ABSTRACT

Risk-based regulation is being adopted in a variety of industries. Inherent in such regulation is the notion that estimates of risk will be compared against some acceptance criteria. Unfortunately, all estimates of risk contain significant uncertainties. These uncertainties raise a series of questions that must be answered in order for risk-based regulation to be effective:

1. Which uncertainties are to be considered?
2. How should uncertainties be treated when comparing to acceptance criteria?
3. How can uncertainties be effectively communicated to decision-makers and the public?

While there are no definitive answers to these three questions, this paper addresses them based on our current knowledge of risk assessment and uncertainty analysis. Nuclear reactor regulation is used to provide appropriate examples.

*This work was supported by the United States Department of Energy under Contract DE-AC04-94AL85000.
DISCLAIMER

Portions of this document may be illegible in electronic image products. Images are produced from the best available original document.
I. Introduction

Over the past several years, we have begun to fully appreciate the value of probabilistic risk assessment (PRA) as a decision support tool. Risk assessment has allowed us to focus on problems of real importance and provided discipline to prioritization processes. Many government agencies now consider risk assessment as a normal and essential element of their decision making.

Due to the inherent uncertainty in the results, use of absolute PRA numbers to make specific decisions was not encouraged by risk assessment experts in the past. The current trend, however, is to make more and more use of the absolute numbers and (in some cases) to use them directly to make regulatory decisions. Whether or not we approve of this trend, it will almost certainly continue. Therefore, it is incumbent upon risk assessment experts to provide information to decision-makers that is properly characterized. This characterization should include a clear presentation of the uncertainties involved in the risk estimates. Uncertainty analysis is often considered undesirable by decision-makers, because it muddies up the waters of an otherwise clear cut decision.

Rarely does 100% of a distribution lie on one side of a decision threshold. As shown in Figure 1, there is usually some probability that the acceptance threshold is exceeded. By including uncertainties, the decision-maker now has two decisions to make: (1) is the point estimate (usually mean or median) acceptable? and (2) is the uncertainty acceptable? Despite this added complexity, it is important to consider the uncertainties. They exist, and a decision that does not consider them is not fully informed. The real question is how to consider them in a reasonable manner. The remainder of this paper discusses some of the issues surrounding the treatment of uncertainties in
decision-making. The nuclear reactor industry and Nuclear Regulatory Commission (NRC) regulations will provide the context for the discussions.

II. Types of Uncertainties

Uncertainties exist in all parts of a risk assessment. These uncertainties exist in the construction of PRA models and in the values of the input variables that go into the models. These uncertainties then produce uncertainty in the PRA results. Different types of uncertainties exist in PRAs, and their treatment varies. Alternative interpretations and definitions exist for classifying the different types of uncertainty. These topics are discussed in Kaplan\textsuperscript{1}, Apostolakis\textsuperscript{2} and Perry\textsuperscript{3}. Two general types of uncertainties (stochastic uncertainties and state-of-knowledge uncertainties) have been proposed in the past [NUREG-1489]\textsuperscript{4} and are presented here with slight modifications:

- Stochastic uncertainty is due to inherent variability in some measurable physical quantity.

- State-of-knowledge uncertainty results from a lack of complete information about systems, phenomena, and processes.

Stochastic uncertainty results when an experiment is repeated under effectively identical conditions and different outcomes are observed. Examples of stochastic processes include flipping a coin or starting a pump. Within the context of the PRA models, stochastic uncertainty is inherent in the physical process involved; it cannot be reduced by enlarging the data base. The context, or level of detail, of the PRA models is important, because a better model might remove the randomness from
the process. If we could build a perfect model of a pump that accounted for construction flaws, maintenance activities, wear, room environment, etc., then we could predict with certainty whether the pump would start on the next attempt and the randomness would be gone.

State-of-knowledge uncertainty is driven by a lack of information and can generally be reduced by obtaining more data. State-of-knowledge uncertainty can be broken down into two major subsets, parameter uncertainty and model uncertainty:

- **Parameter uncertainty** results from lack of knowledge about the correct inputs to models being used in the analysis. The parameters of interest may be inputs to either the PRA models themselves, or a variety of physical and process models that influence the PRA process. Examples include equipment failure rates, human error probabilities, amount of metal oxidation that occurs in the core, etc.

