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USING DETERMINISTIC AND PROBABILISTIC METHODS FOR MELCOR SEVERE ACCIDENT UNCERTAINTY ANALYSIS

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Abstract. This paper describes the methodology used to assess severe accident modeling uncertainties for nuclear power plants in an integrated approach to quantify the relative impact of uncertain model parameters on predicted accident consequences. The methodology provides insights regarding the key phenomenological models related to these consequences and identifies important effects of modeling uncertainty on severe accident predictions. The methodology has been applied to several recent analyses using MELCOR, a software developed to model the progression of severe accidents in nuclear power plants [1-3]. This methodology couples a quantitative uncertainty analysis conducted using results from a two-step Monte Carlo simulation with a deterministic phenomenological verification of individual sample sets from the simulation result matrix. The quantitative uncertainty analysis provides measures of both the individual effects and effects due to interactions for each of the uncertain model parameters using multiple statistical regression methods in a process termed sensitivity analysis. Statistical regression results are verified using deterministic analyses and convergence studies. The statistical regression results are corroborated in conjunction with a careful evaluation of physical behavior and of each response or non-response for individual realizations. In this way, the methodology presented in this paper has been used to understand potential reactor safety system responses, including core behavior, while inherently building confidence that the probabilistic results are within the range of validity for the model. Coupling regression methodology with a traditional, deterministic, and phenomenologically-driven analysis allows for qualitative and quantitative measures of the model and parameter uncertainties when using MELCOR to evaluate the system response to postulated severe reactor accident scenarios and potential release of radionuclides. The results can be used to identify important areas where further data collection or study could provide the most impact in reducing the uncertainty in the potential consequences of severe accidents in nuclear power plants.

Keywords Uncertainty Analysis, Sensitivity Analysis, Severe Accidents, MELCOR

1. INTRODUCTION

Probabilistic risk assessments use a systematic process to identify possible points of vulnerability within a complex system (such as a nuclear power plant) before an incident or emergency situation occurs. Important questions must be answered about the nature, quality, and significance of calculated results. Uncertainty and sensitivity analyses are central to answering such questions. The objective of uncertainty analysis (UA) is to calculate the range of predicted simulation outcomes that results from uncertainty in simulation inputs. The objective of sensitivity analysis is to determine the effects of, or sensitivity to, the uncertainty in simulation inputs on the uncertainty in simulation outcomes.

Appropriately designed uncertainty and sensitivity analyses are essential to enhancing the usefulness and credibility of severe accident modeling by providing an unbiased representation and assessment of the uncertainty inherent to the development and execution of models that approximate complex physical phenomena. Uncertainty and sensitivity analyses support the verification and validation of the model under consideration, provide guidance on how to appropriately invest additional resources to reduce the uncertainty in analysis outcomes, and ultimately build confidence in these high fidelity simulations.

Most uncertainty and sensitivity analyses involve five components when viewed at a high level:

- Definition of probability distributions to characterize the uncertainty in analysis inputs
- Generation of samples from the probability distributions for the uncertain analysis inputs
- Propagation of the generated samples through the model under consideration to produce a mapping between values for uncertain analysis inputs and corresponding simulation outcomes
- Organization and display of the probabilistically generated uncertainty in the simulation outcomes
- Exploration of the mapping between simulation inputs and simulation outcomes with a variety of statistical procedures to obtain and verify sensitivity analysis results

Computer codes such as MELCOR [1-3] and MACCS [4-5] dynamically model the initiation and progression of a reactor accident (MELCOR) through potential radiological release and atmospheric dispersion, as well as economic and health consequences (MACCS). Severe accident modeling represents the convergence of a large number of situational variants and uncertain inputs. Uncertainty and sensitivity analysis prove instrumental in producing useful and informative simulations.

The State of the Art Reactor Consequence Analyses (SOARCA) project presents a recent example of the application of these methods to severe accident modeling [6-8]. Sandia National Laboratories (Sandia) worked with the U.S. Nuclear Regulatory Commission (NRC) on this project to apply modern analysis tools and techniques to models of severe reactor accidents to understand severe accident modeling phenomena including thermal-hydraulic response; core heat-up, degradation, and relocation; hydrogen production; transportation; combustion; and fission product release and transport behavior. The SOARCA project developed a body of knowledge regarding the realistic outcomes of severe reactor accidents and integrated modeling of accident progression and on-site consequences with uncertainty using both state-of-the-art computational analysis tools and best modeling practices from the severe accident analysis community. Uncertainty and sensitivity analyses for this project were conducted in a systematic way and evaluated various sources of uncertainty including: model uncertainty, input uncertainty, and solution precision and accuracy.

This paper presents the approach employed by Sandia and the U.S. NRC in the SOARCA project as a case study for a comprehensive uncertainty analysis methodology developed to quantify the uncertainty in simulation results and the relative impact of uncertain model parameters on predicted accident consequences.

