INL/CON-16-39742
PREPRINT

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ICAPP 2017

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November 2015

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Demonstration of Uncertainty Quantification and Sensitivity Analysis for PWR Fuel Performance with BISON

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BISON is an advanced fuels performance code being developed at Idaho National Laboratory and is the code of choice for fuels performance by the U.S. Department of Energy (DOE)'s Consortium for Advanced Simulation of Light Water Reactors (CASL) Program. An approach to uncertainty quantification and sensitivity analysis with BISON was developed and a new toolkit was created. A PWR fuel rod model was developed and simulated by BISON, and uncertainty quantification and sensitivity analysis were performed with eighteen uncertain input parameters. The maximum fuel temperature and gap conductance were selected as the figures of merit (FOM). Pearson, Spearman, and partial correlation coefficients were considered for all of the figures of merit in sensitivity analysis.

I. INTRODUCTION

The current emergency core cooling system (ECCS) acceptance criteria for loss-of-coolant accidents (LOCA) in light-water reactors (LWRs) are described in 10CFR50.46. Two of the five criteria specify that the calculated peak cladding temperature (PCT) and maximum cladding oxidation shall not exceed 2200°F (1478K) and 17% equivalent cladding reacted (ECR), respectively (Ref. 1). Ever since the establishment of these cladding embrittlement criteria, more extensive research and experiments have been conducted which resulted in an increased understanding of fuel and clad behavior under both normal operating conditions and LOCA transient conditions. The new studies indicated that the current regulatory acceptance criteria may be non-conservative for high burnup fuel. The Nuclear Regulatory Commission (NRC) is considering a rulemaking change that would revise the requirements in 10CFR50.46. In the proposed new rulemaking, designated as 10CFR50.46(c), the NRC proposed a fuel performance-based ECR criterion as a function of cladding hydrogen content before the accident (pre-transient), to include the effects of fuel burnup on cladding performance (Ref. 2). The pre-transient cladding hydrogen content, in turn, is a function of the fuel burnup and cladding materials. A characteristic of the proposed new rulemaking, as illustrated in Fig. 1, imposes more restrictive and fuel rod-dependent cladding embrittlement criteria. Consequently fuel and cladding performance and ECCS performance need to be considered in a stronger coupled way in LOCA analyses.

The Idaho National Laboratory (INL) initiated a project to develop analytical capabilities to support the industry in the transition to the new rule (Ref. 3). The general idea behind the initiative was the development of an integrated multiphysics evaluation model. The motivation was to revisit how uncertainties are propagated across the stream of physical disciplines and data involved, as well as how risks are evaluated in a LOCA safety analysis as regulated under 10 CFR 50.46c. This integrated evaluation model is called LOTUS which stands for LOCA Toolkit for the U.S. Light Water Reactors (Ref. 3).

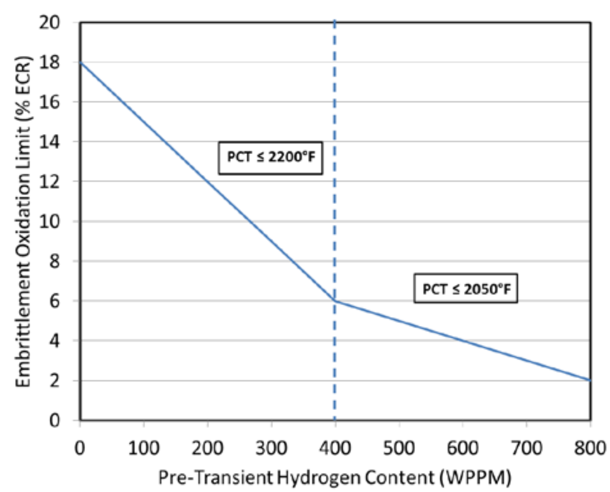

Fig. 1. Analytical generic limit proposed by the NRC for existing fuel (Ref. 2).

The LOTUS framework is notionally illustrated in Fig. 2. The primary characteristic of LOTUS is an integrated multiphysics simulation based tool to manage data flow stream, uncertainty propagation and risk assessment. The focus of LOTUS is to establish the automation interfaces among the five disciplines, as depicted in Fig. 2, such that uncertainties can be easily propagated with large number of simulations.

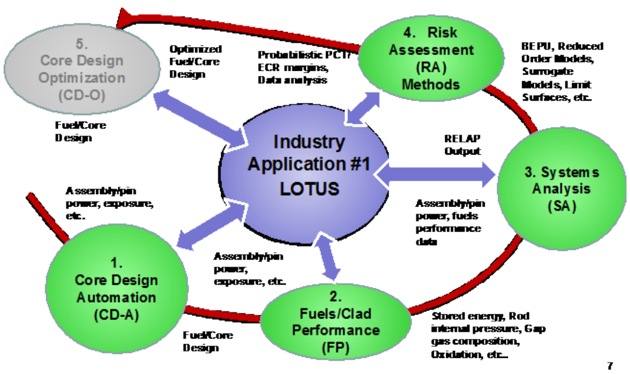

Fig. 2. Schematic illustration of LOTUS.