- **Model uncertainty** occurs because perfect models cannot be constructed. Models of physical processes generally have many underlying assumptions and often are not valid or complete for all possible cases. Usually, there are alternative models proposed by different analysts, and it is not known which (if any) of the models is the most appropriate one since each alternative will have its own deficiencies. The PRA models themselves, such as the event trees and fault trees, can be constructed in different ways and with different intent, and those alternative constructions can change or bias the results. Examples of PRA model uncertainties include the number of pumps required for success, the effect of timing, or the exclusion of important phenomena. Examples of process model uncertainties include
alternative thermal hydraulics models, human behavior models, or accident progression models.

The reader should keep in mind that the division between parameter and model uncertainty is often fuzzy and can change, depending upon the intent of the model. For example, whether one's goal is to determine a probability of an event or its frequency of occurrence can change the categorization. The categorization used here is commonly used in reactor risk assessments.

III. Treatment of Uncertainties in Risk Assessments

The types of uncertainty discussed in Section II exist throughout all parts of a PRA. However, in practice the treatment of uncertainty is usually incomplete and can vary in different parts of the PRA. There are two reasons why the treatment can vary. First, the PRA practitioners generally focus on those things that they consider to be most important. Second, methods for treating uncertainty are not equally developed for all parts of the analysis. We will consider the treatment of uncertainties in the context of the three levels of a nuclear reactor PRA:

- Level 1 Analysis of accident sequence and plant damage state frequencies
- Level 2 Analysis of accident progression and source terms
- Level 3 Analysis of consequences and public risk

Figure 2 shows these levels of a PRA and summarizes the uncertainties typically included. Further discussion is presented below.
III.1 Level 1 PRAs

Stochastic uncertainty in a Level 1 PRA is expressed in the formulation of event trees and fault trees. The trees account for alternative outcomes that are expected to vary from one accident to the next in a random manner. For example, given a loss of offsite power, the emergency ac power system may succeed or not. Alternative branches on the event trees account for these two alternatives. State-of-knowledge uncertainty is present in both forms, parameter uncertainty and modeling uncertainty. Parameter uncertainty occurs in the values assigned to the inputs to the PRA models (e.g., the failure rates for the diesel generators in the ac power system). This uncertainty is usually treated by assigning probability distributions to the inputs and performing some type of Monte Carlo simulation to explore the range of uncertainty. Modeling uncertainty exists in the development of success criteria, the models used for human error analysis, the construction of the event trees and fault trees, and elsewhere. This type of uncertainty is rarely treated in PRA, although sometimes sensitivity studies are performed.

III.2 Level 2 PRAs

The accident progression portion of a Level 2 PRA has uncertainty characteristics very similar to a Level 1 PRA. The events are different, but the types and treatment of uncertainty are the same. As in the Level 1 analysis, stochastic uncertainty is accounted for by the various branches in the Level 2 accident progression event tree. For example, the occurrence of different types of fuel-coolant interactions can be delineated by event tree branches. The state of knowledge uncertainty associated with the input parameters of the accident progression event tree is also explicitly included.
Alternative models, such as different zirconium oxidation models, are sometimes considered as part of expert judgment processes to evaluate certain probabilities, but the treatment is usually limited.

In recent PRAs, such as NUREG-1150\(^5\), source term uncertainties are typically limited to uncertainties in the input parameters to the source term model. Stochastic uncertainties and modeling uncertainties are usually not taken into account in any formal way, although sometimes the parameter uncertainties may be subjectively enlarged to partially consider them.

III.3 Level 3 PRAs

Consequence uncertainties have not been routinely treated in as much detail as Level 1 and Level 2 PRA uncertainties. Traditionally, only the stochastic uncertainties caused by weather have been explicitly treated in uncertainty analyses. Uncertainties in the evacuation process and health and economic effects are usually not treated or are only treated through sensitivity studies. Research is underway to better address these issues [NUREG/CR-6244]\(^7\).

When all parts of the PRA are combined into a risk estimate, uncertainties from each part are propagated through the models. As a practical matter, the PRA practitioners generally choose only the most important uncertainties from each part of the analysis for propagation through the models to form the risk estimate.