2. UNCERTAINTY ANALYSIS METHODOLOGY

The application of uncertainty analysis to severe accident models is based on the method of uncertainty propagation, which varies uncertain model inputs to produce a set of deterministic model calculations, defined as a probabilistic simulation. The deterministic model characterizes the known physics and phenomena of the reactor and scenario. This model, when provided the exact same input conditions, produces a single replicable result. Uncertainty analysis seeks to study the variation that occurs in this model result if the input conditions provided to the deterministic model are varied rather than constant. The goal of an uncertainty analysis is to determine the range of potential outcomes that could occur based on the range of possible or plausible uncertain input conditions.

2.1 Treatment of uncertainty

In the design and implementation of analyses for complex systems, two types of uncertainty are considered: aleatory uncertainty and epistemic uncertainty [9-11]. Aleatory uncertainty arises from an inherent randomness in the properties or behavior of the system under study. For example, the weather conditions at the time of a reactor accident are inherently random with respect to our ability to predict the future and would be considered to have aleatory uncertainty. Other potential examples of aleatory uncertainty include the variability in the properties of a population of system components and the variability in the possible future environmental conditions to which a system component could be exposed. Alternative designations for aleatory uncertainty include variability, stochastic, and irreducible. Epistemic uncertainty derives from a lack of knowledge about the appropriate value to use for a quantity that is assumed to have a fixed value in the context of an analysis. Examples of epistemic uncertainty include the minimum voltage required for the operation of a system and the maximum temperature that a system can withstand before failing. Alternative designations for epistemic uncertainty include state-of-knowledge, subjective, and reducible. It is important to note that some input parameters may have both aleatory and epistemic attributes, but can be treated as epistemic for analytic convenience.

Uncertainty analysis conducted using the methodology presented in this paper involves numerical modeling of the system conditional on specific aleatory realizations, evaluating the entire range of epistemic uncertainty in a nested loop structure. The nested loop method uses an inner loop for aleatory uncertainty and an outer loop for epistemic uncertainty. This preferred order of the loops is governed by the interpretation of both types of uncertainty although this order could in theory be reversed. Aleatory uncertainty in the context of risk is perceived intuitively as a probability and is represented as a summary statistic (e.g., mean or median) and/or a distribution. For a given epistemic set (i.e., for a specific value in the outer loop), risk can be represented conditional on the assumption of perfect knowledge at the aleatory level. Epistemic uncertainty is then represented as a distribution on the representative value (e.g., mean or median) or a set of distributions showing the confidence in the results given the current state of knowledge. The definitions of aleatory and epistemic uncertainty depend in a fundamental way upon the system under study [9-11].

2.1.1 Uncertain input parameters & distributions

The selection of uncertain input parameters is an iterative process. Selected phenomena, parameters, and distributions need to be reviewed to: (1) confirm that the parameter representations appropriately reflect major sources of uncertainty, and (2) ensure that model parameter representations (i.e., probability distributions) are reasonable and have a defensible technical basis. When conducting uncertainty analyses for severe accidents, code limitations and limited availability of models and/or data may restrict the ability to evaluate some potentially important phenomena or uncertainty. Such limitations must be discussed and related to final conclusions regarding uncertainty in model outputs.

Each component of the model is a potential source of uncertainty, which can be due to assumptions about mathematical model form, the application of a model beyond the conditions of its design, simplifications due to computational constraints, or approximations of unknown conditions or quantities. Some model uncertainties can be incorporated as uncertainty propagated through the deterministic model, in which case the impact of this type of uncertainty on uncertainty in the consequence is observable. For example, the oxidation model was treated as uncertain in an uncertainty analysis of the Sequoyah nuclear power plant (NPP) [8]; three models were implemented and each was assigned a weight and sampled accordingly such that the effects of the uncertainty in oxidation model form on radionuclide release could be observed.

The most explicitly treated uncertainties in severe accident UAs are generally physical and environmental inputs, model fitting parameters, or model variability. These typically take the form of uncertainty distributions on model conditions and parameters. Calibration parameters for specific sub-models within the accident model may be uncertain as well as physical conditions and material properties that are either not well understood or are understood to be stochastic (aleatory) in nature. Uncertainty distributions that have been critically and expertly derived and justified are used for each of the uncertain inputs. This process inherently restricts the possible values of uncertain inputs to values that are known or assumed to be possible. Hence, when samples from the distributions are propagated through the deterministic model, the results should characterize a collection of accident conditions that is reasonable. However, due to the high dimensionality of the uncertain input space in severe accident UAs, distributions that are independently reasonable may lead to combinations of uncertain inputs that are not physically possible or that are inconsistent with the models to which they are applied. As a result, implementation of input uncertainty is often iterative; the model is run on an initial test set of uncertain inputs and the results from the model are interrogated for non-physical combinations or unreasonable results in order to identify distributions or sampling procedures that must be modified. Even with careful derivation and analysis of the uncertain input distributions, both realizations that are typical of the total population of results and realizations that appear atypical are analyzed in detail over the course of the accident scenario to identify any potentially non-physical simulations.

