Criteria for Assessing the Quality of Nuclear Probabilistic Risk Assessments

by

Yingli Zhu

Submitted to the Department of Nuclear Engineering
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Nuclear Engineering

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2004

Author ....
Department of Nuclear Engineering
September 2004

Certified by ....
Michael W. Golay
Professor of Nuclear Engineering
Thesis Supervisor

Read by ....
George Apostolakis
Professor of Nuclear Engineering
Thesis Reader

Accepted by ....
Jeffrey A. Coderre
Professor of Nuclear Engineering
Chairman, Department Committee on Graduate Students

Criteria for Assessing the Quality of Nuclear Probabilistic Risk Assessments

by

Yingli Zhu

Submitted to the Department of Nuclear Engineering on September 2004, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Nuclear Engineering

Abstract

The final outcome of a nuclear Probabilistic Risk Assessment (PRA) is generally inaccurate and imprecise. This is primarily because not all risk contributors are addressed in the analysis, and there are state-of-knowledge uncertainties about input parameters and how models should be constructed. In this thesis, we formulate two measures, risk significance (RS) and risk change significance (RCS) to examine these drawbacks and assess the adequacy of PRA results used for risk-informed decision making.

The significance of an event within a PRA is defined as the impact of its exclusion from the analysis on the final outcome of the PRA. When the baseline risk is the final outcome of interest, we define the significance of an event as risk significance, measured in terms of the resulting percentage change in the baseline risk. When there is a proposed change in plant design or activities and risk change is the final outcome of interest, we define the significance of an event as risk change significance, measured in terms of the resulting percentage change in risk change. These measures allow us to rank initiating events and basic events in terms of relative importance to the accuracy of the baseline risk and risk change. This thesis presents general approaches to computing the RS and RCS of any event within the PRA. Our significance measures are compared to traditional importance measures such as Fussell-Vesley (FV), Risk Achievement Worth (RAW), and Risk Reduction Worth (RRW) to gauge their effectiveness.

We investigate the use of RS and RCS to identify events that are important to meet the decision maker's desired degree of accuracy of the baseline risk and risk change. We also examine the use of 95^{th} confidence level acceptance guideline for assessing the adequacy of the uncertainty treatment of a PRA. By comparing PRA results with the desired accuracy and precision level of risk and risk change, one can assess whether PRA results are adequate enough to support risk-informed decisions.

Several examples are presented to illustrate the application and advantages of using RS and RCS measures in risk-informed decision making. We apply our framework to the analysis of the component cooling water (CCW) system in a pressurized water nuclear reactor. This analysis is based upon the fault tree for the CCW system presented in the plant's PRA analysis. One result of our analysis is an estimate of the importance of common cause failures of the CCW pumps to the accuracy of plant core damage frequency (CDF) and change in CDF.

Thesis Supervisor: Michael W. Golay
Title: Professor of Nuclear Engineering

Acknowledgments

I would like to express my gratitude to all those who made this thesis possible. My greatest appreciation goes to my dissertation advisor, Professor Michael Golay of the Nuclearing Engineering Department at MIT for his constant encouragement and guidance throughout my research and the writing of this thesis.

The other members of my committee, Professor George Apostolakis and Professor Kent Hansen of the Nuclear Engineering Department at MIT each made valuable contributions to my work as well. I wish to thank them for all of their support and valuable comments.

I would like to thank my friends at MIT for sharing and being a part of this learning experience.

My acknowedgements would not be complete without expressing my special thanks to my parents, my sister and brothers for their endless love and support.

This thesis is dedicated to my husband, Kenny, for without his efforts, love and daily support, this work could not have been completed.

Contents

List of Figures

List of Tables

Chapter 1

Overview and Background

1.1 Overview of This Thesis

The final outcome of a Probabilistic Risk Assessment (PRA) is often considered inaccurate and imprecise to some degree. The primary reasons include: certain risk contributors were not considered in the analysis, the analysts may be uncertain about the values of certain input parameters and how the models embedded in the PRA should be constructed.

In this thesis, we explore methods for assessing the adequacy of PRA results with respect to PRA incompleteness and uncertainty treatment. In particular, we develop measures of risk significance (RS) and risk change significance (RCS), which rank events within a PRA in terms of their importance to the accuracy of the baseline risk and risk change. We investigate the use of RS and RCS to categorize events as either important or unimportant to achieving the desired accuracy level of risk and risk change. We also investigate the use of 95^{th} confidence level acceptance guideline for examining the adequacy of uncertainty treatment of a PRA.

This section is followed by a review of the problem of using incomplete and limited scope PRAs for risk-informed decisions. We demonstrate that the adequacy of PRA results required to support an application should be measured with respect to the application supported and the role that PRA results play in the decision making process. We then discuss how the framework developed in this thesis can be used to assess PRA adequacy.

In Chapter 2 we describe the approach for using PRA results in risk-informed decisions. We first describe existing methods for quantifying logic models such as fault trees and event trees. The methods discussed include qualitative methods for determining minimal cut sets and quantitative methods for computing risk and risk change using the minimal cut sets. We focus particularly on the rare event approximation because it gives fairly accurate results in most cases and it can be computed in less computation time than other approximations. We then describe regulatory guidance for use of PRA analysis in risk-informed activities. The guidance discussed include the U.S. Nuclear Regulatory Commission (NRC) Safety Goal Statement for the baseline risk and the NRC Regulatory Guide (RG) 1.174 on the proposed change in plant design and activities. In the end, three alternative approaches for comparing PRA results with the acceptance guidelines are presented. These approaches include the point estimate value approach, the mean value approach, and the confidence level approach.

In Chapter 3 we develop the concepts of RS and RCS. These measures assess the importance of an event with respect to the impact of its omission from the analysis on the final outcome of a PRA. When the baseline risk is the final outcome of interest, we define the significance of an event as risk significance, measured in terms of the resulting percentage change in the baseline risk. When there is a proposed change in plant design or activities and risk change is the final outcome of interest, we define the significance of an event as risk change significance, measured in terms of the resulting percentage change in risk change. Next, we develop general approaches for computing the numerical values of RS and RCS. These approaches are developed for four groups of events in a logic model: initiating events, basic events whose first operators are AND gates, basic events whose first operators are OR gates, and basic events whose first operators are both AND gates and OR gates. Our significance measures are compared to traditional importance measures such as Fussell-Vesley (FV), Risk Achievement Worth (RAW), and Risk Reduction Worth (RRW) to gauge their effectiveness.

In Chapter 4 we describe three types of epistemic uncertainties in a modern PRA: parameter uncertainty, model uncertainty, and incompleteness uncertainty. We discuss existing approaches for the treatment of each type of uncertainty. We demonstrate that incompleteness uncertainty and model uncertainty can greatly impact both the mean values of PRA results and our confidence in the accuracy of these values. Lack of treatment of these uncertainties is very likely to result in a technically unacceptable PRA.

In Chapter 5 we investigate the use of RS and RCS to identify events that are important to achieving the acceptable degree of accuracy of risk and risk change. We also examine how the 95^{th} percentile acceptance guideline can be used to assess the adequacy of the uncertainty treatment of a PRA. The decision maker's desired degree of accuracy and precision of risk and risk change is typically defined based upon the social consequences of the activity subject to analysis and the role that PRA results play in the decision making process.

Chapter 6 consists of a detailed case study of the component cooling water (CCW) system of a pressurized water nuclear reactor. We first describe the system and the various failure modes considered in our analysis. We then define a base case for computing the RS and RCS for each event in the system. Next, we define a current case where common cause failures of the CCW pumps are omitted from the risk analysis. We then use the framework that we develop to examine the adequacy of the results obtained from the current case PRA in support of a specific applications: the proposed CCW pumps allowed outage time (AOT) extension from 25 hours to 100 hours. Our results suggest that although the FV and RAW importance measures of the common cause failure of pumps 1-1 and 1-3, and the common cause failure of pumps 1-2 and 1-3 during normal operation are relatively low, they are found to be important to achieving the desired degree of accuracy of change in CDF. The PRA model without addressing these two events underestimates the resulting change in CDF by a great amount.

In Chapter 7 we summarize the major contributions of this thesis work and indicate how the importance measures we have developed might be used in assessing the adequacy of PRA results for risk-informed activities. We see how the results obtained using RS, RCS, and the 95^{th} confidence level acceptance guideline can indicate which events are important to the accuracy of risk and risk change, and whether the desired accuracy and precision levels have been achieved. It can therefore be useful to decision makers in gauging their confidence level in the risk insights derived from PRA results.

1.2 The Problem of the Adequacy of PRA Results

In this thesis, we focus on the adequacy analysis of PRA results used for risk-informed decisions. The quality of PRAs has been addressed by a number of regulatory and industry organizations [35, 13, 17, 44]. Some have argued that a good PRA should be a complete, full scope, three level PRA, while others have claimed that the quality of a PRA should be measured with respect to the application and decision supported.

In this section, we show by way of an example that the adequacy of a PRA results is important to risk-informed decision making process and should be measured with respect to the application and decision supported. We then discuss several particular decision contexts in which our proposed framework might be useful.

To begin, suppose we have a system consisting of four components. The system configuration is shown in Figure 1-1. Assuming that all component failures probabilities are known to the analyst and independent of each other. The failure probability of each component is given as follows:

$$\begin{aligned} p_1 &= 1 \times 10^{-3}, \\ p_2 &= 1 \times 10^{-3}, \\ p_3 &= 6 \times 10^{-3}, \\ p_4 &= 8 \times 10^{-3}. \end{aligned} \tag{1.1}$$

From Figure 1-1 we note that the system can fail if component 3 fails, component

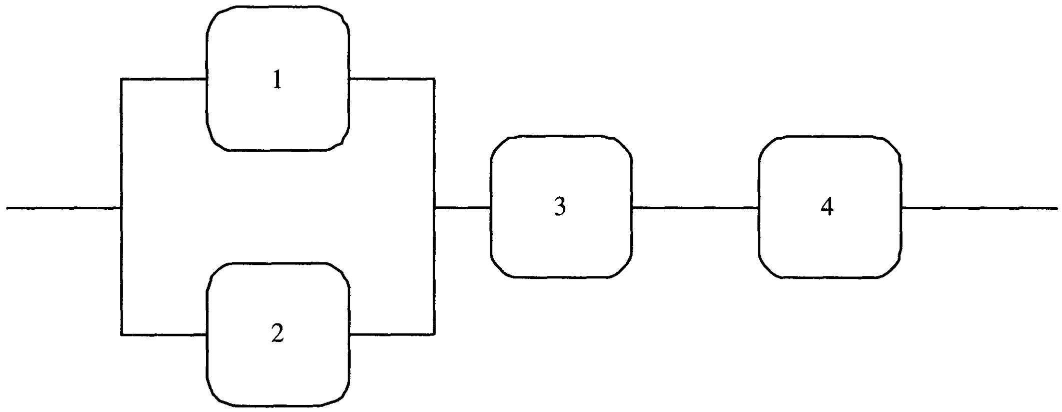

Figure 1-1: A sample system to illustrate the problem of PRA adequacy

4 fails, or components 1 and 2 fail simultaneously. The failure probability of the system can thus be represented as

$$\begin{aligned} Q_0 &= P(C_1C_2 + C_3 + C_4) \\ &= P(C_1C_2) + P(C_3) + P(C_4) \\ &- P(C_1C_2C_3) - P(C_1C_2C_4) - P(C_3C_4) \\ &+ P(C_1C_2C_3C_4). \end{aligned} \tag{1.2}$$

$C(i)$ is the event that component i fails, and $P(C_i)$ is the probability of the occurrence of event i, or the probability that component i fails. By replacing $P(C_i)$ with q_i and truncating the above equation at the linear terms we obtain

$$Q_0 \cong q_1q_2 + q_3 + q_4 = 1.4001 \times 10^{-2}. \tag{1.3}$$

Suppose we have two proposed cost-saving changes in the maintenance practice of the components in the system. We would like to know the system failure probability when either of the two proposed changes has been accepted individually. Suppose the two proposed changes in the maintenance practice are:

1. extend the inspection interval of component 2, which results in an increase in the failure probability of component 2 by a factor of four

2. extend the inspection interval of component 3, which results in an increase the failure probability of component 3 by a factor of two

From Equation 1.3, we obtain the system failure probability given that the first proposed change has been accepted as

$$Q_1 \cong q_1 q_2' + q_3 + q_4 = 1.4004 \times 10^{-2}. \tag{1.4}$$

And similarly, the system failure probability given that the second proposed change has been accepted would be

$$Q_2 \cong q_1 q_2 + q_3' + q_4 = 2.0001 \times 10^{-2}. \tag{1.5}$$

These results indicate that the first proposed change would result in an increase in the system failure probability by 0.021%, while the second proposed change would result in an increase in the system probability by 42.85%.

Until now, we have assumed that all causes for the failure of the system have been identified and accounted for in calculating the failure probability of the system. However, certain causal failures may not have been addressed in the risk analysis. This is typically unintentional and results when the existence of these causal failures is not recognized by the analyst due to knowledge constraints, or when their contributions to the system failure is known estimated to be negligible.

In our example, now we suppose the failure of component 1 was not taken into consideration in estimating the failure probability of the system. Under this assumption, the potential causes of system failure are: the failure of component 1, failure of component 2, and failure of component 3. In such case, the system failure probability before accepting any proposed changes can therefore be represented as

$$
\begin{aligned}
Q'_0 &= P(C_2 + C_3 + C_4) \\
&= P(C_2) + P(C_3) + P(C_4) \\
&- P(C_2C_3) - P(C_2C_4) - P(C_3C_4) \\
&+ P(C_2C_3C_4). \qquad (1.6)
\end{aligned}
$$

Again, by replacing $P(C_i)$ with q_i and truncating the above equation at the linear terms we obtain

$$Q'_0 \cong q_2 + q_3 + q_4 = 1.5 \times 10^{-2}. \qquad (1.7)$$

The system failure probability after accepting the first proposed change would be

$$Q'_1 \cong q'_2 + q_3 + q_4 = 1.8 \times 10^{-2}, \qquad (1.8)$$

and the system failure probability after accepting the second proposed change would be

$$Q'_2 \cong q'_2 + q_3 + q_4 = 2.1 \times 10^{-2}. \qquad (1.9)$$

These results indicate that, in the case where component 1 is not considered in the model, the first proposed change would result in an increase in the system failure probability by 20.0%, while the second proposed change would result in an increase by 40.0%.

For comparison, the system failure probability for all the six cases is presented in Figure 1-2, Figure 1-3, and Figure 1-4. From these figures we see that the exclusion of component 1 from the analysis results in an overestimate of the baseline system failure probability by 7.14%, while the system failure probability after accepting the first proposed change is overestimated by 28.54%, and after accepting the second proposed change is overestimated by 4.99%. These numerical values indicate that the simplified model which does not take component 1 into account provides a fairly accurate estimate of the baseline system failure probability and the impact of the second proposed change on the system failure probability. However, its estimate of the impact of the first proposed change on the system failure probability is significantly inaccurate.

Thus, for this particular performance measure, the model which omits the causal failure of component 1 provides adequate information to decision makers who are concerned with the system baseline failure probability and the impact on the system failure probability of the second proposed change. But, it does not provide an accurate risk assessment for decision makers who are interested in knowing the impact of the first proposed change on system reliability.

From this example, we claim that the adequacy of a PRA's results are important for decision makers to make well informed decisions, and that the quality of a PRA should be measured based upon the application and decision supported. A PRA provides adequate information for risk-informed activities in some cases. However, as we have seen in the previous example, in other cases the information derived is inadequate or inaccurate and the PRA model should be improved such that more meaningful information will be obtained and provided to the decision makers for use in risk-informed activities.

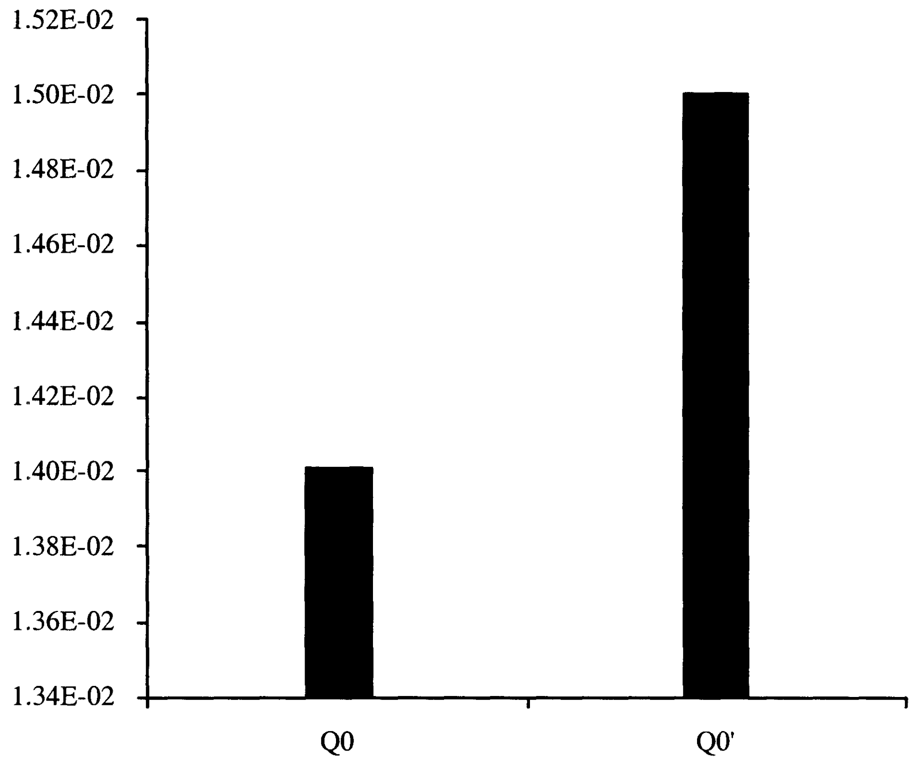

Figure 1-2: System failure probability before accepting any proposed changes

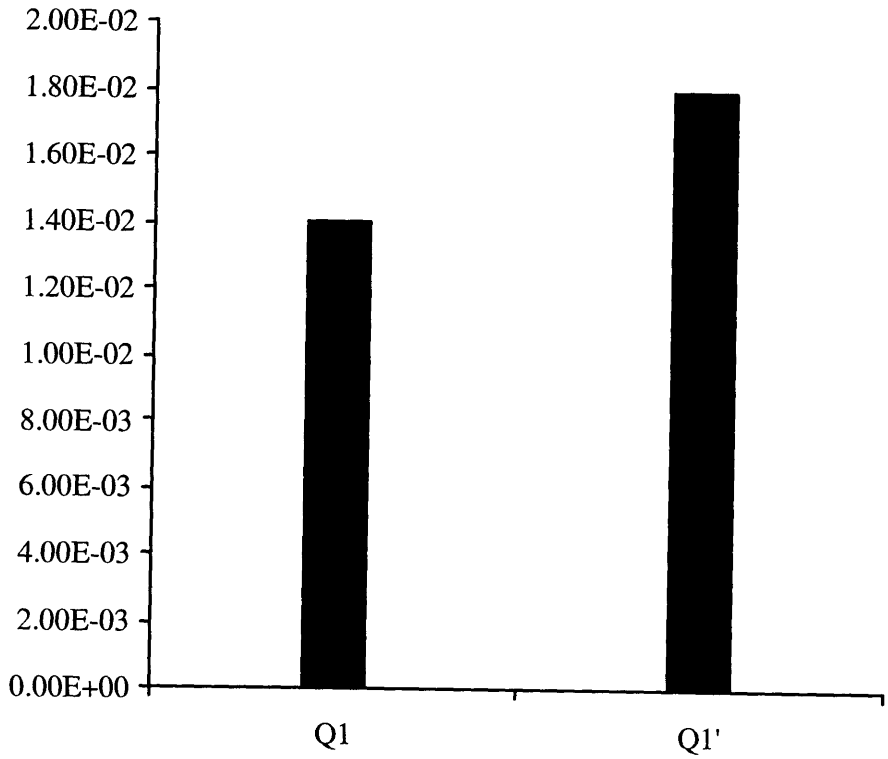

Figure 1-3: System failure probability after accepting the first proposed change

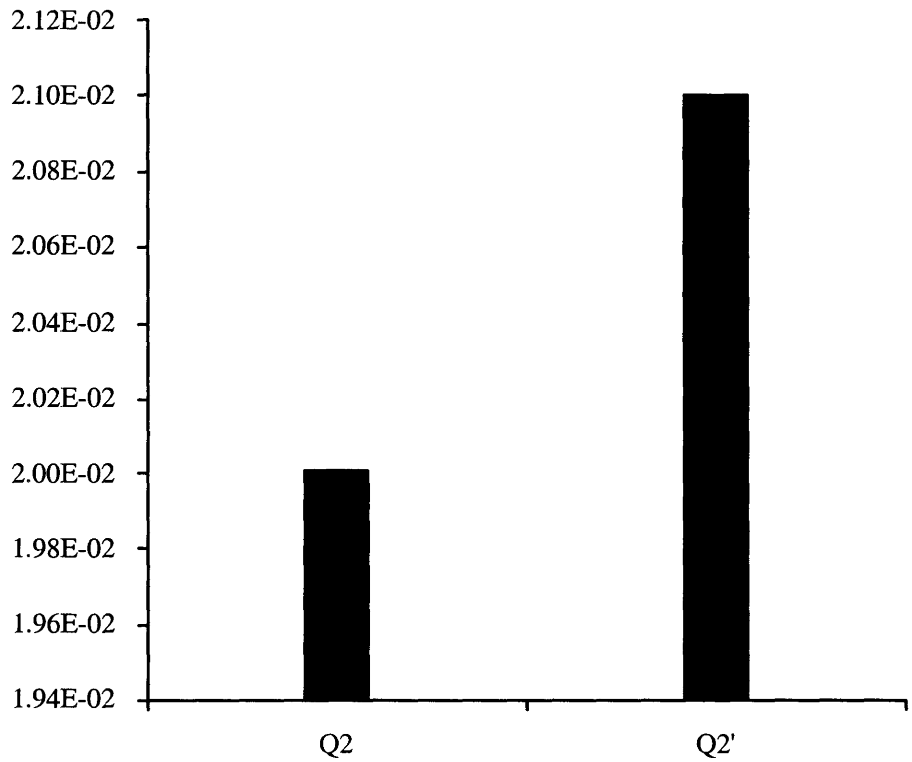

Figure 1-4: System failure probability after accepting the second proposed change

1.3 Regulatory Approaches for Addressing PRA Adequacy

Since PRAs can provide useful information to decision makers for managing plant risk and making efficient uses of resources, many nuclear PRAs have been performed throughout the world. In the United States, in order to encourages the use of PRA analysis to improve safety decision makings, the NRC issued a Policy Statement [47] in 1995 stating that

> " ...The use of PRA technology should be increased in all regulatory matters to the extent supported by the state-of-the-art in PRA methods and data and in a manner that complements the NRC's deterministic approach and supports the NRC's traditional defense-in-depth philosophy...."

Since then, PRA results have been widely used to measure the risk significance of systems, structures, components(SSCs), to identify the design and operational features critical to risk, and to identify the events or scenarios leading to system failure. The current activities which involve the use of PRA results in risk-informed regulatory activities are summarized in a Risk-Informed Regulation Plan issued by the U.S. NRC in 2000 [45] and outlined in the SECY-00-0162 [44]. These activities include: the reactor oversight process for inspection on those activities with the greatest potential impact on safety, operating events assessment for evaluating the risk significance of operational events, license amendments for providing guidance on risk-informed changes to a plant's licensing basis for inservice testing, inspection, graded quality assurance and technical specifications, risk-informed technical specifications for developing improvements to the technical specifications, and maintenance rules for monitoring the effectiveness of maintenance actions.

PRA, as a quantitative tool, has many strengths as well as weaknesses. There are several limitations on the use of PRA techniques for risk modelling and analysis. First, the true values of most model inputs are unknown. Ideally, probability distribution models are well developed and assigned to the unknown input parameters to reflect the analyst's state of knowledge of the values of these input parameters. However, due to the analyst's lack of knowledge of where the actual values lie, probability distributions for some parameters can be defined with either overly wide confidence intervals or extremely narrow confidence intervals. The problem of overconfidence and lack of confidence in the values of certain model input parameters can lead to inaccurate PRA results.

Secondly, the analyst's lack of knowledge of a system's practical application as opposed to its theoretical operation can lead to modelling errors. PRAs, like other models, use approximations to make the model manageable and use assumptions to address the uncertainties associated with model structure and input data. When the approximations and assumptions used in developing the PRAs are inappropriate, the PRA results tend to be inaccurate.

Furthermore, most PRAs are incomplete with only a limited scope. Karl N. Fleming [20, 4] pointed out that as many as 20% of events evaluated by the Accident Sequence Precursor (ASP) program including initiating events and accident sequences are not modelled in existing PRAs. When certain significant component failure modes, initiating events, or plant operating modes are not taken into account in the PRA, both the expectations of PRA results and uncertainties about the expectations are likely to be underestimated.

The difficulty in quantifying common cause failures and human errors also contributes to the limitation on the usefulness of PRA techniques. Since common cause failure can cause the failures of several components or systems simultaneously and human action plays an important role in mitigating accidents, they tend to contribute significantly to risk. The inadequate estimates of the common cause failures and human errors can lead inaccurate and imprecise estimate of risk.

Acknowledging these limitations, many nuclear regulatory and industry organizations have established guidance for using PRA analysis in support of nuclear activities. This guidance includes: the American Society of Mechanical Engineers(ASME) standard [35] for probabilistic risk assessment for nuclear power plant applications, SECY-00-0162 [44] on PRA quality in risk-informed activities, NRC Regulatory Guide

DG-1122 [17] on technical adequacy of PRA results for risk-informed activities, NRC Regulatory Guide 1.174 [13] for the use of PRA in risk-informed decisions on changes to the licensing basis, NRC Regulatory Guide 1.175 [14] on risk-informed in-service testing, NRC Regulatory Guide 1.176 [15] on risk-informed graded quality assurance, NRC Regulatory Guide 1.177 [16] on risk-informed technical specifications, and NRC Regulatory Guide 1.178 [18] on risk-informed in-service inspection.

Among the above regulatory guidance and industry programs, the ASME PRA standard identified nine elements which comprise an at-power, internal-events, Level 1 and limited Level 2 PRA. It sets forth the minimal scope and level of detail for PRAs to meet this Standard by specifying a set of requirements for each of the nine PRA elements. Like the ASME standard, SECY-00-0162 addresses the issue of PRA quality by defining the desired scope and technical elements which comprise a PRA model at a function level. The Draft Regulatory Guide DG-1122 defines a technical acceptable PRA by setting forth a set of elements and corresponding characteristics and attributes. We note that, these standards and guidance only define a functional PRA, and they do not ensure confidence in the PRA results.

On the other hand, Regulatory Guide 1.174 states that "*...The quality of a PRA analysis used to support an application is measured in terms of its appropriateness with respect to scope, level of detail, and technical acceptability. The scope, level of detail, and technical acceptability of the PRA are to be commensurate with the application for which it is intended and the role the PRA results play in the integrated decision process....*"

The guidance provided indicates that there is a diverse set of factors influencing PRA quality. However, there appears to be many similarities in these factors. In particular, all guidance recognizes that scope, level of detail, and technical acceptability are key factors in determining the overall adequacy of a PRA. However, they all focus on defining the minimum requirements for a good PRA, and none of them provides an approach for assessing the adequacy of PRA results for specific applications and decisions supported other than in a general sense.

1.4 Applicability of Techniques for Assessing the Adequacy of PRA Results

In some cases, decisions may focus on ways of improving the completeness of a PRA, for example, by taking into account some of the omitted events in a PRA. Measures of significance, developed in Chapter 3, rank the events in the PRA in terms of the impact of their exclusion from the analysis on the risk level and risk change, and can be a useful tool in this context.

In many other cases, risk-informed decisions focus simply on the acceptability of the estimated risk level, the change in the risk, and perhaps, on the uncertainty about the risk and risk change. In such cases, methods of adequacy analysis of PRA results as those discussed in Chapter 5 can be a valuable tool for the decision making process.

In order to be confident in the final decisions on the acceptability of various activities, decision makers may also attempt to reduce the uncertainty level about the risk level and risk change, e.g. by gathering more information about the probability of particular events in the PRA. In such cases, uncertainty importance measures discussed in Chapter 4 can be used to identify which events in the PRA contribute significantly to the overall uncertainty.

There are several limitations on the use of quantitative methods for evaluating the quality of PRAs. This is primarily because results of the evaluation are only as good as the estimates of the model inputs and how accurately the model's structure approximates the actual system subject to analysis.

First of all, the values of certain model inputs may be incorrect because the overall methodology for treatment of common cause failures and human error is not yet mature. Secondly, most PRAs lack of treatment of dependencies among components, systems, and human actions. In other words, the estimates of the failure probabilities of certain components, systems, and human actions are inadequate given knowledge that other components or systems have failed, or that human errors have occurred. In addition, the analyst's inadequate understanding of the occurrence of certain initiating events or causes to the failure of certain components may result in formulating models that lead to an incorrect estimate of initiating event frequencies and component failure probabilities.

Another limitation on the use of quantitative methods for evaluating the quality of PRAs is that significant initiating events or component failure modes may be left out of the analysis because their existence was not recognized by the analysts. In such cases, both the PRA results and the evaluation of the adequacy of these results would be incorrect.

Acknowledging these limitations, two important assumptions are made in order to develop our framework for assessing the adequacy of PRA results for risk-informed activities. These two assumptions are:

- Model uncertainty is well treated, and all models embedded in the PRA are technically correct.
- The PRA are fairly complete, and all significant risk contributors are addressed in the analysis.

Despite these limitations and assumptions, the techniques of significance analysis and adequacy analysis provided in this thesis can provide useful information to decision makers who are concerned with making well-informed decisions on the acceptability of various nuclear activities.

Chapter 2

Existing Approach for Using PRA in Risk-Informed Decisions

A comprehensive and systematic risk assessment for a nuclear power plant typically consists of deterministic (engineering) analysis and probabilistic analysis. While the deterministic approach provides the analyst with information on how core damage may occur, a PRA estimates the probability of core damage by considering all potential causes. The use of the risk insights derived from PRA results to aid in decision making processes is called risk-informed integrated decision making which is often abbreviated to risk-informed decision making.

The Policy Statement issued by the NRC in 1995[47] states that "...the use of PRA technology should be increased ...in a manner that complements the NRC's deterministic approach and supports the NRC's traditional defense-in-depth philosophy." A risk-informed integrated decision making process consists of five elements as described in the RG 1.174[13]. These five elements are shown in the Figure 2-1. Figure 2-2 shows the key elements of a risk-informed, plant-specific decisionmaking process as described in the RG 1.174. From the statement and these figures we note that information derived from the use of PRA methods is only one element of the risk-informed decision making process, and it does not substitute for the results of a traditional engineering evaluation in the decision making process.

The use of risk insights in a risk-informed decision making process typically in-

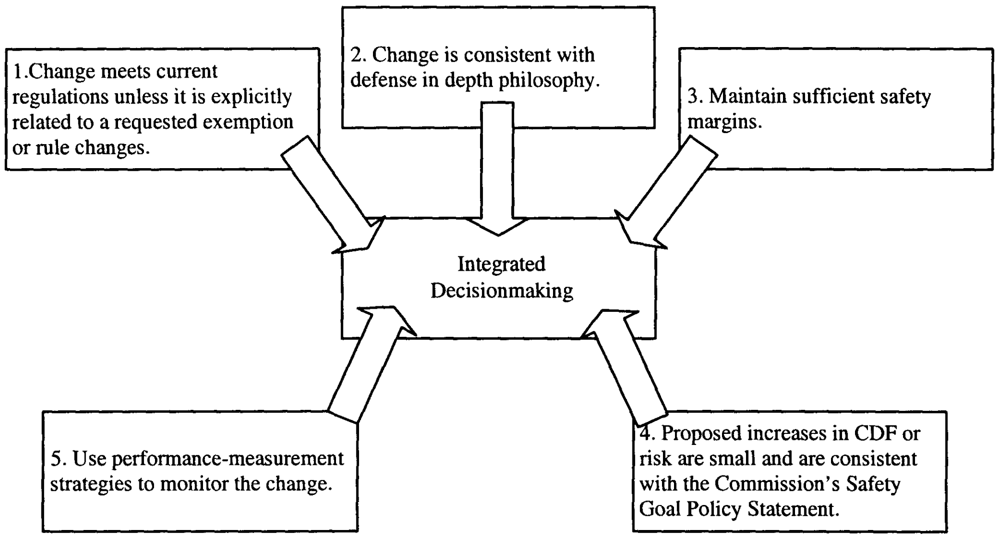

Figure 2-1: Principles of risk-informed integrated decisionmaking

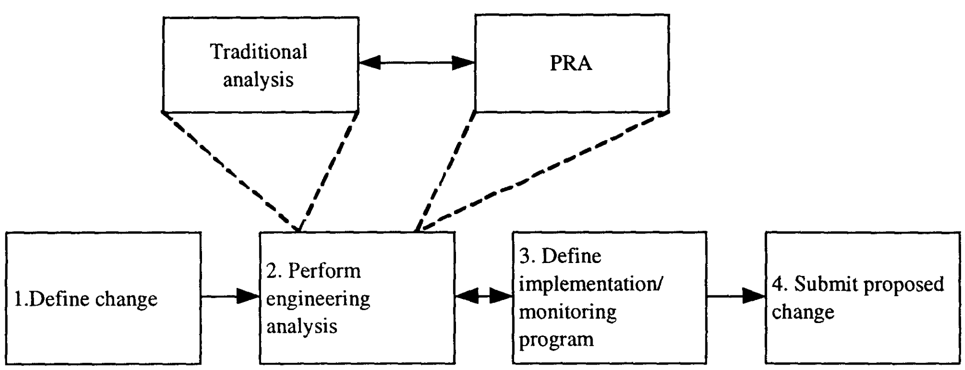

Figure 2-2: Principal elements of risk-informed, plant-specific decisionmaking

volves three aspects: the quantification of PRAs, the development of acceptance guidelines, and the comparison of PRA results with acceptance guidelines.

In this chapter, we first describe existing methods for the evaluation of PRA models in general. We then discuss existing regulatory acceptance guidelines for the use of PRA results for risk-informed activities. We also present alternative approaches for comparing PRA results with acceptance guidelines.

2.1 Evaluation of PRAs

The PRA results used to support risk-informed decision making for various nuclear activities typically include: an evaluation of the core damage frequency (CDF) and large early release frequency (LERF), an evaluation of the change in CDF and LERF, an identification and understanding of major contributors to these risk metrics and risk changes, and an understanding of the sources of uncertainty and their impact on the results [44].

Evaluation of PRA models typically involve two different approaches: qualitative evaluation and quantitative evaluation [30]. Qualitative evaluation of PRA models generates minimal cut sets using Boolean algebra analysis for fault trees and event trees. The minimal cut sets are then be used by quantitative methods to produce PRA results and derive risk insights for risk-informed activities.

Several methods exist for both qualitative evaluation and quantitative evaluation of PRA models. In this thesis, we use the rare event approximation as the quantitative method to evaluate PRAs. The primary advantage of using the rare event approximation is that it is computationally efficient while providing fairly accurate results.

2.1.1 Qualitative Evaluation of Fault Trees

The fundamental elements of a fault tree model are basic events and gates. Basic events refer to component failure and human error which do not need further development. AND and OR gates are two basic types of logic gates used in the fault tree model.

The AND gate in a fault tree represents the intersection of input basic events. The gate output occurs only if all of the input events occur. For example, the boolean expression of the output event C of an AND gate with two input events A and B can be written as $C = A \cap B$ or $C = A \cdot B$. This expression states that, in order for event C to occur, both event A and B must occur. The OR gate, on the other hand, refers to the union of input basic events. The output of an OR gate occurs if one or more of the input events occur.

The top event of a fault tree represents the state of the system of interest, such as the failure of a system to accomplish its function. A cut set of a fault tree is a set of basic events whose simultaneous occurrence leads to the occurrence of the top event. A minimal cut set of a fault tree model is the smallest set of basic events needed to cause the top event to occur. For example, if a fault tree consists of top event C with two basic input events A and B combined by an OR gate, the cut sets are A, B, and AB. The minimal cut sets are A and B. In other words, the occurrence of either event A, or event B, or the simultaneous occurrence of both event A and event B may cause event C to occur. However, in order to cause event C to occur, the occurrence of either event A or event B is sufficient. The simultaneous occurrence of both event A and event B is not necessary to lead to the occurrence of event C.

In order to formulate the minimal cut sets of a fault tree model, we use various rules from Boolean Algebra. The most commonly used rules include:

$$X_i = \begin{cases} 1 & \text{if event } i \text{ is true} \\ \\ 0 & \text{if event } i \text{ is false,} \end{cases} \tag{2.1}$$

$$\begin{aligned} 1 + X_i &= 1, \\ \overline{X_i} &= 1 - X_i, \\ X_i^n &= X_i. \end{aligned} \tag{2.2}$$

For the top event C as discussed above, its Boolean expression can thus be represented as:

$$X_C = X_A + X_B. \tag{2.3}$$

For a fault tree with more than one gate, the output of one gate, gate i, is very likely to be the input of another gate, gate j. In this case, the Boolean expression of the output of gate i is then substituted into the Boolean expression of the input of gate j, and so on. This method is the successive substitution method and is the most widely used method in generating minimal cut sets for a fault tree model.

As an example, let's consider the fault tree shown in Figure 2-3. Each node in the fault tree represents an event.

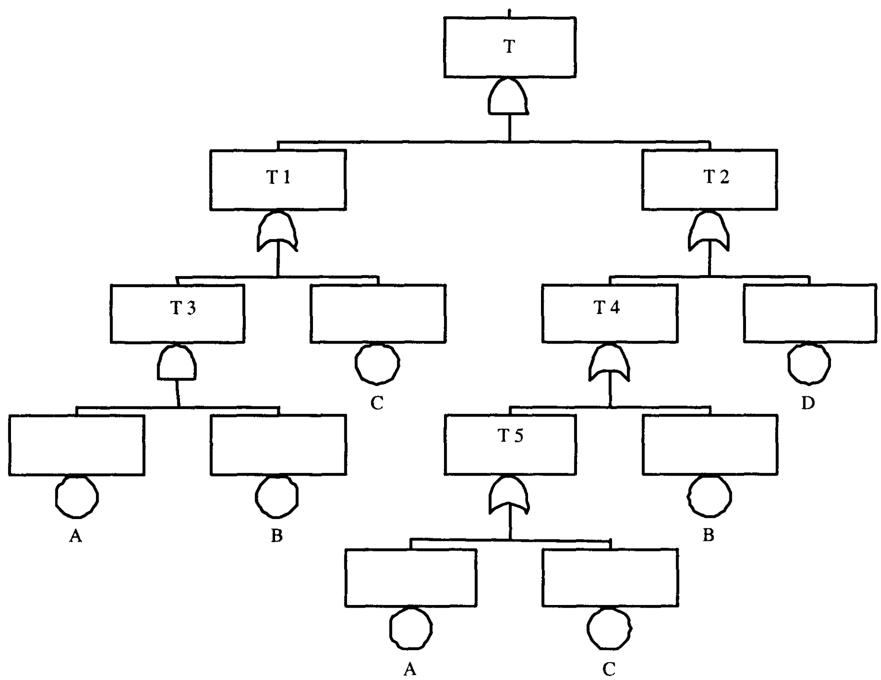

Figure 2-3: An example fault tree to illustrate the formulation of minimal cut sets

Starting from the top of the fault tree, the Boolean expression of top event X_T is given as

$$X_T = X_{T_1} \cdot X_{T_2}. \tag{2.4}$$

Where, X_{T_1} can be written as

$$X_{T_1} = X_{T_3} + X_C = X_A \cdot X_B + X_C, \tag{2.5}$$

and X_{T_2} can be written as,

$$X_{T_2} = X_{T_4} + X_D = X_B \cdot X_{T_5} + X_D. \tag{2.6}$$

Given

$$X_{T_5} = X_A + X_C, \tag{2.7}$$

we can substitute X_{T_5} into X_{T_2}, and substitute X_{T_1} and X_{T_2} into Equation 2.4 to obtain

$$\begin{aligned} X_T &= (X_A \cdot X_B + X_C) \cdot (X_B \cdot (X_A + X_C) + X_D) \\ &= (X_A \cdot X_B + X_C) \cdot (X_A \cdot X_B + X_B \cdot X_C + X_D) \\ &= X_A \cdot X_B \cdot (1 + X_C + X_D + X_C) + X_B \cdot X_C + X_C \cdot X_D \\ &= X_A \cdot X_B + X_B \cdot X_C + X_C \cdot X_D. \end{aligned} \tag{2.8}$$

The final Boolean expression obtained for top event T represents three minimal cut sets with two basic events. The minimal cut sets are events A and B, B and C, and C and D.

