ABSTRACT

Output from a high-order simulation model with random inputs may be difficult to fully evaluate absent an understanding of sensitivity to the inputs. We describe a sensitivity analysis procedure applied to a large-scale computer simulation model of the processes associated with NRC Generic Safety Issue (GSI) 191. Our GSI-191 simulation model has a number of distinguishing features: (i) The model is large in scale in that it has a high-dimensional vector of inputs; (ii) Some model inputs are governed by probability distributions; (iii) A key model output is the probability of system failure—a rare event; (iv) The model’s outputs require estimation by Monte Carlo sampling, including the use of variance reduction techniques; (v) It is computationally expensive to obtain precise estimates of the failure probability; (vi) We seek to propagate key uncertainties on model inputs to obtain distributional characteristics of the model’s outputs; and, (vii) The overall model involves a loose coupling between a physics-based stochastic simulation sub-model and a logic-based Probabilistic Risk Assessment (PRA) sub-model via multiple initiating events in the latter sub-model. Our approach uses ideas from the literature and is guided by the need to have a practical approach to sensitivity analysis for a computer simulation model with these characteristics. We use common random numbers to reduce variability and smooth output analysis; we assess differences between two model configurations; and, properly characterize both sampling error and the effect of uncertainties on input parameters. We show selected results of studies performed at STP for sensitivities to parameters used in the GSI-191 risk-informed resolution project.

Acronyms & Nomenclature

CAD  Computer Aided Design
CASA Grande  Containment Accident Stochastic Analysis
    (CASA) Grande, where Grande refers to the STPNOC large, dry containment
ccdf  Complementary Cumulative Distribution Function
CDF  Core Damage Frequency
ECCS  Emergency Core Cooling System
GSI-191  NRC Generic Safety Issue 191
LBLOCA  Large Break Loss of Coolant Accident
LOCA  Loss of Coolant Accident
MBLOCA  Medium Break Loss of Coolant Accident
NLHS  Nonuniform Latin Hypercube Sampling
NPSHA  Net Positive Suction Head Available
NPSHR  Net Positive Suction Head Required
PRA  Probabilistic Risk Assessment
PWR  Pressurized Water Reactor
SBLOCA  Small Break Loss of Coolant Accident
STP  South Texas Project Electric Generating Station
ZOI  Zone of Influence

1 Background

In 1992, an event occurred at the Barsebäck Unit 2 boiling water reactor in Sweden in which an Emergency Core Cooling System (ECCS) filter screen plugged with insulation material during a regularly scheduled test [15]. Water carried previously dislodged mineral wool to the ECCS sump screen when...
the pumping system started, and two of the system strainers became partially blocked. Other similar events occurred after the Barsebäck event. After resolution of the BWR strainer issue through wide-scale strainer replacement, several years of phenomenology testing by the NRC regarding Pressurized Water Reactor (PWR) ECCS screen performance prompted issuance of NRC Generic Safety Issue 191 (GSI-191).

Since the time report [15] was issued, several engineering models of the hypothesized event progression have been developed. These include head loss in fiber beds, two-phase jet formation, chemical precipitate formation in post-Loss of Coolant Accident (LOCA) fluids, fiber and painted coatings failure, and so forth. Since 1996, methods of resolution have been proposed that would solve the engineering models in a classic engineering framework, but very few have been successful.

1.1 STP Method of Resolution

The South Texas Project Electric Generating Station (STP) undertook a new approach [13], which the NRC indicated as possible [24] for resolving GSI-191. The proposed approach uses a risk evaluation in a PRA. STP chose to evaluate risk with a high-order simulation of the containment building response, loosely coupled in an integrated framework with the PRA through basic events as illustrated in Figure 1.

Figure 1 shows an event tree with the initiating event frequency, LOCA, and with top events, Support, Start & Run, Screen, and Core. Screen and Core are circled because they are only related to the concerns of GSI-191 while Support and Start & Run are not directly related to GSI-191. Support and Start & Run are concerned with whether power is available to emergency equipment and, even if support is available, whether the pump starts up and runs, again, considering issues not related to GSI-191. However, if Support and Start & Run are Success, then equipment becomes further exposed to the concerns of GSI-191 (Screen and Core).