2.1.2 Convergence testing

Severe accident UAs introduce uncertainty to a deterministic model such that the results of the model include uncertainty. However, severe accident models also include numerical calculations that, because they are approximations, can introduce further uncertainty into the results. It is therefore necessary to evaluate the stability of UA calculations. Stability for an uncertainty analysis is quantified by demonstrating that the variation in accident consequences is due to the varying uncertain inputs and not due to issues of convergence of numerical solutions. Additionally, stability is studied to ensure that sufficient sampling of extreme (but possible) values from the uncertain distributions has resulted in a statistically stable distribution of results. From a strictly computational perspective, a well-designed, correctly implemented numerical model should produce results that are explainable and appropriate for the model's intended purpose. A series of development steps including input verification and convergence tests must be conducted to identify and reduce variability in the model outputs that results from time-step size, numerical accuracy, and sample size to ensure the model has converged before identifying key uncertainties. For the purposes of this discussion we consider three broad types of convergence testing: temporal, numerical, and statistical.

Temporal convergence refers to the use of an appropriate time step size necessary to achieve a converged model solution. The temporal discretization may affect the accuracy of the solution and thus may also affect the distribution of the calculated outputs. Numerical convergence refers to the numerical approximation of an exact value. Complex system models have intrinsic numerical variability due to choices that are made during model and code development and convergence criteria that are established by the code developer. Often, a finite reduction can be done in regards to intrinsic numerical variability by iterating on time step sizes, solver convergence criteria, and other parameters controlling solution precision and accuracy. Both temporal and numerical stability can add difficulty in resolving the variability in the model outputs that can be attributed to the uncertain parameters. Statistical stability refers to the confidence that the sample size (number of deterministic realizations) or sampling methodology is sufficient to accurately determine a numerically converged mean, median, or other statistical quantities of interest. The choice of sampling methodology (e.g., simple random sampling, Latin hypercube sampling, importance sampling), number of uncertain parameters considered in the analysis, the distribution types, and model approximations used can impact the statistical stability of the results. Understanding and characterizing all possible sources of variability in probabilistic results is an integral step in the identification of the variability that can be attributed to the uncertainty in the system.

There are multiple ways to examine stability. Commonly used methods usually demonstrate that the estimated consequences vary within a small acceptable range. These tools are necessarily heuristic in nature; there is no way with a finite sample of points to determine if a simulation correctly characterizes the results that would be obtained from an infinite sample. One such tool, bootstrapping (repeated sampling with replacement) can be used to obtain confidence bounds, for example, on the mean fraction of iodine released over time [12]. An example of stability results obtained using bootstrapping is demonstrated in

Figure 1. For comparison, the entire population of realizations was randomly sampled without replacement to partition the realizations into three independent replicates and each replicate was used to calculate a mean fraction of iodine released. As can be seen in the figure, the confidence bounds calculated by bootstrap sampling the entire population of realizations closely bound the means calculated for each smaller replicate. This shows that the behavior of the whole population is well captured by a smaller population, suggesting convergence. These types of heuristic analyses, in addition to the analysis of the reasonableness of simulation results, are used to determine if the sample size used for a UA can be considered sufficient.

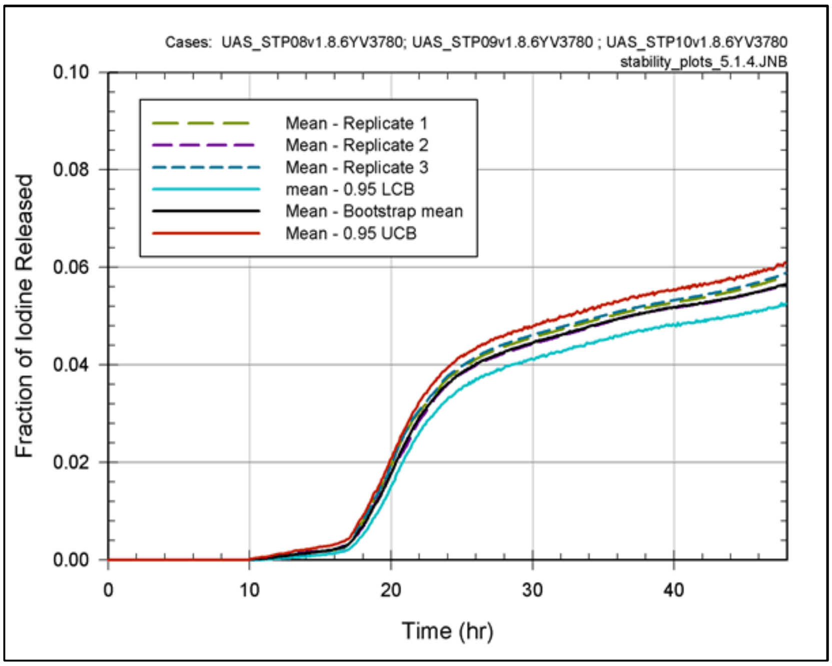

Figure 1. Demonstration of stability analysis results from the Peach Bottom UA[6].