As indicated above, one overarching goal of the LOTUS development is to develop a methodology to systematically propagate uncertainties across the multiple disciplines involved in the LOCA analysis in order to perform best-estimate plus uncertainty (BEPU) analyses in response to the proposed 10 CFR 50.46c new rules. Therefore, understanding how uncertainties are propagated within each discipline is essential toward achieving the overall objective set forth here. As depicted in Fig. 2, fuels performance is an important component of LOTUS. The prediction of the behavior and failure modes of the fuel and clad is extremely difficult because it involves predicting the interacting and competing nuclear, thermal, mechanical, chemical and fluids flow processes. These multi-physics processes often have multiple scales in space and time and hence make fuels performance modeling very challenging. The models developed for these complex physical processes are often non-linear with various mathematical models and parameters. Hence uncertainties have to be considered in fuels performance simulations. The uncertainties may come from the fuel fabrication, code limitations, inaccurate material properties, scaling inaccuracies embedded in the experimental data, and system parameters. Consequently, uncertainty quantification and sensitivity analysis methodologies for fuels performance simulations have to be developed to achieve the goal set forth for LOTUS to perform BEPU analyses. It is worthy to point out that the uncertainty quantification (UQ) and sensitivity analysis (SA) work traditionally has been focused on thermaldraulics and neutronics. It has not gained much attention in fuels performance.

The advanced fuels performance code BISON (Ref. 4) is the code of choice for fuels performance by the U.S. DOE’s Consortium for Advanced Simulation of Light Water Reactors (CASL) Program and is also one of the codes of choice for fuels performance analysis within the LOTUS framework. Developing a methodology to perform uncertainty quantification and sensitivity analysis for BISON is the objective of this work. UQ and SA methods seek to improve knowledge and understanding of a considered model. Uncertainty quantification refers to the determination of uncertainty in model outputs based on the uncertainty in model inputs. Sensitivity analysis seeks to determine the contribution of the uncertainty in a single model input to the uncertainty in model results (Ref. 5). However, this work only identifies sensitive input parameters without attempting to quantify the amount of model uncertainty produced by each parameter. Results from sensitivity analysis provide a clearer picture of how system inputs correlate to system outputs. Parameters with negligible or no contribution to the system response can be removed in future studies while those parameters with significant contribution present a guide to where areas of future research should be focused on reducing the input uncertainty. Ikonen (Ref. 6) compared a number of global sensitivity analysis methods by use of the nuclear fuel performance code VTT-modified FRAPCON-3.4. Global sensitivity analysis methods explore the whole input parameter space by sampling chosen input parameters simultaneously rather than performing perturbations of input parameters one-at-a-time. Global sensitivity analysis has the advantage of being able to identify nonlinear uncertainty structures over the global admissible input parameter space. The non-influential parameters in nonlinearly parameterized models can be fixed for subsequent model calibration or uncertainty propagation (Ref. 7). Local sensitivity analysis tied to perturbing input parameters one at a time and is not able to identify these structures. There exist numerous sensitivity analysis methods (Refs. 4 and 5) that should be carefully chosen based on the complexity and specific model to be evaluated. In this work, a Monte Carlo, or sampling based, approach is used to evaluate those parameters that most profoundly affect the figures of merits. In Monte Carlo based methods, a large number of model simulations are performed to produce a significant number of samples that can be used for both uncertainty quantification and sensitivity analysis. Therefore, probability distribution functions (PDF) and cumulative distribution functions (CDF) can be computed for each of the FOMs. The PDF can indicate how the correlation between model inputs and model outputs behaves (Ref. 5) while the CDF can be used to quantify the uncertainty in the FOMs (Ref. 8). It is noted that UQ and SA work presented in this work focuses solely on properties of the BISON model and does not rely on comparisons to experimental data.

II. BRIEF DESCRIPTION OF THE BISON CODE

BISON is a finite-element multidimensional multiphysics fuel performance code being developed at

INL (Ref. 4) for a single fuel rod. It is a fully implicit code which solves fully-coupled equations of thermomechanics and species diffusion and allows large time steps to be used in simulations. Oxide fuel models are included to describe temperature, burnup and porosity dependent material properties, fission product swelling and densification strains, thermal and irradiation creep, fracture, and fission gas production and release. The cladding behavior models include plasticity, thermal expansion, irradiation growth, hydrogen uptake and creep. Models are also available to simulate gap heat transfer, mechanical contact, and the evolution of the gap/plenum pressure with plenum volume, gas temperature, and fission gas addition. BISON can efficiently solve problems using standard workstations or very large high-performance computers. The code is applicable to both steady and transient fuel behavior. BISON is built using the INL Multiphysics Object-Oriented Simulation Environment (MOOSE) (Ref. 9). MOOSE is a massively parallel, finite element-based framework to solve systems of coupled non-linear partial differential equations. BISON's 2D axisymmetric option is a fast running version of the code and is used in this work.

III. PROBLEM DESCRIPTION

The fuel performance computer codes are normally developed to analyze the behavior of a single fuel rod. A 2D full length BISON model is built for a single fuel rod. BISON is a deterministic fuel performance code that can calculate the response of light water reactor fuel rods under both the steady-state and transient conditions. Boundary conditions such as the fuel irradiation power history, axial power shapes are supplied as input to the code. Other user inputted boundary conditions include the coolant properties such as inlet coolant temperature, inlet coolant mass flux and system pressure. Since BISON is a multi-dimensional finite element code with arbitrary geometry, a mesh file generated with the fuel rod fabrication parameters has to be supplied to the code. The mesh file is a binary file format in Exodus II (Ref. 10).