As can be seen from this example, it is difficult to determine the minimal cut sets for a large fault tree by hand using the above approach. A number of computer algorithms were developed to determine the minimal cut sets for the analysis of fault tree models[40, 39, 49]. In this thesis, we use the SAPHIRE program developed at Idaho National Engineering and Environmental Laboratory (INEEL) which implements these algorithms to generate minimal cut sets.

2.1.2 Qualitative Evaluation of Event Trees

Unlike the fault tree, which starts with the top event and determines all of the possible ways for this event to occur, the event tree begins with an initiating event and proceeds with the state of each event heading (representing safety system or human action). The occurrence of an event heading i represents the failure of the corresponding system or human action, and the nonoccurrence of event i represents the success of the corresponding system or human action. If the Boolean expression for the occurrence of event heading i is denoted as X_i, the Boolean expression of the success of the event heading i is $\overline{X_i}$, or "$1 - X_i$". However, if an event heading has more functioning states other than success and failure, it would not be possible to represent the event heading using Boolean algebra. In this analysis, we assume that all event headings in an event tree have only two functioning states.

An event tree exhaustively generates all possible combinations of success or failure of all event headings. Any one of such combinations is called an event sequence. Because an event heading either occurs or not occurs at a time, when success and failure of all event headings are combined to generate event sequences, these event sequences are mutually exclusive. The end state of some event sequences is success, while the end states of other sequences is failure. In most cases, only event sequences whose end states are system failure are of great interest to the analysts.

By analogy, the substitution method can also be applied to event trees to generate minimal cut sets. In this case, the cut set of the event sequence with a failed ultimate outcome is the intersection of the failed event headings along the sequence, no matter whether the event heading fails at the beginning of the sequence or at a later time. The overall failure, F, is the union of the cut sets of those event sequences whose end state is failure. If an event heading has its own Boolean expression, its Boolean expression can be substituted into the logic representation of the overall failure F. The reduced Boolean expression of F can then be obtained through the use of Boolean algebra rules.

For example, let's consider the event tree given in Figure 2-4. The event sequences whose outcome is failure include event sequences $2, 4, 5, 6$, and 7. The cut sets of each of these sequences are

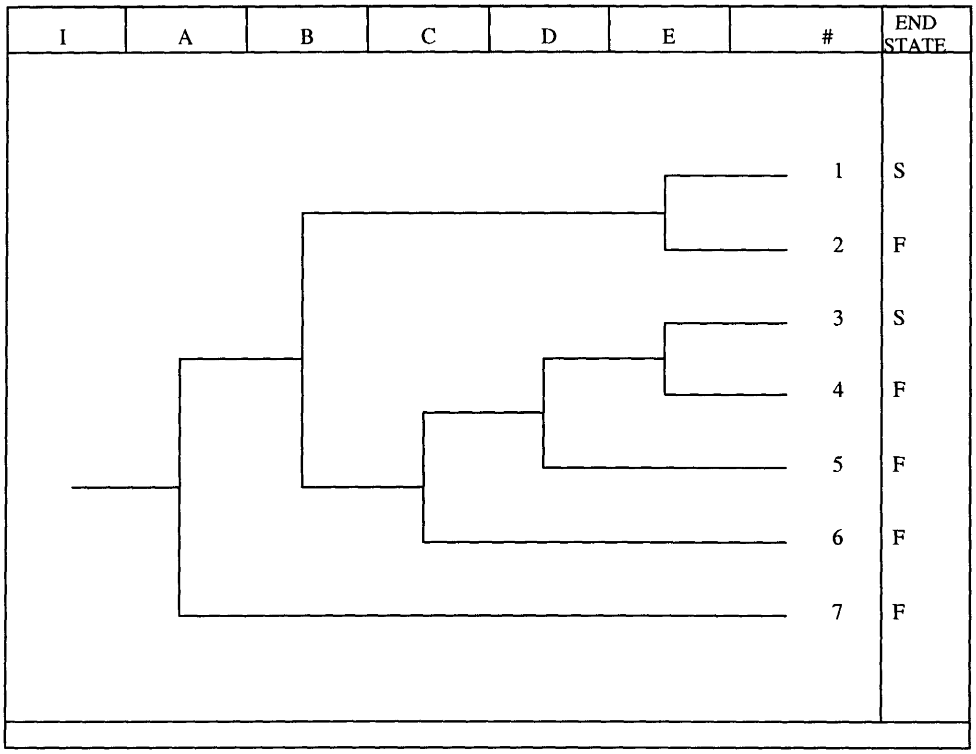

Figure 2-4: An example event tree to illustrate the formulation of minimal cut sets

$$\begin{aligned} X_{F_2} &= X_I \cdot X_E \\ X_{F_4} &= X_I \cdot X_B \cdot X_E \\ X_{F_5} &= X_I \cdot X_B \cdot X_D \\ X_{F_6} &= X_I \cdot X_B \cdot X_C \\ X_{F_7} &= X_I \cdot X_A. \end{aligned} \tag{2.9}$$

The Boolean expression of the overall failure F, as a union of the above cut sets, is obtained and reduced through the use of Boolean algebra rules as

$$
\begin{aligned}
F &= X_{F_2} + X_{F_4} + X_{F_5} + X_{F_6} + X_{F_7} \\
&= X_I \cdot X_E + X_I \cdot X_B \cdot X_E + X_I \cdot X_B \cdot X_D + X_I \cdot X_B \cdot X_C + X_I \cdot X_A \\
&= X_I \cdot X_A + X_I \cdot X_B \cdot X_C + X_I \cdot X_B \cdot X_D + X_I \cdot X_E \cdot (1 + X_B) \\
&= X_I \cdot X_A + X_I \cdot X_B \cdot X_C + X_I \cdot X_B \cdot X_D + X_I \cdot X_E. \qquad (2.10)
\end{aligned}
$$

The Boolean representation obtained above represents two minimal cut sets with two events, and two minimal cut sets with three events. If event heading X_A and X_E are represented by the following Boolean expressions

$$
\begin{aligned}
X_A &= X_a \cdot X_b + X_a \cdot X_c + X_d \\
X_E &= X_a + X_b \cdot X_d + X_e,
\end{aligned}
\qquad (2.11)
$$

then the reduction of the above Boolean expression proceeds as follows:

$$
\begin{aligned}
F &= X_I \cdot X_A + X_I \cdot X_B \cdot X_C + X_I \cdot X_B \cdot X_D + X_I \cdot X_E \\
&= X_I \cdot (X_a + X_d + X_e) + X_I \cdot X_B \cdot X_C + X_I \cdot X_B \cdot X_D \\
&= X_I \cdot X_a + X_I \cdot X_d + X_I \cdot X_e + X_I \cdot X_B \cdot X_C + X_I \cdot X_B \cdot X_D. \qquad (2.12)
\end{aligned}
$$

The ultimate minimal cut sets of the event tree are therefore

$$X_I X_a, X_I X_d, X_I X_e, X_I X_B X_C, X_I X_B X_D.$$

A typical event tree may contain hundreds of event headings. If the number of sequences leading to failure is large, the generation of minimal cut sets by hand using the above procedure is infeasible, especially when event headings contain several additional basic events. However, most PRA software tools are designed to perform this function, thus the formulation of minimal cut sets for fault trees and event trees can be done easily accomplished.

2.1.3 Quantitative Evaluation of the Logic Models

In the previous section, we discussed how to generate minimal cut sets for fault trees and event trees using the substitution method. In this section, we discuss several methods for quantifying fault trees and event trees based upon the minimal cut sets formulated.

Since the occurrence of a minimal cut set results in the occurrence of the top event of a fault tree, or the failed end state of an event tree, the probability of the occurrence of the top event or failed end state equals to the probability of the union of all its minimal cut sets. For example, if R is the top event or the failed event state of interest, and MCS_i is the minimal cut set i (i = 1, 2, ..., n), the exact value of R can therefore be obtained as:

$$R = p(\sum_i MCS_i). \tag{2.13}$$

The above equation can be expanded as:

$$\begin{aligned} R &= \sum_i p(MCS_i) \\ &- \sum_{i,j} p(MCS_i \cdot MCS_j) \\ &+ \sum_{i,j,k} p(MCS_i \cdot MCS_j \cdot MCS_k) \\ &- \cdots. \end{aligned} \tag{2.14}$$

The above expression is an exact formulation of R as a function of the probability of each minimal cut set and the probability of the products of the minimal cut sets. When the minimal cut sets are not independent of each other, the evaluation of the cross product terms are difficult. For example, if a basic event appears in several minimal cut sets, then the occurrence of this basic event is likely to cause the simultaneous occurrence of all the minimal cut sets, but the likelihood of simultaneous occurrence of the set of minimal cut sets is difficult to quantify. Thus, when cut sets are dependent, the cross product terms are difficult to evaluate.

If we assume that all minimal cut sets are independent of each other, Equation 2.14 becomes

$$\begin{aligned} R &= \sum_i p(MCS_i) \\ &- \sum_i \sum_{j>i} p(MCS_i)p(MCS_j) \\ &+ \sum_i \sum_{j>i} \sum_{k>j} p(MCS_i)p(MCS_j)p(MCS_k) \\ &- \cdots. \end{aligned} \tag{2.15}$$

The above expression is an exact formulation of R as a function of the probability of each minimal cut set. By considering that a minimal cut set often consists of several basic events and/or initiating events, we thus have

$$p(MCS_i) = p(\coprod_m BE_i^m). \tag{2.16}$$

BE_i^m is basic event m in minimal cut set i. If several basic events in a minimal cut set are not independent of each other because of common cause failure or functional dependence, the evaluation of the minimal cut set probability is also a difficult task.

Dependencies among the probabilities of basic events can be treated either explicitly by reflecting them in the structure of the logic trees used to model the system in question, or implicitly by reflecting them in probabilities of basic events and/or initiating events. For example, the failure probability of a system consisting of components A and component B in parallel is governed by Boolean expression as follows:

$$Q = p(AB), \tag{2.17}$$

which can be expanded as:

$$Q = p(A) \cdot p(B|A) = p(B) \cdot p(A|B). \tag{2.18}$$

In the above expression, Q is the failure probability of the system, $p(A)$ is the failure probability of component A, and $p(B)$ is the failure probability of component B. $p(B|A), p(A|B)$ is the conditional failure probability of one component given the other component has already failed. If components A and B are functionally or spatially dependent upon each other, the likelihood that one component will fail given that the other component has failed is likely to be higher than independent failure probability. This conditional failure probability must be determined before the system failure probability can be quantified. In the case where the failure probabilities of components A and B are independent of each other, the above equation becomes

$$Q = p(A) \cdot p(B). \tag{2.19}$$

Now by assuming that the dependence among basic events is modelled either explicitly in the analysis, Equation 2.15 becomes

$$\begin{aligned} R &= \sum_i (\prod_m q_i^m) \\ &- \sum_i \sum_{j>i} (\prod_m q_i^m \cdot \prod_n q_j^n) \\ &+ \sum_i \sum_{j>i} \sum_{k>j} (\prod_m q_i^m \cdot \prod_n q_j^n \cdot \prod_l q_k^l) \\ &- \cdots . \end{aligned} \tag{2.20}$$

The above expression is an exact formulation of R with independent minimal cut sets and independent basic event probabilities. The assumptions of independence result in a much simpler quantitative evaluation of R than the general case shown in Equation 2.14.

We note that, for a PRA model with n minimal cut sets, there are 2^{n-1} cross product terms, such as $(\prod_m q_i^m \cdot \prod_n q_j^n)$, in the above equation. In order to facilitate the quantitative evaluation of R, some assumptions need to be made. One simplification is to assume that the cross product terms are typically small and can be neglected. The summation of the probability of individual minimal cut sets is thus used as an approximation of the true value of R. Mathematically, we have

$$R = \sum_i p(MCS_i) = \sum_i (\prod_m q_i^m). \tag{2.21}$$

We note that, this approximation of R yields an upper bound on the true value of R, therefore it is denoted as the upper bound approximation of R. Since the cross product terms are truncated for their low probabilities of occurrence, this approximation is also called the rare event approximation.

By analogy, we can obtain the lower bound on the true value of R by keeping the cross product terms containing two minimal cut sets, and neglecting the ones containing three or more minimal cut sets as follows:

$$\begin{aligned} R &= \sum_i p(MCS_i) - \sum_i \sum_{j>i} p(MCS_i) \cdot p(MCS_j) \\ &= \sum_i (\prod_m q_i^m) - \sum_i \sum_{j>i} (\prod_m q_i^m \cdot \prod_n q_j^n). \end{aligned} \tag{2.22}$$

In general, the lower bound approximation tends to be more accurate than the rare event approximation. However, the rare event approximation is much simpler in the physical form and easier to compute than the lower bound approximation. Furthermore, the rare event approximation gives fairly accurate results for most applications. Therefore, the rare event approximation is used throughout this thesis.

Although initiating events or basic events may appear in many different minimal cut sets, they generally appear at most once in each minimal cut set[51, 53]. The rare event approximation can thus be generalized with respect to a specific initiating event or basic event as:

$$R = a_i \cdot q_i + b_i. \tag{2.23}$$

Where q_i is initiating event frequency or basic event probability. $a_i \cdot q_i$ is the sum of all the minimal cut sets that contain event i, and b_i is sum of all other minimal cut sets that do not contain event i.

The above expression is the most widely used formulation of R with respect to basic event probabilities. It is derived from the rare event approximation and under the assumption of exclusive independence among basic event probabilities. By analogy, the formulation of R with respect to any two events can be obtained as [51]:

$$R = a_{ij}q_iq_j + a_iq_i + a_jq_j + b_{ij}. \tag{2.24}$$

Where,

- $a_{ij}q_iq_j$ represents all of the minimal cut sets which contain both events i and j
- a_iq_i represents all of the minimal cut sets which contain event i but not j
- a_jq_j represents all of the minimal cut sets which contain event j but not i, and
- b_{ij} represents all of the minimal cut sets which contain neither events j nor i

By analogy, we can obtain the formulation of R as a function of any three events in the PRA, any four events in the PRA, and so on. However, when the number of events involved increases, the formulation of R becomes rapidly more complex and is of little use in practice.

2.2 Quantitative Evaluation of Risk Changes

In the previous section, we present two commonly used approximations for the risk metric R. In this section, we discuss the quantitative evaluation of risk changes based upon the rare event approximation and the assumption that all event probabilities are mutually independent.

By taking the derivative of Equation 2.14 with respect to q_i and rearranging the terms we obtain

$$\frac{\partial R}{R} = \frac{a_i \cdot q_i}{R} \cdot \frac{\partial q_i}{q_i}. \tag{2.25}$$

This expression is a general formulation of the resulting change in risk that could result from an infinitesimal change in probability of event i. This relationship can also apply to a finite change in the probability of event i. In this case, the resulting change in the overall risk level is

$$\frac{\Delta R}{R} = \frac{a_i \cdot q_i}{R} \cdot \frac{\Delta q_i}{q_i}. \tag{2.26}$$

This above equation indicates that the change in R is proportional to the change in the event probability.

However, in most cases, a proposed change in the plant design or activities is likely to affect a set of basic events. According to Equation 2.24, when both basic events i and j are affected by an activity simultaneously, the resulting change in R is governed by

$$\Delta R_{i,j} = a_{ij}(\Delta q_i \Delta q_j + q_i \Delta q_j + q_j \Delta q_i) + a_i \Delta q_i + a_j \Delta q_j. \tag{2.27}$$

By rearranging the terms in the above expression we can show that

$$\begin{aligned} \Delta R_{i,j} &= (a_{ij} q_j + a_i)\Delta q_i + (a_{ij} q_i + a_j)\Delta q_j + a_{ij}\Delta q_i \Delta q_j \\ &= \Delta R_i + \Delta R_j + a_{ij}\Delta q_i \Delta q_j. \end{aligned} \tag{2.28}$$

where ΔR_i is change in risk that could result from a Δq_i change in the probability of basic event i while all other event probabilities are fixed at their nominal values. ΔR_j is risk change due to a Δq_j change in the probability of basic event j while keeping all other event probabilities unchanged. By dividing both sides by the baseline risk,

R, we have

$$\frac{\Delta R_{i,j}}{R} = \frac{a_i q_i}{R}\frac{\Delta q_i}{q_i} + \frac{a_j q_j}{R}\frac{\Delta q_j}{q_j} + \frac{a_{ij} q_i q_j}{R}\frac{\Delta q_i}{q_i}\frac{\Delta q_j}{q_j}. \tag{2.29}$$

We note that the first two terms are percentage changes in risk that could result from changes made to basic event i and j one at a time. The third term represents the additional risk change due to simultaneous changes in both basic event probabilities.

If an activity under consideration affects more than two basic events, Equation 2.29 can be generalized as

$$\begin{aligned}\frac{\Delta R}{R} &= \sum_i \frac{a_i q_i}{R}\frac{\Delta q_i}{q_i} \\ &+ \sum_i \sum_{j>i} \frac{a_{ij} q_i q_j}{R}\frac{\Delta q_i}{q_i}\frac{\Delta q_j}{q_j} \\ &+ \cdots \\ &+ \frac{a_{ij\cdots n} q_i q_j \cdots q_n}{R}\frac{\Delta q_i}{q_i}\frac{\Delta q_j}{q_j}\cdots\frac{\Delta q_n}{q_n}.\end{aligned} \tag{2.30}$$

Under some circumstances, e.g. the change in the probabilities of basic events are small, the cross term is small enough to be dropped. In such cases, the above equation reduces to

$$\frac{\Delta R}{R} = \sum_i \frac{a_i q_i}{R}\frac{\Delta q_i}{q_i}. \tag{2.31}$$

Unfortunately, there will be situations where the cross terms are not negligible. In these cases, knowing only the risk change of individual basic events from Equation 2.26 does not provide enough information to compute the risk change that could result from changes in the probabilities of a group of basic events. To overcome this problem, a so called risk/safety monitor program[26, 32, 23] has been developed. A risk monitor is a software algorithm that can quickly reevaluate the PRA model when one or more changes are made, especially during maintenance activities.

In general, nuclear PRAs are complicated and it is impossible to analytically derive the overall risk change for a group of events. Analytical calculation becomes feasible only when the cross product terms are relatively small compared to first-order terms such that they can be dropped. However, the development of fast algorithms for evaluating the logic enables us to evaluate the impact of various activities on the risk level very quickly, even when these activities impact many different components and plant configuration. For example, risk monitoring program have been used in a number of nuclear power plants throughout the world to evaluate the impact of various maintenance activities on plant risk level quickly.

2.3 Regulatory Safety Goals and Acceptance Guidelines for Using PRA in Risk-Informed Decisions

In order to assess the acceptability of nuclear power plant risk levels and various nuclear activities, regulatory acceptance guidelines have been developed. In this section, we first present the NRC Safety Goal. We then describe the NRC Acceptance Guidelines for proposed changes to a plant's current licensing basis as defined in RG 1.174.

The objective of the USNRC Safety Goal Policy Statement [12] is *"to establish goals that broadly define an acceptable level of radiological risk."* Two qualitative safety goals, supported by two quantitative health objectives, in terms of public prompt fatality and cancer fatality health risks were defined in the safety goal statement. The qualitative safety goals clearly state the NRC's principle that nuclear risks should not be a significant addition to other societal risks.

The NRC safety goal for prompt fatalities is that the risk to an average individual in the vicinity of a nuclear power plant that might result from reactor accidents should not exceed 0.1% of the sum of prompt fatality risks resulting from other accidents to which members of the U.S. population are generally exposed. Since the accident risk in the U.S. is about 5×10^{-4} per year[46], this translates to a prompt fatality goal of 5×10^{-7} per year.

The NRC safety goal for latent cancer fatalities is that the risk to the population in the area near a nuclear power plant that might result from plant operation should not exceed 0.1% of the sum of latent cancer fatality risks resulting from all other causes. Since the cancer fatality risk in the U.S. is about 2×10^{-3} per year[46], this translates to a cancer fatality risk goal of 2×10^{-6} per year.

Due to the considerable amount of uncertainty associated with a level-3 PRA for estimating offsite risks, many utilities chose not to perform a level-3 analysis. In practice, to be consistent with industry practices, a subsidiary CDF objective of 1×10^{-4} per reactor year and a subsidiary LERF objective of 1×10^{-5} per reactor year are used as surrogates for the NRC quantitative health objectives[8]. By comparing the plant CDF and LERF with the safety goals, one can determine the acceptability of the societal risk that could result from plant operation.

In order to review proposed changes to the licensing basis, the NRC developed quantitative risk acceptance guidelines for judging whether a proposed change is acceptable in terms of the resulting change in CDF or LERF. As presented in the NRC Regulatory Guide 1.174, the acceptance guidelines for the CDF states that if the proposed change clearly results in a decrease in the CDF or a smaller increase than 10^{-6} per reactor year in the baseline CDF, the proposed change is generally considered acceptable regardless of the baseline CDF. If the proposed change results in an increase in the CDF greater than 10^{-5} per reactor year, the proposed change would normally not be acceptable. When an application results in an increase in the CDF in the range of 10^{-6} per reactor year to 10^{-5} per reactor year, the acceptability of the proposed change depends upon the baseline CDF. If the total CDF is shown to be less than 10^{-4} per reactor year, the proposed change is considered acceptable. Otherwise, it is not acceptable. By multiplying the above threshold values by a factor of ten, we obtain the corresponding acceptance guidelines for LERF.

The applications of the NRC CDF and LERF acceptance guidelines can be illustrated in a recent study at a U.S. nuclear power plant on extending the plant's (Type

A) integrated leak rate test (ILRT) interval from 10 to 15 years. The results of this study indicate that the ILRT does not impact the plant CDF, but the resulting change in the LERF is 1.14×10^{-8} per reactor year. Since the increase in CDF and LERF are well below the NRC acceptance guidelines for CDF and LERF, extending the ILRT test frequency from 10 to 15 years would not have a significant impact on the plant risk level, and thus proposed test relaxation is acceptable.

2.4 Comparison of PRA Results with Acceptance Guidelines

General approaches for quantifying PRAs and regulatory acceptance guidelines for the use of PRA results in risk-informed decision making are described in the previous two sections. In this section, we describe several approaches for comparing PRA results with the acceptance guidelines as those discussed in SECY-97-211 [7].

The first approach is to compare the point estimated PRA risk and risk change with the acceptance guidelines. This approach uses point values of the model inputs to obtain point estimates of the risk and risk increments through the minimal cut sets. The point values of input parameters are usually obtained directly from plant historical operations, testing, expert judgment, and data from similar equipment or human activities. These point values can be the mode, mean, median, and other confidence level values of model inputs. The point estimate approach for quantifying PRAs has the potential to provide the decision makers with very precise information about the magnitude of risk and change in risk. However, the true values of many model inputs may be unknown, and the use of point values for model inputs does not take the state-of-knowledge uncertainty into account. This limitation would indicate that point estimated risk and risk changes are likely to be inaccurate.

The second approach is the use of mean values of risk and risk change in comparison with acceptance guidelines. In this approach, the expectations of risk and risk changes are compared with the safety goal and acceptance guidelines to determine the acceptability of a risk level or activity. The state-of-knowledge uncertainties are properly taken into account by assigning probability distributions to uncertain input parameters and candidate models. The probability associated with a value represents the analyst's confidence in the value being the correct value for the input parameter, and the probability associated with a model represent the analyst's belief in the model being the correct model. These epistemic uncertainties are then propagated through the minimal cut sets to obtain probability distributions for risk and risk change. The mean values of risk and risk change are then obtained from the corresponding probability distributions.

Compared to the point estimate approach, the use of the mean value approach is more robust because the mean value contains information on the uncertainty associated with the results. However, this method is more computational expensive than the point estimate approach. It is also difficult to apply in some cases because of the lack of knowledge of the appropriate probability distribution forms for input parameters and the appropriate value for each candidate model which represents the analyst's belief in the model being the correct model.

An alternative for comparing PRA results with acceptance guidelines is by way of estimating the degree of confidence that the acceptance guidelines have been met. This is typically done by calculating the probabilities that the plant risk level is lower than the safety goal and the increase in risk is lower than the acceptance guidelines. In practice, 95% is used as the confidence level for acceptability. In other words, a risk level is acceptable only if the degree of confidence that the safety goal has been met is higher than 95%. In such cases, as SECY-97-221 pointed out, the confidence level in the satisfaction of the safety goal and acceptance guidelines is sensitive to the form of the tails of the distributions of risk and risk changes. If the tails are abnormal, this approach would give a false sense of assurance.

2.5 Summary

In this chapter, we described methods for quantifying PRAs. We first describe existing methods for quantifying logic models such as fault trees and event trees. The methods discussed include qualitative methods for determining minimal cut sets and quantitative methods for computing risk and risk change using the minimal cut sets. We focus particularly on the rare event approximation because it gives fairly accurate results in most cases and it can be computed in less computation time than other approximations.

We also discussed existing regulatory acceptance guidelines for the use of PRA results in risk-informed decision making. The acceptance guidelines discussed include the NRC safety goal for regulating the overall risk that could result from the operation of a plant, and the NRC acceptance guideline as those presented in the RG 1.174 for the acceptability of proposed changes in plant design and activities. We then presented and compared several methods for comparing PRA results with acceptance guidelines. The use of point estimate values was found to be by far the simplest of the methods discussed. However, this method would most likely lead to biased estimates of the baseline risk and risk changes. The use of the mean values method was found to be simple and is the most frequently used method which takes epistemic uncertainty into account, while the confidence level approach provides decision makers with the degree of confidence that the acceptance guidelines have been met.

Chapter 3

New Measures of Risk Significance and Risk Change Significance

In Chapter 2, we discussed methods for evaluating the overall risk, typically CDF and LERF for nuclear power plants, from initiating event frequencies and basic event probabilities. We also discussed a method for computing the change in risk resulting from changes in event probabilities under the rare event approximation and the assumption of independence among event probabilities. Based on these discussions, we now introduce new measures of risk significance and risk change significance for initiating events and basic events in a logic model. These two significance measures will be used to assess the adequacy of PRA results for risk-informed decision making.

The significance of an event within a PRA is defined as the impact of its exclusion from the analysis on the final outcome of the PRA. When the baseline risk is the final outcome of interest, we define the significance of an event as risk significance (RS), measured in terms of the resulting percentage change in the baseline risk. When there is a change in plant design or activities and risk change is the final PRA outcome of interest, we define the significance of an event as risk change significance (RCS). These two significance measures can therefore be useful in identifying basic events and initiating events that are important to the accuracy of the baseline risk and risk change.

This chapter begins with a general discussion of several importance measures which have been most commonly used in risk-informed activities. Next, we discuss the limitations of these existing measures. We then develop the concepts of risk significance and risk change significance for events in the PRA, and general approach for calculating these two measures. These new measures are then compared with the traditional importance measures by use of an example.

3.1 Existing Importance Measures

One of the many applications of a PRA's findings and results is to use importance measures to identify events, minimal cut sets and accident sequences that contribute significantly to risk. By focusing resources on the major risk contributors, nuclear power plants can improve safety in an efficient way.

Most work on importance measures has focused on estimating the resulting change in the risk level due to either an infinitely small change or an extreme change in the event probability. Several such measures of importance which were suggested by researchers and widely used are discussed below.

The Fussell-Vesely (FV) importance measure was first introduced by W.E. Vesely and later applied by Fussell in 1975 [27, 43, 9, 48]. The FV importance of basic event i is defined to be the fractional contribution to the baseline risk of all the minimal cut sets containing the specified basic event. According to Equation 2.23, this importance measure can be represented mathematically as follows:

$$FV(i) = \frac{\sum_j P(MCS_j(BE_i))}{R} = \frac{a_i \cdot q_i}{a_i \cdot q_i + b_i}. \tag{3.1}$$

The above expression can be rewritten as

$$FV(i) = 1 - \frac{b_i}{a_i \cdot q_i + b_i}. \tag{3.2}$$

When $a_i \cdot q_i << b_i$, Equation 3.1 becomes

$$FV(i) = \frac{a_i}{b_i} \cdot q_i. \tag{3.3}$$

We note that, for this case, FV importance is proportional to the probability of basic event i. In other words, the FV importance increases as the event probability goes up. The reverse would be true if the event probability decreases.

In general, FV of an event does not directly measure how much the event contributes to risk, but measures the fractional risk that is relevant to the event. Thus, events that participate in the same set of minimal cut sets but differ in the probabilities of occurrence generally have the same FV importance.

FV importance of a structure, system, and component(SSC) can be defined in a similar way. In this case, FV importance is useful in identifying risk significant SSCs for risk-based inservice testing programs or special treatment programs. However, since an SSC is typically not represented by a single basic event or initiating event in the logic model, and FV importance is not additive at the basic event level, the evaluation of the FV importance of individual SSC is likely to be difficult.

The Risk Achievement Worth(RAW) importance [27, 43, 9] for a basic event is a measure of the extreme change in risk when the Boolean variable for the basic event is set to true. RAW can be defined either as a ratio or as a difference. According to Equation 2.23, as a ratio, this measure can be represented as:

$$RAW(i) = \frac{R(q_i = 1)}{R} = \frac{a_i + b_i}{R}. \tag{3.4}$$

RAW estimates the conditional increase in risk given a basic event has occurred. For example, the RAW value of a component in a system measures the maximal increase in the system failure probability when the component fails. This measure is therefore useful for identifying the failure of which components results in the greatest degradation of system reliability.

We note that the RAW importance cannot be extended to initiating events. In most cases, the frequency of occurrence of an initiating event is modelled by the use of fault trees. When an initiating event is modelled only as a data variable, setting the initiating event frequency to one does not guarantee the occurrence of the initiating event.

Vesley [50] pointed out that FV and RAW measure different attributes of an event and therefore there is no direct correlation between these two measures. He stated that FV measures the importance of an occurring event while RAW measures the importance of an existing condition, e.g. conditional upon the occurrence of the event.

The Risk Reduction Worth(RRW) importance [27, 43, 9] is defined in a similar way to the RAW importance. This measure estimates conditional reduction in risk given a basic event would never occur. Using this notation and by considering Equation 2.23, RRW can be represented as a ratio as:

$$RRW(i) = \frac{R}{R(q_i = 0)} = 1 + \frac{a_i}{b_i} \cdot q_i. \tag{3.5}$$

By rearranging the terms in the above equation, we obtain

$$RRW(i) = \frac{1}{1 - FV_i}. \tag{3.6}$$

This relationship shows that the RRW measure is equivalent to FV importance but given in different physical forms. In practice, RRW can be useful in identifying the optimal components for improving system reliability.

Lambert [27, 3] argues that basic event probabilities may differ by several orders of magnitude, and for this reason the importance of basic events should be compared on the basis of percentage rather than absolute change in probabilities in a sensitivity analysis. According to this notation, the measure he proposed is governed by

$$Lambert(i) = \frac{\partial R/R}{\partial q_i/q_i}. \tag{3.7}$$

This measure is defined as the ratio of percentage change in risk per unit percentage change in the basic event probability. Lambert pointed out that his measure is the most appropriate measure to use in deciding how to reduce risk. For example, by assuming that the cost of reducing the failure probability of any basic event only depends on the size of reduction in percentage terms, then in order to achieve a reduction in system unavailability, the optimal basic event to select will be the one with the largest value of Lambert's importance measure.

By substituting Equation 2.23 into Equation 3.7, we obtain the Lambert importance for basic event i as

$$Lambert(i) = \frac{\partial R}{\partial q_i} \cdot \frac{q_i}{R} = \frac{a_i \cdot q_i}{R} = FV(i). \tag{3.8}$$

This expression indicates the Lambert importance of a basic event is equivalent to its FV importance and RRW importance but written in a different form.

Emannuele Borgonovo [5, 6] points out that traditional importance measures are not defined for a group of basic events and do not directly relate to risk changes. To overcome these drawbacks, he introduced another importance measure, the Differential Importance Measure (DIM). This measure is defined as the fractional contribution to the overall risk change from a sufficiently small change in a specified model input parameter. Mathematically, DIM can be represented as follows:

$$DIM(x_i) = \frac{dR_{x_i}}{dR} = \frac{\frac{\partial R}{\partial x_i} \cdot dx_i}{\sum_j \frac{\partial R}{\partial x_j} \cdot dx_j}. \tag{3.9}$$

Where,dx_i is a sufficiently small change in the value of parameter x_i, dR_{x_i} is the resultant change in R due to the change in the value of parameter x_i, and dR is the overall change in R as a result of a small change in the value of each individual input parameter of the PRA model.

DIM has two operational forms. For a uniform change in all parameter, $dx_i = \omega$, Equation 3.9 can be replaced as:

$$DIM(x_i) = \frac{dR_{x_i}}{dR} = \frac{\frac{\partial R}{\partial x_i}}{\sum_j \frac{\partial R}{\partial x_j}}. \tag{3.10}$$

For a uniform percentage change in all parameters, $\frac{dx_i}{x_i} = \omega$, Equation 3.9 can be replaced as:

$$DIM(x_i) = \frac{dR_{x_i}}{dR} = \frac{\frac{\partial R}{\partial x_i} \cdot x_i}{\sum_j \frac{\partial R}{\partial x_j} \cdot x_j}. \tag{3.11}$$

The DIM importance introduced by Borgonovo simplifies the computation of risk changes and takes epistemic uncertainty into account, especially when a model input parameter is shared by several basic events. DIM is also additive. DIM of multiple basic events can be computed as the sum of the DIMs of individual basic events. However, the computation of DIM is conditional on small variations in the values of the parameters. In order not to apply partial derivative approach to the computation of DIM, a suitably small change in parameters has to be defined. However, in practice, no particular small change has been proven to be more adequate than others. In reality, changes in the parameters might be relatively large so that DIM is no longer applicable.

3.2 Limitations of Existing Importance Measures

There are a number of limitations of the existing importance measures that directly arise from their definitions and computations. First of all, most of the measures evaluate the importance of an event or parameter in terms of the resulting change in the baseline risk that could result from an infinitesimally small change or an extreme change in the event probability or parameter value. Therefore, they indicate the degree of sensitivity of risk to event probability. These measures can provide useful information for various tasks such as maintenance, testing, and plant modifications to reduce plant risk level. However, none of the existing measures can be used directly to measure the importance of an event with respect to the accuracy of PRA results. In other words, none of these measures can be used directly to assess the impact of the omission of an event from the logic model on the risk.

Secondly, the traditional measures are evaluated based upon the limited scope PRA. When certain events are omitted from the analysis, the numerical values of PRA results, including these traditional measures, can change significantly. Furthermore, the PRA software tools are programmed to compute FV, RAW, and RRW from the truncated model when truncation limit is used to speed up the quantification of the PRA. As a result, these importance measures for some SSCs may be underestimated or overestimated by a significant amount [4].

In addition, most of the existing importance measures are defined with respect to the baseline risk. However, when risk change is an important input to the risk-informed decision making processes, events that are important to achieve an accurate estimate of risk change should be identified and addressed explicitly in the PRAs, even though they may not contribute significantly to the baseline risk.

These limitations suggest that it is necessary to introduce new measures of significance which rank events in terms of their importance to the degree of accuracy of PRA results, in particular the accuracy of risk and risk changes. The new measures will be useful to decision makers who are concerned with achieving accurate estimates of risk and risk change, and providing justification for events being screened out the analysis.

3.3 A Proposed Measure of Risk Significance

3.3.1 Definition

Based upon the above discussion of importance measures, we define our proposed measure of risk significance of an initiating event or a basic event in the PRA in terms of the percentage change in the baseline risk due to the omission of the event from the logic model. By letting $R_{w,i}$ be the baseline risk after taking event i into consideration, and $R_{w/o,i}$ be the risk evaluated when event i is omitted from the analysis, our proposed measure of risk significance of event i with respect to the baseline risk can be written as:

$$RS_i = \frac{R_{w/o,i} - R_{w,i}}{R_{w,i}}. \tag{3.12}$$

This expression indicates that RS of an event measures the impact of the omission of the event from the analysis on the accuracy of the baseline risk in terms of the discrepancy between the the baseline risk obtained by considering event i in the analysis and that obtained without considering event i in the analysis.

From the definitions of the existing importance measures, we note that most traditional importance measures evaluate the resulting change in risk that could result from a given change in event probability. They therefore indicate the degree of sensitivity of the baseline risk to the event probability. On the contrary, our measure of RS of an event measures the degree of sensitivity of the accuracy of the baseline risk to the exclusion of the event from the analysis. Therefore, RS is useful to decision makers who are concerned with improving the accuracy of the baseline risk, e.g. by addressing events with a high RS measure in the PRA, while the traditional measures are helpful to decision makers whose objective is to manage risk, if not reduce risk, e.g. by reducing the failure probability of those SSCs with high RAW and RRW importances.

From Equation 3.12 we note that the value of RS_i depends upon which model is used as the reference model when computing RS. If the complete model which addresses all events that are identified by the analyst is used as the reference model, $R_{w,i}$ in the above equation is the baseline risk of the complete model. In practice, the baseline risk of the complete model is often referred to as the nominal baseline risk and represented by R_0. By replacing $R_{w,i}$ with R_0, Equation 3.12 becomes

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0}. \tag{3.13}$$

Under a different situation, if the current incomplete model, from which a set of events are omitted, is used as the reference model, $R_{w/o,i}$ in Equation 3.12 is the baseline risk of the current model. By denoting the baseline risk of the current incomplete model as R_c, Equation 3.12 becomes

$$RS_i = \frac{R_c - R_{w,i}}{R_{w,i}}. \tag{3.14}$$

Clearly, these two situations are not equivalent and the estimates of RS_i should be different. The conditions under which one should use the complete model as the reference model and under which one should use the incomplete model as the reference model depend upon the model and the problem at hand. If the size of the PRA is small and the complete model can be easily developed and quantified, both the complete model and the current incomplete model can be used as the reference model to compute RS. If the size of the PRA is large and it is difficult to develop a complete model by addressing all identified events, the current incomplete model should be used as the reference model. In this chapter, we will restrict our attention(except where otherwise specified) to the case where the complete model is used as the reference model to compute RS. Discussion about the computation of RS in case where the current incomplete model is used as the reference model is presented in Appendix A.

Finally, we define the RS for a set of events as follows. For any set of events, the measure RS is defined to be the percentage baseline risk not considered which could result from the exclusion of the set of events from the analysis. For event which is the only event in the minimal cut set, the RS of any set of such events can be computed by summing the RS of each event in the set:

$$RS_s = \sum_{i \in s} RS_i. \tag{3.15}$$

In practice, a minimal cut set often consists of several events. The effect of the exclusion of the set of events from the analysis on the baseline risk could not be evaluated by use of the above equation.

Now we would like to compute the RS of any event in the PRA. We begin with the simple system presented in Chapter 1. The fault tree of the system is shown in Figure 3-1.