2.2 Flowchart of uncertainty analysis methodology

Due to the complexity of severe accident models and the high-dimensionality of the uncertain parameter space, uncertainty analysis for severe accidents is inherently iterative. As such, it is common for an uncertainty analysis to be conducted with repeated iterations for defining the uncertainties, exercising the model, and analyzing the results. At almost every step in the process, illustrated in

Figure 2, there is the potential to identify refinements that may include input error corrections, non-physical values from unbounded distributions, and computation outside of the range of validity for one or more models within the complex system code. Improvements must then be made to the model or to the implementation of uncertainties to produce a comprehensive analysis of potential outcomes.

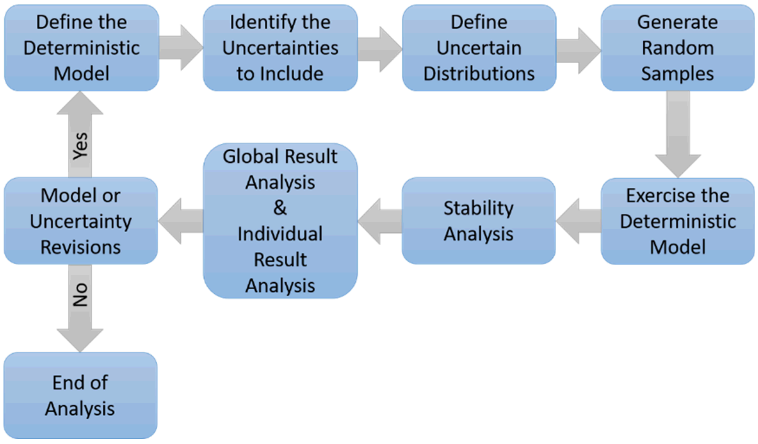

Figure 2. Flowchart of the basic steps for conducting an uncertainty analysis for a severe accident scenario.

The process begins first with a definition of the scenario, the model under consideration, and a decision about which input uncertainties will be included. There are, for example, different models that could be used to model the propagation of hydrogen within a reactor building. There may also be models with varying degrees of complexity and computational intensity that could be selected depending on the scenario, reactor design and the plant configuration, as selected by a subject matter expert to most accurately represent the engineered system. Defining the physical model for the system and including which subsystems will be part of the severe accident simulation establishes the deterministic portion of the analysis. Inherent to this step in the process is the notion of state-of-knowledge; the model itself characterizes (up to the level of computational capability) the current state-of-knowledge of every feature of the plant and accident considered in the simulation.

Once the deterministic model is established, the inclusion of uncertainty in the simulation is accomplished using model inputs. Examples of model inputs include coefficients for mathematical models of physical phenomena, material properties, transients, sample sizes, and alternative models. These inputs represent the features of the model whose values, as previously described in this paper, are either not precisely known due to a lack of information or data (epistemic), or are inherently random in nature (aleatory). Additionally, some inputs can be selected to evaluate the sensitivity of the model to specific design or other options (e.g., number of safety relief values that open or use of alternative models). For each variable, a range of validity and distribution are determined. These distributions are then sampled for each realization (independent simulation of the accident). The deterministic model is evaluated for each set of uncertain input conditions and the final results reflect the uncertainty in model response due to uncertainty in model inputs.

The ultimate goal of the sensitivity analysis component of a severe accident UA is to understand the relationship between variation in the inputs and variation in the model response. Each realization of the simulation provides a data point that describes this relationship. Understanding the global effects of specific inputs on model outputs is therefore a question of detecting trends. This is performed via regression analysis. One of the underlying assumptions behind the regression analysis, however, is that the data from the realizations is sufficient to identify the relevant trends and acquire reasonable estimates of accident consequences. This condition is known as statistical stability and is essential for building confidence in model results and the regression analysis.

The data analysis step in uncertainty analysis is also an iterative step in the model. The regression analysis (see Section 2.3 and Section 2.4) detects global trends and identifies potentially important parameters. Individual realization analysis studies the phenomenology involved in the accident sequence for a particular analysis. It is important both for detecting effects that may not be detected by the regression analysis and to forensically verify regression results and tie them to accident phenomena. Thus the regression analysis and the individual realization analysis work to simultaneously validate each other, increasing confidence in both.

Finally, the last step in the uncertainty analysis methodology is to determine if the results indicate that further refinement of the model, uncertainty distributions, or sample size is necessary to confidently quantify the variability in system response that can be attributed to the uncertainty in the system. The flow chart in

Figure 2 reflects the iterative nature of this step. The process ensures uncertainty analysis results are stable, comprehensive, and realistic.