The parameters used in the BISON model are for a typical 17x17 PWR fuel assembly design. The geometric parameters are shown in Table I. The propagation of uncertainties is studied under steady-state irradiation conditions with BISON. The analyzed scenario is a hypothetical normal operation irradiation of a UO2 fuel rod in a typical four-loop PWR reactor. The scenario is designed to bring the fuel rod to a relatively high burnup of 60 GWd/MT. The power history used for this BISON model is shown in Fig. 3. The axial power shapes versus burnup time in days used for this model are shown in Fig. 4. The power histories and axial power profiles are obtained from core design work done for a typical 4-loop PWR with 17x17 fuel assembly design (Ref. 3).

TABLE I. Fuel Rod Design Parameters and Boundary Conditions Used in the BISON Model

Parameter	Value	Unit
Active Core Length	365.76	cm
Rod Pitch	1.26	cm
Clad Material	ZIRC-4	-
Clad Outer Radius	0.475	cm
Clad Inner Radius	0.418	cm
Fuel Material	UO_2	-
Fuel Pellet Outer Radius	0.4096	cm
Gap Initial Width	0.0084	cm
Fuel Enrichment	4.85	%
Fuel Theoretical Density	93.5	%
Coolant Pressure	15.51	MPa
Coolant Inlet Temperature	561	K
Coolant Inlet Mass Flux	3460	$\frac{kg}{m^2 \cdot s}$

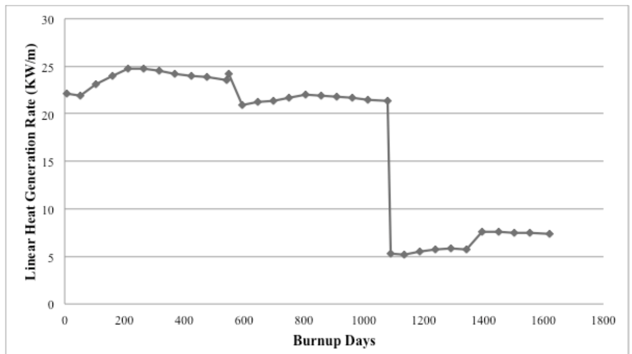

Fig. 3. Fuel rod power history.

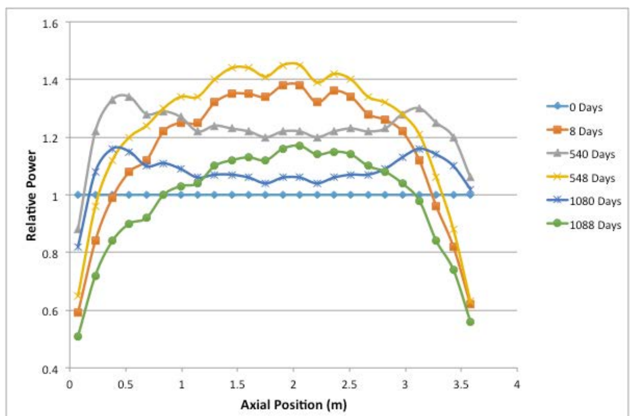

Fig. 4. Axial power shapes versus time

IV. METHODOLOGY

IV.A. Figures of Merit

Performing uncertainty and sensitivity analysis requires that a relevant system response output variable, or figure of merit (FOM), be chosen to analyze. BISON provides a number of system response variables that could be analyzed. These include maximum fuel temperature, clad temperature, gap conductance, gap width, fission gas release, clad hoop stress, plenum pressure and clad radial elongation, etc. For brevity, in this work, we selected the maximum fuel temperatures and the gap conductance as the FOMs to perform sensitivity analyses.

IV.B. Input Uncertainty

TABLE II. Uncertain Input Parameters

Input Parameters	Range	Distribution
Fuel Thermal Conductivity	±10%	Uniform
Fuel Thermal Expansion	±15%	Uniform
Clad Creep Rate	± 30%	Uniform
Clad Oxidation	± 40%	Uniform
Clad Thermal Conductivity	± 20%	Uniform
Clad Thermal Expansion	± 30%	Uniform
Coolant Heat Transfer Coefficient	± 5%	Uniform
Pellet Initial Diameter (mm)	± 0.02	Uniform
Clad Initial Thickness (mm)	± 0.025	Uniform
Gap Initial Width (mm)	± 0.0005	Uniform
Fuel Enrichment (%)	± 0.003	Uniform
Fuel Density (%)	± 1.6	Uniform
Coolant Pressure (MPa)	± 0.31	Normal
Coolant Inlet Temperature (K)	± 3	Normal
Coolant Inlet Mass Flux ($\frac{kg}{m^2 \cdot s}$)	± 69	Normal
Linear Power	± 5%	Uniform
FGR Intra-granular Diffusion Coefficient	+200%/-67%	Uniform
FGR Grain-boundary Diffusion Coefficient	+200%/-67%	Uniform

There exist large uncertainties in many of system and model input parameters. The primary objective of this work is demonstrate the uncertainty propagation and sensitivity analysis methodology developed in this work with the focus on system and model parameter uncertainty as the uncertainty in user inputted values to the BISON input file. The specific number of input parameters to consider in uncertainty quantification is sometimes defined by the analysis method itself. In non-parametric methods, such as the Monte Carlo approach used in the current work, the amount of parameters is not specified by the method itself but there is still motivation to limit the number of uncertain parameters (Ref. 8). The specific parameters should be judiciously chosen based on those that are expected to have the most influence on the FOMs for sensitivity analysis. A table of uncertain parameters can be developed that indicates the most important inputs to the model and their expected range of uncertainty. The input parameters are assumed to be mutually independent. Correlation between model inputs will have an effect on how these parameters are sampled for uncertainty quantification and sensitivity analysis and this is left for future work. The uncertain input parameters and their relevant uncertain ranges used in this work are shown in Table II. Most of the parameters ranges are consistent with those used by Ikonen in Ref. [6].