With this in mind, Figure 2 shows the fault tree logic used to obtain the change in frequency of failures when GSI-191 issues are addressed in the PRA. The probability of success (1 − P), ignoring GSI-191, is determined separately. Likewise, the failure probability associated with GSI-191 concerns (P′) are separately assessed. With these two probabilities in hand, the incremental change in failure likelihood can be found, (1 − P)P′, and the new probability for Success is (1 − P)(1 − P′).

Figure 3 shows a more detailed conceptual illustration of the process for coupling one of the basic events to the PRA. At a high level, the approach supplies a random vector (X) to a simulation model, which provides a random vector Z(X) as output.

2 Sensitivity Analysis

Paraphrasing Kleijnen [9],

Sensitivity analysis of a computer simulation model, estimates changes in the model’s outputs with respect to changes in the model’s inputs.

Both STP and the NRC have a strong interest in understanding the sensitivity of the outputs of the coupled model that we
FIGURE 3: Conceptual process in the integrated framework to obtain probability distributions from the simulation model that serve as input to a PRA basic event.

sketch above to changes in the model’s inputs. Engineering sensitivity studies often express responses in terms of the underlying engineering units of measure. Our study instead expresses output in terms of Core Damage Frequency (CDF). In a typical PRA, we think of sensitivities in terms of importance measures widely documented in the literature [23], such as risk achievement worth and risk reduction worth. In this work, traditional PRA importance measures are abandoned in favor of others commonly associated with graphical presentation.

Why choose measures different than those commonly used in engineering analysis? One application of the sensitivity analysis is to help investigators reviewing the analyses underlying the risk-informed resolution of GSI-191 understand where to focus their review efforts. A difficulty arises because inputs to engineering models are usually parameters, not necessarily the probabilities needed for importance measures. We focus on inputs to engineering models (temperature, pressure, mass, etc.) whose solution is used to estimate failure probabilities (ccdf) similar to what is shown in Figure 3.

2.1 Application to GSI-191

We focus on techniques with practical value in the context of resolving GSI-191 through a risk-informed approach. The model outputs are estimates from Monte Carlo sampling via a computer simulation model, Containment Accident Stochastic Analysis (CASA) Grande, where Grande refers to the STPNOC large, dry containment (CASA Grande).

A stochastic simulation model’s output may be deterministic or random. Consider the probability of system failure in the context of GSI-191. If we condition the input on a random initiating frequency, the output of the model is a conditional probability of system failure; i.e., the output is a random variable. On the other hand, if we integrate with respect to the distribution governing the random initiating frequency, the probability of failure is a deterministic output parameter. We consider both alternatives.

We cannot compute even a deterministic output measure exactly. Rather, we must estimate using Monte Carlo sampling. We have sampling-based errors associated with Monte Carlo methods, and these errors can be quantified. These errors can also be reduced by increasing the sample size and/or by using so-called variance reduction techniques. The latter methods are particularly important because of our interest in rare-event simulation in which failure probabilities are very small.

It is important to distinguish three sources of error: First, we have sampling-based errors associated with Monte Carlo methods discussed above. Second, we have errors due to uncertainties on some model inputs. Third, we have errors due to a lack of fidelity of the model itself. We can attempt to reduce the second type of error by gathering more data or eliciting (more) information from experts. We can also use data and elicitation to reduce the third type of error if we have competing hypothesized models, or sub-models. In all three cases, sensitivity analysis can help guide where such efforts should focus.

A key notion regarding sensitivity analysis in the context of decision problems involves understanding which differences in inputs make a difference in the decision rather than simply differences in model outputs. In this context, Clemen and Reilly [3] characterize sensitivity analysis by saying:

Sensitivity analysis answers the question, “What makes a difference in this decision?” . . . Determining what matters and what does not requires incorporating sensitivity analysis throughout the modeling process.

