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Model Uncertainty Analysis in Operational Risk Analysis

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Norwegian University of Science and Technology
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MASTER THESIS

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Preface

This specialization report is written in culmination of the International Master Program in Reliability, Availability, Maintainability and Safety (MSc. RAMS) within the Production and Quality Engineering Department (IPK) at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. This work has been performed during the Spring of 2016. This report is based on background of the Modelling Instantaneous Risk for Major Accident Prevention (MIRMAP) project, financed by the Norwegian Research Council. And Model Uncertainty Analysis is the central topic of this report. It starts with a overview about uncertainty, then a systematic modelling process is described which is used as a start point of model uncertainty analysis is described. Methods for model uncertainty analysis from relevant fields is reviewed, a method for model uncertainty sources identification is proposed and applied in MIRMAP model.

The intended reader for this report should have good knowledge in uncertainty. Some knowledge with operational risk analysis in oil and gasoline industry, practical experience with modelling would also be helpful in understanding the report.

The topic of this thesis is based on the practical demand in MIRMAP project.

Trondheim, 2016-06-09

Tiantian Zhu

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T.Z.

Summary and Conclusions

A model is a simplified representation of the real world. Model uncertainty is a common issue in predictive models, and discussions on this can be found in many subjects. Model uncertainty is a branch of uncertainty analysis and is widely discussed, but in reality uncertainty analysis mainly focuses parameter uncertainty.

An overview of uncertainty is established by reviewing different definitions of uncertainty in various applications, three dimensions, classifications, representations of uncertainty and relations between uncertainty and risk for decision making. There are different understandings and definitions regarding uncertainty and model uncertainty in varied fields. Own definitions of these terms must be clearly stated and be meaningful for the problem at hand. Definitions about uncertainty and model uncertainty, which apply in this thesis, are given to avoid ambiguity and limit topic range.

"Model Uncertainty" is sometimes used about "Model Output Uncertainty" which in some published works are an integrated result from all kinds of uncertainty. Conceptual uncertainty, model error, model structure uncertainty, modelling uncertainty are used in some papers. Being cautious is necessary when dealing with these terms. An uniformation of these terms can better scientific communication and the application of outcomes.

A general and systematic modelling process is described to see how model uncertainty can be analyzed using a systematic model development process as a starting point. Proposed probabilistic models, relevant modelling techniques, and a modelling process for operational risk analysis are described. This part contributes to form the main concept of analysing model uncertainty in this thesis.

Methods to deal with model uncertainty are identified and described by reviewing relevant application fields, including probabilistic risk analysis used in the Nuclear Power Sector, Environmental modelling, and Computational Modelling and Simulation. There are different characterization methods for model uncertainty. Methods about model uncertainty resources identification, characterization and analytical treatment, and model uncertainty reduction are simply summarised.

These methods for model uncertainty treatment can be concluded to three groups. "Input-

Driven", "Output-Driven", and Hybrid. "Input-driven" methods provide a better understanding of the impact of identified model uncertainty sources. They are mainly qualitative methods. "Output-driven" methods provide a "closer" result to "truth" of the model outputs.

Besides, a method for systematic model uncertainty sources identification is proposed. This method is based on the systematic modelling process described in the previous chapter. A fish bone diagram showing model uncertainty sources, which might occur at each modelling step, is presented.

Proposed method for model uncertainty identification is applied to identify model uncertainty sources in MIRMAP model. Further applications of the identification information are also described. Proposed method for model uncertainty sources identification is a systematic, easy and applicable method and it is verified by its application in MIRMAP model. It is very suitable for big and hierarchical models, and it do opens for further improvement to be made.

Identified model uncertainty sources in MIRMAP model are mainly in following groups: Limitation and scope of analysis, ignored dependence, ignored sub-barrier system or components, surrogate values are used as model inputs (e.g industrial average values are used for plant specific values), simplification of system and assumption in model structure from event tree to BBN, descritization and approximation in numerical solution. Different model uncertainty sources have varied-degree impact on the model outputs. Characterization methods for these model uncertainty sources should vary according to the importance, location and cause of these model uncertainty sources.

Contents

Chapter 1

Introduction

A model is an imperfect representation of the real world or a system using idealizations tailored to its objective. Model uncertainty is a common issue in predictive models, which reduce our confidence of the model outputs (e.g. quantities of interest). This is especially the case where the outputs are used as inputs for decision support. For quantiative models the model output uncertainty comes usually from two resources; parameters (data) and model. Parameter uncertainty have been exhaustive studied, while model uncertainty still lacks investigation and understanding, although mountains of papers and reports from different subjects can be found describing the latter as well. The Modelling Instantaneous Risk for Major Accident Prevention (MIRMAP) project is to model instantaneous risk of major accident, which is relative to average long term risk. A probablistic model is proposed in this project, which model description can be found at Chapter 5.1. The purpose of this risk model is to provide input information for operational decisions to control risk. Model uncertainty should be studied, reduced as possible, and also clearly presented, thereby providing solid information for robust decision making.

1.1 Background

The current work is part of the Modelling Instantaneous Risk for Major Accident Prevention (MIRMAP) project, which is a joint research project between Safetec, the Norwegian University of Science and Technology and the Industry. The simplified relation between this master theis and MIRMAP project is shown in Figure 1.1. Currently, a probabilistic risk model of a "Major

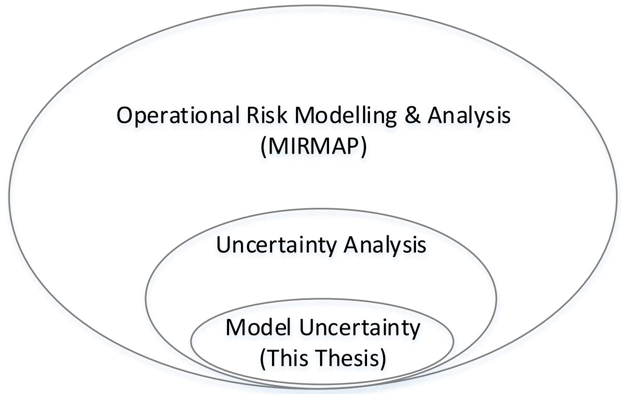

Figure 1.1: The relation between this Master Thesis topic and MIRMAP

Accident", referring to marjor hazard risk related to fire and explosion, is proposed and developed in the MIRMAP project to predict instantaneous risk involving operational activities. The generic model is a hybrid casual model combining Event tree, Fault tree and Bayesian Belief Network (BBN).

A new, attractive main feature of the MIRMAP generic model is that it involves activities which increase major hazard risk, and these activities are carefully identified and integrated at the model locations (mainly as basic events in the fault tree) where the activity effects become correctly implemented. The outputs from the model can give support to operational decision makers during the operational planning phase (e.g. decisions relating to execution of or interval for testing of process shutdown valve, when experience shows that the testing often causes trips, which may result in leaks).

Uncertainty is a common issue when it comes to prediction and model-based decisions. While Uncertainty from model itself might be the main contribution of uncertainty, as said by Apostolakis (1989) etc. Unavoidably, This is an issue in the proposed model in MIRMAP as well. This thesis is to start the investigation of model uncertainty in MIRMAP model which has a potential critical influence in decision making if it is ignored.

1.1.1 Basic Information about MIRMAP

MIRMAP is a project which intends to provide methods to quantitatively model, present and visualize instantaneous major hazard risk, and furthermore give support to operational decision makers to eliminate or control the risk of major accident in the oil and gasoline industry (MIRMAP, 2013). The overall objective of this project is to explore and define the concept of instantaneous major hazard risk and how this can be analysed in living risk analysis, as a basis for providing better decision support in an operational setting. Developing a method/model for "Operational risk analysis" is the fourth task of this project.

Since the present methods for quantitative risk analysis(QRA) or total risk analysis(TRA) mainly cover technical aspects of the design with a limited coverage of operational and organizational issues. And usually it is conducted every several years. The results from them are kind of average risk over a long period (may be several years). It means that the current QRA/TRA cannot reflect the volatility of risk over short time (instantaneous risk) or provide adequate support for operational decisions of a specific situation. They are more suitable being treated as strategic analysis.

New tools for instantaneous risk, referring to "Operational risk analysis", "Living risk analysis" or "Risk Monitoring", are in high demand and of great necessity for the oil and gas industry. This tool should go to a very detail level for the situation in question and be able to model the interactive and synthetic effect of equipment failure and design, as well as operational and organization issues. Several models for this purpose are described in Chapter 3.2.1. Model uncertainty of these models were not that well discussed or presented. This is perhaps due to the nature of model uncertainty, which is an issue relevant to the maturity of techniques.

A risk model involving risk impact from activities is one way to go. A graphical demonstration of how plant risk fluctuate with activities in time axis is showed by Yang and Haugen (2015). Besides, The quantitative risk framework structured to follow a causal effect relation, while having integrated risk influence factors, has shown to be robust (Øien, 2001a; Aven et al., 2006; Røed et al., 2009; Gran et al., 2012). Specific time-dependent parameter values of these risk influence factors are going to be used in the model instead of average values to produce dynamic risk value. These form the concept of MIRMAP generic Model. And by modelling and predicting instantaneous risk and major hazard risk contribution from these activities, risk is possible to be controlled by managing these activities.

1.2 Problem Formulation

Since the existence of model uncertainty is sure. And it is necessary to be well understood and analysed to give solid information for decision support which relies on the accuracy of model output. Then following questions come: 1) how model uncertainty is formed, 2)how to systematically identify the sources of it, 3) whether there are some analytical treatments of it, 3)how to present or measure (quantify) and interpret it, 4) how to reduce it, 5) how to cope with it to make robust decisions.

Some reasons to set up this topic are listed as following:

1) Risk is about the future; what we are modeling is to predict instantaneous risk, uncertainty is a common discussed problem in risk prediction, we should not ignore this issue;

2) Model-based decision support gets more and more popular. No model is totally right, but some are more useful than others. A model simplifies a complex reality; however, the cost is uncertainty related to the simplification. Uncertainty from the model itself (model uncertainty) should be well studied and analysed to establish confidence in model outputs which will be used to support decision-making;

3) Model uncertainty is not that well studied or treated as parameter uncertainty even though researchers have mentioned it for many years;

4) A good understanding of model uncertainty sources and their impacts on the result helps us refine our model and provides better interpretation of the model outputs also;

5) A good analysis of model uncertainty can benefit both model developers and model users.

1.3 Objectives

The main objective of this Master's project is to study model uncertainty in MIRMAP model, and see how can we reduce it, or how to cope with it in decision making if we cannot reduce it. The main objective can be achieved by achieving following sub-objectives:

1. Establish an overview of the concept of uncertainty, and how it is understood and formulated in different fields of application.

2. Describe how model uncertainty can be analyzed using a systematic model development process as a starting point.

3. Identify and describe methods to deal with model uncertainty from relevant fields of application.

4. Apply the above to identify and analyze model uncertainty in the MIRMAP model to give input for model refining and model users (decision makers). Due to time limitation this is limited to the identification of model uncertainty sources, which is the start of model uncertainty analysis.

1.4 Limitations

There are several limitations in this thesis, they are:

1. Approach related

   Due to time limitation, the proposed method to identify model uncertainty sources is not fully verified, which means that it can be improved.

   The identified model uncertainty sources in MIRMAP is limited by the knowledge of the analyst.

   The identified sources of model uncertainty in MIRMAP is of generic nature, i.e. not for a specific plant or area. As a consequence other model uncertainty sources may come up for a specified plant, or area, due to its distinct properties. Such a part of model uncertainty sources should be examined and characterized before application of model in decision support.

2. Study scope related

   Regarding model uncertainty analysis in MIRMAP model to give input for model refining and model users (decision makers), the contents of model uncertainty analysis include the model uncertainty sources identification, characterization, integration, propagation, impact assessment and representation. These tasks always cannot be finished within one master thesis, there are many technical issues within it. So, in this thesis, the content of model uncertainty analysis is limited to identification of model uncertainty sources.

1.5 Approach

The main approach in this thesis is literature review. For the first objective, a literature reviewing of different application fields where uncertainty is a important issue.

For the second objective, A systematic model development process will be described. then it follows a brief description of probabilistic operational risk modelling summarized from proposed probabilistic operational risk modelling in the literature.

For the third objective, literature reviewing of relevant fields where model uncertainty is well discussed studied and analysed in the practical model. such as probabilistic risk analysis in nuclear sector, environmental modelling, computerized modelling and simulation etc. The big subject of model uncertainty analysis will be divided into sub issues to be easier solved.

As for the last objective, a systematical identification approach will be proposed and used to identify model uncertainty sources in MIRMAP generic model.

1.6 Structure of the Report

The rest of the report is organized as follows:

- Chapter 2 gives an introduction to the concept of uncertainty, including different understanding and interpretation in different fields. Definitions of uncertainty, model uncertainty etc. which are applied in this thesis, are given at the end of this chapter.

- Chapter 3 includes two parts. First part provides a general and systematic modelling process as a preparation to decompose the formation of model uncertainty. The second part is about operational risk modelling including other proposed probabilistic operational risk models, relevant modelling techniques which are used for operational risk modelling and generic operational risk model outcomes.

- Chapter 4 is the literature review of model uncertainty analysis in some sectors where model uncertainty is thoroughly discussed, including probabilistic risk analysis, environmental modelling, computational modelling and simulations etc. A systematic method for model uncertainty sources identification is proposed.

- Chapter 5 is the chapter about model uncertainty in MIRMAP model. First, the MIRMAP generic model is described. Then model uncertainty sources in this model are identified using the proposed method. Further applications of the identification information are described.

- Chapter 6 summarizes and give the conclusion of the work. Discussion and recommendation for future work are also given in this chapter.

There are 3 appdendix to provide necessary additional information for this thesis. They are:

- Appendix A is a list of abbreviations used in this thesis.

- Appendix B is the information of MIRMAP model, including model construction process, Barrier function, Fault trees, defined activity list, basic events list, RIFs information for each activity.

- Appendix C is the detail information about identified model uncertainty sources in MIRMAP model.

Chapter 2

Uncertainty

This chapter mainly introduce different definitions of uncertainty in the context of application domains, three dimensions of uncertianty, taxonomy of uncertainty, representations of uncertainty and relation between uncertainty and risk. The main contents in this chapter is from literature review.

2.1 Different Definitions

Uncertainty has different definitions in different applications and subjects. Here we can have a look at how uncertainty is defined according to the subjects.

In wikipedia, *Uncertainty* is understood as ‘’the situation which involves imperfect and / or unknown information, It applies to predictions of future events, to physical measurements that are already made, or to the unknown. Uncertainty arises in partially observable and/or stochastic environments, as well as due to ignorance and/or indolence”(Wik, 2016).

In metrology and chemical analysis, "Uncertainty" generally means doubt; it refers both to the general concept of uncertainty and to any or all quantitative measures of the concepts when no adjectives for specific measure is used. The following definition is given to uncertainty of measurement:

"A parameter associated with the result of a measurement, that characterises the dispersion of the values that could reasonably be attributed to the measurand".(BIPM et al., 2008; Ellison and Williams, 2012)

The parameter may be a standard deviation, or a given multiple of it, or width of a confidence interval. Generally, *uncertainty of measurement* comprises many components. These components may be evaluated from statistical distributed results of measurement series, and can be characterised by standard deviations or from assumed probability distributions based on experience or other information. Furthermore, the result of the measurement is the best estimate of the measurand value. All components of uncertainty contribute to the dispersion. This includes components arising from systematic effects, such as those associated with corrections and reference standards. The uncertainty of the result of a measurement reflects the lack of exact knowledge of the value of the measurand.

Fish bone method is used for identifying model uncertainty causes systematically by examining measurement equipment and environment, etc.

For a model-based decision situation, Walker et al. (2003) define *"uncertainty as being any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system to provide a conceptual basis for the systematic treatment of uncertainty in model-based decision support activities such as policy analysis, integrated assessment and risk assessment"*.

De Haag and Ale (1999) define uncertainty as a measure of distinction between the model calculation and the actual situation in Quantitative Risk Assessment (QRA), which is used as a tool to determine the risk caused by an activity involving dangerous substances.

NASA give following definition to uncertainty for NASA probabilistic risk and reliability analysis(Dezfuli et al., 2009): "Uncertainty is a state of knowledge, and it is measured by probability and represented by aleatory and epistemic elements".

NASA probabilistic risk and reliability analysis focus more on the parameter uncertainty (numerical value of the parameter) of the given model than model uncertainty (validity of the model), because they think that the risk model used(simplification and approximation) is reasonably complete. Verifying that the model actually satisfy the requirement is problematic and it constitute completeness uncertainty. Bayesian inference are used for parameter uncertainty propagation. WinBUGs which is developed for Monte Carlo simulation is the software used for Bayesian inference. The issue of model uncertainty is usually handled by a sensitivity study(Stamatelatos et al., 2011).

Bedford and Cooke (2001) in the book *Probabilistic Risk Analysis: Foundations and Methods* declare that:

"Uncertainty is a state of mind about a proposition (e.g. existence of characteristics of a state, event, process, or phenomenon) that disappears when the condition of truth for that proposition exists (i.e., observed). A mathematical representation of uncertainty comprises three things:(1) axioms, specifying properties of uncertainty; (2)interpretations, connecting axioms with observables;(3) measurement procedure, describing methods for interpreting axioms."

Probability is one of several ways to express uncertainty. And ambiguity which exists linguistically due to our inability to express a meaningfully declarative sentence should be removed in order to discuss uncertainty properly. This concept of uncertainty is adapted by Modarres (2006) in his book Risk Analysis in Engineering: Techniques, Tools and Trends.

The definition of Uncertainty in Intergovernmental Panel on Climate Change (IPCC) is(Pachauri et al., 2014):

"A state of incomplete knowledge that can result from a lack of information or from disagreement about what is known or even knowable. It may have many types of sources, from imprecision in the data to ambiguously defined concepts or terminology, or uncertain projections of human behaviour. Uncertainty can therefore be represented by quantitative measures (e.g., a probability density function) or by qualitative statements (e.g., reflecting the judgment of a team of experts)."

IPCS (2004) define uncertainty as "Imperfect knowledge concerning the present or future state of an organism, system, or (sub)population under consideration".

It might be difficult to get a consistent definition about uncertainty, which is the similar situation in giving one definition to risk. But we still can find some agreements, uncertainty is about something we don't know and whether we can know it depends on the degree of perfection of our information (a state of mind). It can be understood as a deviation from the future "truth"; however, this is not that helpful in the practical sense, since we may never know the "truth" until it becomes past. Maybe it is not necessary to look for one definition, since practitioners can give theirs own definition to to uncertainty according their applications. And the definition should be is meaningful to solve the problem.

2.2 Three Dimensions of Uncertainty

There are three dimensions of uncertainty that are recommended to differentiate; location, level and nature of uncertainty (Walker et al., 2003).

1) Location: where the uncertainty manifests itself within the whole model complex; it is identified by the logic of the model formulation. The locations of uncertainty includes a context, a model (model for structure uncertainty and model for technical uncertainty), inputs, parameters, and a model outcome.

2) Level: where the uncertainty manifests itself along the spectrum between deterministic knowledge and total ignorance; Four terminologies are adopted to distinguish between the different levels of uncertainty: determinism, statistical uncertainty, scenario uncertainty, recognised ignorance, and total ignorance. There is a progressive transition between determinism and total ignorance. Determinism is the extreme and ideal situation that we know everything precisely, it is the opposite of total ignorance which is the deepest level of uncertainty. Statistical uncertainty can be described properly in statistical terms (formulated by statistical expressions, e.g. probability density functions), and it may exist in any location in the model if a deviation from the true value can be defined statistically. *Measurement uncertainty (uncertainty of measurement)* is an obvious example of statistical uncertainty. Scenario uncertainty is the level beyond statistical uncertainty, it means that there is a range of possible outcomes and we cannot formulate the probability of the occurrence of any specific outcome since we still cannot well understand the mechanisms that lead to those outcomes. Recognised ignorance is a further deep level of uncertainty, and associated with the case when we don't know functional relationships or statistical properties or scientific basis for developing scenarios is weak. It is treated as a fundamental uncertainty about the mechanisms and functional relationships. Total ignorance is uncertainty to the extent where we even do not know that we do not know.

3) Nature: whether the uncertainty is due to the imperfection of our knowledge or is due to the inherent variability of the phenomena being described. Epistemic uncertainty is the uncertainty due to the imperfection of our knowledge. It may be related to limited and inaccurate data, measurement error, incomplete knowledge, limited understanding, imperfect models, subjective judgment, ambiguities and so on. Epistemic uncertainty may be reduced by more

research and empirical efforts, but new information can either decrease or increase uncertainty. While variability uncertainty (term ontic, ontological, or aleatory uncertainty might be used in other literatures) is the uncertainty due to inherent variability or randomness introduced by variation associated with external input data, input functions, parameters, and certain model structures. Variability uncertainty sources includes following aspects: inherent randomness of nature, human behaviour, societal variability (social, economic, and cultural dynamics), and technological surprise. It is especially applicable in human and natural systems and concerning social, economic, and technological developments.

2.3 Taxonomy of Uncertainty

Uncertainty can be categorised into different types.

2.3.1 Epistemic Uncertainty vs Aleatory Uncertainty

Both in Nuclear industry and NASA probabilistic risk and reliability analysis, Uncertainty are divided into two types according to causes that Uncertainty mainly stems from. They are aleatory uncertainty and epistemic uncertainty (Parry, 1996; Drouin et al., 2009).

Aleatory Uncertainty: Aleatory uncertainty is a natural variation, it is related to physical variability, inherent, natural randomness of the system or process, and this kind of uncertainty is irreducible. Aleatory uncertainty is also called natural uncertainty and variability. The PRA model is an explicit model of the random processes which means that it is a model of aleatory uncertainty.

Epistemic Uncertainty: Epistemic uncertainty relate to the degree of belief in the model (State of mind), and it arises due to lack of knowledge about the system or process being modelled. This kind of uncertainty can be reduced if knowledge or information increases by using, for example, a combination of calibration, inference from experimental observations and improvement of the physical models. In the PRA model, Then it means ‘’ How well the PRA model reflects the design and operation of the plant, how well it predicts the response of the plant to postulated accidents”.

Epistemic Uncertainty is categorised into three types according to the uncertainty sources:

Completeness Uncertainty, Model Uncertainty and Parameter Uncertainty (Drouin et al., 2009; Jin et al., 2012).

2.3.2 Parameter Uncertainty vs Model Uncertainty

Parameter Uncertainty: Parameter Uncertainty is the uncertainty related to model parameter values. Monte Carlo simulation, Bayesian network etc. are the methods to propagate the uncertainty from parameters to output values. For empirical quantities, uncertainty sources of these quantities include statistical variation, subjective judgement, linguistic imprecision, variability, inherent randomness, disagreement, approximation (Morgan et al., 1992).

Model Uncertainty: Model Uncertainty arises from the fact that any model, conceptual or mathematical, is a simplified reality of system or process. Model uncertainty can be evaluated by comparing different models. Choosing a better model can reduce the model uncertainty even though sometimes it is difficult to judge which model it better because of variations in judgment criteria.

Completeness Uncertainty: Completeness uncertainty is about factors that are not properly included in the analysis. And it can be distinguished between 1) Known completeness uncertainty due to factors that are known but ignored and not included by purpose, the causes include simplifications and assumptions and 2) Unknown completeness uncertainty due to factors that are still not identified or without any information.

Model uncertainty overlaps with known completeness uncertainty such as uncertainty from simplifications and assumptions etc. In this thesis, completeness uncertainty is considered as part of model uncertainty.

2.3.3 Reducible Uncertainty vs Irreducible Uncertainty

For practical purpose, uncertainty can also be distinguished according to reducibility. Usually, aleatory uncertainty are considered as unreducible, while epistemic uncertainty are reducible by increasing knowledge. A detailed explicitness of these two types of uncertainty is identified in practical applications by de Rocquigny et al. (2008, chapter 14, page 202).

Nevertheless, pointed out by de Rocquigny et al., reducible uncertainty is not equal to the epistemic nature of the uncertainty. Reducibility also involves some industrial or practical constraints, or even a cost-benifit perspective.

2.3.4 Type A vs Type B Uncertainty in Metrology

In meteorology, there are two types of uncertainty evaluation named type A and type B, and the uncertainty obtained from these two evaluation approaches are called type A or type B uncertainty. Both of them are based on probability distributions.

Type A uncertainty is the uncertainty calculated from series of repeated observations and is the familiar statistically estimated variance using available knowledge (a pool of comparatively reliable information).

Type B uncertainty is obtained from subjective probability or an assumed probability density function from a certain degree of belief that an event will occur.

2.4 Representations of Uncertainty

There are different approaches to represent uncertainty in context of diffrent application domains, including classical set theory, probability theory, fuzzy set theory, fuzzy measure theory, and rough set theory (Isukapalli, 1999). In risk modelling, probabilistic approach, interval representation, probability bounds approach, fuzzy respresentation are ways used to represent uncertainty regarding variables(Marcus, 2002).

In risk analysis, probability distribution is used the most to represent uncertainty regarding a quantity. If uncertainty is represented by probability, then usually, percentage of error or variablity (e.g. coefficient of variation), expected value and variance, confidence interval, quantiles, probability of exceedance, ranges or simply the maximal value are can be used to measure uncertainty (Modarres, 2006; de Rocquigny et al., 2008). If uncertainty of a quantity is represented by interval but no further information to obtain a distribution, then the distance between upper bound and lower bound may be used as measure of uncertainty.

But also pointed out by Apostolakis (1989), it may not be enough to measure uncertainty by the sole use of probabilities. The potential usage of two dimensions representation of uncertainty might be worth to explore, e.g. probability and necessity.

In some practical applications, uncertainty is described by semi-quantitative description or qualitative statement, which can be seen as a thought of "level of confidence". Examples include uncertainty representation in climate change study (Pachauri et al., 2014), and Danish guidelines for quantitative risk analysis (COWI, 1996).

2.5 Relation between Uncertainty, Risk, and Decision-making

The definitions of uncertainty and risk, and their association, have been extensively argued and discussed. How we define and treat them is an important issue in decision-making. Samson et al. (2009) had a review of different perspectives on uncertainty and risk, where the review goes back to 1901 and covers 34 bibliographical sources in several different fields including operational research, economics and finance, and engineering. Different groups of opinion regarding the relationships between risk and uncertainty identified from literature study are summarised in a diagram by the authors, shown here by Figure 2.1.

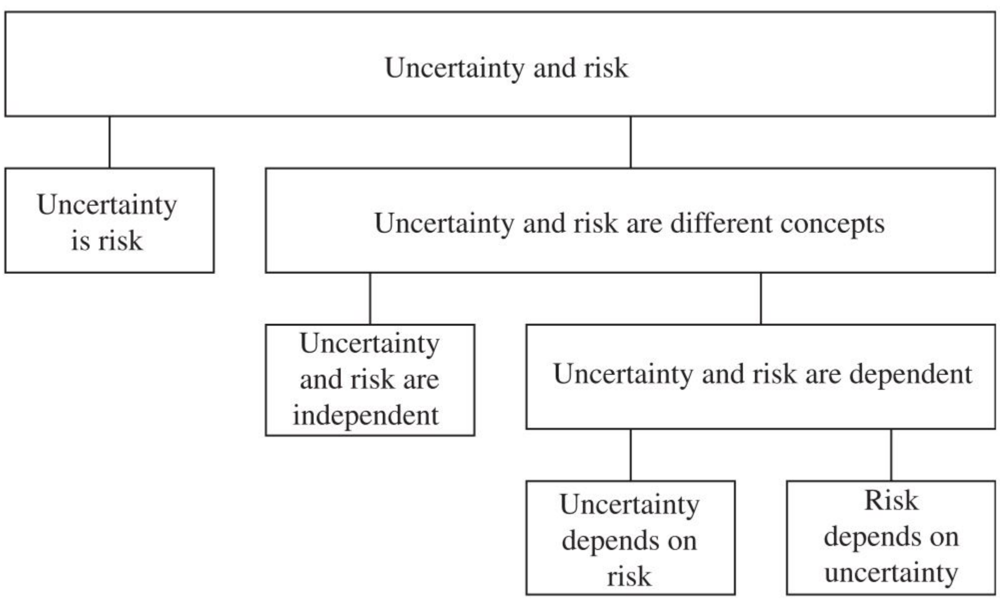

Figure 2.1: Relation between uncertianty and risk from Samson et al. (2009)

There are basically two main groups of opinions regarding the relation between uncertainty and risk: 1. uncertainty is risk, 2. uncertainty and risk are different concepts.

1. "Uncertainty is risk" is supported by the following understanding:

In principle, risk is the uncertainty of a loss or the occurrence uncertainty of an unfavorable contingency, or the uncertainty of outcomes. The degree of risk is measured by the probable variation of actual experience from expected experience, or by the worst expected loss over a given horizon under normal market conditions at a given confidence level (value at risk). The assumption of these definitions is that uncertainty is quantifiable or follows a distribution to be specifically. Therefore, it is argued that these definitions are not proper when uncertainty is not quantifiable (do not follow any specific distribution) and defined by an interval with lower bound and upper bound in some decision problems.

2. "Uncertainty and risk are different concepts" group contains different relations between uncertainty and risk. They include three sub groups: "uncertainty and risk are independent", "uncertainty depends on risk", and "risk depends on uncertainty".

"Uncertainty and risk are independent" is supported by following pairs of definitions about uncertainty and risk:

There is a classification of certainty-risk-uncertainty made by Luce and Raiffa (2012, Chapter 2) explained by a case that "a choice has to be made (decision-making) between two actions under

(a) Certainty if each action is known to lead invariably to a specific outcome (the words prospect, stimulus, alternative, etc., are also used).

(b) Risk if each action leads to one of a set of possible specific outcomes, each outcome occurring with a known probability.

(c) Uncertainty if either action or both has its consequence a set of possible specific outcomes, but where the probabilities of these outcomes are completely unknown or are not even meaningful."

Knight (2012) differentiates risk and uncertainty basically by concluding that risk is quantifiable and uncertainty is non-quantifiable.

Pfeffer (1956) gives a other pair of definitions to uncertainty and risk: " Risk is a state of world and is measured by objective probability; Uncertainty is a state of mind which is a subjective degree of belief. They are counterparts of each other."

"Uncertainty depends on risk" is only supported by the conclusion " the concepts of risk is an objective phenomenon, and uncertainty is a state of mind, but risk often gives rise to uncertainty" from Crowe and Horn (1967).

"Risk depends on uncertainty" is supported by many suggested definitions from scholars and application cases within the reviewed scope. Uncertainty gives rise to risk and is vital for decision-making.

Based on "Risk depends on uncertainty", Samson et al. (2009) proposed a conceptual 2-step modelling approach for uncertainty and risk for decision-making. In this approach, uncertainty is the independent variable and risk is the dependent variable. Uncertainty is the non-quantifiable randomness represented by a interval with lower bound and upper bound from observations. "Non-quantifiable" simply means that there is not enough information to assume any distribution for uncertainty. Risk is modelled as the quantifiable randomness represented by the distributions of a random function's values at each point of the uncertainty.

