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Robustness of RISMC Insights under Alternative Aleatory/Epistemic Uncertainty Classifications

Draft Report under the Risk-Informed Safety Margin Characterization (RISMC) Pathway of the DOE Light Water Reactor Sustainability Program

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September 2012

Pacific Northwest
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ABSTRACT

The Risk-Informed Safety Margin Characterization (RISMC) pathway is a set of activities defined under the U.S. Department of Energy (DOE) Light Water Reactor Sustainability Program. The overarching objective of RISMC is to support plant life-extension decision-making by providing a state-of-knowledge characterization of safety margins in key systems, structures, and components (SSCs). A technical challenge at the core of this effort is to establish the conceptual and technical feasibility of analyzing safety margin in a risk-informed way, which, unlike conventionally defined deterministic margin analysis, would be founded on probabilistic characterizations of uncertainty in SSC performance.

In the context of probabilistic risk assessment (PRA) technology, there has arisen a general consensus about the distinctive roles of two types of uncertainty: aleatory and epistemic, where the former represents irreducible, random variability inherent in a system, whereas the latter represents a state of knowledge uncertainty on the part of the analyst about the system which is, in principle, reducible through further research. While there is often some ambiguity about how any one contributing uncertainty in an analysis should be classified, there has nevertheless emerged a broad consensus on the meanings of these uncertainty types in the PRA setting. However, while RISMC methodology shares some features with conventional PRA, it will nevertheless be a distinctive methodology set. Therefore, the paradigms for classification of uncertainty in the PRA setting may not fully port to the RISMC environment. Yet the notion of risk-informed margin is based on the characterization of uncertainty, and it is therefore critical to establish a common understanding of uncertainty in the RISMC setting.

The RISMC framework contrasts sharply with the PRA structure in that the underlying models are not inherently aleatory. Rather, they are largely deterministic physical/engineering models. However, there are uncertainties associated with appropriate quantification of many of the model input parameters. The current RISMC paradigm for uncertainty quantification is to adopt the criteria by which epistemic and aleatory uncertainties are distinguished in PRAs (irreducibility, whether the source is random variability, etc.) as the basis for classifying input parameter uncertainties. However, since the underlying structure of RISMC is deterministic and not aleatory, and (almost) all input parameters are purely deterministic, judging whether a given input uncertainty should be viewed as aleatory or deterministic presents more of a challenge. Note that this ambiguity is a well-recognized issue, even in the context of conventional PRA. However, a viewpoint sometimes expressed is that if this ambiguity does not affect the insights from a study relevant to decision-making, then it is unimportant. Our intent in this report is to assess the robustness of study insights to alternative categorizations of uncertainty – addressing the question "does it *matter* whether an uncertainty is categorized as epistemic versus aleatory?" The underlying physical model used in this demonstration analysis is one that has been developed for integration into the RISMC suite: a model to assess the failure pressure of dissimilar metal welds subject to stress corrosion cracking.

A two-loop Monte Carlo approach was used to propagate input probability distributions through the physical model: an inner loop for aleatory uncertainties and an outer loop for epistemic uncertainties. Then, a series of model output forms was developed, each hypothesized to provide insight to a decision-maker. The robustness of the model output forms was assessed under variations in the categorization (epistemic versus aleatory) of input uncertainties. The output forms were:

- **Hybrid**: This approach lumps together all the calculated rupture pressure realizations. That is, all Monte Carlo realizations of failure pressure are pooled (without distinction between epistemic and aleatory sources), and this pool is the basis for defining the *hybrid* output probability distributions. The premise for this form is that the decision-maker is indifferent to the categorization of uncertainties.

- **Epistemic Distribution of Aleatory Means**: In this approach, the mean of the rupture pressure is calculated over all aleatory realizations for each epistemic realization. This results in an epistemic probability distribution over aleatory means. The premise here is that aleatory means are of interest to the decision maker, acknowledging epistemic uncertainty in those means.

- **Epistemic Distribution of Aleatory Percentiles**: In this output, percentiles of the rupture pressure are calculated over the aleatory sample for each epistemic realization. This approach results in an epistemic probability distribution over a chosen aleatory percentile. The premise here is that a prospective basis for a conservative decision is, say, consideration of the aleatory 5^{th} percentile of failure pressure, albeit subject to epistemic uncertainty.

- **Multiple Epistemic Sets**: In this approach, the variability in calculated rupture pressure is shown as a scatter plot over all aleatory realizations for a several epistemic realizations. The premise is that this gives a strong visualization of the scatter associated with epistemic versus aleatory uncertainty.

The conclusion reached from this limited analysis is that if the distinction between epistemic and aleatory uncertainties is to be preserved in a RISMC-like modeling environment, then it is unlikely that analysis insights supporting decision-making will in general be robust under recategorization of input uncertainties. That is, if it is believed that there is a true conceptual distinction between the two uncertainty types (as opposed to the distinction being primarily a legacy of the PRA paradigm), then more consistent and defensible bases may need to be established for categorizing input uncertainties.

Contents

1.0 Introduction

The Risk-Informed Safety Margin Characterization (RISMC) pathway is a set of activities defined under the U.S. Department of Energy (DOE) Light Water Reactor Sustainability Program [1]. The overarching objective of RISMC is to support plant life-extension decision-making by providing a state-of-knowledge characterization of safety margins in key systems, structures, and components (SSCs). A technical challenge at the core of this effort is to establish the conceptual and technical feasibility of analyzing safety margin in a risk-informed way, which, unlike conventionally defined deterministic margin analysis, would be founded on probabilistic characterizations of SSC performance. The anticipation is that evaluation of probabilistic safety margins will in general entail the uncertainty characterization both of the prospective challenge to the performance of an SSC (“load”) and of its “capacity” to withstand that challenge. These two uncertainty characterizations are represented conceptually in Figure 1-1 without attempting to quantify acceptable ranges of either load or capacity.

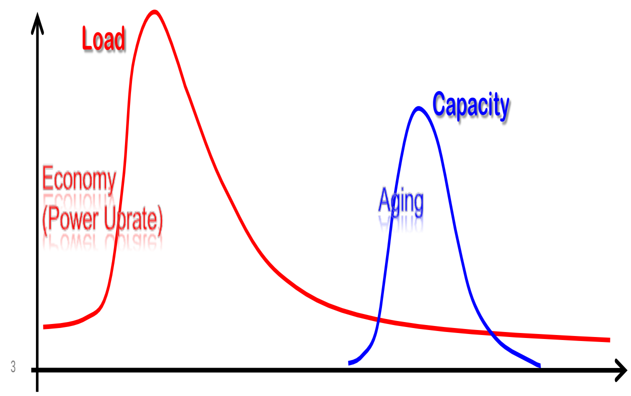

Figure 1-1: Probability Densities Representing Probabilistic Margins (Power uprates and aging are factors that may shift the curves)

There is a substantial history to the treatment of uncertainty in the context of probabilistic risk assessment (PRA). From this history has emerged some consensus on the varieties of uncertainty that pertain to the evaluation of risk, on the conceptual distinctions between these varieties, and on the differing means of treatment in an analytical and computational setting. Perhaps still the most recent suite of PRAs to have systematically distinguished and extensively modeled the varieties of uncertainty was the NUREG-1150 study [2]. Within these PRAs can be seen the distinctive roles of epistemic and aleatory uncertainties. While there can often remain some ambiguity about how any one contributing uncertainty in an analysis should be classified, there has nevertheless emerged a broad, general consensus on the meanings of these uncertainty types in the PRA setting.

However, while RISMC methodology shares some features with conventional PRA, it will nevertheless be a distinctive methodology set. Therefore, the paradigms for classification of uncertainty in the PRA setting may not fully port to the RISMC environment. Yet the notion of risk-informed margin is based on the characterization of uncertainty, and it is therefore critical to establish a common understanding of uncertainty in the RISMC setting.

This report is not intended to be a comprehensive review of the distinctive natures and interpretations of epistemic and aleatory uncertainties - such reviews already exist [3, 4]. Rather, the intents are (1) to consider how the RISMC modeling environment differs from that of a conventional PRA and outline what issues this difference may introduce in distinguishing epistemic from aleatory uncertainties, and (2) to consider the range of uncertainties associated with a demonstration model, and assess the impact on the model outputs and insights of reclassifying those uncertainties with regard to the epistemic and aleatory categories. This analysis is intended to provide one basis for determining the robustness of model insights under varying uncertainty classifications. This issue is key, particularly where there exists ambiguity in the appropriate classification of uncertainties.

1.1 RISMC Environment

The methodology paradigm being developed under the RISMC pathway is not a conventional PRA-based one. Rather, it is based on a reactor systems simulation framework in which physical conditions of normal reactor operations, as well as accident environments, are explicitly modeled subject to uncertainty characterization. The platform being developed under RISMC to model the thermal hydraulic and neutronics environments in which SSCs operate is RELAP7 [1]. Parallel to and interacting with RELAP7, other codes will model the general simulation control environment, characterizing, for instance, operator performance, plant control systems, and SSC performance. Figure 1-2 shows a simplified representation of this analysis framework, focusing on SSC performance (which is relevant to the demonstration analysis to be reported here).

The component models being developed for RISMC are not conventional component reliability models. In the current paradigm, component reliability must be characterized in the context of the physical environments that RELAP7 predicts. Conventional reliability models are parametric and rely on the statistical analysis of service data. Reliability models in the RISMC context must be physics-based and driven by the physical boundary conditions RELAP7 predicts, thus allowing full integration of passive models into the multi-physics environment (see Figure 1-2). We use a passive component performance model developed specifically for RISMC integration to demonstrate the distinctive nature of epistemic and aleatory uncertainties.