Now we suppose that the failure probability of component 1 is 6×10^{-3} instead of 1×10^{-3}. This would indicate that the failure probabilities of components 1 and 3 are the same. In such case, by considering Equation 1.3, the system failure probability becomes

$$Q_0 \cong q_1 q_2 + q_3 + q_4 = 1.4006 \times 10^{-2}. \tag{3.16}$$

In the case where the contribution to the system failure probability of the failure of component 1 is not taken into account, according to Equation 1.7, the system

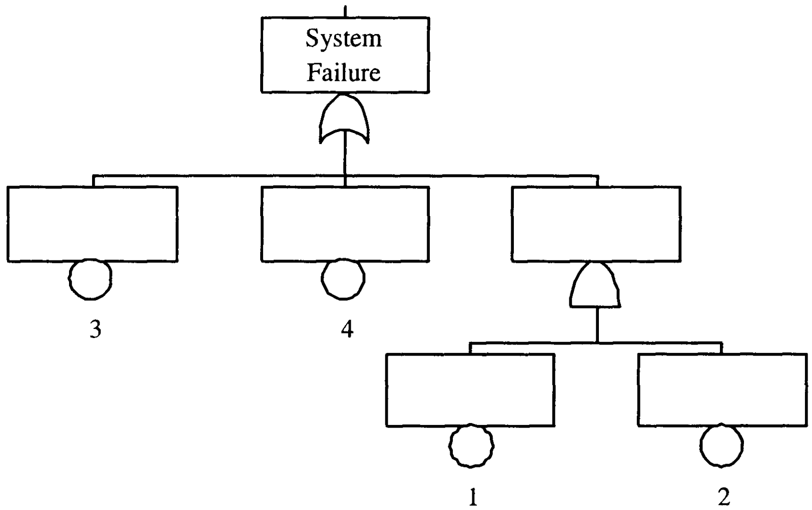

Figure 3-1: An example system to illustrate the impact of the exclusion of an event

failure probability is

$$Q_{w/o,1} \cong q_2 + q_3 + q_4 = 1.5 \times 10^{-2}. \tag{3.17}$$

Now suppose we remove component 3 from the analysis and recalculate the system failure probability. The causes of the failure of the system are the joint failure of components 1 and 2, and the failure of component 3. The system failure probability is thus

$$Q_{w/o,3} \cong q_1 q_2 + q_4 = 8.006 \times 10^{-3}. \tag{3.18}$$

By comparing $Q_{w/o,1}$ with $Q_{w/o,3}$, we note, by not considering component 1 in the analysis, the system failure probability is overestimated by roughly 1.0×10^{-3}. By not considering component 3 in the analysis, the system failure probability is underestimated by 6.0×10^{-3}. These results indicate the impact of the omission of component 1 from the analysis on the system failure probability is quite different from that of the omission of component 3 from the analysis, even though the failure probabilities of components 1 and 3 are the same. We therefore remark the impact of the exclusion of an event from the analysis on the risk depends upon not only the probability of the event, but also the location of the event in the logic model.

In order to compute the RS of any event in the PRA, we group the events in a PRA into four types:

- initiating events
- basic events whose first operators are AND gates
- basic events whose first operators are OR gates
- basic events whose first operators are both AND gates and OR gates

The following four sections present the general approach for computing RS for each of the four types of events, respectively.

3.3.2 Computation of RS for Initiating Events

When an initiating event is removed from the analysis, all the accident sequences initiated by this event will also be removed. The effect of omitting an initiating event from the analysis on risk is therefore equivalent to that of setting the event frequency to zero. We thus have,

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(q_i = 0) - R_0}{R_0}. \tag{3.19}$$

It is worth noting that, when initiating event i is not considered in the analysis, the probabilities of those events which are related to event i should be adjusted correspondingly when calculating $R(q_i = 0)$ in the above equation.

To see this, let us consider the failure probability of a component in a nuclear power plant. We assume that the conditional failure probability this component is 2.0E-01 given that an earthquake has occurred, and the failure probability of this event due to all other causes is 6.0E-03. By assuming that the annual frequency of occurrence of an earthquake at the plant site is 4.0E-02, the overall failure probability of this component is 1.4E-02. In the case where seismic events are not considered in the analysis, the contribution of seismic events to the failure of the component should not be considered either, and the failure probability of the component would be 6.0E-03.

For the case where the frequency of occurrence of initiating event i is independent of all other events, Equation 3.19 becomes

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(q_i = 0) - R_0}{R_0} = \frac{1}{RRW_i} - 1 = -FV_i. \tag{3.20}$$

The above expression indicates that the RS of independent initiating event i is equivalent to its RRW and FV measures of importance. Given that $0 < FV_i \leq 1$, the RS of this initiating event satisfies the inequality

$$-1 \leq RS_i < 0. \tag{3.21}$$

This reflects the fact that the omission of initiating events from the analysis results in an underestimate of the nominal risk. The lower bound,

$$RS_i = -1, \tag{3.22}$$

is attained only when initiating event i is the only initiating event in the analysis.

The expression of RS as shown in Equation 3.20 as a function of the RRW and FV of the events facilitates the computation of RS. The reason is that the RRW and FV of an event can be calculated using existing PRA software, such as SAPHIRE and RISKMAN program which was developed at PLG Inc.

3.3.3 Computation of RS for Basic Events at AND Gates

In this section, we investigate the impact of the omission basic event at AND gates on the minimal cut sets and baseline risk. We begin with a simple system. The fault tree model of the example system is shown in Figure 3-2.

The minimal cut sets of the fault tree are

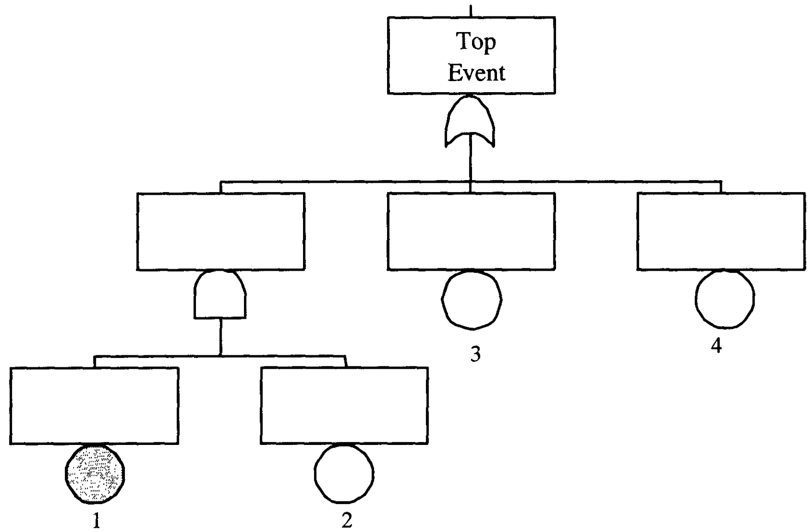

Figure 3-2: An example fault tree with the omitted basic event at AND gates

$$X_1X_2,\ X_3,\ X_4.$$

The probability of the top event, R, is therefore,

$$R_0 = q_1q_2 + q_3 + q_4 - q_1q_2q_3 - q_1q_2q_4 - q_3q_4 + q_1q_2q_3q_4. \tag{3.23}$$

R_0 denotes the nominal value of R. We now explore the resulting change in the logic model structure and minimal cut sets due to the omission of event 1 from the analysis. When event 1 is taken out of the fault tree while all other events remain unchanged, the logic model becomes the fault tree as shown in Figure 3-2.

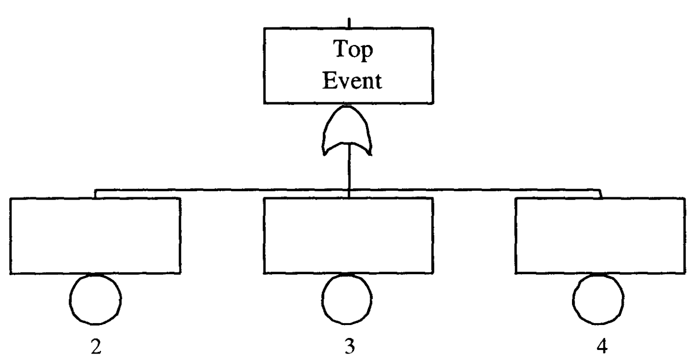

Figure 3-3: The example fault tree when basic event 1 is omitted from the AND gate

The minimal cut sets of the modified fault tree are

$$X_2,\ X_3,\ X_4$$

. The corresponding probability of the top event is therefore

$$R_{w/o,1} = q_2 + q_3 + q_4 - q_2q_3 - q_2q_4 - q_3q_4 + q_2q_3q_4. \tag{3.24}$$

$R_{w/o,1}$ is the value of R evaluated without considering event 1 in the analysis. By comparing Equation 3.24 with Equation 3.23, we note that $R_{w/o,1}$ is equal to R_0 when the Boolean variable of event 1 is set to true, or unity. Mathematically, this relationship can be represented by

$$R_{w/o,1} = R_0(X_1 = 1). \tag{3.25}$$

Although the above expression is obtained from the case where event 1 only appears once at AND gate in the logic model, it also applies to the case where an event appears at multiple AND gates in a more complicated fault tree model. Thus, when such a basic event is not considered in the analysis, the minimal cut sets and top event probability of the modified fault tree can be obtained by setting the Boolean variable of the event to true, or unity.

The general formulation of RS of basic events at AND gates can thus be written as:

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(X_i = 1) - R_0}{R_0}. \tag{3.26}$$

In the case where the probability of event j is dependent on the analysis of event i, when event i is not considered in the analysis, the probability of event j should be adjusted correspondingly when calculating $R_{w/o,i}$. For basic event whose probability is independent of the probabilities of other events, we have

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(X_i = 1) - R_0}{R_0} = RAW_i - 1. \tag{3.27}$$

Given RAW_i is greater than one, RS of basic events at AND gates then satisfies the inequality

$$RS_i > 0. \tag{3.28}$$

This expression indicates that the omission of basic events at AND gates generally results in an overestimate of the nominal baseline risk. This can be explained by the fact that components at AND gates are in a parallel configuration, and they provides functional redundancy or "defense in depth" to each other. When one of the components in the parallel configuration is not taken into consideration, the degree of functional redundancy decreases, and the system risk level increases.

The relationship between RS of basic events at AND gates and their RAW importance shown in Equation 3.27 enables the computation of the RS by use of standard PRA software. Therefore, RS of basic events at AND gates can also be computed with minimal cost.

3.3.4 Computation of RS for Basic Events at OR Gates

In the previous section we investigated the effect of the omission of basic events at AND gates on minimal cut sets and risk. In this section, we explore the effects of the omission of basic events at OR gates on the minimal cut sets and risk. We also begin our investigation with a simple fault tree as shown in Figure 3-4.

The minimal cut sets of the example fault tree are

$$X_1X_3X_4,\ X_2X_3X_4.$$

The probability of the top event, R, is therefore

$$R_0 = (q_1 + q_2 - q_1 \cdot q_2) \cdot q_3 \cdot q_4. \tag{3.29}$$

R_0 is the nominal value of R. When event 1 is not considered in the logic model, the logic model becomes the one shown in Figure 3-5.

The minimal cut set of the modified fault tree is

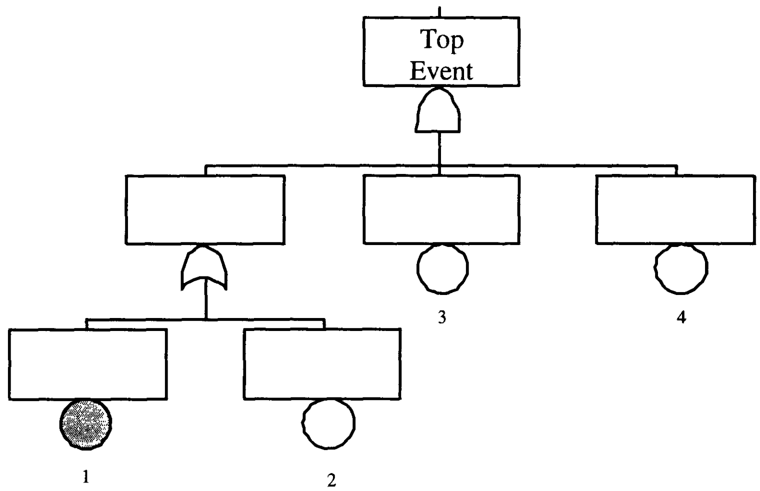

Figure 3-4: An example fault tree with the omitted basic event at OR gates

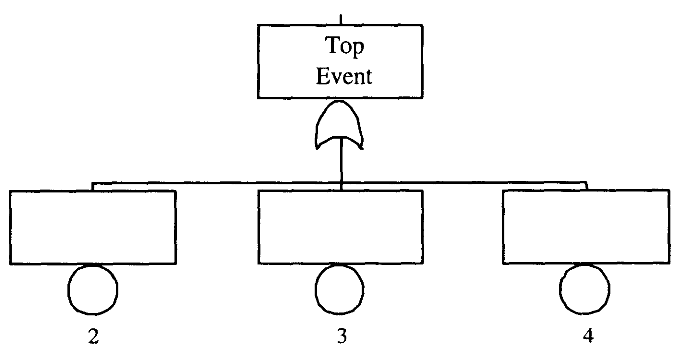

Figure 3-5: The example fault tree when basic event 1 is omitted from the OR gate

$$X_2X_3X_4.$$

The corresponding probability of the top event of the modified logic model is therefore

$$R_{w/o,1} = q_2 \cdot q_3 \cdot q_4. \tag{3.30}$$

$R_{w/o,1}$ is the top event probability evaluated without addressing event 1 in the analysis. By comparing Equation 3.30 with Equation 3.29, we note that $R_{w/o,1}$ equals to R_0 when the Boolean variable of basic event 1 is set to false, or zero. Mathematically, we have

$$R_{w/o,1} = R_0(X_1 = 0). \tag{3.31}$$

Although this finding is derived from a basic event which is input to one OR gate, it also applies to basic event which is input to multiple OR gates. To generalize, Equation 3.13 for basic events at OR gates becomes

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(X_i = 0) - R_0}{R_0}. \tag{3.32}$$

For events whose probability is independent of the probabilities of other events, we have

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = \frac{R(X_i = 0) - R_0}{R_0} = \frac{1}{RRW_i} - 1 = -FV_i. \tag{3.33}$$

This expression indicates, similar to the case where the omitted event is an initiating event, the omission of basic events at OR gates results in an underestimate of the nominal risk. The percentage change in risk due to the omission of such a basic event also satisfies the inequality:

$$-1 \leq RS_i < 0. \tag{3.34}$$

The lower bound,

$$RS_i = -1, \tag{3.35}$$

is attained only when basic event i is the only basic event in the minimal cut set of the top event.

We note, as initiating events, the RS of independent basic events at OR gates can be also computed by use of PRA software programmed to compute RRW and FV importance measures.

3.3.5 Computation of RS for Basic Events at both AND Gates and OR Gates

The above three sections investigated the effect on the minimal cut sets and risk of the omission of initiating events, or basic events which only appear at AND gates or OR gates. In this section, we investigate the effect on the minimal cut sets and risk if the omitted basic event appears at both AND gates and OR gates.

We begin by considering the fault tree shown in Figure 3-6. The system represented by this fault tree includes only three minimal cut sets. One consisting of basic events 1 and 3, one consisting of basic events 2 and 3, and one consisting of basic events 1 and 5.

By using the rare event approximation, the top event probability of the fault tree is

$$R_0 = q_1 q_3 + q_2 q_3 + q_1 q_5. \tag{3.36}$$

We now remove event 1 from the logic model. The reduced fault tree is shown in Figure 3-7. The minimal cut sets of the modified model are

$$X_2 X_3,\ X_5.$$

The corresponding probability of the top event can therefore be written as

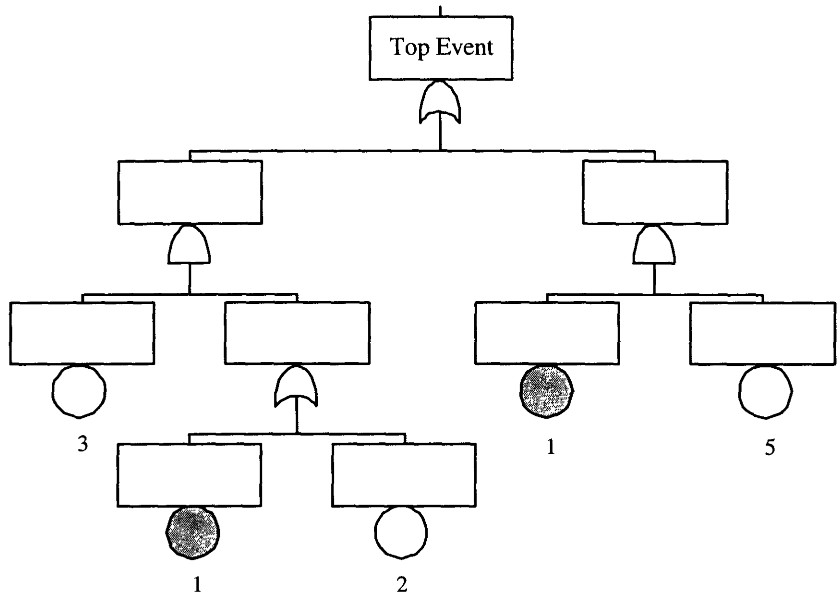

Figure 3-6: An example fault tree with the omitted basic event at both AND gates and OR gates

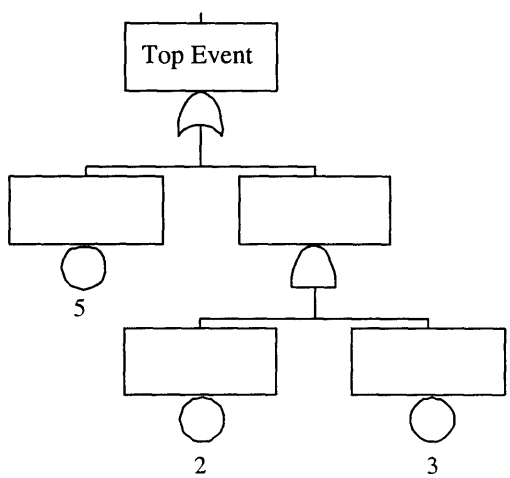

Figure 3-7: An example fault tree for a basic event omitted at an AND gate

$$R_{w/o,1} = q_2q_3 + q_5 - q_2q_3q_5. \tag{3.37}$$

By comparing Equation 3.36 with Equation 3.37, we note that $R_{w/o,1}$ is equal to R_0 when the Boolean variable of event 1 is set to unity for its appearance at the AND gate, and to zero for its appearance at the OR gate. The RS of event 1 thus equals to

$$RS_1 = \frac{R_{w/o,1} - R_0}{R_0} = \frac{q_5 - q_1q_3 - q_1q_5 - q_2q_3q_5}{R_0}. \tag{3.38}$$

Since the FV of basic event 1 is governed by

$$FV_1 = \frac{\sum MCS(q_1)}{R_0} = \frac{q_1q_3 + q_1q_5}{R_0}, \tag{3.39}$$

and the RAW of basic event 1 is governed by

$$RAW_1 = \frac{R(X_1 = 1)}{R_0} = \frac{q_2q_3 + q_3 + q_5}{R_0}, \tag{3.40}$$

the RS of basic event 1 cannot be related to either its FV importance or its RAW importance.

From our discussion above, we note that the overall effect of the exclusion of basic events at both AND gates and OR gates from the analysis on the minimal cut sets and risk can be obtained by setting the event's Boolean variable equal to true for its appearances at AND gates and equal to false for its appearances at OR gates. Mathematically, the formulation of R for basic events at both AND gates and OR gates as can be written in terms of

$$\begin{aligned} RS_i &= \frac{R_{w/o,i} - R_0}{R_0} \\ &= \frac{R(X_i = 1 \text{ for event } i \text{ at AND gates}, X_i = 0 \text{ for event } i \text{ at OR gates}) - R_0}{R_0}. \end{aligned} \tag{3.41}$$

In this case, since RS of event i can not be related to either the FV importance or the RAW importance of the event, the computation of the RS involves a reformulation of the minimal cut sets, which is typically not straightforward. Thus, the computation of the RS for events at appear both at AND gates and OR gates is far more complex than that for initiating events or basic events which appear only at AND gates or OR gates.

3.3.6 The Effect of Dependence on the Computation of RS

The existence of dependence among basic event probabilities implies that changes made to one basic event probability will change the probabilities of the other related basic events as well. For example, for a system consisting of several identical components from the same manufacturer, a single failure rate is usually applied to all components. This type of dependence reflects the analyst's knowledge about the failure probability of various components. Another situation in which dependence might arise would be a set of components that are functionally dependent upon each other. In this case, failure of one component would result in the failure of all other components simultaneously.

The RRW yields a maximal decrease in risk when "the event is impossible or the equipment is totally reliable." [9] The RAW yields a maximal increase in risk when "the event has occurred or the equipment has failed." [9] These definitions indicate that the dependencies among basic event probabilities and initiating event frequencies should be taken into account in computing an event's RRW and RAW measures of importance, especially for the case where the failure probabilities of come components are perfectly correlated to each other. For example, if the probability of event i is assumed to be perfectly correlated to the probability of event j, then the occurrence of the failure of event i also implies the simultaneous failure of event j. The reverse would be true for the impossibility assumption. Therefore, the RRWs and RAWs of event i and j in the correlated case would differ from those in the independent case.

From the previous example of a component failure probability presented in the beginning of this section, we note that the dependencies among event probabilities or frequencies also affect the computation of RS and RCS. The RS of event i is defined as the percentage change in the nominal risk when event i is not considered in the model. If event i is an input to AND gates, the effect of removing it from the analysis on the minimal cut sets and risk is the same as setting the event Boolean variable to true. If event i is an input to OR gates, omitting it from the analysis has the same impact on risk as setting the event Boolean variable to false. Although setting the Boolean variable of event i to true or false does not imply a guaranteed occurrence or nonoccurrence of the event, the probabilities of those events which are related to the analysis of event i should be adjusted correspondingly when event i is not considered in the analysis.

In many circumstances, the adjustment made in the probabilities of related events given event i has occurred or would never occur may be different from that given event i is omitted from the analysis. The relationships between RS and RRW and RAW as presented in Equation 3.42 are generally only valid for independent event probabilities or the cases where same adjustments would be made in the probabilities of related events in computing RAW, RRW, and RS.

$$RS_i = \begin{cases} RAW_i - 1 & \text{for basic events at AND gates} \\ \\ \frac{1}{RRW_i} - 1 & \text{for basic events at OR gates.} \end{cases} \tag{3.42}$$

The relationship between the RS and FV as shown in Equation 3.43 is also generally only valid for independent event probabilities.

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0} = -FV_i. \tag{3.43}$$

To illustrate the impact of dependence among event probabilities or frequencies on the importance measures, let us consider a fault tree as shown in Figure 3-2. Suppose the probability of components 1 and 3 is perfectly correlated. The minimal cut sets of the system represented by the fault tree are:

$$X_1X_3, X_1X_4, X_2X_3, X_2X_4, X_5.$$

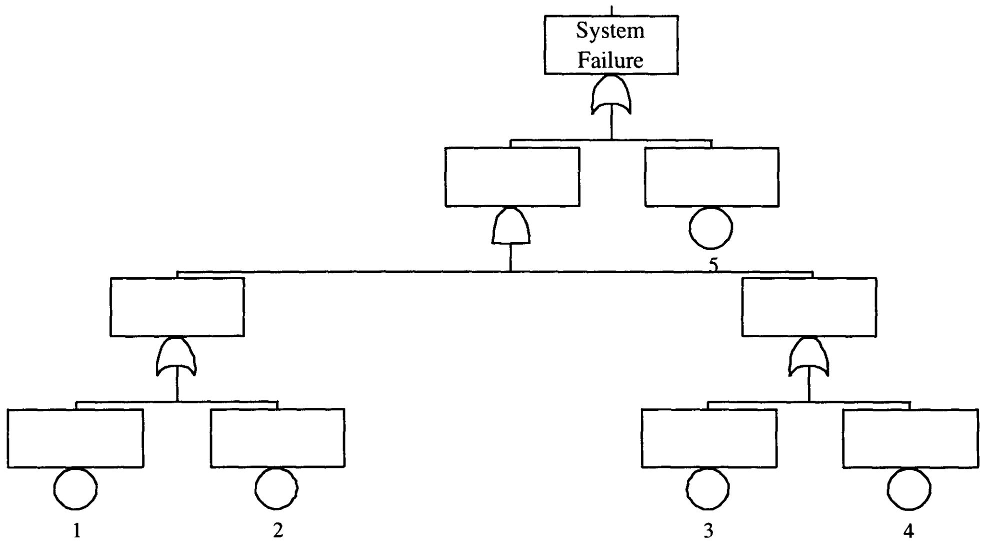

Figure 3-8: An example fault tree to illustrate the effect of dependencies on the computation of importance measures

By setting $X_1 = 1$, the minimal cut sets of the system in the independent case becomes

$$X_3, X_4, X_5.$$

In the correlated case, when the failure probability of component 1 is set equal to unity, we assume a guaranteed failure of the component. Based upon the perfect correlation assumption, when the failure probability of component 1 is set to unity, that of component 3 should be set to unity as well. When both components 1 and 3 fail, the system fails. This result indicates that the existence of perfect correlation among failure probabilities of components 1 and 3 results in an increase in the RAW of component 1 by a factor of $\frac{1}{q_3+q_4+q_5}$, where q_i is the failure probability of component i.

Now let us explore the impact of such a perfect correlation on the RRW of event 1. By setting $X_1 = 0$, the minimal cut sets in the independent case becomes

$$X_2X_3, X_2X_4, X_5.$$

After taking the perfect correlation between the failure probabilities of components 1 and 3 into account, the minimal cut sets reduce to

$$X_2X_4, X_5.$$

By comparing the minimal cut sets in the independent case with those in the correlated case, we note the RRW of component 1 increases by a factor of $\frac{q_2q_3}{q_2q_4+q_5}+1$ from the independent case to the correlated case.

By letting Q_0 be the nominal system failure probability, the FV of component 1 is governed by:

$$FV_1 = \frac{q_1q_3 + q_1q_4}{Q_0}. \tag{3.44}$$

Since the definition of FV does not involve the change in the event probability, the above formulation of FV for component 1 applies to both the independent and the correlated cases.

In order to illustrate the dependence among event probability on the value of RS, we now remove component 1 from the logic model. The minimal cut sets of the new logic model for the independent case are

$$X_2X_3, X_2X_4, X_5.$$

For the correlated case, when component 1 is excluded from the model and not considered as a contributor to the system failure by the analyst, the contribution of component 3 to the system failure remains be modelled explicitly in the analysis, and the estimate of the failure probability of component 3 does not change either. For this reason, the minim cut sets of the modified model in the correlated case are the same as those in the independent case.

These results indicate, for basic event at AND gates, if the probability of this event is correlated to the probabilities of other events in the logic model, the RS of this event may be different from its RAW importance. This would also be true for RCS and RRW of basic event at OR gates.

3.4 A Proposed Measure of Risk Change Significance

3.4.1 Definition

We have so far proposed a new measure of risk significance for identifying events that are important to the accuracy of risk. In many instances, risk-informed decision making processes also require an assessment of the resulting change in risk, such as change in the CDF and LERF that could result from proposed changes in plant design and operation or maintenance activities[13]. The comparison results of the baseline risk and risk changes with regulatory acceptance guidelines, along with insights derived from deterministic analyses, are then used to determine the acceptability of a risk level or an activity.

Events that are important to estimating risk may not be important to assessing risk change. The reverse may also be true. In order to achieve an accurate estimate of risk change, all events impacted by the activity under consideration and reflecting the cause-effect relationship should be addressed in the analysis, particularly the ones that contribute significantly to the accuracy of risk changes. In this section, we propose a new measure of risk change significance, RCS, which ranks events in terms of their importance to the accuracy of risk change.

By analogy with our proposed new measure of risk significance, RS, the proposed measure of risk change significance of an event is defined to be the resulting percentage change in risk change that could result from the omission of the event. Mathematically, the risk change significance of event i with respect to the nominal baseline risk and risk change can be represented as:

$$RCS_i = \frac{\Delta R_{w/o,i} - \Delta R_{w,i}}{R_{w,i}}. \tag{3.45}$$

When the relative complete model which addresses all the events identified by the analyst is used as the reference model for computing RCS_i, the above equation becomes

$$RCS_i = \frac{\Delta R_{w/o,i} - \Delta R_0}{R_0}. \tag{3.46}$$

Where

- $\Delta R_{w,i}$ is risk change estimated by considering event i in the analysis,
- ΔR_0 is the nominal risk change,
- R_0 is the nominal risk, and
- $\Delta R_{w/o,i}$ is risk change evaluated when event i is omitted from the analysis.

The above expression indicates that RCS_i measures how much risk change is not accounted for when event i is not considered in the logic model. This measure can therefore be useful to decision makers who are concerned with the acceptability of proposed changes in plant design and activities by use of information derived from the size of risk change from a PRA.

Similar to the computation of RS, the computation of RCS of an event also depends on the type of the event, in terms of initiating event or basic event. If the event subject to analysis is a basic event, the computation of RCS for this event also depends upon its location in the logic model. The section below discusses the computation of RCS for each of the four types of events which we defined in the beginning of this chapter.

3.4.2 Computation of RCS

When event i is considered in the anlaysis, the general formulation of risk R with respect to the probability of event i shown in Equation 2.23 is

$$R_0 = a_i \cdot q_i + b_i. \tag{3.47}$$

$a_i \cdot q_i$ is minimal cut sets that contain event i, and b_i is minimal cut sets that do not contain event i. The risk change due to changes in plant design and activities can thus be as represented by

$$\Delta R_0 = \Delta a_i \cdot \Delta q_i + \Delta b_i. \tag{3.48}$$

$\Delta a_i \cdot \Delta q_i$ is the resulting change in the minimal cut sets containing event i, and Δb_i is the resulting change in the minimal cut sets that do not contain i. This expression gives a general formulation of risk change in terms of the resulting change in the event probability and the probabilities of the minimal cut sets.

The analysis presented in the previous sections indicate that the impact of the omission of an event from the analysis on the minimal cut sets and risk is equivalent to that of setting the event

- frequency to zero if the event is initiating event,
- Boolean variable to unity if the event is basic event at AND gates,
- Boolean variable to zero if the event is basic event at OR gates, and
- Boolean variable to unity for its appearances at AND gates and to zero for its appearances at OR gates if the event is basic event at both AND gates and OR gates.

These findings can also be used to compute RCS of any event in the PRA. For basic event at AND gates, after the event is omitted from the logic model, Equation 3.47 becomes

$$R_{w/o,i} = a_i + b_i. \tag{3.49}$$

The resultant change in R due to the proposed change in plant design or operational practices can therefore be written as

$$\Delta R_{w/o,i} = \Delta a_i + \Delta b_i. \tag{3.50}$$

Substituting the above equation into Equation 3.46 we obtain,

$$RCS_i = \frac{\Delta a_i \cdot (1 - \Delta q_i)}{R_0}. \tag{3.51}$$

In this notation, given that

$$0 < q_i < 1, \tag{3.52}$$

we can show that

$$0 < 1 - \Delta q_i < 1. \tag{3.53}$$

Since

$$0 < R_0 < 1, \tag{3.54}$$

the sign of RCS_i in Equation 3.51 depends only upon the resulting change in a_i. If a proposed change in plant design or activities results in an increase in a_i, the omission of event i from the analysis will result in an overestimate of risk change. On the other hand, if the proposed change results in a decrease in a_i, the omission of event i from the analysis will result in an underestimate of risk change. We note that the impact of the omission of event at AND gates on the baseline risk is different from that on risk change in that the omission always results in an overestimate of the baseline risk.

For the case where event i is a basic event at OR gates or an initiating event, when event i is not considered in the model, Equation 3.47 becomes

$$R_{w/o,i} = b_i. \tag{3.55}$$

The resultant change in R due to the proposed change in plant design or activities with respect to q_i can thus be written in the form of

$$\Delta R_{w/o,i} = \Delta b_i. \tag{3.56}$$

Substituting the above equation into Equation 3.46 we obtain

$$RCS_i = \frac{-\Delta a_i \cdot \Delta q_i}{R_0}. \tag{3.57}$$

This expression indicates that, for the case where event i is a basic event at OR gates or an initiating event, the impact of the omission of event i on risk change depends only upon the resulting change in a_i. But unlike the case where event i is a basic event at AND gates, when a proposed change in plant design or activities results in an increase in a_i, omitting event i from the analysis leads to an underestimate of risk change. If the proposed change results in a decrease in a_i, the exclusion of event i from the analysis results in an overestimate of risk change.

For basic events at both AND gates and OR gates, the general formulation of RCS using Equation 3.47 does not exist. In general, the proposed measure of RCS can not be related to the traditional measures of importance, such as FV, RRW, and RAW directly, and the computation of RCS involves the reformulation of the minimal cut sets when an event is omitted from the analysis. The minimal cut sets can be obtained by setting the event

- Boolean variable to zero for basic events at OR gates or initiating events,
- Boolean variable to unity for basic events at AND gates, and
- Boolean variable to unity for its appearance at AND gates and to zero for its appearance at OR gates for basic events at both AND gates and OR gates

After the minimal cut sets are obtained, risk change can be recalculated. This risk change can then be used, along with the nominal risk change, to compute RCS according to its definition as given in Equation 3.46.

Since the reformulation of the minimal cut sets is not straightforward, the computation of the RCS is likely to be complex, especially for systems with a large number of components or minimal cut sets. However, the availability of fast running PRA software [26, 32, 23] enables us to compute RCS for any event in the PRA quickly.

3.5 Example - Computation of RS and RCS for Components in a Simple System

In this section, we compare our proposed measure of risk significance and risk change significance with several other importance measures widely used in practice using an example. The differences are then illustrated by presenting the importance measures of each component in the example system.

As shown in Equation 3.42 and Equation 3.43, our proposed measure of RS can be related to the measures of FV, RRW, and RAW any event the probability of which is independent of the probabilities of other events in the PRA model. More specifically, if an event is at AND gates and the event probability is independent of the probabilities of other events, the RS of this event is equivalent to its RAW measure in terms of

$$RS_i \;=\; RAW_i - 1. \tag{3.58}$$

If an event is basic event at OR gates or initiating event, and the event probability is independent of the probabilities of other events, the RS of this event can be related to its RRW and FV measures in terms of

$$RS_i \;=\; \frac{1}{RRW_i} - 1 = -FV_i. \tag{3.59}$$

The DIM measure proposed by Borgonovo is related to our proposed measure of RCS in that it, too, measures the importance of an event with respect to risk change.

To illustrate the application of these measures to fault trees, we consider a system consisting of six components. The fault tree of this system is presented in Figure 3-9.

The failure probabilities of all components are assumed to be lognormally distributed with means and standard deviations as given in Table 3.1. In this example,

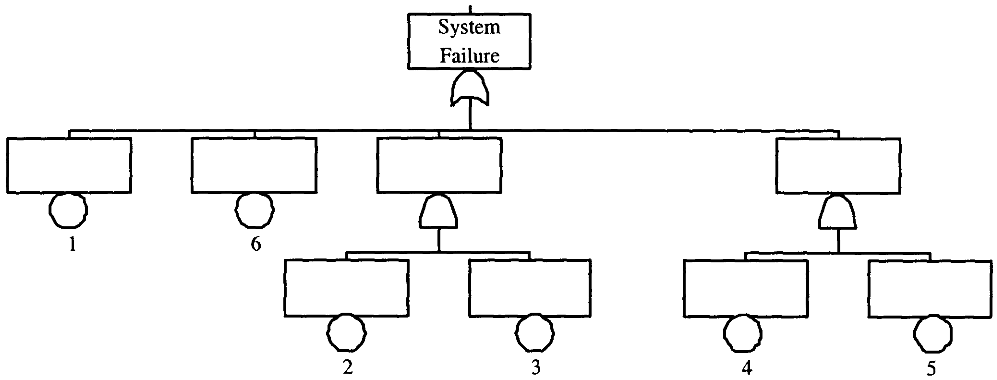

Figure 3-9: An example fault tree to illustrate the computation of RS and RCS

the failure probability of components 3 and 5 are assumed to be perfectly correlated. Aside from this dependence, all other component failure probabilities are assumed to be independent of each other.

Other assumptions made include the hypothesis used for the computation of DIM and the proposed change in the plant's operational practice. The basic event probabilities in the system fault tree have the same dimensions, so both H1 (uniform change in component failure probabilities) and H2 (uniform percentage change in component failure probabilities) are applicable for the computation of DIM for all components in this system. Since H1 is more computational efficient than H2, we chose to use H1 in this case study.

The proposed change under consideration is to double the test interval of component 2 and increase the inspection interval of component 4 by a factor of four. If we assume that all other aspects of components 2 and 4 remain the same, the failure probability of component 2 will double and the failure probability of component 4 will quadruple.

Uncertainty analysis is then performed using Monte Carlo sampling to propagate the epistemic uncertainties associated with component failure probabilities through the minimal cut sets. 10,000 iterations were used and the expected system failure probability was found to increase from 4.509×10^{-3} in independent case to 4.511×10^{-3} in the correlated case. Table 3.2 and Figure 3-11 summarize the expected importance

Table 3.1: Basic event data for the components in the example system

Component	Mean failure probability	Standard deviation
1	1×10^{-3}	5×10^{-4}
2	3×10^{-2}	1.5×10^{-2}
3	1×10^{-2}	5×10^{-3}
4	2×10^{-3}	1×10^{-3}
5	1×10^{-2}	5×10^{-3}
6	3×10^{-3}	1.5×10^{-3}

and relative ranking of each component in this system in the independent case. Table 3.3 and Figure 3-10 summarize the expected importance and relative ranking of each component in the correlated case where the dependence among the probabilities of components 3 and 5 were implicitly taken into account. The RRWs and RAWs of each component for both the independent and correlated cases are also presented in Figure 3-12 and Figure 3-13, respectively.

According to these numerical results, we note that the FV, RRW, and RAW importance of components 3 and 5 increases when correlation is taken into account. Compared with the independent case where the RRW and RAW rankings of components 3 and 5 are the same, component 5 is ranked one number lower than component 3 in the correlated case. Even though the expected FVs, DIMs, RSs, and RCSs in the correlated case are slightly different from those in the independent case, the relative rankings of the components according to these measures remain the same in two cases.