III.4 Implications

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.
The treatment of uncertainty in current PRAs is incomplete. Therefore, the overall uncertainty is underestimated. This underestimation is not necessarily catastrophic, because data exists to provide a reasonableness check on some of our results. For example, typical core damage frequency estimates are in the range of 1E-5 to 1E-4/reactor year and five to ninety-five percentile ranges generally cover one to two orders of magnitude. We know that these estimates are not orders of magnitude too low or we would see more core damage events. We have less data to support Level 2 and Level 3 estimates, and should use those results more cautiously. Currently, the NRC uses any one of the three levels of PRA in its decision-making, depending on the issue. For example, the reliability of decay heat removal systems is evaluated using Level 1 techniques. On the other hand, direct containment heating is being evaluated based on conditional containment failure probability (approximately Level 2), while the backfit rule is based on a Level 3 cost-benefit comparison.

Another point to consider regarding the underestimation of uncertainty is that such underestimation affects point estimates. PRA uncertainty distributions tend to be highly skewed distributions. Changes in the tails of the distributions can have a profound effect on the mean of the distribution, while the median is usually less affected. This issue will be discussed further in the next section. In most cases the NRC uses the mean as the measure to be used in decision making. Therefore, we should continue to be cautious, particularly when using mean values from a Level 3 PRA.

IV. Comparison to Acceptance Criteria

Risk based decisions tend to fall into one of two categories. (There is a third case where risk estimates are simply used as additional subjective information in an engineering decision; we will not
discuss that case here.) The simplest case is one where a risk estimate is being compared to a threshold number that defines an acceptable level of risk. There are many variations of this case, and either conservative screening or best-estimate analyses can be done. In some cases, the comparison to a threshold is done to prioritize issues for further study, while in other cases a direct regulatory decision may result. The second case is one where various alternatives are being compared, for example on a cost-benefit basis, and the best alternative is being sought.

IV.1 Threshold Comparisons

When comparing to a threshold, the first issue is what to compare to the threshold value. If an analysis is performed that does not include an uncertainty analysis, then only a point estimate is available. Usually a point estimate is difficult to characterize, because of the complex behavior of the PRA model. For example, using medians or means as inputs to the model does not guarantee that the output value will be a median or mean; usually it is not the case. For most significant PRA studies, the NRC has specified that the measure to compare is the mean of an uncertainty analysis. Therefore, performance of an uncertainty analysis is a requirement in most cases.

PRA output distributions tend to be asymmetric, with long tails that strongly influence the mean value and produce means that can be significantly higher than the medians. Therefore, even if the uncertainty distribution will not be used directly in the decision making process, properly forming the distribution is important to assure that a reasonable mean value is generated. Unfortunately, the input distributions for PRAs are usually generated with emphasis on the central part of the distributions. For example, a general shape is usually specified, along with a mean or median and an error factor
or range factor. Sometimes, bounds are specified; however, the extreme values usually receive little attention, even though they can significantly impact the outcome. This problem is compounded by the fact that the treatment of uncertainties is incomplete, as discussed in Section III.

Even if the input distributions were perfect, there will be uncertainty in the mean value of the output distribution due to the sampling processes involved. For example, for core damage frequencies, factors of two to five variation in the mean can occur as a result of changes in the sampling in the tails of the input distributions. For other risk measures, these variations are not as well known but are probably significant. How then does one make meaningful comparisons? There are three possible approaches discussed below, although none of them is entirely satisfactory:

1. Set the threshold for comparison at a low enough level that the uncertainties are not important and compare a point estimate to the threshold,

2. Perform the PRA with conservative input distributions and compare the mean to the threshold, or

3. Set uncertainty thresholds as well as thresholds for the mean values.

The first approach is straightforward, although somewhat subjective. For example, if one wishes to be confident that an event occurs less than 1E-4 times per year, then set the threshold for comparison of the mean at a lower number, such as 1E-5 per year. To use this approach, one needs to have at least an intuitive feeling for the uncertainty that is present in the analysis and choose a value that
inspires a sufficient level of comfort. This approach lacks mathematical rigor and can lead to arguments over the degree of conservatism that is present.