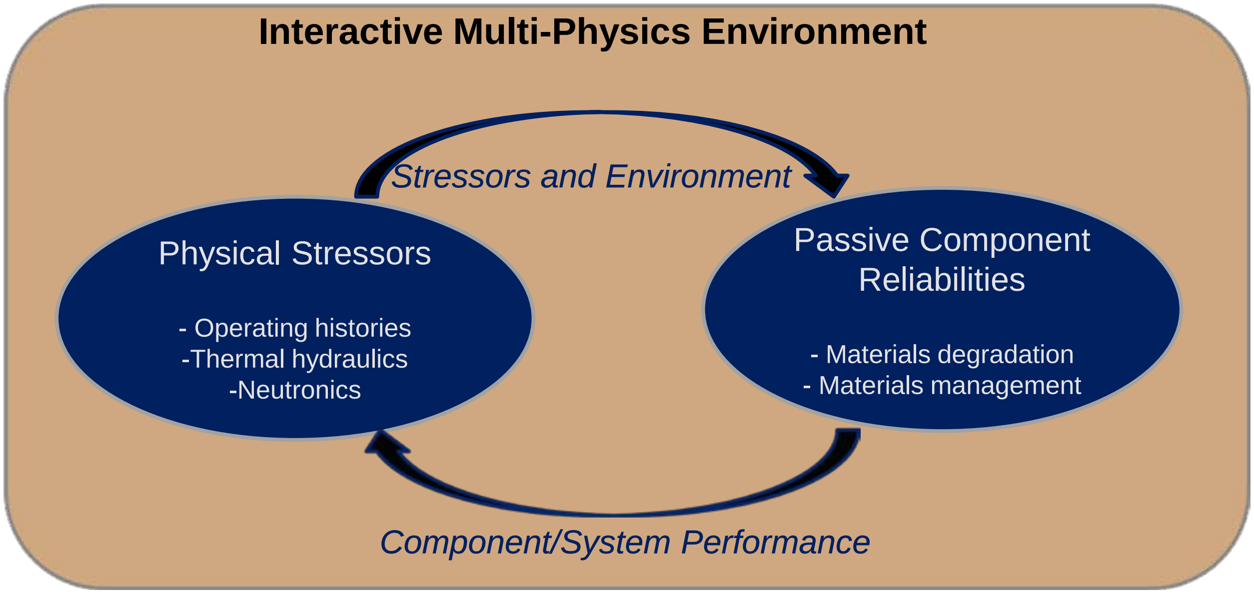

Figure 1-2: RISMC Component Modeling Environment

1.2 Report Guide

Section 2.0 of this report is a brief overview of the conventional natures of aleatory and epistemic uncertainties and the way in which they will be modeled in the RISMC environment. Section 3.0 establishes a demonstration problem focusing on the performance of a selected passive component. Section 4.0 establishes the alternative ways in which uncertainties associated with the component model could be interpreted. Section 5.0 presents the contrasting insights from the alternative uncertainty classifications. Finally, Section 6.0 presents conclusions on the robustness of insights.

2.0 Uncertainty Types

While there can be numerous bases for uncertainty taxonomies, including their technical source (model parameter input values versus model accuracy versus model completeness) and their domain source (physical/engineering contributors versus social/human contributors versus economic contributors), the taxonomy considered here is a fundamental one that is generally considered to be independent of the application domain or the specifics of an analytical approach: namely the assignment of aleatory versus epistemic uncertainty. The implications are extremely practical since, in the setting of a PRA, aleatory and epistemic uncertainties are treated in computationally distinctive ways.

2.1 Aleatory versus Epistemic Uncertainty

This classification of uncertainty is applied in numerous modeling domains [3, 5, 4, 6]. Aleatory uncertainty, sometimes referred to as stochastic or random uncertainty, is that which is (as a practical matter) inherent in the system under study. This uncertainty is considered to be an attribute of the system itself and cannot be narrowed through increased knowledge on the part of the analyst. Aleatory *variability* is perhaps a more suitable term since this form of uncertainty reflects the random variability in the attributes of a system, such as the random variations between the performance of equivalent engineered systems or between physical properties of materials and components. Given that this source of uncertainty is considered to be inherent in the random variability associated with the class of components to which the subject component belongs, and/or the random variability in the conditions to which it is exposed, it is often characterized as an *irreducible* uncertainty.

In contrast, epistemic uncertainty reflects a state of limited knowledge about the system on the part of the analyst. Epistemic uncertainty can, in principle, be narrowed or eliminated through acquisition by the analyst of additional information. For example, the value of a physical parameter (that has a precise, objective, but unknown value) entering a model can be subject to epistemic uncertainty.

As in many taxonomies, the line between these two varieties of uncertainty is not a bright one. As a practical matter, it could be argued that the uncertainty that is ultimately experienced by the analyst or decision maker has the same practical implications regardless of whether it is irreducible and inherent in the system or it stems from limited knowledge. Furthermore, the notion of *irreducible* uncertainty (at least outside the quantum domain) is more one of practicality than of principle. The characterization of these two types of uncertainty, in a mathematical sense, is often similar also. Probabilities, interpreted in a classical frequentist sense, provide a natural framework in which to accommodate stochastic/aleatory uncertainty. While non-probabilistic approaches to characterizing epistemic uncertainty have been proposed and sometimes adopted [7-11], probability theory (interpreted in a Bayesian rather than frequentist sense) remains the most widely applied framework for modeling epistemic uncertainty. In the following subsection, the practical, modeling implications of these distinctions are outlined.

2.2 Implementation: PRA versus RISMC

PRA has its conceptual roots in reliability theory and the probabilistic modeling of component performance. A parameter that typically appears in a PRA or reliability model is the probability that a component fails to function on demand, p. The conceptual framework for interpretation of such a probability is to envision a large population of equivalent components on each of which a large set of equivalent demands is placed, and p can then be viewed as the fraction of that population that fails on demand (averaged over the set of equivalent demands). That is, p, representing the probability that the component of interest is among the failed fraction, reflects an aleatory probability of failure. In some sense, p is an objective measure since, in principle, such a population of components and demand conditions could be assembled and p determined. It could also be considered an irreducible measure of uncertainty in the performance of the component in that it reflects random variation inherent in the component class to which it belongs.

Now, in a practical setting, there is uncertainty about the value of p. While, in principle, a limited data set would allow confidence intervals to be formed on the value of p using classical statistical methods, practical considerations (revolving around sparseness of data and the feasibility of uncertainty propagation) have led to the common use of Bayesian methodology to characterize the uncertainty in p. This uncertainty about p is considered to be “state of knowledge” or epistemic uncertainty, since collection of more operating data can often be used to reduce the uncertainty.

Figure 2-1 shows the means by which we can represent epistemic uncertainty about the value of p, which itself represents aleatory uncertainty about the response of the component. That is, we can define an (epistemic) probability distribution that reflects uncertainty about the value of a parameter that represents aleatory uncertainty in the component response. Since aleatory probabilities are, in principle, objective measures with unique but unknown magnitudes, it is considered conceptually acceptable to characterize uncertainty in these measures.

So, while both forms of uncertainty are characterized probabilistically, their entry into a PRA model is quite distinctive, with a model output that is typically an epistemic uncertainty distribution over an aleatory core damage frequency. On a terminology note, since PRAs, like reliability studies, are inherently aleatory in their underlying structure, uncertainty analysis in the context of a PRA refers to a study in which the epistemic uncertainties are modeled. That is, a PRA that models aleatory uncertainties only would not be considered a study that includes uncertainty analysis. Restated, the "P" in PRA refers to the underlying probabilistic aleatory structure, and not to the overlay of probabilistic epistemic uncertainty.

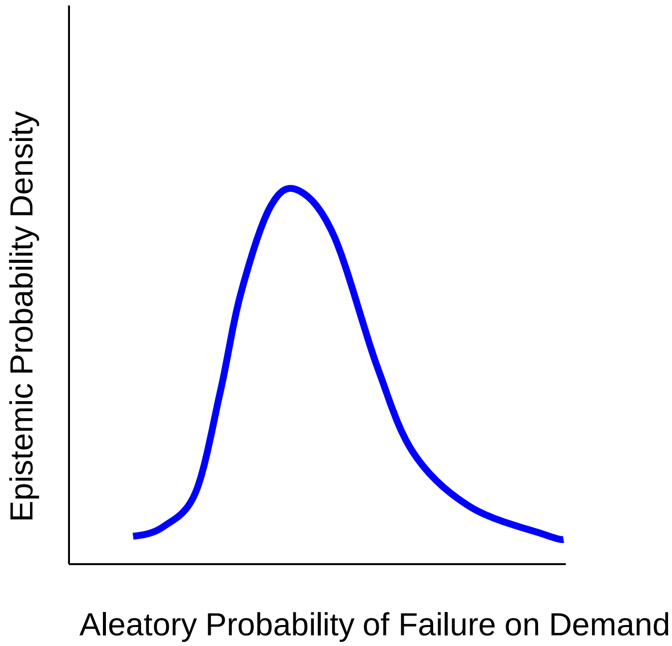

Figure 2-1: Epistemic Uncertainty about Aleatory Uncertainty in PRA

The RISMC framework contrasts sharply with the PRA structure in that the underlying models are not inherently aleatory. Rather, they are largely deterministic physical/engineering models. However, there are uncertainties associated with appropriate quantification of many of the models input parameters. The current RISMC paradigm for uncertainty quantification is to adopt the criteria by which epistemic and aleatory uncertainties are distinguished in PRAs (irreducibility, whether the source is random variability, etc.) as the basis for classifying input parameter uncertainties. However, since the underlying structure of RISMC is deterministic and not aleatory, and (almost) all input parameters are purely deterministic, judging whether a given input uncertainty should be viewed as aleatory or deterministic presents more of a challenge. So, while PRAs are not free of ambiguity and difficult judgments in classifying uncertainties (particularly in the *back-end* where severe accident phenomenology is modeled), the challenge is exacerbated considerably in the RISMC context where PRA uncertainty conventions and precedents on which we often rely are not transferable. Furthermore, the issue of uncertainty classification may be particularly important in the RISMC context where the meaning of margins (see Figure 1-1) pivots on the meaning of the probabilities that characterize them.