2.3 Statistical regression

Uncertainty analysis for complex severe accident models is inherently multi-dimensional. Each uncertain input used in the analysis may introduce a multitude of potential effects both directly and through interactions with one or more other uncertain input parameters. In addition, a robust analysis consists of a large sample size and corresponding number of deterministic realizations. This necessitates the use of regression techniques in order to interrogate the set of results and determine the relationship between the uncertainty in simulation conditions and uncertainty in model results. In a one-dimensional case, regression analysis is familiar and somewhat straightforward; find the function of a certain form that minimizes the distance, on average, between the function and the data points. Even then, a choice must be made about the form of the function and the method used to find it, which requires some initial data analysis. For the multi-dimensional parameter space that is typical of uncertainty analysis for severe accident models, the regression problem reduces to the same essential goal; identify the best statistical model form and select a method for building a model of that form. The complicating factor, however, is that it can be much more difficult to identify the best model form for a parameter space that includes discrete parameters, continuous parameters, interactions, thresholds, and non-monotonic relationships than for a one-dimensional parameter space that contains only one or two such characteristics. Because of this, the uncertainty analysis for severe accident models uses multiple regression models, each one uniquely well suited to identifying a particular type of model behavior.

Four regression techniques: linear rank, quadratic, recursive partitioning, and multivariate adaptive regression splines (MARS), are presented for use in uncertainty analysis for severe accident simulations. The first technique, linear rank regression, is the simplest technique and is used to identify the monotonic influence of individual parameters on the model response. First, the input parameters and the model responses are rank transformed to negate the effects of scale on identifying effects. Then, a linear model is fit to the rank transformed data in a stepwise fashion, meaning that parameters are iteratively added to and removed from the model in the model fitting process. Example results from a linear rank regression are shown in TABLE 1 (green) [8]. The leftmost column of this table contains the name of uncertain inputs whose uncertainty has been identified as important to the uncertainty in the model outputs. The rows of this table correspond to the regression results for each of these inputs. The R^2 denotes the proportion of the variance in the model response (in this case fractional cesium release) that is explained by the model, $R^2\ contr.$ denotes the increase in R^2 when the parameter is included in the model, and the standardized rank regression coefficient ($SRRC$) is the slope of the line fitted to each individual parameter and the response.

While linear rank regression is straightforward to interpret, it can only detect monotonic relationships between individual parameters and the severe accident model response. The remaining regression techniques presented are all able to detect non-monotonic and interaction effects. In TABLE 1, example results of these regression techniques are presented using Sobol indices to separate the main effects from the interaction (conjoint) effects. The S_i represents the main effect of each individual parameter and the T_i represents the sum of the main effect and the effect due to interactions. Hence, parameters with higher S_i values have a stronger main effect on the accident model response and parameters for which $T_i \gg S_i$ have a measurable interaction effect [13].

Though presented using the same result measures, these three regression methods have unique strengths and weaknesses. Quadratic regression was included because it builds upon the basic concepts of linear regression, but adds two-way effects so it can capture the relationship between two-parameter interactions and the model response. Therefore, quadratic regression maintains some of the ease of interpretation of a linear rank regression, but can capture slightly more complicated effects.

Recursive partitioning was included because it is uniquely able to detect thresholds and effects due to discrete (or categorical) parameters, to which linear and quadratic regressions are less sensitive. Recursive partitioning models are regression trees that are built by recursively binning the model response based on values of the uncertain parameters in order to identify the parameters that provide the best (most heterogeneous) bins. Such models, due to the many levels of binning, are also able to detect multi-dimensional interactions beyond the two-dimensional interactions detected by quadratic regression.

Finally, the MARS regression method is included because it is uniquely able to detect multi-dimensional effects between continuous parameters. The recursive partitioning and MARS models are conceptually similar and both characterize interaction effects that cannot be captured by linear rank and quadratic regression. The primary difference between the two is that recursive partitioning fits its model by binning in many dimensions and MARS fits its model by including basis functions in many dimensions, hence recursive partitioning is better suited to discrete data and MARS is better suited to continuous data.

TABLE 1. Example regression results from the Sequoyah SOARCA severe accident uncertainty analysis [8] showing the impact of uncertainty in input parameters on uncertainty in the fraction of cesium released.

	Rank Regression		Quadratic		Recursive Partitioning		MARS		Main Contribution	Conjoint Contribution
Final R2	0.40		0.77		0.51		0.77			
Input	R2 contr.	SRRC	Si	Ti	Si	Ti	Si	Ti		
priSVcyc	0.26	-0.53	0.32	0.86	0.58	0.96	0.41	0.76	1	1
Cycle	0.01	0.15	0.04	0.10	0.01	0.02	0.21	0.21	2	5
Rupture	0.05	-0.22	0.01	0.14	---	---	0.01	0.09	3	3
Eu_Melt_T	0.02	-0.15	0.02	0.27	0.02	0.40	0.01	0.30	4	2
Shape_Fact	0.04	0.21	---	---	0.00	0.00	0.00	0.00	5	9
Ox_Model	0.01	0.09	0.01	0.16	---	---	0.00	0.00	6	4
Fseal_Pressure	---	---	0.00	0.02	---	---	0.01	0.01	7	7
Seal_Open_A	0.01	-0.07	0.00	0.01	---	---	0.00	0.00	8	8
Burn_Dir	0.00	0.07	0.00	0.02	---	---	0.00	0.01	9	6

**** highlighted if main contribution metric measure larger than 0.02 or conjoint contribution metric measure larger than 0.1***

Though these example regression methods were used in previous MELCOR analyses [6-8], the choice of regression methods depends on the problem under consideration. The goal is to define a set of regressions that are comprehensive in capturing the behavior of the severe accident model.