For decision makers, they need to choose a preferred option from the small set of all efficient options bases on their knowledge, experience and preferences. In this case, they have freedom to arrive at a decision influenced by their knowledge and experience.

In the NASA Continuous Risk Management (CRM) concept in project (Stamatelatos et al., 2011, Chapter 2), risk depends on the uncertainty and risk tolerance level (blue area), see Figure 2.2. Reducing the uncertainty is an way to reduce risk. As the program/project evolves over time, design and procedural changes are implemented in an attempt to mitigate risk, therefore, as risk concerns are lowered or retired and the state of knowledge about the performance measures improves, uncertainty should decrease, with an attendant lowering residual risk.

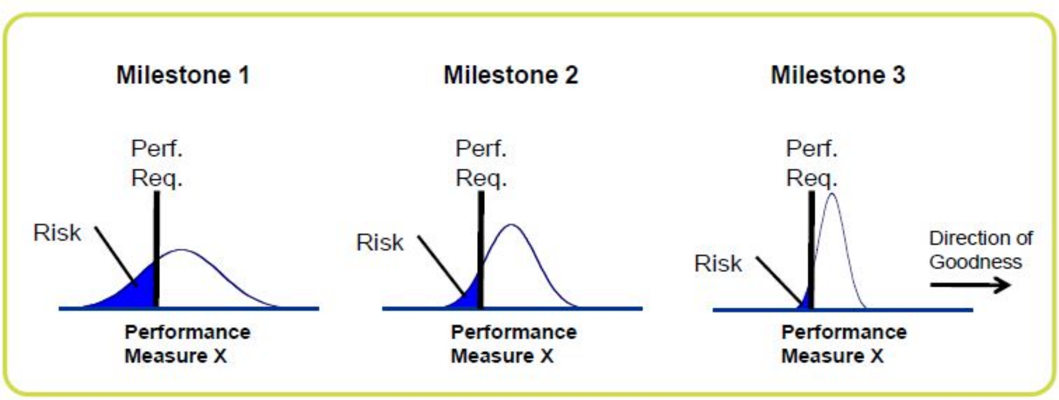

Figure 2.2: Decreasing Uncertainty and Risk over Time from Stamatelatos et al. (2011)

For decision makers, when comparing the assessed risk with requirement to support decision support, it is not enough if only comparing the mean value, the uncertainty should be included as well. This is also addressed in Probabilistic Risk Assessment (PRA) in nuclear sector (Wheeler, 2010).

2.6 Definitions Applied in Thesis

As can be seen in Section 2.1 and 2.5, there are different definitions on uncertainty in different application fields, and different understanding towards the uncertainty and risk with the relation between them. It is necessary to clarify here that in this report, uncertainty analysis is part of the risk analysis, and it is a sub activity among risk modelling.

☞ **Quantity of interest**: Quantity of interest is the quantity that we are intended to measure by real data measurement or by modelling. It can be a vector, a value or a distribution.

☞ **Uncertainty**: uncertainty, in this context, is the "state-of-art" variation of the quantity of interest, stemming from both aleatory and epistemic property. The "state-of-art" variation of the quantity of interest represent the "state-of-art" knowledge about the quantity of interest, it can be obtained from the most advanced model with the least restrictions from its assumptions and so on, or can obtained from observations.

The reason to have "state-of-art" variation is that the "true" value is impossible to obtain since we do not have a "true" model of nature or the observed fact which occurs in the future. However, a "state-of-art" model, or historical system response data, is possible to obtain which makes this definition practical.

☞ **Model Uncertainty**: the uncertainty of the model output stem from the model itself instead of due to the uncertainty of model parameters or in the data. One possible measure of model uncertainty is the distance to "state-of-art" model independent of the uncertainty from parameters.

Completeness uncertainty is included in this definition of model uncertainty. Similar terms including structural model uncertainty, model form uncertainty, conceptual model uncertainty and modeling uncertainty are also used by some researchers.

☞ **Model Uncertainty Analysis**: model uncertainty analysis is the whole process of treating model uncertainty that is defined above for this thesis. It includes model uncertainty sources identification, characterization, integration, propagation, impact assessment and representation.

Chapter 3

Generic Modelling Process

Since model uncertainty mainly forms during the modelling process or analysis process phase, instead of the model application phase, a description of the model process can help us understand model uncertainty better. Such a description can also further help us to identify model uncertainty sources, integrate them, and analyze model uncertainty in a systematic way. This chapter introduce the systematic modelling process in general as a start, and then describe the operational risk modelling. Most of the content is from a literature review.

Similar ideas of analyzing model uncertainty from the model development process can be seen from De Haag and Ale (1999); Isukapalli (1999); Oberkampf et al. (2002); Refsgaard et al. (2006, 2007); Roy and Oberkampf (2011); Stamatelatos et al. (2011); Riley et al. (2011) etc. Nevertheless, how wrong the model results becomes or how far the model results deviate away from truth (or potential truth) is depended on the data, the model itself, and the application of the model.

For most quantitative risk analysis, also the case in MIRMAP, a risk model would be built according to the characteristics and philosophy of the system under analyzing. Such a risk model is usually of mathematical nature, having built-in risk concepts. Computer algorithm may provide numerical simulation and solution to the model. The outputs or results (risk measure or quantity of interest) of the risk model are used to support decision-making. This model-based and risk-informed decision-making procedure can be simplified as Figure 3.1.

For large-scale or complex systems, multiple models, which might be mathematical or conceptual, are likely needed. Each of them may represent a specific aspect of the system, and

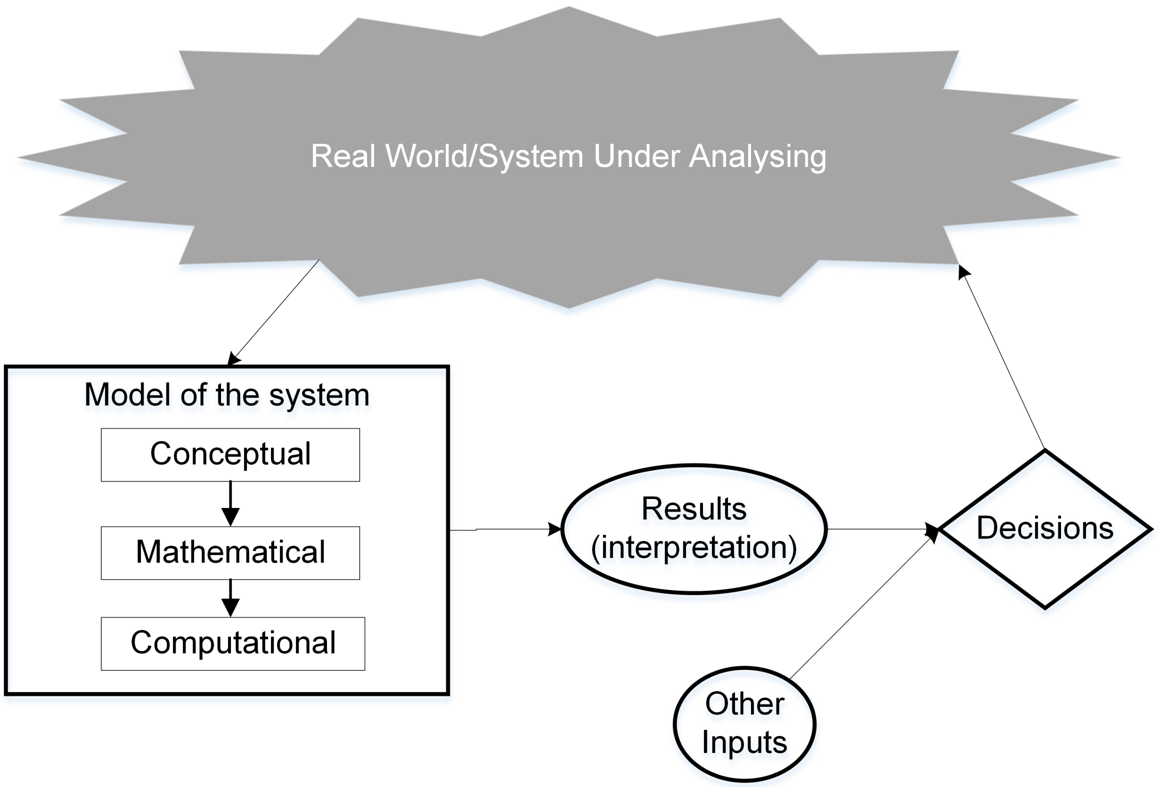

Figure 3.1: model-based and risk-informed decision-making

connected these models become integrated to display an effective representation of the system(Haimes, 2012).

For extreme events, generic term "expected risk" or "average risk" is not that suitable. Instead modelling expected catastrophic or unacceptable risk becomes more valuable(Haimes, 2008b, Chapter 8: Risk of Extreme Events and the Fallacy of Expected Value). This kind of event usually has a very low probability in long term which leads to ignorance sometimes.

We also need to bear in mind that we should take a pragmatic view of models in practical terms. Therefore, whether a model is acceptable should be guided by "usefulness for the given problem" instead of "truth" (Ljung, 1999).

3.1 A Systematic Modelling Process

By adapting "Systems thinking", we seek approaches which are more holistic than the scientific (and other) methodologies that concentrate attention on a relatively narrow set of predefined variables. Although aspired to holism, we also admit that it is impossible for human thought to be all encompassing, which refer to the meta-uncertainty of the analysis as well.

3.1.1 Real World/System Under Modelling

According to the definition in *Webster's Third New International Disctionary*, a system can be:

"a complex unity formed of many often diverse parts subject to a common plan or serving a common purpose; an aggregation or assemblage of objects joined in regular interaction or interdependence; a set of units combines by nature or art to form an integral, organic, or organizational whole"

A system under modelling is in the present work a predefined system which exist before the modelling process. The system can be industrial, environmental, meteorological, etc. Since the predefined system exist before the modelling process, it is part of the real world with well-specified physical boundaries, inputs, outputs and events or phenomena taking place within it. From the point of system complexity, the system is generally considered a constitute of many subsystems. It is impossible to fully understand the system. This is also the source of epistemic uncertainty. And no model can clearly capture the multiple dimensions and perspectives of the system and many submodels would be built in some cases. This is the reason why defined model uncertainty always exists.

From the point of risk analysis, the system considered generally includes an industrial facility or an environmental asset where undesired consequences may take place.

Before modelling, it is also usually necessary to clarify the boundaries of the system modelling, collected data, phenomena, events, and states of the real world/system.

3.1.2 Model Characteristics

A model is a simplified representation of a real system in terms of its important properties for the intended application, which can be a conceptual, graphical, mathematical, computational. The model should describe or reflect somehow the properties of the real system in the aspect of modelling goal with reduced complexity. Therefore, it is never identical to the real system.

For quantitative risk analysis, the mathematical model will be developed, or at least, used to be able to use data and mathematical and statistical methods to estimate reliability, safety, or risk parameters, based on the system undergoing analysis, to support decision-making. For such models, the following characteristics apply (Rausand and Høyland, 2004; Cameron and Hangos, 2001):

1) The model should be sufficiently simple to be handled by available mathematical and statistical methods.

2) The model should be sufficiently "realistic” such that the deducted results are of practical relevance.

3) The results that we derive from the model are only valid for the model, and are only "correct” to the extent that the model is realistic.

4) Models can be developed in hierarchies, where we can have several models for different tasks or models with varying complexity in terms of their structure and application area.

5) Models cause us to think about our system and force us to consider the key issues.

6) Model are developed at a cost in terms of money and effort. These need to be considered in any application.

7) Models may be difficult or impossible to adequately validate.

For models used for risk analysis of complex engineering system such as transportation and energy system, the following should apply (Modarres, 2006):

1) Consistent with the primary characteristics of the complex engineering systems. These primary characteristics are: evolving, integrated, dynamic.

2) Having provisions for internal and external feedback, allowing for opportunistic and incremental improvement.

3) Uncertainty and ambiguity associated with the characteristics and properties of the various elements and their relationships in complex systems should also be incorporated, even meta-uncertainty or uncertainty to estimate the uncertainty itself.

4) Allowing for representation of system element couplings and integration, and specification and updating of relationships between system elements (connections), while also being able to recognize uncertain, nonlinear, and counter-intuitive relationships.

5) Being able to capture the continuous feedback along time (dynamic characteristic) in the system, and allowing for incorporation and integration of diverse but related subsystems (sub-

structures, subfunctions, and intermediate goals) without imposing constraints to the size. It means that the model would be large as an effect.

6) Exhibiting abilities to capture systems' properties such as self-organization and learning.

From a practical point of view, these criteria from Modarres (2006)are quite difficult to achieve due to cost-benefit considerations, people's perspective of risk, limitation of techniques that are required to build the model, etc. These criteria are better treated as guide for future risk model development.

There are several ways of classify mathematical models. Each model type has its own features and fitness to application areas and solution techniques. Therefore, some model types may be suitable under certain circumstances while being inappropriate and causing problems under other ones. Models can be mechanistic or empirical, stochastic or deterministic, parameter lumped or distributed, linear or nonlinear, continuous or discrete or hybrid. Details about these model types and applications are described in (Caldwell and Ng, 2006; Caldwell and Ram, 2013).

Mechanistic models are also called phenomenological models because they are derived from system phenomena or mechanisms. Empirical models are the result of experiment and observation. Stochastic models apply to the cases which contain elements with natural random variations typically described my probability distributions. In these cases, cause-effect relationships between variables are not that clear, but can be described by probabilities or likelihoods. Deterministic models are the opposite of stochastic model. There are clear cause-effect relationships in the phenomena or system variables.

In addition, there is a trade-off between the parameters(input data availability, quality) and complexity or level to details of the model structure from an uncertainty point of view. It has limited value to establish a very detailed model of the system if we cannot find the required input data. Some studies from other subject fields also expressed the same opinion, for example in life cycle assessment modelling(van Zelm and Huijbregts, 2013), and modelling in water resources planning and management(Loucks et al., 2005). It is better to get an optimal model complexity instead of a very exhaustive, large and detailed model, or even a full model. Besides, a risk analysis of a system will always be based on a wide range of assumptions and boundary conditions. We need to bear in mind that the results are conditionally precise, accurate, and useful.

3.1.3 Model Building Process

A model is an imitation of reality and a mathematical model is a particular form of representation which provide us tractable results and solutions. The overall and simplified framework from understanding the real system to apply results in the real system is represented schematically in figure 3.1. In each joint of framework, specific issues should be raised and carefully treated in order to build the optimal model. A general model schematic is displayed in figure 3.2

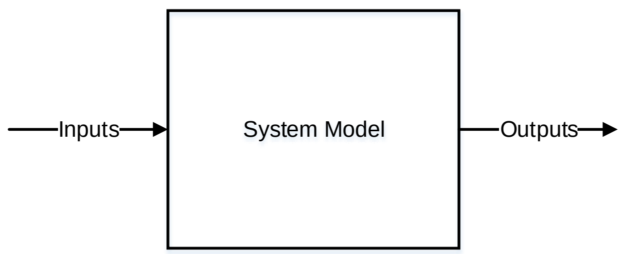

Figure 3.2: General model schematic from Cameron and Hangos (2001)

Systemic Modelling Procedure

The actual procedure of modeling is application dependent, and often it has its root in the tradition and specific techniques of the application area at hand. Here, a systemic seven step modelling procedure described by Cameron and Hangos (2001) is adopted, which is applicable in most mathematical modelling cases, as shown in figure 3.3:

The figure give the description of each modelling step, but we should also bear in mind that model development is never a one pass process in real cases, it requires iteration quite much. In the case of a problem the modellers usually go back to an former step and repeat it.

Step 1. Problem definition

This step should define the specification of the system to be modelled and the modelling goal. Other details relevant to the modelling should also be decided, like, inputs and outputs, hierarchy levels relevant to the model, or hierarchy levels of the models, spatial characteristic

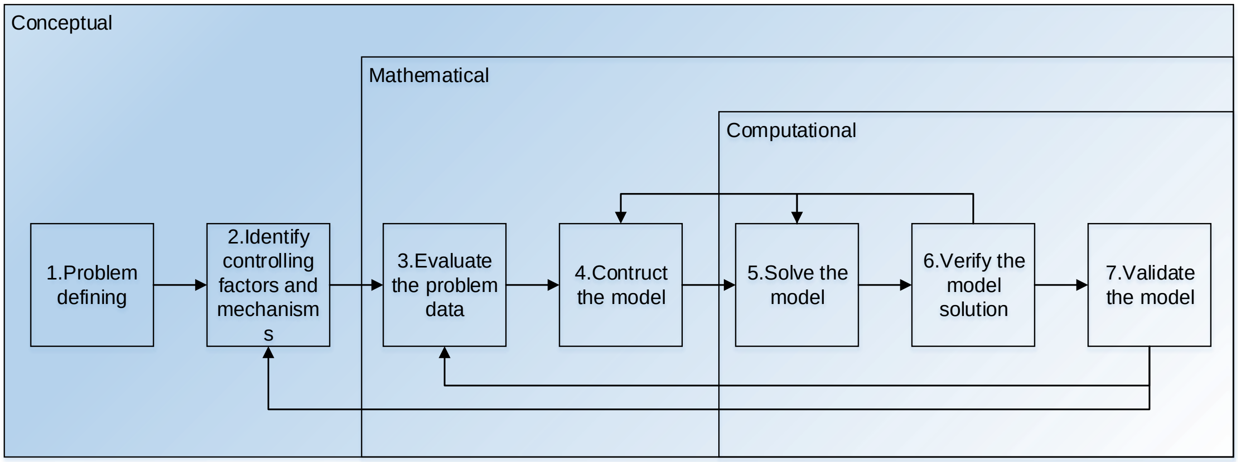

Figure 3.3: 7 steps modelling procedure modified from Cameron and Hangos (2001)

(parameter distributed or lumped), time characteristics (static or dynamic), and validation criteria.

Step 2. Identify the controlling factors or mechanisms

This step is to investigate and understand the phenomena, events, mechanisms, characteristics, and causal-effect relationships within the system, which are relevant to the modelling goal. In this step, we may end up ignoring some system characteristics intentionally or unintentionally because it is impossible to fully understand the system and fully identify essential characteristics, which are carefully treated in the mode, and some non-essential characteristics, which may lead to unnecessary complexity, model order or model size. We may also misunderstand some parts of the system which may lead to incorrect modelling structure. A figure of these characteristics is showed in Figure 3.4

Step 3. Evaluate the data for the problem

In this step, we evaluate the available data, and together with their uncertainty or accuracy. Both directly measured data and estimated parameter values are possibly used in the model. If there is no suitable data available in the literature or measured data to estimate required parameter values, then we need to go back to step 1 and step 2 and reconsider our decisions there.

Step 4. Construct the model

This step is to find out the proper mathematical equations, expressions between inputs and outputs, or internal variables, states if necessary according to the identified and screened con-

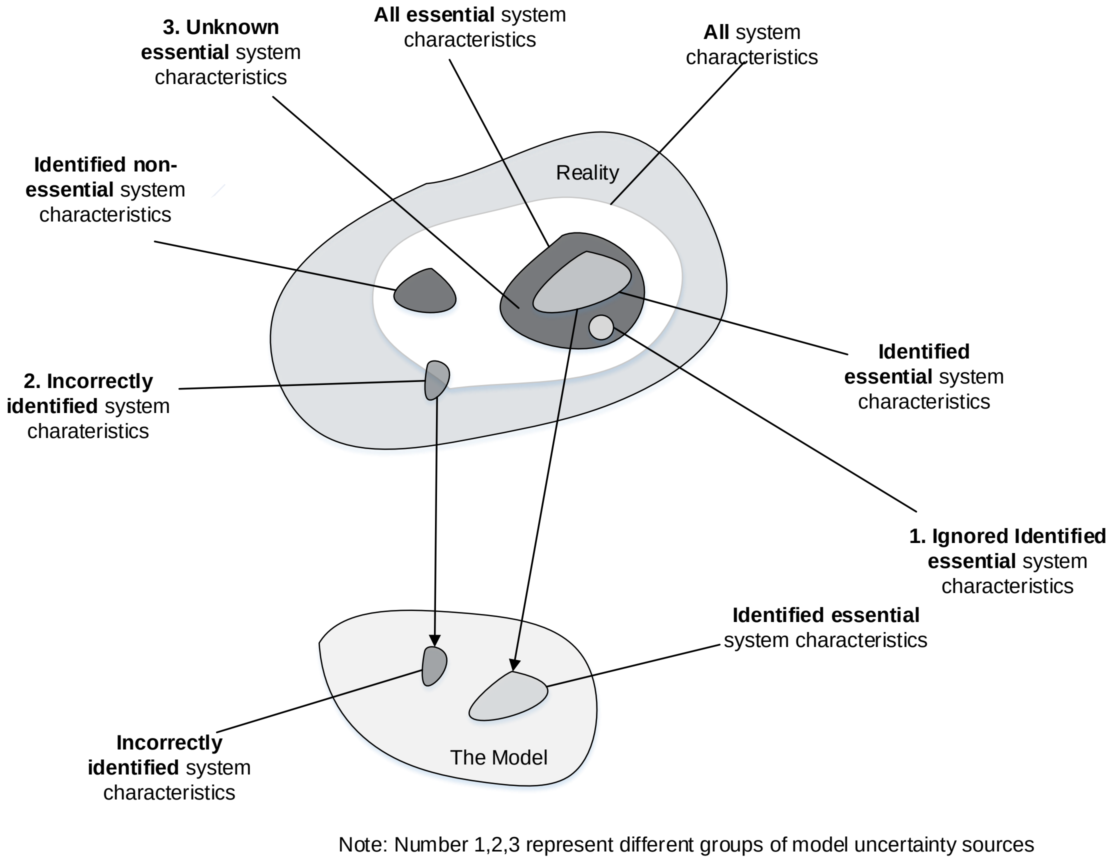

Figure 3.4: Characteristics of system and model modified from Cameron and Hangos (2001)

trolling factors or mechanisms of the system. Sub-steps may be required to be carried out sequentially. These sub-steps includes defining system and subsystem boundaries, defining characterizing variables, stabilizing equations, algorithms, etc., and specifying relations, controls constraints and modelling assumptions. These assumptions may apply to a specific part or position of the system in order to characterize variables, establish equations, classify system events and states, and specify relations and so on. And assumptions are usually built up incrementally during the whole model construction process. A good modelling behavior is to identify and locate assumptions in the model for modelling validation convenience.

Step 5. Find and implement a solution procedure

This step is to find or implement a solution procedure to make sure that the model is mathematical tractable to get the intended results. Lack of solution techniques may lead to additional simplifying assumptions in order to obtain a solvable or easier model. It may also prevent modellers using a particular type of modelling techniques or methods.

Step 6. Verify the model solution

After having a solution, it is necessary to verify or check whether the model behaves correctly. This includes carefully checking whether we get intended results, whether there are mistakes or errors in the computational code, and whether the model is implemented correctly. For large-scale models, it is important to have structured programming using "top-down" algorithm design, and to use modular code which can be tested thoroughly.

Step 7. Validate the model

After setting up the model, it is important to validate it. This step is to check the model against reality or quality of the resultant model which is different from the former step. This step might become quite difficult because it requires a deep understanding of the system, modelling and data acquisition etc. And it is almost impossible to validate risk models. In some practical cases only a partial validation might be possible to carry out. The results of model validation usually point out the inadequate areas in the model development, and how to improve the model. A sound and holistic validation can reduce model uncertainty.

Following are some ways to validate a model, but one is not necessarily limited to them. They are: verifying assumptions and simplifications, comparing the model behavior with the system behavior, developing analytical models for simplified cases and comparing the behaviour, comparing other models using a common problem, comparing the model outputs and intermediate outputs with observations.

3.1.4 Model Elements

A model is an integral of a lot of information, and is presented by a model structure with key elements or ingredients. These model elements includes variables, assumptions and simplifications, boundary conditions, mathematical formulas, data sources, and computer code if applicable.

Assumptions and simplifications: assumptions and simplifications may relate to, but are not limited to, time and spatial characteristics, controlling mechanisms or factors, neglected dependencies, required ranges of states, and associated accuracy and so on. It is recommended to assign each assumption with a unique identifier and a referred location of the model. Some assumptions are legitimate sources for degree of belief and how are a matter of choice because of convenience or cost. It worth paying attention to disentangle these assumptions (Devooght, 1998).

Initial and boundary Conditions: Initial conditions should be specified in dynamic models in applicable. Boundary conditions must be specified for the models in spatially distributed or applicable area distributed models.

Mathematical Formulas (Modelling techniques) / form / structure: it includes all kinds of formulas, equations and relations governed by system characteristics relevant to modelling goal. For some issues or problem, a certain kind of modelling techniques or methods would be applied. Then the kind of formulas or equations which might be used for problem solving are already predecided from the modelling techniques or methods. The resultant model formulas, structure still varies from case to case.

Variables: variables which characterize the system include input variables, output variables, internal variables. In hierarchical models, some output variables of one sub-model may become the input variables of the other sub-model.

Data Sources: this element specifies the data sources of model variables and refers to step 3 in the 7 steps modelling procedure.

Computer Code: for some models, computer coding might be required to give the numerical solution. It is also part of the whole model.

3.1.5 Increments of Sub-models and Model Integration

Model development is an iterative job, and model construction of sub-procedures is iterative as well. Model equations and structure are built up incrementally repeating the sub-steps in model construction. When building up sub-models, assumptions applying to the sub-models may be introduced at the same time for modelling convenience. The overall model is an integration of sub-models. This is especially the case for hierarchical models.

Introduced by Cameron and Hangos (2001), there are three types of model hierarchy driven force. A model hierarchy can by driven by level of details, or by characteristic sizes, or characteristic time, see Figure 3.5. For model with hierarchy levels driven by level of details, the number

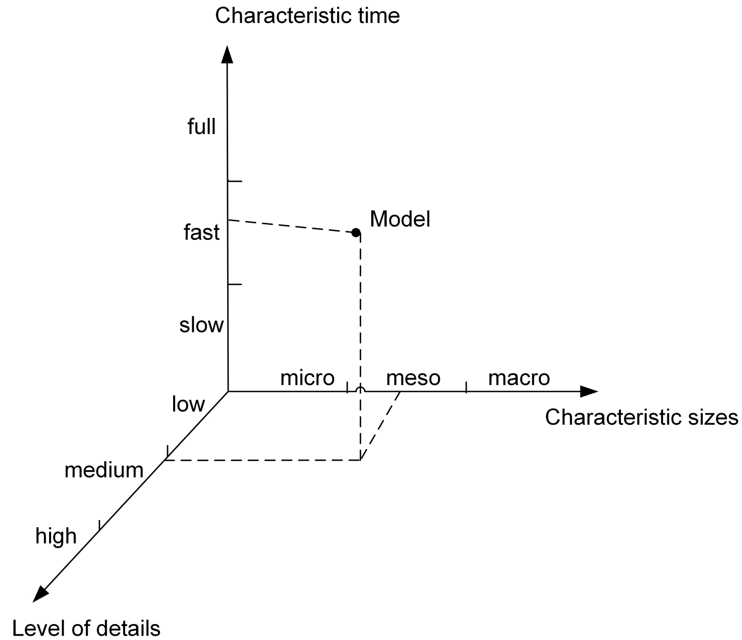

Figure 3.5: Model hierarchy dimensions modified from Cameron and Hangos (2001)

of model levels varies according to the complexity of the system and modelling purpose. If one perform a system analysis in a top-down approach, then the sequence of models in this hierarchy is naturally developed. The more details taken into account, the more levels will be in the model.

For model with hierarchy levels driven by sizes, the more we zoom in on the original macro level model the lower the level of model we obtain. We will arrange the models in this hierarchy if a bottom-up modelling approach is used for the system. It can be understood it from the difference between " top-down" (level of detail) and "bottom-up" (characteristic sizes) approaches. An example of hierarchy driven by level of details is fault tree, we build it from the failure of barrier function and then decompose it's intermediate causes to a certain necessary level of details (to root causes in the end), Example of hierarchy driven by sizes can be seen from, fire area to analysis area until the whole plant in MIRMAP, first we build a model for fire area, then we wider the model for whole analysis area.

For model with hierarchy levels driven by characteristic time, it models the dynamic property of the system in different degree. Full timescale models are detailed dynamic models which describe the dynamic behavior of the whole system. Fast timescale models only describe the fast modeled dynamic response of a system and neglect every phenomenon which is "slow" or have slow time variation or is close to constant. Models describing a steady state of the system can be seen as slow timescale models. "Slow" and "fast" are here relative.

For any hierarchical model, the structure of the model can be built according to the hierarchy of driving-forces, i.e. level of detail, time usage, size etc.

3.2 Proposed Probabilistic Model in Operational Risk Analysis

Operational risk analysis, which is also called living risk analysis, or risk monitor in the nuclear sector, or dynamic risk analysis by some researchers(Paltrinieri et al., 2014), has been an important topic for many researchers and institutes mainly in the nuclear sector, oil and gasoline industry, chemical industry, air traffic (Groth et al., 2010) etc. The main purpose of these studies is trying to control risk by monitoring or predicting risk continuously. The model applied in these analysis should be able to capture the transient changes in risk level. The outputs of the model are used to support operational decision making to control risk. And uncertainty is a common issue in all these predictive models.

3.2.1 Operational Risk Models and Their Uncertainty Expression

There are different models which are proposed or developed for the operational risk analysis, including probabilistic, deterministic(Knegtering and Pasman, 2013) and deterministic-probabilistic models. Even though no comparison is made to say which one is better than the other, what is sure is that each model has its own properties, advantages and disadvantages.

In the nuclear sector, the concept of living risk analysis or risk monitoring began in the 1980s. The method has become very well developed, and has been put into practical usage for a long time. Living PRA or PRA (probabilistic safety analysis) or risk monitoring are modelled by fault tree and event tree by online updating the risk assessment with actual and dynamic plant configuration (including equipment availability), operating regimes, environmental conditions etc. (Johanson and Holmberg, 1994; IAEA, 1999; Coble et al., 2013). An enhanced risk monitor can incorporate equipment condition into a more accurate estimate of the probability of component failure.

Uncertainty in PRA modeling arises from a number of sources, including parameter uncertainty of failure, probability and accident sequences (event and fault trees) developed according to our knowledge about accident.Component failure and event data are gathered to support propagation of parametric uncertainty. Much of the nuclear industry's component failure data uncertainty is expressed as a lognormal (or normal) probability distribution with specified errors factors (EFs) that define the 10th and 90th percentile of the probability distribution. Parameter uncertainty propagation is performed through a sampling strategy (e.g., Monte Carlo sampling) over some number of observations.