To preserve the uncertainty classes under input/output propagation, the current RISMC framework requires a two-tier Monte Carlo process (see Figure 2-2). Uncertainties assessed to be aleatory will be propagated through the model using a Monte Carlo sample of input parameter realizations generated from the input aleatory probability distributions. The epistemic sampling will occur in an outer Monte Carlo loop. That is, a complete aleatory sample (of appropriate size) is propagated through the deterministic model for each single member of the outer epistemic sample. Reiterated, a single epistemic Monte Carlo realization generates a set of input aleatory distributions from which an input sample of parameter values is generated. This allows, for example, two parameters defining an aleatory input distribution (say, mean and variance) to themselves be subject to epistemic uncertainty.

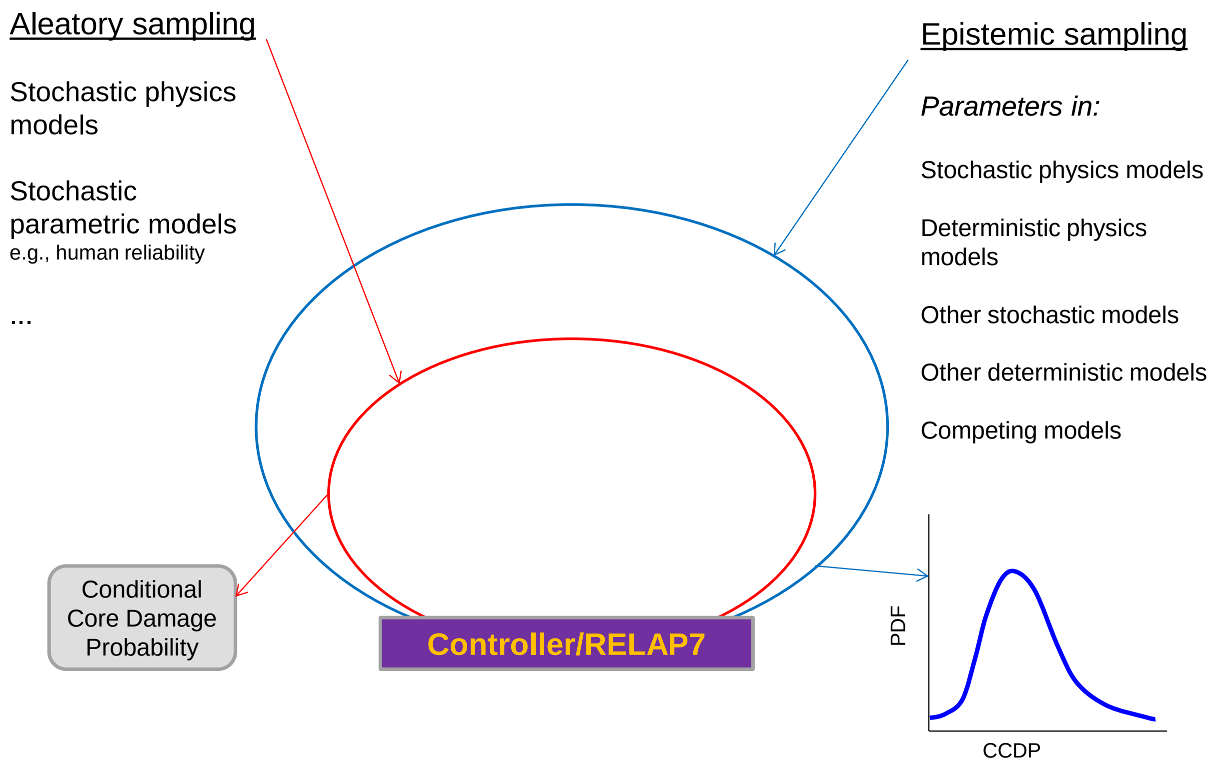

Figure 2-2: Two-Tier Monte Carlo Process in RISMC for Propagating Epistemic and Aleatory Uncertainties

The intent of this report is not to establish the principles by which a RISMC input uncertainty is categorized; rather, it is to assess the extent to which the insights from an analysis are sensitive to the choice in uncertainty classification. Furthermore, we wish to determine which analysis insights are the most robust given ambiguity in the appropriate categorization of uncertainties. Note that this ambiguity is a well-recognized issue, even in the context of conventional PRA. However, a viewpoint sometimes expressed is that if this ambiguity does not affect the insights from a study, then it is unimportant [4, 12]. In this report, we assess the robustness of insights in the context of a demonstration model being developed to support RISMC.

3.0 Demonstration Problem

Multistate, physics-based models of passive component reliability are currently being developed for integration into the RELAP7/RISMC modeling environment [13-15]. A simplified version of a model has been chosen as the basis for a demonstration analysis of alternative uncertainty classifications. The simplified model is outlined in the following subsection.

3.1 Physical Mechanisms and Models

A model of primary water stress corrosion cracking of reactor coolant system Alloy 82/182 dissimilar metal welds is selected for analysis [13]. This is a potentially risk-significant degradation mechanism in Class 1 piping because of its relevance to loss of coolant accidents. Alloy 82/182 welds are found in several key locations in Class 1 piping structures such as the vessel reactor coolant pipe welds and pressurizer surge line pipe welds. This latter location is our analysis case. Figure 3-1 shows a Westinghouse surge line nozzle with an Alloy 182 weld joining the stainless steel safe end to the low alloy steel nozzle. Cracks that form in these structures will grow from inner to outer diameter with one of two principal morphologies. In the first of these the crack tends to grow primarily outward from the initiation site towards the outer diameter - a radial crack. In the second, the crack grows relatively evenly around the circumference, potentially resulting in a stress corrosion crack that can transition to rupture before a leak is detected - a circumferential crack [16].

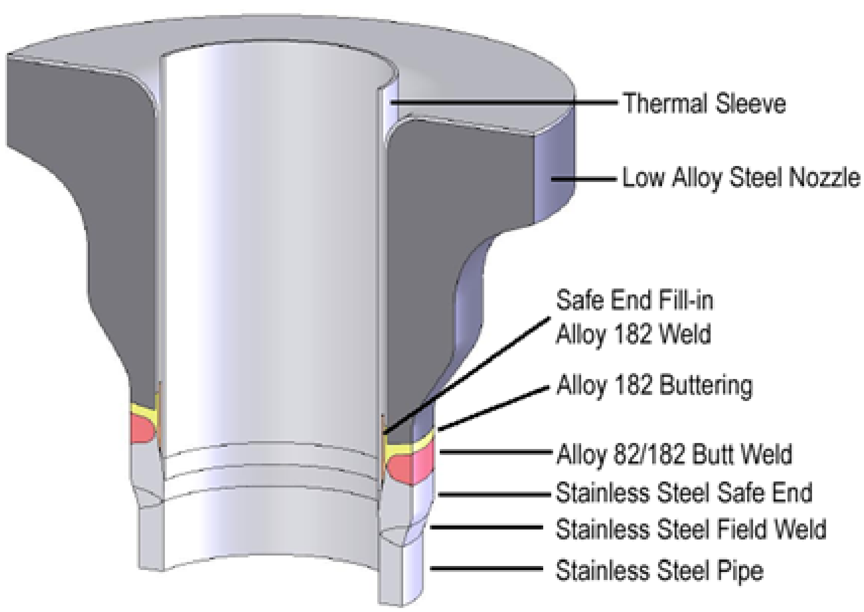

Figure 3-1: Layout of a Westinghouse PWR surge line nozzle connection to the pressurizer (Courtesy of Westinghouse).

Stress corrosion cracking is considered in Alloy 82/182 to be a two-step process consisting of (1) crack initiation, followed by (2) crack propagation. Similar to other nucleation and growth phenomena, stress corrosion cracking is generally modeled as, first, a nucleation step governed by statistical (aleatory) processes, and then as crack growth that has a more deterministic basis.

In the current simplified model, the vulnerability of the pipe weld to rupture (or its capacity, as generically represented in Figure 1-1) is measured by its failure pressure, which is a function of the depth of the crack. The following sections provide the models for crack initiation, crack growth and rupture pressure.

3.1.1 Crack Initiation

The probability of nucleation is governed both by the presence of pre-existing surface flaws in the material and the rate of formation of surface flaws due to the environment. The Weibull distribution is the most common framework for quantifying stress corrosion cracking initiation probability [17-20]. In the Weibull model, the cumulative probability, *F(t)*, of crack initiation by time *t* is given by:

$$F(t) = 1 - e^{\left[-(t/\eta_I)^{\gamma}\right]} \qquad (3.1)$$

where

- η_I is the Weibull scale parameter for crack initiation time (years)
- γ is the Weibull shape parameter.

The time constant (η_I) has been observed to have both stress and temperature dependence and can be expressed as

$$\eta_I = A\sigma^n e^{\left(\frac{Q_I}{RT}\right)} \qquad (3.2)$$

where

- A is a fitting parameter with material and environmental dependences. The units of A are such that the product $A\sigma^n$ has units of years.
- σ is the applied tensile stress (MPa)
- n is the stress exponent (unitless)
- Q_I is the activation energy for crack initiation (kJ/mole)
- T is the operating temperature (K)
- R is the universal gas constant (kJ/mole-K).

The applied tensile stress (σ) in the crack initiation model is implemented as the sum of four stress components: pipe pressure stress, pipe bending stress, pipe deadweight and thermal stress and the weld residual stress σ_R.

3.1.2 Crack Growth

A stress corrosion cracking rate equation reported by several authors [21, 22, 20, 23] is used, which is based on phenomenological models and the fitting of crack growth data:

$$\dot{\alpha} = \varepsilon\, f_{alloy}\, f_{orient}\, K^{\beta}\, e^{\left[-\left(\frac{Q_G}{R}\right)\left(T^{-1}-T_{ref}^{-1}\right)\right]} \tag{3.3}$$

where

$\dot{\alpha}$	is the crack growth rate (m/s)
ε	is the crack growth amplitude fitting constant
T	is the operating temperature at the crack location (K)
T_{ref}	is the reference temperature (K)
Q_G	is the thermal activation energy for crack growth (kJ/mole)
R	is the universal gas constant (kJ/mole-K)
K	is the crack tip stress intensity factor (MPa√m)
f_{alloy}	is a fitting factor for alloy type (unitless)
f_{orient}	is a fitting factor for crack orientation (unitless)
β	is the stress intensity exponent.