It can also be seen that although the importance rankings of the components using FV, RRW, RAW, and DIM importance are slightly different, components 1 and 6 are found to be the most important components in both the independent and correlated cases. Using the RS and RCS significance measures, components 3 and 5 are found to be the most significant events in achieving accurate estimates of the system failure probability and the change in the system failure probability due to the proposed test

Table 3.2: The expected importance measures for the components in the example system, independent case

Component	FV	FV	RRW	RRW	RAW	RAW
		Ranking		Ranking		Ranking
1	2.34E-01	2	1.34E+00	2	2.47E+02	1
2	7.18E-02	3	1.08E+00	3	3.38E+00	6
3	7.18E-02	3	1.08E+00	3	8.14E+00	3
4	4.82E-02	4	1.05E+00	4	3.40E+00	5
5	4.82E-02	4	1.05E+00	4	5.82E+00	4
6	6.46E-01	1	3.27E+00	1	2.47E+02	2

Component	DIM	DIM	RS	RS	RCS	RCS
		Ranking		Ranking		Ranking
1	4.83E-01	1	-2.34E-01	6	0.00E+00	5
2	4.89E-03	4	2.38E+00	4	-7.01E-02	4
3	1.44E-02	2	7.14E+00	1	7.14E+00	2
4	4.86E-03	5	2.40E+00	3	-1.46E-01	3
5	9.63E-03	3	4.82E+00	2	1.46E+01	1
6	4.83E-01	1	-6.46E-01	5	0.00E+00	5

Table 3.3: The expected importance measures for the components in the example system, correlated case

Component	FV	FV	RRW	RRW	RAW	RAW
		Ranking		Ranking		Ranking
1	2.35E-01	2	1.34E+00	2	2.50E+02	1
2	7.20E-02	3	1.08E+00	4	3.36E+00	5
3	7.20E-02	3	1.15E+00	3	1.32E+01	3
4	4.77E-02	4	1.05E+00	5	3.38E+00	4
5	4.77E-02	4	1.15E+00	3	1.32E+01	3
6	6.45E-01	1	3.30E+00	1	2.50E+02	2

Component	DIM	DIM	RS	RS	RCS	RCS
		Ranking		Ranking		Ranking
1	4.83E-01	1	-2.35E-01	6	0.00E+00	5
2	4.83E-03	4	2.36E+00	4	-7.16E-02	4
3	1.45E-02	2	7.34E+00	1	7.33E+00	2
4	4.83E-03	4	2.38E+00	3	-1.43E-01	3
5	9.64E-03	3	4.87E+00	2	1.47E+01	1
6	4.83E-01	1	-6.45E-01	5	0.00E+00	5

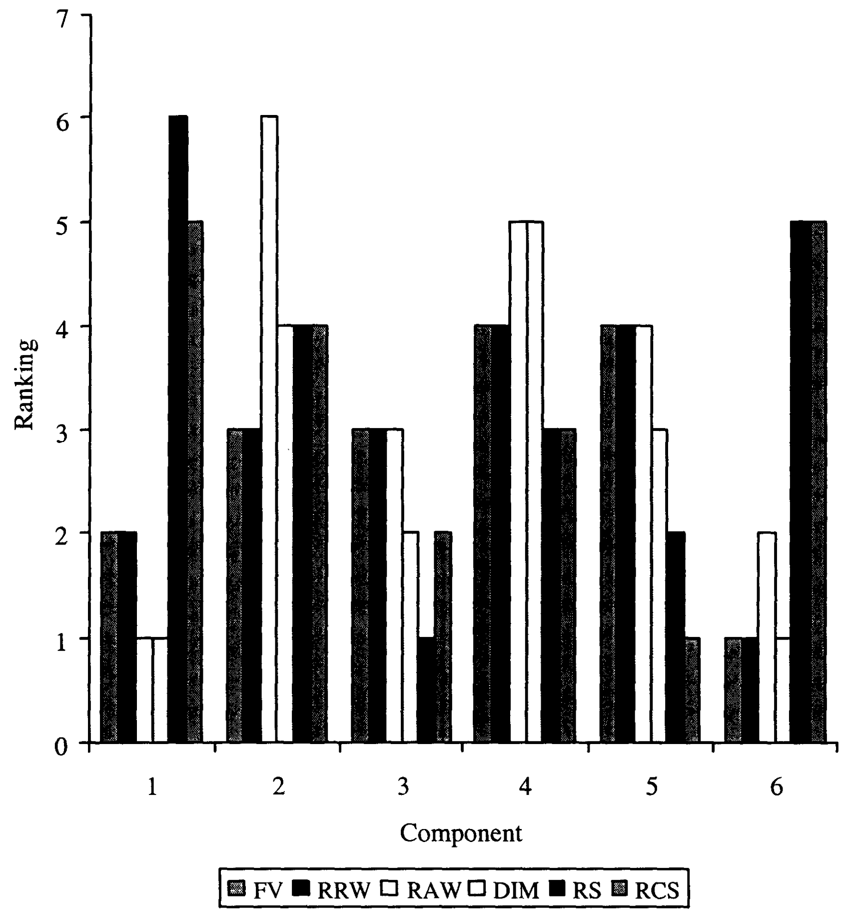

Figure 3-10: The importance rankings of the components in the example system, the independent case

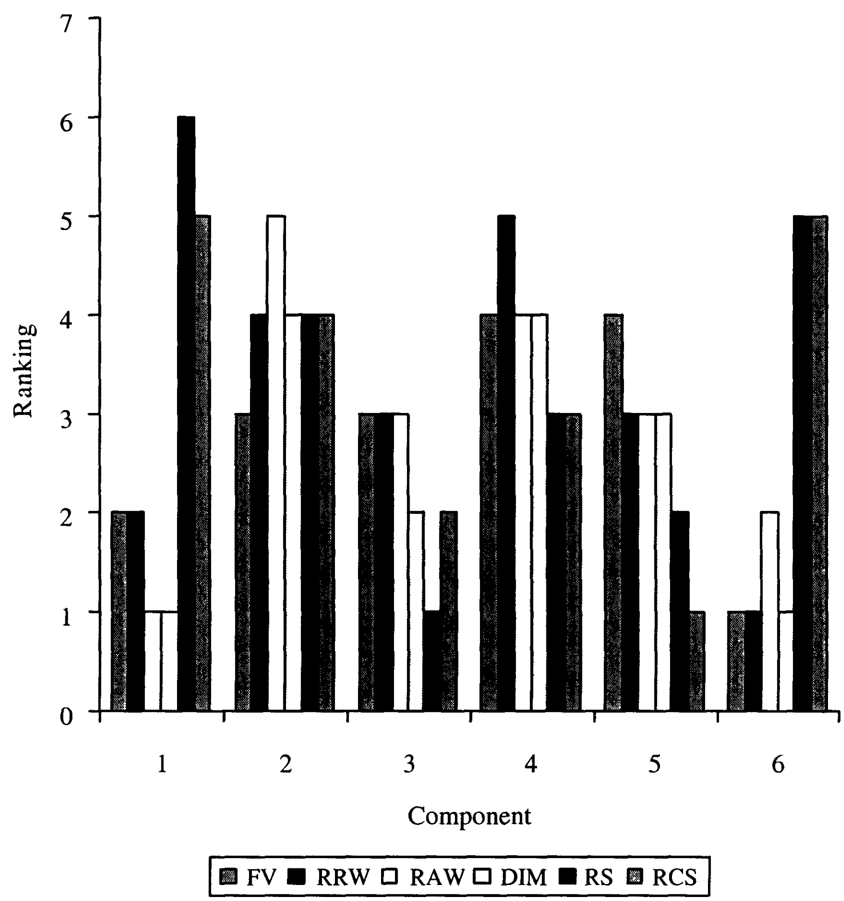

Figure 3-11: The importance rankings of the components in the example system, the correlated case

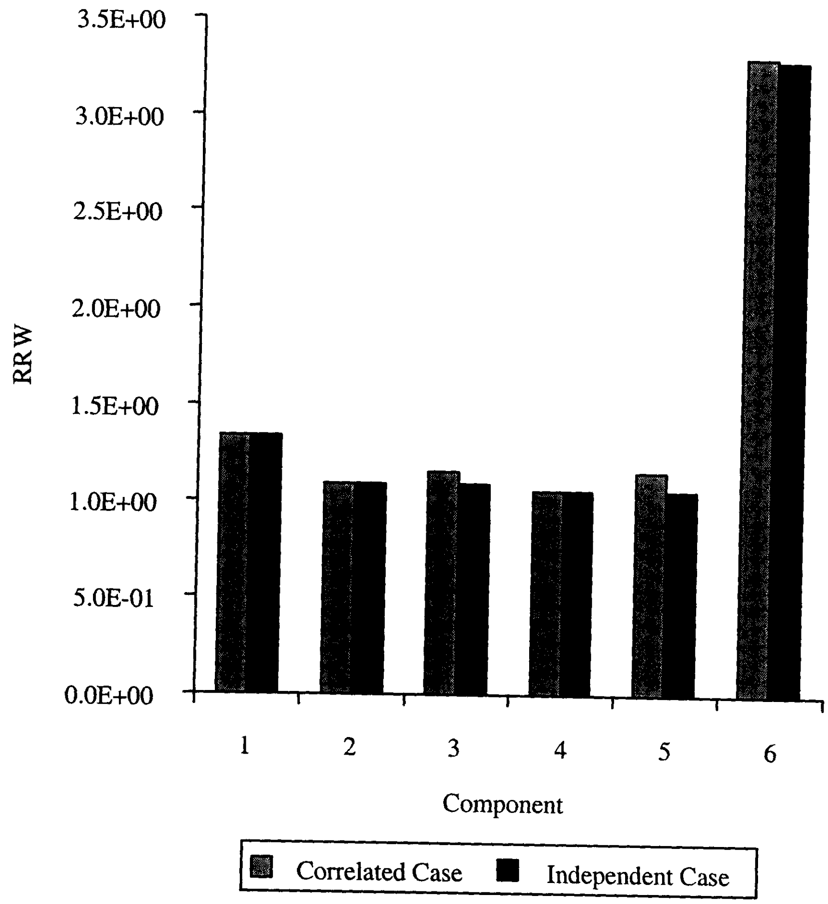

Figure 3-12: The RRW of the components in the example system in both the independent and correlated cases

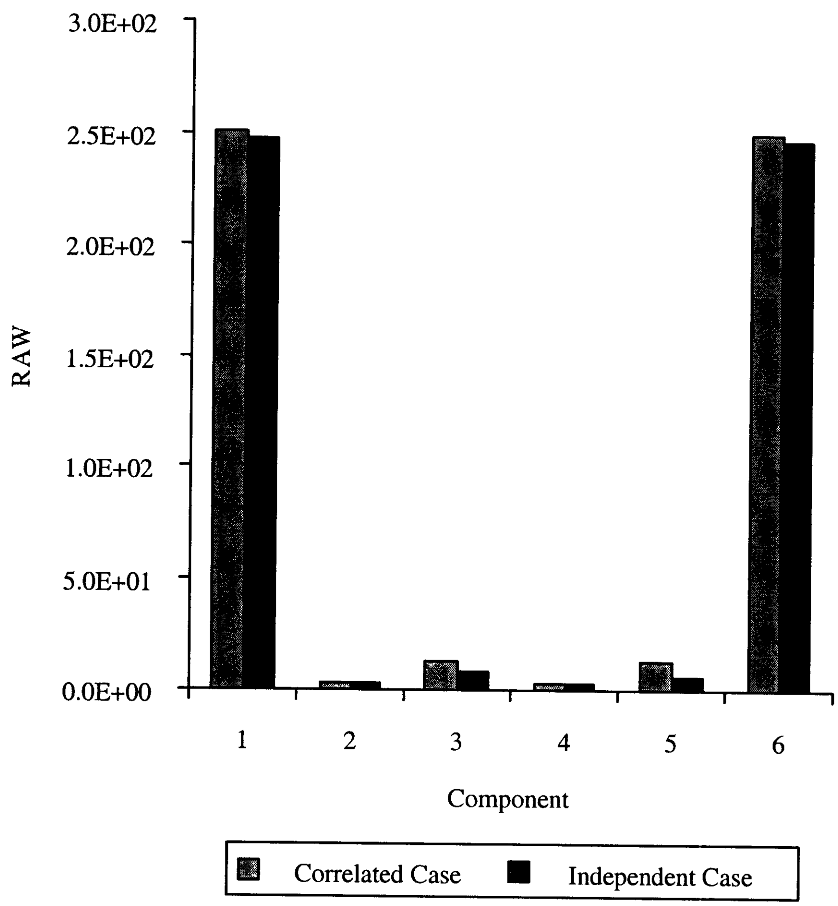

Figure 3-13: The RAW of the components in the example system in the both independent and correlated cases

interval extension in both the independent and correlated cases.

As the results indicate, our proposed measures of RS and RCS give very different rankings of the components in the system when compared to traditional importance measures. The reason that the DIM ranking is different from the RCS ranking is because DIM is defined for very small changes in the event probabilities and computes the contribution of the small change in an event probability to the overall change in risk which could result from simultaneous changes in the probabilities of a set of events. On the other hand, RCS measures the resulting change in risk change that could result from the omission of the event from the analysis when all other events remain unchanged in the model. Even though the RS ranking is the same as the RAW ranking for components at the AND gate, and is the same as the FV ranking for components at the OR gate, the overall RS ranking, which is a combination of RAW ranking and FV ranking, does not agree with either the RAW ranking or FV ranking in both the independent case and correlated case.

From these findings we remark the exclusion of events which are defined not important to risk using FV and RAW measures might results in a significant overestimate or underestimate of risk and risk change. For decision makers who are concerned with obtaining more meaningful information from the PRA results for use in making risk management decisions, it would be undoubtedly necessary to address the events with high RS and RCS explicitly in the analysis.

3.6 Summary

In the first part of this chapter we presented and discussed several existing importance measures: FV, RRW, RAW, Lambert and DIM. We then introduced the new measures of risk significance and risk change significance. These measures are developed in response to the need of assessing the adequacy of PRA results to support risk-informed decisions. In fact, because RS and RCS are defined in terms of percentage change in baseline risk and risk change when an event is omitted from the model, they are very helpful to decision makers in identifying events that are important in achieving accurate estimates of the baseline risk and risk change.

We also developed methods for computing the values of the proposed measures in the case where the complete model is used as reference model. Since RS may be directly related to FV, RRW, and RAW, one can compute RS with minimal effort by using existing PRA software. On the contrary, the computation of RCS importance is much more complicated because it involves a reformulation of minimal cut sets. This is generally time consuming. However, for highly reliable systems, the probability that a basic event participates in multiple minimal cut sets is very likely to be negligible. In such cases, computation cost does not pose limitations to the application of RCS.

We then presented the various importance measures of each component in a simple system to illustrate the computation of the proposed measures of RS and RCS, and compared them with the traditional importance measures. The results from the case study lead to some interesting insights into the behavior of our proposed measures of RS and RCS. In particular, we found that an event determined to be less important using traditional importance measures might contribute significantly to the accuracy of risk and risk change. The reverse may also be true for risk important events identified using traditional importance measures. Thus, in order to obtain accurate estimates of risk and risk change, it is necessary to consider the events with high RS and RCS explicitly in the analysis even though the FV and RAW importance of these events are low.

Chapter 4

Epistemic Uncertainty and Treatment in the PRA

4.1 Introduction

In Chapter 3, we introduced the new measures of risk significance and risk change significance. These measures are useful to the analysts in identifying events that are important to achieving accurate estimates of the baseline risk and risk change. However, even a PRA that includes all initiating events and basic events is of little value if it is based on deficient models and incorrect inputs. To develop the logic models, the analysts make use of a variety of tools including both deterministic and probabilistic models. The technical correctness of these models determines how confident we are in the probabilities of basic events and frequencies of occurrence of initiating events in the PRA, and how confident we are in final outcome of the PRA.

The PSA Applications Guide [19] and RG 1.174 [13] categorize the state-of-knowledge uncertainties in a PRA into three types: parameter uncertainty, model uncertainty, and incompleteness uncertainty. This categorization was proposed primarily based upon the approaches used to characterize their impact on PRA results.

Parameter uncertainty is typically defined as state-of-knowledge uncertainties associated with the input parameters of a model. Model uncertainty arises primarily due to the lack of knowledge of the physical situation under consideration. Incompleteness uncertainty arises either because of the incomplete identification all possible component failure modes and initiating events, or because of the contributions of certain events to risk are extremely low [13, 37, 36, 38].

Parameter uncertainty and model uncertainty can be propagated through the minimal cut sets to obtain the degree of epistemic uncertainties associated with PRA results. The incompleteness uncertainty, on the other hand, is difficult to address in the PRA, especially for the case where certain events are left out of the analysis because they were not recognized by the analysts. All these three types of uncertainty contribute to both the accuracy and precision level of PRA results. Therefore, uncertainty analysis which can identify sources of uncertainty and assess their impact on a PRA's results is considered an integral part of a PRA.

We begin by discussing the most frequently used approaches for the treatment of parameter uncertainty in PRAs. Next, we describe existing methods for dealing with model uncertainty. We then discuss the causes of PRA incompleteness.

4.2 Parameter Uncertainty

For nuclear PRAs, model input parameters include equipment failure rates, component failure probabilities, initiating event frequencies, and human error probabilities. The estimates of input parameters usually come from a power plant's historical operational data, measurement, tests, data from relevant activities, and expert judgement. Due to the absence of sufficient relevant data, the true values of the majority of model input parameters are unknown to the analysts and thus regarded as random variables.

State-of-knowledge uncertainty of model inputs is often taken into account in the analysis by establishing probability distributions for uncertain parameters to represent the analyst's knowledge about the values of the parameters. These distributions are then propagated through the analysis to obtain probability distributions for the estimate of the final outcome of interest. This can be done in different ways. The two most commonly used approaches are the Monte Carlo simulation and the analytical moment approach.

When Monte Carlo simulation is used to propagate uncertainty on input parameters, point values for input parameters are sampled from corresponding probability distributions during each trial. These point values are then used to obtain point estimates of the PRA's final outcome of interest. The Monte Carlo sampling is repeated many times, and the point value of the outcome from each trial is then used to obtain a probability distribution on the estimation of the outcome. The PRA outcome used in risk-informed activities often includes the baseline risk of CDF and LERF, change in CDF and LERF, and importance measures. However, most software packages used to perform PRAs typically only provide uncertainty analysis for the baseline risk. Uncertainty analysis for risk change and importance measures must be done by the use of other tools which use Monte Carlo simulations to obtain the probability distribution for a function $y = f(x_1, x_2, ..., x_n)$ given the probability distribution of $x_i (i = 1, 2, ..., n)$ [11].

The analytical moment propagation approach calculates the mean and variance of the risk metrics of interest from the first and second moments of input parameters. At the basic event and initiating event level, the risk metric, R, can be represented as a linear function of any event probability as shown in Equation 3.47. However, basic event probabilities or initiating event frequencies are often calculated from more fundamental parameters based upon additional models [5, 6]. In such cases, R is typically a polynomial function of the fundamental input parameter. By letting x_1, x_2,......, and x_n all be input parameters, R can thus be written as:

$$R = f(x_1, x_2, ..., x_n). \tag{4.1}$$

According to Taylor's formula, R can be expanded about the mean values μ_1, μ_2, ..., and μ_n as:

$$\begin{aligned} R &= f(\mu_1, \mu_2, ..., \mu_n) \\ &+ \sum_i \frac{\partial R}{\partial x_i}(x_i - \mu_i) \end{aligned}$$

$$
\begin{aligned}
&+ \quad \frac{1}{2}\sum_{i,j}\frac{\partial^2 R}{\partial x_i \partial x_j}(x_i - \mu_i)(x_j - \mu_j) \\
&+ \quad .... \qquad (4.2)
\end{aligned}
$$

By taking the expectations of both sides of the above equation, we can obtain the second-order approximate mean of R as

$$
\mu_R \cong f(\mu_1, \mu_2, ..., \mu_n) + \frac{1}{2}\sum_i \sum_j \frac{\partial^2 R}{\partial x_i \partial x_j} Cov(x_i, x_j). \qquad (4.3)
$$

$Cov(x_i, x_j)$ is the covariance of x_i and x_j. In the above equation, the derivatives are evaluated at the mean values $\mu_1, \mu_2, ...$, and μ_n. If we assume that the parameters are uncorrelated with each other, the above equation becomes

$$
\mu_R \cong f(\mu_1, \mu_2, ..., \mu_n) + \frac{1}{2}\sum_i \frac{\partial^2 R}{\partial x_i^2} Var(x_i). \qquad (4.4)
$$

Var_i is the variance, or second moment, of x_i. This expression indicates that the analytical estimate of the mean value of R from the mean values and variances of the input parameters is only feasible for the case where input parameters are uncorrelated. For PRAs with correlated input parameters, the analytical moment propagation approach would involve specifying covariance for each set of correlated input parameters, which would be extremely difficult to do.

By truncating Equation 4.2 at the linear terms, we obtain the variance of R as follows:

$$
Var(R) \cong \sum_i \sum_j \frac{\partial^2 R}{\partial x_i \partial x_j} Cov(x_i, x_j). \qquad (4.5)
$$

In the case where input parameters are independent of each other, the above equation reduces to

$$Var(R) \cong \sum_i \frac{\partial^2 R}{\partial x_i^2} Var(x_i). \tag{4.6}$$

This expression is an approximate estimate of the variance of R with uncorrelated input parameters. When the size of the PRA is large and input parameters are correlated with each other, it is not possible to calculate the variance of R by use of the analytical moment approach.

It is worth noting that, the analytical approach is preferred for smaller systems with independent inputs because it tends to produces accurate estimates, while the Monte Carlo approach is advantageous for larger systems with correlated parameters because it tends to be fast and can easily take dependencies into account.

When uncertainty propagation is performed, input parameters can be ranked in terms of their contributions to the overall uncertainty with regard to the mean values of PRA outputs. Several uncertainty importance measures have been proposed in a recent PRA study [31]. For example, R.L. Iman [24] suggested measuring the uncertainty importance of an event in terms of the ratio of the uncertainty level by setting the event uncertainty to zero for the nominal uncertainty level. Mathematically, the uncertainty importance measure introduced by Iman can be represented as

$$EPR_i = \frac{Var_{q_i}(E[R|q_i])}{V} \times 100\%. \tag{4.7}$$

Where V is the nominal uncertainty level, R is the risk metric of interest, and Var_{q_i} is the uncertainty level about the expected R by ascertaining the probability of event i, q_i. This measure involves calculating V and Var_{q_i}, which difficult to do analytically, especially for a large logic model. Thus V and Var_{q_i} are often calculated using Monte Carlo simulation. However, the Monte Carlo simulated values of V and Var_{q_i} are instable. In order to overcome this difficulty, Iman and S.C. Hora [25] suggested another measure of importance as follows:

$$UI_i = \frac{Var_{q_i} E[log(R|q_i)]}{Var(logR)}. \tag{4.8}$$

Another uncertainty importance measure was suggested by Jae-Gyeum Cho and

Bong-Jin Yum [10] in the form of

$$UIMB_i = \frac{\text{Uncertainty of lnR due to uncertainty of } lnq_i}{\text{total uncertainty of } lnR}. \tag{4.9}$$

The quantification of the contribution of each input parameter to the overall uncertainty in R, and the identification of the parameters that influence the uncertainty in R by the most may also be performed by using global sensitivity analysis (GSA) techniques. Examples of this technique include the Morris screening method and Variance based techniques (VBTs) [5, 33, 22].

These uncertainty importance measures and techniques are useful to decision makers who are concerned with reducing the overall uncertainty of PRA results in order for the results to be meaningful.

The treatment of parameter uncertainty by establishing distributions for the values of uncertain parameters enables us to explicitly address the state-of-knowledge uncertainty in a PRA. Ideally, the shape of the distribution chosen should accurately describe the actual nature of our uncertainty about the parameter values. In practice, lognormal distributions are the most frequently used distribution form in characterizing the possible values of uncertain parameters. In some instances, other distribution forms, in addition to the lognormal distribution, may also be chosen because they fit equally well to the historical data. This difficulty in choosing an accurate distribution form for the uncertain input parameter introduces additional model uncertainty.

4.3 Model Uncertainty and Technical Acceptability

PRAs use logic models such as event trees and fault trees to identify events that could lead to core damage, or radioactive releases. PRAs rely on submodels to calculate the failure probabilities of components, the frequencies of occurrence of initiating events, the probabilities of and human errors. These submodels reflect the analyst's understanding about component failure mechanisms or physical phenomena. In many cases, the state-of-knowledge of these failure mechanisms and physical situations is incomplete, and the models deviate from the reality. This introduces model uncertainty.

The existence of model uncertainty and its impact on PRA results have been recognized for a long time. RG 1.174 states that technical acceptability of a PRA *"can be understood as being determined by the adequacy of the actual modelling and the reasonableness of the assumptions and approximations."* Many efforts have been made in formalizing the concept of model uncertainty and in developing methods for dealing with model uncertainty. A good deal of discussion on these topics was performed at a workshop on advanced topics in reliability and risk analysis held in 1993 at Annapolis [34]. Many methods for the treatment of model uncertainty were presented and discussed at the workshop, including the alternative hypotheses approach and the adjustment factor approach.

The alternative hypotheses approach introduced by G. Apostolakis [21, 54] assumes that there is a set of mutually exclusive and collectively exhaustive model candidates for the problem under study. Each model is assigned a weighting factor by the experts. This weighting factor represents the experts' relative confidence in the model being correct. For normalization purpose, all weighting factors sum up equal to unity.

This approach treats model uncertainty as parameter uncertainty in that the number associated with each model represent the degree of confidence in the model being correct. Vicki Bier and Corwin Atwood [2, 1] pointed out that in most cases, it is impossible to have a set of complete and mutually exclusive models, and that $P(M_i$ is usually not well defined either, especially when a new model is introduced.

Despite these limitations, this approach still provides useful insights in dealing with model uncertainty and has been used in various contexts in the past. As an example, Apostolakis considers [54] the treatment of uncertainty on the frequency of occurrence of future earthquakes in the seismic risk analysis. In this case, a family of hazard curves are first obtained based upon alternative hypotheses and assumptions. Discrete distributions over the alternate hazard curves are then developed with the probability associated with each hazard curve representing the analyst's degree of belief in that hazard curve as being the most appropriate. The family of hazard curves are then probabilistically combined to obtain the hazard curve which will be used for further analysis. Figure 4-1 illustrates the family of hazard curves and the resulting mean hazard curve of a U.S. nuclear power plant.

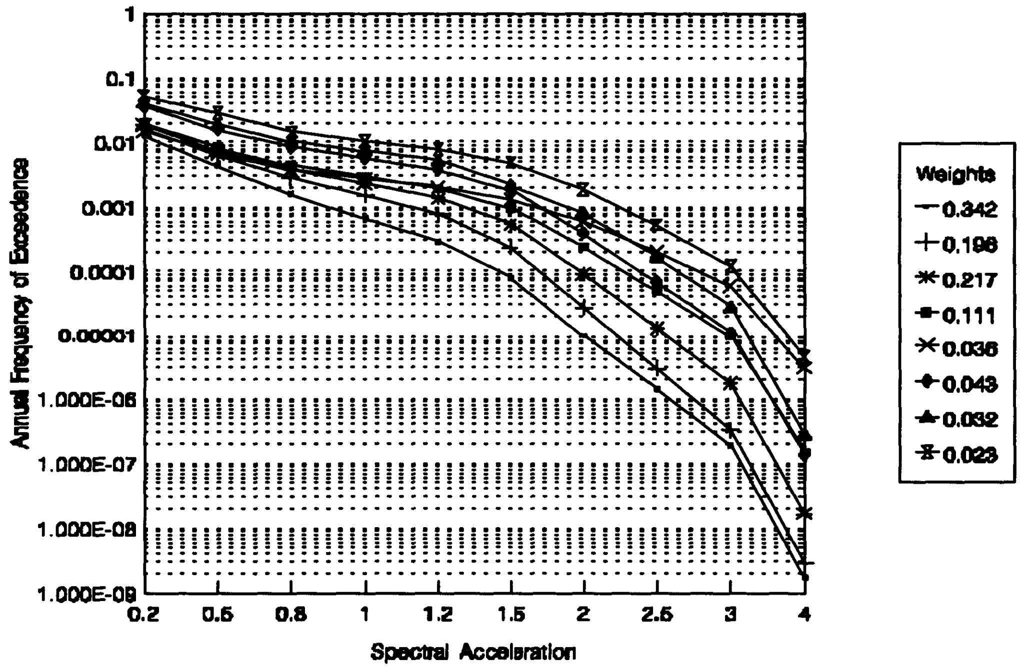

Figure 4-1: The seismic hazard curves of a U.S. nuclear power plant

In this example, eight different hazard curves were obtained. As shown on the right side of the figure, the belief associated with each curve is:

0.342, 0.196, 0.217, 0.111, 0.036, 0.043, 0.032, 0.023,

respectively. The average of these eight curves was then obtained to represented the analyst's best estimate of the frequency of occurrence of future earthquakes at this particular site.

Given that, in most cases, only a single representative model is used to reflect the real world, the adjustment-factor approach was developed to address model uncertainty associated with this single best model. This approach was also suggested by Apostolakis [54]. In this approach, an adjustment factor is introduced to adjust the results of the single best model. The adjustment factor can be either additive or multiplicative. The estimated value for the unknown quantity can therefore be written as:

$$y = y^* + E_a^*, \tag{4.10}$$

or

$$y = y^* \times E_m^*. \tag{4.11}$$

Where y is true value of the unknown quantity, y^* is the estimate of the unknown quantity from the model, and E_a^* and E_m^* are the adjustment factors for the model prediction, which are generally unknown.

This approach also has wide applications. As an example, Apostolakis considers the actual time to damage of an object in the fire risk assessment area,

$$T_d = T_{d,drm} \cdot E^*. \tag{4.12}$$

Where T_d is the actual time to damage of an object, $T_{d,drm}$ is the time to damage from a deterministic reference model, and E^* is an adjustment factor which accounts for the deterministic model's prediction error and is assumed to be lognormally distributed with a mean equal to μ and variance equal to σ^2.

The drawback of this approach is the difficulty in determining the value of the adjustment factor. As pointed out by Apostolakis [21], any information that can help the analyst evaluate the adjustment factor can also be used to adjust the model itself.

To summarize, both of these two methods can be used to account for model uncertainty. However, the use of the alternative hypotheses approach would involve identifying a set of mutually exclusive alternative models and specifying beliefs in each model to be correct. While it might be feasible to obtain a set of alternative models, it is difficult to obtain a set of alternative models which are mutually exclusive. On the other hand, the use of the adjustment factor approach would need the analyst to establish values for the adjustment factor, which is often difficult to do.

Acknowledging the difficulty in quantifying model uncertainty, the impact of model uncertainty on the adequacy of PRA results is not analyzed in this thesis work. All of the work presented in this thesis is based upon the assumption that model uncertainty is well addressed in the PRA, and all models embedded in the PRA are technically sound.

4.4 PRA Incompleteness

Ideally, analysts can identify a set of component/system failure modes which produce accurate estimates of the failure probabilities of components and systems when modelled correctly, and the set of initiating events which produce all of the important accident sequences when fully developed. However, there is no proof that all of these obvious component failure modes and initiating events can be identified, and therefore no proof that a PRA is complete.

PRA completeness has advanced over the time in the past 30 years. The Reactor Safety Study was the first available PRA model for nuclear power plant. This model is often considered incomplete because it only analyzes risks from internal events and at-power operation. The treatment of external events such as fires and seismic events was incorporated into PRAs between 1975 and 1992 when most U.S. reactors performed a PRA. Thereafter, lower power PRA, shutdown PRA, and internal flood event analysis were also introduced into PRAs.

Although PRAs today are considered more complete than their predecessors, the tremendous complexity of a nuclear power plant suggests that there is no guarantee that all major risk contributors have been identified and addressed in the analysis. These risk contributors include initiating events and potential failure modes of components, systems, and human actions required to perform mitigation functions following an initiating event. The incomplete identification of those initiating events, component failure modes, and human actions results in inaccurate PRA results.

To see the impact of the omission of certain initiating events on risk, the top 20 initiating events of a U.S. nuclear power plant, in terms of contribution to CDF, are shown in Table 4.1. As can been seen from this table, the omission of any top six initiating event results in an underestimate of CDF by more than 5%. In particular, we note that the seismic events contribute to nearly 60% of the total CDF. This indicates that the incomplete identification and treatment of certain initiating events can greatly underestimate the overall plant risk level.

The possible operating modes of a nuclear power plant include full-power, lower-power, hot standby, hot shutdown, cold shutdown, and refuelling. In most cases, only the risk from full power operation is addressed in the PRA. This is primarily because at-power risk is often considered the dominate contributor to the overall plant risk. However, in many cases, risk from other operating modes is large such that they can not be neglected. To see this, let us consider the contribution to the CDF of each operating mode of a U.S. nuclear power plant as shown in Table 4.2. From this table we see that shutdown risk contributes to 14% of the total CDF, while refueling risk contributes to 20% of the total CDF. These numerical values indicate that in some cases, operating modes other than at-power may contribute significantly to the overall plant risk, and the omission of these operating modes from the analysis may provide decision makers with incorrect information for risk-informed decision making.

A component is typically designed to perform many functions and thus can fail in many different ways. When the failure probability of a component is estimated by use of fault tree models, the top event is the failure of the component, and the basic events are all possible causes of the component failure. In this case, the contribution of each component failure mode to the overall risk level can be estimated using Equation 3.47, with q_i being the probability of the occurrence of failure mode i. However, as the complexity of a component increases, it becomes more difficult for the analyst to identity every possible failure mode. As a result, basic events which represent the unrecognized component failure modes are not addressed in the analysis, and the PRA model is thus incomplete.

This incompleteness has been recognized from the beginning of the development of PRA methodology and is considered one of the major limitations on the usefulness

Table 4.1: Contributions to the CDF of the top 20 initiating events for a U.S. nuclear power plant

Initiating Events	Frequency (per reactor year)	Contribution (%)
Seismic level 5	2.94E-05	19.06%
Seismic level 4	1.24E-04	17.72%
CSR fire 1 - Loss of ASW/CCW	6.70E-03	10.37%
Seismic level 6	7.64E-06	9.88%
CSR fire 2 - PORV induced LOCA	6.70E-03	5.93%
Seismic level 3	1.56E-04	5.77%
Loss of buses HF HG	6.93E-05	4.95%
Loss of CCW due to flooding	1.40E-04	4.26%
Loss of offsite power	2.59E-02	3.37%
Loss of ASW initiator	1.04E-04	3.29%
Seismic level 1	1.72E-02	2.33%
Seismic level 2	8.69E-04	2.11%
Total loss of component cooling water	3.78E-05	1.15%
RCP seal catastrophic seal failure	2.45E-03	1.14%
Loss of both MD AFW pumps	4.36E-04	0.87%
Reactor trip	6.03E-01	0.79%
Control room fire at VB-4	4.90E-03	0.69%
Medium LOCA	4.00E-05	0.60%
Non-isolated SGTR For level 2	5.00E-03	0.60%
Turnine trip	4.49E-01	0.59%
Partial loss of main feedwater	3.60E-01	0.48%

Table 4.2: Contributions to the CDF of each operating mode for a U.S. nuclear power plant

Mode	Description	CDF	Contribution
Mode 1	Full-power(> 70% power)	4.28E-5	63%
Mode 2	Lower-power(< 70% power)	0.15E-5	2%
Mode 3	Hot Standby	0.08E-5	1%
Mode 4	Hot Shutdown	0.05E-5	1%
Mode 5	Cold Shutdown	0.91E-5	13%
Mode 6	Refueling	1.38E-5	20%

of the PRA technique. After reviewing the Reactor Safety Study (WASH-1400), the Risk Assessment Review Group led by Lewis [28] concluded that *"It is conceptually impossible to complete in a mathematical sense in the construction of event-trees and fault trees; what matters is the approach to completeness and the ability to demonstrate with reasonable assurance that only small contributors are omitted. This inherent limitation means that any calculation using this methodology is always subject to revision and to doubt as to its completeness."* Until now, there has been no approach available for ensuring the completeness of the PRA and for assessing the impact of incompleteness on PRA results.

From the above discussion, we note certain initiating events or component failure modes are omitted from the analysis because their existence was not recognized by the analysts. More often, certain basic events and initiating events which have already been identified by the analysts are omitted from the analysis for their low frequency of occurrence or insignificant contributions to the overall risk. In such case, the omission of an event from the analysis can be done in two different ways: not addressing the event explicitly in the model as discussed in Chapter 3, and by us of truncation limits.

Truncation limits are introduced to reduce the quantification scope of the PRA to those PRA elements which contribute significantly to the model results. The existence of truncation limits imply that the contribution to overall risk from some

PRA elements are relative small when compared to other elements. One such situation would be a system consisting of several components in series, one of which is extremely unreliable compared to all of the others according to tests and historical data. In this case, the system failure frequency can be approximated by the failure frequency of the unreliable component. The contribution to system failure from all other components can be neglected or truncated during the quantification process.

Truncation limits can be applied at the minimal cut set level, system level, or accident sequence level. At the minimal cut set level, only those minimal cut sets whose probability of occurrence is above the cutoff frequency remains in the quantification process. The minimal cut sets whose probabilities are below the cutoff value will be excluded from the overall risk evaluation process. At the accident sequence level, those sequences with frequencies of occurrence above the cutoff value remain in the model quantification. The sequences whose frequencies drop below the cutoff value before reaching a final end state will be excluded from the overall risk evaluation. Given the fact that the number of sequences increases exponentially as sequence frequency decreases, the truncation limit technique provides us with an efficient way to speed up the quantification process with little cost to model accuracy.

ASME RA-S-2002 [35] states that the truncation limit should be set such that the overall PRA results are not significantly changed and no important risk contributors are eliminated. RG 1.174 suggests using truncation limits such that the retained PRA elements capture at least 95% of CDF.

Given an acceptance guideline for truncation limits, the truncation limit can be established in three different ways: the point estimate approach, the mean value approach, and the confidence level approach. In the case of the point estimate approach, point values for input parameters are used to obtain a point estimate fractional truncated risk. For the case of the mean value approach, the expected truncated risk from Monte Carlo simulation is used in comparison with the acceptance guidelines to determine the acceptability of a given truncation limit. In case of the confidence level approach, the confidence that risk truncated has met the acceptance guideline is calculated by use of Monte Carlo simulation. Appendix B demonstrates the selection of truncation limits using each of the three approaches by way of an example. Appendix C investigates the general relationship between the percentage truncated risk using the point estimate approach and that obtained using Monte Carlo simulation.

To summarize our discussion, when the system subject to analysis using the PRA technique is extremely complex, it is typically not possible for analysts to identify and address every risk contributor. The omission of significant initiating events, plant operating modes, component failure modes, and the use of inappropriate truncation limit can significantly impact the correctness of a PRA's results. A PRA which does not take into account all significant risk contributors is likely to systematically underestimate both the mean values of the PRA's results and the corresponding uncertainties. However, the impact of the incompleteness due to unrecognized risk contributors on PRA results is impossible to quantify.

Given the difficulty in quantifying the impact of model uncertainty and incompleteness uncertainty of PRA results, two important assumptions are made when we develop the proposed framework for assessing the adequacy of PRA results for risk-informed activities. First, we assume that all models embedded in the PRA are technically correct. Second, we assume that all initiating events, component failure modes, and plant operating modes have been identified by the analysts. Some events are omitted from the analysis only because they are estimated to be negligible in terms of their low frequency of occurrence or insignificant contributions to risk. These assumptions should be kept in mind when applying the framework we develop in this thesis.

4.5 Summary

In this chapter, we have discussed the definitions and treatment of three types of epistemic uncertainties in PRAs. Parameter uncertainty is often addressed by assigning probability distributions to the value of uncertain parameters to reflect the analyst's state-of-knowledge about the values of the parameters. The problem with this treatment is found to be the difficulty in selecting appropriate types of distribution form to be used in characterizing the values of certain input parameters.

Two methods for treating model uncertainty are discussed. The alternative hypotheses approach and the adjustment factor approach proposed by Apostolakis. Although both approaches find their applications in the PRA, they are difficult to apply in many instances because the alternative hypotheses approach requires a set of mutually exclusive alternative models, while the adjustment factor of the adjustment factor approach is often unknown.

Three sources of incompleteness uncertainty were discussed: events that were not recognized by the analyst, events were not addressed explicitly in the model for their low frequency of occurrence, and events were truncated from the quantification process or their insignificant contributions to risk. Incompleteness uncertainty due to the incomplete knowledge of existing risk contributors has been considered one of the major limitations of the usefulness of PRA technique. Since this type of incompleteness counts for the fractional risk that was not recognized by the analysts, it's effect on the PRA model is typically difficult to evaluate.

Chapter 5

Evaluation of the Adequacy of PRA Results for Risk-informed Decision Makings with Respect to Incompleteness and Uncertainty Treatment

Our discussion presented in Chapter 4 indicates that PRAs are incomplete to some extent, and there is considerable uncertainty in determining the values of certain input parameters and how some models embedded in a PRA should be constructed. As a result, PRA results are very likely to be inaccurate and imprecise, and there are no guarantees that the regulatory safety goals and acceptance guidelines have been achieved.

In order to assess how confident we are in a PRA, and how adequate its results are for risk-informed decision making, we must first have a method for estimating its quality in terms of accuracy and precision. The degree of accuracy is difficult to evaluate because the true values of PRA results are often unknown. However, the degree of precision can be directly obtained from the probability distributions of PRA results.

The baseline risk, including CDF and LERF, and risk change, including change in CDF and change in LERF, are often the PRA's primary outcome of interest when used for risk-informed activities. In this Chapter, we develop an approach for assessing the adequacy of the accuracy and precision of risk and risk change. We begin with a general discussion of the framework we use in this thesis for evaluating the quality of a PRA. Next, we investigate the use of RS and RCS for identifying events that are important to achieving the desired accuracy of risk and risk change. Since uncertainty about risk and risk change can be a significant factor in making decisions, we investigate the use of the 95^{th} confidence level acceptance guideline for examining the adequacy of the uncertainty treatment of a PRA. Our framework is developed keeping in mind that the adequacy of PRA results should be measured with respect to the application supported and the role that the results play in the decision making process. The last section presents the results of the application of our framework to a simple system.

5.1 Introduction

It is common in statistics to break down model prediction error into components of accuracy and precision [29]. Mathematically we have

$$\begin{aligned} E[(y-\theta)^2] &= E[(y-\mu_y)^2] + (\mu_y - \theta)^2 \\ &= Var(y) + (\mu_y - \theta)^2. \end{aligned} \tag{5.1}$$

Where y is the model prediction, μ_y is the expected value of y, and θ is the true value of y. $Var(y)$ is a measure of precision, and $\mu_y - \theta$ is a measure of accuracy. In general, the quality of a model can be determined from the accuracy and precision of its predictions. A model that produces more accurate and precise predictions is desired. When both baseline risk and risk changes are inputs for risk-informed decision making, the quality of a PRA can be determined from the accuracy and precision of the baseline risk and risk change.