In process industry, a hybrid structure of event tree and fault tree is not used to conduct quantitative risk analysis (QRA), which makes monitoring risk by updating QRA impractical. But monitoring and predicting risk levels may be achieved by monitoring major accident indicators (Haugen et al., 2011). A lot of research about risk indicators are conducted by Haugen et al.; Vinnem; Vinnem et al.; Øien. Risk frameworks linking the risk level measure and RIFs(Risk influence factors) or risk indicators, which are measurable representations of the RIFs, were proposed; see ORIM (Øien, 2001b,a), BORA(Aven et al., 2006), HCL method(Røed et al., 2009)and RISK_OMT project(Gran et al., 2012). Continuously updating risk indicators can predict and monitor the risk level. Operational and organizational factors are included.

In these studies, uncertainty analysis haven't been addressed in detail. What is sure is that uncertainty stems from input indicator values (parameter uncertainty) and the risk framework linking risk level and RIFs or risk indicators (model uncertainty). Indicators are usually presented by qualitative or semi-quantitative states. Uncertainty of these indicator states can be described qualitatively or quantitatively. How uncertainty is propagated depends on the model techniques and uncertainty representation methods.

SHIPP methodology(System hazard identification, prediction and prevention) presents the process accident model with predictive and continue monitoring capabilities(Rathnayaka et al., 2011a,b). This model mainly include three parts: Fault tree, Event tree, and an Bayesian updating mechanism. The event tree is built according to a accident sequence and relevant barriers. The prior failure probability of each barrier is calculated from fault tree before observing new information about abnormal events. The basic event probabilities given in point value form in fault tree calculation are from reliability databases, literature and expert judgement. Bayesian updating mechanism is used to update failure probability of each barrier by recalculating likelihood using real plant abnormal events. In this way, the posterior probability of barriers are obtained and used in the Event tree to estimated updated accident occurrence probability in different severity levels. To achieve the predictive capability, Bayesian analysis is used for estimates of probability of the number of abnormal events occurring in the next time interval, given current abnormal event data of the observed plant. This model needs to collect process history and accident precursor information.

Uncertainty about the risk measure is not addressed that much in this model. The only aspect of uncertainty which is mentioned is about using real plant abnormal events information to update failure probability of each safety barriers, which are initially calculated using information from reliability databases, literature and expert judgement. These initially calculated values have high uncertainty or an property of inhabiting inaccuracy.

Safety barometer(Knegtering and Pasman, 2013) is proposed to measure and control the dynamic behavior of process safety. It uses the Bow-tie model by feeding risk factors into both sides of the Bow-tie. The effect of risk factors on the failure probabilities has to be further formulated, where the effect is not necessary to be linear. Risk factors include for instance welding activities, delayed inspections, maintenance not on schedule, and corrosion problems etc. They are classified into long-term, mid-term, short-term by their impacts on the risk level. Bayesian belief network is used to do the inference of factors to obtain the present(predicted) hazard potential, and to update risk figure. This model mainly focus on the achievement of the dynamic risk level measuring function, and describes the conceptual method to achieve it. As for the uncertainty concerned in this thesis will be quite relevant to the practical building of this model.

From the models presented above, we can see that there are some common features between them or some of them.

- To capture the dynamic feature of risk and achieve predictive, monitoring risk level function.
- Involve technical, design, human and organizational factors and dependence between

them.

- Causal-consequence relationship are modelled by different tools. Event tree, fault tree, bow-tie, accident sequence analysis and BBN, or a combination of them etc. are used to construct the risk framework.
- Uncertainty should be expressed.
- These models go to a certain level of detail or complexity in order to catch the dynamic nature of the system.
- "Validity" is one of the challenges these models are faced with.

3.2.2 Main Modelling Techniques

Probabilistic risk modelling, different modelling techniques or combination of several modelling techniques might be applied from case to case (Rausand, 2013). To build the accident model, accident sequence analysis might be applied to understand the phenomena or casual-effect relationship of the accident occurrence. Event Tree, Fault Tree, Influence Diagram (Bayesian Belief Network), Bow-tie Model etc. are methods for calculation of the failure probability or occurrence frequency/ probability. To estimate the failure probability from actually observed data or experiment data, statistic models are required. In order to incorporate risk contribution from activities, human, operational and organizational factors, fault tree, Bayesian belief network, regression-based techniques or weighting techniques etc. are common methods to use. In some cases, physical models about the system features are necessary to be included as well, like fire models and leakage models in nuclear power sector. Some other non-probabilistic techniques including Risk index method and risk matrics(CCPS, 2010; Knegtering and Pasman, 2013) which are applied to measure the safety performance of a plant or a system are excluded. Even though if uncertainty exists in their input variables, the uncertainty can still be propagated to model outcome using sampling method or other analytical treatment.

Here, we are not going to introduce these modelling techniques comprehensively, examples are their features which are relevant to uncertainty will be described briefly instead.

- *Event Tree*

Event tree analysis is a graphical and probabilistic method for modeling and accident scenario analysis. It is a inductive method and it follows a forward logic. In a event tree, the start point is the initial events, and then pivot events are following in sequence. The accident scenarios are developed when end events are reached. Pivot events may be functions or failures of barriers, other states or events. For each pivot event, the probability that the event is "True"(on demand) is a conditional probability given the initial event and the specific event sequence leading up to the pivotal event. If pivot event is analyzed by fault tree, the top event probability is the probability that the split goes to "Failure". Usually, event tree have binary splitted into two branches: "Success" or "Failure". It is also possible to construct event tree with more than two branches.

Pivot events needs to be modelled corresponding to the time and occurrence of events in the accident scenario. Misplace pivot events will result in a wrong tree. In other words, the sequence of pivot events should be foreseen, and each pivot event must be understood conditional on the occurrence of its precursor events. The probability (frequency) of each pivot event must be conditional. Therefore, dependency between different pivot events, pivot event and initial event needs to be carefully handled. In addition, when to stop developing the event tree is a problematic question; for example, an end event can be that a major explosion occurs, or that people get injured which is the following consequence of an explosion affecting exposed people. When to stop an event tree should be decided as part of the objectives or risk concepts and the scope of the risk analysis. Since the binary splitting, defined end events must be mutually exclusive and cannot occur at the same time, the sum of all end events probabilities (frequencies) is 1 (frequency of initial event).

- *Fault Tree*

A fault tree is a top-down logic diagram that displays the interrelationships between a potential critical event in a system and the causes of this event using Boolean logic to combine a series of lower-level events. Fault tree analysis is a deductive method. It starts from a defined top event and reason backward in the casual sequence until a suitable level of details is reached. All events from the top event down to basic events are binary: failure or success, which is the same as in the standard event tree. There are two main kinds of logic gates: "Or-gate" representing parallel relationship and "And-gate" representing serial relationship.

This modelling technique has limitations when it comes to events which cannot exclusively described as binary events or when the relations between events cannot meet a Boolean logical relation (either parallel or serial). Assumptions and simplification may be introduced to construct the fault tree. Some failure causes which are ignored or unidentified result in incompleteness and therefore reduce the accuracy of top event probability. For big fault trees, top event probability may be calculated using approximation. This also leads to uncertainty of top event failure probability.

To fulfill dynamic functionality of some model requirement, the point value of basic event can be updated in a required updating frequency. If uncertainty exists in failure or occurrence probability of basic event, a sampling method (e.g. Monte Carlo simulation) are usually used to propagate the uncertainty from the basic event to the top event. The quality of propagated uncertainty of top event failure probability depends on the number of samples.

3.2.3 Operational Risk Modelling Process

For a probabilistic risk model, before the modelling process, it is necessary to define the risk and risk measures which are among the output variables of the risk model. Jonkman et al. (2003) did a overview of quantitative risk measures of loss of life and economic damage. It provides some good suggestions.

As mentioned in 2.6, in this report, uncertainty analysis is defined as a sub activity of risk modelling. Quantitative or qualitative uncertainty representation is trying to provide confidence about the uncertainty of risk measures from a model, when these are an integrated result from parameter uncertainty and model uncertainty.

The procedure of operational risk model generally follows the systemic modelling process described in Section 3.1, even though there might be some minor deviations.

To model the risk, objectives, governing risk concepts, scope of the analysis, system boundaries, depth or complexity of model (level of details) etc., should be specified. The level of detail with which a model describe a system should be consistent with the modelling objective. Modellers should have a good knowledge about the system under modelling, modelling techniques, relevant and available data. Specific risk measures which are the output should be decided.

To identify system controlling factors and mechanism, important system features, risk contributors and dependence should be exhaustively identified.

To model dynamic feature of operational risk, different time interval for calculating hazard event probability, failure probability or frequency, and therefore also risk measures for different purposes, should be decided. Other timing features should be modelled well.

To express uncertainty regarding risk measure, certain ways to represent uncertainty is necessary. A propagation method of parameter uncertainty should be known and used. Specific methods to analysis uncertainty from model should be discovered and used if available.

3.2.4 Model Outputs and Uncertainty

Usually, the model outputs have more than one quantity. What the model outputs are should be stated in the objectives of the operational risk modelling. There might be some derived quantities too. To decide what the outputs from the model are, the following questions can be asked:

What is the operational risk? What are the operational risk measures?

What kind of decisions are we faced with?

What information is required to support decision making from risk modelling?

One formulation of the overall objective for operational risk analysis from Vinnem and Haugen (2012) is to provide input to relevant decisions relating to planning and execution of maintenance and operational issues in order to control risk. And there are two main situations of decisions: *Planing of long term and short term maintenance and modifications*, *Day to day management of maintenance, inspections and modifications.*

For operational risk modelling, examples of model outputs are:

- Potential loss of life during a certain relative short period of time (e.g. per day) and associated uncertainty of it;

- Probability of accident during a certain relative short period of time and associated uncertainty of it;

- Potential risk increasing from a certain planned activity and associated uncertainty of it;
- Risk increasing in rank among planned activities and associated uncertainty of it.
- etc.

Besides the model outputs listed above, other information including description of the risk model, model scope, limitation, assumptions, model uncertainty sources, potential impact from these model uncertainty sources etc are other kinds of model outputs information which also should be presented as a part of input information for decision-making.

When making the decision, we also need to bear in mind that the decision made is based on the information from the model outputs which also depends on the knowledge, experience. understanding of decision makers. How the model results are interpreted is decision maker dependent. In addition, the right decision at a certain point in time does not necessarily mean the outcomes from decision is good.

Chapter 4

Model Uncertainty Analysis

This chapter mainly review studies related to model uncertainty analysis in some industries, including probabilistic risk analysis in the nuclear, aerospace, and oil and gas sectors, in addition to environmental impact analysis, computerized modelling and simulation etc. Probabilistic risk analysis is the major focus of this review. The main elements in model uncertainty analysis are model uncertainty identification, characterization and treatment of model uncertainty sources, impact assessing, model uncertainty integration and propagation, and model uncertainty reducement etc. The result from uncertainty analysis are used for decision support to make robust decision.

In the end of this chapter, frameworks of model uncertainty analysis, a proposed systematic approach for model uncertainty sources identification, and summary of model uncertainty treatment methods are presented.

4.1 Model Uncertainty in Probabilistic Risk Analysis

As defined by Hanseth and Monteiro (1994), Model is an abstract representation of reality used to simulate a process, understand a situation, predict an outcome or analyse a problem. Then model uncertainty can be called the degree to which a model is an accurate representation of the real world (Modarres, 2006). Uncertainty analysis is the process of determining to which degree a model is an accurate representation of the real world. As pointed out by Modarres (2006), there is meta-uncertainty in the analysis process itself.

It is agreed that all models contain simplification and approximation. Different approaches may exist to present certain aspects of the same process or system but none is clearly more correct than others. Assumptions and simplifications are usually different.

The model difference may due to our knowledge limits in understanding the process or system, or be limited by our knowledge in modelling techniques. The methods to handle model uncertainty and completeness uncertainty are different from parameter uncertainty. They may be not able to be characterized by a probability distribution. In some field, the issue of model uncertainty more or less associated with the validity of the model or approach. A gradually improvement of the approach (increase knowledge and degree of belief) and verification or standardization might be the way to reduce model uncertainty.

Pointed out by Apostolakis (1989), in Probabilistic Safety Analysis (PSA), a major source of uncertainty could be the model itself. Examples include model assumptions, models for common cause failures and human reliability analysis, expert judgement. It also comes from the application of probability theory in PSA itself, since not every event can be precisely defined. Also, in probability theory, probabilities of mutually exclusive and exhaustive events are required to be normalized to 1, while new possible events may be identified, and then the model has to be reconstructed and recalculated in reality. He also pointed that the sole use of probabilities may not be enough to measure uncertainty. The potential usage of two dimensions representation of uncertainty might be worth to explore, e.g. probability and necessity.

Ramana (2011) conclude that the probabilistic risk assessment method applied for nuclear reactors theoretically suffers from several problems:

a. Model completeness. ''Conceptually impossible to be complete in a mathematical sense in the construction of event-trees and fault-trees ... This inherent limitation means that any calculation using this methodology is always subject to revision and to doubt as to its completeness". In the case of many accidents, probabilistic risk assessment models do not account for unexpected failure modes.

b. The difficulty of modeling common-cause or common-mode failures. The probabilistic risk assessment method does a poor job of anticipating accidents in which a single event, such as a tsunami, causes failures in multiple safety systems.

Both of these shortcomings are related to the model uncertainty of this method.

4.1.1 Different Understanding of Model Uncertainty

One opinion on model uncertainty, given by Reinert and Apostolakis (2006), is that model uncertainty is uncertainty of the model output, which is introduced by uncertainty in accuracy of the model. Uncertainties which come from input values and structure errors are included in the model uncertainty. This definition of model uncertainty can be found in some other articles and books. This is also termed "Model Output Uncertainty" by some other researchers, the same in this report.

While, Droguett and Mosleh (2008) have different statement, they think that parameters and structures are the two characters of a predictive model. Therefore, parameter uncertainties of the model stem from uncertainties in the input values assumed by the model parameters, and model uncertainties are uncertainties and errors associated with the structure of the model. Similar terms including structural model uncertainty, model form uncertainty and conceptual model uncertainty are also used by some researchers. "Model Uncertainty" in this report is in this side of opinion.

4.1.2 Model Uncertainty Sources Identification

Uncertainty sources or model uncertainty sources have been discussed broadly by many scholars. Different classification of them have been made. Here the main focus wil be on model uncertainty sources.

De Haag and Ale (1999) classified uncertainty sources in Quantitative Risk Assessment (QRA) calculation according to the level in the calculation: starting points, models, parameter values and the use of the model. Uncertainty sources from starting points and models are within the study scope of this report.

Clear start points which demonstrate the purpose of calculation define the scope of modelling and specific approaches forwards. One illustrative example is *"if the QRA is meant to estimated the actual risk of the activity, the probability that the flammable cloud will ignite should be calculated using the location of ignition sources around the activity. On the other hand, if the*

QRA is meant to calculate an individual risk independent of the surroundings of the activity, the ignition sources around the activity should be ignored and agreements will have to be made on the ignition of flammable clouds". A list of start points is provided to minimise the uncertainty from this.

It is also noted that models used in QRA is not strictly established. They vary in complexity and accuracy. Model uncertainty sources for QRA include:

- Potentially important processes which should be included in the model are ignored or overlooked. Examples are tank-roof collapse, atmospheric deposition processes and chemical reactions in the dispersing cloud;
- The applied model is not valid for the specific local situation. For example, the dispersion models used are only valid for a flat terrain in the absence of large obstacles, whereas numerous obstacles can be present in and around industrial sites;
- Simplifications done to the modelled processes. For instance, a uniform wind speed is used, which ignores the variation in wind speed with height;
- Natural variability is ignored. For instance, all humans are assumed to react similarly to an exposure to toxic substances. However, people considered impaired to the circumstances are probably more vulnerable and thus at greater risk;
- Models are sometimes used outside the range of applicability;
- Numerical approximations in the computer code.

Modarres (2006) adopted categorization of model uncertainty sources from Isukapalli (1999), which is based on environmental risk analysis; see Section 4.2.2. These are: model structure, level of detail, resolution, boundaries.

Haimes (2008a, Chapter 6: Defining Uncertainty and Sensitivity Analysis) made a classification of major model uncertainty sources of risk modelling of systems in general. There are 6 major model uncertainty sources. They are surrogate variables, excluded variables, abnormal situations, approximation uncertainty, incorrect form and disagreement.

Surrogate variables are quantities used to replace the actual quantities of concern which are too difficult or too expensive to assess. Surrogate variables are assumed to be close substitutes that are easier to be dealt with and therefore are resource-saving. For example, using results from drug testing on rodents to determine a drug's effect on humans. Surrogate variables should be used with caution since they are approximations of real values and may increase the uncertainty of the results specially when the relation between the surrogate estimate and real value is not completely understood and well analysed.

Excluded variables are those factors or quantities that has important influence on the result but are overlooked during the modelling process because the modellers deem them unimportant. The removal of this kind of variables in the model may introduce large uncertainty to the model output. And we may not know them until evidence has been found, which makes it difficult to account for this kind of variables.

Abnormal situations are those anomalies which make the model non-suitable because they exist outside of the model's design. Even though the model is applicable in almost all similar cases, there might still some abnormal ones that the model cannot represent. Failure to recognize or foresee the limits of a model to a specific abnormal situation within the process increases error and uncertainty in the conclusion drawn from the model.

Approximation uncertainty covers the approximation approach used in the model development. An example of this is the case when a discrete probability distribution is used to represent a continuous real-world process, or in the limitation of finite runs used in Monte Carlo analysis.

Incorrect form category mainly concerns the validity, or accuracy or the basic model which is used to represent the real world.

Disagreement represents the uncertainty sources from conflicting expert opinion or data interpretation because of difference in beliefs about the fundamental processes.

In nuclear sector, both model uncertainty and completeness uncertainty are included by the defined model uncertainty in this thesis.

NUREG-1855 (Drouin et al., 2009) focuses on identification and evaluation of sources of model uncertainty, especially those key uncertainty sources of the PRA model that would influence the decision. Then efforts and resources can be used to reanalyze these key uncertainty sources which have a significant influence on the output instead of spreading to the whole input set.

The treatment of model uncertainty sources also depends on the application of base PRA model. To get a list of the sources of model uncertainty, and the related assumptions of PRA model for a certainty application, **the first step is to identify sources of model uncertainties, related assumptions of base PRA model, and model uncertainty sources arising from plant-specific features** (Base PRA is the PRA which is developed to support the various applications, and it is independent of an application). **The second step is then to identify sources of model uncertainties and related assumptions relevant to a certain application** (e.g. to evaluate various design options or to determine the baseline risk profile as part of a license application for a new plant).

EPRI (2008) provide a generic list of potential model uncertainty sources by examining the ASME/ANS PRA standard 2008 and avilable industry/NRC PRAs. Both root causes of epistemic uncertainty from literature study and ASME/ANS PRA standards high-level requirements are examined to provide a structure and cross checking. The list are shared by NUREG-1855. Examine plant-specific features and modeling approaches covers the model uncertainty sources which are not incorporated into the generic list.

The model uncertainty concerned by NRC NUREG include the approach or the model itself and its constituent parts. Examples are 1) How to address a common cause of failure in the PRA model, 2) The approach to identify and quantify operator error (human reliability model), 3) Unclear failure mechanism, logic gate etc.

In addition, for each model uncertainty source, indication is provided for what typical parts of the model that are affected (e.g. change of logic, change of accident sequence, and introduction of a new event). The parts are affected by the model uncertainty itself and the representative sample approaches.

Completeness uncertainty sources are risk contributors which are not included and that may be ignored due to simplifications and assumptions. The risk contributors are not significant after assessing known uncertainties; furthermore, they can be totally ignored when we have no knowledge about them (unknown uncertainties). Examples of known uncertainties sources are some initiating events, hazards, or the model of operations which are not included in the scope of PRA, and phenomena, failure mechanisms, or other factors which are omitted in the level of analysis because their relative contribution is believed to be negligible. Examples of unknown uncertainties are phenomena, failure mechanisms, or other factors which are omitted in the analysis because we do not know of their existences, and of certain related effects (aging or organizational factors etc.) where no agreement exits on addressment by the PRA.

4.1.3 Characterization and Analytical Treatment of Model Uncertainties

After we know that model uncertainty sources exist, which means that the direct outputs of model are not as trustable as we thought before. We may have further questions: What are the "true" results we can use as inputs for decision support? How do these uncertainty sources influence the output or how do these they make the outputs deviate from "true" results? Will these identified uncertainty sources change the decisions?

In order to get a result closer to the "true" result, expert judgement and Bayesian inference are approaches for this purpose. These kinds of methods can be called "output-driven" methods. Assessment of impact from model uncertainties and importance measures are ways to see how these uncertainty sources influence the output. This kind of method can be called a "input-driven" method. A combination of "input-driven" and "out-put-driven" methods are also possible to apply, which is called a hybrid method. The distinction of "Output-Driven" method, "Input-Driven" and "Hybrid" method is extended from Pourgol-Mohammad (2009).

The "Input-Driven" method is a "white-box" decomposition approach. It goes to the details of the model (treat it as a while box). In the end, both uncertainty sources in parameters and models are propagated through the overall model structure to the resultant model outcome, which may be represented by distributions or ranges. The "Output-Driven" method, model uncertainty is characterized by comparing measured and calculated output if applicable or by correcting model output which only consider parameter uncertainty.

There exist some analytical treatment approaches of model uncertainty. Some of them are mentioned by Apostolakis (1989). Approach 1) to 5) are "Output-Driven" methods. Approach 6) is "Input-Driven" method.

1) Introduce *Uncertainty Factor (Adjustment Factor)*

The uncertainty factor is some sort of representation of the confidence in the prediction of the model. The quantity of interest is the multiplication of the uncertainty factor and the prediction result incorporating parameter uncertainty; see Formula 4.1. The uncertainty factor distribution is based on expert judgment concerning both qualitative information about the uncertainty sources of the model, and rough comparison of predicted values with published values (Siu and Apostolakis, 1982).

$$\tau_G = E_\tau \tau_{G,DRM} \tag{4.1}$$

τ_G is the outcome probability distribution considering both model uncertainty and parameter uncertainty;

$\tau_{G,DRM}$ is the model output distribution only concerning parameter uncertainty;

DRM means deterministic reference model, which is used to represent the name of the physical model of cable tray fire;

E_τ is the model uncertainty factor. A lognormal distribution with characteristics: $\mu = 0.582, \sigma = 0.489$, mean= 2.0, $E_{\tau,0.95} = 4.0, E_{\tau,0.05} = 0.8$ is assigned to it in the case in Siu and Apostolakis (1982).

The probability distribution τ_G is gained by combining both the model uncertainty factor E_τ and the DRM prediction, after discretizing the distribution for E_τ using the discrete probability distribution arithmetic described by Kaplan (1981).

The E_τ in formula 4.1 is called multiplicative adjustment factor. Additive adjustment factor can also be applied according to Reinert and Apostolakis (2006), see formula 4.2.

$$y_a = y^* + E_a^* \tag{4.2}$$

In the formula above, y_a is the adjusted prediction, y^* is the direct output from model, E_a^* is the additive adjustment factor or uncertainty factor. Both the multiplicative adjustment factor and additive adjustment factor can be applied at same time if necessary.

2) Introduce *Uncertainty Factor* according to uncertainty source classes

The Danish guidelines (COWI, 1996) for QRA uses uncertainty factors to determine the

Table 4.1: Suggestions of the model uncertainty factor according to assessment result of sub-classes

	Small uncertainty 1<UF<2	Moderate uncertainty 2<UF<10	Large uncertainty 10<UF
Relevance	High	Medium	Low
Validity	High	Medium	Low
Variability	Low	Medium	High

uncertainty from QRA mathematical models. A model uncertainty class constitutes three sub-classes, which are relevance, validity and variability. Relevance means to what extent the model used covers the specific situation. Validity represents how well the model has been validated. Variability is the natural variability of the modelled phenomenon. These three sub-classes are assessed separately by expert judgement and then aggregated to one model uncertainty factor by formula 4.3. This approach is easy to operate and force the analyst to consider model uncertainty in the analysis instead of only considering parameter uncertainty. One obvious drawback is that the quantification is somehow arbitrary.

$$UF = \exp\left(\sum_{i=1}^{n} (\text{In} UF_i)^2\right)^{1/2} \tag{4.3}$$

The semi-quantitative assessment is performed for these three sub-classes using tables in the guidelines. A qualitative description of the three sub-classes is also required besides uncertainty factor numbers. Suggestions for decision of model uncertainty factors are presented in Table 4.1.

Besides the model uncertainty class, there are three other classes of uncertainty; thereby, four classes constitute the result uncertainty of the QRA. The other three classes of uncertainty are: Uncertainty in prevailing analysis conditions or environments (e.g. experience and competence of analyst team, available time and resources); Uncertainty due to assumptions in scenario generation; Uncertainty in input data. There is an uncertainty factor for each class of uncertainty, and the total uncertainty factor of result from QRA is calculated in the same manner as presented in formula 4.1. The input data uncertainty factor is assessed according the output distribution which is propagated from input data uncertainty by sampling method. The treatment of the other two class of uncertainty is similar to that of model uncertainty described above. This concept assume that the different classes of uncertainty are independent to ensure that no part of uncertainty is accounted for more than once.

3) Introduce *Uncertainty Factors* at intermediate level

To use this approach, uncertainty analysis is performed at an intermediate level. The quantity of interest is calculated from a number of different sub-models, and accounts for the uncertainty arising from model-to-model variability by multiplying the quantity of sub-model with an uncertainty factor. The distribution for the uncertainty factor is assessed subjectively, using the different predictions of the various models to indicate the possible range of variation. The resulting model uncertainty is propagated in the same manner that parameter uncertainties are treated, for example, Monte Carlo sampling (Chu and Apostolakis, 1984).

4) Introduce *Subjective Model Probabilities*

For the case of a finite number of alternative models, one opinion regarding model uncertainty is that the issue of model uncertainty can be treated by creating a parameter whose value is dependent on the model used. Combining results from alternative models by introducing subjective model probability for each model can be a method for dealing with model uncertainty. Such a method is called model set expansion(Zio and Apostolakis, 1996). Model probability represents the correctness of the model.

Subjective model probabilities are generated by different ways in practical cases, including mixture (Apostolakis, 1994), the NUREG-1150 approach (Commission et al., 1991; Keeney and Von Winterfeldt, 1991), the joint US/Commission of European Communities'(EC) Probabilistic Accident Consequence Uncertainty Analysis (PACUA) approach (Cooke and Harper, 1997). If experiment data is available, model probability can be updated according to Bayesian theorem from original subjective model probability by incorporating experiment data(Park et al., 2010).

In the mixture approach, a set of plausible models is obtained from experts. Then these experts agree on the model probability (weighting factor) of each model. In the end, these models are combined linearly with their weighting factors. In this case, the result is a weighted average of probability distributions from each model.

There is another approach used in the report NUREG-1150 in which multiple experts are used. Each experts produce his or her own model probability distribution of multi-models. Then, the final model probability distribution is obtained by combining individual result linearly with equal weight on each expert. However, there was a great deal of debate around it since an extensive use of expert opinions in this report.

The PACUA approach gives different weights to experts instead of equal weights in NUREG-1150. The weights of each experts represent the confidence in each expert. First, the experts are asked to produce distributions from seed variables, for which data is known. Then, their distributions are compared to the distributions from known data. Experts with better performance in estimating see variable distribution are given higher weights.

5) ***Bayesian Inference***

Bayesian inference is the approach mentioned and applied by many scholars not only in probabilistic models but also deterministic models to treat model uncertainty. Details can be found at (Link and Barker, 2006; Droguett and Mosleh, 2008; Kazemi and Mosleh, 2012; López Droguett and Mosleh, 2014) etc.

Baye's Theorem are used in different ways to treat model uncertainty. When experiment data is available, it can be used to update the predicted model outcomes considering parameter uncertainty. It is a way to check the model accuracy by system response (Pourgol-Mohamad et al., 2010). It can be used to construct a meta-model from a set of plausible models(Winkler, 1994). It can be used to update subjective model probability described in Approach 4) (Park et al., 2010). It also can be used to assess model uncertainty using historical model performance data paired by true quantity values(Droguett and Mosleh, 2008).

In addition, López Droguett and Mosleh (2014) extended the Bayesian methodology from (Droguett and Mosleh, 2008) to incorporate subjective information in terms of model credibility and applicability when the model is outside its intended domain of application. There are two approaches described by López Droguett and Mosleh (2014) to improve the accuracy of model prediction in the overall Bayesian methodology. One is *Bayesian Model Output Adjustment Approach*, the other one is *Weighted Likelihood Approach*.

6) Sensitivity analysis

After sources of model uncertainty are identifies, sensitivity analysis is implemented to get a list of key uncertainty sources. When model uncertainty sources impact decision-making (e.g. the risk metric), through the result of a sensitivity analysis, these become defined as key uncertainty sources.The result of the sensitivity studies and characterization of these key uncertainty sources are given to decision-makers for decision-making support.

With completeness uncertainty sources (for those which are known) screening and a conservative or bounding analysis can be used to demonstrate that risk contributors, which have not been included in he scope of the PRA or the level of detail of the PRA, are non-significant in affecting decision outcome. Otherwise the PRA should be upgraded to include the missing pieces. When is come to unknown uncertainties, since they are truly unknown, screening is not applicable anymore and other methods should if available be used to address this type completeness uncertainty(Drouin et al., 2009).

Sensitivity analysis is often based on the concept of sensitivity derivatives, the gradient of the output of interest with respect to input variables. The overall sensitivity is then evaluated using a Taylor series expansion, which, for the first order would be equivalent to a linear relationship between inputs and outputs.

Sensitivity analysis does not require input data uncertainty characterization from a real device; it can be conducted purely based on the mathematical form of the model. As a conclusion large output sensitivities (identified using SA) do not necessarily translate in important uncertainties because the input uncertainty might be very small in a device of interest.

Sensitivity analysis is a quantitative examination of how the outputs from the analysis varies with the changing of (Rausand, 2013):

– The input parameters (e.g., failure rates, probabilities, repair times)

- The assumptions of the analysis (e.g., related to operation, maintenance, independence)
- The structure of the model (e.g., structure of a fault tree)

Traditional sensitivity analysis is conducted by changing one uncertain input at a time and showing how the results of a model change over the range of possible values of that one input. Two-way sensitivity analysis is also common (varying two inputs at the time and plotting the results in a two-dimensional space).

Sensitivity analysis is used as an important approach for Uncertainty analysis. In probabilistic risk analysis, sensitivity analysis is applicable for the uncertainty due to the input values to check how much the top event probability changes when one or more input parameters are changed, example parameters are failure rate, test interval etc. Monte Carlo simulation is a way to do it as well. Most fault tree programmes have the module of doing this kind of sensitivity analysis or uncertainty/error propagation (Rausand, 2014, Chapter 5, sensitivity analysis).

