Statistical Uncertainty of RELAP5-3D

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As scientists, we wish to quantitatively answer any given question with a solution that is accurate and without bias. With any simulation, or measurement there are inherent uncertainties that affect our solution. It is necessary to utilize practices that limit the number of uncertainties we consider for any particular problem. This is where the studies of Statistical Uncertainty Analysis and Sensitivity Analysis have resulted from (Ronan). The RELAP5-3D team has been focused on utilizing uncertainty analysis to improve RELAP5-3D's modeling capabilities.

The project, completed during Spring 2012, is an initial exploration of such an uncertainty analysis application. This work involved analyzing high, medium, and low ranked phenomena from an INL PIRT (Phenomena Identification and Ranking Table) on a small break LOCA (Loss-Of-Coolant Accident), as well as using a previous INL study to create a preliminary statistics-based PIRT. We performed statistical analyses using correlation coefficients. To perform the studies, computer programs were written that modify a template RELAP5-3D input deck to produce one deck for each combination of key input parameters. Python scripting enabled the running of the generated input files with RELAP5-3D on INL's massively parallel cluster system. We collected data from the studies and analyzed the data with SAS. In this article, we present the process we used to create input files, the studies we completed, and present our findings, conclusions, and future work.

The PIRT is a structured and facilitated elicitation process in which experts are asked to rank various phenomena pertaining to a particular scenario. It includes the utilization of best-estimate (BE) codes to assist in the ranking process of phenomena. The phenomena in a PIRT are typically classified as "low", "medium", or "high."

Correlation coefficients are the most important measure of the degree of correlation between two variables, as they standardize the covariance (a measure of the amount of association between two variables) by eliminating the dependency on scale of measurement for a particular data set. A correlation coefficient is a descriptive statistical measure that depicts the strength of the relationship between two or more variables. In our case, we calculated the correlation coefficient between two variables (an input phenomena and the key output parameter).

There are several types of correlation coefficients. The three that we used (Pearson Product Moment Correlation Coefficient, Spearman Ranking Correlation Coefficient, and Kendall's Tau) are the three most commonly used. The absolute value of the correlation coefficient indicates the strength of the relationship between the input phenomena and the key output parameter. As with any statistical computation, it is important to determine the significance of the calculation. In our studies we utilized the p-value (also known as the significance probability) as the inferential statistical test to evaluate the statistical significance of the correlation coefficient. We considered a p-value less than or equal to 0.05 to indicate statistical significance. If the p-value was greater than 0.05 we were unable to make any conclusions about that phenomena based on its correlation coefficient. Upon calculation of the correlation coefficients, we were able to compare the absolute value of the correlation coefficient to a PIRT ranking through as summarized in Table 1.

Table 1: PIRT Level vs. Correlation Coefficient Value

LEVEL	Absolute Value of Correlation Coefficient	PIRT
High	0.70 to 1.00	3
Medium	0.30 to 0.69	2
Low	0.01 to 0.29	1

In order to find a way to mathematically evaluate the accuracy of PIRTs, and to provide insight to validate and/ or to make suggested changes to a given PIRT, or to create a ranking in the absence of a PIRT, it is possible to apply statistical analysis to a RELAP5-3D input model of the plant in question.

We utilized the PIRT for AP600 and the LOFT L2-5 experiment and corresponding RELAP5-3D input decks to determine variables of interest. We wrote computer programs and scripts that calculated the correlation coefficients for a large number of combinations of values of these variables. The number of combinations was so large, that an INL supercomputing cluster was needed to run the cases in a tractable amount of time. The process is depicted in Figure 1.

