pool	0	3.60E-4	0.378

In high pressure, the probability of failure of containment penetrations is assumed to be around 0.2 when the LDW flooding fraction is smaller than 0.5. If the flooding fraction is larger, the probability is around 0.1. Without flooding at all, the probability is around 0.5. In low pressure, the probability is 0, if the flooding is even partially successful.

5.9 Late containment failure

The only failure mode for late containment failure is basemat melt-through. The mean basemat melt-through probabilities are also taken from NKS-395 [22] and lognormal distributions are applied. If the LDW flooding fraction is larger than 0.5, the mean melt-through probability is 0.852 in the case of large melt flow, 0.283 in the case of medium flow, and 0.0361 in the case of dripping flow. Otherwise, the melt-through probability is 1.

5.10   Results

The model was simulated 1000 cycles, which takes a bit less than half an hour. Calculated release category frequencies are presented in Table 5. Release frequencies are smaller than in the previous study [2], because the conservative assumption of core melting in the case of successful ECCS recovery was removed. On the other hand, ex-vessel steam explosion and basemat melt-through probabilities were increased, which compensated the direction of the core melting modelling. Hydrogen explosion causing very early containment failure dominates the risk, because it is the only way for the containment to fail if core cooling is recovered early in addition to isolation failure. Hydrogen explosion modelling is also likely very conservative.

Table 5: Release category frequencies.

Release category	OK	ISOL	VEF	EF	LF	FV
Frequency	2.82E-7	9.29E-9	1.35E-7	1.66E-8	1.24E-8	4.66E-7
Frequency computed with old model [2]	2.60E-7	1.20E-8	2.29E-7	3.08E-8	2.51E-8	7.01E-7

Table 6 presents release category frequency increase factors of CET functions. A release category frequency increase factor is the relative increase of the release category frequency given that the analysed CET function has probability 1, basically the equivalent to the risk increase factor in level 1. Values below 1 mean that the frequency is decreased by the CET function. Release category frequency increase factors appear currently only in a developer version of FinPSA.

Table 6: Release category frequency increase factors of CET functions.

CET function	Section	VEF	EF	LF
DEPR_OK	DEPR	0.989	0.116	0.0789
DEPR_DM	DEPR	1.00	1.10	1.13
NO_DEPR	DEPR	0.991	9.79	3.20
NO_HPR	EFWS	1.03	4.46	4.33
HPR	EFWS	0.989	0.331	0.229
LPR	ECCS	1.00	0.827	0.879
LATE_LPR	ECCS	1.02	7.87	5.97
NO_LPR	ECCS	0.988	34.4	20.1
FL	FLOOD	1.00	1.00	0.999
NO_FL	FLOOD	1.00	0.992	1.01

Release category frequency increase factors indicate that the ECCS system is the most important safety system to mitigate severe accidents. The depressurisation and EFWS also have significant impact on the risk, while the LDW flooding has very small impact. The risk of very early containment failure was not changed much by any of the CET functions. The reason for this is that the risk of hydrogen explosion dominates the very early containment failure risk, and the main safety function against it is inerting of the containment, which is not represented by a CET function. The analysed safety functions have larger impacts on the early containment failure risk and late containment failure risk.

The reason for the small impact of the LDW flooding is that the risks of early and late containment failure are dominated by sequences where core cooling is recovered, because successful recovery is so likely. In those accident sequences, the LDW flooding is successful with certainty, and the frequencies of those sequences are kept in their nominal values also in the analysis of NO_FL, because NO_FL is not an option in those sequences. An alternative way to calculate the increase factors for NO_FL would be to set also the core cooling recovery failure probabilities to 1, because the failure of flooding requires the failure of core cooling. Then, the frequencies of early containment failure and late containment failure would be increased by factors of 36 and 48. On the other hand, the factors would then not measure only the impact of the LDW flooding failure. This underlines that the numbers cannot be read blindly. Instead, some effort is needed for their interpretation.