Before this "input-driven", "output-driven" distinction, Zio and Apostolakis (1996); Reinert and Apostolakis (2006) concluded on the methods dealing with model uncertainty by addressing them as two kinds: prediction expansion and model set expansion. All of them are "Output-Driven" methods in this classification. For prediction expansion, a single model is chosen as the best one to present the system. Uncertainty factors or adjustment factors can be applied to get a more accurate prediction. For model set expansion, a meta-model of the system can be constructed from alternative models. There are several methods which have been proposed to construct this meta-model, including Mixture (Apostolakis, 1994), Bayesian updating (Winkler, 1994), the NUREG-1150 approach (Commission et al., 1991; Keeney and Von Winterfeldt, 1991), the joint US/Commission of EuropeanCommunities'(EC) Probabilistic Accident Consequence Uncertainty Analysis (PACUA) approach (Cooke and Harper, 1997), and the Technical Facilitator-Integrator approach (Committee et al., 1997). Expert judgement is applied in all of these methods for model set expansion.

While, Modarres (2006) classifies model uncertainty characterization methods according to the number of plausible models available for the question at hand. There are usually two pos-

Table 4.2: Criteria on Model Uncertainty from Modarres (2006)

Criteria on Model Uncertainty		
Decision Criteria	Options	
Source of data and information	Multi sources	Same sources
Assumptions	Different assumptions	Same assumptions
Model form/Structure	Multiple-model form/structure	Single-model form/structure
Model extrapolation	Yes	No
Model Output	Multiple output	Single output

sible situations of model prediction of a property of interest: single model or multiple models (different structural forms). If there are multiple models exist, then following cases may be encountered:

a. Multiple models using the same assumptions, data and information

b. Multiple models using different assumptions, but the same data and information

c. Multiple models using different assumptions, data and information

A subset of criteria to decide the model uncertainty characterization methods are made for these situations, see Table 4.2:

For the case of single model, one option of characterisation approach is to assign a subjective conditional probability interval to the predicted model output. An adjunct option is to Bayesian update the predicted model output, when some evidence in form of actual observation exist from experiments, events or similar. For such single model, the output is conditionally validated with respect to model assumptions. Sensitivity studies can be performed to investigate assumptions that are suspected of having a potentially significant impact on the model output, which in turn may lead to wrong decisions.

In the case when multiple models exist to estimate the same property of interest (where the structure form of the models are different, but still developed from the same underlying knowledge, information, data and assumptions), A weighted average of various model outputs can represent an aggregate estimation of the quantity of interest. The weights can be subjectively assigned or equally assigned. Bayesian updating can still be used to refine the averaged uncertainty of the quantity of interest if evidence show up.

Consider a situation where multiple models with different assumptions exist to be used on the same case, even though the data and information are the same. If the estimates generated by the models become considerably different, because the models rely on exclusively different underlying theories (different assumptions), then the averaged model output is physically meaningless to calculate. Characterization of epistemic uncertainty of the models can only be done separately for each model as in the single-model case. As a consequence only qualitative (or semi-quantitative) explanations are realistic in the comparison of the goodness of each model. One such an example is estimating structural failure caused by fatigue due to a random load applied to the structure. Both linear elastic fracture mechanics and elastic-plastic theory of fatigue may be used to estimate the service life. The former assumes no plastic deformation at vulnerable location, the latter model allows some plasticity at the tip of the crack. The assumptions of these two model are fundamentally different in that they refer to different phenomena of crack growth due to fatigues, and both models may satisfy the same data and information available. However, the life estimation models for the structure are quite different, then there is no meaning to combine the result from both models. In this case, It becomes the final decision maker's partiality (e.g. risk manager's decision as to which of the model output he/she prefers to use).

4.1.4 Uncertainty Integration and Propagation

Uncertainty integration and propagation is a typical issues if model uncertainty sources exist, especially for hierarchical models. This issue is pointed out by Pourgol-Mohammad (2009); Sankararaman (2012); Sankararaman and Mahadevan (2015).

The "Output-Driven" methods are trying to get the "true" uncertainty of the quantity of interest, which is already an integrated result from model uncertainty and parameter uncertainty. This provides direct resultant input for decision-making, while the "Input-Driven" methods are trying to assess the impact from single model uncertainty sources or coupled pairs of model uncertainty sources. In this case, decision makers get the result of the quantity of interest with its resultant uncertainty from input parameters and a list of possible variations from a certain model uncertainty source or two. If there are many uncertainty sources, the total impact from them cannot be seen from the many separated and single uncertainty sources. For hierarchical model, the overall model is a integrated result from many sub-models at different levels. The influence from model uncertainty sources, which are located at different levels, also varies, and an integrated uncertainty of the quantity of interest might also help in decision making in this regard.

4.1.5 Model Uncertainty Reducing

There are several ways to reduce or control model uncertainty, including but not limited to:

1) Choose an appropriate model according to application.

2) Bayesian updating of model output if evidence (observation) exist; Bayesian Network, incorporating different models; or using weighted result from different models.

3) Using a consensus model that has publicly available published basis and has been peer reviewed and widely adopted.

4) Apply standardized modelling process.

5) Apply a sound and holistic model validation procedure.

6) Increase the knowledge about real world or system and modelling techniques.

The best reduction of model uncertainty is to reduce the overall uncertainty to parameter uncertainty for which the combined use of statistics theory and expert opinion collection is an adequate treatment(Devooght, 1998).

4.2 Model Uncertainty Analysis in Environmental Modelling

Environmental modelling is a wide issue, both deterministic, probabilistic, integrated models are used in different sub fields and environmental issues.

A ten iterative steps in environmental model development and evaluation was proposed by Jakeman et al. (2006). This ten iterative steps process is also adapted in book *Models in Environmental Regulatory Decision Making* (National Research Council (US). Committee on Models in the Regulatory Decision Process, 2007). Quantification of uncertainty is the ninth step in this process. The authors also mentioned: "few approaches explicitly consider model uncertainty...

And it is hard to take this kind of uncertainty into account, because it is an issue about developers' preferences and capability, fashion within technical communities, shortage of time and resources, availability of software tools, etc... But the positive side is that, uncertainty is widely recognised and increasing resources are being devoted to it".

Hession and Storm (2000) demonstrated a method for incorporating uncertainty analysis in watershed-level modelling. Three uncertainty sources were examined. They are parameter errors, parameter stochasticity and lumping error. Probability density function of output resulted from each uncertainty sources and all three uncertainty sources are compared. The comparison shows that parameter errors is the greatese contributor to the total output uncertainty. As argued by the author, lumping error is difficult to be classified into specific category of uncertainty. It can be understood as model uncertainty since it presents a simplification of the real world required by the model. It also can be seen as a parameter uncertainty since it result in a estimate of parameter presenting our lack of knowledge of the real value. Or it can be reviewed as a spatial variability according to the authors' classification of uncertainty.

Refsgaard et al. (2006) classifies strategies for assessing structural uncertainties in environmental models into two categories after reviewing a range of existing strategies. One is " interpolation" for those field data is available for the predicted variable of interest. The other is "extrapolation" for those field data is not available. A framework for the situation of "extrapolation" is presented in this paper. This framework involves multiple conceptual models, assessment of tenability and completeness of conceptual models.

Refsgaard et al. (2007) briefly review 14 different methods that are commonly used in uncertainty assessment and characterization. They are: data uncertainty engine (DUE), error propagation equations, expert elicitation, extended peer view, inverse modelling (parameter estimation), inverse modelling (predictive uncertainty), Monte Carlo analysis, multiple model simulation, NUSAP, quality assurance, scenario analysis, sensitivity analysis, stakeholder involvement and uncertainty matrix (Jeroen P. van der Sluijs and Huijs, 2003; Walker et al., 2003). NUSAP(numeral, unit, spread, assessment, and pedigree) is for multidimensional uncertainty assessment to provide an analysis and diagnosis of uncertainty in science for policy (Funtowicz and Ravetz, 1990; Van Der Sluijs et al., 2005). This system can integrate qualitative uncertainty and quantitative uncertainty but the scoring of pedigree criteria is based on subjective judgement. The author mapped these methods according to their applicability into purpose of application, stage of modelling process and source and type of uncertainty addressed. The role of uncertainty assessment is presented together with the modelling process and with its interaction with broader water management process. It concluded that uncertainty assessment should not just be added after the completion of the modelling work but be seen as a red thread throughout the modelling study. It also concluded that the identification and characterization of all uncertainty sources should be performed jointly by the modeller, the water manager and the stakeholders.

Uusitalo et al. (2015) review various methods that have been or could be applied to evaluate the uncertainty related to deterministic models' output for environmental model. Expert judgment, model emulation, model sensitivity analysis, temporal and spatial variability in the deterministic models, applying multiple models and data-based approaches are covered in this review. The authors doesn't not conclude which method is better than the other but conclude that the best way to evaluate the uncertainty depends on the definitions of the source models and the amount and quality of available information. One difference between deterministic models and non-deterministic (probabilistic) models is that the causal-effect relationship between model variables is very clear in deterministic models while causal-effect relationship is not clear in non-deterministic models. But the method to characterizing model uncertainty may be similar in some aspects. Both of these two kind of models are a simplified representation of the real world.

As for uncertainty in integrated environmental models, it was discussed by Van Asselt and Rotmans (2002) and Matott et al. (2009) did a review of concepts and tools for this topic.

In water resource management, uncertainty has been discussed quite intensively. Relevant literature for model uncertainty can be find from Beck (1987); Butts et al. (2004); Gourley and Vieux (2006); Ajami et al. (2007); Blumensaat et al. (2014). One important feature for model applied in this subject is that observed data or measurement of quantity of interest can be obtained from field observations. In this way, model uncertainty can be evaluated or quantified by field data. Model calibration is an important support to reduce model uncertainty and obtain a more accurate model output.

Model evaluation defined by EPA's Committee on Regulatory Environmental Models is the term that has a similar function as model uncertainty analysis defined in this thesis. The definition of model (or data) evaluation is:

"The process for generating information over the life cycle of the project that helps to determine whether a model and its analytical results are of a quality sufficient to serve as the basis for a decision. Model quality is an attribute that is meaningful only within the context of a specific model application. In simple terms, model evaluation provides information to help assess the following factors: (a) How have the principles of sound science been addressed during model development? (b) How is the choice of model supported by the quantity and quality of available data? (c) How closely does the model approximate the real system of interest? (d) How well does the model perform the specified task while meeting the objectives set by quality assurance project planning?"

In the context of *model evaluation* from EPA, uncertainty analysis contribute to the model evaluation and is part of evaluation process(National Research Council (US). Committee on Models in the Regulatory Decision Process, 2007; Council for Regulatory Environmental Modeling, 2009).

Since environmental modelling is a wide and multidisciplinary issue and uncertainty is a very critical problem for them. But due to time limitation, it is impossible have comprehensive literature reviews in all these fields. Therefore mainly examples from climate change study, transport-transformation models, exposure assessment, which all can provide us more detailed information and good understanding, are studied.

4.2.1 Model Uncertainty in Climate Change

In reports from IPCC, uncertainty is expressed by probability (quantified measure) or by subjective description (an assigned level of confidence) (Mastrandrea et al., 2010). A level of confidence is expressed using five qualifiers: “very low,” “low,” “medium,” “high,” and “very high.”

Some sights about model uncertainty can be see from following definitions(Pachauri et al., 2014): Climate models are applied as a research tool to study and simulate the climate and for operational purposes, including monthly, seasonal and inter-annual climate predictions, A climate model is a numerical representation of the climate system based on the physical, chemical and biological properties of its components, their interactions and feedback processes and accounting for some of its known properties. The climate system can be represented by models of varying complexity; that is, for any one component or combination of components a spectrum or hierarchy of models can be identified, differing in such aspects as the number of spatial dimensions, the extent to which physical, chemical or biological processes are explicitly represented, or the level at which empirical parametrizations are involved. Coupled Atmosphere–Ocean General Circulation Models (AOGCMs) provide a representation of the climate system that is near or at the most comprehensive end of the spectrum currently available. There is an evolution towards more complex models with interactive chemistry and biology.

Ensemble is defined as "a collection of model simulations characterizing a climate prediction or projection. Differences in initial conditions and model formulation result in different evolutions of the modelled system, may give information on uncertainty. For climate forecasts this uncertainty is associated with model error and error in initial conditions, while for climate projections it is associated with model error and with internally generated climate variability."

Results from multi models are used to improve the accuracy of prediction. Why model combining works is presented by Makridakis (1989); Armstrong (1989); Clemen (1989).

4.2.2 Model Uncertainty In "Transport-Transformation" Models

Isukapalli (1999) studied the treatment of uncertainty in transport-transformation models of environmental and biological systems. These models describe the fate and transport of a chemical species that originates from a source, travels through a medium (“transport”), undergoes changes due to chemical or radioactive processes (“transformation”), and eventually comes in contact with a receptor (e.g., a human, or specifically an organ, or a tissue). These transport-transformation models are based on the continuity equation, and on a mass-balance of chemical or radioactive species in a control volume. Even though the complexity of these models varies significantly, they are categorized together because the underlying physical and chemical processes, and the mathematical equations describing these systems, are similar.

Model Uncertainty sources

Isukapalli (1999) defines 4 types of model uncertainty sources of this kind of transport-transformation models. They are:

Structure/form: Uncertainty arises when there are assumptions for developing a model. In such cases, if the results from alternative models (using other data, information, and knowledge) yield the same answer to a problem, then one can be more confident that the results obtained from the model are realistic in the face of uncertainty. If, however, alternative models yield different conclusions, further model evaluation might be required. One evaluation may involve verifying model estimation with the actual data observed or obtained from experiments. Sometimes the uncertainty associated with the risk model assumptions is characterized with sensitivity analysis.

Level of detail: Often, models are simplified for purposes of tractability. An example of this is converting a complex nonlinear model to a simple linear model to trace calculations. Uncertainty in the predictions of simplified models can sometimes be characterized by comparison of their predictions to those of more detailed, inclusive models. Also, certain aspects of a process, phenomena, event or system may not be considered in a model, because the modellers may believe that they are unimportant in comparison to other aspects of the model. Often this aspect of model uncertainty is referred to a completeness uncertainty

Extrapolation: Models that are validated for one portion of input space may be completely inappropriate for making predictions by extrapolating the model into other interesting regions of space. For example, a dose-response model based on high-dose, short-term animal tests may involve significant errors when applied to study low-dose, long-term human exposures. Similarly, models that are evaluated only for application in a unique set of conditions may involve enormous uncertainties when they are employed to study significantly different conditions.

Resolution: In the application of mathematical or logical models, selection of a spatial or temporal grid or lattice size often involve uncertainty. On one hand, there is a trade-off between the computation time (hence cost) and prediction accuracy. On the other hand, there is a trade-off between resolution and the validity of the governing equations of the model at such scales. Very often, a coarse grid resolution introduces approximations and uncertainties into model results since certain phenomena, events, or processes may be bypassed or neglected altogether sometimes, a finer grid resolution need not necessarily result in more accurate predictions, for example, when a fine-grid produce incorrect results because the governing equation may be insensitive the fine changes.

Table 4.3: Classification of uncertainty sources from Modarres (2006)

A classification of the Sources of Uncertainty	
Uncertainty in model formulation (Structural Uncertainty)	**Uncertainty in Model application** (Data/Parametric Uncertainty)
Conceptual	Parameter selection
Simplifications	Input Data
Development / Selection	
Completeness	Source Information
Level of Details	
Initial and boundary conditions	
Mathematical formulation	
Simplifications in mathematical formulation	Operational model evaluation
Physics-type hypotheses	Uncertainty in model estimates
Idealizations in formulation	Uncertainty in observations
Independence hypotheses	Nonexistence of observations
Spatial averaging	
Temporal averaging Response interpretation	
Process decoupling	
Lumping of parameters	
Numerical solution	
Discretization	
Numerical algorithm/operator splitting	
Approximations in computer coding	
Representation of results	
Precision	
Bias	

Boundaries: Any model may have limited boundaries in terms of time, space, number of input variables, and so on. The selection of a model boundary may be a type of simplification. Within the boundary, the model may be an accurate representation. But other overlooked phenomena not included in the model may play key roles.

Modarres (2006) summarized the classes of sources of uncertainty based on the classification of Isukapalli (1999) with some modifications, see Table 4.3.

Model Uncertainty Characterization

To study the uncertainties associated with model formulation, construct of a hierarchy of models with increasing detail and compare outputs from these models, is recommended by Isukapalli (1999) . The comparison of the model results can provide insight into what level of detail is sufficient to produce results similar to more detailed models. Such knowledge is very useful in building an “optimal model”, one that produces outputs similar to more detailed models, but requires much less detailed inputs and much fewer computational resources. Further, results from models with varying detail provide an estimate of the range of model calculations, thus helping in characterizing the uncertainty associated with model formulation and detail.

To characterize model uncertainty of transport-transformation models. Photochemical air quality modeling applications are used as example and case study of transport-transformation models. Two versions of Reactive Plume Model(RPM) are used to describes the evolution of a photochemical plume and estimate pollutant concentrations in the atmosphere from "point sources " of emissions such as the stacks of refineries and of power plants in the model uncertainty study. Reactive Plume Model(RPM) is an EPA (Environmental Protection Agency) regulatory atmospheric photochemical trajectory model. The RPM-IV version is two-dimensional. It lacks vertical resolution, since uniform mixing in the vertical direction is assumed. RPM-3D is developed from RPM-IV by incorporating vertical resolution. It is a three-dimensional version.

There are two aspects of the model studied in the case: (a) the model uncertainty as a result of the choice of horizontal resolution. (b) the model uncertainty as a result of the assumption of uniform vertical concentration profile. To study the model uncertainty associated with horizontal resolution, the results from the RPM-IV at varying horizontal resolutions are compared. To study the model uncertainty associated with assumption of uniform vertical concentration, results from RPM-IV and RPM-3D are compared.

The drawback of this approach is that it is quite costly and requires time to build a hierarchy of models. It does not give a "true model" but gives an "optimal model", which is a balance between cost and accuracy, by comparing the output from a hierarchy of model ranging from simplified to more detailed. It also helps to screen out the unimportant model uncertainty sources.

4.2.3 Model Uncertainty Analysis in "Exposure Assessment"

"*Exposure assessment* is the process of estimating or measuring the magnitude, frequency and duration of exposure to an agent along with the number and characteristics of the population exposed"(IPCS, 2004). Assessing the dose within the body after the agent enters the body via ingestion, inhalation or dermal absorption is also included in the term "exposure assessment" in some health studies. *Exposure* is the contact between an *agent* (chemical) and a *target* (e.g children, adults or sensitive subgroups), where contact takes place on an *exposure surface* (external human boundaries, e.g. skin, or internal organs, e.g. lung surface) over an *exposure period* (e.g. minutes to a lifetime). The health effect of exposure may be acute, intermittent or chronic.

Quantification of the magnitude and timing of personal exposures to agents of concern requires the identification of sources and media of concern, key exposure microenvironments, and routes and pathways of exposure that contribute most to an individual's exposure. But the information needed to estimate emissions, concentrations, exposures and doses associated with each of these steps is sometimes completely lacking, frequently incomplete, not representative or uncertain.

The first step of an exposure analysis is to establish a conceptual model. This conceptual model maps out a framework designed to reflect the links between the pollutant source and the contact for human exposure and its processes. The conceptual model helps to define the physical, chemical and behavioural information and exposure algorithms by which resulting mathematical/statistical model captures actual scenarios. The conceptual model must address the scenario definition. The scenario definition includes specification of the pollutant source, environmental transport and transformation, exposure pathways, exposure routes and the amount of chemical, attributable to specific pathways and sources, that are taken up through various routes. According to the conceptual scenario, a model can be simple or complex. An exposure model is "a conceptual or mathematical representation of the exposure process" (IPCS, 2004). Exposure models can be developed to estimate exposures and doses of individuals, defined population groups or entire populations (IPCS, 2005). Exposure may be estimated as a continuous variable or integrated over time ranging from minutes to a lifetime. The modelled outputs may include mean or median values, distribution parameters (standard deviations, quartiles, ranges) or complete probability density distributions. Consequently, exposure models vary widely in complexity, approach, inputs and outputs.

In exposure assessment, uncertainty pertains to different steps and approaches in the assessment. In WHO IPCS(2008) guideline (IPCS, 2008) , a tiered approach is used for uncertainty analysis in exposure assessment. There are four steps in this hierarchical method: screening

(Tier 0), Qualitative (Tier 1), Quantitative (Tier 2) and probabilistic (Tier 3) uncertainty analysis. The uncertainty analysis is an integral part of the exposure assessment. The advantage of this tiered approach is its efficiency. It starts by considering all uncertainties qualitatively (Tier 1). If the outcome is clear enough for decision-makers to reach a decision, then Tier 1 is sufficient. Otherwise, the uncertainties that appear critical to the outcome may be analysed deterministically (Tier 2) or probabilistically (Tier 3).

In exposure assessment, uncertainty is classified into three broad categories:

- ***Scenario uncertainty***: Uncertainty in specifying the exposure scenario that is consistent with the scope and purpose of the assessment.

  Exposure scenario is defined as a set of conditions or assumptions about sources, exposure pathways, amounts or concentrations of agent(s) involved, and exposed organism, system, or (sub)population (i.e., numbers, characteristics, habits) used to aid in the evaluation and quantification of exposure(s) in a given situation (IPCS, 2004).

  Scenario is built based on the scope and purpose of each exposure assessment, and it includes the "facts, assumptions and inferences" that are considered and used. So it is not an actual representative of the scope and purpose of the assessment. Exposure models are selected or built based on the defined scenarios. Models include conceptual and mathematical description of the exposure process. Computer programs which are used to calculate exposure are also included.

  Scenario uncertainty includes 1) descriptive errors about information which lead to wrong or incomplete information, 2) aggregation errors from approximation, for instance of volume and time, 3) errors of assessment from choosing wrong model etc. and 4) errors of incomplete analysis, for example, missing an important exposure pathway.

  Examples of scenario uncertainty are: 1) Coffee is not considered as an important source of acrylamide exposure due to lack of knowledge; 2) Air exchange is not considered when characterizing room air concentration.

- ***Model uncertainty***: Uncertainty due to gaps in scientific knowledge that hamper an adequate capture of the correct causal relations between exposure factors.

- ***Parameter uncertainty***: Uncertainty involved in the specification of numerical values (be they point values or distribution of values) for the factors that determine the exposure.

Nevertheless, it is also stated that the classification is not as strict as it may seem. Uncertainties arise in overlapping areas in practice. It is difficult to decide which category the uncertainty belongs to. Identification of the sources of scenario uncertainty is a matter of interpretation and depends on the clarity of the scope and purpose of the assessment at hand. Scenario uncertainty can be seen as part of model uncertainty defined in this thesis because it is about how we understand the real world/system, and it is part of the modelling process introduce in Chapter 3. However, it is more like a model application issue since it applies to a given situation. For one; subjective issues counts more than scientific issues. Secondly, the way of characterization might be different. Therefore, temporarily in this thesis, it feels natural to exclude it out of the model uncertainty definition.

Model Uncertainty Sources Identification

In exposure assessment, model uncertainty is principally from modelling errors and relation (dependency) errors. Non-consideration of certain parameters can be an example of modelling errors. Drawing incorrect conclusions from correlations can be a example of relation errors. IPCS (2008) lists following model uncertainty sources:

- Exposure estimator: definition of the target variable
- Model boundaries: Representation of the adopted scenario
- Conceptual errors and wrong assumptions in the translation of the scenario into a set of model equations
- Dependency errors: assuming interdependence of the input variables
- Model assumptions
- Model Detail: e.g. simple and complex model
- Extrapolation

- Implementation of tools and software

Gerhard Heinemeyer (2015) points out that typical exposure model uncertainty sources include:

- Failures to take account of the influencing factors
- Incorrect aggregation
- Assumptions of incorrect non-associations or oversimplification of the relationships between exposure factors (input variable)
- Extrapolation errors if transferring validated models to new application areas

There is no specific model uncertainty identification methods addressed in (IPCS, 2008) or (Gerhard Heinemeyer, 2015), and model uncertainty sources mentioned above are not strictly categorised.

In the qualitative uncertainty analysis characterization method used by (IPCS, 2008), the first step is to specify uncertainty sources. Three basic uncertainty sources; "Scenario", "Model" and "Parameter" should be separately specified, and can be further detailed. Model uncertainty can be divided into conceptual model and mathematical model. It can also be detailed into model assumption, model dependency, model structure, equation, model extrapolation and model implementation etc.

Model Uncertainty Characterization

The methods to characterize uncertainty in IPCS (2008) are classified into two broad types: qualitative, quantitative. They provide contrasting ways of characterizing the relative importance of the uncertainties affecting an assessment and of characterizing the overall uncertainty of the assessment output (more stemming from parameter uncertainty than scenario and model uncertainty). All of them provide an essential input for decision-making.

A "Three-dimensional" qualitative characterization method is proposed by IPCS (2008); the dimensions being: "level of uncertainty", "appraisal of the knowledge base", and "subjective of choices". There are three scales to characterize each dimension: "Low", "Medium", "High". This qualitative uncertainty characterization method applies to any kind of uncertainty: Scenario, Model, and Parameter. The evaluation of each uncertainty source is separated.

The "level of uncertainty" express the degree of severity of the uncertainty from the assessors' perspective. The whole scale of it ranges from determinism to ignorance in theory. The "appraisal of knowledge base" is the adequacy of the available knowledge base for the exposure assessment. There are several criteria for evaluating the uncertainty of knowledge base. The "Subjective of choices" evaluates the choice process of exposure assessors when they make assumptions and especially focuses on the value-ladenness of assumptions. There are several criteria for evaluating it too.

When evaluating model uncertainty sources, "level of uncertainty" is the first dimension to evaluate, then you get a screened list of model uncertainty sources which are marked "High" or "non-applicable" in the "level of uncertainty". These screened model uncertainty sources are major sources. "Appraisal of the knowledge base" is the second dimension to evaluate for these major sources. From this dimension, a further reduced number of model uncertainty sources will be obtained, which are called controversial sources of uncertainty. "Subjectivity of choices" is the last dimension to evaluate for these controversial sources. If the evaluated result is high for a certain model uncertainty source, a new cycle of evaluation of this uncertainty source should be executed. After all these steps, a map of qualitative values for the model uncertainty sources will be obtained and tabulated. A subjective integration can be made to get the overall degree of uncertainty from all three dimensions of uncertainty; nevertheless, it is important to document the reasoning so others can evaluate the reached conclusions.

Similar qualitative characterization methods are also used for chemical safety exposure assessment (ECHA, 2011) and food safety dietary exposure assessment (EFSA, 2006; EFSA Scientific Committee, 2016).

Gerhard Heinemeyer (2015) is a guidance (draft) designed for the application fields at the Federal Institute for Risk Assessment (BfR). For the model uncertainty part, it compiled a question list regarding 7 increased criteria based on the "three-dimensional" qualitative characterization method. These 7 criteria are:

- Estimation of exposure: definition of the target variable

- Concept and assumptions for the transfer of the scenario into a mathematical model;
- Connections/Correlations;
- Model structure, e.g. stratification;
- Choice of model equation;
- Extrapolations of the model;
- Risk management measures.

4.3 Model Uncertainty Analysis in Computerized Modelling and Simulation

The key words which are very close to the context of model uncertainty analysis defined in the field of computerized Modelling and simulation is "Model Verification, Validation and Uncertainty Quantification". Verification is the process to determine that the model is accurately implemented and represents the developer's conceptual description of the model and the solution to the model. Validation is the process to determine the degree that the model is an accurate representation of the real world from the perspective of intended model usage. Model quantification is the process that mathematically is characterizing unknown/random features and variables in the target application and predicting their influence on a quantity of interest (Hu et al., 2015).

Model uncertainty sources include initial conditions, level of fidelity (e.g. three-dimensional geometries are simplified to two-, or one-dimensional numerical representation), numerical accuracy (e.g. inadequate algorithms, inadequate resolution, and code bugs), choose a cutoff scale in modelling multi-scale phenomena, parametric settings (about the correct values to assign to the parameters in the correct physics models) (National Research Council, 2012). Besides these, one large model uncertainty source is "the unknown unknowns" (Trucano, 1998).

Oberkampf et al. (2002) proposed a framework for modelling and simulation which can help identifying error and uncertainty in computational simulations that deal with the numerical solution of a set of partial differential equations.

Roy and Oberkampf (2011) presented a comprehensive framework to estimate the uncertainty of the quantity of interest from predictive models for scientific computing applications. It incorporate uncertainty due to the mathematical form of the model. Model uncertainty is estimated by the process of model validation and then it is incorporated to the computed model output in which only parameter uncertainty is propagated. But experiment data is required for the model uncertainty estimation.

4.4 Methods Summary

4.4.1 Uncertainty analysis

Uncertainty Matrix

Walker et al. (2003) proposed an uncertainty matrix, see Figure 4.1, to get a systematic and graphical overview of the essential uncertainty features of the models used for decision support activities. The tool inspires both model developers and model users to make an explicit effort to identify, estimate, assess and prioritise all important uncertainty contributions associated with the model outcomes. Each identified uncertainty contributor identified from the framework of policymaking are located in a particular location category of the matrix and typified in terms of uncertainty level and nature.

The matrix can be applied for different purposes at different phases of the decision support activity. For example, it can function as a heuristic during the preparatory pre-analysis phase, or as a checklist during the analysis phase, or as a quality control checklist which used in peer review or for self-evaluation.

This uncertainty matrix is mainly applied in uncertainty analysis in exposure assessment as a qualitative uncertainty analysis approach.

A methodological framework of quantitative uncertainty assessment

A common methodological framework of quantitative uncertainty assessment is presented by de Rocquigny et al. (2008). This framework include four steps and feedback process afterwards:

Location		Level			Nature	
		Statistical uncertainty	Scenario uncertainty	Recognised ignorance	Epistemic uncertainty	Variability uncertainty
Context	Natural, technological, economic, social and political, representation					
Model	Model structure					
	Technical model					
Inputs	Driving force					
	System data					
Parameters						
Model outcomes						

Figure 4.1: Uncertainty matrix from Walker et al. (2003)

Step 1. To specify quantities of interest and corresponding measure of uncertainty for each quantity;

Step 2. To undertake uncertainty modelling;

Step 3. To launch uncertainty propagation;

Step 4. To launch sensitivity analysis.

In this framework, a feedback process after one step or another should be followed.

But this framework mainly focuses on parameter uncertainty. Roy and Oberkampf (2011) proposed a similar framework, but incoporating estimated model uncertainty to the propagated model output from parameter uncertainty to estimate the uncertainty of the quantity of interest from predictive models for scientific computing applications.

NUREG-1855 framework

NUREG-1855 framework (Drouin et al., 2009), for uncertainty treatment in PRA, separates the characterization of parameter uncertainty and model uncertainty. Parameter uncertianty is represented by probability theory and propagated to model output by sampling techniques. Model uncertainty sources identification is the first step for model uncertainty characterization. In this framework, Model uncertainty is treated by sensitivity analysis. Key model uncertainty sources are screened by assessing the impact on model output. Information from sensitivity analysis and parameter uncertainty propagation are all provided to decision-makers for decision-support.