2.4 Multiple regression analysis

The use of multiple regression analyses, while essential, complicates the ranking of uncertain parameters by importance. Understanding multi-dimensional influences from multiple statistical regression analyses enhances confidence in identifying the parameters that contribute the most to uncertainty in the simulated response to a severe accident.

In a first order approach, variable importance can simply be represented by ordering the parameters according to confidence in the regression techniques [6]. Because linear rank regression is robust and straightforward to interpret, parameters can be ordered based on rank regression results, then quadratic, recursive partitioning and MARS. A quantitative approach, such as that using two metrics referred to as the Main Contribution and the Conjoint Contribution in previous MELCOR studies [7-8], is less sensitive to qualitative judgements for the presentation of multiple regression analysis results.

The Main Contribution is calculated as an average of the individual parameter contribution measure for each regression method (SRRC and S_i) weighted by the strength of the regression model (R^2). The Conjoint Contribution is calculated as an average of the conjoint parameter contribution measures for each of the methods that detect conjoint contribution ($T_i - S_i$) also weighted by the strength of the regression model. This methodology for determining parameter importance over multiple regression methods gives more weight to results from models that explain more variance in the severe accident response and also gives more weight to parameters that are identified as important by multiple methods. Example results are presented in the last two columns of TABLE 1 as ranks of the contribution measures. Cutoffs were selected qualitatively and verified with scatterplots to differentiate parameters with potentially significant main and conjoint influences from parameters with detectible, but spurious effects. Cells in the table that are highlighted in yellow identify those parameters that were determined to have potentially significant effects.

As with the specific regression methods chosen, the method for combining results from multiple regression methods is flexible. Ultimately, the effects that are detected should always be further investigated using plots and individual realization analysis to identify the phenomenology behind the effect. The purpose of implementing measures for identifying important parameters is to guide this process and to check that expected model responses are evident in the simulation results through an iterative process of phenomenological investigation to identify all of the important parameters.

2.5 Deterministic analysis – model verification

Statistical regression results are corroborated using deterministic analyses to carefully evaluate physical behavior and check each response or non-response. Analysis of single realizations provides a specific insight into the physical phenomena controlling the variability in the probabilistic results. A comprehensive explanation is derived detailing how the system response is affected by various components of the reactor system under varying physical-chemical-thermal-mechanical conditions evaluated for the UA. This derivation provides both confidence that the processes are working as expected and insights to the phenomena driving the results. This in turn connects the phenomenology to key uncertain parameters identified in the parameter uncertainty analyses.

Individual deterministic realizations are selected out of the population of probabilistic results to be representative of the population. For instance, a deterministic realization representative of the upper quantiles, the median or mean, and the lower quantile behavior are generally selected, as shown for the Peach Bottom SOARCA UA [6] in Figure 3.

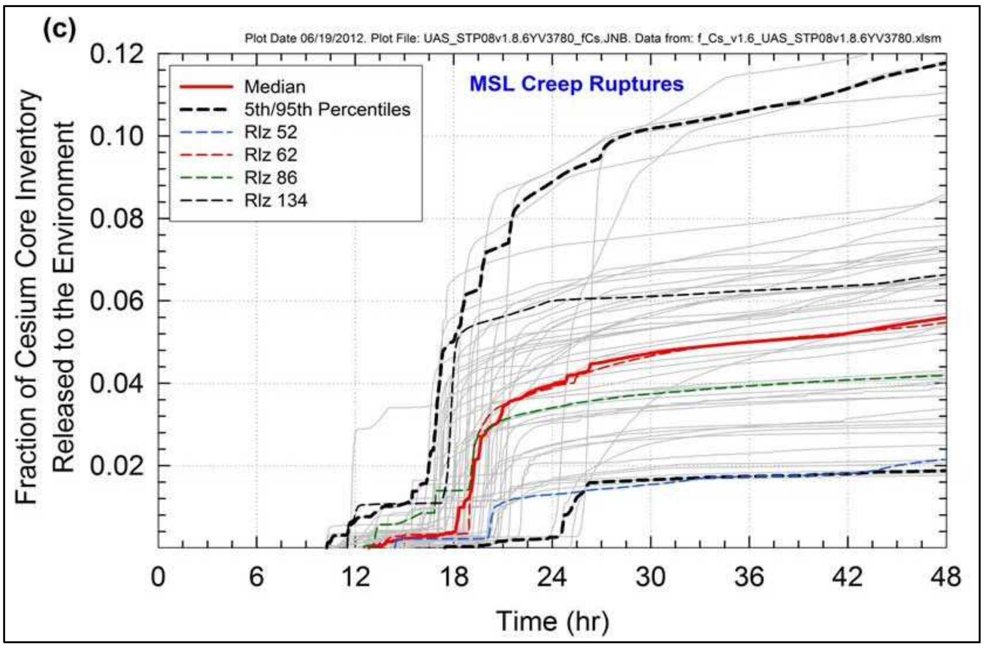

Figure 3. Demonstration of single realizations selected from the Peach Bottom UA[6].