5.11   Uncertainty analysis

The part of the CET covering early depressurisation and ECCS recovery during core melting (sequences 4-11 in Figure 14) was analysed with two-phase uncertainty analysis in Excel. The analysis focused on

- the vessel failure probability

- the probability of ECCS recovery in the critical time window

- the probabilities of the melt flow modes

- the LDW flooding.

It was studied how the vessel failure probability correlates with different variables representing epistemic uncertainties. The highest correlations were with the ECCS recovery time mean value and the error factor. A regression model was developed to calculate approximate vessel failure probability based on the mean and error factor. Figure 15 shows how the fit of the regression model correlates with the real vessel failure probability. The regression model is used in an alternative version of the high pressure melting CET to calculate the vessel failure probability.
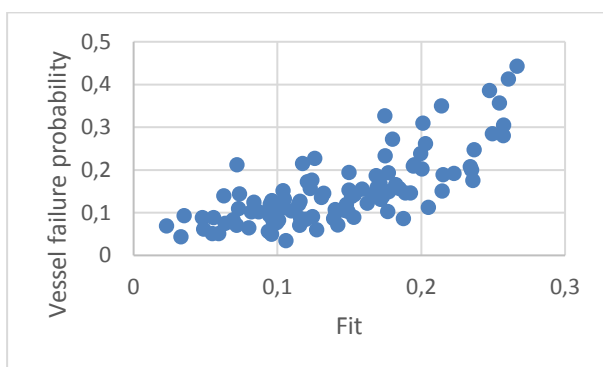

Figure 15: Scatter plot between the real vessel failure probability and the fit of the regression model.

Similarly, it was studied how the probability of ECCS recovery in the critical time window correlates with different variables. Again, the highest correlations were with the ECCS recovery time mean value and the error factor. The correlation with the error factor was higher, and it was used as the only explanatory variable in a regression model, which was implemented in the new model version.

When analysing the probability of large melt flow from the pressure vessel, it has to be noticed that the probability has to be analysed as conditional to the vessel failure. Raw simulation data cannot therefore be applied directly. Instead, the conditional probability has to be calculated on each simulation cycle of the outer loop of the two-stage procedure:

$$P_n(LF|VF) = \frac{\sum_{m=1}^M P_{n,m}(LF) \cdot P_{n,m}(VF)}{\sum_{m=1}^M P_{n,m}(VF)},$$

where $P_n(LF|VF)$ of the conditional probability of large melt flow in n:th simulation cycle of the outer loop, M is the number of simulation cycles in the inner loop, $P_{n,m}(LF)$ is the probability of large melt flow in n:th simulation cycle of the outer loop and m:the simulation cycle of the inner loop, and $P_{n,m}(VF)$ is the probability of vessel failure in n:th simulation cycle of the outer loop and m:the simulation cycle of the inner loop. Based on $P_n(LF|VF)$ values, the cumulative distribution of the conditional probability of large melt flow was created. It is presented in Figure 16. The conditional probability does not correlate much with other parameters. Therefore, the conditional probability of large melt flow was simply approximated with even distribution between 0.5 and 0.9 in the new model version.
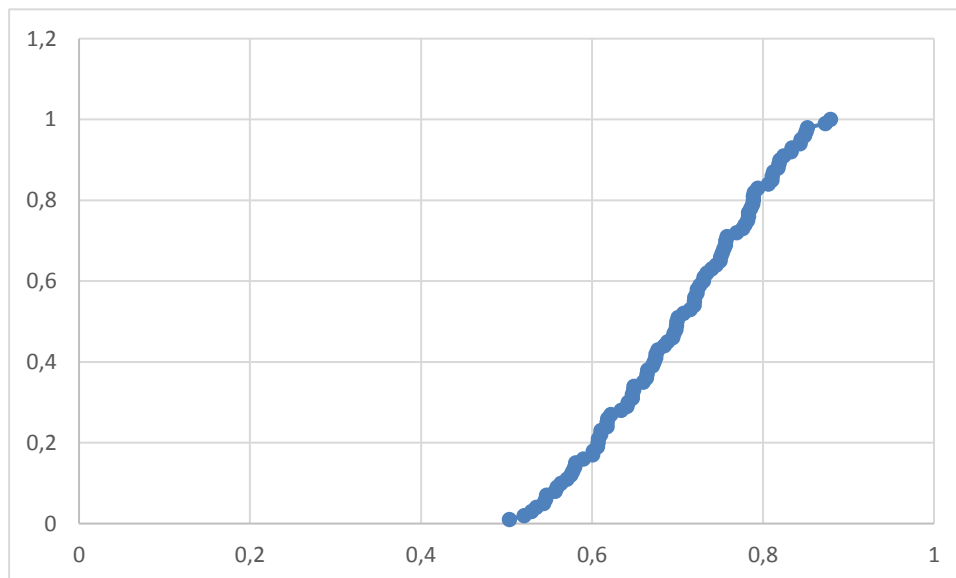