Tiered approach

A tiered approach is used for uncertainty analysis in exposure assessment (IPCS, 2008) . There are four steps in this hierarchical method: screening (Tier 0), Qualitative (Tier 1), Quantitative (Tier 2) and probabilistic (Tier 3) uncertainty analysis. The uncertainty analysis is an integral part of the exposure assessment. The advantage of this tiered approach is its efficiency. It starts by considering all uncertainties qualitatively (Tier 1). If the outcome is clear enough for decision-makers to reach a decision, then Tier 1 is sufficient. Otherwise, the uncertainties that appear critical to the outcome may be analysed deterministically (Tier 2) or probabilistically (Tier 3). Uncertainty sources may be treated by different tiers.

4.4.2 Model Uncertainty Sources Identification

Model Uncertainty Sources are classified into different groups in a simple or detail way. For example, in the uncertainty matrix proposed by Walker et al. (2003), model uncertainty is model structure and Technical model. In the extended application of this uncertainty matrix in exposure assessment, model uncertainty contains two sources, one is the conceptual model and the other is the mathematical model. Some exposure assessment may go further detail. A most detailed classification of model uncertainty is from Isukapalli (1999) for "transport-transformation models". And Modarres (2006) further modified Isukapalli (1999)'s classification of model uncertainty sources into three big groups: conceptual, mathematical formulation and numerical solution.

In nuclear power sector, EPRI (2008) provide a generic list of potential model uncertainty sources by examining the ASME/ANS PRA standard 2008 and avilable industry/NRC PRAs. Both root causes of epistemic uncertainty from literature study and ASME/ANS PRA standards high-level requirements are examined to provide a structure and cross checking. To covers the model uncertainty sources which are not incorporated into the generic list, plant-specific features and modeling approaches are examined. As for model uncertainty sources due to incompleteness, level of details and the scope of analysis, conservative analysis applied in the model is further screened qualitatively. These form a very comprehensive and detailed list of model uncertainty sources. And at the time of identification, part of model affected and possible approaches for characterization are specified. This information can be used further for characterization.

But PRA in nuclear sector is very well developed and applied. Standards are developed as well. While for operational risk analysis in oil and gasoline industry, it is still new and under development. This means that we cannot generally follow the way of model uncertainty identification in nuclear sector.

In Meteorology, fish bone method is used for identifying model uncertainty causes systematically. This identification including examine the measurement equipment, environment etc.(Ellison and Williams, 2012)

4.4.3 Model Uncertainty Characterization and Analytical Treatment

The methods for model uncertainty characterization vary quite much according to system being modelled, the feature of model uncertainty, information or data available etc.

These methods including but not limited to:

- Sensitivity analysis;
- Introduce uncertainty factor (or adjustment factor);
- Introduce subjective model probabilities if multi-model involves;
- Bayesian inference;
- NUSAP(numeral, unit, spread, assessment, and pedigree);
- Uncertainty matrix;
- Construct of a hierarchy of models with increasing detail and compare outputs from these models;
- "Three-dimension" qualitative characterization method;

- Estimate model uncertainty from model validation process by comparing with model output and experiment data.

- Etc.

These methods can be classified into three groups "input-driven" methods, "output-driven" method, hybrid methods which is a combination of "input-driven" and "out-put-driven" methods.

The "input-driven" method is a "white-box" decomposition approach. It identifies model uncertainty sources first, and then assess the impact of each model uncertainty source to model output. Sensitivity analysis, NUSAP(numeral, unit, spread, assessment, and pedigree), uncertainty matrix, construct of a hierarchy of models with increasing detail and compare outputs from these model, "three-dimension" qualitative characterization method, are in this category.

"Ouput-driven" methods are used to get a result closer to the "truth" . The uncertainty of model calculations is characterized by correcting model output (from model output only incorporating parameter uncertainty) by expert judgement, Bayesian inference, using experiment data or observations. Introduce uncertainty factor (or adjustment factor); Introduce subjective model probabilities if multi-model involves, Bayesian inference, estimate model uncertainty from model validation process by comparing with model output and experiment data belong to this category.

A further comparison of these methods according to their application fields, resource requirements etc. would be very beneficial and valuable.

4.4.4 Model Uncertainty Reduction

In principle, model uncertainty can be reduced by increasing knowledge about the real world/system and developing more advance modelling techniques in long term. This means, some model uncertainty sources exist today will not be a issue in the future.

But in short term, model uncertainty can also be reduced in following ways:

- Choose an appropriate model according to application.

- Using a consensus model that has publicly available published basis and has been peer reviewed and widely adopted.
- Bayesian Network, incorporating different models; or using weighted result from different models.
- Bayesian updating of model output if evidence (observation) or well structured qualitative information about model applicability exist.
- Model calibration.
- Apply standardized modelling process.
- Apply a sound and holistic model validation procedure.
- Etc.

4.5 Systematic Model Uncertainty Sources Identification– A Proposed Method

As described above, there are different classifications of model uncertainty sources. These classifications help us identify model uncertainty sources in a certain model. To figure out the issue regarding model uncertainty, going back to the modelling process to see where model uncertainty contributors are and how they are formed is a solution worth trying. In addition, the track of such an effort can be seen from some researches.

Here, a method to systematically identify model uncertainty by examining modelling process is proposed. Identified model uncertainty sources with an identical identifier can be located to resultant model elements with noted potential impact and reasons (legitimate sources for degree of belief or a matter of choice for convenience/cost), see Table 4.4. Location means a detailed description about where it is among the model elements. Model structure might be where most model uncertainty sources locate. It is necessary to document which level (if the model is hierarchical) or which place the model uncertainty sources locate in the model structure. If the model has hierarchical levels, then many of these model uncertainty sources can be located to different levels of the hierarchical model since the model is a simplified representation of the system after the whole modelling process. As for the first potential impact of these can be stated at the same time of identification, which could contribute to the characterization of these model uncertainty sources. The reason to classify reasons of the occurrence of these model uncertainty sources is that we can investigate further whether it is possible to reduce their impact and what effort can be done to achieve it.

For hierarchical models, model uncertainty sources identification can follow the model hierarchy from top level to bottom level. If there are more than one driving-force deciding the model hierarchies, see Figure 3.5, it is necessary to go through every hierarchy.

First, a fish-bone diagram is used to exam possible reasons which lead to model uncertainty is presented in Figure 4.2. Please note that fish-bone is just a graphical presentation of the examination, and it is not the only way of presentation.

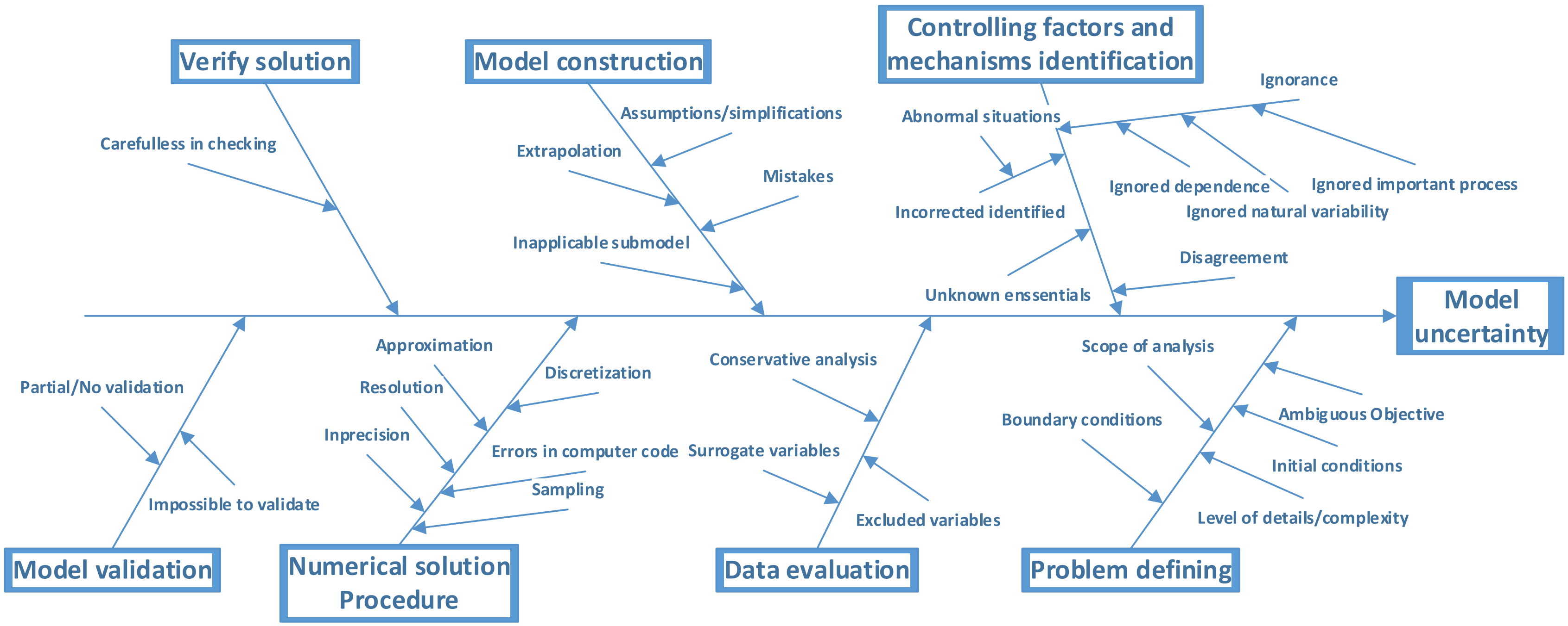

Figure 4.2: Identifying model uncertainty sources from modelling process

Description of model uncertainty sources from each modelling steps is:

- Problem defining

  Model uncertainty sources in this step are mostly related to the limitation of the model. They also occur when it comes to specify initial and boundary conditions, and required level of detail/complexity of model for the given problem.

- Identification of system control factors and mechanism

  Model uncertainty sources from this step include three groups: 1. ignored (but identified) essential system characteristics, 2. incorrectly identified system characteristics, and 3. unknown essential system characteristics, as shown in Figure 3.4. During model uncertainty identification, we would identify all ignored system characteristics, part of them are essential which should be included in the model but not in reality, part of them are real unessential for the given problem. Unknown essential system characteristics cannot be identified, since we do not know their existence. This can be seen as the meta-uncertainty of analysis. Disagreement among modellers or experts regarding fundamental process features also lead to model uncertainty.

- Data evaluation

  Model uncertainty may come from surrogate input variables due to resource-saving since we do not have what is meant to be used in the model to present the system feature. This is a model issue, but it also can be seen as a parameter uncertainty issue. Excluding some variables may happen in this step but then these end up as ignored essential system characteristics and can be identified above. A conservative analysis might be used to elicit the required value of some input variables which leads to uncertainty.

- Model construction

  Model uncertainty sources from this steps include assumptions, simplifications and mistakes which lead to undesired incorrect form, model extrapolation which is not intended for the issue at hand but developed for other issues and issues related to level of details/complexity. Issue relating to level of details/complexity of modelling can be identified when identifying model uncertainty sources from problem defining, but it is easier to address some detailed issues here.

- Find and implement solution procedure

  Model uncertainty sources from this step are main relevant to numerical solution used to get the output or intermediate outputs, e.g. approximation, sampling.

- verify solution

  Issue in this step which may lead to model uncertainty is carefulness in verifying job. If all model uncertainty sources are identified from steps above, then model uncertainty sources from this step are unexpectations.

- validate the model

  Issues relevant to model uncertainty in this step exist if only partial validation, or no validation is executed, when it should have been done. It is also relevant to models that are impossible to validate, such as a risk model which is to model a one-time experiment (accident).

Then, we can get the resultant table of model uncertainty sources, shown as Table 4.4. But here is one issue with the unknown essentials of the system (excluded in the table). It means that we do not know of their existence, which have an important influence on the modelling target. Then we are also unable to identify them. This is one of the more serious shortcomings of this identification.

The method itself is simple. But it is tedious work, and requires the analyst to have good knowledge and experience about the system and risk modelling. It is better that people from process engineers, modellers and decision makers (model users) join it. Actually, this process should be seen as part of the modelling process. And every model uncertainty sources can be identified and documented at the same time of modelling.

Table 4.4: Location of model uncertainty sources

Model uncertainty Source		Location	Potential impact	Reasons	Reference & Comments
S 1	Issue description				

Chapter 5

Model Uncertainty Analysis in MIRMAP

This chapter includes two parts. The first part is to describe the presently developed generic model in MIRMAP and general uncertainty concerns of the current model. The second part is to identify model uncertainty sources of the current generic model by using the proposed method in Section 4.5 and further possible application of the identification information. Due to time limitation, the whole process of model uncertainty analysis cannot be done, which is not the purpose of this master thesis either. Still, the qualitative outcome of identified uncertainty sources is the first step to get to know and understand what issues exist influencing the model output accuracy and resultant decisions. Effort on characterization and quantification can be done later if specific methods are available and have been decided to use.

5.1 MIRMAP

The basic information of MIRMAP have been described at the Introduction Chapter of this thesis–subsection 1.1.1. Here the following will give a description regarding the model and some related issues.

5.1.1 Model Description

The model is developed to rank activities, work permits and work orders according to their contribution to risk of a major accident and associated uncertainty. The model gives support for operational decisions, about the operational work, with aim to achieve the objective of managing day to day risk. Probability of Major Accident (PMA) and Potential loss of life (PLL) within associated working period are used as risk measures, which are used further to calculate the risk contribution from activities, work permit, work order and their ranks.

The core part of the model is a probabilistic hybrid causal model combining Event tree, Fault tree and BBN to model a defined major accident in one fire section to calculate risk measures. The simplified graphical presentation is showed in Figure 5.2. The event tree is developed according to the accident sequence of delayed ignition, see Figure 5.1. There are 5 barrier functions in this accident sequence. BF5 is not included in the event tree, it means that BF5 is excluded in the scope of this model. BF2 is divided into three sub barrier functions: Gas detection, Isolation and Depressurizing, in order to limit the size of the fault tree. Following each end event of the event tree there is a simplified consequence model only considering human risk to calculate the expected fatality number of each scenario. The expected fatality number is a product of fatality probability of given scenario and exposed manning.

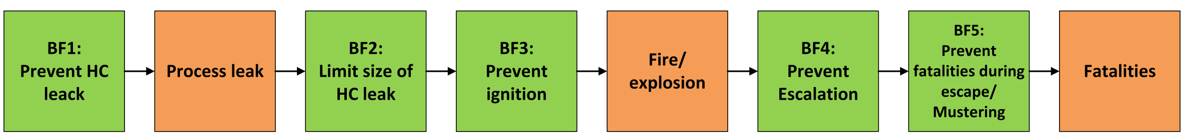

Figure 5.1: Delayed ignition accident sequence used to build event tree in MIRMAP

Each barrier function is a pivot event in the event tree and is developed using fault tree, where detailed fault trees are presented in Appendix B. The top event of these fault trees are the failure of the corresponding barrier function. Basic events of these fault trees are related design failure, technical failure or activity caused of barrier elements. A list of basic event is presented in Appendix B.

Activity caused failure probability is modelled by Influence Diagram (BBN) incorporating human and organizational factors, or using simplified reliability assessment. An example of BBN diagram is shown in Figure 5.3.

To achieve the dynamic and predictive function of the model, The basic events should be updated to the predictive period (e.g. a certain day). An activity usually last for few hours. A work permit usually contains several defined activities and last for 1 day. A work order contains many work permits and the period varies from several days to several months. Many work permits

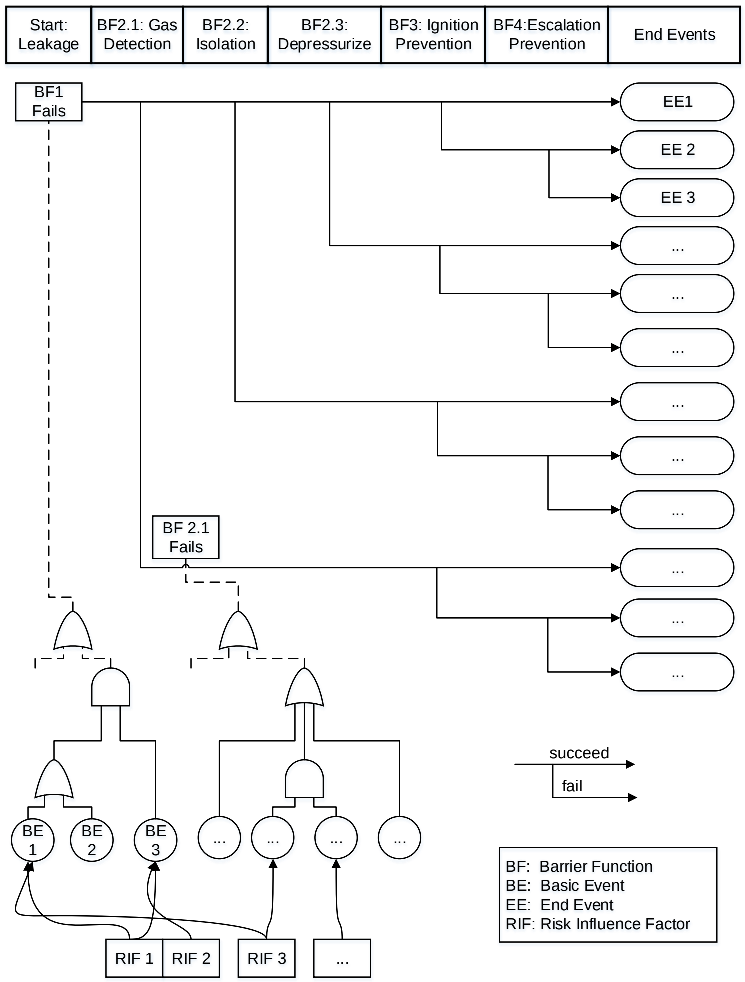

Figure 5.2: Hybrid Casual Model in MIRMAP

including different work orders may have to be executed at the same day.

A hierarchical structure driven by level of details and time of the model with variables is presented in Figure 5.4. Another hierarchy driven force is the spatial size from fire area to analysis area (or plant). An analysis area usually contains many fire area.

The outputs of this model include probability of major accidents per day per fire area with associated uncertainty, potential loss of life per day per fire area with associated uncertainty, PMA and PLL contribution per activity per day and ranks, PMA and PLL contribution per work permit and ranks, PMA and PLL contribution per work order over expected execution period and ranks for fire area and for analysis area, etc.

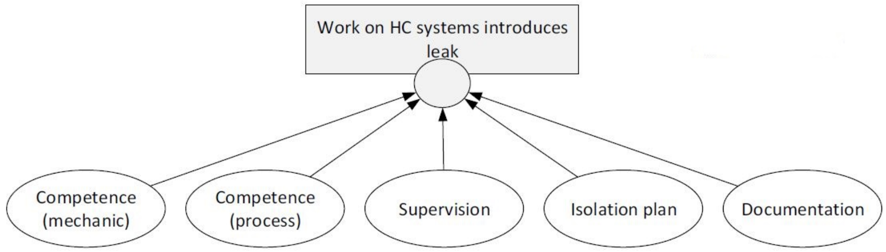

Figure 5.3: Influence diagram (BBN) of activity "work on HC system introduces leak" from MIRMAP method handbook (draft)

5.1.2 Probability as A Degree of Belief

Two levels of probability

In this context, We have two level of probability. Level 1 is the probability of occurrence of a certain event, which basically means chance. Level 1 can be obtained by combining observed data and subjective information. It is a Bayesian's view of probability instead of a Frequentist's view of probability.

As said by Bruno de Finetti in the preface of *The Theory of Probability*, "Probability does not exist". However, observations are real or of potentially real existence.

In this report, these probabilities are interpreted as degree of belief. The probabilities of basic events are estimated subjectively or are combining subjective information and observations. Others are computed according to the causal logic through the fault tree and event tree. Since probability present uncertainty of occurrence, the uncertainty of probability becomes uncertainty of an uncertainty. Critics rightfully ask: "why not uncertainties of uncertainties of uncertainties?", and so on. A doubt concerning the approach can easily arise when trying to perceive such a perspective; however, it will be misleading and it deviates focus from the more important concerns of this topic. The reason is simply that information on the uncertainty of uncertainty becomes extremely difficult to obtain after just one step, and one will easily get lost or loose track of what one is dealing with. *"Uncertainty concerns possible observations. Therefore we can be uncertain about a probability only if this probability can be identified with results of possible observations"*(Bedford and Cooke, 2001). In this understanding, we are uncertain about the chance of occurrence of the defined event, and the uncertainty is presented by probability.

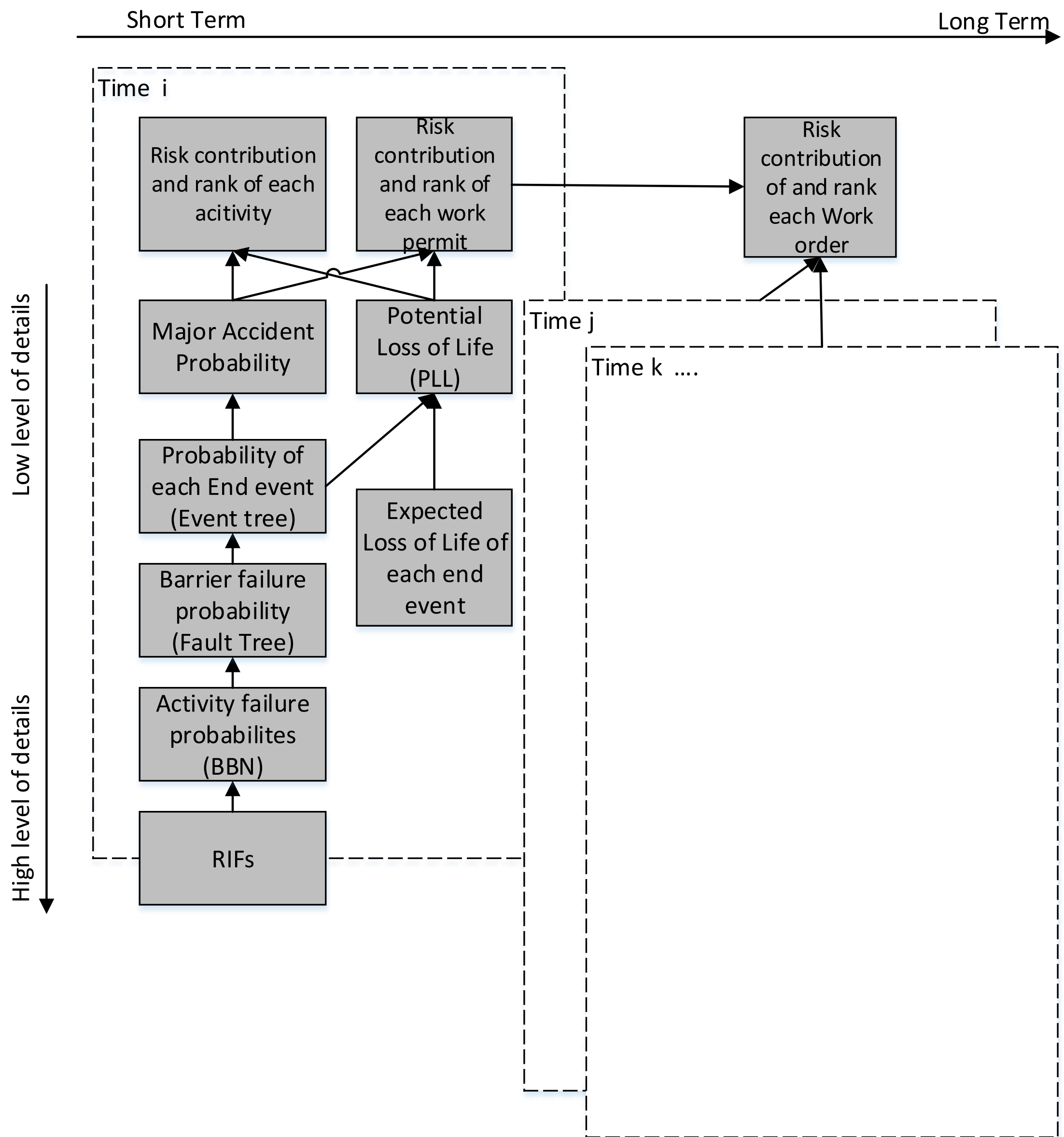

Figure 5.4: Hierarchical structure of the model with variables

The level 2 probability is called uncertainty, or, uncertainty which is represented by probability.

5.1.3 Model Uncertainty Concerns in MIRMAP

There are following concerns regarding model uncertainty in MIRMAP:

1. Approach for uncertainty presentation: qualitative description, semi-qualitative measure, or probability etc.?

2. Model uncertainty sources related: model uncertainty sources from accident model, activity model, logic, excluded risk-increasing factors, common causes, unknown unknowns.

   Effort should be devoted from qualitative description to quantification (if possible) of them.

   It is necessary to make sure whether uncertainty would make a significant impact on decisions, to try to find what uncertainty sources would have the major contribution and to improve our confidence in the model. Uncertainty importance measure might can be used to find out those uncertainty sources that contribute to output uncertainty or risk the most.

3. Model uncertainty characterization

4. Uncertainty integration and propagation

5. Uncertainty visualization

6. How to reduce model uncertainty? For those residual model uncertainty sources which cannot be relieved, then how to cope with it in decision making?

5.2 Model Uncertainty Sources Identification

The proposed method for model uncertainty sources identification described in section 4.5 is used to identify the model uncertainty sources in MIRMAP model.

The method itself is simple as already mentioned, just examine all issues leading to the model uncertainty through the whole model building process. But it requires the analysts have a good knowledge about both the system being modelled and the constructed model. It is better that modellers, process engineers, decision-makers join.

When a model uncertainty source is found, give it a unique identifier, and identify location, closest potential impact, and reasons (why it ends up a model uncertainty source?) at the same time. Location means a detailed description about where it is among the model elements. Model structure might be where most model uncertainty sources locate. It is necessary to document which level (if the model is hierarchical) or which place of the model structure uncertainty sources are located. Closest potential impact means how it is going to influence the model . For example, introduce a new variable, make a approximation of a certain variable, or change the logic. Since any model uncertainty sources will have a final impact on the output (more or less), final impact on the output is not what should be stated in the potential impact here. Instead, the closest potential impact can be identified and is meaningful for the uncertainty sources characterization.

There are two routes for the identification, one is the modelling process, the other is the model structure hierarchies. Since there are three model hierarchy driven force: level of details, time, size. Every hierarchy should be examined.

The identified model uncertainty sources are described and tabulated in Appendix C. Summary of this identification result is presented in this chapter section.

Identified model uncertainty sources in MIRMAP model are mainly in following groups: Limitation and scope of analysis, ignored dependence, ignored sub-barrier system or components, surrogate values are used as model inputs (e.g industrial average values are used for plant specific values), simplification of system and assumption in model structure from event tree to BBN, descritization and approximation in numerical solution.

- *Step 1: problem defining* associated model uncertainty sources are:

  S1.1 The definition of "major accident" which may lead to a ambiguous output value;

  S1.2 To model the instantaneous risk for major accident prevention including activities, only the risk contributors to the occurrence of major accident is included;

  S1.3 Emergency plan and evacuation is not considered;

  S1.4 One fire area is the spatial boundary of analysing, but how large the fire area is not clear defined and there are other options;

S1.5 The validation period of the model is during normal production, instead of process starting or shutdown;

S1.6 Only fire/explosion from delayed ignition is considered.

Some of these model uncertainty sources are related to the scope of analysis and modelling purpose, some of them lead to limitation of the application of this model.

- *Step 2: system controlling factor and mechanism identification* associated model uncertainty sources mainly are those important system characteristic which should be included in the model but ignored because the modellers think they are not important for the quantity of interest. But the total identified ignorance include two groups: those are truly important which will lead to uncertainty in modelled quantity of interest, and those are not truly important which are not model uncertainty sources.

  A list of model uncertainty sources associated with this step is:

  S2.1 Cold vent does not give credit;

  S2.2 Failure of PSD control unit is ignored;

  S2.3 ESD push-button may initiate gas detection and fire detection at the same time. We ignore the the fact the fire detection will be activated;

  S2.4 PSVs are not credited as a mean of preventing escalation;

  S2.5 Depressurisation are not credited to lower the failure probability of escalation of fire to other equipment and segments;

  S2.6 The possibility of a gas leak from one fire area to another is not considered;

  S2.7 Common utility failure is not considered;

  S2.8 Ignored (but known to reduce the number of RIFs and burden of data collection) RIFs in influence diagram (BBN);

  S2.9 RIFs: competence of lifting guider, working environment (lighting, lifting routine etc.), weight of lifting object are not included,etc.

  S2.10 Control Unit of Fire detection, ESD, PSD is reliable, failure of them is not taken into account;

S2.11 Dropped Object may also cause immediate ignition, which means that this part of statistic data should be excluded to calculate average leakage probability due to this activity;

S2.12 ESD signal from center control room is ignored, only field control is taken into account;

S2.13 Ignore the fact that many activities just last for few hours instead of the whole day;

S2.14 (Ignored dependence) Time dependence between sub-barrier systems among the same barrier function is not considered;

S2.15 (Ignored dependence) system dependence among time sequence is ignored when model risk profile and risk contribution from work orders.

In this case the ignorance can be concluded into several groups: 1) Ignored dependence between sub-barrier functions; 2) Ignored uncritical sub-barrier systems or sub-barrier system components for some certain barrier functions; 3) Ignored RIFs in BBN model for activities; 4) Ignored dependence of system among different days; 5) Ignored time dependence between different sub-barrier system in the same barrier function; 6) Ignore the fact that many activities just last for few hours instead of the whole day.

- *Step 3: data evaluation* associated with model uncertainty sources are:

  S3.1 (Surrogate variable is used to calculate average leakage probability from activities) To calculate the average leakage probability from activities, "industrial average value is used as a parameter for the calculation instead of plant specific average value;

  S3.2 (Surrogate variable is used to calculate average ignition(introduce ignition source) probability from activities). To calculate the average ignition probability from activities, "industrial average value is used as a parameter for the calculation instead of plant specific average value;

  S3.3 (Simplification) Default value of fatality probability is used;

  S3.4 (Simplification) Default value of fatality probability is relevant to fire size (usually related to leakage size);

S3.5 PSV/PSD (Process safety valve/Process Shutdown) demand is a dynamic process feature, in this model, but a average constant value is used in the model instead.

These issues are all relevant to the parameter settings for resources saving. Industrial average values plant specific features; Default values are used for event specific features; Static value is used for dynamic feature.

- *Step 4: model construction* associated

  There are 41 identified model uncertainty sources which are associated with the model construction. The identification work was done according to the hierarchy following the hierarchy driven direction (from event tree to BBN, from short term to long term, from fire area to analysis area). Model uncertainty sources are located at different place of the model. Since the MIRMAP model is a hierarchical model, the output of lower level (submodels) is the input of the upper level, the closest potential impact of the model uncertainty source in lower level is the resultant uncertainty of input variable in upper level.

  Examples of model uncertainty sources are:

  S4.3 (Event Tree)(Simplification) Failure influence of barrier function due to the event development variability is presented by introducing a basic event. This basic event is a thought of failure probability of barrier function even the hardware barrier function success.