In this model, both μ_y and $Var(y)$ can be obtained from uncertainty analysis. However, if we want to quantify the accuracy of y in addition to the mean value and precision of y, knowing only μ_y and $Var(y)$ is insufficient. For this reason, we make some simplifying assumptions: all models embedded in the PRA are technically correct; all initiating events and component failure modes have been identified by the analysts; and incompleteness arises only when certain events are not considered in the analysis for their low frequencies of occurrence or insignificant contributions to risk. Under these assumptions, we propose to use the baseline risk and risk change of the complete model, which addresses all events identified by the analyst, to represent the true values of risk and risk change.

Our proposed framework for assessing PRA adequacy draws heavily from existing approaches and standards on the use of PRA for risk-informed decisions and adds the additional considerations of accuracy and precision to assess model quality.

5.2 The Accuracy of the Baseline Risk and Identification of Risk Significant Events

Given the assumption that a PRA is technically correct and all risk initiating events and component failure modes have been identified by the analysts, addressing all these events in the PRA is desired in order to obtain an accurate estimate of the baseline risk. However, when the size of a PRA becomes large in terms of the number of initiating events and basic events, addressing all initiating events, basic events, and operating modes in the analysis becomes difficult and impractical. In addition, many basic events, initiating events, and operating modes might not contribute significantly to the baseline risk. In practice, these risk insignificant events may be not considered in the PRA analysis in order to simplify the model structure and facilitate the quantification process without sacrificing the accuracy of the baseline risk.

In order to examine whether the baseline risk of an incomplete PRA is adequate enough to support a decision, we first need to determine whether the estimate of risk meets the analyst's desired accuracy level for the specific decision supported. In this thesis, we refer to the desired accuracy level as the adequacy guideline. If the baseline risk accuracy does not meet the adequacy guideline, initiating events and basic events that are important to achieving the desired accuracy level of the baseline risk need to be identified and addressed in the analysis.

By letting R_0 be the baseline risk of the complete model, or the nominal baseline risk, and R be the baseline risk of the incomplete model, we propose to measure the baseline risk accuracy of the incomplete model in terms of

$$\frac{\mu_R - \mu_{R_0}}{\mu_{R_0}}. \tag{5.2}$$

Where μ_{R_0} is the expectation of R_0, and μ_R is the mean value of R. This expression indicates that the degree of accuracy of baseline risk can be measured in terms of the discrepancy between the expected nominal risk and the expected baseline risk of the current incomplete model. The smaller the discrepancy, the more accurate the baseline risk is. As discussed in Chapter 4, the expectations of the estimated risk and nominal risk are often obtained from uncertainty analysis by the use of Monte Carlo simulation.

By letting ε_s be the desired degree of accuracy of the baseline risk, the adequacy of the baseline risk accuracy can therefore be measured by examining whether the following inequality is satisfied:

$$\left|\frac{\mu_R - \mu_{R_0}}{\mu_{R_0}}\right| < \varepsilon_s. \tag{5.3}$$

ε_s reflects the decision maker's tolerance for prediction error in the baseline risk. This expression indicates that if the discrepancy between the estimated risk and the nominal risk is lower than the acceptable amount of prediction error, the current incomplete model provides an adequately accurate estimate of the baseline risk for the application and decision supported.

ε_s also reflects risk-aversion and is typically determined by the social impact of system failure. In other words, ε_s of activities that result in severe consequences is typically lower than ε_s of activities that result in relatively moderate damages. For example, suppose we have two PRA models. One estimates the probability of automobile accident during a drive, while the other evaluates the probability of airplane crash during a flight. Since the social consequences of the airplane crash are far more severe than those of an automobile accident, the estimate of airplane crash probability is generally required to be more accurate than that of automobile accident.

The value of ε_s also depends upon the application supported and the role that risk insights play in that specific decision making process. In general, the more emphasis that is placed upon risk insights and on PRA results in the decision making process, the higher the degree of accuracy that a PRA must have [13]. In the previous airplane crash example, we now suppose that the PRA that estimates the airplane crash probability has two applications. In one application, the PRA result is used as the basis for analyzing the cost effectiveness of an airplane's operation and maintenance practices. In another application, the PRA result is used as an aid to the deterministic engineering analysis of critical components to improve airplane safety. Given the different roles that the PRA result plays in the decision making process, the value of ε_s defined for the first application should be much smaller than that defined for the second application.

Once ε_s is defined for the application and decision supported by the decision maker, the adequacy of the baseline accuracy can then be assessed by use of Equation 5.3. If the baseline risk accuracy does not meet the adequacy guideline, the PRA should be improved such that events which are important to achieving the desired accuracy of the baseline risk are addressed explicitly in the analysis.

By letting R_0 be equal to the nominal baseline risk and $R_{w/o,i}$ be equal to the baseline risk evaluated when event i is omitted from the analysis, our proposed measure of RS is defined as follows:

$$RS_i = \frac{R_{w/o,i} - R_0}{R_0}. \tag{5.4}$$

RS_i measures the impact of the exclusion of event i on the PRA in terms of the resulting percentage change in the baseline risk.

In order to identify safety significant components for nuclear activities such as a risk-informed inservice testing program, a threshold value of 0.005 was suggested for FV at the component level, 0.05 for FV at the system level, and 2 for RAW [19, 42, 41, 52]. Apostolakis and Borgonovo [6] suggested using relative threshold values for FV, RAW, and DIM instead of universal threshold values. Once the FV and RAW importance of an SSC have been calculated, the SSC can be defined as either "High-Safety Significance" or "Low-Safety Significance" by comparing its importance with corresponding threshold values.

Since we are concerned with whether the desired degree of accuracy of the baseline risk has been met, we suggest using ε_s as a threshold value for RS. The importance of an event in meeting the adequacy guideline can then be determined by examining whether the following inequality has been satisfied:

$$|RS_i| > \varepsilon_s. \tag{5.5}$$

This expression indicates that if the omission of event i alone results in an overestimate or underestimate of the baseline risk by more than ε_s, the event is generally considered to be important to achieving the desired degree of accuracy of risk.

Equation 4.1 indicates that $R_{w/o,i}$ and R_0 in Equation 5.4 are typically polynomial functions of model input parameters. Since most PRA input parameters are often described as random variables, RS_i is also a random variable. A point value of RS_i can then be obtained by using point estimated values of the input parameters. The probability distribution of RS_i can also be obtained by propagating uncertainties on model input parameters using Monte Carlo simulation. Similar to the case where the baseline risk of a plant is compared with NRC Safety Goals for acceptability, and risk changes are compared with NRC acceptance guidelines to determine the acceptability of modifying an activity, the comparison of RS_i with ε_s can also be performed in three different ways: the point estimate approach, the mean value approach and the confidence level approach.

In the case of the point estimate approach, the point estimated value of the RS measure is used in comparison with ε_s. The point estimate RS can be obtained by the use of point estimated values of model inputs. This approach provides the decision makers with very precise information about the absolute magnitude of the RS of any event in the PRA.

The point estimate approach is simple to apply but does not take into account information on the state-of-knowledge of the model inputs. In practice, sensitivity analysis is often performed to test the robustness of the point estimate categorization of risk significance or risk insignificance by changing the point estimate values of one or more key model inputs or assumptions about which there is uncertainty. If an event does not change categories, the analyst then obtains a confirmation of the categorization of the event.

In the case of the mean value approach, the expected value of RS is used in comparison with ε_s. In order to obtain the expected value of RS, uncertain model inputs and model structures are characterized by probability distributions. The probability associated with a value represents the analyst's confidence in the value being the correct value for the input parameter, and the probability associated with a candidate model represents the analyst's belief in the model being the correct model. These epistemic uncertainties are then propagated through the logic model to obtain probability distributions for the baseline risk and RS.

Compared to the point estimate approach, the use of mean values in the comparison analysis is more robust in that the epistemic uncertainty associated with uncertain input parameters and submodels are addressed explicitly in the PRA analysis and reflected in the mean value. However, in some cases, this approach is considered difficult to apply because, in some circumstances, several distribution forms can be fitted into historical data equally well. It is therefore difficult for the analyst to determine which probability distribution form represents his state-of-knowledge uncertainty about the input parameter the best.

Because of a large amount of uncertainties about the mean value of RS, there is no guarantee that the threshold value has been met. This introduces the confidence level approach. In this approach, an event is categorized as either important or unimportant by estimating the degree of confidence that the threshold value has been met. As with the mean value approach, to compute the confidence level, one needs perform uncertainty analysis. The confidence level can then be obtained by calculating the probability that the RS is lower than the threshold value. In practice, the 95% confidence level is often used for acceptability.

5.3 The Accuracy of Risk Change and Identification of Risk Change Significant Events

We have so far investigated the use of ε_s to assess the adequacy of the baseline risk for specific applications and decisions supported. We also discussed the use of RS to identify events that are important to achieving the desired accuracy of risk. By analogy, we now develop an approach for examining the adequacy of risk change accuracy. We begin by introducing the concept of risk change accuracy. We then propose to use the measure of RCS to identify events that are important to achieving the desired accuracy of risk change.

Proceeding by analogy with Equation 5.3, we define

$$|\frac{E[\Delta R] - E[\Delta R_0]}{E[R_0]}| \tag{5.6}$$

as the accuracy of risk change of the incomplete model. Where, $E[\Delta R_0]$ is the expected nominal risk change, $E[R_0]$ is the expected nominal baseline risk, and $E[\Delta R]$ is the expected risk change of the current incomplete model subject to analysis. $E[\Delta R] - E[\Delta R_0]$ is the discrepancy between the nominal value of risk change and risk change estimated from the current incomplete model, and is a measure of the degree of accuracy of risk change. $E[\Delta R_0]$, $E[\Delta R]$, and $E[R_0]$ are often obtained from uncertainty analysis.

Once the accuracy of risk change is determined, the adequacy of risk change of the incomplete model can then be assessed by examining whether the following inequality has been satisfied:

$$\left|\frac{E[\Delta R] - E[\Delta R_0]}{E[R_0]}\right| < \varepsilon_l. \tag{5.7}$$

As with ε_s, ε_l reflects the decision maker's desired accuracy level of risk change. ε_l is also determined by the application supported, the role that PRA results play in the decision-making process, and the consequences of the failure of the activity or system subject to analysis.

The above expression indicates that if the risk change unaccounted for in the incomplete model is lower than the acceptable discrepancy in risk change, the estimated risk change is accurate such that information derived from it can be directly used for risk-informed decisions. On the other hand, if the adequacy guideline, ε_l, is not met, events that are omitted from the analysis but important to risk change accuracy should be identified and addressed explicitly in the analysis.

According to Equation 3.46, RCS of event i is defined as

$$RCS_i = \frac{\Delta R_{w/o,i} - \Delta R_0}{R_0}. \tag{5.8}$$

Where ΔR_0 is the nominal value of risk change, R_0 is the nominal baseline risk, and $\Delta R_{w/o,i}$ is risk change evaluated without considering event i in the analysis. RCS measures how much risk change is overestimated or underestimated if event i is excluded from the PRA. It is obvious that events with high RCS are more important to achieving high accuracy of risk change than events with low RCS.

In order to identify events that are important to achieving the desired degree of accuracy of risk change, we propose to use the following inequality:

$$|RCS_i| > \varepsilon_l. \tag{5.9}$$

Given that the value of ε_l has been defined for the application and decision supported, an event can be categorized as either important or unimportant by examining whether the above equation has been satisfied.

Since ΔR_0, $\Delta R_{w/o,i}$, and R_0 in Equation 5.8 are polynomial functions of input parameters, RCS_i is also a function of input parameters. When all uncertain input parameters are described as random variables, RCS_i becomes a random variable itself. As in the case where RS is compared with ε_s to identify events that are important to achieving the desired degree of accuracy of the baseline risk, the comparison of RCS with ε_l can also be done in three different ways.

In the case of the point estimate approach, the point estimate RCS_i is compared with the threshold value, ε_l. In the case of the mean value approach, the expected RCS_i from uncertainty analysis is used in comparison with ε_l. In the case of the confidence level approach, the degree of confidence that the threshold value, ε_l, has been met is used to determine the importance of an event. The advantages and drawbacks of each approach are discussed in detail in Chapter 2.

To summarize, the following steps are involved in examining the adequacy of the accuracy of risk and risk change used to support risk-informed decisions:

1. Compute RS and RCS for each event in the PRA, and estimate the accuracy level of the baseline risk and risk change.

2. Establish ε_s and ε_l based on the application supported, the role PRA results play in the decision making process, and the social consequences of the activity under consideration.

3. Compare the accuracy of risk and risk change with ε_s and ε_l to determine whether the estimates of risk and risk change are accurate such that the information derived from these values can be directly used in the risk-informed decision making process.

4. Finally, if the desired degree of accuracy of risk and risk change is not met, identify events that are important to achieving the adequacy guidelines by using Equation 5.5 and Equation 5.9.

5.4 Assessment of the Adequacy of Uncertainty Treatment

In Chapter 4, we discussed sources of uncertainty, types of uncertainty in the PRA and corresponding approaches for the treatment of each type of uncertainty. In this section we first show that uncertainty about the baseline risk and risk change can be an important factor to decision-making. We then investigate the use of the 95^{th} confidence level acceptance guideline for assessing the adequacy of the uncertainty treatment of a PRA.

5.4.1 Important Factor to Decision Makings

To begin, we assume that two different probability distributions for the CDF of a nuclear power plant were obtained from two independent PRAs. We also assume that both probability distributions are lognormally distributed with mean values and standard deviations are given as follows:

$$\begin{aligned} \mu_1 &= 5 \times 10^{-5}, \\ \sigma_1 &= 2 \times 10^{-5}, \\ \mu_2 &= 5 \times 10^{-5}, \\ \sigma_2 &= 6 \times 10^{-5}. \end{aligned} \tag{5.10}$$

The distributions corresponding to the above distribution characteristics are plotted and shown in Figure 5-1.

For simplicity, we assume that core damage in successive years are mutually independent. This would imply that if a plant experiences core damage in the first year, it would still have the same probability of experiencing core damage in subsequent years.

With that assumption, the expected core damage probability per two successive

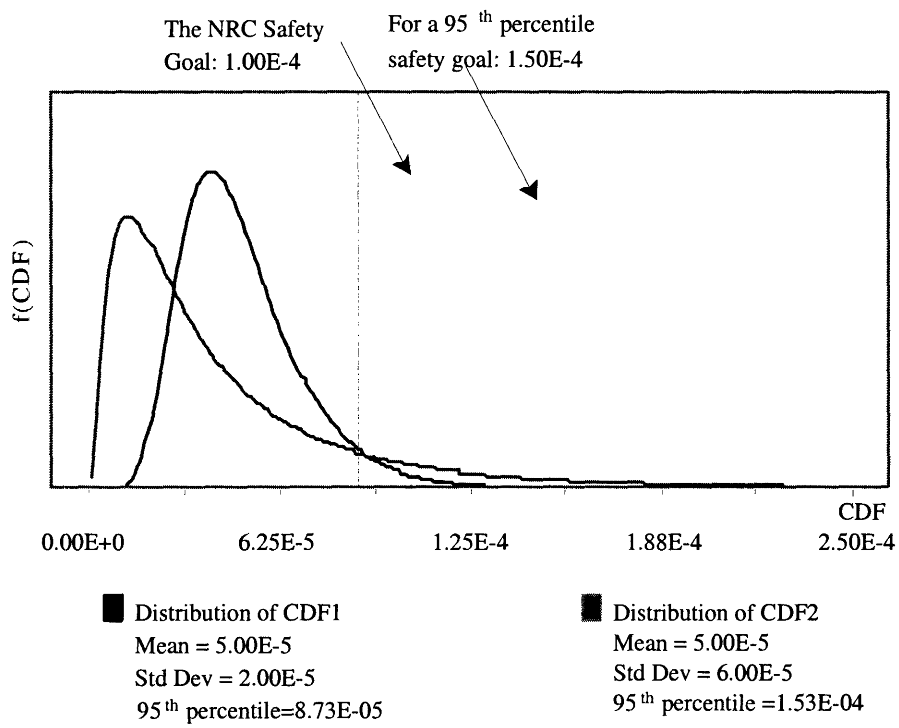

Figure 5-1: The probability distributions of the example plant CDF

reactor years is equal to

$$E[x_1x_2] = E[x^2] = Var(x) + E^2[x]. \tag{5.11}$$

Thus, by considering the probability distribution of plant CDF from the first PRA, the expected core damage probability per two successive reactor years is equal to

$$E[x_1x_2] = Var(x) + E^2[x] = (5 \times 10^{-5})^2 + (2 \times 10^{-5})^2 = 2.9 \times 10^{-9}. \tag{5.12}$$

Substituting μ_2 and σ_2 into Equation 5.11 yields the expected core damage probability per two successive reactor years as follows:

$$E[x_1x_2] = Var(x) + E^2[x] = (5 \times 10^{-5})^2 + (6 \times 10^{-5})^2 = 5.1 \times 10^{-9}. \tag{5.13}$$

We note that the expected core damage probability per two successive reactor years obtained using the results of the second PRA model is greater than that obtained using the results of the first PRA model by nearly a factor of two. For this particular performance measure, the plant risk level obtained from the first PRA would be more acceptable to the public than that obtained from the second PRA, even though the mean values of annual CDFs from the two PRAs are the same, and the plant subject to analysis is the same.

People are often more risk-averse towards activities that could potentially result in severe consequences than towards activities that could result in moderate consequences. For example, the public's acceptability of cars is very different from that of commercial nuclear power plants. The primary reason is that the social consequences of a car accident is much smaller than that of a nuclear accident. In general, activities which could potentially result in severe consequences need to be well understood to be acceptable, while activities that could result in moderate consequences can be accepted even with a sizable amount of uncertainty in the expected risks of these activities.

As can be seen from the above example, activities whose risk level is well understood may be considered more acceptable than those whose risk is not well known. Activities that result in the same amount of expected risk but different degrees of uncertainty about the expected risk may differ greatly in their acceptability, depending on which performance measure is of interest.

As Bier[3] pointed out, in many cases, the expected benefit to be gained from reducing the degree of uncertainty about plant risks and risk changes may well outweigh the relative cost of reducing that uncertainty. The value of postponing a final decision until more information is available may well exceed the the expected benefit to be gained by making an immediate decision based upon the existing state-of-knowledge of plant risk and risk changes.

From our discussion above we note that the state-of-knowledge uncertainty about the expected plant risk level can have great impact on the value to be gained from risk-informed decisions. However, the existing NRC safety goal and acceptance guidelines for the use of PRA in risk-informed decisions were defined in terms of mean values, and uncertainty was not taken into account explicitly in formulating these regulations. In such a circumstance, acceptance criteria for the degree of uncertainty about the expected plant risk and risk changes can be of great value.

5.4.2 Investigation of the Use of the 95th confidence Level Acceptance Guideline for Assessing the Adequacy of Uncertainty Treatment

In the above section, we showed that uncertainty about risk and risk change can be relevant to decision making and that the expected benefit of postponing a decision can be desirable in most cases. In this section, we investigate the use of a high confidence level acceptance guideline to evaluate the adequacy of the uncertainty treatment of a PRA in risk management decisions.

It is common in statistics to use the standard deviation as a method of conveying the amount of uncertainty on mean values. The smaller the standard deviation, the less the uncertainty. From the discussion presented in the previous section, we note that the acceptability of the degree of uncertainty generally depends upon the expected risk level of an activity under consideration. For this reason, the acceptable uncertainty of the baseline risk has to be set individually for each nuclear power plant based on its expected risk level, which is generally impractical from a regulatory point of view.

Acknowledging these aspects, we suggest using the 95^{th} confidence level acceptance guideline in addition to the existing regulatory acceptance guidelines, to assess the adequacy of an uncertainty treatment of a PRA. Inherent in this concept is that the closer a plant's expected risk level is to the existing safety goal, the better the understanding of plant risk needs to be. In other words, if the expected risk level of a plant is much lower than the existing safety goal, a relatively large amount of uncertainty can be allowed such that the 95^{th} confidence level risk is still lower than the 95^{th} confidence level acceptance guideline. On the contrary, if the expected risk level of the plant is high and close to the current safety goal, in order to meet the 95^{th} confidence level acceptance guideline, the amount of uncertainty about the mean risk level must to low.

Once the 95^{th} confidence level acceptance guideline or safety goal is defined, the adequacy of the uncertainty treatment of a PRA can be assessed by comparing the 95^{th} confidence level risk against the 95^{th} percentile safety goal. If the 95^{th} confidence level safety goal has been met, the current understanding about the plant risk level is generally acceptable. Otherwise, more information needs to be gathered such that the plant risk is better understood and greater confidence can be placed in the understanding of risks that could potentially result from the operation of a plant.

To see this, let us consider the estimates of CDF for two nuclear power plants. We assume that the probability distributions of these CDFs are lognormally distributed with mean values, standard deviations, and the 95^{th} confidence level CDFs as given in Table 5.1.

We also assume that the 95^{th} confidence level safety goal, as opposed to the

Table 5.1: The distribution characteristics of the CDFs of two example plants

	Mean	St.D.	95^{th} percentile	Acceptable St.D.
CDF1	6.00E-05	4.00E-05	1.35E-04	4.85E-05
CDF2	8.00E-05	4.00E-05	1.56E-04	3.72E-05

existing mean value safety goal, is 1.5×10^{-4}. From the numerical values presented in Table 5.1, we note that the expected risk level of the first plant is lower than that of the second plant. We also see that the 95^{th} confidence level CDF of the first plant has met the 95^{th} confidence level safety goal, while the 95^{th} confidence level CDF of the second plant has exceeded the 95^{th} confidence level safety goal.

The adequacy of the uncertainty treatment of a PRA may also be determined by comparing the current uncertainty about the expected risk, in terms of standard deviation, against the acceptable degrees of uncertainty. This alternative is only possible when the probability distribution of the baseline risk approximates a standard distribution form. In such a case, the acceptable degree of uncertainty can be calculated by the use of the expected risk level and setting the 95^{th} confidence level safety goal to the 95^{th} confidence level of risk.

In practice, the lognormal distribution is the most frequently used distribution form in actual PRA analysis. One reason for this is that it is thought to capture many aspects of our uncertainty about component failure probabilities. The other reason is that if the failure probability of all basic events in a minimal cut set is lognormally distributed, the probability of the occurrence of the minimal cut set will also be lognormally distributed. In the case where the overall risk is dominated by a few minimal cut sets, the estimate of risk is also very likely to be lognormally distributed.

For a lognormal distribution with a mean equal to μ, and standard deviation equal to σ, its 95^{th} confidence level value can be represented in term of μ and σ as:

$$X_{95} = e^{1.645 \cdot \sqrt{ln(1+\frac{\sigma^2}{\mu^2})}} \cdot \frac{\mu}{1+\frac{\sigma^2}{\mu^2}}. \tag{5.14}$$

This expression is an exact formulation of the 95^{th} confidence level risk as a function of mean risk level, μ, and standard deviation, σ, of a lognormal distribution. For a given 95^{th} confidence level safety goal and the expected risk, μ, from uncertainty analysis, this equation can then be used to obtain the acceptable degree of uncertainty, σ, about the expected risk level.

The acceptable degree of uncertainty about the expected CDF for each plant in the above example was estimated and presented in Table 5.1. Figure 5-2 and Figure 5-2 present the probability distributions of CDF from uncertainty analysis and that obtained from the acceptable uncertainty level for each plant. We note that the acceptable uncertainty about the expected CDF of the first plant is estimated to be higher than that of the second plant. The reason is that the expected risk of the first plant is lower than that of the second plant. Given the same 95^{th} safety goal for both plants, the understanding of the risk of the second plant must be better to compensate for its higher expected risk level when compared with the first plant. By comparing the actual uncertainty with the corresponding uncertainty, we note that the current uncertainty in the expected CDF of the first plant has met its acceptable uncertainty level, while the current uncertainty of the second plant has exceeded the corresponding acceptable uncertainty level. Thus, more information about the operation of the second plant should be gathered such that the potential risk of this plant is well understood.

The decision to use the 95^{th} confidence level safety goal rather than some other confidence level safety goal as a basis to assess the adequacy of uncertainty treatment of the PRA is not critical. In fact, the use of the 90^{th} or 99^{th} confidence level safety goal instead of the 95^{th} confidence level safety goal is very likely to yield the same result on the adequacy of uncertainty treatment of a PRA, especially for risk distributions with narrow confidence intervals or long right tails.

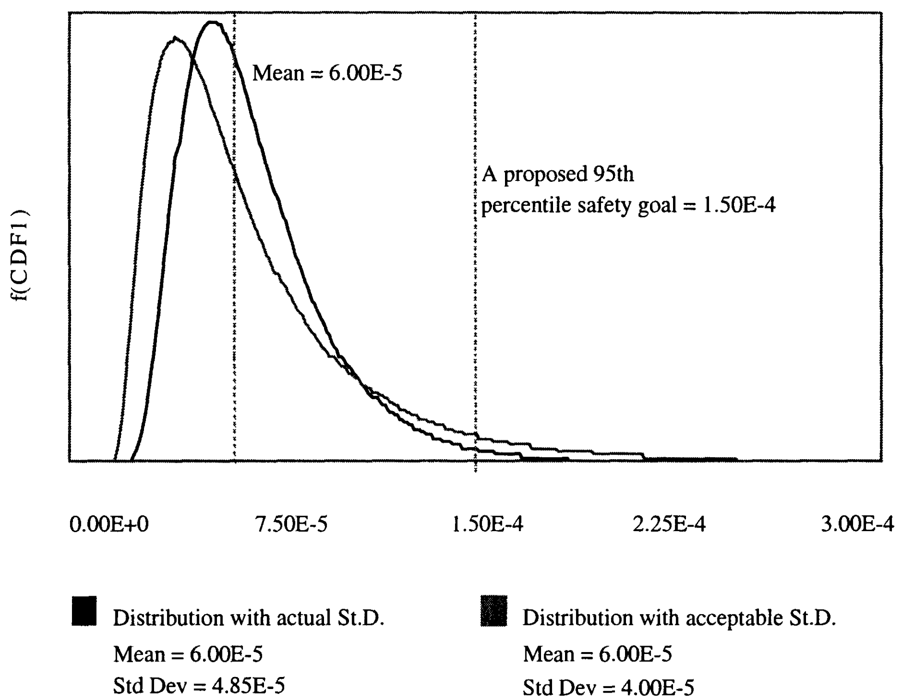

Figure 5-2: The actual and acceptable uncertainty about the expected CDF of the first plant

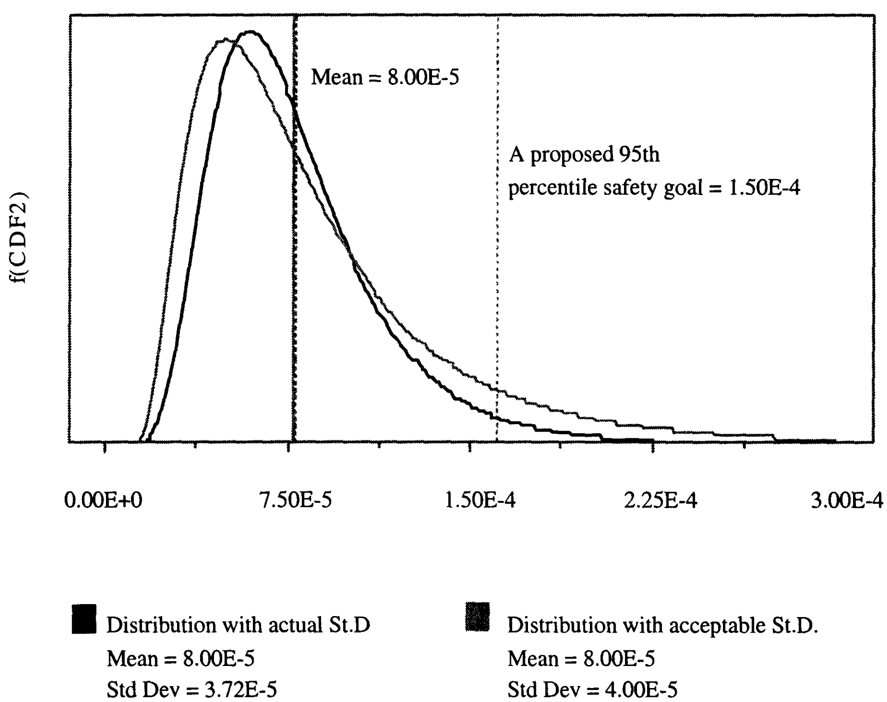

Figure 5-3: The actual and acceptable uncertainty about the expected CDF of the second plant

5.5 Example - Measures of Importance of the Components in a Simple System

In this example, we illustrate the application of the proposed framework to a fault tree of a simple system. The framework will be used to demonstrate whether the results of the fault tree are adequate to support a specific risk-informed decision. The complete fault tree of the system under consideration is presented in Figure 3-9. We suppose that component 1 was not considered in the analysis. The incomplete fault tree subject to analysis is shown in Figure 5-4.

We assume that the failure probabilities of all components are lognormally distributed with distribution parameters as given in Table 3.1, and that all component failure probabilities are mutually independent. We also assume that the proposed change under consideration is to double the inspection interval of component 2 and increase the inspection interval of component 4 by a factor of four. Finally, we assume that the desired accuracy of system failure probability, ε_s, is 25%, and that the desired accuracy of change in system failure probability that could result from the inspection relaxation of components 2 and 4, ε_l, is 5%.

The fault tree presented in Figure 5-4 was analyzed to generate the minimal cut sets for system failure. Then, the software program Crystal Ball, was used to propagate the uncertainties on input parameters through the minimal cut sets and perform all necessary calculations. For this example, a sample size of $n = 10,000$ was used in the Monte Carlo simulation.

By considering Equation 5.2, the expected system failure probability from uncertainty analysis was found to be overestimated by 23.54% due to the omission of component 1 from the analysis. However, this accuracy level still meets the desired degree of accuracy. By using Equation 5.7 we note that omitting event 1 from the analysis does not affect the estimate of change in system failure probability. These results indicate that the fault tree presented in Figure 5-4 provides adequate information to decision makers who are concerned with the acceptability of relaxing the inspection of components 2 and 4.

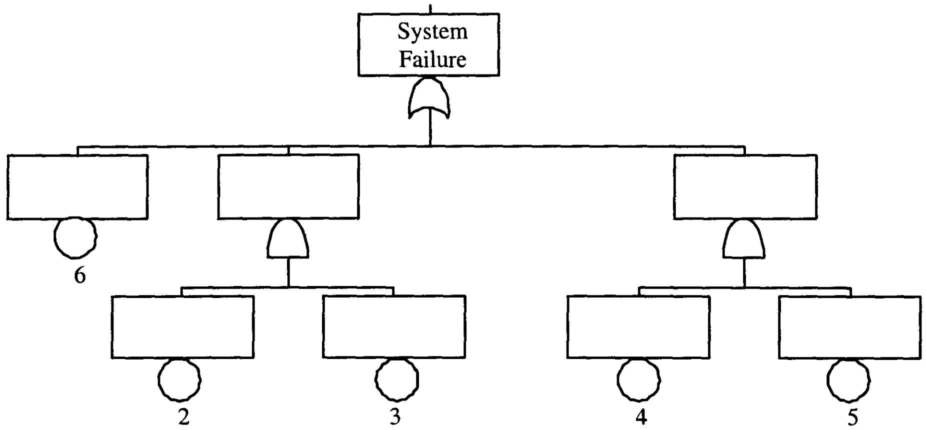

Figure 5-4: The fault tree of the example system without component 1

To verify our results, we also computed the point estimate values and the expected values of RS for the components in the system in the independent case. These results are presented in Figure 5-5. Figure 5-6 shows the point estimate RCS and the expected RCS for each component in the system. The point estimated values and the expected values of RS and RCS for the components in the system are also summarized in Table 5.2. The point estimated values of RS and RCS were obtained using the expected failure probability of each component, while the mean values of RS and RCS were obtained from uncertainty analysis.

Table 5.2: RS and RCS measures for the components in the example system

Component	Point estimated RS	$E[RS]$	Point estimated RCS	$E[RCS]$
1	-2.22E-01	-2.34E-01	0.00E+00	0.00E+00
2	2.16E+00	2.38E+00	-6.67E-02	-7.01E-02
3	6.60E+00	7.14E+00	6.60E+00	7.14E+00
4	2.18E+00	2.40E+00	-1.33E-01	-1.46E-01
5	4.40E+00	4.82E+00	1.32E+01	1.46E+01
6	-6.67E-01	-6.46E-01	0.00E+00	0.00E+00

According to the results presented in Figure 5-5, Figure 5-6, and Table 5.2, the point estimated values of RS and RCS are slightly different from the corresponding

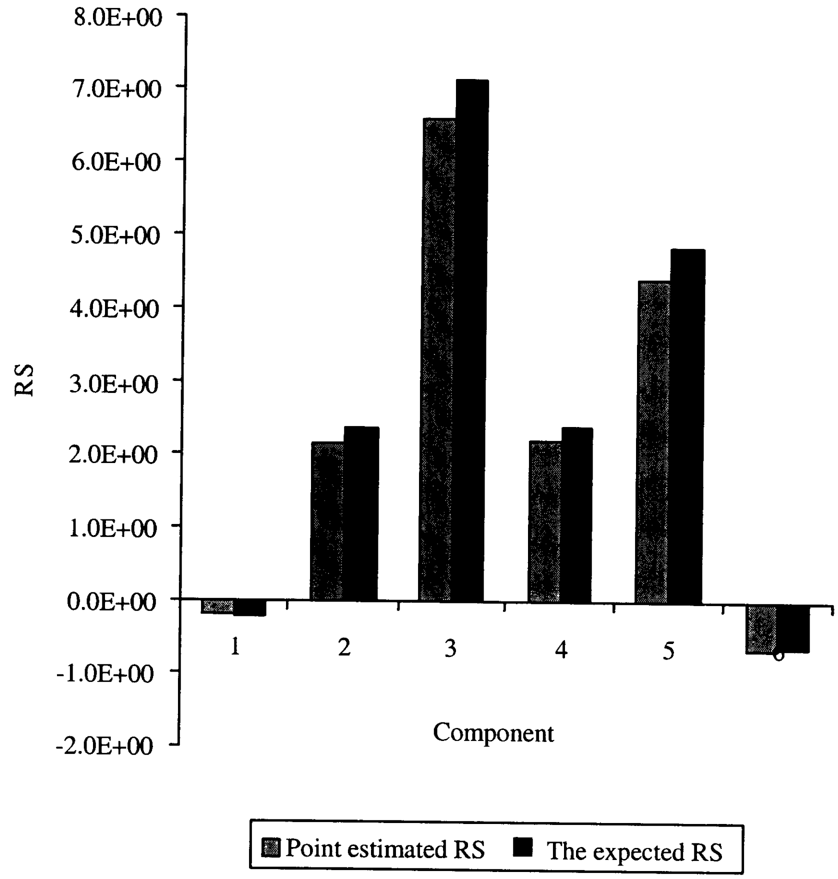

Figure 5-5: RS measures of the components in the example system

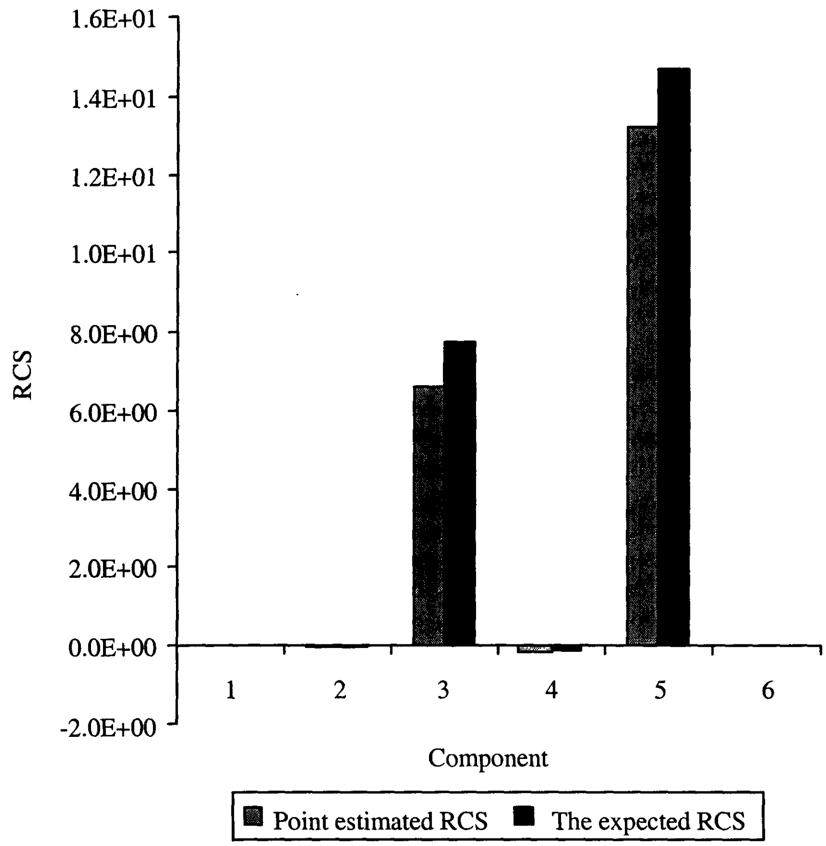

Figure 5-6: RCS measures of the components in the example system

mean values, but the categorization of all components remain the same. In both cases, component 1 is found to be unimportant to achieving an accurate estimate of system failure probability. Components 1 and 6 are found to be irrelevant to the estimate of change in system failure probability.

We now would like to categorize the components in the system using the confidence level approach. The probabilities that the RS and RCS of each component are below the corresponding threshold values, 25% for RS and 5% for RCS, were calculated and presented in Table 5.3.

Table 5.3: The degree of confidence that the RS and RCS of the components in the example system have met the threshold values

Component	$p(\|RS\| > 25\%)$	$p(\|RCS\| > 5\%)$
1	38.64%	0.00%
2	100.00%	72.04%
3	100.00%	100.00%
4	100.00%	98.17%
5	100.00%	100.00%
6	100.00%	0.00%

From these numerical values we note that if 95% is used for acceptability, then component 1 is unimportant to achieving the desired accuracy of system failure probability, components 1 and 6 are irrelevant to the estimate of the change in system failure probability, and component 2 is unimportant to achieving the desired accuracy of change in system failure probability. These findings indicate that, in this example, the categorization of the importance of each component using all three approaches agree closely with each other.

The results from all three approaches indicate that component 1 is not important to achieving the desired accuracy of system failure probability and is irrelevant to the estimate of change in system failure probability. This information is consistent with our observations obtained earlier. The estimate of system failure probability and change in system failure probability of the fault tree model of the system shown in Figure 5-7 has met the desired degree of accuracy. Information derived from these results can thus be directly used to supported risk-informed decisions on the inspection relaxation of components 2 and 4.

Finally, we would like to examine whether the uncertainty treatment of the current fault tree is adequate. In order to perform this task, we assume that the acceptable 95^{th} confidence level system failure probability for this system is 8×10^{-3}.

The probability distribution of system failure from uncertainty analysis is presented in Figure 5-7. We note that it approximates a lognormal distribution with a mean of 3.478×10^{-3}, and a standard deviation of 1.505×10^{-3}. By setting 8×10^{-3} to be the 95^{th} confidence level system failure probability, we obtain the acceptable uncertainty level with respect to the expected system failure probability as 2.406×10^{-3}. The probability distribution corresponding to this acceptable uncertainty level is shown in Figure 5-7.

The numerical values presented above indicate that the 95^{th} confidence level system failure probability has met the 95^{th} confidence level acceptance guideline, and that the current uncertainty about the mean system failure probability is lower than the acceptable degree of uncertainty. We thus conclude that the fault tree presented in Figure 5-7 provides fairly precise estimates of system failure probability and change in system failure probability, and no more information needs to be gathered such that risk insights derived from the estimated system failure probability and change in system failure probability can be used to directly aid in the decision on the proposed inspection relaxation of components 2 and 4.