IV.C. Sensitivity Analysis

IV.C.1. Scatterplots

Scatterplots are often the first step to examine the relationship between the uncertainty in model inputs and analysis results while revealing any non-linearity or unexpected behavior (Ref. 5). Scatterplots provide the starting point for development of a more qualitative sensitivity analysis strategy. Rank transformed data can also be used to create scatterplots when the data exhibits a non-linear yet monotonic relationship (Ref. 8). Rank transformation is used to rank the input and output data from the smallest values, with a rank of 1, to the largest values with a rank corresponding to the number of samples. Rank transformed scatterplots are then formed by plotting the rank transformed output data y versus the rank transformed input data x.

IV.C.2. Pearson and Spearman Correlation Coefficients

Although scatterplots are instrumental in examining the relationship between the model input and output parameters, quantitative methods such as correlation coefficients provide the degree of linearity that exists between inputs and outputs. Various methods for computing correlation coefficients exist in the literature (Refs. 4 and 5) and the method used must be sensibly chosen based on the sensitivity analysis approach. Correlation coefficients are valued between -1 and +1 where -1 represents a perfect inversely correlated linear relationship and +1 represents a perfect linear relationship. A value close to 0 indicates that the input has insignificant effect on the output. Absolute values of the correlation coefficients between model inputs and a particular FOM can then be ranked from those inputs that are the most influential to those that are the least influential on the FOM. The Pearson (or sample) correlation coefficient (CC) between inputs x_j and output y as defined by Helton et al. (Ref. 5) is:

$$c(x_j, y) = \frac{\sum_{i=1}^{N}(x_{ij}-\bar{x}_j)(y_i-\bar{y})}{\left[\sum_{i=1}^{N}(x_{ij}-\bar{x}_j)^2\right]^{1/2}\left[\sum_{i=1}^{N}(y_i-\bar{y})^2\right]^{1/2}} \quad (1)$$

where

$$\bar{x}_j = \sum_{i=1}^{N}\frac{x_{ij}}{N} \quad (2)$$

$$\bar{y} = \sum_{i=1}^{N}\frac{y_i}{N} \quad (3)$$

and N is the number of samples. The Pearson correlation coefficient can also be applied to the rank transformed data and is then known as the Spearman, or rank, correlation coefficient (RCC).

IV.C.3. Partial Correlation Coefficients (PCC)

In a global sensitivity analysis approach, perturbations in the model output are not purely a function of that of a single input, but rather a combinational effect from the perturbation of all model inputs simultaneously. To evaluate the comprehensive quality of the sensitivity analysis the square of the Pearson correlation coefficient (R^2) can be calculated for each input parameter and summed. If the value remains significantly below unity then higher order sensitivity analysis methods, such as partial correlation coefficients (PCCs), must be used to analyze nonlinearities in the model (Ref. 5). PCCs characterize the linear relationship between a model input and model output after corrections have been made for the linear effects on the output by all other model inputs.

IV.C.4. Sensitivity Analysis Toolkit

The overall computational method to perform the uncertainty and sensitivity analysis (Fig. 4) forms the BISON Uncertainty and Sensitivity Analysis Toolkit (BISAT). BISAT contains two main portions. In Fig. 5 the solid lines indicate the first BISAT portion of pre-processing and BISON execution. This pre-processing step uses a Python script to perform the overall perturbation of the nominal values. BISON uses a hierarchical, block-structured input file and the syntax is completely customizable and replaceable. This makes it amiable to use Python scripts to modify the input files. A BISON input file was first created for a fuel rod case with the nominal input values shown in Table I. The table of uncertain parameters was also created as an input to the Python script. The Python script is then called to read the nominal BISON input file, sample the variables defined in the table of uncertain parameters from the ranges defined in the table of uncertain parameters input file, and then create N new BISON input files with perturbed parameters. For each of the new BISON input files with perturbed parameters, a new mesh file is generated with the same perturbed rod geometry data. The mesh file is generated by CUBIT (Ref. 11) which is a mesh generator developed by Sandia National Laboratories. The Python scripts which are available with the BISON installation were used to drive CUBIT to generate the mesh file for the respective BISON input file. BISAT then submits all of the new perturbed cases to INL's high performance computing queue.

For each of the N simulations a BISON output file is created for the modeled fuel rod. The post-processing portion of the BISAT (dashed lines in Fig. 5) utilizes Python scripting to search the quantities of interest. The final step of the BISAT retrieves the FOMs from each of the case summary files as well as the values for each of the perturbed parameters defined by the table of uncertain parameters input file. A FOM summary file is then written that contains the FOMs and perturbed values for each case.