The stress intensity, *K*, is a function of the crack depth and length and the stress distribution through the wall thickness (see Figure 3-2). Stresses in the axial direction are of primary interest for their contribution to growing circumferentially oriented flaws through the thickness of the pipe wall. Axial flaws are of less concern because the flaw length for primary water stress corrosion cracking growth is limited to the width of weld line (i.e., the width of the sensitized weld material). In this figure, *h* is the pipe wall thickness, R_i is the pipe inside radius, *a* is the crack depth and *b* is the crack half-length.

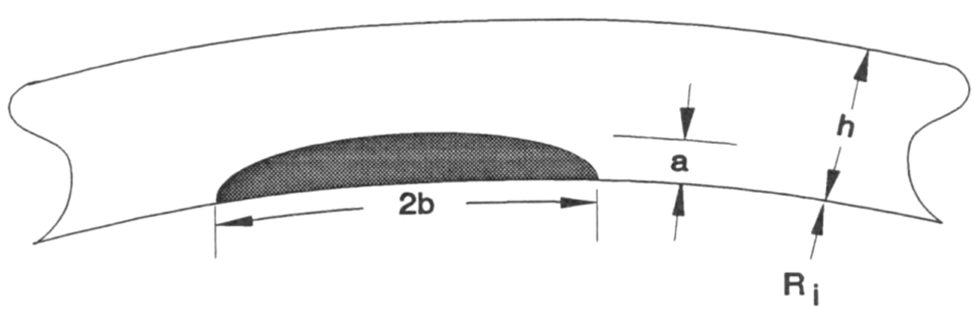

Figure 3-2: The Geometry of a Finite Length, Partial Through-Wall Crack

The through wall stress distribution is the sum of the pressure induced operating stress, thermal and deadweight stresses, and most importantly, the weld residual stress. The weld residual stress is expressed as a third order polynomial with distributions on the inside wall stress (σ_{0WRS} also denoted as σ_R elsewhere in this report), the depth in the wall where the stress reverses sign (x_c), and the stress at the outside of the wall (σ_f) (Figure 3-3).

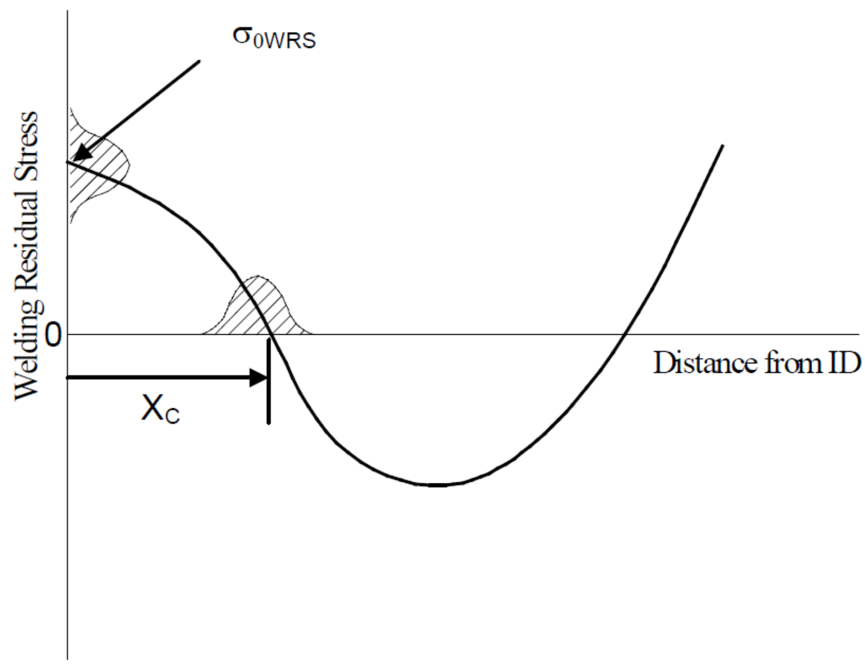

Figure 3-3. 3rd order polynomial, self-equilibrating residual stress distribution (NRC and EPRI, 2011).

The residual stress is a self-equilibrating stress, and therefore, the area under the curve in Figure 3-3 must be zero. The residual stress polynomial (as a function of depth through the pipe) is expressed as:

$$\sigma_{residual} = S_0 + S_1\left(\frac{x}{h}\right) + S_2\left(\frac{x}{h}\right)^2 + S_3\left(\frac{x}{h}\right)^3 \qquad (3.4)$$

where x is the depth in the wall, and h is the wall thickness. The coefficients are calculated as:

$$S_0 = \sigma_0 \qquad (3.5)$$

$$S_1 = \sigma_f - \sigma_0 - S_3 - S_2 \qquad (3.6)$$

$$S_2 = \frac{2(\sigma_0 + \sigma_f)\left(\frac{1}{x_c} - x_c\right) + \left(\frac{\sigma_0 - \sigma_f}{x_c}\right) - \frac{\sigma_0}{x_c^2}}{1 - \frac{2x_c}{3} - \frac{1}{3x_c}} \qquad (3.7)$$

$$S_3 = 2(\sigma_0 + \sigma_f - \frac{S_2}{3}) \tag{3.8}$$

The stress intensity factor, *K*, is then expressed as a function of the stress coefficients plus the applied section moment on the pipe, *M*.

$$K = \left[S_0 G_0 + S_1 G_1 \left(\frac{a}{h}\right) + S_2 G_2 \left(\frac{a}{h}\right)^2 + S_3 G_3 \left(\frac{a}{h}\right)^3 + S_B G_B \right] \frac{\sqrt{\pi a}}{Q}) \tag{3.9}$$

where G_0, G_1, G_2, G_3, G_B are influence functions as calculated by Anderson [24]. S_B and G_B are the global bending stress on the pipe section and the corresponding influence function. The associated variable *Q* accounts for the crack depth to length ratio.

$$Q = 1 + 1.464\left(\frac{a}{b}\right)^{1.65} \tag{3.10}$$

The stress intensity factor solutions as implemented by NRC and EPRI [25] were used in the calculations of this report.

3.1.3 Rupture Pressure

The pipe rupture model estimates the weld failure pressure as a function of crack size, crack morphology and material properties. A modified version of the Battelle model [13] is adopted. The rupture pressure, P_f, is estimated as

$$P_f = \frac{4\sigma_f h}{H}(1 - \frac{a}{h}M) \quad \text{where} \quad M = 1 - e^{\left[-0.157\frac{b}{\sqrt{H(h-a)/2}}\right]} \tag{3.11}$$

where

h	is the pipe wall thickness (m)
H	is the pipe diameter (m)
σ_f	is the material flow stress (MPa)
a	is the crack depth
b	is the crack half-length (m).

The capacity parameter of interest will be the rupture pressure of the potentially cracked weld at a specified age, such as 60 years. This demonstration model is a simplified form of the component model developed for RISMC (which also addresses leaks before break and intervention actions [13]), but it provides a basis for assessing the impact of alternative uncertainty classifications.

3.2 Calculation Methods

As described in section 2.2, the current calculations utilize a two-tier Monte Carlo process. Sampling of epistemic variables occurs in the outer loop and sampling for aleatory variables occurs in the inner loop. Thus, a complete aleatory sample is propagated through the deterministic model for each single member of the outer epistemic sample.

A new computer code was written for this analysis, but the new code incorporates many existing software routines. In essence, the new code wrapped existing routines into a coherent sampling and analysis framework. The statistical sampling routines have been used on other projects [26]. Routines to solve the stress intensity solutions came from other published work [27, 24]. Routines to solve the crack growth equation (equation 3.3) originated from work on another PNNL task.

The conceptual flow of the statistical sampling (see Figure 2-2) and the calculation of the effect of cracks on rupture pressure uses the following steps:

- Generate all epistemic random variables
- Loop on epistemic realizations
    - Generate all aleatory random variables for this epistemic realization
    - Loop on aleatory realizations
        - Calculate the crack initiation time using equations 3.1 and 3.2
        - Calculate the crack depth (if crack initiates) using equations 3.3 through 3.10
        - Calculate the rupture pressure using equation 3.11
    - End aleatory realization loop
- End epistemic realization loop
- Calculate and output summary performance measures

Sampling at the epistemic level can yield specific values for the primary uncertain variables, or it can define the parameters of the statistical distributions of primary variables in a two-stage sense. For example, suppose that the uncertainty in material flow stress is to be described using a normal distribution. The two-stage sampling allows the mean and variance of the specified normal distribution to be subject to epistemic uncertainty.

3.3 Assignment of Parameters and Statistical Distributions

A long term goal of the U.S. Nuclear Regulatory Commission is to develop a modular probabilistic mechanics tool capable of determining the probability of failure of reactor coolant system components. Supporting this goal, the xLPR Pilot Study [25] is a proof-of-concept effort to develop an initial assessment tool for dissimilar metal (DM) pressurizer surge nozzle welds. That pilot study developed and published statistical distributions for a number of the current model parameters. However, other parameters used in this study do not have similar published information. The statistical distributions chosen for the model parameters are described in this section.

In general, we used a symmetric triangular distribution to represent the uncertainty in parameters with little or no published uncertainty information. The mode of the triangular distribution was set to the nominal value derived from the literature. The two ends of the distribution were set to 90% and 110% of the nominal value, thus the distribution has both mean and median equal to the nominal value. While the distributions used throughout are not viewed as final and definitive, they are considered adequate for the current objectives of understanding the prospective impact of uncertainty reclassification.