Figure 16: Cumulative distribution of the conditional probability of large melt flow.

It was found out that the probability of dripping melt flow is quite small (the mean value smaller than 0.02, maximum smaller than 0.04). Therefore, to simplify analysis, it was conservatively assumed that the probability of medium melt flow is the complement of the probability of large melt flow, and the probability of dripping flow is 0 in the alternative model.

With regard to the LDW flooding, the model was simplified a bit. The results indicated that the probability of a shallow pool in the LDW (flooding between 20% and 70%) is very small (less than 0.01), because the flooding rarely occurs so close to the vessel failure time. Therefore, the flooding was divided only to the two cases used in the basemat melt-through modelling: flooding fraction larger than 0.5 and smaller than 0.5. A regression model for the probability of small flooding fraction was developed using the mean value and the error factor of the flooding start time distribution as explanatory variables. In the ex-vessel steam explosion computation,

the pool was now conservatively assumed deep if the flooding fraction was over 0.5 (previously 0.7) and shallow if the flooding fraction was smaller than 0.5. As earlier, it was assumed that late containment failure occurs with certainty if the flooding fraction is smaller than 0.5. Therefore, it was considered better to estimate the probability of small flooding fraction slightly conservatively.

With the updates described above, it was possible to perform one-phase uncertainty analysis for the analysed part of the CET using FinPSA. The results are presented in Table 7. The mean frequencies are generally relatively close to the original values, which gives confidence that the model simplifications were successful. It can be noticed that the 2000 simulation cycles performed are not enough for the frequencies to converge to the "accurate" values, which means that the results naturally vary a bit between simulation runs. New frequencies are systematically a bit larger because of such variation, but the model simplifications have also increased the frequencies of some sequences.

Table 7: Uncertainty analysis results for sequences 4-11.

Sequence	Release category	Original frequency	New mean frequency	5th percentile	Median	95th percentile
4	OK	7.40E-10	7.60E-10	3.38E-12	1.31E-10	3.34E-9
5	FV	1.26E-9	1.35E-9	7.80E-12	2.43E-10	5.80E-9
6	OK	1.92E-11	2.78E-11	7.61E-14	4.00E-12	9.75E-11
7	FV	3.10E-11	4.92E-11	1.63E-13	7.79E-12	1.83E-10
8	LF	1.09E-10	1.73E-10	7.10E-13	2.85E-11	6.53E-10
9	EF	1.13E-10	1.93E-10	6.31E-13	3.20E-11	8.26E-10
10	VEF	3.93E-10	4.29E-10	1.78E-12	6.75E-11	1.81E-9
11	VEF	4.29E-11	9.23E-11	3.17E-13	1.31E-11	3.58E-10

5.12 Discussion

Even though the new high pressure melting model is mostly based on fictitious data, it is an attempt for more realistic modelling by explicit consideration of timings of events and their impacts. The main purpose has been to study and demonstrate dynamic modelling rather than to make conclusions about the safety of a real nuclear power plant. Because of that, liberties have been taken to make some strong assumptions in the model not backed up by real data, physical equations or deterministic analyses.