A similar sentiment is reflected in Eschenbach [6]:

This sensitivity analysis may be used (1) to make better decisions, (2) to decide which data estimates should be refined before making a decision, or (3) to focus managerial attention on the most critical elements during implementation.

Should some pipes that cause debris to be carried with the LOCA water be redesigned to mitigate risk associated with a possible GSI-191 LOCA event? Such an action would incur significant cost and significant radiation exposure to workers. What differences in input parameters lead to a “yes” versus “no” answer to this question? A surrogate question involves the notion of Regions I, II, and III from Regulatory Guide 1.174 [4]. Suppose nominal values of our model’s input parameters lead to an assessment that the plant is in Region III. Then, we may ask: What changes in the input parameters would lead us to conclude that the plant is instead in Region I or II? We describe a framework that, when properly applied, can help answer such questions.
3 Simulation Model

We refer to Letellier et al. [12] for a discussion of CASA Grande (the “Simulation operator” of Figure 3). The simulation model is applied for different hypothesized LOCA sizes and for different availabilities of several ECCS pumps. CASA Grande employs a stratified sampling estimator in which the stratification is on the initiating LOCA frequency (Figure 1). The probability distribution governing this initiating frequency is derived from NUREG-1829 [21] as we describe in [18]. The stratified sampling estimator can be thought of as an “outer loop” of replications executed in CASA Grande, which we refer to as frequency replications. This outer loop facilitates preservation of the probability distribution for initiating frequency in the sense of the uncertainty quantification plots (Section 4.7) and the stratified estimator reduces variance versus a naïve Monte Carlo estimator.

Within each frequency replication, we perform i.i.d. replications to estimate conditional probabilities for each failure mode (Screen and Core) and LOCA break size (small, medium, and large), conditioned on the pump state and the initiating frequency. We stratify the initiating frequency, and the sampling in distinct cells of the strata is done independently. We select a sample size for each cell of the stratification, and the boundaries of each cell of the strata, as we describe in [14]. Below we provide a high level overview of the engineering models solved in CASA Grande in one scenario, i.e., sample path of the simulation model. Approximately 50 random variables are defined as inputs to the engineering models used in CASA Grande.

Initialize the Scenario Because there are multiple pumps, and other equipment, several different plant configurations prior to “Screen and Core” (Figure 1) can be realized in any particular scenario. In addition, a LOCA location, LOCA size (break diameter), and break direction (less than a full double-ended break) are defined for a given LOCA scenario. The LOCA size also defines which PRA category (Small Break Loss of Coolant Accident (SBLOCA), Medium Break Loss of Coolant Accident (MBLOCA), or Large Break Loss of Coolant Accident (LBLOCA)) the scenario falls into, which, in turn specifies several other parameters.

Amount and Types of Debris Created The location, size, and direction of the break, together with Computer Aided Design (CAD) data determine debris quantities and types depending on the materials found within the Zone of Influence (ZOI). The ZOI is truncated by interference from concrete walls (defined in the CAD information).

Transport to ECCS Sumps As LOCA fluid and debris flow through containment, the different debris types can be captured or sequestered. At the lowest elevations of the containment are ECCS sumps equipped with inefficient strainers designed to capture debris to prevent damage to the ECCS pumps and associated equipment. However, if excessive amounts of debris are collected, the Net Positive Suction Head Available (NPSHA) to an ECCS pump may go below Net Positive Suction Head Required (NPSHR), causing failure of the pump.

The Screen Once LOCA water carries debris to an ECCS sump, it is captured on the ECCS filter screen according to the screen’s efficiency. The screen has different failure modes depending on the number of pumps in the scenario, the temperature of the water, and the amount of debris collected, which also depends on the scenario definition. A failure could occur due to too much air release, vaporization (insufficient sub-cooling), high pressure drop causing mechanical collapse, or excessive reduction in ECCS pump NPSHA.

The Core Because the ECCS screens are inefficient, some of the debris collected may pass through and deposit in the reactor core. Additional core failure modes may be realized due to blockage from the debris that may cause insufficient flow to remove decay heat, or even if the decay heat removal is sufficient, blockage that would cause soluble boron to precipitate and block cooling flow through fuel channels.