The second approach is similar to the first, although there is the added complexity of determining just what is meant by "conservative" input distributions. Sometimes it is not obvious whether the occurrence of an event during the accident progression is good or bad with regard to the ultimate outcome. For example, in-vessel zirconium oxidation may lead to early hydrogen burns, but more benign conditions later on in the accident. Also, the degree of conservatism, e.g., 90th percentile, 95th percentile, etc., can be a subject of great debate. Often, there is some combination of the first two approaches, with a conservative comparison threshold combined with at least some conservatism in the selection of inputs. This combined approach has been used in the evaluation of pressurized thermal shock. It is typical in such approaches that well-known variables tend to be treated in a best-estimate sense, while other variables are treated conservatively. While this philosophy has some practical advantages, it makes characterization of the results even more difficult.

The third approach is the only one that uses the output distributions directly. The advantage of the approach is that it allows the mean value to be preserved as a sort of best estimate and provides more information about what the analysts really think. The disadvantage, of course, is that now more things are being compared in the decision making process and the decision becomes more difficult to make and explain. The most obvious way to implement this approach is to pick a percentile of the output distribution, e.g., 95th percentile, and require that the value of the output variable be less than a specified threshold at that percentile. For example, we could specify a decay heat removal system reliability of 1E-5 (mean value) and a 95th percentile value of less than 1E-4. To implement such an
approach, we must choose the percentile for comparison and then the appropriate threshold. As we will see, both choices are difficult to make and justify.

In specifying percentiles for comparison, we must first understand the degree of confidence necessary for the decision of interest. There is not a single percentile value that is appropriate for all decisions. The potential consequences of being wrong weigh heavily in this selection. The problem is further complicated by the limitations of human processing of this information. There is evidence that people can make decisions based on probabilities of one in ten or one in a hundred. However, as the probabilities get smaller, the human mind begins to lose its ability to distinguish the difference. Therefore, choosing percentiles greater than the 99th percentile would usually not make sense.

There are additional reasons not to choose extreme percentiles. In most PRAs there is a certain arbitrariness in the input distributions. Usually, we have a reasonable justification for a central value, such as a mean or median, as a result of data analysis. We may even have a basis for a general shape of a distribution and a rough idea of the variance. However, the tails of the input distributions generally receive little or no attention. Small changes in the general form of the distributions can have a substantial impact on the tails. The tails of a particular input distribution may or may not have a substantial effect on the tails of the output distribution. However, we should be skeptical of the use of extreme values in the output distributions unless evidence is provided to substantiate them. Also, as discussed in Section 3, we have not included all of the uncertainties. Further, we find that the tails of the output distributions are highly sensitive to small changes in the Monte Carlo sampling process, and extremely large sample sizes are necessary to achieve an adequate degree of accuracy. A method exists to calculate percentiles of output distributions without resorting to Monte Carlo sampling, but
This process still requires accurate input distributions [NUREG/CR-6166].

There is no established method for choosing percentiles for comparison. The choice will vary from one problem to the next. Sensitivity studies can examine the importance of variations in the tails of the input distributions. Percentiles should not be selected that are particularly sensitive unless the analyst is willing to put in a substantial amount of work assuring accuracy in the input distributions. Note that in some highly skewed output distributions, the mean value can exceed the 95th percentile, making these comparisons even more difficult to interpret.

There are no easy answers that lead one to choose among the three methods above. It is likely that more attempts will be made to adopt the third approach, because it provides the appearance of rigor. However, given the stated limitations, it is no less subjective than the first two methods. In fact, any approach that does not acknowledge the subjectivity of the ultimate decision is misleading. It is unlikely that uncertainty analysis methods will ever advance to the point that decision makers will not have to apply considerable judgment in the final decisions.

IV.2 Choosing among Alternatives

In many regulatory applications, such as backfitting, the NRC staff has to choose among alternative solutions to a problem. The decisions are often made using a PRA-based cost-benefit analysis. The cost of a backfit is compared to a resulting reduction in risk, usually based on a value of $1000 per person-rem averted. Uncertainty in the cost-benefit ratios can have an impact on these decisions. For example, if decision makers are comparing two estimates, whether or not the differences between
High level managers and the public are generally not experts in either risk assessment or uncertainty analysis. Often, there are problems communicating the meaning of the point estimates, let alone the uncertainty. In fact, acknowledging the uncertainty and admitting the potential fallibility of the analysts often leaves the unfamiliar very uncomfortable with risk-based decisions. Therefore, it is important that the presentation of uncertainty results not be overly complicated or couched in complex statistical terminology. Decision makers can benefit from a description of the sources of uncertainty, but rarely profit from a delineation of different types of uncertainty, such as stochastic versus state of knowledge.