  S4.5 (Consequence Model)(Simplification) Exposed Number of People for uncontrolled fire /explosion is estimated as 2/4 times of people within the area.

  S4.7 (BF2.1)(Assumption) Leakage can be manually detected as long as there is operator in area.

  S4.16 (BF3)(Simplification) Gas cloud formulation simplified as part of failure of dispersing gas function (intermediate event) .

  S4.33 (BBN) Assumption 1 for conditional probability elicitation(If BBN is used): The longer distance between parent node state and child node state, the less probable that the child node will stay at that state for the given parent node state.

  S4.40 (Assumption) There is no HC from neighbouring fire area that would provide fuel.

S4.41 Knockout drum is shared by several area, the activity on knockout drum is a common cause failure, but not well explained in this model.

- *Step 5: numerical solution* associated model uncertainty sources are:

  S5.1 (approximation) The failure probability of top event is calculated using approximation formula not accurate computation: using Upper Bound Approximation (based on the fault tree's minimal cut sets;

  S5.2 Discretization of failure probability of basic event type A;

  S5.3 Ignored parameter uncertainty of basic event type B and type C;

  S5.4 Discretization of RIFs which have a continuous property.

5.3 Application of the Identification Information

The identification information can be used for further model uncertainty characterization. It can contribute to following further work:

1. Screen important model uncertainty sources. Not every model uncertainty source has critical contribution to the model output or would influence the decision. The importance of model uncertainty sources is eventually depended on how much it will influence the model output. The influence can be evaluated from two criteria: the importance of the location (or closest impacted variable) of model uncertainty sources for the model output and the how great the model uncertainty source will change location (or closest impacted variable). If the location is not important for the model output, then the importance of this model uncertainty source will obviously be decreased. Screen important model uncertainty sources will help to allocate the resources of model uncertainty reduction and also give input information to decision making.

2. Refine the model where possible which can reduce model uncertainty and uncertainty of model output. Location and reason of each model uncertainty source is described. It helps to screen what can be reduced and what cannot. And what effort should be devoted

for future development. As said by Devooght (1998), the choice of a predictive model is a decision tied to a loss function and a cost of using the model.

3. Look for characterization method for each model uncertainty source, since the location and closest potential impact are described for each model uncertainty source where possible.

4. Model uncertainty quantification and propagation. Even though the accident especially major accident is one-time experiment. And the risk model almost cannot be validated by observations or experiment data. But many model uncertainty are located at a very lower level of the hierarchical model (e.g. BBN, and fault tree). Observations of these lower levels (or called sub-models) have the chance being available. This can help the quantification of the low level located model uncertainty sources. For model uncertainty propagation, as can be seen that MIRMAP model is a hierarchical model and output from lower level is the input of upper level, then the impact of each model uncertainty source which is located at lower level can be treated as parameter uncertainty of upper level. In this way, model uncertainty can be transferred to parameter uncertainty and propagated combining original parameter uncertainty to the final model output.

5. Understand the limitation of model application;

6. Understand the possible discrepancy of model output with real observation due to limited scope of modelling (e.g.predicted PLL value and observed PLL value if a major accident happens).

Chapter 6

Summary and Recommendations for Further Work

This chapter will first sum up the work done in this thesis, before presenting the concluding result. This is then followed by a discussion of the findings and limitations of this thesis work. The last part is recommendations for future work on model uncertainty analysis.

6.1 Summary and Conclusions

A model is a simplified representation of the real world. Model uncertainty is a common issue in predictive models, discussions can be found in many subjects. Model uncertainty is a branch of uncertainty analysis, but in reality uncertainty analysis mainly focuses on parameter uncertainty. To meet the objective of analysing model uncertainty in operational risk analysis, where MIRMAP is the background project of this topic, the following has been done in this thesis:

First, an overview of uncertainty is established by reviewing different definitions of uncertainty in various applications, three dimensions, classifications, representations of uncertainty and relations between uncertainty and risk for decision making. Definitions of uncertainty and model uncertainty which apply in this thesis are given to avoid ambiguity and limit topic range. This part of work is described in chapter 2. Then, a general and systematic modelling process is described to see how model uncertainty can be analyzed using a systematic model development process as a starting point. Proposed probabilistic models and relevant modelling techniques, and modelling process for operational risk analysis are described in chapter 3. This part contributes to form the main concept of analysing model uncertainty in this thesis. Afterwards, in chapter 4, methods to deal with model uncertainty are identified and described by reviewing relevant application fields, including probabilistic risk analysis used in the Nuclear Power Sector, Environmental modelling, and Computational Modelling and Simulation. Methods about model uncertainty resources identification, characterization and analytical treatment, and model uncertainty reduction are simply summarised. Besides, A method for model uncertainty sources identification is proposed at the end of Chapter 4. A fish bone diagram showing model uncertainty sources which might occur at each modelling step is presented. This method is based on the systematic modelling process described in Chapter 3. Resultantly chapter 5 is about applying methods of model uncertainty analysis in the MIRMAP model. A proposed method for model uncertainty identification is applied to identify model uncertainty sources in the MIRMAP model. Further applications of the identification information are also described.

Main conclusions are made at the conceptual, methodological and application levels:

- **At conceptual level**

  There are different understandings and definitions regarding uncertainty and model uncertainty in various fields. Own definitions of these terms must be clearly stated and meaningful for the problem at hand.

  "Model Uncertainty" is sometimes also used about "Model Output Uncertainty" which in some published works is an integrated result from all kinds of uncertainty. Conceptual uncertainty, model error, model structure uncertainty, modelling uncertainty are used in some papers. Being cautious is necessary when dealing with these terms. A uniformation of these terms can improve scientific communication and the application of outcomes.

- **At methodological level**

  There are different characterization methods for model uncertainty. The methods have been divided into three groups in this thesis; "Input-Driven", "Output-Driven", and Hybrid. "Input-driven" methods provide a better understanding of the impact of identified model uncertainty sources. They are mainly qualitative methods. "Output-driven" methods provide a "closer" result to "truth" of the model outputs.

Model uncertainty analysis from a systematic model development process is a practical concept since the formulation of model uncertainty is mainly relevant during model development.

Model uncertainty can also be reduced by applying a standardized modelling process and a sound and holistic model validation procedure.

The proposed method for model uncertainty sources identification is a systematic, easy and applicable method and it is verified by application in MIRMAP model. It is a modelling process-based approach. Model uncertainty sources can be identified by going through the standardized modelling process from problem defining to validation and model hierarchies (if the model is a hierarchical model). This approach also locates model uncertainty sources at the model elements and structure. This information can further be used in model uncertainty source impact assessment, uncertainty integration and propagation. Causes of model uncertainty issue also identified, which can contribute to model refining. It is very suitable for big and hierarchical models and further improvement can be made.

- **At application level regarding MIRMAP**

  Identified model uncertainty sources in MIRMAP model are mainly in following groups: Limitation and scope of analysis, ignored dependence, ignored sub-barrier system or components, surrogate values are used as model inputs (e.g industrial average values are used for plant specific values), simplification of system and assumption in model structure from event tree to BBN, descritization and approximation in numerical solution.

  Different model uncertainty sources have varied-degree impact on the model outputs. Characterization methods for these model uncertainty sources should vary according to the importance, location and cause of these model uncertainty sources.

6.2 Discussion

Uncertainty is defined as a "state-of-art" variation of the quantity of interest, stemming from both aleatory and epistemic property, in the context of this thesis. Whether this definition stands was not systematically examined. Argument should be made regarding this definition.

Scenario uncertainty in exposure assessment is excluded in the scope of model uncertainty in this thesis since it is treated as an application issue. This can be reviewed.

Regarding the application of the proposed method of model uncertainty identification, there might be that some model uncertainty sources are ignored or unidentified, due to the limitation of experience and knowledge of the analyst.

"Unknown unknowns" cannot be identified by the proposed method. The identification of "unknown unknowns" may mainly rely on the development of techniques, collection of data, and by increasing information about the system and accident occurrence.

The identified sources of model uncertainty in MIRMAP are of generic nature, i.e. not for a specific plant or area. As a consequence, other model uncertainty sources may come up for a specified plant, or area, due to its distinct properties. Such a part of model uncertainty sources should be examined and characterized before application of model in decision support.

Only the model uncertainty resources identification phase is conducted, regarding the model uncertainty analysis in MIRMAP, due to the time limitation. Further model uncertainty sources screening, characterization and model uncertainty reduction need to be done later.

6.3 Recommendations for Further Work

The recommendations for future work are classified into conceptual level, methodological level and application level:

- **At conceptual level**

  1) Establish operational definitions about uncertainty and model uncertainty.

  2) Compare uncertainty representation approaches according to their availability, applicability and limitations etc.

  3) Analyse how uncertainty should be used in decision-making?

- **At methodological level**

  1) Develop systematic uncertainty analysis approach which can provide comprehensive understanding and support for decision makers. 2) Compare of qualitative uncertainty analysis and quantitative uncertainty analysis.

  3) A further comparison of these methods according to their application fields, resource requirements etc. would be very beneficial and valuable. 4) Develop method for identification, description, prediction of the effects of model uncertainty on the analysis outputs.

  5) Integrate those significant sources of model uncertainty into probabilistic modelling exercise.

  6) How to quantify model uncertainty sources if no field data are available.

  7) How to reduce model uncertainty?

  8) Develop method to identify the relative magnitudes of the uncertainties associated with data and model formulation. Such a comparison is useful in focusing resources where it is most appropriate (e.g., filling data gaps versus refining a model).

  9) Develop method to assess the magnitude of the different sources of uncertainty while different representation approaches are used. For example, if qualitative representation is used for model uncertainty, while quantitative representation is used for parameter uncertainty, how can we compare them?

  10) Establish method to quantify and balance the uncertainty trade-off between parameter uncertainty (input) and model structure uncertainty (complexity of model) to get an optimal model.

  11) Establish practical and systematical procedure to build comprehensive hierarchical models for the systematic evaluation of the simplified models.

  12) Improve the current methods for model uncertainty treatment to make them credible and universally accepted.

  13) If the model contains sub-models at different level, then how integrate model uncertainty from different levels (parts) of model to the overall output?

14) It is a challenge to use various subjective information and experimental data (with different credibility and applicability) to assess the uncertainty about the internal models' performance (sub-models and correlations).

15) How to account for model uncertainty from "unknown unknowns"?

- **At application level regarding MIRMAP**

1) Involve more experienced modellers, stakeholders, and process engineering to review identified model uncertainty sources.

2) Screen important model uncertainty sources.

3) Refine the model where possible which can reduce model uncertainty and uncertainty of model output.

4) Look for characterization method for each model uncertainty source.

5) Model uncertainty quantification and propagation at lower level of the hierarchical model(e.g. BBN, and fault tree).

6) Investigate how model uncertainty information can be used in ranking work orders?

7) Compare different uncertainty representation method to see which is the best for model uncertainty representation.

Appendix A

Acronyms

BBN Bayesian Belief Network

BF Barrier Function

ESD Emergency Shutdown

FTA Fault tree analysis

MIRMAP "Modelling Instantaneous Risk for Major Accident Prevention" Project

QRA Quantitative risk assessment

PRA Probabilistic Risk Analysis

PSA Probabilistic Safety Analysis

IPCC Intergovernmental Panel on Climate Change

PMA Probability of Major Accident according to defined "Major Accident" in MIRMAP

PLL Potential Loss of Life

PSD Process Shutdown

RIF Risk Influence Factor

Appendix B

MIRMAP Model Information

This is an example of an Appendix. You can write an Appendix in the same way as a chapter, with sections, subsections, and so on.

B.1 MIRMAP generic model construction framework

Figure B.1 illustrates the MIRMAP generic model construction, this corresponds step 4: Model construction in the systematic model developing process.

Figure B.1: MIRMAP generic model construction framework

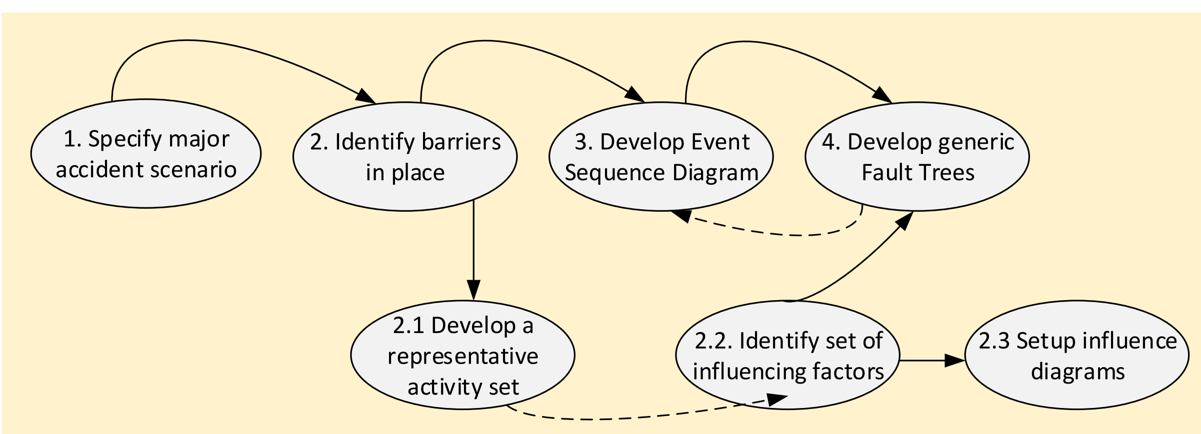

Table B.1: Modelled Barrier Functions in the MIRMAP generic model

Barrier Function	Barrier sub-function	Barrier System
BF1: Prevent Leakage	Containment (design)	Limit number of leakage points
		External protection from falling loads
		Technical integrity
	Process safety	Process shutdown Pressure relief protection
		Correct operation and maintenance
BF2: Control/ Stop Leakage	Detect Leak	Gas detection
		Inspections
	Isolate process	Process shutdown
		Emergency shutdown
	Depressurize process	Flare and blowdown Cold venting
BF3: Prevent Ignition	Control of ignition sources	Ignition source isolation
		Area/zone classification
		Hot surface temperature control
	Control of ongoing work (external ignition sources)	Hot work control
		Excavation control
		Blasting control
		Car Traffic control
	Prevent gas cloud build up	Ventilation
BF4: Prevent Escalation	Detect fire	Fire detection
	Fire fighting	Active fire protection
		Passive fire protection
	Prevent fire spreading	Fire wall
		HVAC (fire dampers)
	Control fire duration	Open drain
		HVAC (ventilation)

B.2 List of Barrier Functions in MIRMAP Generic Model

A barrier function (BF) is the task or the role of a barrier – specified generally. On the other hand, barrier system and elements refer to the concrete technical, operational or organizational measures which together help realize a particular barrier function. “Barrier Functions” provide protect against uncontrolled progression of the event sequence. Each of the barrier functions are further broken down into subfunctions and their relevant barrier systems, see Table B.1

B.3 Fault Trees in MIRMAP Generic Model

Information about Fault Trees is shown by following figures:

Figure B.2 is the Fault Tree of leakage prevention

Figure B.3 is the Fault Tree of gas detection

Figure B.5 is the Fault Tree of leakage prevention and isolation. Detail isolation Fault Tree is shown in Figure B.4.

Figure B.6 is the Fault Tree of depressurizing

Figure B.7 is the Fault Tree of ignition prevention (A)

Figure B.8 is the Fault Tree of ignition prevention (B)

Figure B.9 is the Fault Tree of ignition prevention (C)

Figure B.10 is the Fault Tree of ignition prevention (D)

Figure B.15 is the Fault Tree of heat load reduction through extinguishing fire. This top event of this Fault Tree is the intermediate event in Fault Trees for escalation.

Figure B.16 is the Fault Tree of ignition(A) and escalation (A). Detail Fault Tree of escalation(A) is shown in Figure B.11 .

Figure B.17 is the Fault Tree of ignition(B) and escalation (B). Detail Fault Tree of escalation(B) is shown in Figure B.12 .

Figure B.18 is the Fault Tree of ignition(C) and escalation (C). Detail Fault Tree of escalation(C) is shown in Figure B.13 .

Figure B.19 is the Fault Tree of ignition(D) and escalation (D). Detail Fault Tree of escalation(D) is shown in Figure B.14

B.4 List of defined representative activity set in MIRMAP Generic Model

In daily operations, barrier impairments either exist alongside ongoing work, are caused as a part of the work or represents the work itself. presents a complete representative activity set for the barrier functions. These activities either:

I. Represents the introduction of a hazard which can compromise the successful functioning of a barrier function, or

II. Directly weaken/ impair a barrier system or element.

Table B.2, B.3, B.4 show representative activity set for an oil and gas facility.

B.5 RIFs and Their Importance for Each Defined Activity

Figure B.20, Figure B.21 are modelled RIFs and example importance for each defined activity. These RIFs for each activity are modelled by influence diagram (BBN) in a similar way as showed in Figure 5.3. In the table, for each activity, only RIFs with corresponding numbers (1, or 3, or 5) are considered in the BBN model. There are three scales of importance:High, Medium, Low. In the table, 5 means "High", 3 means "Medium", 1 means "Low".

Table B.2: Representative Type A1 activity set for an oil and gas facility

Ref.	Type A1 - Activities that represent a hazard/ involve the introduction of a hazard		BF1	BF2	BF3	BF4
1	Work on hydrocarbon equipment - isolation	Involves leak test isolation, purging, bleeding, verification, approval and cross check for zero-energy.	X			
2	Work on hydrocarbon equipment - execution	Involves the actual work on the HC segment, installation of bolts, flanges and respective verification.	X			
3	Work on hydrocarbon equipment - reinstatement	Involves inert gas test, leak test, isolation removal and final reinstatement of the HC process	X			
4	Work on hydrocarbon equipment – normal operations	Relates to generic work on HC systems. Can directly result in a breach of containment or introduce a latent error during the work activity. E.g. Washing of tank, routine maintenance on pumps etc.	X			
5	Critical lifts	Large lifts may damage the structural integrity of the platform or equipment through either falling or swinging loads.	X			
6	Hot Work – Class A	Hot work class A includes work with equipment and tools that constitute an effective ignition source and which, during normal usage, can ignite an explosive atmosphere and/or solid substances or liquids			X	
7	Hot Work – Class B	Hot work class B includes work that constitutes a potential ignition source and which is not defined as hot work class A.			X	
8	Excavation	Potential external ignition source.			X	
9	Blasting	Potential external ignition source.			X	
10	Car Traffic	Potential external ignition source.			X	
11	Static electric sparks released from normal activities	Activities such as fuelling, filling of tanks, vessels etc., and the use of high velocity fluids (sprays or jets), shot blasting, steam cleaning etc. can introduce static electricity sparks which can prove as a potential source of ignition.			X	
12	Temporary electrical equipment in the area	Temporary elec. equipment may introduce a potential ignition source. They must be approved for use in a particular zone and shutdown philosophies ascertained.			X	
13	Other temporary equipment in area (location etc., e.g. scaffolding)	Arrangement of equipment (in this case scaffolding) in an area, especially near ventilation openings can have a major influence on peak overpressures expected in an area. Equipment must be located so as to not increase turbulence, block explosion ventilation openings and thereby increase explosion loads. Further, scaffolding can also block line detectors and represent an increased explosion load in the area.			X	X

Table B.3: Representative Type A2 activity set for an oil and gas facility

Ref.	Type A2 – Activities that represent a deviation/ impairment in a barrier element/system (i.e. work related to…)		BF1	BF2	BF3	BF4
1	Process Shutdown (PSD) – (transmitters, control logic, IO-cards)	Process shutdown valves stop the process and are located as close to the HC vessel as possible so as to limit the number of leak points.	X			
2	Process Shutdown (PSD) – (valves)	As above.	X	X		
3	Pressure Safety Valve (PSV)	Pressure safety valves provide pressure release capability for critical process vessels/ equipment.	X			
4	Fire and gas (F&G) – (control logic, IO-cards)	Fire detection detects fire by type (jet, flame, heat, smoke etc.) and initiates suitable control actions through the control system. Gas detection monitors for the presence of flammable gas, alerts personnel and ensures auto/manual action to prevent additional release, fire and explosion.		X		X
5	Gas Detectors	As above.		X		
6	Emergency Shutdown (ESD) – (pushbuttons, control logic, IO-card, valves)	ESD valves isolate and sectionalize the process in a fast and reliable manner to limit the amount of HC released during a leakage.		X		
7	Flare system	This includes the flare and flare lines (either for hot venting or cold venting of HC). Both are performed to prevent ignition and creation of unacceptable gas clouds). It also includes the knock out drums (for storage of excess HC).		X		
8	Knock-out drum	As above.		X		
9	Depressurization – (pushbuttons, control logic, IO-cards, valves)	Blowdown is used to reduce pressure in process segments and thereby the risk of rupture and escalation. I.e. reduce the leak rate, avoid leakage during a process upset and route gases from vent lines safely.		X		
10	Ignition source control – (pushbuttons, control logic, IO-cards, circuit breakers)	Ignition source isolation ensures fast and proper isolation/shut down of all electrical equipment		X		
12	Ventilation and related HVAC systems	Ventilation serves the purpose of diluting gas concentration, reducing the size of flammable gas clouds and preventing the ingress of smoke and gas etc.			X	

Continue

Table B.4: Representative Type A2 activity set for an oil and gas facility

Ref.	Type A2 – Activities that represent a deviation/ impairment in a barrier element/system (i.e. work related to...)		BF1	BF2	BF3	BF4
13	Open Drain	Control of spills is achieved through the open drain system. It is a1 measure for containment and disposal of excess FW - limits the spread of a spill and routes it away to avoid escalation.			X	
14	Fire Detectors (including manual call points)	As in Item 4.				X
16	Passive fire protection (PFP)	PFP ensures that relevant structures and equipment have adequate fire resistance, integrity and insulation properties. Removal of PFP hampers these properties and requires additional fire water in the case of an ignited leak.				X
17	Fire water system – (Pumps, Fire water main etc.)	FW supply system supplies FW to the various parts of the facility. It must have appropriate capacity.				X
18	Fire water – (deluge, water mist, other release mech.)	These include automatic fire fighting release mechanisms such as deluge, water canons, sprinklers, water mist release systems etc.				X
19	Fire water – (hydrants, water canons)	These include all manual or semi-automatic firefighting equipment.				X
20	Fire doors	Doors or compartments with fire resistance ratings to reduce the spread of fire or smoke between areas and to enable safe egress from an area.				X
21	Explosion walls	Explosion walls disengage from a structure on explosion. This reduces the impact of an explosion by relieving internal pressure and thereby limiting risk of structure collapse and further loss of life.				X
22	Fire dampers – (control logic, IO-card etc.)	As in Item 12.				X