3.3.1 Geometry and Operating Constants

This demonstration assumes constant conditions for a number of parameters even though some of them, such as operating temperature or pressure, could vary with time. Treating these quantities as constants simplifies the current calculations. The parameters with constant values are identified below:

- **Operating Temperature**: The operating temperature is assumed to be a constant 617 K.
- **Operating Pressure**: The operating pressure is assumed to be a constant 15.5 MPa.

The component failure pressure is calculated at a component age of 60 years. This demonstration examines a single type of pipe weld as described in Figure 3-1 of Section 3.1. The modeled pipe has an inside diameter of 0.3048 m, a thickness of 0.0381 m, and the weld material is assumed to be Alloy 182. A section moment of 207 kN-m is applied to calculate the bending stress.

3.3.2 Statistical Distributions for the Crack Initiation Model

The statistical distributions assigned to parameters in the crack initiation model (equations 3.1 and 3.2) are provided in this section. A value of 4.35 for the shape parameter of the Weibull distribution in equation 3.1 for Alloy 182 has been published [28]. Without further information on the uncertainty, we assigned a triangular distribution with a minimum of 90% of this value, a mode equal to the published value, and a maximum of 110% of the published value i.e., triangular (3.915,4.35,4.785).

In equation 3.2, the operating temperature was treated as a constant (617 K) for this analysis.

The fitting parameter (A) has published values of 2.524×10^5 for Alloy 182 [29] and 4.207×10^4 for Alloy 82 [30]. For this demonstration, we assigned a uniform distribution between these two limits. The units for this parameter are such that the product $A\sigma^n$ has units of years.

One reference [30] suggests a value of -7 for the stress exponent for Alloy 182. Without further information on the uncertainty, we assigned a triangular distribution with a minimum of 90% of this value, a mode equal to the published value, and a maximum of 110% of the published value, i.e., triangular (-7.7,-7,-6.3).

One reference [30] suggests a value of 129.7 kJ/mole for the activation energy for crack initiation (Q_I). Without further information on the uncertainty, we assigned a triangular distribution with a minimum of 90% of this value, a mode equal to the published value, and a maximum of 110% of the published value, i.e., triangular (116.73,129.7,142.67).

The applied tensile stress (σ) in the crack initiation model (equation 3.2) is implemented as the sum of four stresses: pipe pressure stress, pipe bending stress, deadweight and thermal stress and residual stress (σ_R). The pressure, deadweight, and thermal stresses are treated as constants. Based on a constant pressure of 15.5 MPa and the pipe diameter and wall thickness, the axial pipe pressure stress is assigned a constant value of 31.0 MPa. The deadweight and thermal stress is assigned a constant of 0.6 MPa. The nominal pipe bending stress is calculated from the pipe dimensions and the bending moment, and has a value of 64.57 MPa. We use the same statistical distribution for the residual stress as assigned in the xLPR Pilot Study [25], which is a normal distribution with mean 330.3 MPa and a standard deviation of 110 MPa.

3.3.3 Statistical Distributions for the Crack Growth Model

The statistical distributions assigned to parameters in the crack growth model (equation 3.3) are provided in this section. In recent research, the fitting constant (ε) is defined as log-normally distributed with a median value of approximately 8×10^{-13} [31]. For this demonstration, the median value is set to 8×10^{-13} and the 5th percentile of the lognormal distribution was set to 40% of the median value. This resulted in the associated normal distribution (in log space) having a mean of -27.64919 and a standard deviation of 0.557065.

The reference temperature in equation 3.3 is a specified reference value rather than a measured value. Thus, we used a constant (598.15 K) in all calculations [22].

The xLPR Pilot Study [25] specified a distribution for the thermal activation energy (Q_G) that is based on expert judgment. We use the same distribution here, which is normal with a mean value of 130 kJ/mole and a standard deviation of 5 kJ/mole.

The crack tip stress intensity factor K (MPa$\sqrt{}$m) is a calculated quantity. Published routines in Appendix C of the xLPR Pilot Study [25] were used to estimate the stress intensity factor.

The two fitting factors (f_{alloy} *and* f_{orient}) in equation 3.3 are described in MRP-115 [21]. The factor f_{alloy} has a value of 1.0 for cracking in alloy 182 and 0.385 of alloy 82. The factor f_{orient} has a value of 1.0 when crack propagation is perpendicular to the dendrite solidification direction. For the current study of radial crack growth in alloy 182 weld metal, these two factors were assigned constant values of 1.

The xLPR Pilot Study [25] specified a value of 1.6 for the stress intensity exponent (β). Without further information on the uncertainty, we assigned a triangular distribution with a minimum of 90% of this value, a mode equal to the published value, and a maximum of 110% of the published value, i.e., triangular (1.44,1.6,1.76).

3.3.4 Statistical Distributions for the Rupture Pressure Model

The only random variable entering directly into the rupture pressure expression (equation 3.12) is the material flow stress. A nominal material flow stress of 333 MPa was estimated as the average of a 210 MPa yield stress and a 455 MPa ultimate stress. These yield and ultimate stresses were approximate values rather than specific for a prescribed alloy. Without further information on the uncertainty, we assigned a triangular distribution with a minimum of 90% of this value, a mode equal to the published value, and a maximum of 110% of the published value, i.e., triangular (299.7,333,366.3).

3.3.5 Other Statistical Considerations

In Sections 3.3.2 through 3.3.4 we discussed assignment of statistical distributions to each of the primary variables in equations 3.1 through 3.11. Additional statistical assumptions are identified in this section.

The weld residual stress (σ_R), which is a component of the stress variable σ in equation 3.2 and also enters in the computation of the K (crack tip stress intensity factor) term in equation 3.3, can be assigned epistemic or aleatory uncertainty. The pipe bending stress component of σ is only assigned aleatory uncertainty, and the uncertainty is applied as the sine of a random angle multiplied by a nominal normal stress value. In effect, the position of the potential crack under consideration is randomly distributed around the circumference of the pipe.

Another source of aleatory uncertainty arises from the implementation of the crack initiation time in equation 3.1. The sampling on the primary variables, whether epistemic or aleatory, defines the parameters of the Weibull distribution at the level of the aleatory loop. Selection of the resulting crack initiation time requires generation of a random (uniform[0,1]) quantity and then the inverse of equation 3.1 is used to convert the random value to an initiation time. This generation and inversion always occurs at the aleatory level.

Although it is not identified as a primary parameter, the implementation of the solution for the crack growth model (equation 3.3) starts with an initial flaw depth (F_d). This variable has little contribution to the spread of rupture pressure results. It is modeled as aleatory uncertainty using a normal distribution with mean 20 microns and standard deviation of 0.5 microns.

As described in Section 3.1.2, the stress distribution through the pipe wall uses a third order polynomial model. The primary variables in determining the coefficients polynomial are the weld residual stress (inner wall) and X_c (depth where the stress first changes sign). In addition, an outer wall stress is required. In some instances the outer wall stress is random (aleatory level) and sometimes it is completely determined by the inner wall residual stress and X_c. We use the same logic and constraints for defining the polynomial as were used in the xLPR Pilot Study [25]. These constraints are: (i) the area under the curve must integrate to zero (only an axis-symmetric distribution is permitted), (ii) the stress on the outer wall is a uniform number (aleatory level) between zero and the inner wall stress, and (iii) if X_c is greater than 0.4 then the outer wall stress has the opposite sign as the inner wall stress, while if it is less than 0.4 it has the same sign. In addition, if X_c is greater than 0.5, the stress is linear through the thickness.

A final source of aleatory uncertainty arises whether the crack geometry is a half-penny crack or a long crack. This demonstration uses a probabilistic assignment crack geometry, with 99% of the cracks having a half-penny geometry and 1% of the cracks having a long geometry [16].

4.0 Uncertainty Characterization Alternatives

4.1 Definition of Alternatives

The computer code developed for this demonstration allows many of the variables in equations 3.1 through 3.11 to be assigned either epistemic or aleatory uncertainty. The uncertainty assignments for seven different modeling cases are identified in Table 1. In Case 1 all primary variables are assigned aleatory uncertainty. In Case 2 all primary variables are assigned epistemic uncertainty (although the sampling of the crack initiation time from the inverse of Equation 3.1 and the location of the crack around the perimeter of the weld are considered aleatory throughout). In Case 3, only stress uncertainties are considered epistemic, in Case 4 stress and Greek exponents are epistemic, in Case 5 only the Greek exponents are epistemic, in Case 6 only residual stress is epistemic, and in Case 7, only flow stress is epistemic.

Table 1 Assignment of aleatory or epistemic uncertainty to primary variables by modeling case

Variable	Equation	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8
γ	3.1	A	E	A	E	E	A	A	A
Q_I	3.2	A	E	A	A	A	A	A	A
n	3.2	A	E	A	A	A	A	A	A
σ_R	In 3.2	A	E	E	E	A	E	A	T
A	3.2	A	E	A	A	A	A	A	A
F_d	In 3.3	A	E	A	A	A	A	A	A
ε	3.3	A	E	A	A	A	A	A	A
X_c	3.3	A	E	A	A	A	A	A	A
β	3.3	A	E	A	E	E	A	A	A
Q_G	3.3	A	E	A	A	A	A	A	A
T_{ref}	3.3	A	E	A	A	A	A	A	A
σ_f	3.11	A	E	E	E	A	A	E	T

A denotes aleatory uncertainty assignment
E denotes epistemic uncertainty assignment
T denotes two stage sampling

The situation in Case 8 differs from the previous 7 cases. In this case, the uncertainty in the residual stress (equation 3.1) and the material flow stress (equation 3.11) are aleatory. However, the parameters describing the shape of the aleatory distributions are epistemically uncertain. That is, we are allowing the parameters of an aleatory distribution assigned to a primary variable to themselves be treated as uncertain.

The statistical distribution for the residual stress was assigned a normal distribution at the aleatory level. However, the mean of the normal distribution at the aleatory level is chosen at the epistemic level using a different normal distribution with a mean of 300.3 MPa and a standard deviation of 30.03 MPa. The standard deviation of the normal distribution at the aleatory level was assigned a constant 110 MPa.