4 Practical Guide to Sensitivity Analysis

4.1 Step 1: Define the Model

We point to our GSI-191-specific simulation sub-model in Section 3. We view STP’s PRA as a second sub-model, and we refer to Wakefield and Johnson [25] for more on this PRA model in the context of GSI-191. We link these two sub-models as we describe in the next step.

4.2 Step 2: Select Outputs of Interest

In this paper we restrict attention to the change in core damage frequency (ΔCDF). Here, the “Δ” in ΔCDF accounts for GSI-191 issues, as opposed to an overall CDF estimate that includes non-GSI-191 issues accounted for in the PRA. Our method for estimating ΔCDF combines estimates from the CASA Grande simulation model with coefficients from STP’s PRA. The simulation model is used to estimate the conditional probabilities of a screen failure and a core failure at various break sizes (small, medium, and large), when we condition on the initiating frequency of a LOCA and the pump state. From the PRA, we use the core damage frequencies associated with a sump or boron vessel failure, further conditioned on each permutation of pump state and break size. The estimate for ΔCDF is calculated by summing the probability of each pump state–initiating frequency pair, and multiplying each term by the corresponding PRA frequency of core damage coupled with the conditional failure probability estimates by CASA Grande.

4.3 Step 3: Select Inputs of Interest

The input parameters we consider are described briefly below. A complete description can be found in [12].
Amount of Latent Fiber in Pool There is an amount of existing dust and dirt in the containment, which is based on plant measurement. The latent fiber is assumed to be in the pool at the start of recirculation. This latent debris is therefore available immediately upon start of recirculation, uniformly mixed in the containment pool. During fill up, this latent debris is also available to penetrate the sump screen.

Boron Fiber Limit The boron fiber limit refers to the assumed success criterion, or threshold of concern where boron precipitation would be assumed to occur for cold leg breaks. The fiber limit comes from the testing performed by the vendor that shows no pressure drop occurs with full chemical effects. The assumption is that all fiber that penetrates through the sump screen is deposited uniformly on the core.

Debris Transport Fractions in ZOI This refers to the three-zone ZOI debris size distribution. Each different type of insulation has a characteristic ZOI, which is divided into three sections to take into account the type of damage (debris size distribution) within each zone.

Chemical Precipitation Temperature CASA Grande assumes, once a “thin bed” of fiber forms on the strainer, the chemical precipitation bump up factors apply when the pool temperature reaches the predefined precipitation temperature.

Debris Transport Outside the ZOI CASA Grande applies a table of transport fractions to transport logic trees. The fraction of each debris type (fiber, paint, and coatings, etc.) that passes through areas to the pool are used to understand what is in the pool as a function of time during recirculation.

Chemical Bump Up Factor The chemical bump up factor is used as a multiplier on the conventional head loss calculated in CASA Grande. The multiplier applies if a thin bed is formed and the pool temperature is at or below the precipitation temperature.

Fiber Penetration Function The fraction of fiber that bypasses the ECCS sump screen is correlated to the arrival time via the amount of fiber on the screen. This function defines the fractional penetration amounts.

Size of ZOI The ZOI is defined as a function (multiplier) of break size and nominal pipe diameter. For example, for NUKON fiber, the ZOI is 17 times the break diameter. The ZOI is assumed to be spherical unless associated with less than a full double-ended break, in which case it is hemispherical. That said, the ZOI is truncated by any concrete walls within the ZOI.

Time to Turn Off One Spray Pump If three spray pumps start, then by procedure one is secured. The time to secure the pump is governed by the operator acting on the conditional action step in the procedure.

Time to Hot Leg Injection Similar to the spray pump turn off time, the time to switch one or more trains to hot leg injection operation is governed by procedure.

Strainer Buckling Limit The strainer buckling limit is the differential pressure across the ECCS strainer at which it fails mechanically. This limit is based on engineering calculations that incorporate a factor of safety.