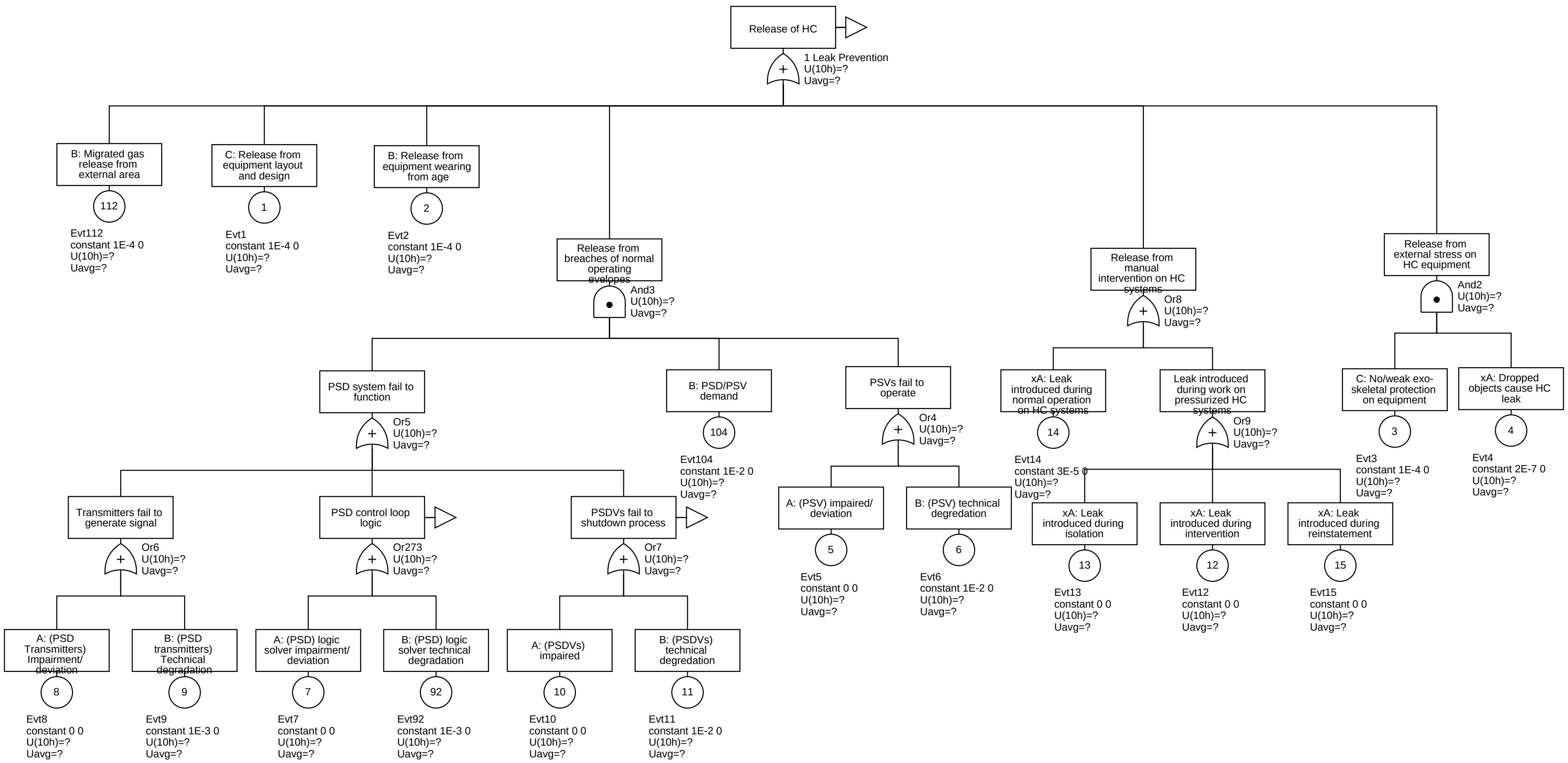

Figure B.2: Leakage Prevention

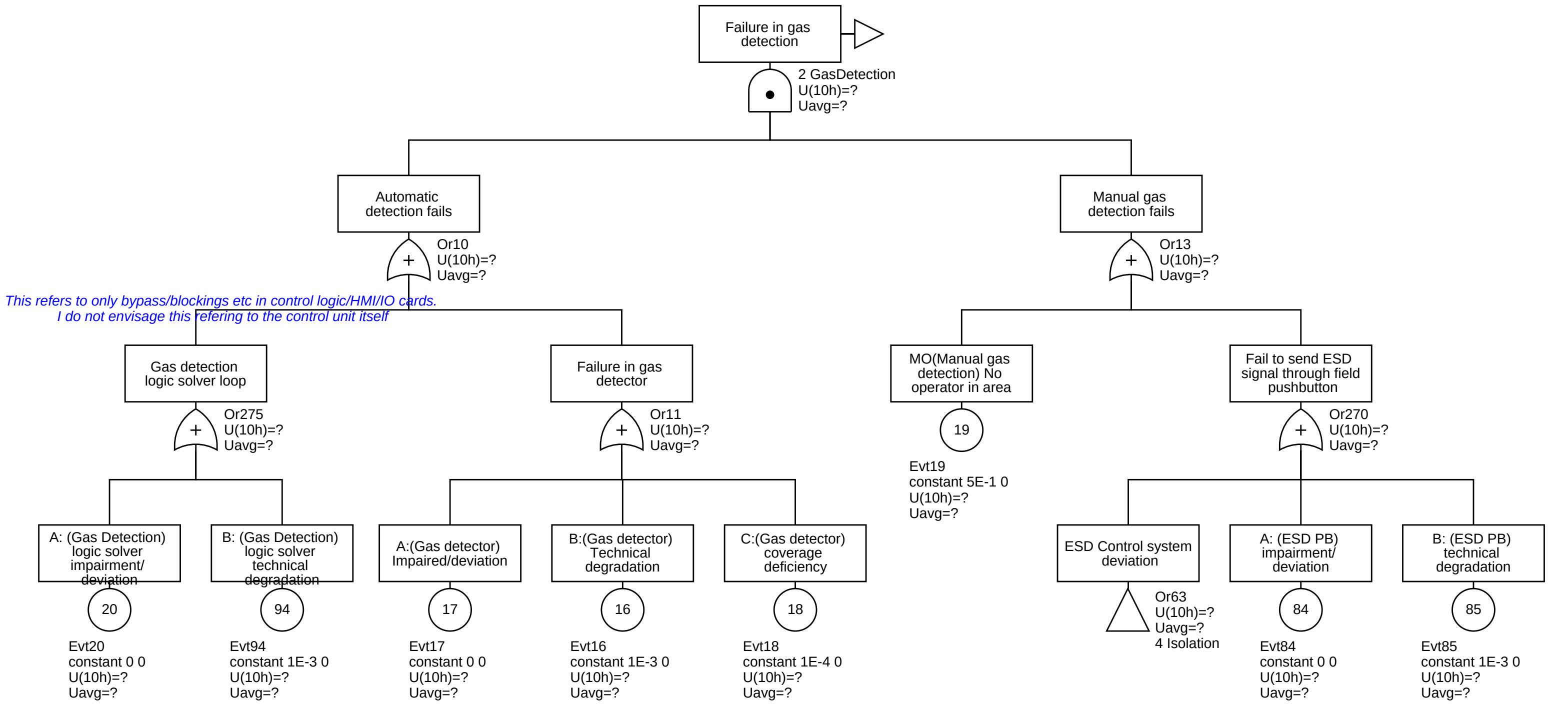

Figure B.3: Gas Detection

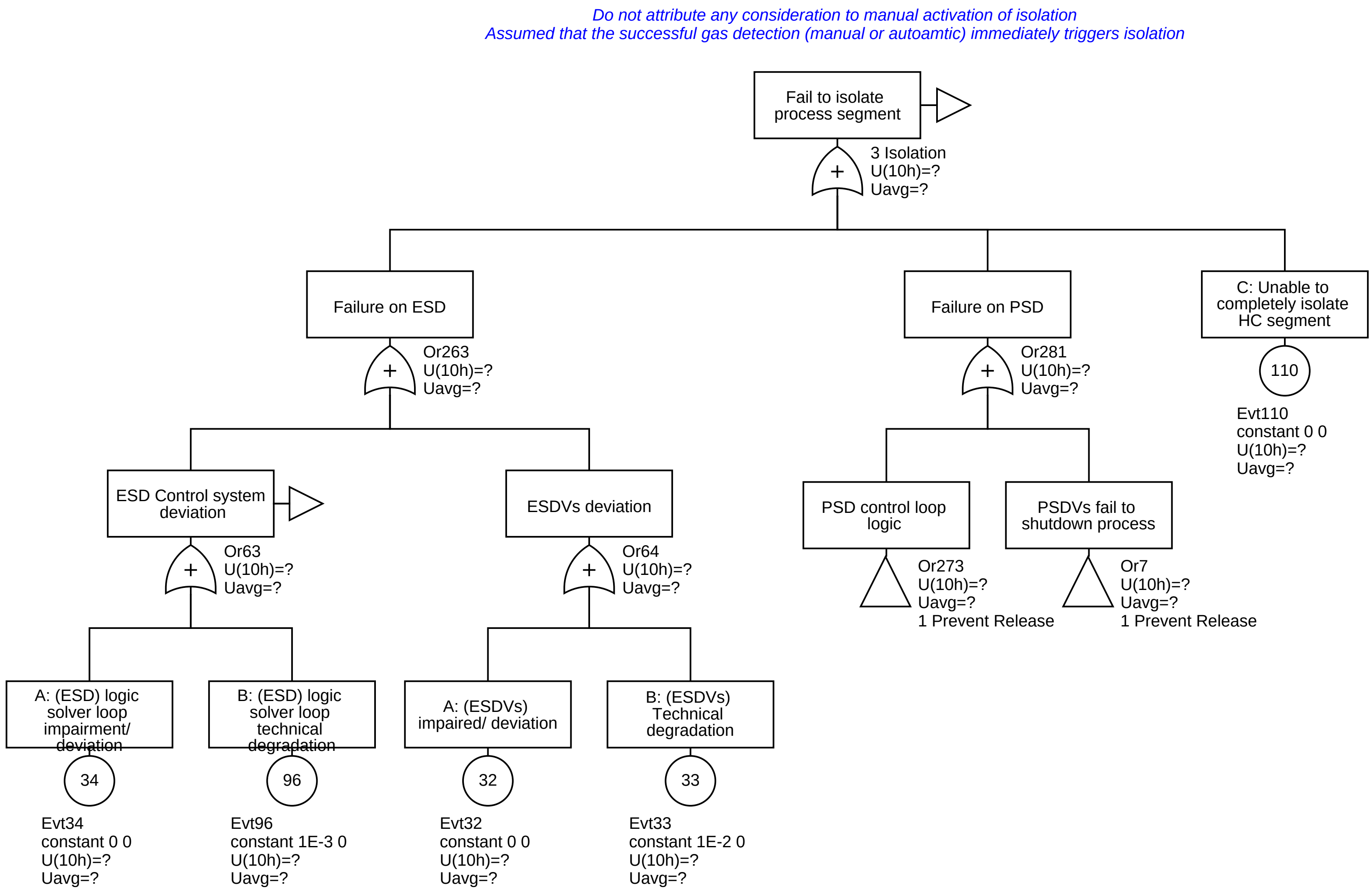

Figure B.4: Isolation

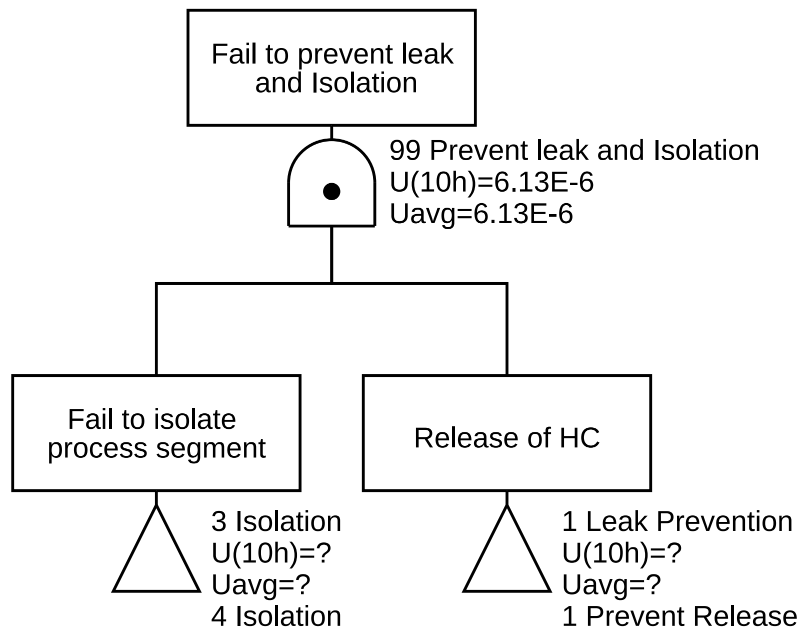

Figure B.5: Leakage Prevention and Isolation

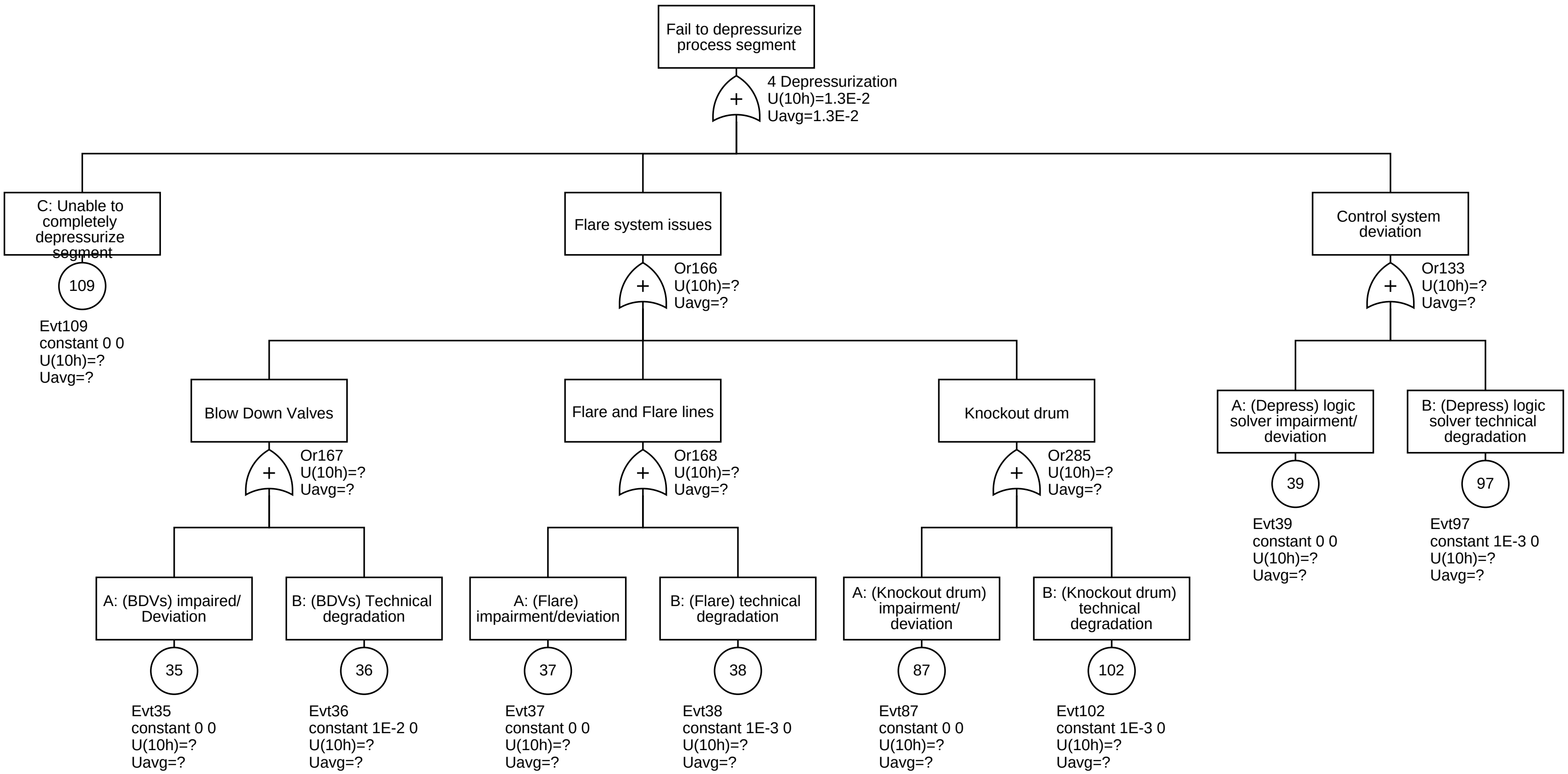

Figure B.6: Depressurizing

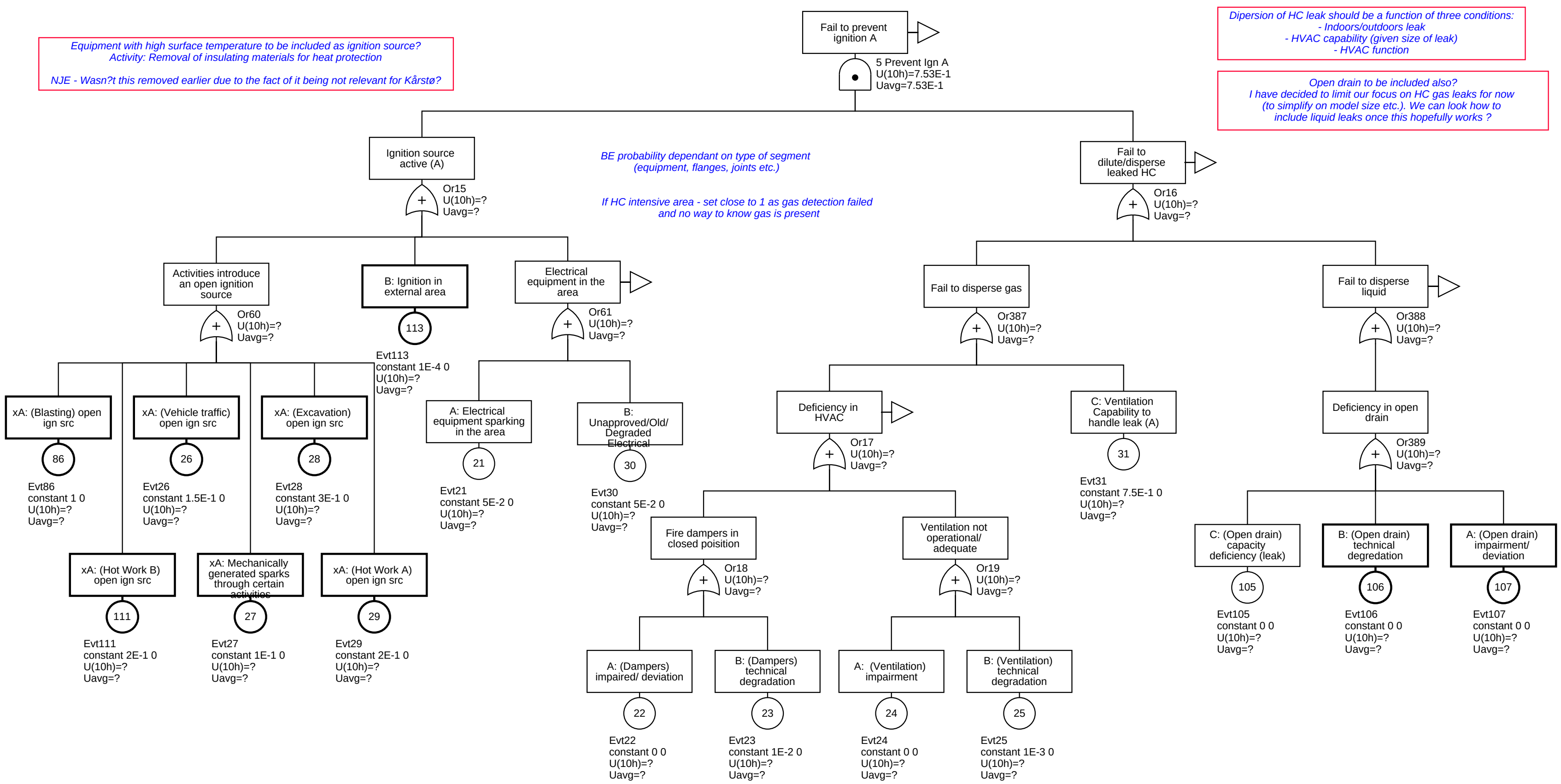

Figure B.7: Ignition Prevention (A)

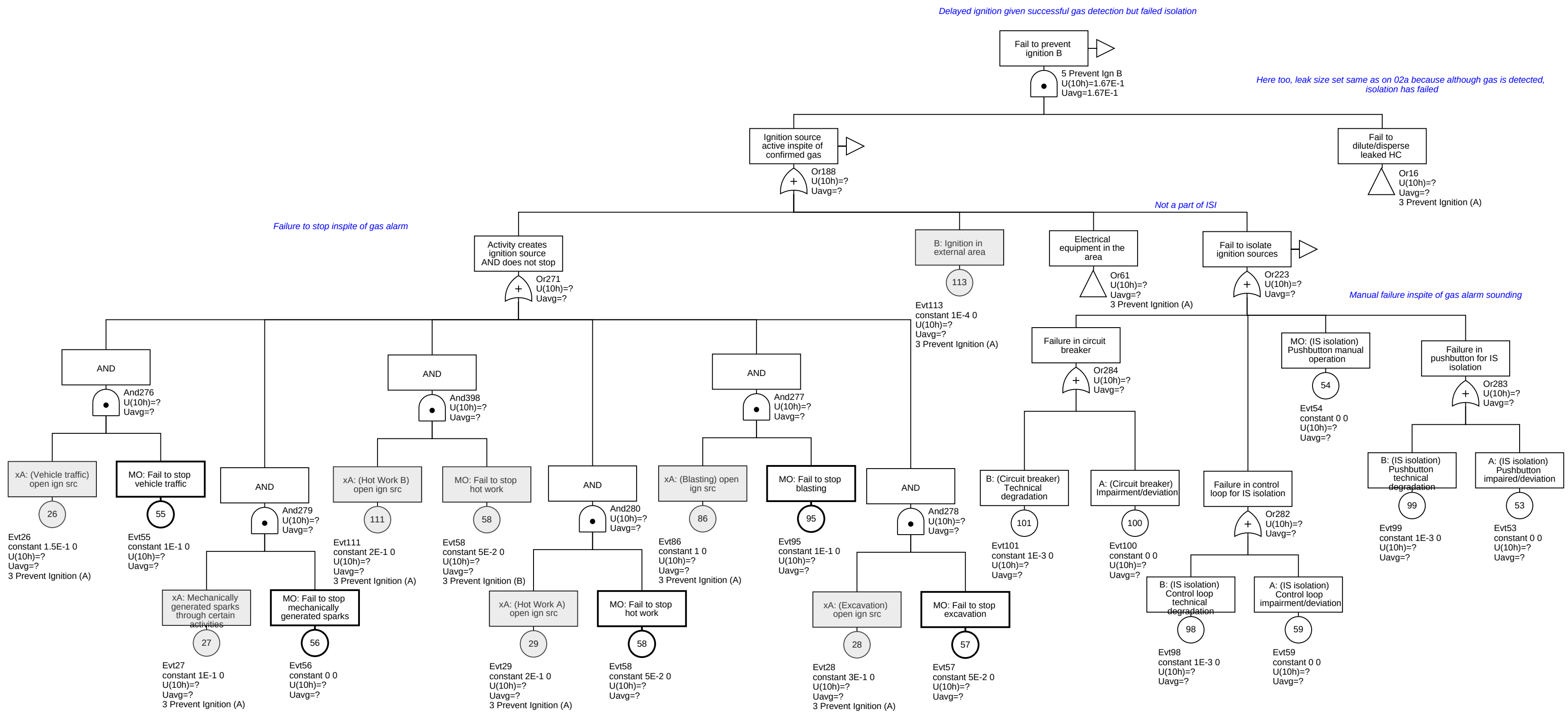

Figure B.8: Ignition Prevention (B)

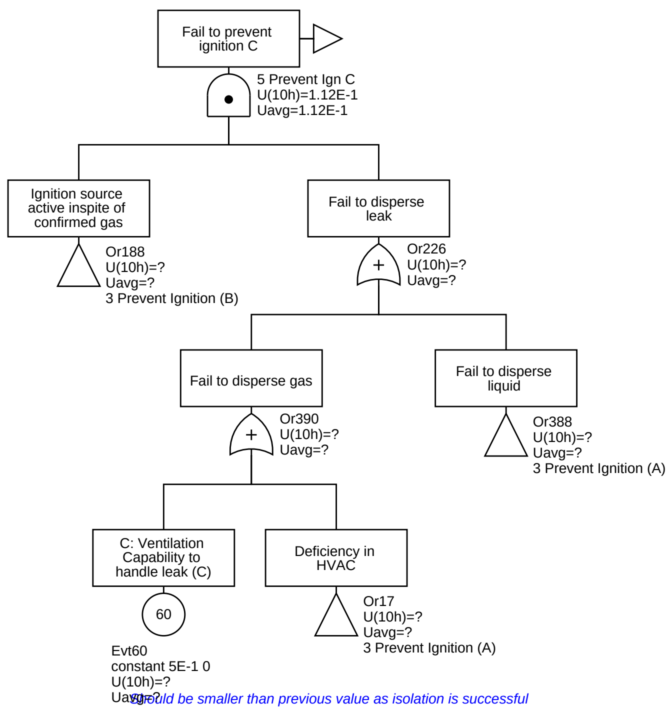

Figure B.9: Ignition Prevention (C)

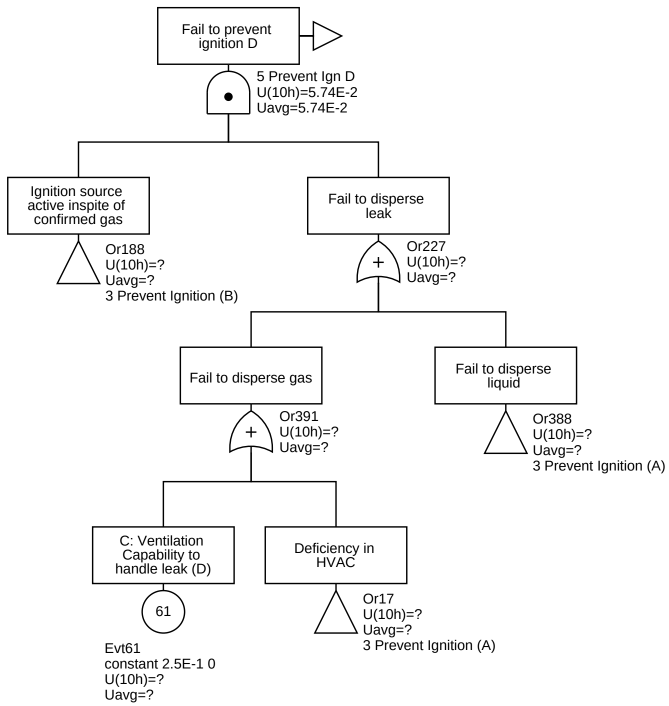

Figure B.10: Ignition Prevention (D)

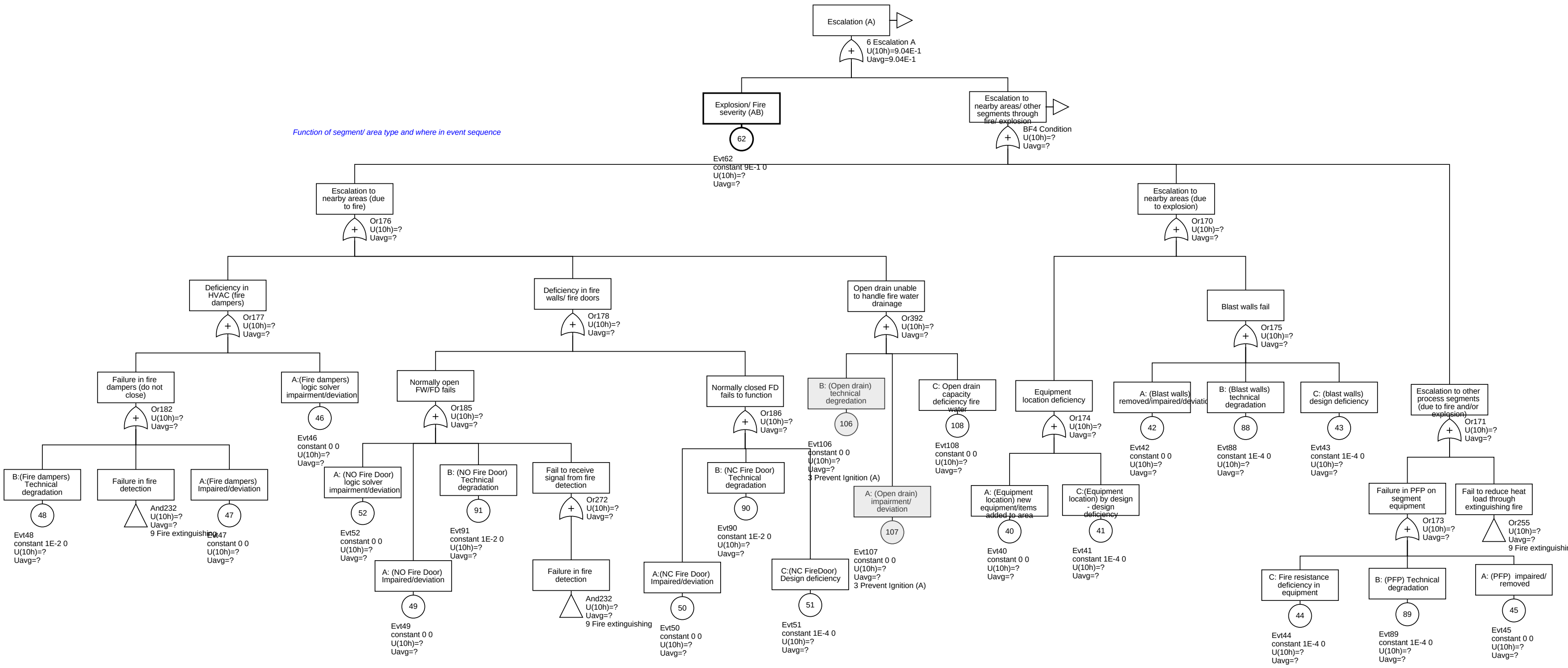

Figure B.11: Escalation(A)

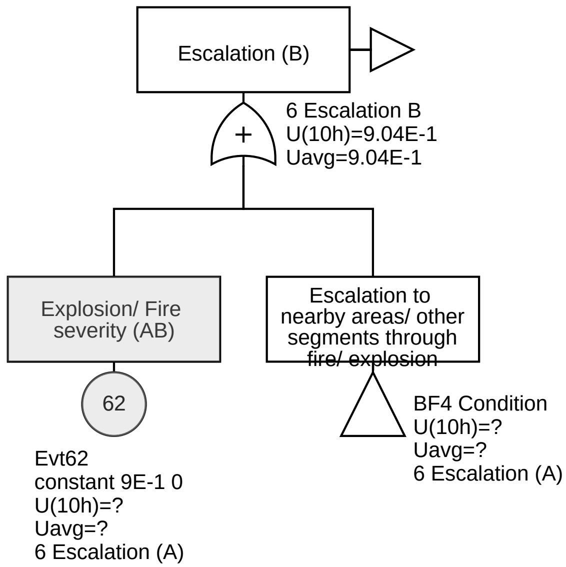

Figure B.12: Escalation(B)

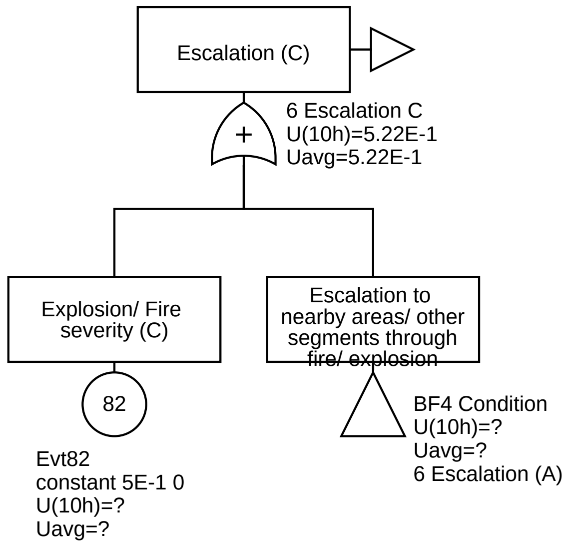

Figure B.13: Escalation(C)

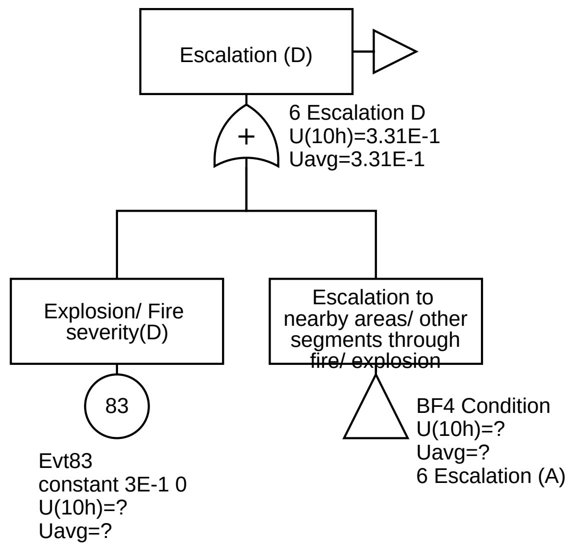

Figure B.14: Escalation(D)

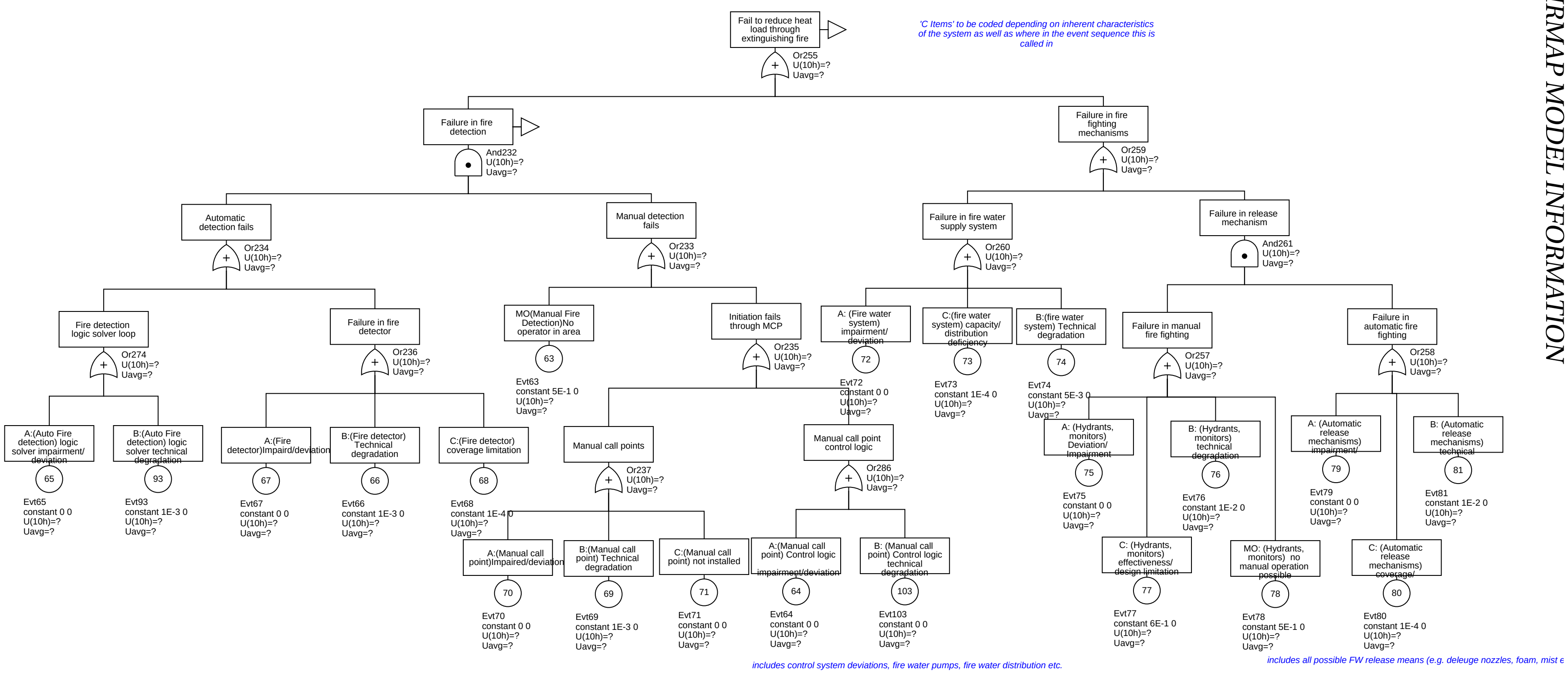

Figure B.15: Heat load reduction through extinguishing fire

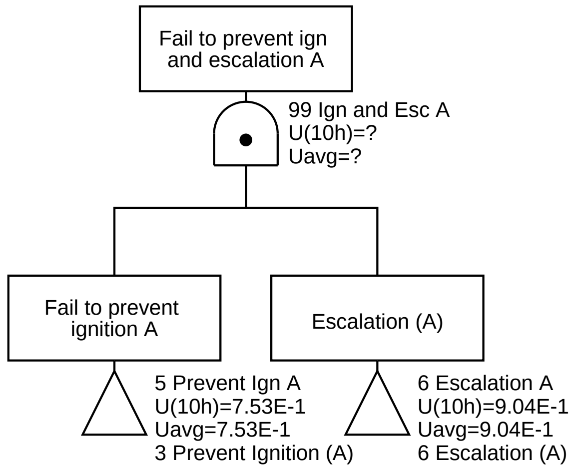

Figure B.16: Ignition(A) and Escalation (A)

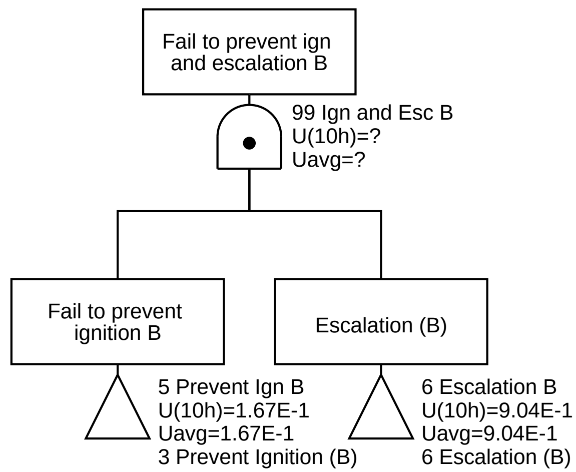

Figure B.17: Ignition(B) and Escalation (B)