The statistical distribution for the material flow stress was assigned a triangular distribution at the aleatory level. However, the minimum of the triangular distribution at the aleatory level is chosen at the epistemic level using a different triangular distribution with minimum, mode and maximum of 284.7, 299.7, and 314.7 MPa, respectively. The mode of the triangular distribution at the aleatory level was assigned a constant 333 MPa. Finally, the maximum of the triangular distribution at the aleatory level is chosen at the epistemic level using a different triangular distribution with minimum, mode and maximum of 351.3, 366.3, and 381.3 MPa, respectively.

4.2 Statistical Convergence

Since this analysis is based on Monte-Carlo methods, it is necessary to verify that sufficient realizations (sample sizes) are evaluated to provide statistical convergence of the results. The implementation was based on stratified sampling [32] for most variables, thus taking advantage of the accelerated statistical convergence generally associated with that technique. After making some preliminary runs, we concluded that 3,000 epistemic realizations and 3,000 aleatory realizations were adequate to demonstrate statistical convergence. This resulted in the evaluation of 9,000,000 rupture pressures for each case, since 3,000 aleatory realizations are evaluated for every epistemic realization.

As an example demonstration of statistical convergence, we considered the hybrid aggregation; that is, pooling all realizations of failure pressure, regardless of whether the sampling source was aleatory or epistemic. Conceptually, one would expect the same output distribution for these hybrid results irrespective of whether each variable was defined as having epistemic or aleatory uncertainty. Thus, we examined the percent of realizations in each modeling case where a crack initiated before the end of the 60 year operating period. The results are shown in Table 2. The values range from 96.1711 to 96.2612 percent, and the difference between the maximum case with the minimum case is 0.0901 percentage points. These seven cases differ only by one unit in the third decimal, thus they demonstrate enough sufficient convergence. We do not include Case 8 (two-stage parameter sampling) in this comparison because the input statistical distributions differ from the other seven cases.

Table 2 Percent of realizations where a crack initiates within 60 years

Percent	**Modeling Case**
96.1852	Case 1 (All Aleatory)
96.2612	Case 2 (All Epistemic)
96.1848	Case 3
96.1814	Case 4
96.1850	Case 5
96.1711	Case 6
96.1884	Case 7

Another visual indication of statistical convergence is to plot the cumulative probability distribution function (CDF) of all modeled rupture pressures (at 60 years) for the hybrid aggregation for each modeling case. Each CDF in Figure 4-1 is based on 9,000,000 rupture pressure calculations. Even though the results are not identical, they vary over such narrow ranges that the lines are indistinguishable.

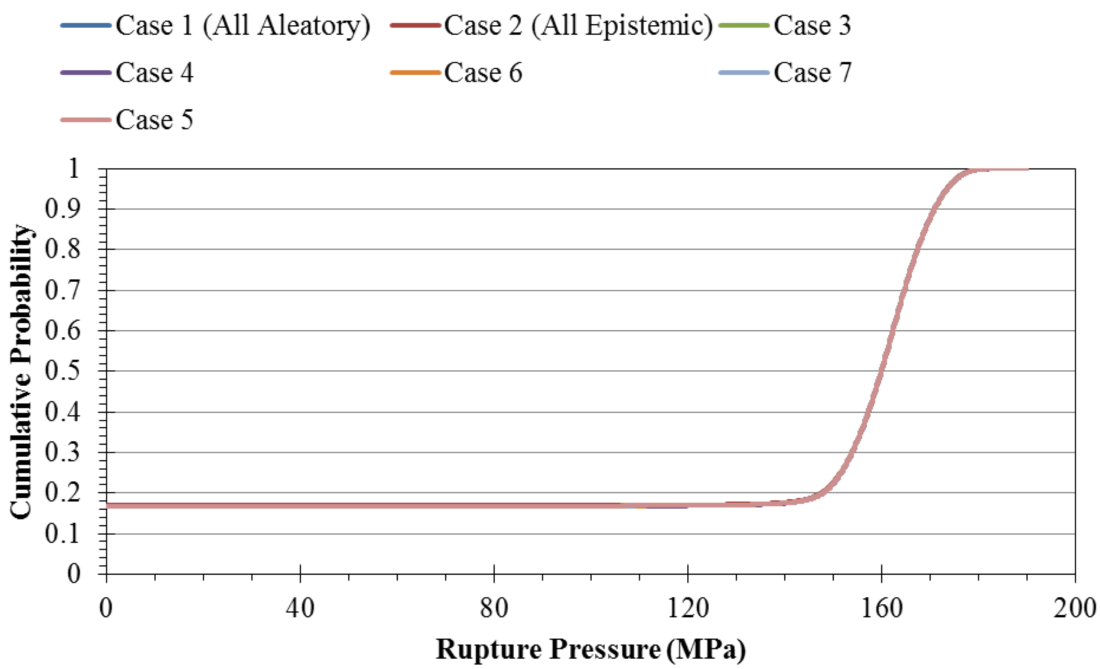

Figure 4-1. Cumulative hybrid probability distribution functions of all modeled rupture pressures for modeling Cases 1 through 7

5.0 Results

5.1 Bases for Comparison

Cases 1 through 7 identified in Table 1 assign uncertainty as either epistemic or aleatory to each of the primary variables in equations 3.1 through 3.11. The probability distribution for any one primary variable is the same irrespective of the assigned uncertainty type.

As discussed in Section 2, while there is seldom clarity on the way in which a given uncertainty should be interpreted (epistemic or aleatory) and, furthermore, the RISMC modeling environment (in contrast to a conventional PRA) may tend to exacerbate this ambiguity, there is nevertheless an emerging view that for real-world decision problems, the insights from an uncertainty analysis may be robust to the way in which individual uncertainties are classified. This current analysis is intended to test that premise.

We have identified four potential output forms for the analysis, each hypothesized to be potentially usable in a decision context. The idea is to test the stability of these output forms under the differing uncertainty interpretations identified as Cases 1-8. These four forms are as follows:

- **Hybrid**: This approach lumps together all the calculated rupture pressure realizations. That is, all Monte Carlo realizations of failure pressure are pooled (without distinction between epistemic and aleatory sources), and this pool is the basis for defining the *hybrid* output probability distributions. The premise for this form is that the decision-maker is indifferent to the categorization of uncertainties.

- **Epistemic Distribution of Aleatory Means**: In this approach, the mean of the rupture pressure is calculated over all aleatory realizations for each epistemic realization. This results in an epistemic probability distribution over aleatory means. The premise here is that aleatory means are of interest to the decision maker, acknowledging epistemic uncertainty in those means.

- **Epistemic Distribution of Aleatory Percentiles**: In this output, percentiles of the rupture pressure are calculated over the aleatory sample for each epistemic realization. This approach results in an epistemic probability distribution over a chosen aleatory percentile. This was done at three aleatory percentile levels: 5^{th}, 25^{th} and 95^{th}. The premise here is that a prospective basis for a conservative decision is, say, consideration of the aleatory 5^{th} percentile of failure pressure, albeit subject to epistemic uncertainty.

- **Multiple Epistemic Sets**: In this approach, the variability in calculated rupture pressure is shown as a scatter plot over all aleatory realizations for a several epistemic realizations. The premise is that this gives a strong visualization of the scatter associated with epistemic versus aleatory uncertainty.

5.2 Results

5.2.1 Hybrid Case Results

The hybrid approach combines all calculated rupture pressure results, irrespective of the combination of parameters assigned to epistemic or aleatory uncertainties. The output cumulative distribution functions of rupture pressures for each modeled case identified in Table 1 are shown in Figure 5-1. As noted previously, each line in the plot represents 9,000,000 calculated rupture pressures.

Approximately 17% of all modeled rupture pressures are zero, indicating the presence of a crack that penetrates entirely through the pipe wall by the end of 60 years of operation. Note, the model could be adjusted (as in Reference 14) to provide more realistic loading criteria for a rupture, given a through-wall crack, but for current purposes, this simplified model is considered adequate.

One conclusion that can be drawn from the curves in Figure 5-1 is that the set of calculated rupture pressures in this hybrid case is not sensitive to the uncertainty classification of the individual parameters. This might be expected since this output form simply aggregates output realizations without regard to the epistemic or aleatory nature of the input distributions.

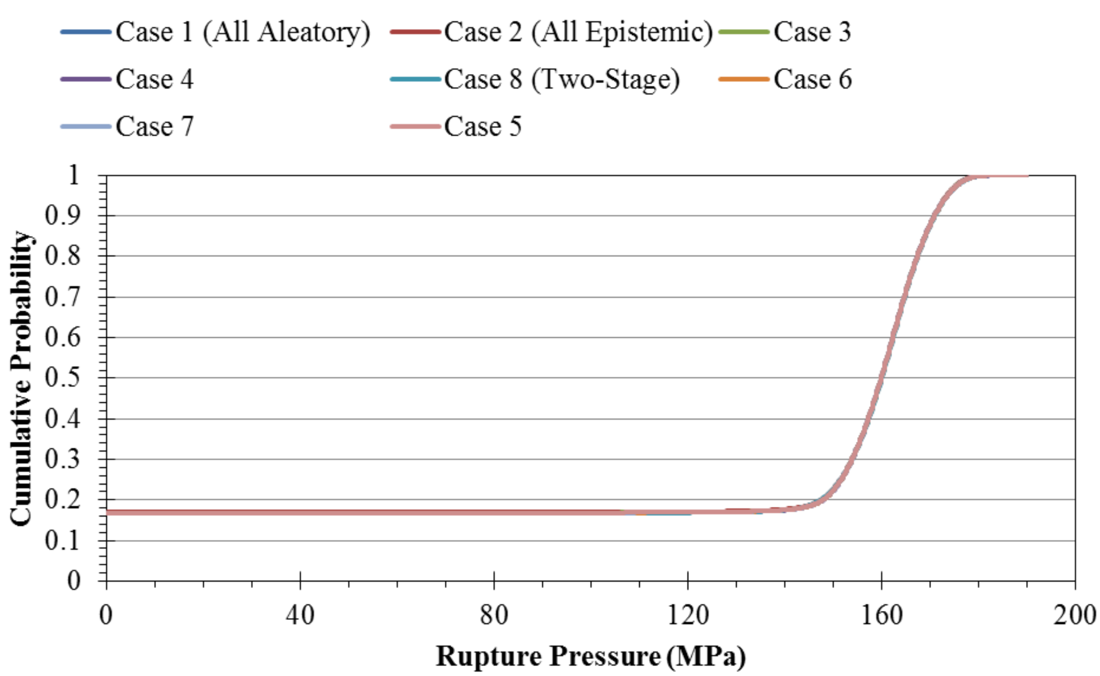

Figure 5-1. Hybrid Output: Cumulative probability distribution functions of all modeled rupture pressures at 60 years for modeling Cases 1 through 8

5.2.2 Epistemic Distribution of Aleatory Means

In this output, the mean rupture pressure over aleatory realizations is calculated for each epistemic realization. The results for Cases 2 through 8 are provided in Figure 5-2. No variables are sampled at the epistemic level for Case 1, thus it is not included in this plot. The residual stress (see equation 3.1) and the material flow stress (see equation 3.11) are the variables with the most effect on the shape of these distributions.