Water Volume in the Pool Depending on the break size, the amount of water that is in the pool, as opposed to held up in the RCS and other areas in containment, is variable. Smaller breaks tend to result in less pool volume than larger breaks.

Debris Densities The debris density depends on the amount and type of debris in the pool. These densities are used in head loss correlations to calculate, for example, debris volume.

Time Dependent Temperature Profiles The temperature of the water in the sump affects air release and vaporization during recirculation. The time-dependent temperature profile comes from coupled RELAP5-3D and MELCOR simulations depending on break size.

4.4 Step 4: Choose Nominal Values and Ranges for Inputs

The nominal value for an input parameter is typically based on the analyst's best point estimate for that input. That said, there are sometimes reasons for selecting an appropriately conservative nominal value and we often follow this path in GSI-191. The nominal values for the amount of latent fiber in the pool, the boron fiber limit in the core, and the chemical precipitation temperature are 12.5 ft³, 7.5 grams per fuel assembly (g/FA), and 140°F, respectively. The unitless chemical bump up factor is modeled as a random variable that is conditioned on the size of the LOCA. For large breaks we use a truncated exponential distribution with mean parameter of 2, truncated to the interval (1,24). The time to turn off one spray pump is also modeled as a random variable whose distribution depends on the size of the break. For large breaks, we use a normal distribution with a mean of 20 minutes and a standard deviation of 5 minutes. The time to hot leg injection is modeled as a uniform random variable with bounds of 345 and 360 minutes. The nominal value of the stratiner buckling limit is specified in terms of the head at 9.35 feet of water. The water volume in the pool is assumed to be a uniform distribution, which depends on the break size. For large breaks the uniform distribution has limits of 45,201 and 69,263 ft³. Other input “parameters”—such as the debris transport fractions, the fiber penetration function, and the size of the ZOI—are specified by a larger set, or table, of parameters.

Lower and upper bounds for the inputs parameters are specified by what the analyst sees as how low or high these parameters might be. Typically these ranges are specified so that the interval contains values that are both reasonable and likely (e.g., we might exclude values that have less than a 10% chance of occurring). It is important to choose ranges for the input parameters that are commensurate. This task can be difficult, and we do not mean to minimize that difficulty. That said, such choices are continually made during the process of modeling a system, and we see this difficulty as implicit in the intimate connection between...
modeling and sensitivity analysis. Sometimes when we are only concerned about the performance of the system worsening, or the nominal value of a parameter is conservative, we only change an input parameter in one direction.

We consider scenarios in which the latent fiber volume decreases from 12.5 ft$^3$ to 6.25 ft$^3$ and increases to 25 ft$^3$ and 50 ft$^3$. For the boron fiber limit we consider decreases of the threshold from 7.5 g/FA to 4 g/FA and increases to 15 g/FA and 50 g/FA. For the chemical precipitation temperature we only consider an increase to 160◦F. For the chemical bump up factor we modify the parameters of the truncated exponential distribution for large breaks from (2, 1.24) to (3, 1.30) and we make analogous modifications to the distributions for small- and medium-sized breaks. For the time to turn off one spray pump, we shift the mean of the associated normal random variable for large breaks from 9.35 ft to 10.30 ft. The parameters of the uniform distribution for the water volume in the pool under larger breaks are changed in our sensitivity study to 39,478 and 63,540 ft$^3$.

4.5 Step 5: Estimating Nominal Model Outputs

Table 1 presents the results from running our coupled CASA Grande-PRA model with all input parameters set at their nominal values, along with estimates of sampling error. We see the point estimate of risk in terms of ∆CDF (events/CY) is 1.565E-08, with lower and upper 95% confidence limits of 1.401E-08 and 1.729E-08, respectively. If we take 1.00E-06 as a threshold of interest then our estimate is not close to this threshold when all input parameters are set to their nominal values. These results are conditional on the most likely plant figuration in which all pumps on all three trains are available.