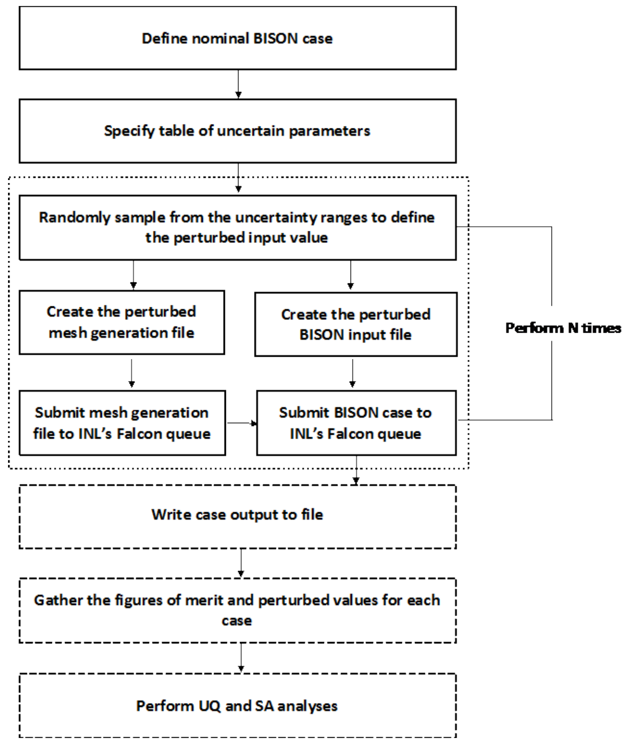

Fig. 5. BISAT flow diagram.

V. RESULTS

The UQ and SA simulations were performed on the Fission supercomputer at the INL. The BISAT toolkit described in section IV was used to create 5000 BISON input files with perturbed parameters outlined by the table of uncertain parameters shown in Table II. All the 5000 BISON cases run successfully and are considered here. The BISAT post-processor was then used to extract the FOMs, perturbed values, and any other quantities of interest.

V.A. Uncertainty Quantification Results

Overall, 5000 BISON model simulations were performed for uncertainty quantification by use of BISAT. The data corresponding to fuel burnup of 40.66 GWD/MT were selected for detailed analysis here. Table III shows the percentile values for each FOM. For the 95th percentile, the standard error is shown calculated by the method in Ref. [12] to obtain the 95 percent probability at the 95 percent confidence interval as shown in the following:

$$Y_{95/95} = \mu_{95\%} \pm 1.96 * SE_{Q95\%} \quad (4)$$

where $\mu_{95\%}$ is the 95 percentile values of the FOM and $SE_{Q95\%}$ is the standard error of $\mu_{95\%}$. In this case, the standard error at the 95th percentile $SE_{Q95\%}$ can be approximated as 2.11 multiplied by the standard error on the mean SE_M. The stand errors are less than one percent of the FOM and hence indicate that 5000 runs are adequate to generate the results with acceptable confidence interval.

TABLE III. FOM UQ Values from the 5000 BISON Simulations

FOM	Percentiles		
	5th	50th	95th $\pm 1.96 * SE_{Q95\%}$
Maximum Fuel Temperature [K]	1423.28	1566.28	1761.15 ± 5.06
Gap Conductance [W/m^2-K]	7624.50	11832.27	17793.16 ± 153.27

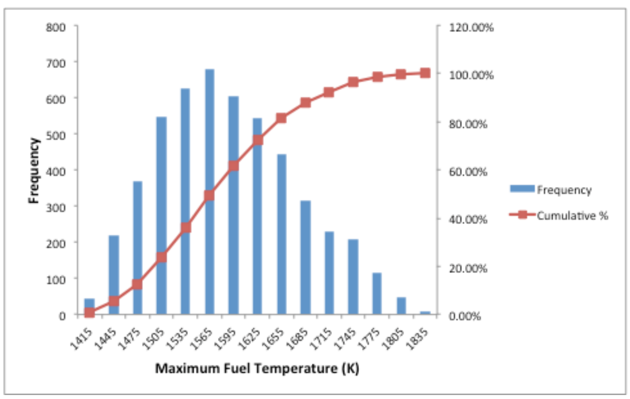

Fig. 6. PDF and CDF for Maximum fuel temperature.

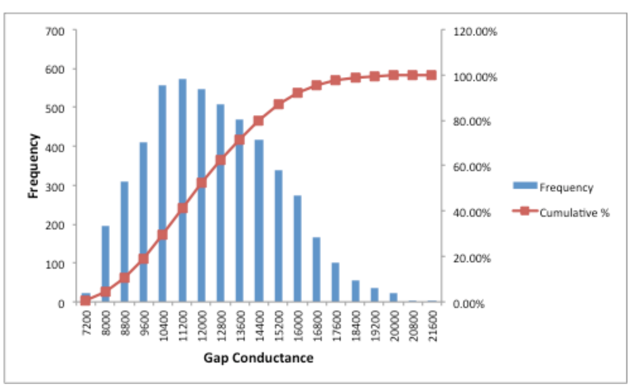

Fig. 7. PDF and CDF for Gap Conductance.

Figures 6 and 7 show the empirical PDF and CDF for the maximum fuel temperature and gap conductance, respectively. For each FOM, the PDF shape closely resembles a skewed Gaussian. From the near Gaussian shaped PDFs it is possible to deduce that the models that produce these distributions from the input distributions is quite simple. Therefore, it is not expected that higher order method of sensitivity analysis will be necessary.

V.B. Sensitivity Analysis Results

The same data used for the uncertainty quantification study is examined for the sensitivity analysis of the BISON runs. The 2 FOMs and 18 input parameters were ranked by the method discussed in section IV using the RANK function in Microsoft Excel to create scatterplots. The scatterplots for ranked maximum fuel temperature versus ranked input parameters are shown in Fig. 8 and a trendline is used on each of the plots to show a linear fit to the data. Scatterplots for gap conductance are shown in Fig. 9. Those inputs that have a more prominent positive slope are the inputs that are most positively correlated with an increase in maximum fuel temperature. For example, the linear power rate has an obvious positive slope meaning that as the linear power rate is increased, the maximum fuel temperature increases as more heat is added to the fuel. Conversely, those inputs that have a prominent negative slope indicate a negative correlation between the input and maximum fuel temperature. For example, as the fuel thermal conductivity is increased the maximum fuel temperature is decreased. Notably, certain parameters do not have a particularly strong correlation with the FOMs. However, correlation coefficients are needed to quantify the contributions of the uncertainty in each input parameter to changes in each FOM.