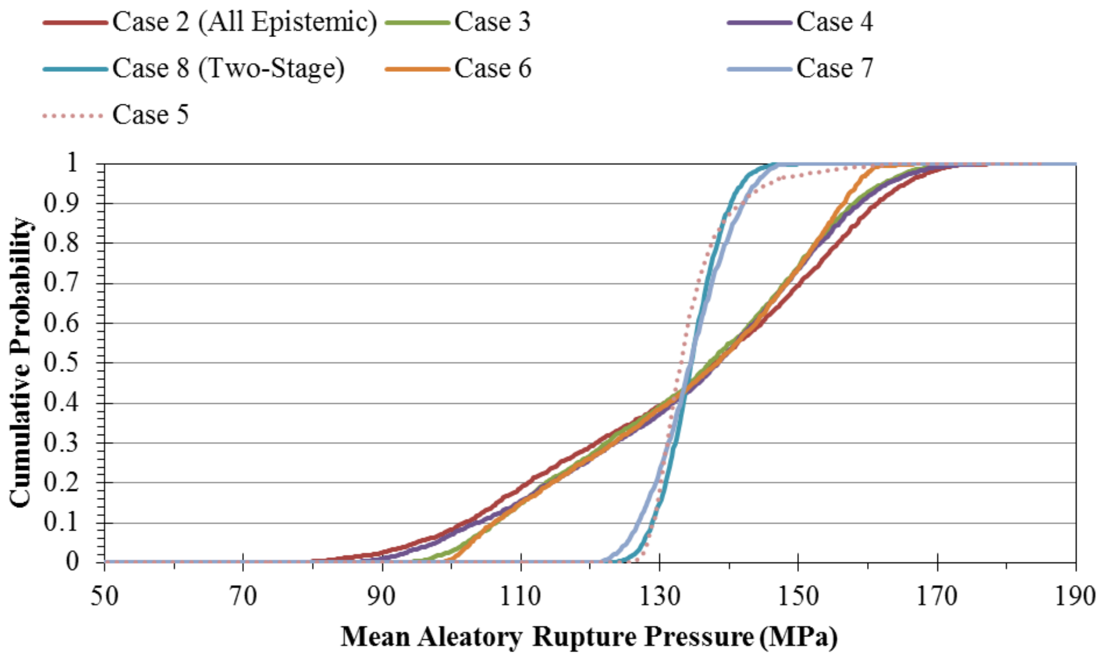

Figure 5-2. Epistemic Distribution of Aleatory Means Output: Cumulative epistemic probability distribution functions of aleatory means of modeled rupture pressures at 60 years for modeling Cases 2 through 8

5.2.3 Epistemic Distribution of Aleatory Percentiles

This output form is an epistemic distribution over a chosen percentile level of the output aleatory distributions. Since hypothetical decisions are likely to be based on conservative estimates of failure pressures, our focus is more on low percentiles of the aleatory failure pressure distributions: 5th and 25th percentiles. The epistemic distributions over these aleatory percentiles are shown in Figures 5-3 and 5-4, respectively. In Figure 5-5, we show the epistemic distribution over the aleatory 95th percentile for contrast.

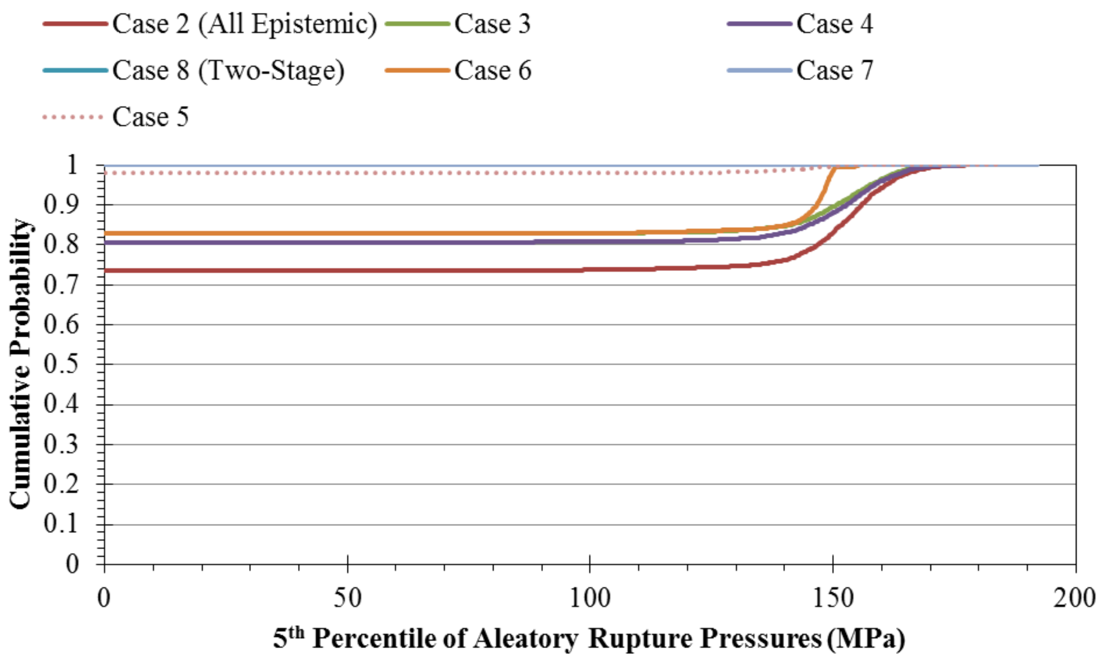

Figure 5-3. Epistemic Distribution of Aleatory Percentiles Output: Epistemic Distribution of the 5th percentiles of aleatory rupture pressures at 60 years for modeling Cases 2 through 8

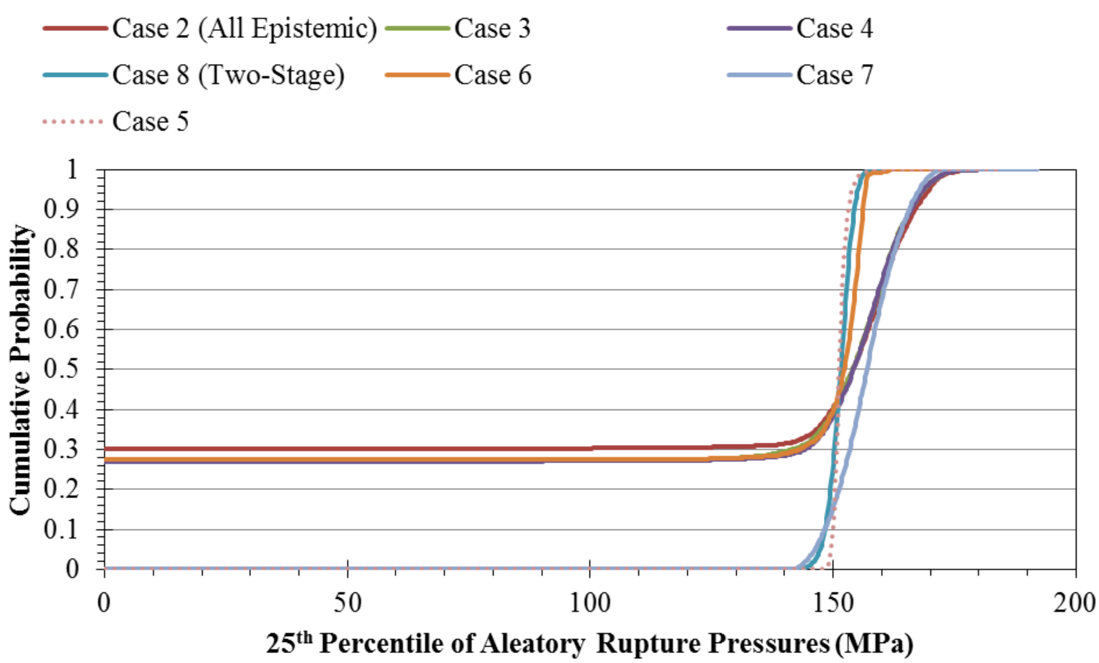

Figure 5-4. Epistemic Distribution of Aleatory Percentiles Output: Epistemic Distribution of the 25th percentiles of aleatory rupture pressures at 60 years for modeling Cases 2 through 8