| TABLE 1: Results with all input parameters set to their nominal values. The first column is ∆CDF in units of events/CY while the remaining columns characterize the sampling error. |
|---|---|---|---|---|---|
| Risk | 95% CI | 95% CI | 95% CI | CI HW % |
| Risk | Half-Width | Lower Limit | Upper Limit | of Mean |
| Mean | 1.565E-08 | 1.641E-09 | 1.401E-08 | 1.729E-08 | 10.49% |

4.6 Step 6: Tornado Diagrams and Sensitivity Plots

From steps 1-4, we have specified a model, restricted attention to key model outputs and inputs, and specified nominal values and ranges for the model inputs. From step 5, we have point estimates, and estimates of sampling error, associated with the model’s outputs under the nominal input parameters. In the rest of Section 4 we describe a framework for a sensitivity analysis drawing on different tools from the literature. Section 5 provides preliminary results for STP’s GSI-191 analysis using both tornado diagrams and an illustrative sensitivity plot.

We use tornado diagrams as an initial tool for identifying the input parameters to which the simulation’s outputs are most sensitive. A sensitivity plot allows for further characterization of sensitivities by capturing nonlinear responses in outputs to changes in inputs. Sensitivity plots restrict attention to one or two model outputs at a time and consider a single input parameter. Tornado diagrams restrict attention to one model output at a time and consider multiple inputs. We follow Clemen and Reilly [3] in referring to sensitivity plots and tornado diagrams as one-way sensitivity analysis because we vary one input parameter at a time, holding all other inputs at their nominal values.

4.7 Step 7: Uncertainty Quantification Plots

An important part of uncertainty quantification (UQ), which distinguishes it from routine sensitivity analysis, concerns propagating a probability distribution on one or more input parameters through the nonlinear function represented by a simulation model and characterizing the resulting probability distribution on an output. We call a graphical plot of the resulting probability distribution a UQ plot. This idea is closely related to the sensitivity plots we form in step 6, except that we now represent information associated with the probability distribution placed on the input parameters.

For a sensitivity plot, the y-axis is the output parameter, the x-axis is the input parameter, and we typically use a uniform grid over the range of the input parameter values. A UQ plot shows a sampling-based estimate of the cumulative distribution function of the output measure, where the x-axis contains levels of the output measure, and the y-axis contains probabilities.

4.8 Step 8: Spider Plots

A spider plot is an x-y graph, in which the x-axis depicts changes in the input parameters and the y-axis captures corresponding changes in the model’s output measure. Like a tornado diagram, a spider plot involves multiple input parameters and a single output variable. The output variable is typically expressed in its natural units. In order to allow the x-axis to simultaneously represent multiple input parameters, which are on different scales with different units, there are two possibilities. One possibility is to express percentage changes in the input parameters from their nominal values. The second possibility is to express changes as multiples of the standard deviation of the input parameters, when those input parameters are governed by probability distributions. In either case, the magnitude we vary the parameters is determined by the ranges we specified in step 4.
A tornado diagram can include a larger number of input variables than a spider plot. A spider plot allows displaying about seven input parameters before it comes cluttered. For a tornado diagram, if the output variable is increasing or decreasing in an input parameter then we only need to estimate the model’s output at the lower bound, nominal value, and upper bound of the input parameter. A spider plot requires estimating the model’s output at enough values of each input parameter that a seemingly continuous plot of \((x, y)\) pairs can be formed. A spider plot contains more information than a tornado diagram. The tornado diagram’s endpoints denote the endpoints of the spider plot, but the spider plot also specifies changes in the output at intermediate values, as does a sensitivity plot. Again like a sensitivity plot, we can assess whether changes in the output are linear or nonlinear with respect to changes in the input. See Eschenbach [6] for a discussion of the relative merits of sensitivity plots and spider plots.

4.9 Step 9: Two-way Sensitivity Analysis

Two-way sensitivity graphs allow for visualizing the interaction of two or more input variables. Two-way sensitivity analyses extend to include multiple decision alternatives, and in such cases the plots typically partition the space into three or more regions in which each alternative is preferred.