The Pearson correlation coefficients between each of the perturbed parameters and considered FOMs were calculated using the PEARSON function in Microsoft Excel. The Spearman coefficients were also calculated by use of the CORREL function in Microsoft Excel on the rank transformed data and results were consistent with the Pearson correlation coefficients. The sum of the R^2 values were examined for each FOM to ensure that Pearson correlation coefficients were suitable for analyzing model correlations and for each of the FOMs the R^2 values was equal to, or nearly equal to, unity. However, partial correlation coefficients are shown here as well to demonstrate the application of sensitivity analysis techniques to BISON. PCCs were calculated using an Excel VBA script based on that available publicly by Listen Data (Ref. 13). Values for all of the correlation coefficients for each FOM are shown in Tables IV-V along with the importance rank of each particular parameter. The results show that the fuel thermal conductivity is the most important parameter for both of the FOMs, regardless of the correlation coefficient calculation technique.

The most correlated parameters are consistent for each of the correlation techniques for at least the first three most influential parameters after which there are some differences. Interestingly, some sign change is noticed between correlation coefficient techniques for the least correlated values (e.g. coolant inlet mass flux for maximum fuel temperature).

II. CONCLUSIONS

This work was performed to develop an uncertainty quantification and sensitivity analysis approach to the advanced fuels performance code BISON. The BISAT toolkit was developed to handle the UQ/SA approach with the ability to perturb any number of selected input parameters, create an arbitrary number of perturbed BISON input files along with perturbed meshes, and post-process the BISON cases to create a single output file containing the FOM and perturbed parameter values for each case. A table of uncertain input parameters was developed for the BISON model considered in this study with inputs expected to influence the FOMs. The results of sensitivity analysis show that a number of correlation coefficients can be calculated for the Monte Carlo global sensitivity analysis considered in this work. Sensitivity analysis results also show that fuel thermal conductivity and linear heat generation rate are most influential to the maximum fuel temperature and fuel thermal conductivity, linear heat generation rate and fission gas release intra-granular diffusion coefficient are most influential on gap conductance as FOMs analyzed in this work.

Future work for SA with BISON will include using higher order sensitivity analysis techniques such as Sobol's variance decomposition to study the effect of variable interactions.

ACKNOWLEDGMENTS

This manuscript has been authored by Battelle Energy Alliance, LLC under Contract No. DE-AC07-05ID14517 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a nonexclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes.

The authors would like to express their appreciation to Steve Novascone and Kyle Gamble on the BISON development team at INL for their support.

REFERENCES

1. http://pbadupws.nrc.gov/docs/ML1114/ML11140A159.pdf, Letter Report: OG-11-143 PWROG 50.46(b) Margin Assessment.
2. http://pbadupws.nrc.gov/docs/ML1111/ML111100391.pdf.
3. R. Szilard, et. al., "Loss of Coolant Accident/Emergency Core Coolant System Evaluation of Risk-Informed Margins Management Strategies for a Representative Pressurized Water Reactor", INL-EXT-16-39805.
4. J. D. Hales, et al., "BISON Theory Manual, The Equations behind Nuclear Fuel Analysis," Idaho National Laboratory, Jan., 2015.
5. J. C. Helton, J. D. Johnson, C. J. Sallaberry and C. B. Storlie, "Survey of sampling-based methods for uncertainty and sensitivity analysis," SANDIA Report SAND2006-2901, June 2006.
6. T. Ikonen, "Comparison of global sensitivity analysis methods - Application to fuel behavior modeling," *Nuclear Engineering and Design*, **Vol. 297**, pp. 72-80, 2016.
7. R.C. Smith, 2014, *Uncertainty Quantification*, Society for Industrial and Applied Mathematics, Philadelphia, PA.
8. W. R. Marcum and A. J. Brigantic, "Applying uncertainty and sensitivity on thermal hydraulic subchannel analysis for the multi-application small light water reactor," *Nuclear Engineering and Design*, **Vol. 293**, pp. 272-291, 2015.
9. www.mooseframework.org.
10. L. Schoof and V. Yarberry, "EXODUS II: A finite element data model," Technical Report SAND92-2137, Sandia National Laboratories, September 1996.
11. https://cubit.sandia.gov.
12. B. Harding, C. Tremblay and D. Cousineau, "Standard errors: A review and evaluation of standard error estimators using Monte Carlo simulations," *The Quantitative Methods For Psychology*, **Vol. 10**, no. 2, 2014.
13. Calculating partial correlation coefficients with Excel VBA," Listen Data, 2015. [Online]. Available: http://www.listendata.com/2013/02/excel-udf-partial-correlation-matrix.html.