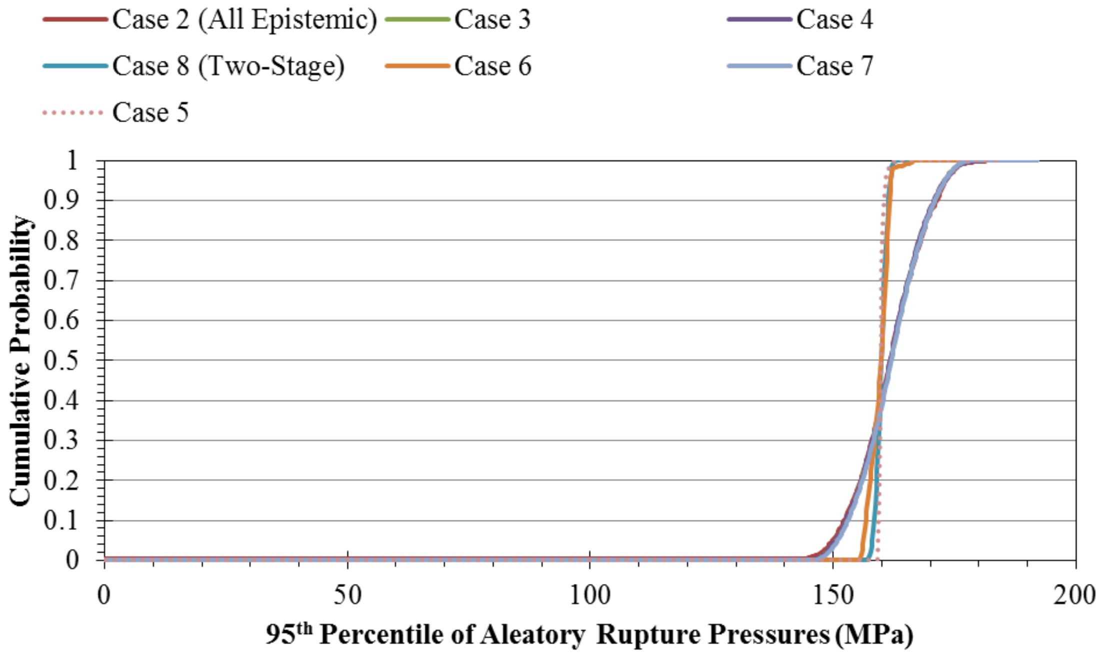

Figure 5-5. Epistemic Distribution of Aleatory Percentiles Output: Epistemic Distribution of the 95th percentiles of aleatory rupture pressures at 60 years for modeling Cases 2 through 8

5.2.4 Multiple Epistemic Sets

This final output representation provides some insight into the underlying variability in output failure pressures associated with aleatory and epistemic uncertainties. These outputs are shown for Case 2 (all primary variables uncertainties are epistemic - noting however, that the crack initiation time is considered to be aleatory) and Case 6 (where only the weld residual stress uncertainty is epistemic).

The rows of Figure 5-6 represents the three main computational steps in the aleatory loop discussed in Section 3.2. Columns in the figure provide results for Case 2 in the left column and Case 6 in the right column. Example results are the crack initiation time (top row), crack depth at 60 years (middle row) and rupture pressure (bottom row). It is not practical to show 9 million individual results on a plot, thus these plots only show 10 epistemic sets of 1250 aleatory realizations. The scatter within each vertical blue block (of arbitrary width) represents the aleatory variability within a single epistemic realization. So, for example, in the top left plot, we see that the scatter due to epistemic variability exceeds the aleatory scatter within any one epistemic realization.

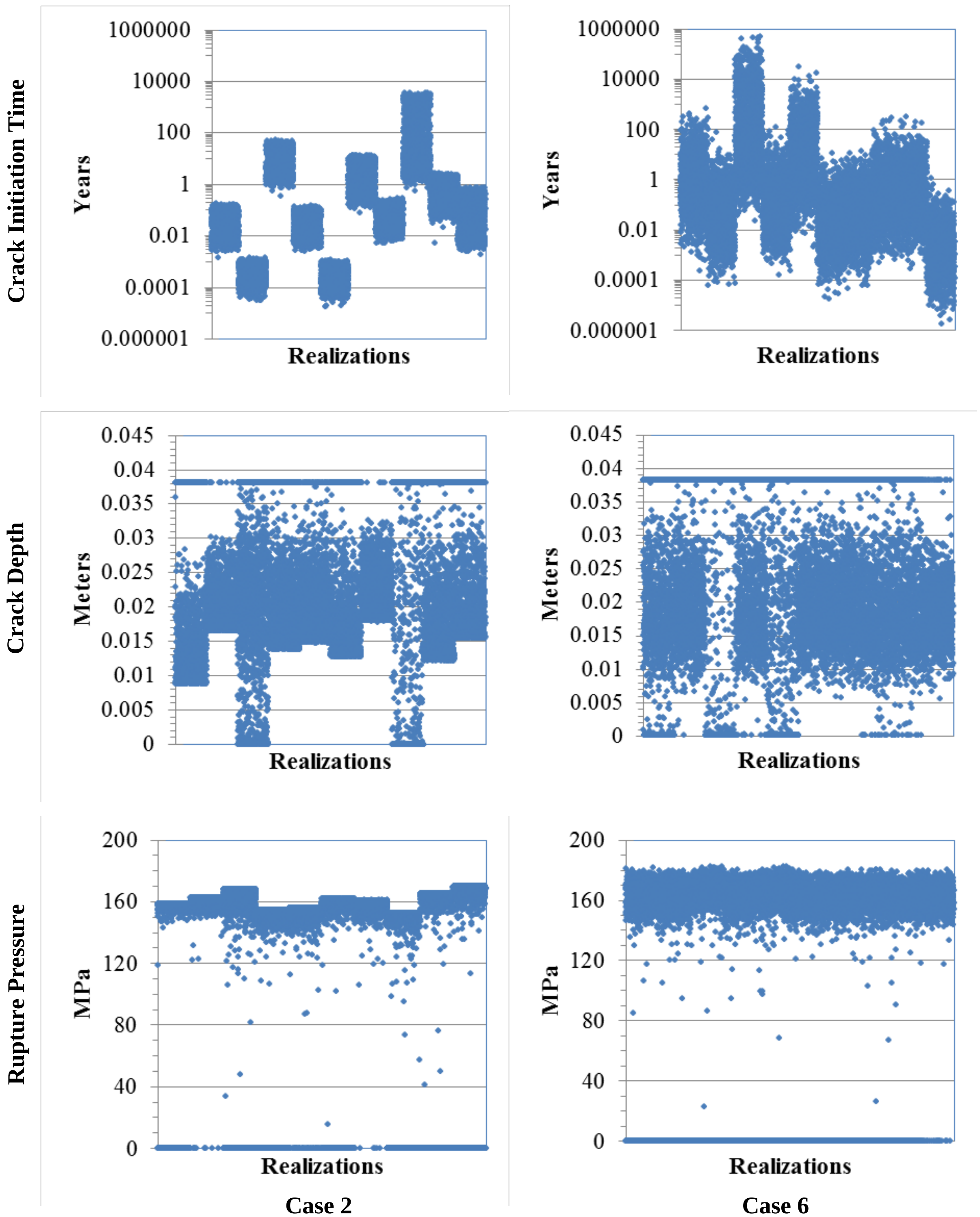

Figure 5-6. Example results for crack initiation time (top row), crack depth at 60 years (middle row) and rupture pressure at 60 years (bottom row) for Case 2 (left column, all epistemic) and Case 6 (right column, only residual stress epistemic). Plots show 10 epistemic sets of 1250 aleatory realizations.

6.0 Conclusions

Our focus is the question of whether insights stemming from uncertainty analysis in a real-world decision environment are likely to be robust under differing interpretations of input uncertainties - aleatory or epistemic. For a model of weld failure pressure, we have defined 8 input cases which differ with respect to the interpretations of individual input uncertainties. We have also defined a series of output forms, and for each of these forms, determined the robustness of the outputs under the differing input cases. These output forms were selected as prospective bases for decision-making. The insights are as follows:

- **Output 1 - Hybrid**: Output distributions for all cases are virtually identical. This might be viewed as a trivial result since in this output form, no distinction is made in the output sample between aleatory and epistemic realizations. There does exist the question however of whether this output form would be of interest to a decision-maker. If so, it would imply that the decision-maker has no interest in the distinction between aleatory and epistemic uncertainties.

- **Output 2 - Epistemic Distribution of Aleatory Means**: Inspection of Figure 5-2 indicates that the output distribution is sensitive to the input case. While the distributions tend to cluster into two distinctive sets (depending on whether the residual stress uncertainty - a major contributor - is treated as aleatory), the cases produce substantially different insights. For example, if a decision were to be based conservatively on the mean aleatory failure pressure with a 95 percent probability of exceedence, then that level varies by more than 30 MPa between cases.

- **Output 3- Epistemic Percentiles of Aleatory Percentiles**: Again, we have substantial variation in results between cases. The notion behind this option was the possibility that, say, the 5th epistemic percentile of the 5th aleatory percentile (a prospective basis for a conservative decision) may be case-insensitive. The difficulty here was that a substantial fraction of each sample resulted in a "zero" failure pressure, rendering comparison of low percentiles problematic. For this reason, the epistemic distribution over aleatory 25th percentiles was also calculated. Inspection of Figure 5-4 gives some indication that if our interest were the 25th epistemic percentile of the 25th aleatory percentile, then a relatively tighter range of failure pressures between cases would result, compared to Output 2. Nevertheless, the argument could not be made from this analysis that the 25th of the 25th is robust.

- **Output 4- Multiple Epistemic Sets**: This output form provides insight into the relative scatter of failure pressures associated with epistemic versus aleatory uncertainty. While this output does not provide a simple statistic for incorporation into a decision, visual comparison of the left and right columns of Figure 5-6 gives some indication of the impact of differing input cases.

In conclusion, the current analysis indicates that if the distinction between epistemic and aleatory uncertainties is to be preserved in a RISMC-like modeling environment, then it is unlikely that analysis insights supporting decision-making will in general be robust under recategorization of input uncertainties. That is, if it is believed that there is a true conceptual distinction between the two uncertainty types (as opposed to the distinction being primarily a legacy of the PRA paradigm) then more consistent and defensible bases must be established by which to categorize input uncertainties.

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