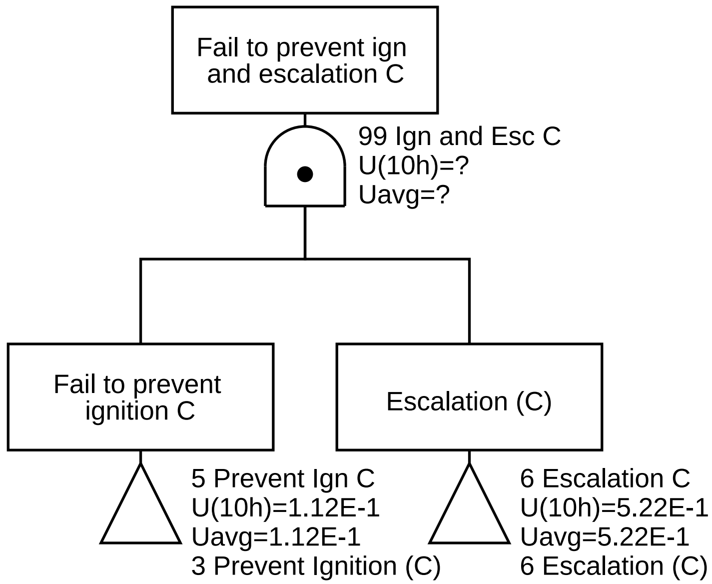

Figure B.18: Ignition(C) and Escalation (C)

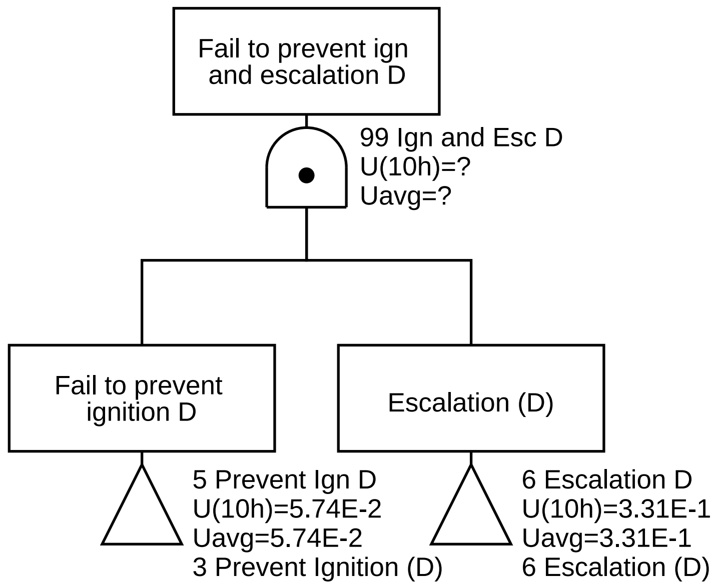

Figure B.19: Ignition(D) and Escalation (D)

Figure B.20: RIFs and their importance for each defined activity

Activity ID	Activities	RIFs and their importance measure															
		Competence (mechanic)	Competence (process)	Time pressure	Design/HMI	Documentation	Supervision	Isloation plan (yes/no)	HC system (yes/no)	Type of equipment	Compensatory measures	Wind conditions	Lifting equipment	Competence (crane operator)	Compensatory measure	Degree of impairment	Redundancy (yes/no)
Evt4	xA: Dropped objects cause HC leak			3			1					3	5	3			
Evt5	A: (PSV) impaired/ deviation														3	3	3
Evt7	A: (PSD) logic solver impairment/ deviation														3	3	3
Evt8	A: (PSD Transmitters) Impairment/ deviation														3	3	3
Evt10	A: (PSDVs) impaired														3	3	3
Evt12	xA: Leak introduced during intervention	5			3		3										
Evt13	xA: Leak introduced during isolation		3				5	5									
Evt14	xA: Leak introduced during normal operation on HC systems		5	3	1	3											
Evt15	xA: Leak introduced during reinstatement		3	3			5	5									
Evt17	A:(Gas detector) Impaired/deviation														3		
Evt20	A: (Gas Detection) logic solver impairment/ deviation														3	3	3
Evt21	A: Electrical equipment sparking in the area														3	3	3
Evt22	A: (Dampers) impaired/ deviation														3	3	3
Evt24	A: (Ventilation) impairment														3	3	3
Evt26	xA: (Vehicle traffic) open ign src		1				3				3						
Evt27	xA: Mechanically generated sparks through certain activities		3	3			3										
Evt28	xA: (Excavation) open ign src		3	3			3										
Evt29	xA: (Hot Work A) open ign src	3	1	3			5		5		3						
Evt32	A: (ESDVs) impaired/ deviation														3	3	3
Evt34	A: (ESD) logic solver loop impairment/ deviation														3	3	3
Evt35	A: (BDVs) impaired/ Deviation															3	3
Evt37	A: (Flare) impairment/deviation														3	3	3
Evt39	A: (Depress) logic solver impairment/ deviation														3	3	3

continue

Figure B.21: RIFs and their importance for each defined activity

Activity ID	Activities	RIFs and their importance measure															
		Competence (mechanic)	Competence (process)	Time pressure	Design/HMI	Documentation	Supervision	Isloation plan (yes/no)	HC system (yes/no)	Type of equipment	Compensatory measures	Wind conditions	Lifting equipment	Competence (crane operator)	Compensatory measure	Degree of impairment	Redundancy (yes/no)
Evt40	A: (Equipment location) new equipment/items added to area														3	3	3
Evt42	A: (Blast walls) removed/impaired/deviation														3	3	3
Evt45	A: (PFP) impaired/ removed														3	3	3
Evt46	A:(Fire dampers) logic solver impairment/deviation														3	3	3
Evt47	A:(Fire dampers) Impaired/deviation														3	3	3
Evt49	A: (NO Fire Door) Impaired/deviation														3	3	3
Evt50	A:(NC Fire Door) Impaired/deviation														3	3	3
Evt52	A: (NO Fire Door) logic solver impairment/deviation														3	3	3
Evt53	A: (IS isolation) Pushbutton impaired/deviation														3	3	3
Evt59	A: (IS isolation) Control loop impairment/deviation														3	3	3
Evt64	A:(Manual call point) Control logic impairment/deviation														3	3	3
Evt65	A:(Auto Fire detection) logic solver impairment/ deviation														3	3	3
Evt67	A:(Fire detector)Impaird/deviation														3	3	3
Evt70	A:(Manual call point)Impaired/deviation														3	3	3
Evt72	A: (Fire water system) impairment/ deviation														3	3	3
Evt75	A: (Hydrants, monitors) Deviation/ Impairment														3	3	3
Evt79	A: (Automatic release mechanisms) impairment/ deviation														3	3	3
Evt84	A: (ESD PB) impairment/ deviation														3	3	3
Evt86	xA: (Blasting) open ign src			3			3			3	3						
Evt87	A: (Knockout drum) impairment/ deviation														3	3	3
Evt100	A: (Circuit breaker) Impairment/deviation														3	3	3
Evt107	A: (Open drain) impairment/ deviation														3	3	3
Evt111	xA: (Hot Work B) open ign src	3	1	3			5		5		3						

B.6 List of basic events of fault trees in MIRMAP Generic Model

Table B.5, B.6, B.7 show the basic event of fault trees in MIRMAP Generic Model.

Table B.5: List of basic events of fault trees in MIRMAP generic model

ID	Basic Event	Description
1	Evt1	C: Release from equipment layout and design
2	Evt2	B: Release from equipment wearing from age
3	Evt3	C: No/weak exo-skeletal protection on equipment
4	Evt4	xA: Dropped objects cause HC leak
5	Evt5	A: (PSV) impaired/ deviation
6	Evt6	B: (PSV) technical degredation
7	Evt7	A: (PSD) logic solver impairment/ deviation
8	Evt8	A: (PSD Transmitters) Impairment/ deviation
9	Evt9	B: (PSD transmitters) Technical degradation
10	Evt10	A: (PSDVs) impaired
11	Evt11	B: (PSDVs) technical degredation
12	Evt12	xA: Leak introduced during intervention
13	Evt13	xA: Leak introduced during isolation
14	Evt14	xA: Leak introduced during normal operation on HC systems
15	Evt15	xA: Leak introduced during reinstatement
16	Evt16	B:(Gas detector) Technical degradation
17	Evt17	A:(Gas detector) Impaired/deviation
18	Evt18	C:(Gas detector) coverage deficiency
19	Evt19	MO(Manual gas detection) No operator in area
20	Evt20	A: (Gas Detection) logic solver impairment/ deviation
21	Evt21	A: Electrical equipment sparking in the area
22	Evt22	A: (Dampers) impaired/ deviation
23	Evt23	B: (Dampers) technical degradation
24	Evt24	A: (Ventilation) impairment
25	Evt25	B: (Ventilation) technical degradation
26	Evt26	xA: (Vehicle traffic) open ign src
27	Evt27	xA: Mechanically generated sparks through certain activities
28	Evt28	xA: (Excavation) open ign src
29	Evt29	xA: (Hot Work A) open ign src
30	Evt30	B: Unapproved/Old/ Degraded Electrical equipment
31	Evt31	C: Ventilation Capability to handle leak (A)

Continue Table B.5

Table B.6: List of basic events of fault trees in MIRMAP generic model

ID	Basic Event	Description
32	Evt32	A: (ESDVs) impaired/ deviation
33	Evt33	B: (ESDVs) Technical degradation
34	Evt34	A: (ESD) logic solver loop impairment/ deviation
35	Evt35	A: (BDVs) impaired/ Deviation
36	Evt36	B: (BDVs) Technical degradation
37	Evt37	A: (Flare) impairment/deviation
38	Evt38	B: (Flare) technical degradation
39	Evt39	A: (Depress) logic solver impairment/ deviation
40	Evt40	A: (Equipment location) new equipment/items added to area
41	Evt41	C:(Equipment location) by design - design deficiency
42	Evt42	A: (Blast walls) removed/impaired/deviation
43	Evt43	C: (blast walls) design deficiency
44	Evt44	C: Fire resistance deficiency in equipment
45	Evt45	A: (PFP) impaired/ removed
46	Evt46	A:(Fire dampers) logic solver impairment/deviation
47	Evt47	A:(Fire dampers) Impaired/deviation
48	Evt48	B:(Fire dampers) Technical degradation
49	Evt49	A: (NO Fire Door) Impaired/deviation
50	Evt50	A:(NC Fire Door) Impaired/deviation
51	Evt51	C:(NC FireDoor) Design deficiency
52	Evt52	A: (NO Fire Door) logic solver impairment/deviation
53	Evt53	A: (IS isolation) Pushbutton impaired/deviation
54	Evt54	MO: (IS isolation) Pushbutton manual operation
55	Evt55	MO: Fail to stop vehicle traffic
56	Evt56	MO: Fail to stop mechanically generated sparks
57	Evt57	MO: Fail to stop excavation
58	Evt58	MO: Fail to stop hot work
59	Evt59	A: (IS isolation) Control loop impairment/deviation
60	Evt60	C: Ventilation Capability to handle leak (C)
61	Evt61	C: Ventilation Capability to handle leak (D)
62	Evt62	Explosion/ Fire severity (AB)
63	Evt63	MO(Manual Fire Detection)No operator in area
64	Evt64	A:(Manual call point) Control logic impairment/deviation
65	Evt65	A:(Auto Fire detection) logic solver impairment/ deviation
66	Evt66	B:(Fire detector) Technical degradation
67	Evt67	A:(Fire detector)Impaird/deviation
68	Evt68	C:(Fire detector) coverage limitation
69	Evt69	B:(Manual call point) Technical degradation
70	Evt70	A:(Manual call point)Impaired/deviation
71	Evt71	C:(Manual call point) not installed
72	Evt72	A: (Fire water system) impairment/ deviation
73	Evt73	C:(fire water system) capacity/ distribution deficiency
74	Evt74	B:(fire water system) Technical degradation

Continue Table B.6

Table B.7: List of basic events of fault trees in MIRMAP generic model

ID	Basic Event	Description
75	Evt75	A: (Hydrants, monitors) Deviation/ Impairment
76	Evt76	B: (Hydrants, monitors) technical degradation
77	Evt77	C: (Hydrants, monitors) effectiveness/ design limitation
78	Evt78	MO: (Hydrants, monitors) no manual operation possible
79	Evt79	A: (Automatic release mechanisms) impairment/ deviation
80	Evt80	C: (Automatic release mechanisms) coverage/ capability limitations
81	Evt81	B: (Automatic release mechanisms) technical degradation
82	Evt82	Explosion/ Fire severity (C)
83	Evt83	Explosion/ Fire severity(D)
84	Evt84	A: (ESD PB) impairment/ deviation
85	Evt85	B: (ESD PB) technical degradation
86	Evt86	xA: (Blasting) open ign src
87	Evt87	A: (Knockout drum) impairment/ deviation
88	Evt88	B: (Blast walls) technical degradation
89	Evt89	B: (PFP) Technical degradation
90	Evt90	B: (NC Fire Door) Technical degradation
91	Evt91	B: (NO Fire Door) Technical degradation
92	Evt92	B: (PSD) logic solver technical degradation
93	Evt93	B:(Auto Fire detection) logic solver technical degradation
94	Evt94	B: (Gas Detection) logic solver technical degradation
95	Evt95	MO: Fail to stop blasting
96	Evt96	B: (ESD) logic solver loop technical degradation
97	Evt97	B: (Depress) logic solver technical degradation
98	Evt98	B: (IS isolation) Control loop technical degradation
99	Evt99	B: (IS isolation) Pushbutton technical degradation
100	Evt100	A: (Circuit breaker) Impairment/deviation
101	Evt101	B: (Circuit breaker) Technical degradation
102	Evt102	B: (Knockout drum) technical degradation
103	Evt103	B: (Manual call point) Control logic technical degradation
104	Evt104	B: PSD/PSV demand
105	Evt105	C: (Open drain) capacity deficiency (leak)
106	Evt106	B: (Open drain) technical degredation
107	Evt107	A: (Open drain) impairment/ deviation
108	Evt108	C: Open drain capacity deficiency fire water
109	Evt109	C: Unable to completely depressurize segment
110	Evt110	C: Unable to completely isolate HC segment
111	Evt111	xA: (Hot Work B) open ign src

Appendix C

Identified Model Uncertainty Sources of MIRMAP Model

Identified model uncertainty sources are presented in tabular form.

Problem defining associated model uncertainty sources are shown in Figure C.1.

System controlling factor and mechanism identification associated model uncertainty sources are shown in Figure C.2, C.3, C.4.

Data evaluation associated model uncertainty sources are shown in Figure C.5.

Model construction associated model uncertainty sources are shown in Figure C.6, C.7, C.8, C.9. C.10, C.11.

Numerical solution associated model uncertainty sources are shown in Figure C.12.

Figure C.1: Identified model uncertainty sources of MIRMAP model related to *step 1: problem defining*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S1.1	Definition of "Major Accident".	Objective	Ambiguous output value.	To cope with our belief of major accident and industry fashion.	
S1.2	To model the instantaneous risk for Major accident prevention including activities, Only the risk contributors to the occurence of Major accident is included.	Objective--Scope of analysis	Accident sequence stops at "Fire/Explosion Escalation".	To narrow the scope and exclude necessary work .	
S1.3	Emergency plan and evacuation is not considered.	Objective--Scope of analysis	Accident sequence stops at "Fire/Explosion Escalation".	To narrow the scope and exclude necessary work .	
S1.4	One fire area is the spatial boundary of analysing, but how large the fire area is not clear defined and there are other options.	Boundary conditions	Validity of the output value.	For model convenience, it is a balance between hazard area size (effectiveness) and workload.	
S1.5	The validation period of the model is during normal production, instead of process starting or shutdown.	Objective-Scope of analysis	Inapplicable during process starting or shutdown period.	For modelling convenience.	
S1.6	Only fire/explosion from delayed ignition is considered.	Objective-Scope of analysis	Major accident from immediate ignition in not included.	For modelling convenience.	

Figure C.2: Identified model uncertainty sources of MIRMAP model related to *step 2: system control factors and mechanism identification*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S2.1	Cold vent does not give credit.	BF2			
S2.2	Failure of PSD control unit is ignored	Intermediate event " PSD system fail to function"	One contributor to failure of PSD system is ignored. Probability of "PSD system fail to function" is	Ignored due to uncritical (degree of belief)	
S2.3	ESD pushbutton may initiate gas detection and fire detection at the same time. We ignore the the fact the fire detection will be activated.	Event tree, time sequence of BF2, BF3, BF4			
S2.4	PSVs are not credited as a mean of preventing secalation.	BF4	sub-barrier system is ignored		
S2.5	Depressurisation are not credited to lower the failure probability of escalation of fire to other equipment and segments.	BF4	sub-barrier system is ignored		
S2.6	The possibility of a gas leak from one fire area to another is not considered.	BF1			
S2.7	Common utility failure is not considered.	Excluded basic events in some barrier function	(Incomplete risk contributors) Basic events which include Risk contribution from utility supply failure excluded	Utility failure will end up production shutdown. Usually, plants use uninterrupted electricity supply, and they have more than one utility supply	
S2.8	Ignored (but known to reduce the number of RIFs and burden of data collection) RIFs in influence diagram (BBN).	BBN model			

Continue Figure C.2

Figure C.3: Identified model uncertainty sources of MIRMAP model related to *step 2: system control factors and mechanism identification*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S2.9	RIFs: competence of lifting guider, working environment (lighting, lifting routine etc.), weight of lifting object are not included.	Evt 4: Critical lifting		Ignored due to uncritical	BBN diagram can be more complicated, see Figure C-1
S2.10	Control Unit of Fire detection, ESD, PSD is reliable, failure of them is not taken into account.	BF 2.1	Risk contributor from control unit failure is ignored	Ignored due to uncritical (degree of belief)	
S2.11	Dropped Object may also cause immediate ignition, which means that this part of statistic data should be excluded to calculate average leakage probability due to this activity.	The average state value of basic event representing type A1 acitivity: Evt 4		Ignored due to uncritical	should check references
S2.12	ESD signal from center control room is ignored, only field control is taken into account.	BF2.2	sub-barrier system is ignored		
Timing property related					
S2.13	Ignore the fact that many activities just last for few hours instead of the whole day.	Activities	Overestimate simultaneous activities		A arguement can be make by assume that if there is a major accident happen the day before, then the system behavior most likely will change due to the accident, but the model still assume that it is the same as before.

Continue Figure C.3

Figure C.4: Identified model uncertainty sources of MIRMAP model related to *step 2: system control factors and mechanism identification*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S2.14	(Simplification)Time dependence between sub-barrier systems among the same barrier function is not considered	All barrier functions	If the dependence between them influence basic event failure probability, then the failure probability over dependent sub-barrier system is underestimated or overestimated	Model convenience(limtation of modelling technique of fault tree)	Check dynamic fault tree
S2.15	(ignored dependence) system dependence among time sequence is ignored when model risk profile and risk contribution from work orders.	Computation of risk profile and risk contribution from work orders which last for more than 1 day			

Figure C.5: Identified model uncertainty sources of MIRMAP model related to *step 3: data evaluation*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S3.1	(Surrogate variable is used to calculate average leakage probability from acitivities) To calculate the average leakage probability from activities, "industrial average value is used as a parameter for the calculation instead of plant specific avarage value.	The average state value of basic event representing type A1 acitivity(Evt 4, Evt 12, Evt 13, Evt 14, Evt 15).	Inaccuracy in estimation of average value of basic event representing type A1 acitivity.	Model convenience (lack of plant specific data).	Plant specific value is more accurate (representative).
S3.2	(Surrogate variable is used to calculate average ignition(introduce ignition source) probability from acitivities). To calculate the average ignition probability from activities, "industrial average value is used as a parameter for the calculation instead of plant specific avarage value.	The average state value of basic event representing type A1 acitivity which may introduce ignition source.	Inaccuracy in estimation of average value of basic event representing type A1 acitivity.	Model convenience (lack of plant specific data).	Plant specific value is more accurate (representative).
S3.3	(Simplification) Default value of fatality probability is used.	Input variable of consequence Model: fatality probability.	Fatality probability is inaccurate.	Model convenience.	Usually, complicated simulation is done to calculate fatality probability.
S3.4	(Simplification)Default value of fatality probability is relevant to fire size (usually related to leakage size).	Input variable of consequence Model: fatality probability.	Fatality probability is inaccurate.	Model convenience.	Usually, complicated simulation is done to calculate fatality probability.
S3.5	PSV/PSD demand is a dynamic process feature, in this model, but a average constant value is used in the model instead.	BF1 Basic event "PSD/PSV demand".	Doesn't meet the dynamic property of the model requirement.	Model convenience, Ignored due to uncritical.	It is possible to build a BBN to predict it.

Figure C.6: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
Hierarchy driven by level of details (Event Tree)					
S4.1	Barrier function response time variation due to facility features is not considered	Event Tree BF2.1 \&BF2.2\&BF2.3	Leakage size is varied due to response time	Model convenience	
S4.2	(Simplification) Depressurization doesn't give credit if isolation fails	Event Tree BF2.3	BF2.3 doesn't split into succeed\&fail given isolation fails	Ignored due to uncritical	
S4.3	(Simplification) Failure influence of barrier function due to the event development variability is presented by introducing a basic event. This basic event is a thought of failure probability of barrier function even the hardware barrier function success.	BF3 and BF4	Inacuracy of top event probability in BF3 and BF4	Model convenience	
Hierarchy driven by level of details (Simplified Consequence Model)					
S4.4	(Simplification)Default value of fatality probability is related fire size (usually related to leakage size): the variablity of fatality probability is the same as end event variablity. Variablity is ignored or simplified.	Consequence Model	fatality probability is inaccurate	Model convenience	Usually, complicated simulation is done to calculate fatality probability
S4.5	(Simplification) Exposed Number of People for uncontrolled fire /explosion is estimated as 2/4 times of people within the area	Consequence Model	Inaccuracy in estimation of exposed number of people	Lack of data	This is not a real-time measure of exposed people, A better way is to record number of people in surround areas
Hierarchy driven by level of details (BF1)					
ID	**Model Uncertainty Sources**	**Location**	**Impact**	**Reasons**	**References & Comments**

Continue Figure C.6

Figure C.7: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

S4.6	(Incorrect form) PSV and PSD function to prevent leakage is modelled in parallel (And gate is used) which means both of them have to fail given a demand to have a leakage.	Intermediate event in BF1	Change of logic gate	Lack of knowledge of system	
Hierarchy driven by level of details (BF2.1)					
S4.7	(Assumption)Leakage can be manually detected as long as there is operator in area	Evt19: MO (Manual gas detection) No operation in area	Manually detection failure probability is underestimated	Lack of data	
Hierarchy driven by level of details (BF2.2)					
S4.8	(Assumption) If leakage is comfirmed by automatic gas detection, then signal will automatically generated and send to ESD	Intermediate event	Underestimated failure probability of ESD failure	Model convenience to reduce dependence	
S4.9	(Assumption)If leakage is comfirmed by automatic gas detection, then signal will automatically generated and send to PSD	Intermediate event	Underestimated failure probability of PSD failure	Model convenience to reduce dependence	
S4.10	(Incorrect logic) ESD and PSD are in series (any failure in any of these two sub-barrier systems will result in isolation failure	Top event "Fail to isolate process segment"	Change of logic gate since logic gate over ESD and PSD are wrong	Lack of knowledge of system	
S4.11	(Simplification) Cannot completely isolate even when PSDV and ESDV close, this is a issue related to quality of PSDV and ESDV. A "or gate" is used to represent this phenomeno	Failure causes of Top event "Fail to isolate process segment"	underestimated failure probability of isolation: if this is the case, then isolation function will fail anyway in that area, the probability of failure should be 1 instead of a value between 0-1.	Model convenience	

Continue Figure C.7

Figure C.8: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
Hierarchy driven by level of details (BF2.3)					
S4.13	The design capability of knockout drum is not considered.		Underestimated failure probability of knockout drum:		
Hierarchy driven by level of details (BF3)					
S4.14	(Simplification) Ignition prevention has two sub failure causes : Fail Dilute/Disperse leaked HC and Ignition source active, And gate is used for these two sub failure causes, which means they are in parallel	Failure causes of Top event "Fail to prevent ignition A"	BF3 might need to be remodelled, HVAC function is overestimated	Model convenience	
S4.15	(Simplification) Disperse gas function variable (intermediate event) is splitted into "Success" and "Failure". The arguement can be made by asking what is the success state of gas dispersing? What is failure of it? It is not easily observable.	Disperse gas function variable (intermediate event: Fail to disperse gas)	Cannot obtain required data	Model convernience	What is the success criteria of diepersing gas?
S4.16	(Simplification) Gas cloud formulation simpified as part of failure of dispersing gas function (intermediate event) .	Fail Dilute/Disperse leaked HC	Important risk contributor may cannot be captured	Model convernience	There are many more complicated diserpsing model alternatives
S4.17	(Simplification) the failure causes of gas dispersing failure are categoried into two: HVAC Ventilation capacity to handle enlarged leakage and unexpected HVAC system failure	Intermediate event :gas dispersing failure	Underestimated failure probability	Model convernience	
S4.18	(Simplification) Ventilation capacity to handle leak of HVAC given enlarged leakage: The failure causes of ventilation that cannnot disperse gas are quite relevant to the leakage size, and the type of material.	Basic event(Evt 31)		Model convernience	Check literatures, More factors of HVAC capability should be included.

Continue Figure C.8

Figure C.9: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S4.20	The failure criteria of "Fail to disperse liquid through open drain" is not clear.	Intermediate event: Fail to disperse liquid		Model converience	
S4.21	What are the factors that will influence the open drain capability to disperse liquid?			Model converience	
S4.22	(Simplification) Active ignition source from neibouring fire area is expressed by a basic event		Inaccuracy in ignition source probability	Model converience	
S4.23	(Assumption) Failure on gas alarm is ignore, assume that if gas is detected, gas alarm will be initiated and work well.	Intermediate events: "Activity creates ignition source and does not stop" and "Fail to isolate		Model converience	
S4.24	Only manually Ignition source isolation is taken into account. Automatic ignition source isolation does not give credit.		Overestimated failure probability	Model converience	
S4.25	(Incorrect form) Ignition source isolation shut down electricity supply of equipment, then they should stop work and are not ignition source anymore.	BF3 B, C, D : Intermediate event (ignition source from equipment) is still in the fault tree		It is not intended, just a mistake made when build fault tree(communicated with Modeller).	List it here just being a example that this kind of mistake can happen.
Hierarchy driven by level of details (BF4)					
S4.26	(Assumption) The failure criteria of Passive fire protection is "Fire/explosion escalated through it within prefined time period (e.g. two hours)	BF4	Overestimated failure probability	Model converience	
S4.27	(Assumption) The function of fire extinguishing is achieved by reduce heat load. If heat load is reduced then fire is controlled.	BF5	Underestimated failure probability	Model converience	
S4.28	(Assumption) The leakage amount of HC is great enough that fire will not be extinguished due to using up all combustable material.	BF6	Overestimated failure probability	Model converience	

Continue Figure C.9

Figure C.10: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S4.29	(Assumption) Any failure in passive fire protection or active fire protection will lead to fire escalation.	BF7	Overestimated failure probability	Model convernience	
S4.30	(Assumption)Any failure of fire doors or blast walls will lead to fire and blast escalation	BF8	Overestimated failure probability	Model convernience	
S4.31	(Simplification)The variability between fire and explosion is ignored.	BF9	Underestimated failure probability	Model convernience	
Hierarchy driven by level of details (Type A1: Influence diagram)					
S4.32	No consensual mode to model activity failure and RIFs			Lack of knowledge	
S4.33	Assumption 1 for conditional probability elicitation(If BBN is used): The longer distance between parent node state and child node state, the less probable that the child node will stay at that state for the given parent node state.	Conditioanl probability elicitation	Inaccuracy in conditional probability (dependency relation)	Model convenience	
S4.34	Assumption 2 for conditional probability elicitation(If BBN is used): The more important of parent node, the more dependency between parent node and child node.	Conditional probability elicitation	Inaccuracy in conditional probability (dependency relation)	Model convenience	
S4.35	Weighting method: (assumption) A certain number of experts is enough to provide good result etc.				Different way of expert judgement to give weight available
S4.36	Structure of BBN	BBN	Inaccuracy in estimated state probability		
Hierarchy driven by level of details (Type A2: Influence diagram)					
S4.37	(Simplification) The structure of influence diagram is a simplified reliability assessment				The reference model is a complete (more complicated) reliability model

Continue Figure C.10

Figure C.11: Identified model uncertainty sources of MIRMAP model related to *step 4: model construction*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
Hierarchy driven by time					
S4.38	Assume that all planned activity are continuously executed in the whole day	Type A basic events	Overestimated failure probability	Model convenience	
S4.39	(Assumption): system is independent among time sequence (day to day)	Work order risk measure	Underestimated risk measure	Model convenience	
Hierarchy driven by size					
S4.40	(Assumption) There is no HC from neighbouring fire area that would provide fuel.	BF1	Underestimated failure probability of BF1	Lack of data	
S4.41	Knockout drum is shared by several area, the activity on knockout drum is a common cause failure, but not well explained in this model	Basic event(Evt 87): (Knockout drum) impairment/deviation	Activity which may lead to failure of knockout drum may be ignored	(issue of modelling technique) Only model one fire area first. Activity which may lead to problem for many areas but belongs to one specific area might be ignored in other area.	

Figure C.12: Identified model uncertainty sources of MIRMAP model related to *step 5: find and implement numerical solution*

ID	Model Uncertainty Sources	Location	Impact	Reasons	References & Comments
S5.1	(approximation) The failure probability of top event is calculated using approximation formula not accurate computation: using Upper Bound Approximation (based on the fault tree's minimal cut sets).	All top event from fault tree.	Overestimated failure probability, This computational error can become large for an AND gate containing an OR gate with a high failure probability basic event.	Balance between computation convenience and critical.	
S5.2	Discretization of failure proability of basic event type A.	All type A basic events.	Inaccuracy in failure probability distribution	Computation cost.	
S5.3	Ignored parameter uncertainty of basic event type B and type C.	All type B and C basic events.	Overestimated or underestimated failure probability of basic event	Computation cost.	
S5.4	Discretization of RIFs which have a continuous property.	RIFs which have a continuous property.	Extreme small failure probability will be ignored.	Limitation of software tool	

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Language Skills

Chinese(Native), English(Good), Norwegian(Beginner)

Computer Skills

- Office software
- GRIF WORKSHOP for quantative reliability and risk analysis
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- Matlab for mathematical computation
- Programming languages: VBA for excel, Java, C++

Education

- 2014-2016 Norwegian University of Science and Technology
  Master – Reliabililty, Availability, Maintainability and Safety Engineering

- 2009-2013 Central South University
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- Jun.2016-Present NTNU, Trondheim, Norway
  Scientific Assistant - Modelling Instantanoeus Risk for Major Accident Prevention (MIRMAP) project

- Jul.2013-Jul.2014 Bosch Group, Shenzhen, China
  Safety engineer - Risk assessment, Machinery safety, Accidents investigation, EHS training

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Hobbies and Other Activities

I have been practicing Tae Kwon-Do for several years. I got my black belt at the end of 2012. I like running, hiking and cooking.