4.10 Step 10: Metamodels & Design of Experiments

The possible pitfalls of changing only one input parameter at a time are well documented in the literature (see, e.g., [8, 10]) and include the fact that interaction effects between input parameters are lost. Graphical sensitivity analyses become more difficult when moving past a one- or two-dimensional analysis, but we can form a metamodel (which is also called a response surface, an emulator, or a surrogate model) and carry out an experimental design to fit that metamodel.

4.11 Further Discussion

Perhaps the foremost caveat in performing a one-way sensitivity analysis is to assess whether it makes sense to vary input parameters one at a time. If two or more inputs depend on an unstated auxiliary factor, this may not be valid. Another caveat in our one-at-a-time sensitivity analysis concerns the notion that all input parameters take their nominal values except for one. This can mask the effect of “cross terms.” The level of one input variable departing from its nominal value may amplify the effect of changes in another input variable. The purpose of the metamodel analysis in step 10 is to unmask such interactions.

Whether done by a formal expert elicitation or an informal scheme, the nominal values of the parameters and their ranges are typically based on expert opinion and hence subject to well-known biases related to anchoring, over confidence, etc. Particularly relevant for GSI-191 analysis are difficulties in assessing rare-event probabilities; see Tversky and Kahneman [22] and O’Hagan et al. [17], and also see Kynn [11].

Model uncertainty is an often neglected part of sensitivity analysis. A simple form of model uncertainty concerns the distributional assumption on input parameters. Hypothesizing competing models for an underlying phenomenon and understanding the domain of applicability of such models is, of course, central to scientific investigation.

5 Sensitivity Analysis Results for STP

We present preliminary sensitivity results for STP’s GSI-191 analysis via a tornado diagram and a one-way sensitivity plot. Again, the results we present are conditional on all pumps working in all three trains. Our tornado diagram corresponds to changing the 14 inputs we detail in Section 4.4. A one-way sensitivity plot focuses on the boron fiber limit.

Because the core damage frequencies we estimate are small, we present the tornado diagram and one-way sensitivity plot for ratios on a logarithmic scale. Figure 4 is a tornado diagram for the 14 input parameters we varied for this sensitivity study. If the ratio has value 10, it means that the point estimate of the ∆CDF under the perturbed scenario is 10 times greater than that under the nominal scenario. Below we discuss four inputs to which the estimate of ∆CDF seems to have the greatest sensitivity.

From Figure 4 we see that the boron fiber limit appears to be the input to which our estimate of ∆CDF is most sensitive. Increasing the limit from its nominal value of 7.5 g/FA decreases the ∆CDF because under a larger limit, more fiber can penetrate the strainer without the simulation model declaring a failure. Increasing the limit from 7.5 g/FA to 15.0 g/FA decreases ∆CDF by about 27%. Increasing the value further to 50.0 g/FA leads to little further decrease in ∆CDF. Decreasing the value from 7.5 g/FA to 4.0 g/FA increases the point estimate of ∆CDF to 1.45E-06, larger than the nominal estimate by a factor of 93.

The tornado diagram suggests the next perturbation to which the estimate of ∆CDF is most sensitive involves changing the filtration function to its lower envelope from the estimates provided in [16]. The filtration function affects how much fiber penetrates the strainer. Modifying the function so that less mass is filtered means that more mass penetrates, and hence, we anticipate this will increase ∆CDF. At this lower envelope, the ∆CDF estimate increases by a factor of 8.5 to 1.34E-07.

The transport fractions for debris inside the ZOI governs the amount of each type of debris transported to the sump. With smaller transport fractions, the estimated ∆CDF should decrease because less debris reaches the strainer, and larger transport fractions should have the opposite effect. Under our perturbation to smaller transport fractions, the point estimate of ∆CDF decreases by about 32% to 1.07E-08, and with more debris transported to the strainer the ∆CDF estimate grows by 334% to 6.8E-08.
Next, we examine the effect of the size of the ZOI. We regard our nominal estimates of the ZOI size as conservative (larger ZOI than expected), and so we examine the result of reducing the size of the ZOI. A smaller ZOI means less debris will be generated, which should reduce ΔCDF. Reducing the size of the ZOI decreases ΔCDF by about 63% to 5.85E-09.