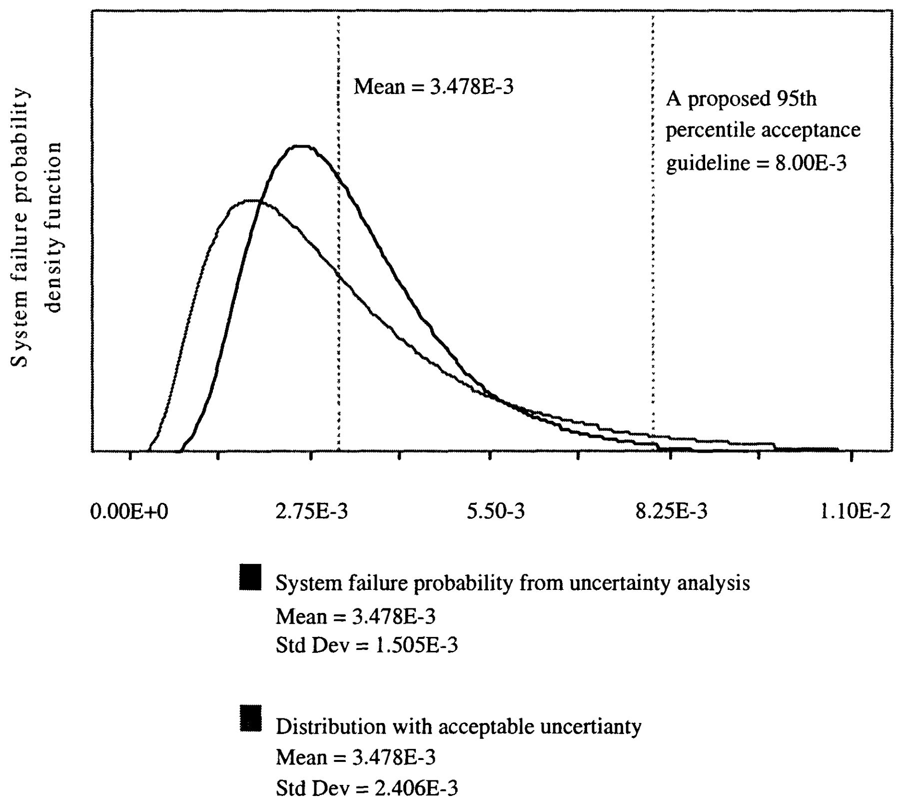

Figure 5-7: The failure probability distribution of the example system

5.6 Summary

In this chapter, we investigated the use of RS, RCS, and the 95^{th} percentile acceptance guideline for assessing the adequacy of PRA results, in particular risk and risk change, for risk-informed activities. Since the true values of a PRA's results are generally unknown, we proposed using the baseline risk and risk change of the complete model which explicitly addressed all events that were identified by the analysts as the true values of the baseline risk and risk change. We proposed to estimate the accuracy of the baseline risk and risk change of an incomplete model in terms of the discrepancy to that of the complete model. These accuracy levels are then compared with the desired accuracy of risk and risk change. The comparison results are used to examine whether the estimate of risk and risk change of the current model are adequate such that the information derived from these estimates can be used to directly aid in the risk-information decision making process. For risk and risk change whose accuracy levels do not meet the adequacy guidelines, we suggested using RS and RCS to identify events that are important to achieving the desired accuracy levels.

Next, we investigated the use of the 95^{th} acceptance guideline to assess the adequacy of the uncertainty treatment of a PRA. Our results indicate that this approach agrees closely with practice in that activities that could potentially result in severe consequences, to be acceptable, need to be better understood than activities that could result in moderate consequences.

Chapter 6

A Case Study of the Reactor Component Cooling Water System

6.1 Description of the System

The Component Cooling Water (CCW) system of a pressurized water nuclear reactor is selected to illustrate the application of the framework developed in this thesis. The CCW system is responsible for supplying cooling water to the residual heat removal (RHR) system during plant cool-down, to vital components during normal operation. In an accident, the CCW system also cools the reactor cooling pump thermal barriers and bearings, seal water coolers for safety injection pumps, and containment fan coolers. This is performed by a closed loop cooling system which transfers heat from various plant components to the auxiliary saltwater system. This closed loop design enables the CCW system to provide a boundary between systems exposed to radioactive material and the environment.

A block diagram of the system is shown in Figure 6-1. The components of the system include three CCW pumps in parallel which are responsible for providing cooling water for the loop, two heat exchangers which transfer heat from components to the auxiliary saltwater system, a surge tank and surge tank pressurization system which prevent possible CCW flashing during a LOCA (large or medium) or steam line break coincident with a loss of offsite power, two crosstie valves between the

CCW headers A and B; and two crosstie valves at the suction of the CCW pumps to provide flow to the piping system.

The system can cause core damage in two different ways. First, after an accident, core damage can occur if the system fails to operate for 24 hours in response to initiating events. Secondly, during normal operation, core damage can occur if the system fails to supply cooling water to various vital components. In this chapter, we analyze the loss of the CCW system and the subsequent inability to supply cooling water to vital components during normal operation as an initiating event.

During normal operation, failure of the CCW pumps and their associated inlet and discharge valves (included in blocks P1, P2 and P3) is the primary contributor to the loss of the CCW system initiating event. Degradation in the performance of all other components in the CCW system, including the valves and the heat exchangers, do not significantly affect system performance.

In general, there are two scenarios that could result in the failure of the CCW pumps. The first scenario occurs during normal system operation and involves the failure of the two primary pumps followed by the failure of the third and standby pump to start and run. The second scenario occurs during the weekly CCW pump rotation. This involves the failure of the standby pump to start followed by the failure of two operating pumps to run during the maintenance of the failed standby pump.

Additional failure modes relate to common cause failures among the pumps. Common cause failures can occur in two ways during normal operation. First, the two running pumps may fail due to a common cause failure during normal operation. Second, after one of the two running pumps fails to run during normal operation, the other running pump and the standby pump may fail to run due to a common cause failure during the maintenance of the previously failed pump. Common cause failure may also occur during the weekly switch over. In this case, the standby pump fails to start and the two running pumps fail to run due to a common cause failure during the maintenance of the failed standby pump in the switch over period.

In order to illustrate the results of the thesis work, this system will be approached in different ways. First, a base case will be defined and the measures of RS and RCS

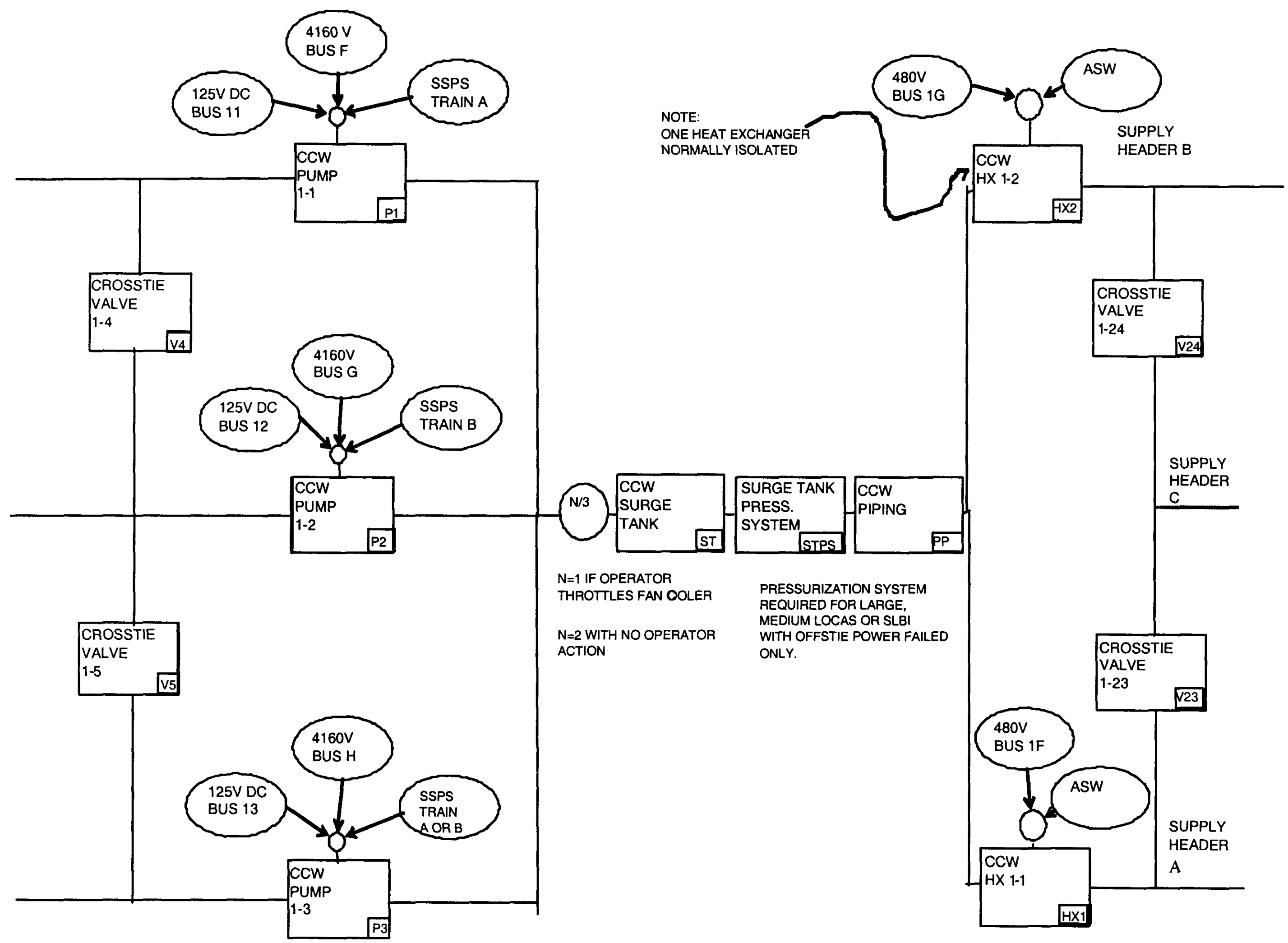

Figure 6-1: Block diagram of the CCW system

which we have developed in Chapter 3 will be computed for each of the basic events in the CCW system's initiating event fault tree. Next, a current case scenario is defined, and the adequacy of the results of the current case PRA analysis is examined using the framework which we have developed in Chapter 5. In the end, the current case will also be used to illustrate how to select an appropriate truncation limit for the system.

6.2 Definition of a Base Case and Computation of RS and RCS of the Events in the System

The aim of this section is to define a base case for our analysis of the CCW system which can be used as the reference model for computing RS and RCS for the events in the system fault tree, and for assessing the adequacy of the current baseline PRA as defined in the next section. We begin by assuming that all basic events of the CCW system have been identified and are addressed in the base case.

We then assume that the CCW system is in a normal operating mode at the time of failure. Normal operation for the CCW system is two of three pumps running with the third in standby and one of two heat exchangers is in service while the other is in standby. Failure of any two pumps results in less flow to the system but does not result in system failure. The system fails only when all three pumps fail. In the maintenance period, both pumps that are not in maintenance are assumed to be in operation. There is no preferred alignment of CCW pumps. Pumps are operated so as to equalize the run time of each pump. For the purpose of this study, it is assumed that pumps 1-1 and 1-2 are the running pumps, pump 1-3 is in standby, and pumps are switched over once each week.

Next, we assume that the proposed change under consideration is to extend the CCW pump's allowed outage time (AOT) from 25 hours to 100 hours. The risk insights derived from the PRA results will be used as one input to decide whether the proposed change is acceptable with respect to plant CDF and change in CDF.

With the above assumptions in mind, the fault tree for the loss of the CCW system initiating event for the base case scenario is developed and presented in Figure 6-8.

Embedded within the CCW system fault tree are independent failures and common cause failures of the CCW pumps and and their associated inlet and discharge valves.

Table 6.1 presents the description and expected probabilities of the basic events in the system. In this example, the probabilities of all basic events are estimated from more fundamental parameters which are shown in Table 6.2. The simplified PRA model for plant core damage is then developed and presented in Figure 6-3 by treating the CCW system initiating event as a basic event. The basic events in this simplified plant CDF fault tree are described in Table 6.3.

Referring to the basic events in Figure 6-2 by number, the minimal cut sets of the CCW system are (1, 13), (2, 3, 8), (3, 8, 9), (3, 8, 12), (3, 19), (5, 7, 11), (11, 18), (2, 4, 6), (2, 14), (4, 6, 9), (9, 14), (4, 6, 10), (17), (4, 17), (6, 15), (10, 14), (14, 15), (14, 16), (15, 16).

Now we would like to compute the measures of RS and RCS of each basic event in the initiating event fault tree for the CCW system using both the point estimate approach and Monte Carlo simulation. For comparison purposes, the FV and RAW importance of each basic event are also calculated.

Table 6.4 and Table 6.5 presents point estimated results for the five importance measures for the base case defined in the previous section. The expectation of each input parameter is used to obtained the point values shown in these two tables. Probabilities of some basic events may be correlated if the same input parameter is used to calculate probabilities of several different basic events.

From these numerical values we observe that RS rankings and RCS rankings do not agree with FV rankings in most cases. To see this, let us consider basic event 17. The FV ranking of this basic events is 2, while it RS ranking is 7 and its RCS ranking is 16. The order rankings of basic events 5 and 7 indicate that the opposite may also be true.

The numerical values presented in Table 6.4 and Table 6.5 indicate that RS rank-

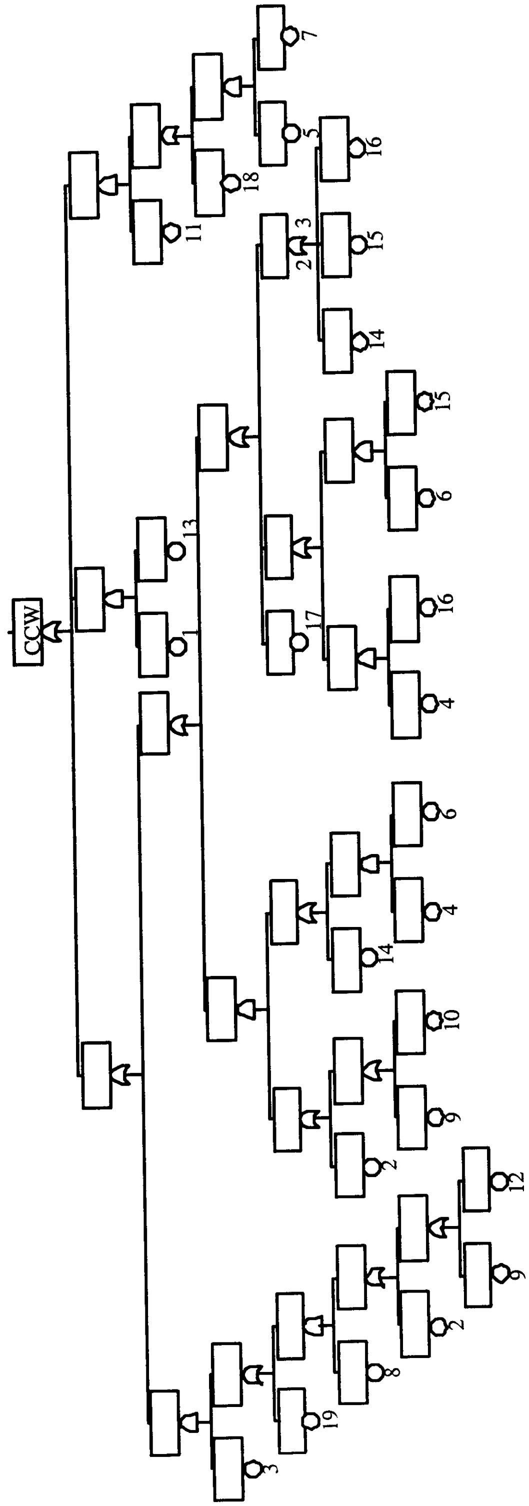

Figure 6-2: Fault tree for the CCW system for the base case

Table 6.1: Basic events data

B.E.	Description	Probability
1	Either of two discharge check valves fails to reseat	3.26E-04
2	CCW pumps unavailability due to maintenance	1.46E-02
3	CCW failure during 1-year period exclusive of maintenance	1.03E-01
4	Failure of pump 1-1	1.72E-04
5	Pump 1-1 fails to run during switch over	1.72E-04
6	Failure of pump 1-2	1.77E-04
7	Pump 1-2 fails to run during switch over	1.77E-04
8	Failure of pump 1-2 during pump 1-1 maintenance period	1.77E-04
9	Failure ofpump to start	1.27E-03
10	Failure of pump 1-3	1.72E-04
11	Pump 1-3 fails to run during switch over	4.95E-02
12	Failure of pump 1-3 during pump 1-1 maintenance period	1.72E-04
13	Failure of Pump 1-1 (or 1-2) over a Period of 1 Year	1.04E-01
14	CCF of pumps 1-1 and 1-2 during normal operation	2.43E-05
15	CCF of pumps 1-1 and 1-3 during normal operation	2.43E-05
16	CCF of pumps 1-2 and 1-3 during normal operation	2.43E-05
17	CCF of pumps 1-1, 1-2, and 1-3 during normal operation	3.22E-06
18	CCF of pumps 1-1 and 1-2 to run during switch over	8.16E-08
19	CCF of pumps 1-2 and 1-3 to run during maintenance	8.16E-08

Table 6.2: Model input parameter data

Parameter	Description	Mean value	St.D.
x1	1 of 3 CCW pumps fails to run	6.83E-06	5.00E-6
x2	2 of 3 CCW pumps fail to run	3.26E-09	1.00E-8
x3	3 of 3 CCW pumps fail to run	4.33E-10	2.50E-9
x4	CCW pumps fail to run, hours	6.91E-06	5.00E-6
x5	1 of 3 CCW pumps fail to start	1.12E-03	7.00E-4
x6	1 of 6 check valves fails on demand	1.47E-04	5.50E-5
x7	Average availability of the plant	8.50E-01	0.00E+00
x8	CCW pump maintenance duration, hours	2.50E+01	0.00E+00
x9	CCW pump maintenance frequency, hours	1.94E-04	2.50E-5
x10	Check valve fail on demand	1.63E-04	5.00E-5
x11	Check valve transfer closed or plug, hours	1.02E-08	7.50E-9
x12	Manual valve transfer open or closed, hours	1.67E-08	2.00E-8

Table 6.3: Basic events in the simplified plant core damage fault tree

Basic Event	Description	Mean	St.D.
CD-CCW-IE	Conditional probability of core damage given the CCW system initiating event has occurred	1.70E-02	5.40E-03
CD-O-IE	core damage due to all other initiating events	5.43E-05	5.00E-05

Table 6.4: Point estimated FV and RAW for the basic events in the base case PRA

Basic event	FV	FV Ranking	RAW	RAW Ranking
1	6.16E-01	1	1.89E+03	2
2	1.11E-02	3	1.75E+00	10
3	5.29E-03	5	1.05E+00	15
4	8.47E-05	11	1.49E+00	11
5	2.67E-05	15	1.16E+00	14
6	8.47E-05	11	1.49E+00	11
7	2.67E-05	15	1.16E+00	14
8	5.09E-03	6	3.05E+01	6
9	9.68E-04	7	1.76E+00	9
10	7.62E-05	12	1.44E+00	12
11	1.00E-04	9	1.00E+00	16
12	5.54E-05	14	1.32E+00	13
13	6.16E-01	1	6.31E+00	7
14	7.09E-03	4	2.93E+02	5
15	9.76E-05	10	5.02E+00	8
16	9.76E-05	10	5.02E+00	8
17	5.87E-02	2	1.82E+04	1
18	7.35E-05	13	9.02E+02	4
19	1.52E-04	8	1.87E+03	3

Table 6.5: Point estimated RS and RCS for the basic events in the base case PRA

Basic event	RS	RS Ranking	RCS	RCS Ranking
1	1.89E+03	1	3.88E-13	14
2	-1.11E-02	9	-9.00E-02	6
3	4.63E-02	8	6.36E-01	4
4	4.92E-01	5	7.03E-01	3
5	1.55E-01	6	4.65E-01	5
6	4.92E-01	5	7.03E-01	3
7	1.55E-01	6	4.65E-01	5
8	2.95E+01	2	8.14E+01	1
9	-9.68E-04	12	-1.23E-03	9
10	-7.62E-05	14	-2.34E-04	12
11	1.92E-03	11	1.19E-02	8
12	-5.54E-05	16	-8.31E-04	10
13	5.31E+00	3	1.60E-15	15
14	-7.09E-03	10	-1.95E-02	7
15	4.02E+00	4	9.40E+00	2
16	4.02E+00	4	9.40E+00	2
17	-5.87E-02	7	1.23E-16	16
18	-7.35E-05	15	-2.20E-04	13
19	-1.52E-04	13	-4.57E-04	11

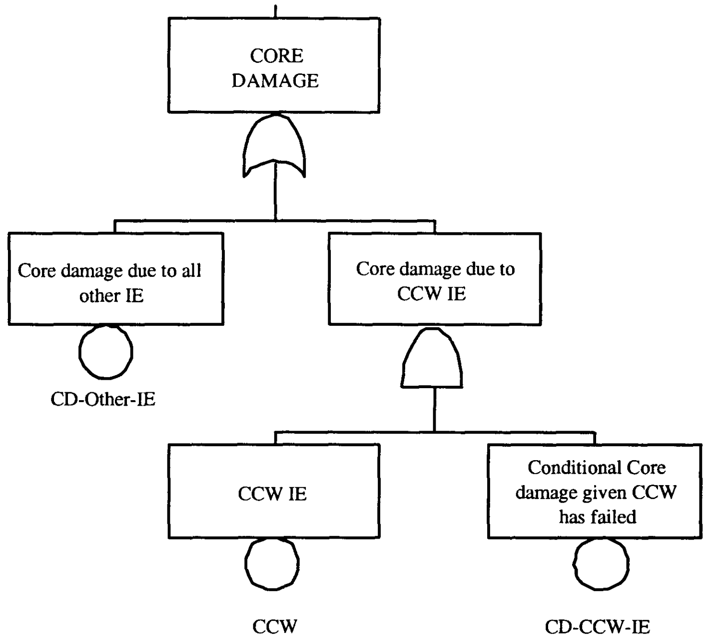

Figure 6-3: The simplified fault tree for plant core damage

ings and RCS rankings often do not agree with RAW rankings either. For example, basic events 18, and 19 are ranked among the top four risk significant events according to RAW importance, but they are ranked 15 and 13 using the RS measure, and 13 and 11 using the RCS measure.

In general, FV measures the fractional overall risk that is related to an event i. RAW estimates the potential increase in risk given that the event has occurred. RS and RCS evaluates the prediction error in the overall risk and risk change given that that the event is not considered explicitly in the analysis. The definitions of FV and RAW involve the assumption that event i has been modelled correctly in the analysis, and they measure the sensitivity of risk to the probability of any event in the model. RS and RCS, on the other hand, are concerned with the sensitivity of the accuracy of risk and risk change to the omission of any event in the model. These observations indicate that FV, RAW, RS, and RCS measure different attributes of an event, and they can not be related directly to each other.

In order to account for state-of-knowledge uncertainties associated with the input parameters in computing the measures of importance, we perform uncertainty analysis by use of Monte Carlo simulation. Since this can not be done by the use of existing PRA software, Decisioneering Inc.'s Crystal Ball risk analysis software is used to propagate the epistemic uncertainties through the minimal cut sets. Each uncertainty analysis is run with 10,000 samples. The expected values were presented in Table 6.6 and Table 6.7.

The relative rankings in the point estimate case and the use of mean value case are also compared in Figure 6-4, Figure 6-5, Figure 6-6, Figure 6-7.

As can be seen from Table 6.4 and Table 6.5, the relative FV ranking, RAW ranking, RS ranking, and RCS ranking of basic event 12 by far change the most when epistemic uncertainties are taken into account. Figure 6-4 shows that the FV importance of basic event 12 (failure of pump 1-3 when pump 1-1 is in maintenance) increases roughly by a factor of six. Its RAW rank order increases by two, RS rank order increases by three, while its RCS rank order increases by one.

From the numerical results presented in Table 6.4 and Table 6.5 we can also see that the point estimated and Monte Carlo simulated measures of importance generally agree quite closely with each other. The point estimate approach preserves the relative rankings of most basic events in the system. It therefore provides adequate information on the relative importance of each event in the CCW fault tree model to decision makers in most situations, and requires only a fraction of the computation time involved in computing the expected values of the measures of importance.

Table 6.6: The expectations of FV and RAW for the basic events in the base case PRA

Basic Event	FV	FV Ranking	RAW	RAW Ranking
1	1.08E+00	1	3.32E+03	3
2	2.43E-02	3	2.65E+00	10
3	1.46E-02	4	1.08E+00	15
4	1.61E-04	12	1.89E+00	12
5	7.40E-05	15	1.28E+00	14
6	1.61E-04	12	1.89E+00	12
7	7.40E-05	15	1.28E+00	14
8	1.40E-02	5	5.41E+01	6
9	2.13E-03	7	2.68E+00	9
10	1.36E-04	13	1.79E+00	13
11	2.04E-04	10	1.00E+00	16
12	3.49E-04	8	1.89E+00	11
13	1.08E+00	1	1.06E+01	7
14	1.26E-02	6	5.25E+02	5
15	1.76E-04	11	8.23E+00	8
16	1.76E-04	11	8.23E+00	8
17	1.05E-01	2	3.27E+04	1
18	1.30E-04	14	1.64E+03	4
19	2.71E-04	9	3.36E+03	2

Table 6.7: The expectations of RS and RCS for the basic events in the base case PRA

Basic Event	RS	RS Ranking	RCS	RCS Ranking
1	3.32E+03	1	1.02E-15	14
2	-2.43E-02	9	-2.32E-01	6
3	7.87E-02	8	1.10E+00	4
4	8.85E-01	5	1.29E+00	3
5	2.82E-01	6	8.50E-01	5
6	8.85E-01	5	1.29E+00	3
7	2.82E-01	6	8.50E-01	5
8	5.31E+01	2	1.49E+02	1
9	-2.13E-03	12	-3.41E-03	10
10	-1.36E-04	15	-4.65E-04	12
11	3.94E-03	11	2.93E-02	8
12	-3.49E-04	13	-5.12E-03	9
13	9.59E+00	3	-1.98E-17	15
14	-1.26E-02	10	-3.74E-02	7
15	7.23E+00	4	1.71E+01	2
16	7.23E+00	4	1.71E+01	2
17	-1.05E-01	7	4.77E-19	16
18	-1.30E-04	16	-4.10E-04	13
19	-2.71E-04	14	-8.59E-04	11

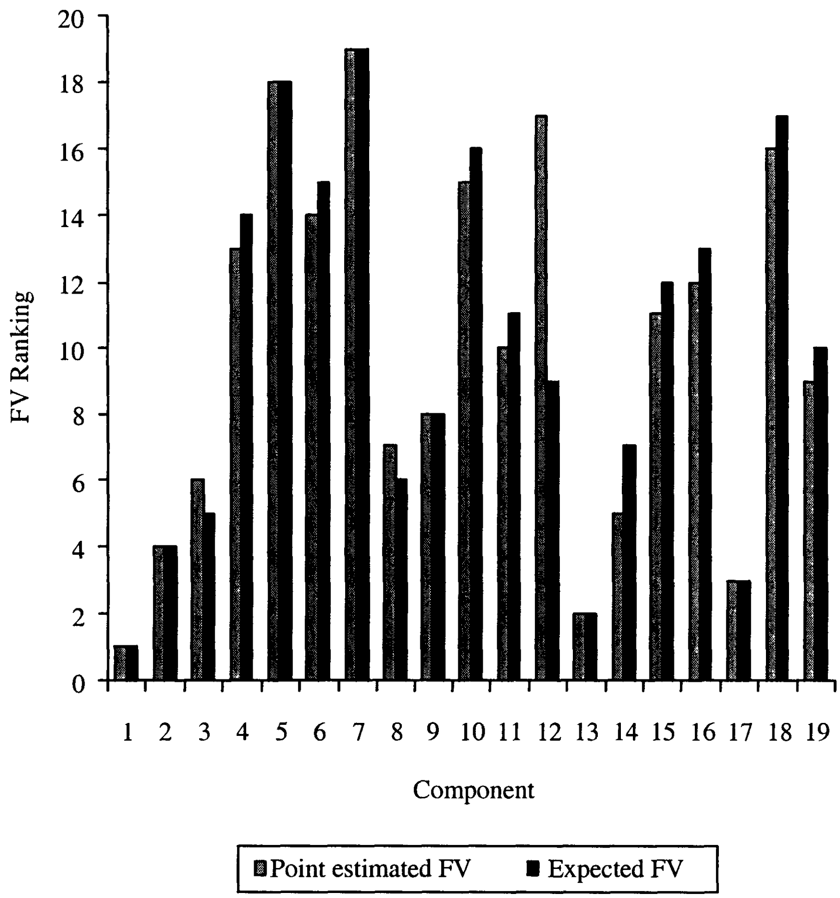

Figure 6-4: FV rankings of the basic events in the CCW System

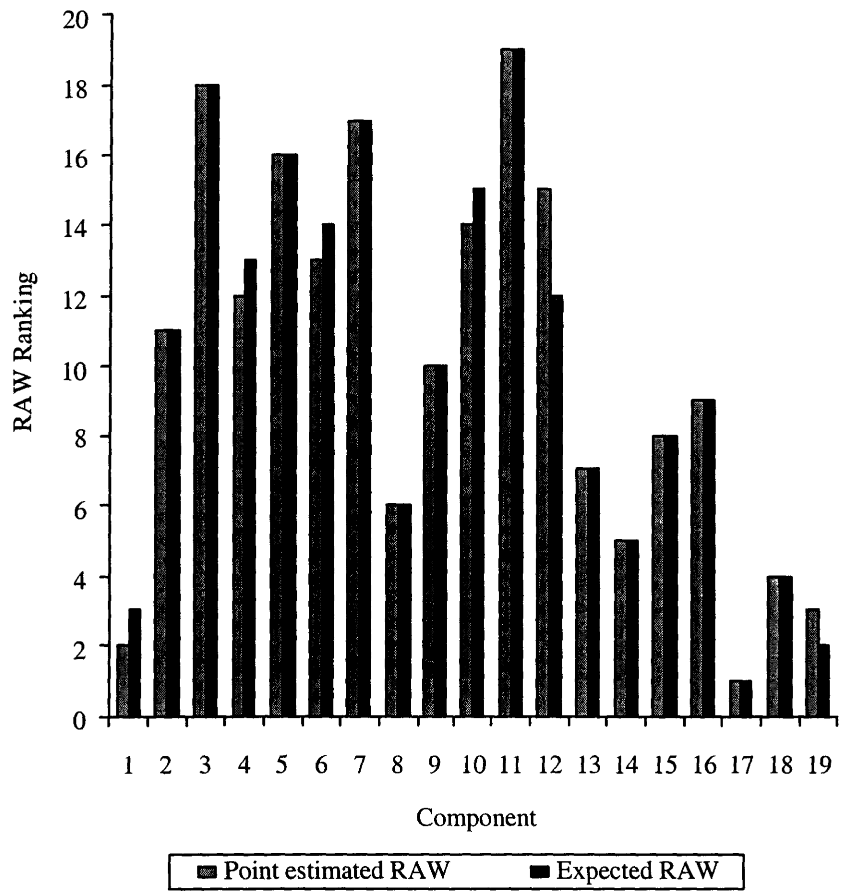

Figure 6-5: RAW rankings of the basic events in the CCW System

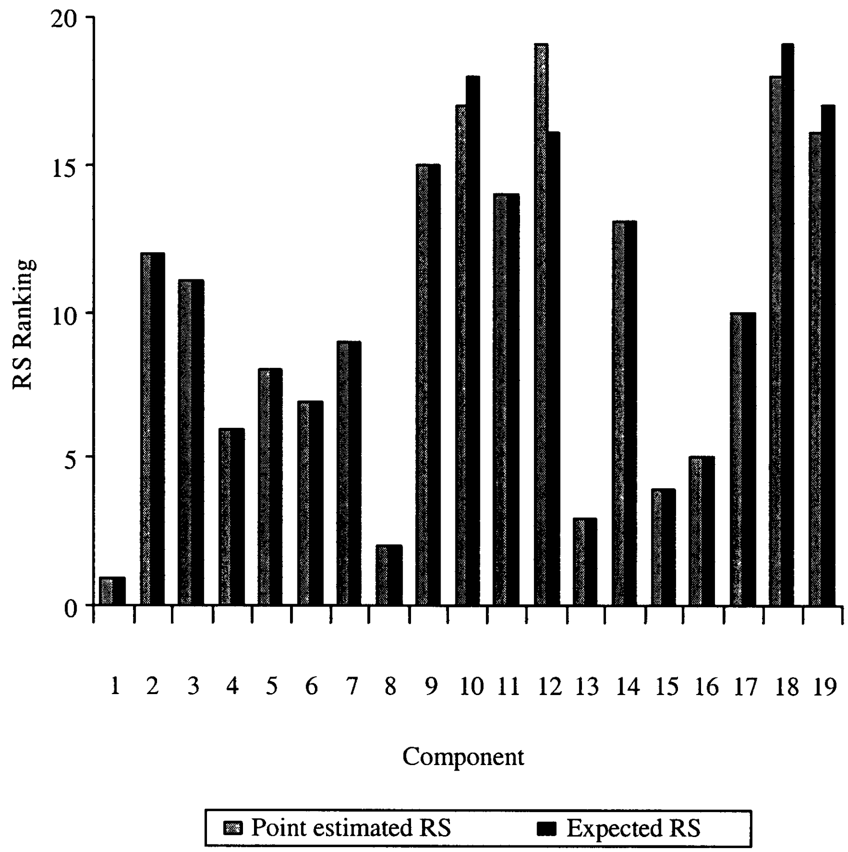

Figure 6-6: RS rankings of the basic events in the CCW System

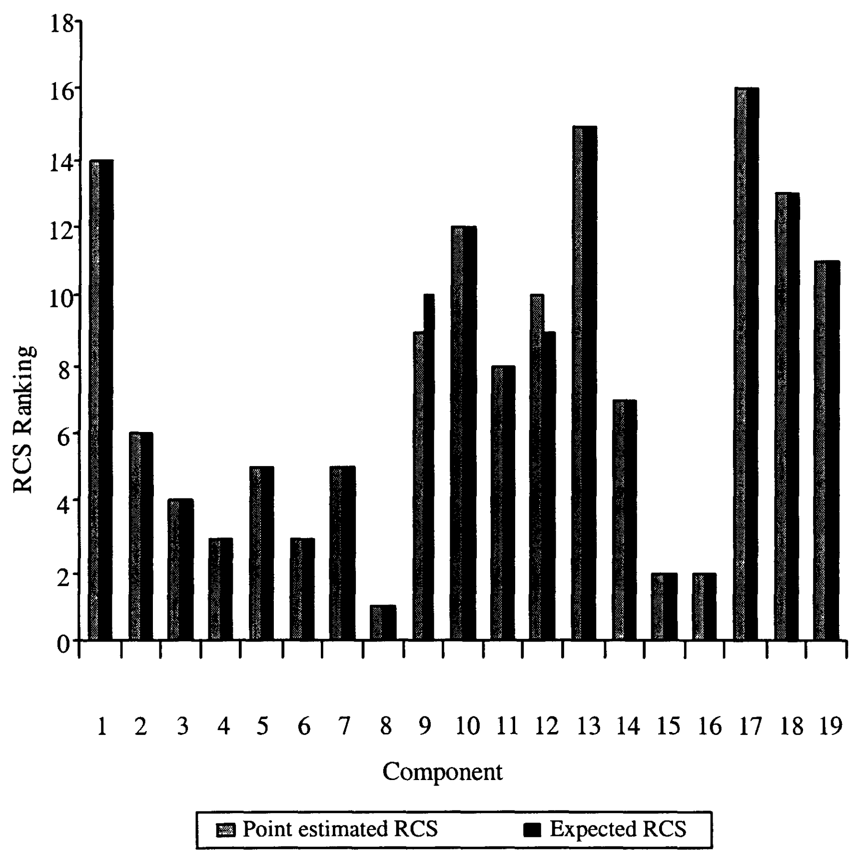

Figure 6-7: RCS rankings of the basic events in the CCW System

6.3 Definition of a Current Case

Until now, we have assumed that all possible causes of the failure of the CCW have been identified and addressed in the base case, including common cause failures of the CCW pumps. As can be seen from Table 6.1, the common cause failures of the CCW pumps can occur during either normal operation or the weekly switch over. During normal system operation, dependent failure or common cause failure can occur in three ways. First, pump 1-1 (or pump 1-2) fails independently, then pumps 1-2 (or pump 1-1) and 1-3 fail to run due to common cause failure events during the period when pump 1-1 is in maintenance. Second, any two pumps may fail due to common cause events during normal system operation, then the third pump fails independently during the maintenance period of the previously failed two pumps. Third, common cause events may fail all three pumps together when pumps 1-1 and 1-2 are running normally. During weekly switch over, the two running pumps may fail to run due to common cause events following the failure of the standby pump to start.

However, from numerical values presented in Table 6.1, we note that the probabilities of common cause failures among CCW pumps are at least two orders of magnitude lower than the corresponding independent failure probabilities. In other words, although the occurrence of common cause events can fail two or all three pumps simultaneously, contributions to risk from these common cause failures may be negligible.

Now we would like to define a current case which can be used to illustrate the framework we develop in Chapter 5. We begin by assuming that all common cause events, basic events numbered 14 to 19 in Table 6.1, are left out the logic model because of their low frequency of occurrence. The fault tree of the current case is shown in Figure 6-8.

Next, we assume that, in order to make well informed decisions on the CCW pump AOT extension by use of information derived from the fault trees presented in Figure 6-8 the decision makers chose 10% as the desired degree of accuracy of plant CDF, and 0.15% as the desired accuracy level of the change in plant CDF. This

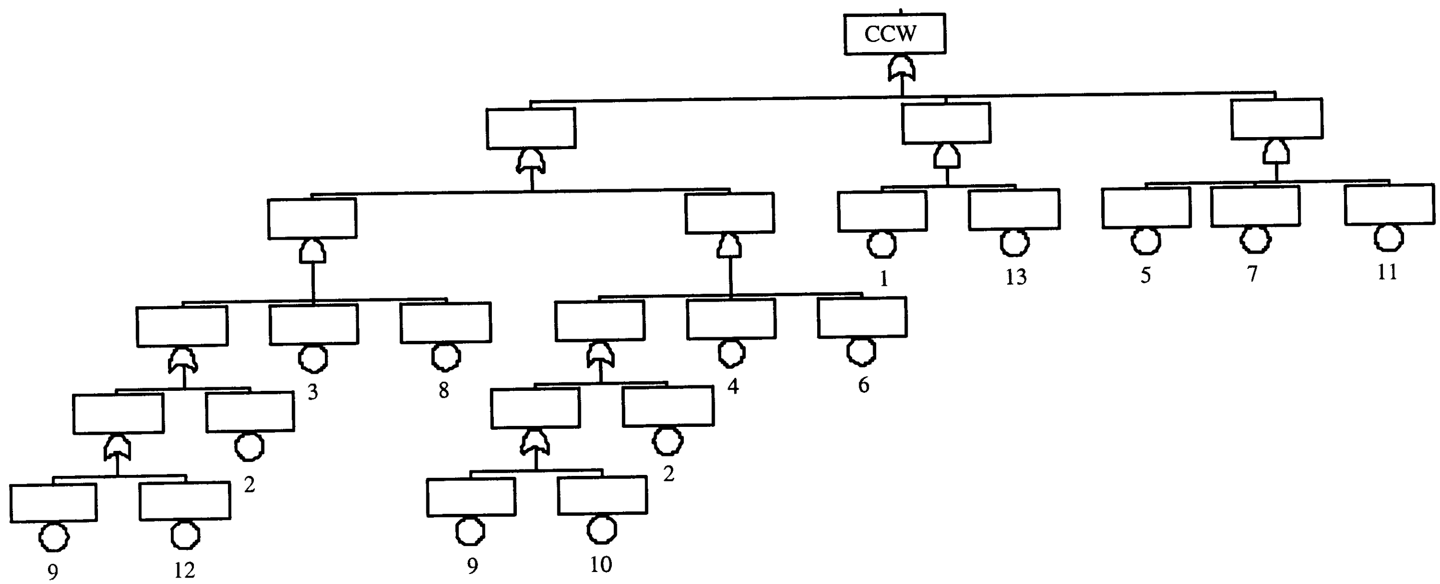

Figure 6-8: The fault tree for the CCW System without common cause events

indicates that the value of ε_s is set to 10%, and ε_l is set to 0.15%.