All decisions are made in the face of uncertainty. Usually, decision makers have no more than a gut feeling about the magnitude of the uncertainties. By providing more quantitative information about the uncertainty, the decision makers can calibrate their gut feelings, even if they do not use the uncertainties directly. Pointing out that the uncertainty analysis provides new information, and not a new problem, goes a long way toward achieving acceptance of the use of uncertainties, whether qualitative or quantitative. If a decision is deferred to obtain more information because of large uncertainties, this is not a failure. Rather, a bad decision may have been prevented.

There are many different ways to communicate the magnitude and nature of the uncertainties to decision makers. For the most part, simple uncertainty displays are best. These include box plots, probability density functions and cumulative distribution functions. Examples of these displays are found in NUREG-1489. These are displays that give an idea of the central tendency and width of the uncertainty. Multiple distribution displays and other complex functions should generally be avoided.
VI. Summary and Conclusions

Risk-based regulation is becoming a reality. Most current applications are based on point estimate comparisons, sometimes with a qualitative treatment of uncertainty. However, there is a desire to consider treating uncertainties more explicitly in decision making. This paper has identified some of the issues associated with the treatment of uncertainties and indicates that there are no easy, universally applicable solutions. Some key concerns are:

1. Input distributions are often not valid out in the tails,
2. The treatment of uncertainty is usually incomplete,
3. Monte Carlo sampling does not produce a high degree of accuracy in the tails of the output distribution,
4. It is difficult to select appropriate percentiles and thresholds for uncertainty comparisons, and
5. Uncertainties complicate the process of communicating the rationale for a decision.

These problems are not insurmountable. For example, alternatives to Monte Carlo sampling have been proposed for evaluating extreme percentiles. However, much more study is needed to produce consistent procedures for incorporating uncertainties into risk-based decision making. As long as the processes remain ad hoc, and different approaches are used for every new issue, then acceptance of the use of uncertainties in decision making will be slow in coming.
the estimates are significant depends upon the uncertainties associated with them. If the uncertainties about the two estimates are much larger than the differences between the two results, then the differences may not be meaningful. Figure 3 illustrates the manner in which uncertainty can affect comparisons among results. In one case the differences in the means may not be unimportant, while in the other case they are very significant. In the first case, the choice would likely be made considering a variety of other practical and political factors. In the second case, the PRA results would play a major role in the choice.

The comparison process could be formalized through the use of hypothesis testing or other statistical techniques. Using such techniques, one can estimate the probability that the true value of one variable is actually less than the true value of the other variable. Now we are once again faced with selection of a probability threshold to use in the comparison. Also, as discussed in the Section III, the comparison process should be formulated so that it is not overly sensitive to the tails of the distributions.

Generally, using PRA results for relative comparisons will yield more robust conclusions than absolute comparisons of the type discussed in Section III. The reasons for this are quite simple. If two estimates are generated using the same methods, then the same limitations will apply to both. That is, the same incompleteness will occur in both cases and the same problems will occur in the tails of the distributions. If the two estimates come from different sources, then more caution is in order.

V. Communication of Uncertainties
Figure 1. Comparison to Acceptance Criteria
Major Uncertainties Included

- Representation of stochastic outcomes
- Parameter uncertainties
- Few modeling uncertainties

Areas of a PRA

- Accident Sequence Analysis (system reliability and events leading up to core damage)
- Accident Progression Analysis (progression of events following core damage)
- Source Term Analysis (release and transport of radionuclides within the plant)
- Consequence Analysis (transport of radionuclides in the environment and their subsequent health and economic impacts)
- Risk Calculation (integrate and present results from the accident frequency, accident progression, source term, and consequence analyses)

Figure 2. Treatment of Uncertainties in PRA (NUREG-1489)
Figure 3. Effect of Distribution Width on Decision Making
References