Given the significant effect of the boron fiber limit on the ΔCDF estimate, we explore this sensitivity further via a one-way sensitivity plot in Figure 5. We again present the ratio of the ΔCDF estimate for each input value to the ΔCDF estimate at the nominal value of 7.5 g/FA, and we present these ratios on a log scale. We employ common random numbers in the simulation runs across these different fiber limit values. From Figure 5 we see there is little change in the ΔCDF estimate as the fiber limit ranges from 6.5 g/FA to 8.5 g/FA. However, the ΔCDF estimate grows quickly as we decrease the fiber limit from 6.5 g/FA.

6 Conclusions and Emerging Sensitivity Tools

We have sketched a 10-step sensitivity analysis procedure that we see as practical for large-scale computer simulation models. To our knowledge, while the framework we propose relies on the literatures from decision analysis, econometrics, statistics, and simulation, the approach is new in the GSI-191 setting and more generally in risk analysis in commercial nuclear power.

A number of important themes repeat throughout our recommendations. These include the use of common random numbers in order to reduce variability and smooth output analysis. We have also focused on assessing differences in input parameters that make a difference in decisions or qualitative characterizations of the system at hand. The relevant ideas we have discussed in this regard include threshold analyses, indifference zones, and establishing dominance relations. Sensitivity analysis simplifies significantly when using deterministic simulation models. However, our simulations are stochastic and hence proper characterization of both sampling error and uncertainties on input parameters has been a pervasive theme in our presentation.

Our discussion is by no means comprehensive for sensitivity analysis of computer simulation models. For example, there is significant work on local sensitivity analysis. Specifically, with \( f(x_1, x_2, \ldots, x_n) \) denoting a single output measure from our simulation model, we could estimate the gradient \( \nabla_x f(x_1, \ldots, x_n) = \left( \frac{\partial f}{\partial x_1}, \ldots, \frac{\partial f}{\partial x_n} \right) \). Local sensitivity analysis is of particular interest when attempting to optimize \( f \), but that is not our focus here. More importantly, if we simply report estimates of the partial derivatives \( \frac{\partial f}{\partial x_i} \), \( i = 1, \ldots, n \), this can mislead with respect to what input parameters are most important because: (i) a per unit change in the temperature of water at a sump pump may not be commensurate with a per gram/fuel-assembly change in debris mass having penetrated the strainer and (ii) even if we compute \( \frac{\partial f}{\partial x_i} \Delta x_i \) for commensurate values of \( \Delta x_i \), a linear approximation may be poor over the range of parameters of interest.

It is for the reasons just discussed that we advocate the global sensitivity analysis that we have proposed in steps 4-10 of Section 4. Here, the notion of “global” is specified by the analyst via ranges associated with the input parameters. These play a central role in sensitivity plots, tornado diagrams, spider plots,
and the experimental designs associated with regression metamodels. Such analyses need not associate a probably distribution with the input parameters. However, in our view it is preferable when such probability distributions can be specified because we can make use of them in UQ plots, and in our other sensitivity analyses, too. In such cases the specific endpoints of the ranges become less important.

We have recommended using tornado diagrams as an initial tool for assessing the most important input parameters, and using sensitivity plots, UQ plots, spider plots, and metamodels to enable a richer exploration of model sensitivity. It is possible to employ more sophisticated statistical schemes for screening factors using metamodels [27], including sequential bifurcation screening [26]. However, even when such schemes are advocated, it is acknowledged that such approaches have yet to see significant application in practice [9]. Originally developed for interpolation in geostatistical and spatial sampling, Kriging (see, e.g., [5, 19, 20]) has seen widespread successful application in the context of deterministic simulation models as an alternative to regression metamodels. More recently, Kriging metamodels have begun to see application to stochastic simulation models; see, e.g., [1, 7, 2]. While these approaches are a promising alternative to regression metamodels, there are a number of outstanding research issues that remain to be solved [9].

REFERENCES