In addition, deterministic realizations that are unique or have a behavior that is of very low frequency can often provide insights into previously unknown important phenomenology or reveal model errors (e.g., input, convergence, non-physical behavior, or outside the range of validity of the models used to simulate the complex system). Identification of the timing and effects of key phenomena for each of the selected deterministic realizations is correlated to the important uncertainty identified in the statistical regression analyses. An example of deterministic realizations selected based on timing and key phenomena is provided in Table 2 for the Sequoyah SOARCA UA [8]. Correlating deterministic model phenomenology with the statistical regressions is a key final step that provides confidence in the methodology.

TABLE 2. Example of deterministic single realizations selected for detailed analysis from the Sequoyah SOARCA UA [8].

I.D.	Selection criterion	Realization number*
1	The base STSBO UA case	Base calculation
2	The case with earliest containment rupture	338
3	A case with containment remaining intact at 72 hr	171
4	The case with the earliest FTC of a pressurizer SV	142
5	A case without a FTC of a pressurizer SV	469
6	A case with coincident RPV breach and containment rupture	338
7	The case with the least in-vessel hydrogen production	469
8	The case with the most in-vessel hydrogen production	225
9	The case with the smallest Cs release to the environment	174
10	The case with the largest Cs release to the environment	142
11	The case with the earliest RPV breach	551
12	The case with the latest RPV breach	148
13	A case without hot leg rupture	77
14	A case with early RPV breach and early containment rupture not coincident	133

*Note, all realizations are without random sources of ignition

4. UNCERTAINTY ANALYSIS EXAMPLE

The following uncertainty analysis example highlights the main steps of the method described in Section 2 and demonstrates the application of each of these steps in practice for the Sequoyah SOARCA UA. Example regression analysis results are presented in TABLE 1**Error! Reference source not found.**. In this example, the combined number of cycles completed by the system of three parallel safety valves atop the pressurizer (priSVcyc parameter) was identified to have a strong influence on cesium release.

Rank regression analysis showed that higher primary SV cycles are associated with lower releases, and this is supported by a scatter plot for the variable Figure 4. In this figure, the release fractions for each realization are colored according to the time in cycle at shutdown (denoted by BOC, MOC, or EOC in

Figure 4), which is the next dominant parameter influencing cesium environmental releases. Realizations with higher cesium releases tend to undergo less than 38 total cycles of the primary SVs, particularly for MOC realizations. There is also a dense cluster of MOC and EOC realizations around 70-75. This clustering reflects the median number of SV cycles that can occur before the primary side depressurizes due to RCS creep rupture. Physically, fewer SV cycles reflect an accident progression where the primary RCS depressurized sooner due to a lower sampled value for priSVcyc. The MELCOR Sequoyah model tends to predict higher cesium environmental releases for cases that have earlier primary depressurization. Depressurization of the RCS primary during the STSBO entails the venting of hot combustible gases laden with radionuclides to the containment. The BOC realizations all have essentially zero cesium releases, and these are depicted on Figure 4 to demonstrate that the BOC cases exhibit higher primary SV cycles. The lower decay heat associated with BOC results in delayed (or totally precluded) creep rupture, which typically occurs before 75 cycles in the MOC and EOC cases, thereby extending primary SV cycling.

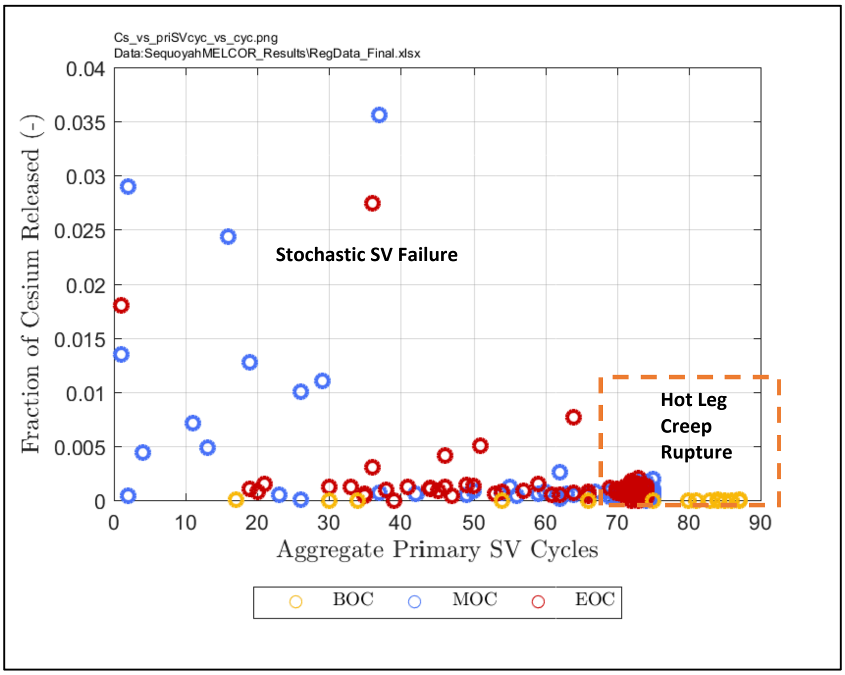

Figure 4. Scatterplot of cesium environmental release fraction versus priSVcyc from the Sequoyah SOARCA UA [8].