TABLE IV. Summary of Correlation Coefficients and Importance Rank for Maximum Fuel Temperature

Maximum Fuel Temperature						
Parameter	**CC**	**CC Rank**	**RCC**	**RCC Rank**	**PCC**	**PCC Rank**
Fuel Thermal Conductivity	-0.7898	1	-0.7925	1	-0.9927	1
Fuel Thermal Expansion	-0.0170	8	-0.0156	8	-0.1696	7
Clad Creep Rate	0.0025	17	0.0057	14	0.0670	11
Clad Oxidation	0.0032	16	-0.0028	17	0.0518	12
Clad Thermal Conductivity	-0.0544	5	-0.0509	5	-0.5458	4
Clad Thermal Expansion	-0.0055	13	-0.0050	15	-0.0105	17
Coolant Heat Transfer Coefficient	-0.0476	7	-0.0465	6	-0.1416	9
Pellet Initial Diameter	-0.0073	12	-0.0099	11	-0.1211	10
Clad Initial Thickness	-0.0477	6	-0.0449	7	-0.2283	6
Gap Initial Width	-0.0047	14	0.0009	18	-0.0514	13
Fuel Enrichment	0.0002	18	-0.0035	16	0.0393	14
Fuel Density	-0.0610	4	-0.0558	4	-0.3900	5
Coolant Inlet Pressure	-0.0036	15	-0.0090	12	-0.0068	18
Coolant Inlet Temperature	0.0131	9	0.0118	10	0.1640	8
Coolant Inlet Mass Flux	0.0094	11	0.0087	13	-0.0187	16
Linear Power	0.6028	2	0.5907	2	0.9872	2
FGR Intra-granular Diffusion Coefficient	0.0814	3	0.0762	3	0.6866	3
FGR Grain-boundary Diffusion Coefficient	-0.0102	10	-0.0134	9	-0.0237	15

TABLE V. Summary of Correlation Coefficients and Importance Rank for Gap Conductance

Gap Conductance						
Parameter	**CC**	**CC Rank**	**RCC**	**RCC Rank**	**PCC**	**PCC Rank**
Fuel Thermal Conductivity	0.6796	1	0.6847	1	0.9729	1
Fuel Thermal Expansion	0.0340	9	0.0317	9	0.1841	7
Clad Creep Rate	-0.0018	17	-0.0042	17	-0.0789	10
Clad Oxidation	0.0027	16	-0.0053	16	0.0360	13
Clad Thermal Conductivity	0.0542	7	0.0496	6	0.3397	5
Clad Thermal Expansion	0.0079	13	0.0068	14	-0.0065	17
Coolant Heat Transfer Coefficient	0.0350	8	0.0347	8	0.0663	11
Pellet Initial Diameter	0.0213	10	0.0209	10	0.1050	9
Clad Initial Thickness	0.0647	4	0.0659	4	0.1970	6
Gap Initial Width	-0.0014	18	-0.0011	18	0.0054	18
Fuel Enrichment	-0.0035	15	-0.0066	15	0.0137	15
Fuel Density	0.0548	6	0.0563	5	0.1838	8
Coolant Inlet Pressure	0.0063	14	0.0111	12	0.0101	16
Coolant Inlet Temperature	-0.0102	11	-0.0114	11	-0.0620	12
Coolant Inlet Mass Flux	-0.0090	12	-0.0077	13	0.0196	14
Linear Power	-0.5795	2	-0.5803	2	-0.9621	2
FGR Intra-granular Diffusion Coefficient	-0.4095	3	-0.3873	3	-0.9323	3
FGR Grain-boundary Diffusion Coefficient	-0.0551	5	-0.0451	7	-0.3563	4