6.3.1 Adequacy of the Accuracy of Plant CDF and Change in CDF

Now we would like to examine whether the plant CDF and change in CDF of the current base PRA has met the desired accuracy levels. The probability distributions of the resulting changes in plant CDF and change in CDF due to the omission of common cause failure events are presented in Figure 6-9 and Figure 6-10. The point estimate values, expectations, and degree of confidence that the desired degree of accuracy of plant CDF and change in CDF have been met are presented in Table 6.8.

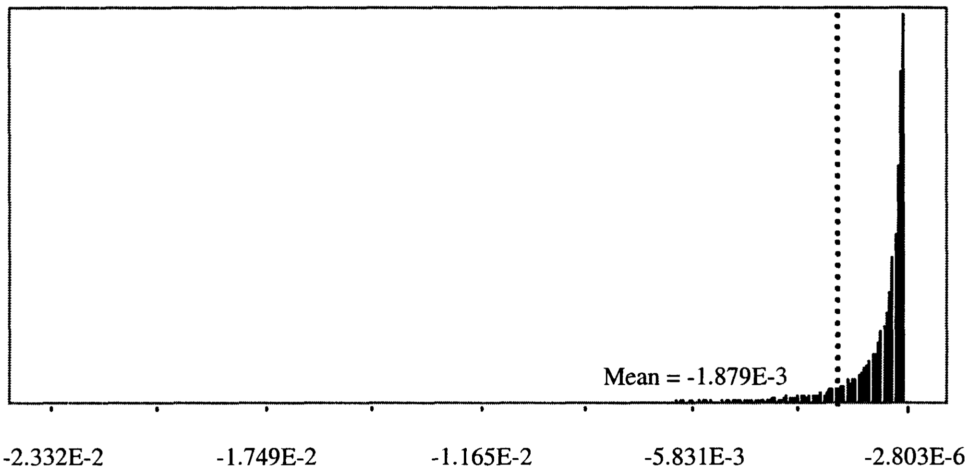

Figure 6-9: Plant CDF unaccounted for due to the omission of common cause events

Table 6.8: Plant CDF and change in plant CDF unaccounted for due to the omission of common cause events

Accuracy level	Point estimate	Expectation	Confidence level	Adequacy guideline
Plant CDF	-0.11%	-0.19%	100.00%	10%
Change in plant CDF	-0.15%	-0.29%	26.20%	0.15%

The results presented in Table 6.8 indicate that the adequacy of the estimates

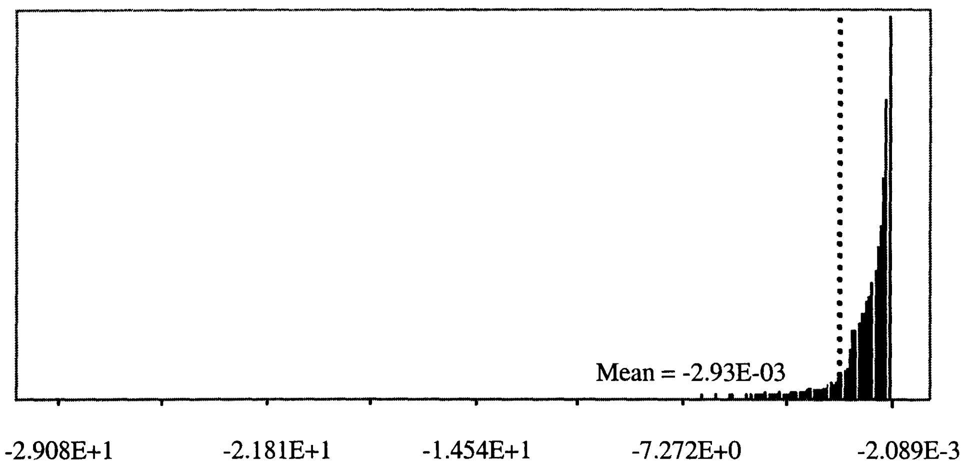

Figure 6-10: Change in plant CDF unaccounted for due to the omission of common cause events

of plant CDF, change in plant CDF obtained from the point estimate approach, the mean value approach, and the confidence level approach generally agree closely with each other. For plant CDF, the comparison of all three approaches indicates that the accuracy level of plant CDF meets the decision maker's expectation with a great confidence. For the case of change in plant CDF that could result from the proposed CCW pump AOT extension, the point estimate value just meets the adequacy guideline. The expected change in plant CDF unaccounted for from uncertainty analysis, however, has exceeded the adequacy guideline by a factor of nearly two. The degree of confidence that the change in CDF has met the adequacy guideline is also extremely low.

To summarize, the plant CDF of the current base PRA is a fairly accurate estimate of the nominal plant CDF. The change in plant CDF of the current base PRA, however, does not meet the desired accuracy level. In order to support the decision on the acceptability of the proposed CCW pump AOT extension by use of information derived from the current PRA results, modifications need to made to the current base PRA.

6.3.2 Improvement of the Current Base PRA

Now we would like to identify events that are important to achieving accurate estimates of risk and risk change. From the results presented in Table 6.5 and Table 6.7, we note that, among all the common cause failure events omitted, the omission of either basic event 15 or basic event 16 alone results in an overestimate of percentage change in the CDF by roughly a factor of 17. This amount of prediction error has far exceeded the adequacy guideline for change in plant CDF which is 0.15%. Given the threshold values for RS and RCS, the degrees of confidence that the threshold values for RS and RCS have been met were also computed for each basic event in the system. These confidence levels are presented in Table 6.9. If a confidence level of 95% is used for acceptability, basic events 15 and 16 are found important to achieving the desired degree of accuracy of change in CDF.

In order to improve the accuracy level of change in CDF, we now add events 15 and 16 back to the current base CCW system fault tree. The accuracy level of plant CDF and change in CDF was recalculated and is presented in Table 6.10. As can be seen from this table, the degree of accuracy of both plant CDF and change in CDF has increased after taking basic events 15 and 16 into consideration. In particular, both the point estimated value and the mean value of change in CDF have met the adequacy guideline. The level of confidence that the adequacy guideline for change in the CDF has been met also increases by 67%.

These results indicate that by addressing events that are important to achieving the desired accuracy of plant CDF and change in CDF in the PRA model, the overall accuracy of plant CDF and change in CDF increases significantly. The information derived from the modified model can therefore be directly used by the decision makers who are concerned with making decision on the acceptability of the proposed relaxation of the CCW pump AOT extension with a greater confidence.

Table 6.9: The degree of confidence that RS and RCS of each basic event has met the threshold values

Basic event	$p(\|RS\| > 10\%)$	$p(\|RCS\| > 0.15\%)$
1	100.00%	100.00%
2	4.42%	5.83%
3	24.14%	100.00%
4	99.14%	100.00%
5	62.55%	100.00%
6	99.14%	100.00%
7	62.55%	100.00%
8	100.00%	100.00%
9	0.00%	0.24%
10	0.00%	0.00%
11	0.00%	1.96%
12	0.00%	0.27%
13	100.00%	100.00%
14	2.06%	2.81%
15	100.00%	100.00%
16	100.00%	100.00%
17	16.05%	4.71%
18	0.00%	0.00%
19	0.00%	0.00%

Table 6.10: Plant CDF and change in plant CDF unaccounted for due to the omission of common cause events 14, 17, 18, 19

Accuracy level	Point estimate	Expectation	Confidence level	Adequacy guideline
Plant CDF	-0.10%	-0.16%	100.00%	10%
Change in plant CDF	-0.11%	-0.14%	93.40%	0.15%

6.3.3 Adequacy of the Uncertainty Treatment

Until now, only the degree of accuracy of the results obtained from current PRA models were examined. Now we would like to examine the adequacy of the uncertainty treatment of the current base PRA used to support risk-informed decisions. We begin by assuming that the 95^{th} confidence level safety goal is set to 2×10^{-4}.

The probability distribution of plant CDF without considering the common cause events is presented in Figure 6-11. The expected CDF, standard deviation, and the 95^{th} confidence level CDF are also presented in Table 6.11. As can be seen from this table, the 95^{th} confidence level CDF is much lower than the 95^{th} confidence level safety goal. This indicates that, given the mean plant CDF has met the current mean safety goal, the uncertainty treatment of current base PRA model is adequate such that risk insights derived from this analysis can be directly used for risk-informed decisions on acceptability of the proposed AOT extension without gathering additional information.

Another approach for examining the adequacy of the degree of precision of PRA results for supporting risk-informed decisions is to compare the current uncertainty level about the expected risk with the acceptable uncertainty level. As shown in Figure 6-11, the plant CDF approximates a lognormal distribution with mean equal to 5.47E-05 and standard deviation equal to 5.08E-05. By setting the 95^{th} confidence level safety goal as the 95^{th} confidence level CDF and keeping the mean CDF unchanged, we obtain a new lognormal distribution. The standard deviation of this distribution is found to be 1.12E-4. This indicates that the current degree of uncertainty, in terms of standard deviation, about the expected plant CDF has met the acceptable uncertainty level by a factor of two. Thus, the current PRA model produces an adequately precise estimate of the plant risk for supporting risk-informed decisions. Thus no more information needs to be gathered for decision makers to decide on the proposed CCW pump AOT extension.

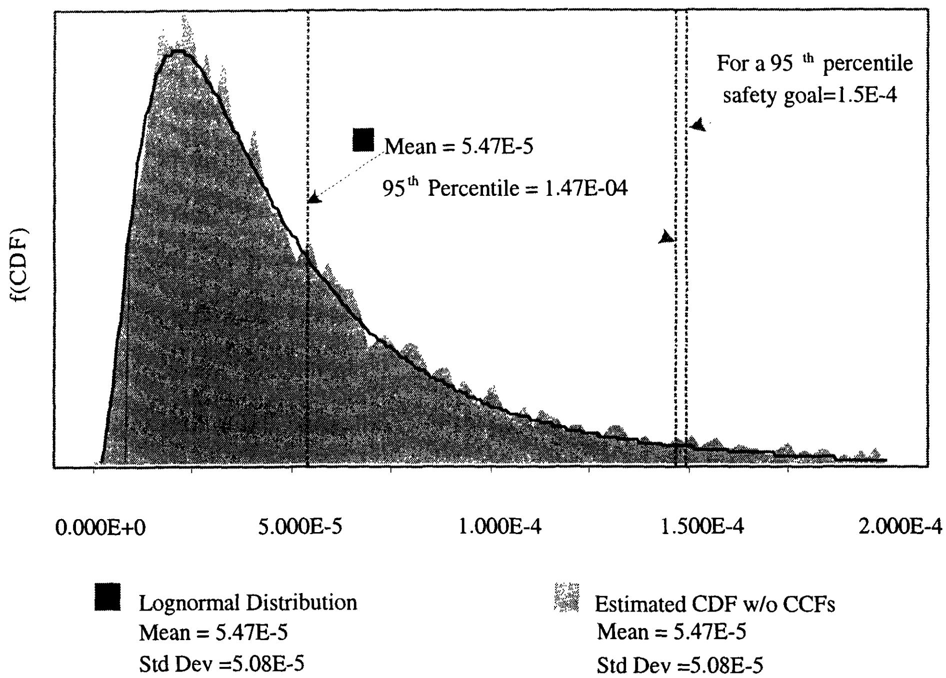

Figure 6-11: Plant CDF without considering common cause events

Table 6.11: Uncertainty analysis results for plant CDF without considering common cause events

Distribution parameter	Mean	95th	St.D.	Distribution model
Current uncertainty level	5.47E-05	1.48E-04	5.08E-05	Lognormal
Acceptable uncertainty level	5.47E-05	2.00E-04	1.12E-04	Lognormal

6.4 Selection of Truncation limit for the Base Case

So far, all results were obtained without using a truncation limit. Since the size of the simplified loss of CCW system initiating event fault tree is small, the quantification of the fault tree is fairly easy even without using a truncation limit. However, when a PRA model consists of a fairly large number of basic events, the computation time involved in quantifying the analysis is unmanageable. A truncation limit is therefore required in most situations in order to reduce the amount of time needed to compute the CDF and importance measures.

A truncation limit should be chosen such that it simplifies the quantification process without sacrificing the quality of PRA results, in terms of both accuracy and precision. The objective of this section is therefore to choose an appropriate truncation limit for the current case plant core damage PRA model according to the acceptance guideline provided in RG 1.174.

All input parameters are assumed to be lognormally distributed with distribution parameters as summarized in Table 6.2. For comparison purposes, both point estimate approach and Monte Carlo simulation are used to estimate the percentage CDF being truncated for each candidate truncation level. The results obtained in both the Monte Carlo simulation with $5,000$ trials and the point estimate approach cases are presented in Figure 6-12. As can be seen from this figure, there is no general trend in the relationship between the percentage CDF truncated using the point estimate approach and that using Monte Carlo simulation. For some truncation limits, the point estimated percentage CDF being truncated is higher than the Monte Carlo simulated results, while for other truncation limits, the Monte Carlo simulated percentage CDF unaccounted for is higher than point estimated results.

The point estimate approach and Monte Carlo simulation generally agree quite well with each other for a truncation limit lower than 1.00E-8. However, for a truncation limit between 1.00E-8 and 5.00E-7, the point estimated percentage CDF being cutoff is constant at 0.93%. In the case of Monte Carlo simulation, the percentage CDF being cutoff, however, varies by a significant amount, from 0.97% to 59.00% in the same range.

Figure 6-13 presents the degree of confidence that the percentage CDF truncated is less than 5%(the acceptance criterion for truncation limit suggested by the RG 1.174) as a function of the truncation limit for the Monte Carlo simulation case. We note that the confidence level is constant at 100% for all truncation limits that are lower than 6.00E-10. The degree of confidence falls slowly as truncation level increases in the range of 5.00E-10 to 5.00E-8. As the truncation limit decreases further, the confidence level drops quickly.

The most appropriate truncation limit for the current case was found to be 2.00E-8. At this truncation level, the Monte Carlo estimated CDF being cutoff is 1.32%, 0.4% larger than in the case of the point estimate. The degree of confidence that the percentage CDF truncated has met the acceptance criterion was found to be 95.35%.

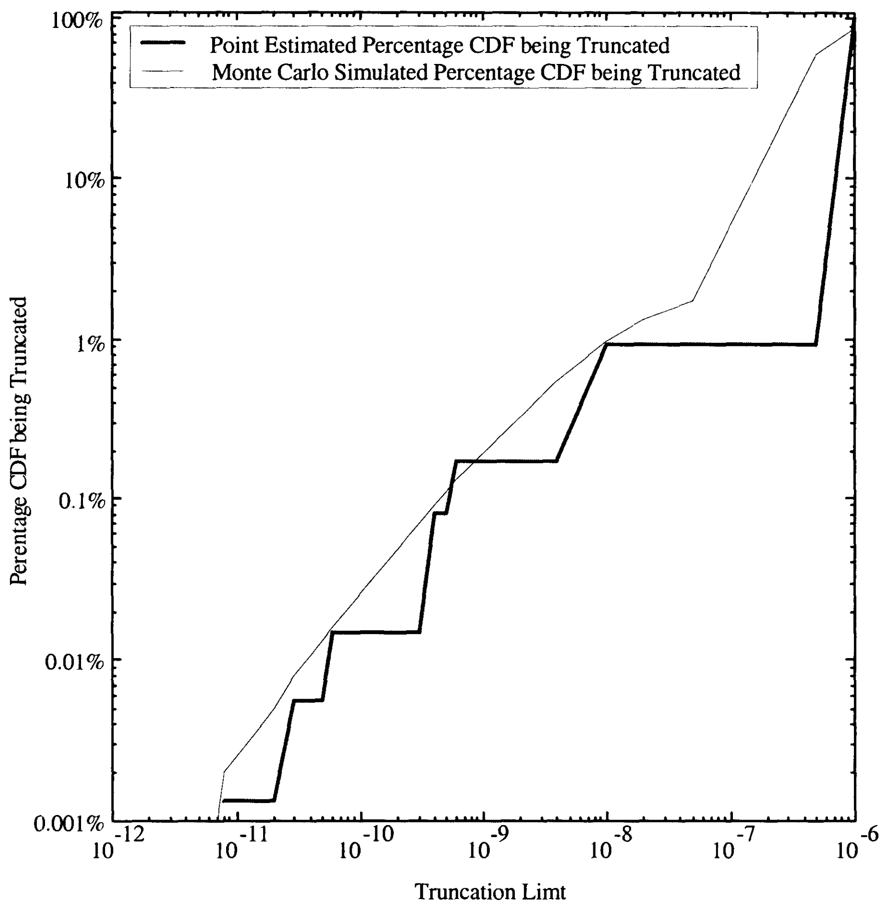

Figure 6-12: Percentage CDF truncated as a function of truncation limit for the base case

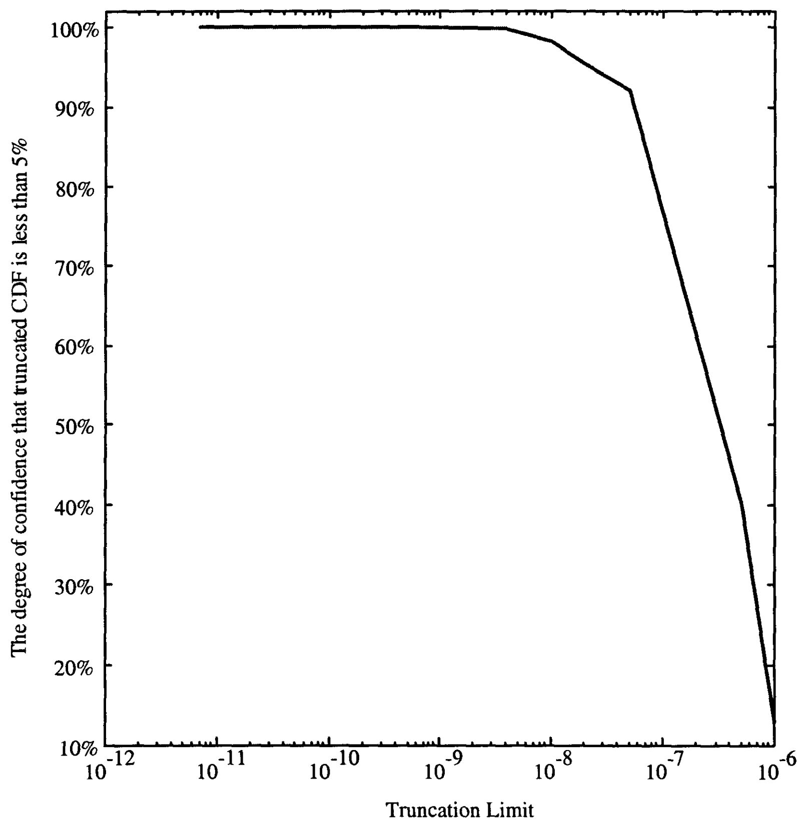

Figure 6-13: The degree of confidence that the truncated CDF has met the acceptance criterion

6.5 Conclusion of the Case Study

Several conclusions can be drawn from this case study. First, the common cause failures of pumps 1-1 and 1-3, and the common cause failure of pumps 1-2 and 1-3 during normal operation are found to be important to achieving the desired degree of accuracy of change in CDF. The exclusion of these two common cause failures from the analysis can significantly impact the accuracy of change in CDF. The current base PRA model which did not take these two common cause events into consideration results in an underestimate of change in CDF by nearly 0.30%. This level of accuracy of change in CDF is far below the 0.15% adequacy guideline. After adding these two events to the analysis, the expectation of the amount of change in CDF underestimated decreases to 0.14%.

From the numerical values presented in Table 6.4 and Table 6.6, we note that the RS importance of basic event 1 is at least two orders of magnitude greater than that of all other basic events. Therefore, any model which does not take basic event 1 into account would have a significant impact on the accuracy of plant CDF, and is generally unacceptable.

Epistemic uncertainties associated with input parameters tend to systematically increase the values of various importance measures. However, the relative rank orders of the events in the system obtained from the point estimate approach are generally consistent with those obtained from Monte Carlo simulation.

For parameter distribution models presented in Table 6.2, the most appropriate truncation limit for the current case PRA was found to be 2.00E-8. At this truncation level or below, the Monte Carlo simulated percentage CDF being cutoff is lower than 5%, and the degree of confidence that the percentage CDF being cutoff is lower than 5% is likely to be above 95%.

These results highlight the major contribution of this thesis: the development of the measures of risk significance and risk change significance which systematically rank the events in a PRA in terms of the importance to the accuracy of PRA results; the investigation of the use of RS and RCS for identifying events that are important to achieving the desired degree of accuracy of risk and risk change. Without the use of RS and RCS, many, if not most risk analysts would probably have identified common cause failures of pump 1-1 and 1-3, and common cause failure of pumps 1-2 and 1-3 during normal operation as unimportant for their low frequency of occurrence, low FV and RAW rankings, and would have omitted them from the PRA. The analysis presented in this chapter shows that this may not be true. The use of RS, RCS, and the 95^{th} confidence level acceptance guideline provide a feasible approach for assessing the adequacy of PRA results in support of specific risk-informed decisions.

Chapter 7

Conclusion

7.1 Contributions of This Work

The primary contributions of this work include:

1. The development of the RS and RCS measures which rank events in a PRA in terms of their importance to the accuracy of risk and risk change.

2. The investigation of the use of RS and RCS to identify events that are important to achieving the desired accuracy of risk and risk change for risk-informed activities.

3. The investigation of the use of the 95^{th} confidence level acceptance guideline for examining the adequacy of the uncertainty treatments of a PRA.

When an event is omitted from a PRA, the RS of that event is defined to be the resulting percentage change in the baseline risk. This measure identifies which events are important to achieving an accurate estimate of the baseline risk. By analogy, when risk change is the final outcome of a PRA, we defined RCS of an event to be the resulting percentage change in risk change due to the exclusion of the event from the analysis. This measure tells us which events are important to achieve an accurate estimate of risk change. RS and RCS are therefore useful to decision makers who are concerned with obtaining accurate and meaningful information and insights to assess the acceptability of proposed changes in plant design or activities.

We show that if an event is an initiating event, the impact of its exclusion from the analysis on the minimal cut sets is the same as setting the event frequency to zero. If an event is a basic event whose first operator is AND gate, the effect of the omission of the event from the analysis on the minimal cut sets is the same as setting the event Boolean variable to true, or unity. If an event is a basic event whose first operator is OR gate, the impact of its exclusion from the analysis on the minimal cut sets is the same as setting the event Boolean variable to false, or zero. Based upon these findings, we group events in the PRA into four types: initiating events, basic events whose first operators are AND gates, basic events whose first operators are OR gates, and basic events whose first operators are both AND gates and OR gates. We also found that RS of the second type of event can be related to its RAW importance, while the RS of the first and third types of events can be related to their FV and RRW importances. The computation of RS for the last type of event and the computation of RCS, however, involves a reformulation of the minimal cut sets, which is typically not straightforward.

In addition to the development of the measures of RS and RCS as described above, another contribution of this work involves the investigation of the use of RS and RCS to identify events that are important to achieving the desired degree of accuracy of the baseline risk and risk change assess. We consider three different approaches for categorizing any event in the PRA. These approaches are the point estimate approach, the mean value approach, and the confidence level approach. The results of this investigation show that the degree of accuracy of risk and risk change is very likely to meet the adequacy guidelines by addressing all important events which are identified by use of RS and RCS explicitly in the analysis.

We also examine the use of 95^{th} confidence level acceptance guideline to assess the adequacy of uncertainty treatment of a PRA. Our analysis indicates that this approach agrees closely with practice in that activities that could potentially result in severe consequences need to be well understood to be acceptable, while activities that could result in moderate consequence can be accepted even with a sizable amount of uncertainty in the results. The desired degree of accuracy of risk and risk change and the 95^{th} confidence level acceptance guideline are typically defined by the social or economic consequences of the activity subject to analysis and the role that PRA results play in the decision making process.

The results of our case study of the component cooling water (CCW) system in a pressurized water nuclear reactor show that the rank orders of the events in the PRA obtained using FV, RAW, RS, and RCS generally do not overlap. The omission of an event with low FV and RAW may have extreme large effects (i.e. two orders of magnitude or more) on the expected risk and risk change. In such cases, the PRA which does not take these events into account can seriously underestimate or overestimate the expected plant risk level. The results also show the values of RS and RCS change significantly after epistemic uncertainty on input parameters were taken into consideration.

7.2 Suggestions for Future Work

One area in which additional work might be desirable is the consideration of dependencies among event probabilities in the computation of several importance measures, including RRW, RAW, RS and RCS. In particular, it might be desirable to develop an algorithm which explicitly accounts for the dependencies among the probabilities of related events in the logic model. When an event is omitted from the analysis, or the event status is set to guaranteed occurrence or guaranteed non-occurrence, the probabilities of related events can then be adjusted automatically.

Another area in which more work remains to be done is the impact of unrecognized events on PRA results, including both the accuracy and precision of the results. Specific topics might include: estimating the amount of risk and risk change unaccounted for due to potentially unrecognized events, evaluating the change in the uncertainty level of the baseline risk that could result from the omission of an event from the analysis, evaluating the change in the uncertainty level of the risk change that could result from the exclusion of an event from the analysis, and investigating the impact of unrecognized events on the uncertainty level of risk and risk change. The impact of unrecognized events on PRA results are generally difficult to estimate, and any contributions to this area would be helpful.

Both of the topics suggested above are essentially extensions of the work presented in this thesis. While a thorough investigation of these topis may be quite challenging, it could be carried out using many of the same approaches as those used in this thesis.

Finally, it would be highly desirable to develop a framework to numerically rank the quality of a PRA. Currently, the quality or adequacy of PRAs are qualitatively evaluated at a function level. On the other hand, this type of analysis could indicate for what applications does the PRA provide adequate results, and how adequate are these results for the specific applications supported. The rank order of a PRA could also enable the comparison of the quality of multiple different PRAs.

Appendix A

Computation of RS Using the Current Incomplete Model as Reference Model

In chapter 3, we developed a general approach for computing RS and RCS for any event in a PRA in the case where the complete PRA which addresses all identified events is used as the reference model. However, in many cases, a complete PRA is not possible either because the number of events is too large to address in the model, or because the contributions to risk of some events are negligible. In such cases, the current incomplete model should be used as the reference model to compute the RS and RCS.

When the current incomplete mode is used as the reference model for computing RS, the formulation of RS, given in Equation 3.14, is

$$RS_i = \frac{R_c - R_{w,i}}{R_{w,i}}. \tag{A.1}$$

Where, R_c is risk of the current incomplete model which does not consider event i, and $R_{w,i}$ is risk evaluated when event i is added back to in the current model.

Equation 2.24 shows the general formulation of risk, R, in terms of probabilities of any two basic events as:

$$R_{w,i} = a_{ij}q_iq_j + a_iq_i + a_jq_j + b_{ij}. \tag{A.2}$$

This first term in the above expression are the minimal cut sets that contain both event i and event j. The second and third items are minimal cut sets that contain only event i or event j. The last term represents minimal cut sets that do not contain either basic event i or event j. From Equation A.2, we note that if the numerical values of a_{ij}, a_i, a_j, and b_{ij} can be obtained by the use of the information derived from the current incomplete model, RS_i can also be obtained directly by use of Equation A.1.

For basic events at AND gates in the logic model, our analysis presented in Chapter 3 shows that, the risk estimated without considering event i in the analysis, $R_{w/o,i}$ or R_c, can be obtained by setting the Boolean variable of the event to true or unity as follows:

$$R_c = a_{ij}q_j + a_i + a_jq_j + b_{ij}. \tag{A.3}$$

Therefore, we can write the FV, RAW, and RRW importance of event j of the current incomplete model as follows:

$$\begin{aligned} FV_j &= \frac{a_{ij}q_j + a_jq_j}{R_c}, \\ RAW_j &= \frac{a_{ij} + a_i + a_j + b_{ij}}{R_c}, \\ RRW_j &= \frac{R_c}{a_i + b_{ij}}. \end{aligned} \tag{A.4}$$

Because RRW_j and FV_j are related to each other, only two out of the above four equations are independent. However, there are four unknowns in Equation A.2: a_{ij}, a_i, a_j, and b_{ij}, that need to be solved in order to solve for $R_{w,i}$. This indicates that it is generally not possible to compute $R_{w,i}$ and RS_i directly by use of information obtained from current model. However, for special cases, e.g. events i and j are inputs to the same set of AND gates, it is possible to compute $R_{w,i}$ and RS_i by use of the analytical approach.

For basic events at OR gates, our analysis in Chapter 3 showed that the risk of the model without considering the event, $R_{w/o,i}$, or R_c, can be obtained from Equation A.2 by setting the Boolean variable of the event to false as:

$$R_c = a_j q_j + b_{ij}. \tag{A.5}$$

In this case, the FV, RAW, and RRW of event j of the incomplete model equate to

$$\begin{aligned} FV_j &= \frac{a_j q_j}{R_c}, \\ RAW_j &= \frac{a_j + b_{ij}}{R_c}, \\ RRW_j &= \frac{R_c}{b_{ij}}. \end{aligned} \tag{A.6}$$

We note that parameters a_j and b_{ij} in Equation A.2 can be directly solved from the above four equations. Since a_{ij} and a_j remains unknown, it is therefore generally not possible to compute $R_{w,i}$ and RS_i directly by the use of information obtained from the current model for basic events i at OR gates.

In the following two sections, we develop an analytical approach for computing RS for two special cases: events i and j are inputs to the same set of AND gates, and events i and j are inputs to the same set of OR gates.

A.1 Omitted Basic Events at AND Gates

For the case where events i and j appear at the same set of AND gates, Equation A.2 becomes

$$R_{w,i} = a_{ij} q_i q_j + b_{ij}. \tag{A.7}$$

When event i is omitted from the analysis, we obtain the risk of the current incomplete model by setting the Boolean variable of event i to unity as

$$R_c = a_{ij} \cdot x_j + b_{ij}. \tag{A.8}$$

By considering Equation 3.1 and Equation A.8, the FV importance for basic event j can be written as

$$FV_j = \frac{a_{ij} \cdot x_j}{R_c}. \tag{A.9}$$

From Equation A.8 and Equation A.9, the values of a_{ij} and b can be solved as

$$a_{ij} = \frac{R_c \cdot FV_j}{x_j}, \tag{A.10}$$

$$b_{ij} = R_c \cdot (1 - FV_j). \tag{A.11}$$

By substituting Equation A.10 and Equation A.11 into Equation A.10, we thus obtain $R_{w,i}$ as

$$\begin{aligned} R_{w,i} &= a_{ij} \cdot x_i \cdot x_j + b \\ &= R_c \cdot [1 - FV_j \cdot (1 - x_i)]. \end{aligned} \tag{A.12}$$

This expression indicates that $R_{w,i}$ can be expressed as a function of R_c, x_i, and FV_j. Since the values of these three parameters are available from the current model, $R_{w,i}$ can therefore be directly computed by use of the information derived from the current model.

Substituting Equation A.12 into Equation A.1 yields

$$\begin{aligned} RS_i &= \frac{R_c - R_{w,i}}{R_{w,i}} \\ &= \frac{R_c - R_c \cdot [1 - FV_j \cdot (1 - x_i)]}{R_c \cdot [1 - FV_j \cdot (1 - x_i)]} \end{aligned}$$

$$= \frac{1}{1 - FV_j \cdot (1 - x_i)} - 1. \tag{A.13}$$

This expression is the general formulation of RS in terms of R_c, x_i, and FV_j for the special case where basic events i and j appear at the same set of AND gates.

We now present illustrative results for the analytical approaches we developed above. The fault tree model used in this example is shown in Figure A-1. Assuming the current model does not address event 1 in the logic model, the minimal cut sets of the current incomplete model are

$$X_2X_5X_6,\ X_3X_4X_5X_6.$$

We further assume the probabilities of all basic events are independent and log-normally distributed with means is:

$$\begin{aligned} q_1 &= 1.25 \times 10^{-3}, \\ q_2 &= 3.75 \times 10^{-2}, \\ q_3 &= 1.25 \times 10^{-2}, \\ q_4 &= 3.75 \times 10^{-2}, \\ q_5 &= 1.25 \times 10^{-2}, \\ q_6 &= 3.75 \times 10^{-3}. \end{aligned} \tag{A.14}$$

By considering the minimal cut sets of the current model, R_c in Equation A.1 can be obtained as:

$$R_c = q_2q_5q_6 + q_3q_4q_5q_6 - q_2q_3q_4q_5q_6 = 1.77 \times 10^{-6}. \tag{A.15}$$

FV of event 2 is therefore

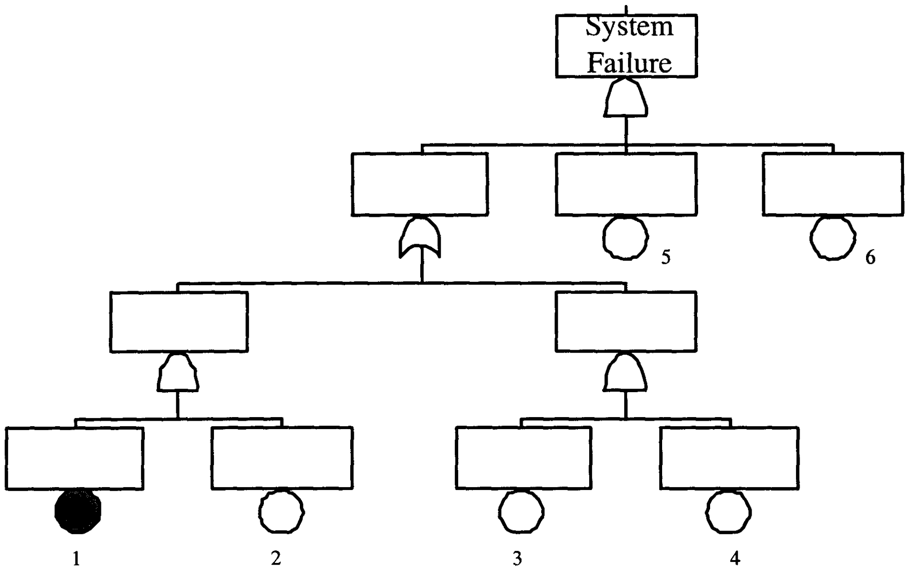

Figure A-1: An example fault tree to illustrate the computation of RS for basic events at AND gates by use of the current incomplete model as reference model

$$FV_2 = \frac{q_2 q_5 q_6}{R_c} = 0.9876. \tag{A.16}$$

We now reconsider basic event 1 in the analysis. By use of Equation A.12, the point estimated RS of event 1 is equal to

$$\begin{aligned} RS_1 &= \frac{1}{1 - FV_j \cdot (1 - q_i)} - 1 \\ &= \frac{1}{1 - 0.9876 \cdot (1 - 3.75 \times 10^{-2})} - 1 \\ &= 7228.40\%. \end{aligned} \tag{A.17}$$

This result indicates that the omission of basic event 1 results in an underestimate of system failure probability by 7455.72%.

For comparison, we now compute RS_1 by use of minimal cut sets. This approach will be referred to as the minimal cut sets approach. After adding event 1 to the current model, the minimal cut sets of system failure becomes

$$X_1X_2X_5X_6, \text{ and } X_3X_4X_5X_6.$$

The corresponding system failure frequency would be given by

$$R_{w,i} = q_1q_2q_5q_6 + q_3q_4q_5q_6 - q_1q_2q_3q_4q_5q_6 = 2.416 \times 10^{-8}. \tag{A.18}$$

By considering Equation A.1, the RS of event 1 would be as follows:

$$RS_i = \frac{R_c - R_{w,i}}{R_{w,i}} = \frac{1.77 \times 10^{-6} - 2.416 \times 10^{-8}}{1.77 \times 10^{-6}} \cong 7226.2\% \tag{A.19}$$

The small discrepancy between the value of RS_1 obtained using the analytical approach as shown in Equation A.13 and that obtained using the minimal cut sets was found to be the rounding error in the minimal cut sets approach.

For all other cases where event j as described above does not exist, it would be impossible to compute RS by the use of the analytical approach we developed. The computation of RS would involve the reformulation of the minimal cut sets after the omitted event is reconsidered in the analysis.

We note that the analytical approach we develop is likely to be simpler and more accurate than the minimal cut sets approach. It will be preferred when event j as described above exists. However, the minimal cut sets approach is more broadly applicable. It can generally be used to compute RS of any basic event in the PRA, in which case no analytical approach exists.

A.2 Omitted Basic Events at OR Gates

Equation 3.33 as given in Chapter 3 provides an analytical approach for computing RS for events at OR gates in the case where the complete model, which addresses all events identified by the analyst, is used as the reference model. We now develop an analytical approach for computing RS for basic events at OR gates in the case where the current incomplete model is used as the reference model.

From our analysis presented at the beginning of this Appendix, we note that it is generally not possible to compute RS_i analytically by use of the current incomplete model as reference model. In this section, we explore the computation of RS_i for basic events at OR gates for the special case where events i and j are inputs to the same set of OR gates. In this case, Equation A.2 can be written as follows:

$$R_{w,i} = 1 - a_{ij} \cdot (1 - ax_i) \cdot (1 - ax_j). \tag{A.20}$$

Where, a_{ij} are the minimal cut sets that do not contain events i or j. a are all other events in the minimal cut sets which contain events i or j.

From our discussion in Chapter 3 we note that the effect of the omission of an event at OR gates on risk and the minimal cut sets is the same as setting the event Boolean variable to zero. The risk of the current incomplete model from which event i is missing can therefore be written as:

$$R_c = 1 - a_{ij} \cdot (1 - ax_j). \tag{A.21}$$

By considering Equation 3.5 and Equation A.21, the RRW value of basic event j, RRW_j, of the current incomplete model is equal to

$$RRW_j = \frac{R_c}{R_c(x_j = 0)} = \frac{R_c}{1 - a_{ij}}. \tag{A.22}$$

Since R_c, RRW_j are available from the current model, a_{ij} and a can be solved by the use of Equation A.12 and Equation A.8 as follows:

$$a_{ij} = 1 - \frac{R_c}{RRW_j}, \tag{A.23}$$

$$a = \frac{RRW_j - 1}{RRW_j - R_c} \cdot \frac{R_c}{x_j}. \tag{A.24}$$

By substituting Equation A.23 and Equation A.24 into Equation A.20, $R_{w,i}$ can be obtained as:

$$
\begin{aligned}
R_{w,i} &= 1 - a_{ij} \cdot (1 - ax_i) \cdot (1 - ax_j) \\
&= R_c \cdot (1 - \frac{(R_c - 1) \cdot (RRW_j - 1)}{RRW_j - R_c} \cdot \frac{x_i}{x_j}).
\end{aligned}
\tag{A.25}
$$

This expression indicates that $R_{w,i}$ is a function of R_c, RRW_j, x_i, and x_j. Since R_c and RRW_j are available from current models, and x_i and x_j are also known, RS of event i can be computed from the information derived from the current model as:

$$
\begin{aligned}
RS_i &= \frac{R_c - R_{w,i}}{R_{w,i}} \\
&= \frac{R_c}{R_c \cdot (1 - \frac{(R_c-1)\cdot(RRW_j-1)}{RRW_j - R_c} \cdot \frac{x_i}{x_j})} - 1 \\
&= \frac{1}{1 - \frac{(R_c-1)\cdot(RRW_j-1)}{RRW_j - R_c} \cdot \frac{x_i}{x_j}} - 1.
\end{aligned}
\tag{A.26}
$$

This expression is the formulation of RS for basic event i in the case where events i and j appear at the same set of OR gates. For all other cases where no such an event j exists, it would not be possible to analytically compute RS of basic event i at OR gates by the use of information derived from the current model. In such cases, the computation of RS would require a reformulation of minimal cut sets after the event is reconsidered in the analysis.