The model could be developed further by performing deterministic analyses varying different timings, such as depressurisation time, core cooling recovery time and LDW flooding time. Particularly, it would be interesting to develop the core meltdown model utilising deterministic analyses, because that part has been overly simplified in the previous models, and the current model is just a sketch based on the assumption that the melting behaves nearly linearly until the recovery of core cooling.

In the model, epistemic and aleatoric uncertainties were separated. Epistemic uncertainties were mainly represented as uncertainties related to parameters of probability distributions, which in turn represented aleatoric uncertainties. The separation was made very roughly

without any in-depth analysis. It is one area that could be studied in the future. Uncertainties related to distribution types were not modelled. The lognormal distribution that was used in many cases might not be the best option to model e.g. timings of events, but for this study it was considered sufficient. The DPD distribution type of FinPSA (a user-given discretized distribution specified by 13 percentile values) [31] is used often in practical modelling, but the modelling of epistemic uncertainties would be even more challenging, because the DPD distribution contains so many parameters. It could be worthwhile to implement some other distributions, such as Weibull distribution, for timing modelling in FinPSA level 2.

A limited two-phase uncertainty analysis was performed in Excel, and an alternative version of the model was created to enable the use of one-phase uncertainty analysis for some accident sequences. This type of procedure could be practical if a full two-phase uncertainty analysis is considered too heavy:

1. Create a dynamic and more realistic model with explicit modelling of timings (scope can be limited rather than cover all aspects of severe accidents).

2. Perform two-phase uncertainty analysis.

3. Create a simplified full scope model to enable one-phase uncertainty analysis.

4. Perform full analyses with the simplified model.

In the creation of the simplified model, correlation and regression analyses are useful. They would likely require collecting several variable values that would normally not be collected, such as different probability parameters, parameters of ECCS recovery time distribution and parameters of flooding start time distribution in this study.

6. Conclusions

This report has studied dynamic containment event tree modelling particularly focusing on the modelling of timings of events and uncertainty analysis. Dynamic CETs provide a good opportunity to analyze the effects of different timings and timing combinations. PRA modelling is more realistic when timings are explicitly included in the model and affect accident sequences in the model.

A drawback of the explicit modelling of the effects of timings is that normal one-phase uncertainty analysis cannot be used to produce proper uncertainty distributions for release frequencies, because the timings involve aleatoric uncertainties. A two-phase uncertainty analysis procedure has been proposed and demonstrated in a limited case study to treat epistemic and aleatoric uncertainties separately. The two-phase uncertainty analysis would improve level 2 analysis, but on the other hand, it is computationally very demanding. It might not be practical to apply it to full scope level 2 PRA. Instead, it could be used to perform some supporting analyses to produce inputs for full scope model. It has been suggested that first limited model version could be made by applying dynamic modelling, and a simplified full scope model could be developed based on the results of two-phase uncertainty analysis. It is recognized that the possibility to perform two-phase uncertainty analysis would be an asset for FinPSA level 2. Note that normal one-phase uncertainty analysis is a special case of the two-phase uncertainty analysis in which only one simulation cycle is performed in the inner loop.

An example BWR model has been developed further by improving the modelling of timings of events and core meltdown modelling, along with some other changes. The study was limited only to the high pressure melting case. Similar updates could also be made to other CETs. The low pressure cases would be simpler because depressurization and the high pressure cooling system do not need to be considered. Even more importantly, a set of deterministic analyses could be carried out to provide input data to make the model more realistic. Core

meltdown fraction would particularly be an interesting variable to study in different scenarios, because its modelling has been very simplified in previous level 2 models. Another direction that could be taken in the modelling would be to implement more physical modelling, e.g. thermo-hydraulic equations, in the CETL scripts as was done in [27].

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