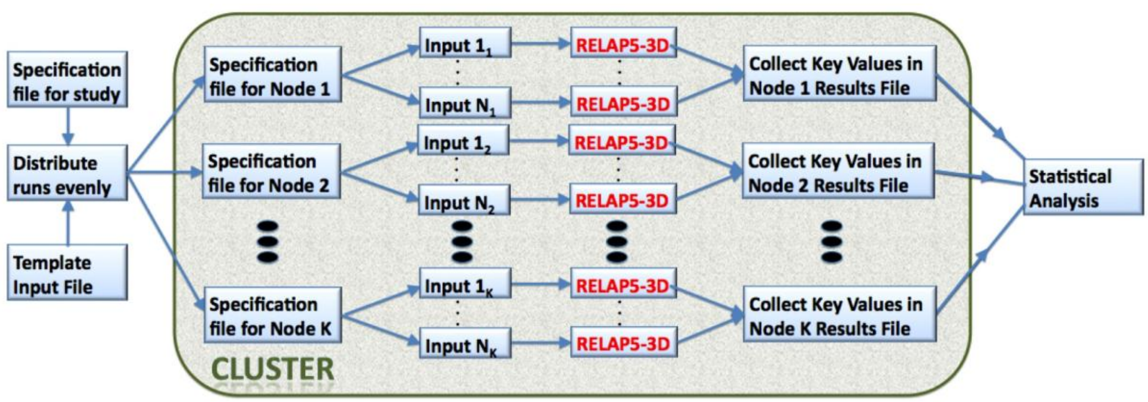

Figure 1: Illustration of the Process used in the Studies

The specification (spec) file and template input file completely define the study. The spec defines important information for the phenomena of the study, such as the minimum and maximum values for each phenomenon, and the number of variations each variable should experience within these bounds (i.e. the number of points uniformly distributed between the minimum and maximum). We wrote a program that subdivides the combination evenly among the nodes of the cluster by creating a control (or node spec) file for each node. Our program fills values into the template input to create specific input files. The scripts run RELAP5-3D for each input file, collect the data, and supply it to SAS for statistical analysis.

In all of the studies, there were variables which had their respective p-value >0.05. This does not indicate that these variables were statistically insignificant, or that they were unimportant to to the key parameter. Rather, it indicates that we cannot make a conclusion regarding their correlation to the minimum core level, and that further investigation is needed for these variables.

The first set of studies we conducted was on a Westinghouse AP600 (600 MW Advanced PWR) Nuclear Power Plant simulation involving a cold leg-break. The PIRT was compiled by Burtt, et al and addresses AP600 behavior expected during small break loss-of-coolant, main steam line break, and steam generator tube rupture accidents. The key *output* parameter of interest, core level, and thirteen *input* variables of interest were identified. Just three values for each input variable would generate 3^(13) = 1,594,323 possible combination, and that many input files and code runs. At 400 sec per run, that would require 7,381 days on a single processor. Even utilizing the INL cluster, which has 32 cores per node and 12 nodes, it would require 19 days to run the study. Ways to reduce the time for studies were devised. The results are shown in Table 2.

Table 2: AP600 Study - Corr. Coef with p-value < 0.05, PIRT rank in parentheses

Break Size	High Corr. Coef.	Medium Corr. Coefficient	Low Corr. Coefficient
2 inch	• Core Power (High)		• PRHR-Flow Resistance I (Low)
4 inch	• Core Power (High)		
6 inch		• Core Power (High) • Level in CMT (High) • PRHR-Flow Resistance I (Low)	• SG-Heat Transfer (Medium)
8 inch		• Core Power (High) • Level in CMT (High)	• SG-Heat Transfer (Medium)

It is expected that the PIRT ranking should be the same or higher than the statistical ranking for conservatism. Therefore, it is surprising that one phenomenon in the 6 inch study (PRHR flow resistance) ranked higher according to correlation coefficients than the PIRT ranking.

Our second study was on a simulation of the LOFT-S1 test facility, a 50 MW PWR which was designed to model a large break loss of coolant (LBLOCA) in a commercial PWR. The key *input* phenomena identified for this study were: Peaking Factor (i.e. core power fractions), Fuel Clad Gap, Fuel Thermal Conductivity, Clad to Coolant Heat Transfer (i.e. fouling factor), Pump Degradation. The key *output* parameter in the study was Peak Clad

Temperature (PCT). No single input deck value corresponded to most of these phenomena, so several (up to 24) had to be varied simultaneously as a group. This caused additional programming complexity, but was accomplished. The results are presented in Table 3. Both PIRT and correlation coefficients produced the same rankings for the variables with p-values < 0.05.

Table 3: LOFT Study – Ranking of the Six Correlation Coefficient Groups

Classification	Group Name(s)
High Correlation Coefficient	• Fuel Clad Gap Width
Medium Correlation Coefficient	• Clad to Coolant Heat Transfer • Peaking Factor
Low Correlation Coefficient	• Break Discharge Coefficient • Fuel Thermal Conductivity
P-value > 0.05	• Pump Degradation

From an engineering perspective, we would rank the phenomena by absolute value of the change in PCT from the minimum value to the maximum value of the phenomena. To approximate that computation, we held the other phenomena at their respective nominal values. ΔT corresponds to the approximate change in temperature when we compare the PCT of the minimum value of the variable to the PCT of the maximum value of the variable, where all other variables are held constant at their respective nominal values. These rankings are presented in the following table.

Table 3: LOFT Study - Corr. Coef with p-value < 0.05, PIRT rank in parentheses

Corr. Coef. Rank	Phenomena	ΔT	Rank by ΔT
1	Fuel Clad Gap Width	200	1
2	Clad to Coolant Heat Transfer	80	3
3	Peaking Factor	50	4
4	Break Discharge Coefficient	90	2
5	Fuel Thermal Conductivity	45	5

The ranking by correlation coefficients almost matches the ΔT ranking.

For the most part our statistical rankings were the same or less than the conservative PIRT ranking with one exception. This exceptional variable and phenomenon bears further scrutiny in the form of more detailed statistical analysis.

This study will be presented in greater detail at the 2012 RELAP5 International Users Seminar.