Another significant parameter for the cesium environmental release fraction is the effective liquefaction temperature of the UO_2–ZrO_2 system (Eu_Melt_T). This parameter has lower individual contribution to cesium release compared to aggregate pressurizer SV cycles (priSVcyc) and the time in cycle at shutdown (Cycle), but it is identified as having substantial conjoint contributions with other parameters. In particular, higher sampled values of Eu_Melt_T are associated with greater cesium environmental release fractions, as illustrated by

Figure 5. However, this trend only exists for realizations with fewer than 70 aggregate cycles of the pressurizer SVs (priSVcyc). For realizations with more than 70 cycles, the cesium environmental release fraction is rather independent of Eu_Melt_T.

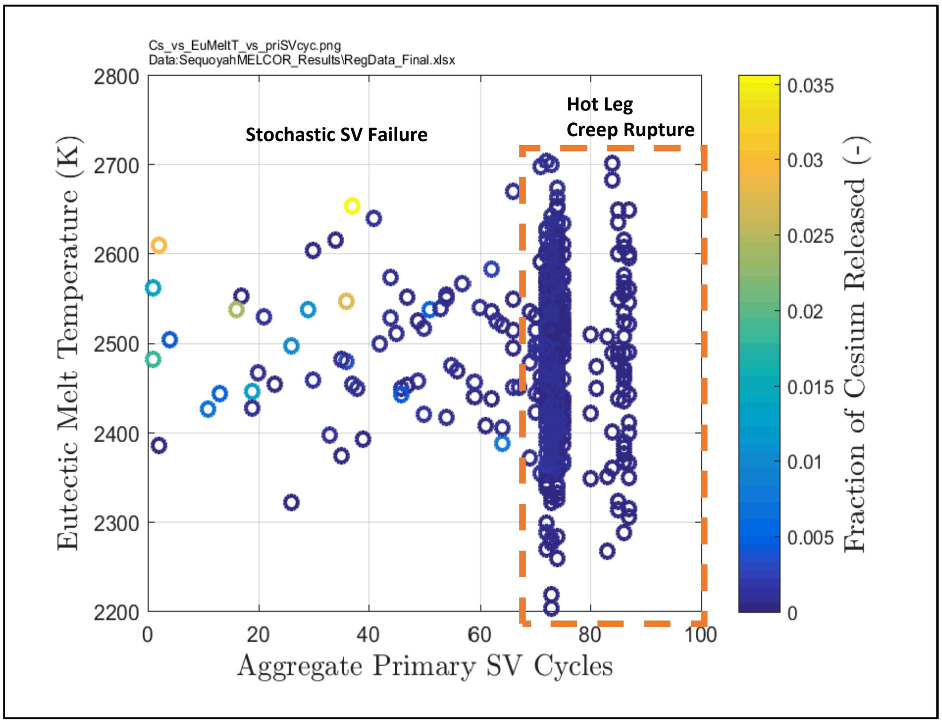

Figure 5 Scatterplot of Eu_Melt_T vs. priSVcyc with color contour for cesium release fraction from the Sequoyah SOARCA UA [8].

5. CONCLUSION

Uncertainty analyses for complex systems have successfully played a central role in many applications supporting nuclear reactor safety analysis. Coupling regression methodology with a traditional deterministic phenomenologically-driven analysis allows for qualitative and quantitative measures of the model and parameter uncertainties when using MELCOR to evaluate the system response to postulated severe reactor accident scenarios and potential release of radionuclides. The use of multiple statistical regression models quantitatively correlates parameter uncertainty with result dependencies. It is necessary to support the understanding of uncertainties and build confidence in regression results that identify important effects due to model or parameter uncertainties. However, each unique regression model presented in this paper has inherent strengths and weaknesses; the selection of the most appropriate set of regression models should be refined depending on the behavior of the severe accident scenario. The deterministic verification of the physics and phenomenological basis provides quantifiable bounds on uncertain model predictions. Statistical regression and deterministic verification can accurately expose non-physical or non-valid model responses or model inputs. The methodology is robust when a sufficient probabilistic sample size is used. The recent series of SOARCA analyses have demonstrated that the application of a rigorous modeling uncertainty analysis such as that described in this paper yields insights into severe accident modeling phenomena including thermal-hydraulic response; core heat-up, degradation, and relocation; hydrogen production; transportation; combustion; and fission product release and transport behavior that are unlikely to be discovered when only a deterministic approach is used.

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