Appendix B

Selection of Truncation Limits

B.1 Point Estimate Approach for Selecting Truncation Limits

In order to compute the point estimated nominal risk, point estimate values of the input parameters must be first determined. Usually these point estimated input parameters are the mean values of their corresponding probability distributions. Once the probability of each minimal cut set is obtained, the value of risk can then be obtained by summing up the probabilities of all minimal cut sets using the rare event approximation.

For example, let us consider a fault tree as presented in Figure B-1.

The minimal cut sets of the fault tree are

$$X_1X_3,\ X_2X_3,\ X_4.$$

By using the rare event approximation, the system failure probability is governed by

$$Q = x_1x_3 + x_2x_3 + x_4. \tag{B.1}$$

Let x_i be the failure probability of component i, and suppose the mean failure probability of each component is given as

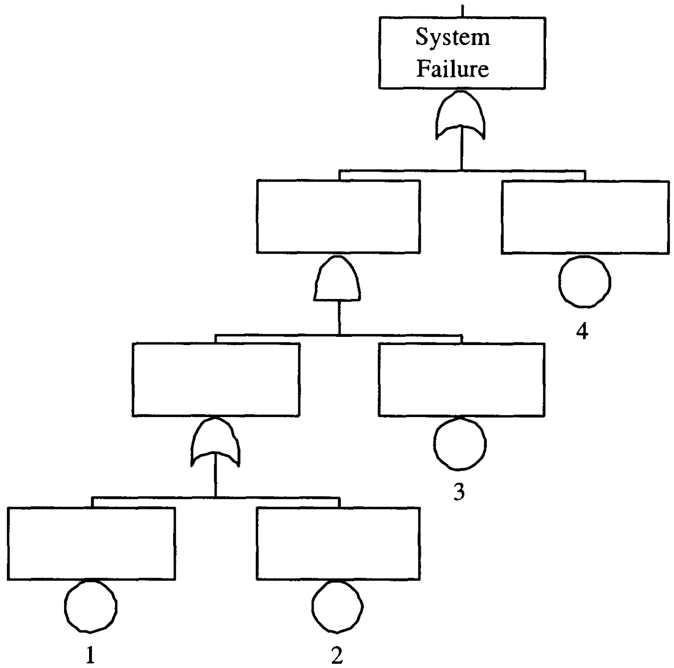

Figure B-1: The fault tree for the example system to illustrate the selection of truncation limit by use of point estimate approach

$$
\begin{aligned}
x_1 &= 5 \times 10^{-3}, \\
x_2 &= 2 \times 10^{-2}, \\
x_3 &= 1 \times 10^{-3}, \\
x_4 &= 1 \times 10^{-3}.
\end{aligned}
\tag{B.2}
$$

The point estimated probability of occurrence of each minimal cut set is thus

$$
\begin{aligned}
p(MCS_1) &= x_1 x_3 = 5 \times 10^{-3} \times 10^{-3} = 5 \times 10^{-6}, \\
p(MCS_2) &= x_2 x_3 = 2 \times 10^{-2} \times 10^{-3} = 2 \times 10^{-5}, \\
p(MCS_3) &= x_4 = 10^{-3}.
\end{aligned}
$$

And the probability of the top event of the fault tree is

$$\begin{aligned} Q &= p(MCS_1) + p(MCS_2) + p(MCS_3) \\ &= 5 \times 10^{-6} + 2 \times 10^{-5} + 10^{-3} \\ &= 1.025 \times 10^{-3}. \end{aligned} \tag{B.3}$$

After a particular truncation limit is introduced at the minimal cut set level into the quantification process, the point estimated probability of occurrence of each minimal cut set is then compared with the truncation limit. If the probability of a minimal cut set is below the truncation limit, the minimal cut set is excluded from the model quantification by setting the probability of this minimal cut set to zero. On the other hand, if its probability is above the truncation limit, no change will be made to the minimal cut set. Then the risk level after the truncation, R', can be computed from the modified probability of each minimal cut set. The percentage of R being truncated at the given truncation limit can then be computed as $\frac{R-R'}{R}$.

In order to determine whether a chosen truncation limit is acceptable, the percentage risk being truncated must be compared with the acceptance criterion. If the percentage risk being truncated is less than the acceptance criterion, the truncation limit is acceptable. Otherwise, the truncation limit should be redefined such that the acceptance criterion will be met.

Acceptance criterion for a truncation limit is often determined by the decision supported. For decisions which depend heavily on PRA results, a relatively low truncation limit should be employed in order to achieve high accuracy of risk and risk change. 5% is often used for acceptability in practice.

As for the above example, if the truncation limit is set to 10^{-6}, none of the minimal cut set probabilities are below this cutoff value. The percentage system failure probability being truncated is thus zero. In this case, a high accuracy of the system failure probability has been achieved, but the computation of Q is not simplified. If the truncation limit is set to 10^{-5}, the first minimal cut set will be truncated from the quantification process while the probabilities of minimal cut sets 2 and 3 remain unchanged in the quantification process. In this case, the percentage system probability truncated is given as:

$$\frac{R - R'}{R} = \frac{5 \times 10^{-6}}{1.025 \times 10^{-3}} \simeq 0.488\%. \tag{B.4}$$

If 5% is used as acceptance criterion for acceptability of a chosen truncation level, the truncation level of 10^{-5} is acceptable because the percentage of R being truncated at this truncation level is less than 5%.

By increasing the truncation level to 10^{-4}. Both minimal cut sets 1 and 2 will be truncated from the quantification process. The resultant percentage system failure probability being truncated is therefore

$$\frac{R - R''}{R} = \frac{5 \times 10^{-6} + 2 \times 10^{-5}}{1.025 \times 10^{-3}} \simeq 2.439\%. \tag{B.5}$$

This results indicates that the truncation level of 10^{-4} is also acceptable. Compared to the truncation limits of 10^{-5} and 10^{-6}, 10^{-4} is generally considered the most appropriate truncation limit because it not only simplifies the computation process, but it also achieves the desired degree of accuracy of system failure probability.

B.2 Monte Carlo Simulation for Selecting Truncation Limits

In order to generate a probability distribution for the percentage risk being truncated at a given truncation level using Monte Carlo simulation, probability distributions for all of the uncertain inputs of a PRA model must first be specified. During each trial, a sample value of each uncertain input is generated from its probability distribution model. These sample inputs are then used to compute a sample value of the probability of each minimal cut set. If the sample value of a minimal cut set probability is lower than the cutoff value, the minimal cut set probability is set to zero. Otherwise, the minimal cut set probability remains unchanged. The modified sample value of each minimal cut set is then used to compute the sample value of the percentage risk retained (denoted as R'), while the original sample value of each minimal cut set is used to compute the sample value of the nominal risk during each trial. A sample value of percentage risk being truncated is then obtained from $\frac{R-R'}{R}$ in each iteration.

After the sampling process is repeated many times, a histogram of the percentage truncated risk is generated, from which the mean, variance, and confidence levels can be obtained. According to elementary sampling theory, the variance of the model outputs are proportional to $\frac{1}{n}$, where n is the number of trials performed in the simulation. Thus, the sampling process must be repeated until enough sample values have been obtained to yield the desired degree of accuracy in the results.

In order to determine whether a given truncation limit is acceptable or not, the expected truncated risk from Monte Carlo simulation is compared with the acceptance criterion. To see this, let us continue our discussion of the previous example system. We assume that the failure probabilities of the components are lognormally distributed, with means and standard deviations as given in Table B.1. For simplification, the failure probability of each component is assumed to be independent of all others.

Using the computation procedures described above, the histogram of the nominal

Table B.1: Means and standard deviations of the component failure probabilities in the example system

Component	Mean	Standard deviation
1	5.0E-03	3.0E-03
2	2.0E-02	1.0E-02
3	1.0E-03	6.0E-04
4	1.0E-03	8.0E-04

system failure probability was obtained and presented in Figure B-2. The histograms of the percentage risk being cut off at each of the four chosen truncation levels were also obtained and presented in Figure B-3, Figure B-4, Figure B-5, and Figure B-6,respectively. Table B.2 summarizes the percentage truncated risk at each truncation level obtained using both the point estimate approach and Monte Carlo simulation.

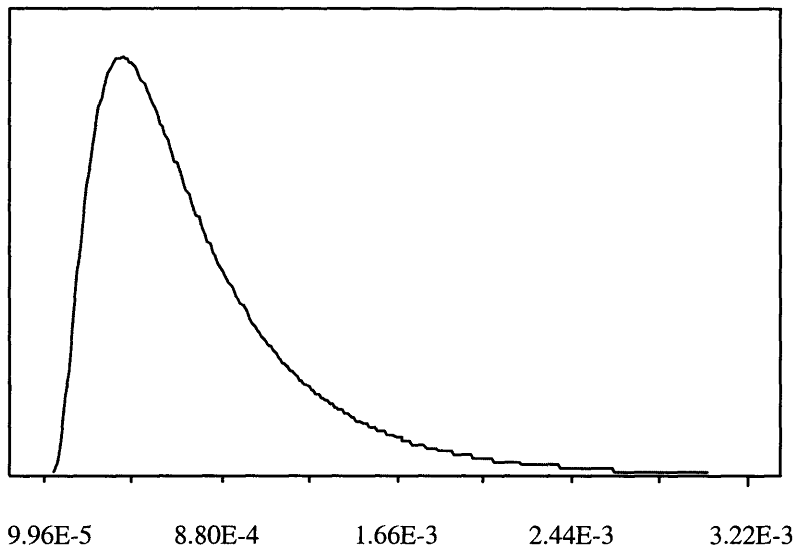

Figure B-2: The failure probability distribution for the example system without applying truncation limit

According to the results presented in Table B.2, at a truncation level of 1.0E-05, 2.0E-05, and 1.0E-04, the expected system failure probability being truncated obtained from Monte Carlo simulation is higher than the point estimated results by approximately a factor of two. At a truncation level of 5.0E-04, the Monte Carlo sim-

Table B.2: The expectation of the percentage truncated system failure probability at each truncation level

Truncation level	1.0E-05	2.0E-05	1.0E-04	5.0E-04
Point estimate approach	0.488%	0.488%	2.439%	2.439%
Monte Carlo simulation	0.742%	1.595%	3.401%	29.251%
$p(\frac{Q-Q'}{Q} \leq 5\%)$	100%	96.86%	78.36%	64.44%

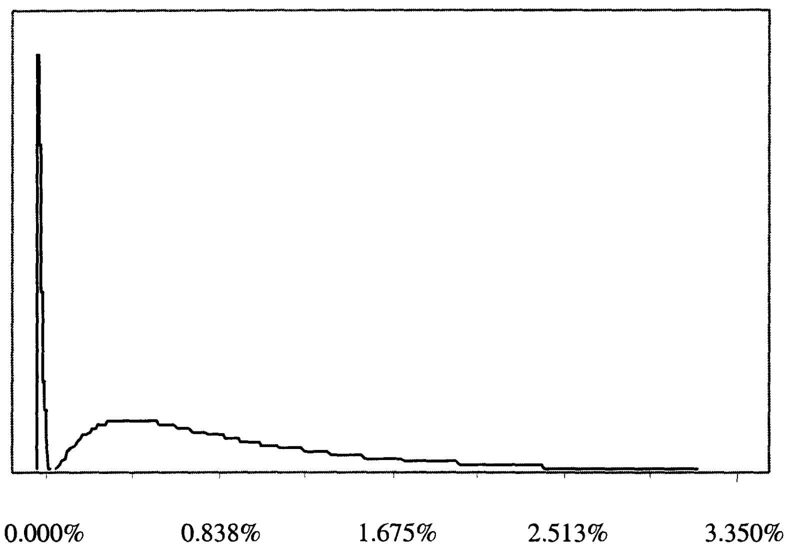

Figure B-3: The failure probability distribution for the example system at truncation level of 1.0E-05

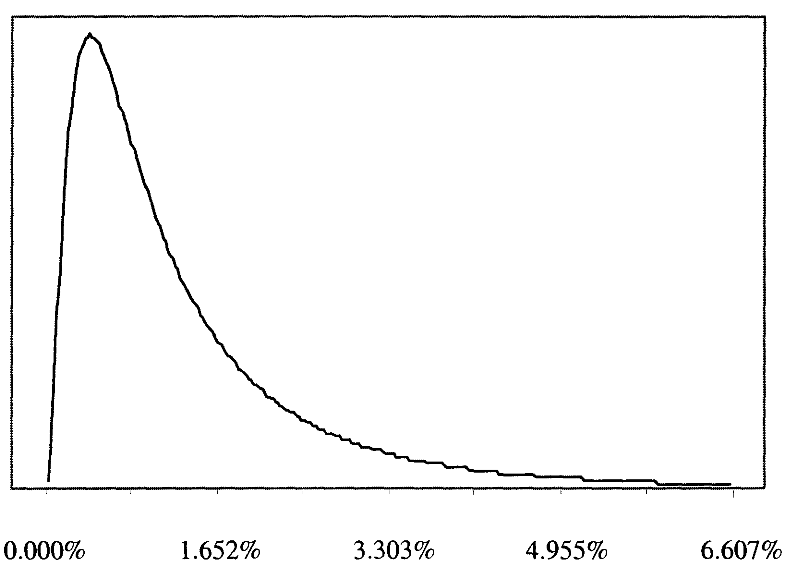

Figure B-4: The failure probability distribution for the example system at truncation level of 2.0E-05

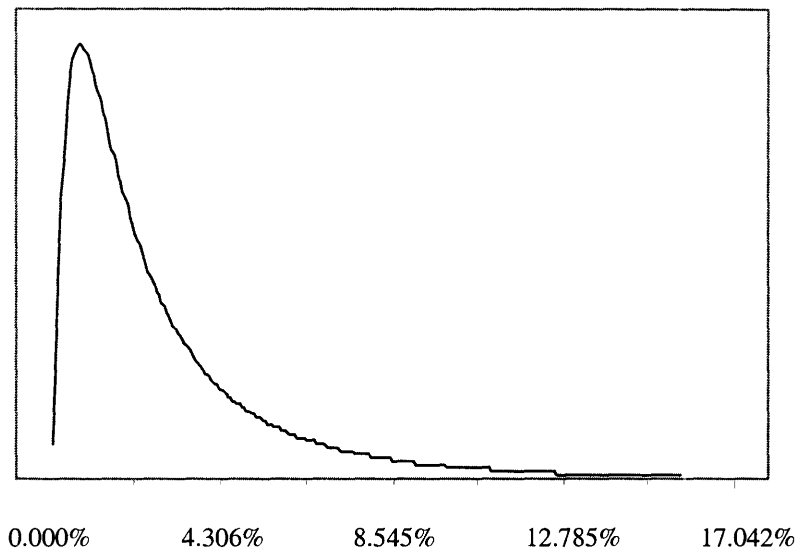

Figure B-5: The failure probability distribution for the example system at truncation level of 1.0E-04

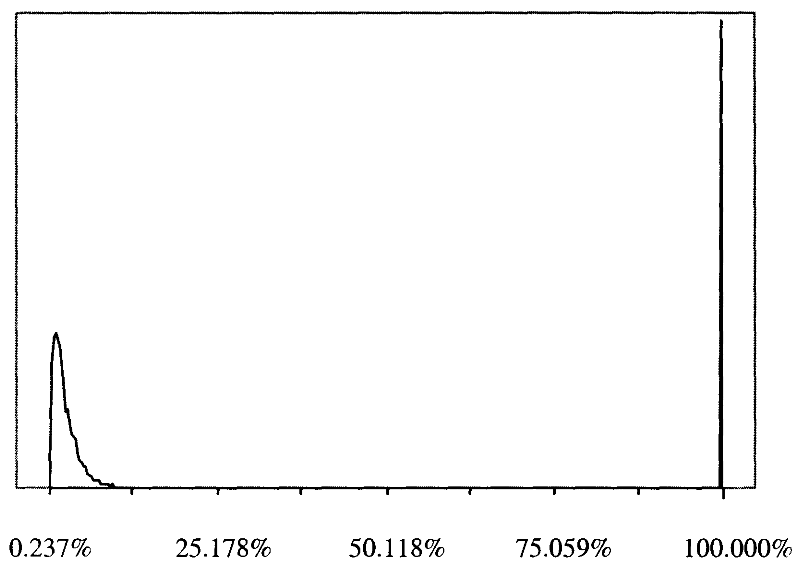

Figure B-6: The failure probability distribution for the example system wat truncation level of 5.0E-04 ulated result is higher than the point estimated result by nearly a factor of 12. These findings indicate that the truncated percentage system failure probability increases after the epistemic uncertainty on input parameters are taken into account for all four chosen truncation levels. The effects of parameter uncertainty on the truncated system failure probability are relatively small (less than an order of magnitude) for the first three truncation levels. Parameter uncertainty will have more of an effect on the truncated system failure probability when the truncation limit is close to the mean probability of MCS_3.

The degree of confidence that the acceptance criterion has been met for each truncation level was also calculated and presented in Table B.2. If the 95% confidence level is used for acceptability, the second truncation limit, $2.0E-05$, is the most appropriate truncation limit for this example. However, the most appropriate truncation limit is 1.0E-04 by use of the mean value approach, and $5.0E-04$ using the point estimate approach.

These results indicate that the most appropriate truncation limit chosen by use of each of the three approaches might be different. Under which conditions should one choose one truncation limit over another depends upon the problem subject to analysis and the application supported. For decisions which do not rely heavily on PRA results, the point estimate approach can be advantageous for its simplicity. But for decisions in which insights derived from PRA results play significant role in risk-informed decision making, the combination of the mean value approach and the confidence level approach is preferred for its accuracy.

Appendix C

Comparison of Results Obtained Using the Point Estimate Approach and Monte Carlo Simulation

C.1 Models with Non-Overlap Minimal Cut Set Probability Distributions

We begin our comparison with a simple logic model which consists of two minimal cut sets. Let Q_1 represent the probability of occurrence of the first minimal cut set, and Q_2 represent that of the second minimal cut set. We also assume Q_1, and Q_2 are lognormally distributed with parameters given in Table C.1. The corresponding probability distributions of Q_1 and Q_2 are shown in Figure C-1.

The fractional risks truncated at each of the six chosen truncation levels obtained using both the point estimate approach and Monte Carlo simulation are presented in Table C.2. For comparison, these results are also graphed together in Figure C-2.

The results presented in Figure C-2 indicate that if the truncation limit is beyond the region of 2.05E-06 and 2.30E-06 or within the region between 1.97E-07 and

Table C.1: Distribution parameters for the two example non-overlap minimal cut sets

Distribution Parameters	Q_1	Q_2
Mean	1.0E-08	1.0E-06
Standard deviation	5.0E-09	5.0E-07
Lower bound	2.05E-09	1.97E-07
Upper bound	2.34E-08	2.30E-06

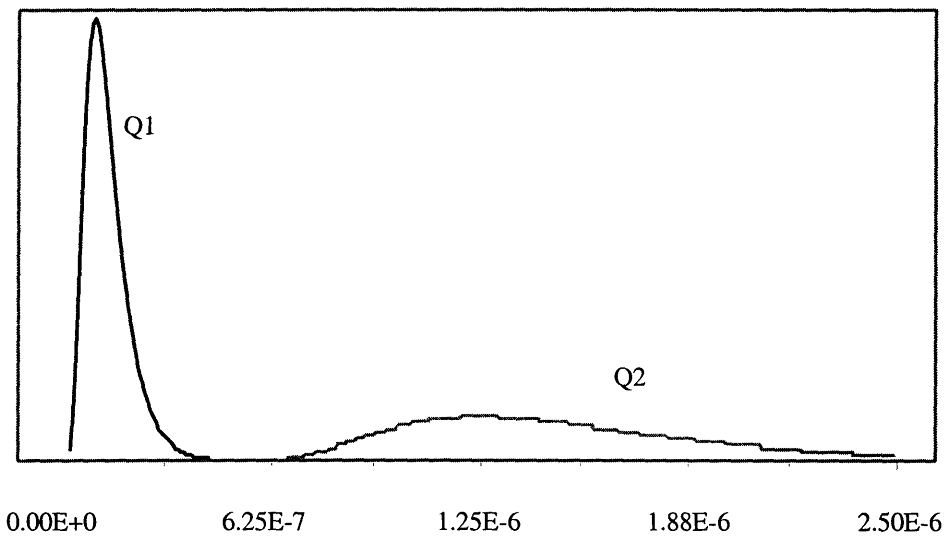

Figure C-1: Probability distributions of the two non-overlap minimal cut sets

Table C.2: Expected fractional truncated risk for the system consisting of the two example non-overlap minimal cut sets as a function of truncation limit

Truncation Limit	Point Estimate	Monte Carlo Simulation
5.0E-06	100.00%	100.00%
1.5E-06	100.00%	90.09%
5.0E-07	0.99%	1.08%
5.0E-08	0.99%	1.16%
1.5E-08	0.99%	0.85%
5.0E-09	0.00%	0.02%

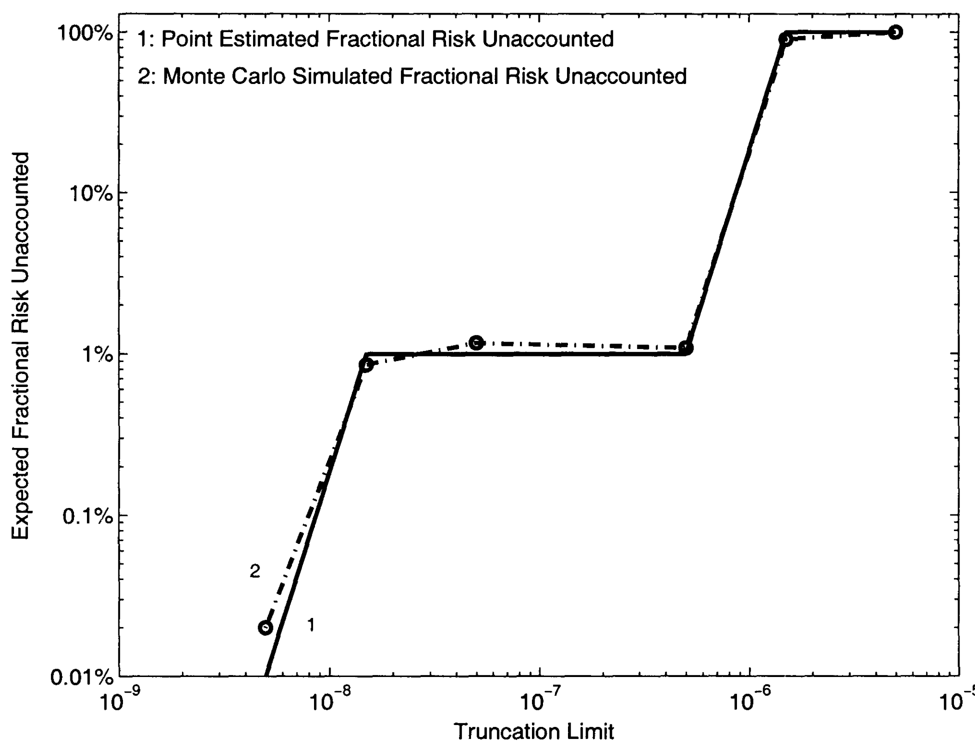

Figure C-2: Expected fractional truncated risk as a function of truncation limit for the system consisting of the two example non-overlap minimal cut sets

2.34E-08, the percentage risks truncated that was obtained using the point estimate approach are the same as those obtained using Monte Carlo simulation. If the truncation limit is in the range of 1.00E-08 to 2.34E-08 or in the range of 1.00E-06 to 2.30E-06, the point estimated percentage truncated risk is higher than that obtained from Monte Carlo simulation. However, if the truncation limit is within the region of 2.05E-09 to 1.00E-08 or within the region of 1.97E-07 to 1.00E-06, the point estimated percentage risk truncated is smaller than that obtained from Monte Carlo simulation.

These observations indicate that, in the case where the probability distributions of minimal cut sets don't overlap, the point estimated results generally do not agree with the results obtained from Monte Carlo simulation. The point estimated percentage truncated risk may be smaller than that obtained using Monte Carlo simulation. It may also be larger than that obtained using Monte Carlo simulation, depending upon the region within which the truncation level falls.

C.2 Models with Overlap Minimal Cut Set Probability Distributions

We now perform another example study by changing the distribution parameters of the two minimal cut sets given in the previous example.

The new distribution parameters are given in Table C.3. The modified probability distributions of Q_1 and Q_2 are shown in Figure C-3. Given that the upper bound of Q_1 is 2.34E-06 and the lower bound of Q_1 is 2.20E-07, Figure C-3 shows an overlap region between the two probability distributions.

The fractional truncated risk at each of the five truncation levels obtained using the point estimate approach and using Monte Carlo simulation are presented in Table C.4 and Figure C-4. The results indicate that if the truncation limit is beyond the range of 1.56E-07 to 4.70E-06, the point estimated truncated risk is the same as that obtained using Monte Carlo simulation. If the truncation limit is within the region of

Table C.3: Distribution parameters for the two example overlap minimal cut sets

Distribution parameters	Q_1	Q_2
Mean	1.0E-06	2.0E-06
Standard deviation	5.0E-07	1.0E-06
Lower bound	1.56E-07	2.20E-07
Upper bound	2.34E-06	4.70E-06

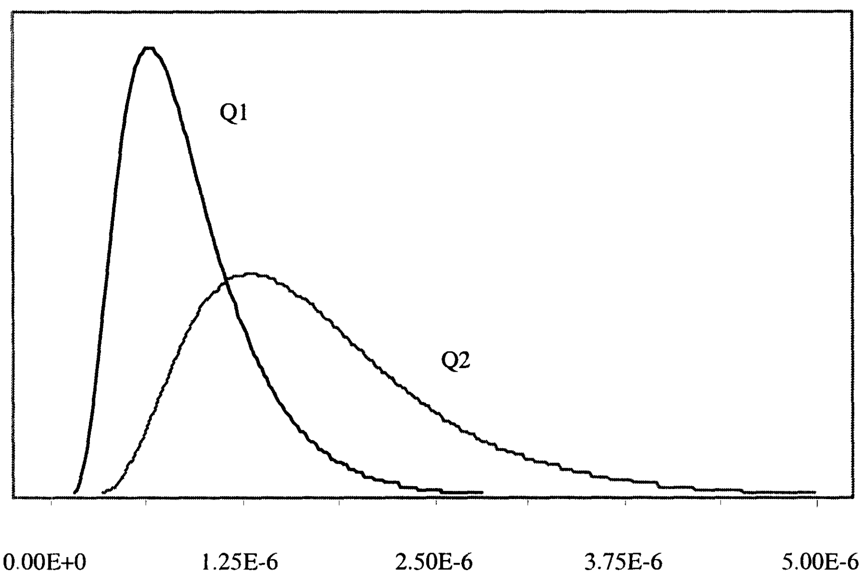

Figure C-3: Probability distributions for the two overlap minimal cut sets

1.56E-07 to 2.0E-06, the point estimated fractional risk unaccounted is smaller than that obtained from Monte Carlo simulation. However, for truncation limits in the range of 2.0E-06 and 4.7E-06, the point estimated fractional risk truncated is greater than that obtained using Monte Carlo simulation. These findings reveal that, for the case where the probability distributions of the minimal cut sets overlap with each other, the general relationship between the point estimated truncated risk and the Monte Carlo simulated truncated risk does not exist.

Although these conclusions are drawn from an example consisting of only two minimal cut sets, they are also applicable to the cases where the logic model consists of the large number of minimal cut sets.

Table C.4: Expected fractional truncated risk the system consisting of the two example overlap minimal cut sets

Truncation Limit	Point Estimate	Monte Carlo Simulation
1.0E-05	100.00%	100.00%
3.0E-06	100.00%	92.17%
1.5E-06	33.33%	46.87%
5.0E-07	0.00%	0.82%
1.0E-07	0.00%	0.00%

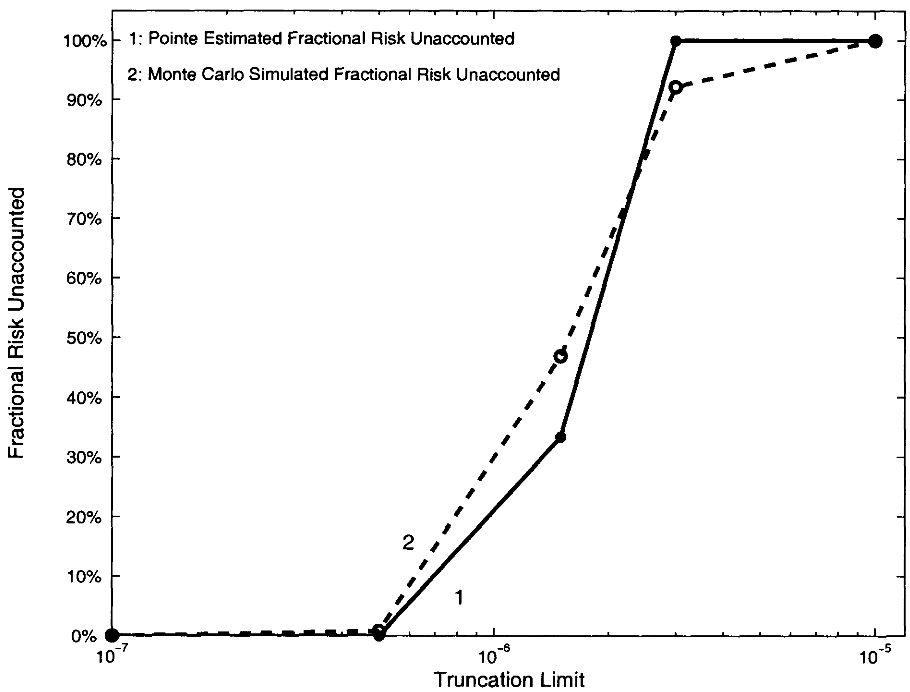

Figure C-4: Expected fractional truncated risk for the system consisting of the two overlap minimal cut sets

Bibliography

[1] Corwin L. Atwood. Individual model evaluation and probabilistic weighting of models. In A. Mosleh, N. Siu, C. Smidts, and C. Lui, editors, *Proceedings of Workshop on Model Uncertainty: Its Characterization and Quantification*, Annapolis, MD, USA, October 1994. U. S. Nuclear Regulatory Commission, NUREG/CP-0138.

[2] Vicki M. Bier. Some illustrative examples of model uncertainty. In A. Mosleh, N. Siu, C. Smidts, and C. Lui, editors, *Proceedings of Workshop on Model Uncertainty: Its Characterization and Quantification*, Annapolis, MD, USA, October 1994. NUREG/CP-0138, U. S. Nuclear Regulatory Commission.

[3] Viki M. Bier. *A Measure of Uncertainty Importance for Components in Fault Trees.* PhD thesis, Massachusetts Institute of Technology, February 1983.

[4] Mario V. Bonaca. Improvement of the quality of risk information for regulatory decisionmaking. Technical report, U. S. Nuclear Regulatory Commission, May 2003.

[5] E. Borgonovo, G. E. Apostolakis, S. Tarantola, and A. Saltelli. Comparison of global sensitivity analysis techniques and importance measures in PSA. *Reliability Engineering and System Safety*, 79, February 2003.

[6] E. Borgonovo and G.E. Apostolakis. A new importance measure for risk-informed decision-making. *Reliability Engineering and System Safety*, 72, May 2001.

[7] L. Joseph Callan. Acceptable guidelines and consensus standards for use in risk-informed regulation. Technical report, U. S. Nuclear Regulatory Commission, September 1997.

[8] L. Joseph Callan. Elevation of the core damage frequency objective to a fundamental commission safety goal. Technical report, U. S. Nuclear Regulatory Commission, September 1997.

[9] Michael C. Check, Gareth W. Parry, and Richard R. Sherry. Use of importance measures in risk-informed regulatory applications. *Reliability Engineering and System Safety*, 60:213–226, 1998.

[10] Jae-Gyeum Cho and Bong-Jin Yum. Development and evaluation of an uncertainty importance measure in fault tree analysis. *Reliability Engineering and System Safety*, 57:143–157, 1997.

[11] U. S. Nuclear Regulatory Commission. NUREG-75/014(WASH-1400) - Reactor Safety Study: An assessment of accident risk in u.s. commercial nuclear power plants, 1975.

[12] U.S. Nuclear Regulatory Commission. NUREG/CR-6372 - policy statement for safety goals for the operations of nuclear power plants, 1986.

[13] U.S. Nuclear Regulatory Commission. Regulatory guide 1.174 - an approach for using probabilistic risk assessment in risk-informed decisions on plant-specific changes to the current licensing basis, June 1998.

[14] U.S. Nuclear Regulatory Commission. Regulatory guide 1.175 - an approach for plant-specific, risk-informed decisionmaking: Inservice testing, August 1998.

[15] U.S. Nuclear Regulatory Commission. Regulatory guide 1.176 - an approach for plant-specific, risk-informed decisionmaking: Graded quality assurance, August 1998.

[16] U.S. Nuclear Regulatory Commission. Regulatory guide 1.177 - an approach for plant-specific, risk-informed decisionmaking: Technical specifications, August 1998.

[17] U.S. Nuclear Regulatory Commission. Draft regulatory guide DG-1122 - an approach for determining the technical adequacy of probabilistic risk assessment results for risk-informed activities, November 2002.

[18] U.S. Nuclear Regulatory Commission. Regulatory guide 1.178 - an approach for plant-specific, risk-informed decisionmaking for inservice inspection of piping, September 2003.

[19] EPRI. PSA applications guide. EPRI TR-105396, August 1995.

[20] K. N. Fleming. Issues and recommendations for advancement of PRA technology in risk informed decision making. Technical report, U. S. Nuclear Regulatory Commission, Technology Insights, April 2003.

[21] Apostolakis G. The distinction between aleatory and epistemic uncertainties is important; an example from the inclusion of aging effects in the PSA. In Mohammad Modarres, editor, *International Topic Meeting on Probabilistic Safety Assessment*, volume I, Washington, DC, USA, 1999.

[22] T. Homma and A. Saltelli. Importance measures in global sensitivity analysis of nonlinear models. *Reliability Engineering and System Safety*, 52:1–17, 1996.

[23] T. G. Hook. Use of the safety monitor in operations decision-making and the maintenance rule at san onofre nuclear generating station. In *International Conference on Probabilistic Safety Assessment, Methodology and Applications*, pages 26–30, Seoul, Korea, November 1995.

[24] R. L. Iman. A matrix-based approach to uncertainty and sensitivity analysis for fault trees. *Risk Analysis*, 7:21–33, 1987.

[25] R. L. Iman and S. C. Hora. A robust measure of uncertainty importance for use in fault tree system analysis. *Risk Analysis*, 10:401–406, 1990.

[26] P. Kafka. Risk monitoring - international status and current developments. In *IAEA Technical Committee Meeting on PSA Applications to Improve NPP Safety*, pages 23 – 27, Madrid, Spain, February 1998.

[27] H.E. Lambert. Measures of importance of events and cut sets in fault trees. *Reliability and Fault Tree Analysis*, pages 77–100, 1975.

[28] HW Lewis. Risk assessment review group report. NUREG/CR-0400, U. S. Nuclear Nuclear Regulatory Commission, September 1978.

[29] Michael D. Mckay. Aspects of modeling uncertainty and prediction. In A. Mosleh, N. Siu, C. Smidts, and C. Lui, editors, *Proceedings of Workshop on Model Uncertainty: Its Characterization and Quantification*, Annapolis, MD, USA, October 1994. U. S. Nuclear Regulatory Commission, NUREG/CP-0138.

[30] M. Modarres. *What Every Engineer Should Know About: Reliability and Risk Analysis.* Marcel Dekker, Inc., New York, N.Y., 1993.

[31] Nam-IL Tak Moon-Hyun Chun, Seok-Jung Han. An uncertainty importance measure using a distance metric for the change in a cumulative distribution function. *Reliability Engineering and System Safety*, 70:313–321, 2000.

[32] T. A. Morgan. Development and use of the san onofre safety monitor. IAEA-J4-TC-855, 1993.

[33] M.D. Morris. Factorial sampling plans for preliminary computational experiments. *Technometrics*, 33:161–174, 1991.

[34] A. Mosleh, N. Siu, C. Smidts, and C. Lui, editors. *Proceedings of Workshop on Model Uncertainty: Its Characterization and Quantification*, Annapolis, MD, USA, October 1994. U. S. Nuclear Regulatory Commission, NUREG/CP-0138.

[35] American Society of Mechanical Engineers. Standard for probabilistic risk assessment for nuclear power plant applications, ASME RA-S-2002, April 2002.

[36] Gareth W. Parry. Model uncertainty and probability. In A. Mosleh, N. Siu, C. Smidts, and C. Lui, editors, *Proceedings of Workshop on Model Uncertainty: Its Characterization and Quantification*, Annapolis, MD, USA, October 1994. U. S. Nuclear Regulatory Commission, NUREG/CP-0138.

[37] Gareth W. Parry. Uncertainty in PRA and its implications for use in risk-informed decision-making. In A. Mosleh and R.A. Bari, editors, *Probabilistic Safety Assessment and Management, PSAM 4: Proceedings of the 4th International Conference on Probabilistic Safety Assessment and Management*, New York City, USA, September 1998. Springer, New York.

[38] M. Elisabeth Pat-Cornell. Uncertainties in risk analysis: Six levels of treatment. *Reliability Engineering and System Safety*, 54:95–112, 1996.

[39] F.A. Patterson-Hine and B.V. Koen. Direct evaluation of fault trees using object-oriented programming techniques. *IEEE Trans. Computers*, 38:186–192, 1989.

[40] Ladislav Rosenberg. Algorithm for finding minimal cut sets in a fault tree. *Reliability Engineering and System Safety*, 53:67–71, July 1996.

[41] C.W. Rowley. Risk-based in-service testing - development of guidelines. Volume 2, Light Water Reactor (LWR) Nuclear Power Plant Components, ASME Draft Report, ASME, 1995.

[42] C.W. Rowley. Risk-based in-service testing pilot project. EPRI Report TR-105869, EPRI, 1995.

[43] E.R. Schmidt, K.M. Jamali, G.W. Parry, and S.H. Gibbon. Importance measures for use in PRAs and risk management. In *Proceedings of the International Topical Meeting on Probabilistic Safety Methods and Applications*, EPRI NP-3912-SR. Electric Power Research Institute, 1985.

[44] William D. Travers. Addressing PRA quality in risk-informed activities. Technical report, U. S. Nuclear Regulatory Commission, July 2000.

[45] William D. Travers. Risk-informed regulation implementation plan. Technical report, U. S. Nuclear Regulatory Commission, March 2000.

[46] Doug True, David Leaver, Ed Fenstermacher, and John Gaertner. Risk characterization of the potential consequences of an armed terrorist ground attack on a u.s. nuclear power plant. Technical report, U. S. Nuclear Regulatory Commission, Februray 2003.

[47] USNRC. Use of probabilistic risk assessment methods in nuclear activities: Final policy statement. 60 FR 42622, Federal Register, Vol. 60, U. S. Nuclear Regulatory Commission, August 1995.

[48] M. van der Borst and H. Schoonakker. An overview of PSA importance measures. *Reliability Engineering and System Safety*, 72:241–245, 2001.

[49] J. Vatn. Finding minimal cut sets in a fault tree. *Reliability Engineering and System Safety*, 36:59–62, 1992.

[50] W. E. Vesely. Supplemental viewpoints on the use of importance measures in risk-informed regulatory applications. *Reliability Engineering and System Safety*, 60:257–259, 1998.

[51] Ian B. Wall and David H. Worledge. Some perspectives on importance measures. *PSA96 International Topical Meeting on Probabilistic Safety Assessment*, 1996.

[52] W.J.Parkinson. Risk-based in-service testing program for commanhe peak steam electric station. EPRI Report TR-105870, EPRI, 1995.

[53] David. H. Worledge. Insights from epri maintenance rule projects. EPRI Report TR-106280, EPRI, 1996.

[54] Apostolakis GE Zio E. Two methods for the structured assessment of model uncertainty by experts in performance assessments of radioactive waster repositories. *Reliability Engineering System Safety*, 54:225–241, 1996.