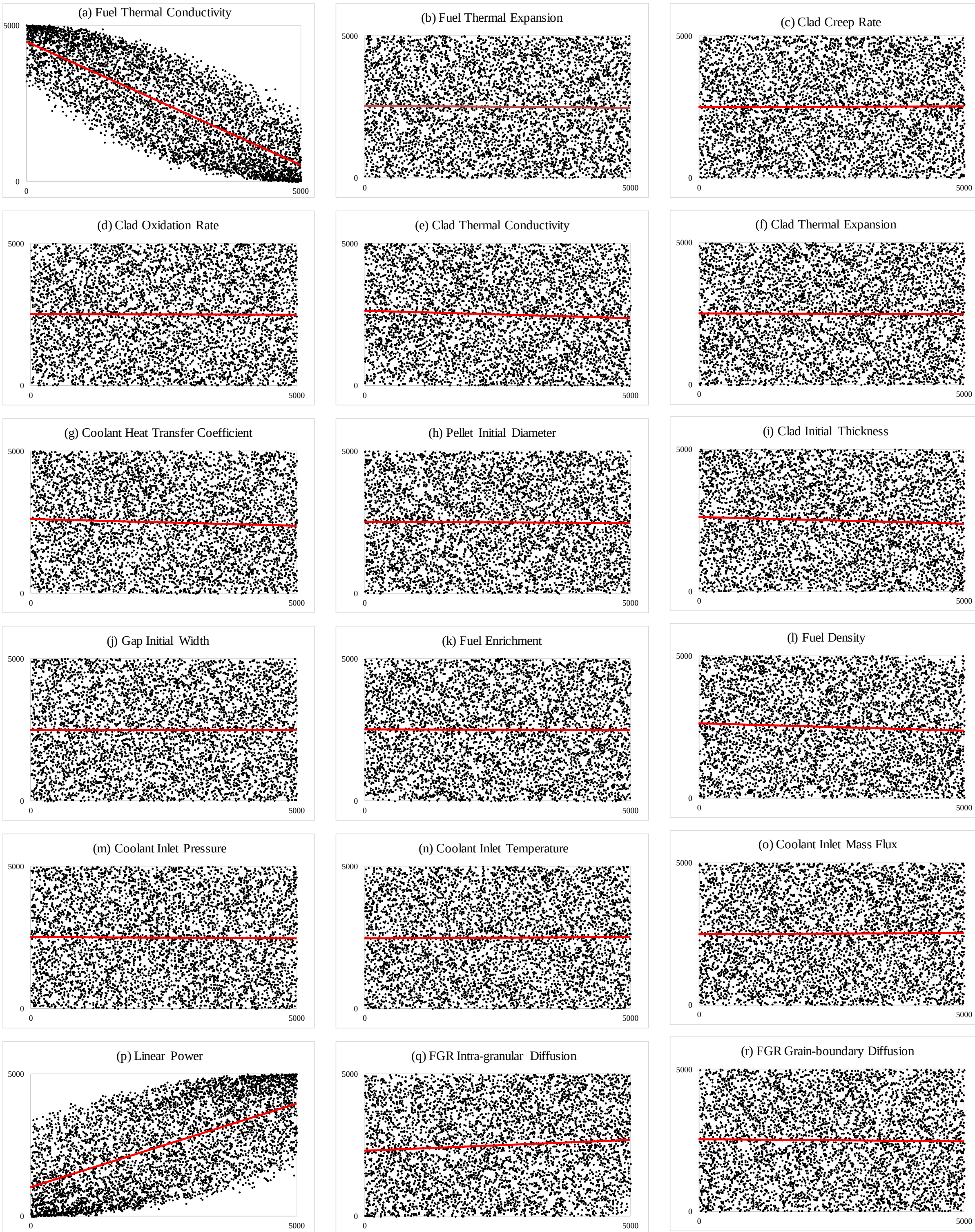

Fig. 8. Ranked maximum fuel temperature versus ranked input parameter for sensitivity analysis.

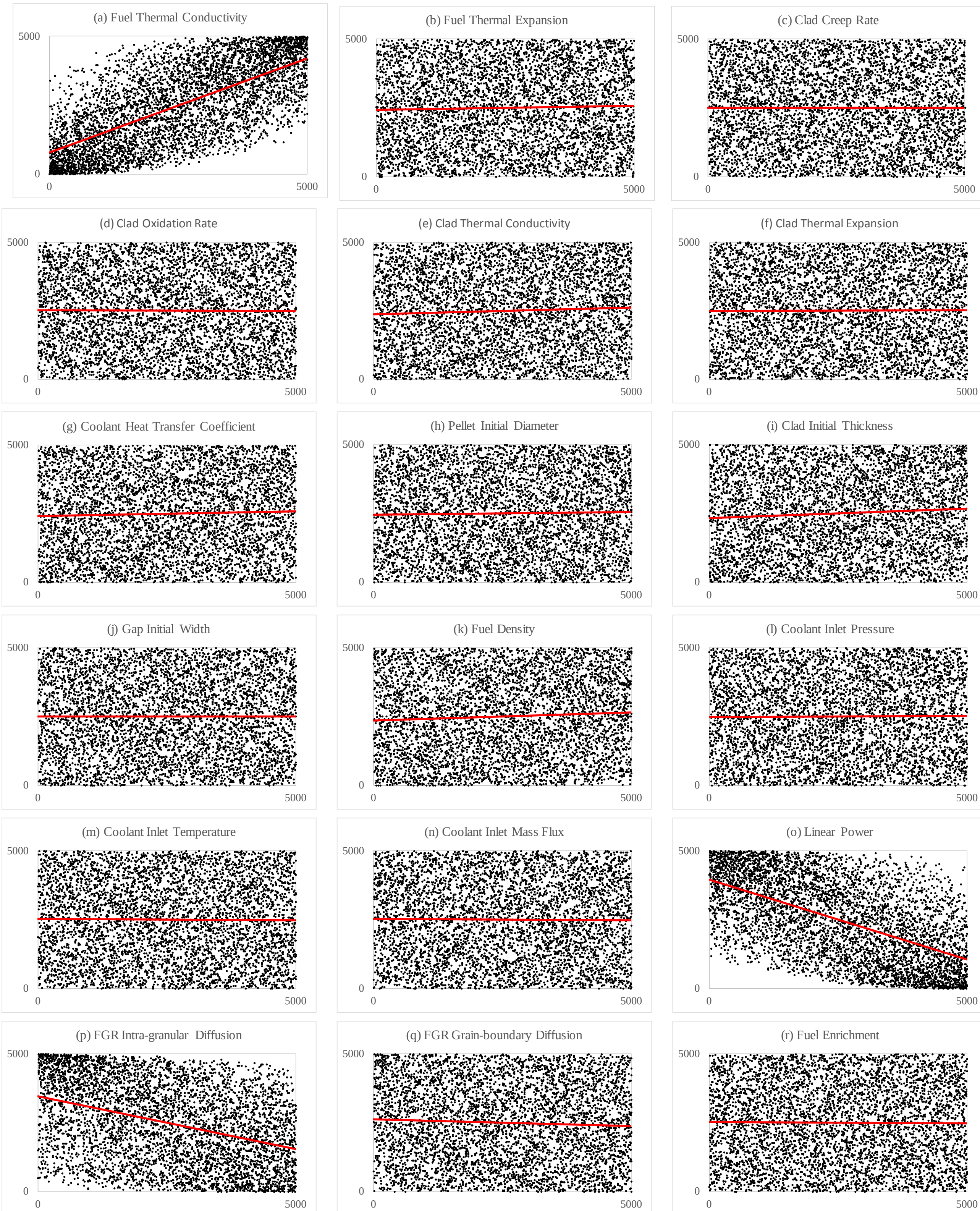

Fig. 9. Ranked gap conductance versus ranked input parameter for sensitivity analysis.