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BEST ESTIMATE PLUS UNCERTAINTY ANALYSIS OF LBLOCA FOR A PICKERING B CANDU REACTOR

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ABSTRACT

The Pickering B Nuclear Generating Station consists of four CANDU reactors. These reactors are horizontal pressure tube, heavy water cooled and moderated reactors fuelled with natural uranium. Under a postulated large break loss of coolant accident (LOCA), positive reactivity results from coolant void formation. The transient is terminated by the operation of the safety systems within approximately 2 seconds of the start of the transient. The initial increase in reactor power, terminated by the action of the safety system, is termed the power pulse phase of the accident. In many instances the severity of an LBLOCA can be characterized by the adiabatic energy deposited to the fuel during this phase of the accident. Historically, Limit of Operating Envelope (LOE) calculations have been used to characterize the severity of the accident. LOE analyses are conservative analyses in which the key operational and safety related parameters are set to conservative or limiting values. Limit based analyses of this type result in calculated transient responses that will differ significantly from the actual expected response of the station. As well, while the results of limit calculations are conservative, safety margins and the degree of conservatism is generally not known.

As a result of these factors, the use of Best Estimate Plus Uncertainty (BEPU) analyses in safety analyses for nuclear power plants has been increasing. In Canada, the nuclear industry has been pursuing best estimate analysis through the BEAU (Best Estimate Analysis and Uncertainty) methodology in order to obtain better characterization of the safety margins. This approach is generally consistent with those used internationally. Recently, a BEAU analysis of the Pickering B NGS was completed for the power pulse phase of a postulated Large Break LOCA. The analysis comprised identification of relevant phenomena through a Phenomena Identification and Ranking (PIRT) process, assessment of the code input uncertainties, sensitivity studies to quantify the significance of the input parameters, generation of a functional response surface and its validation, and determination of the safety margin. The results of the analysis clearly demonstrate that the Limit of Operating Envelope (LOE) results are significantly conservative relative to realistic analysis even when uncertainties are considered. In addition, the extensive sensitivity analysis performed to supplement the primary result provides insight into the primary contributors to the results.

1.0 INTRODUCTION

Large LOCA accident analysis is traditionally performed assuming initial operating conditions representative of a conservative and improbable configuration of the plant. In this approach, commonly known as Limit of Operating Envelope or LOE analysis, key operational and safety system parameters are simultaneously set to conservative or limiting values in the combination that yields very conservative accident consequences. The objectives of the LOE analysis are (a) to demonstrate the consequences of the accident are within allowable limits, including, in particular, a demonstration of the effectiveness of the special safety systems in mitigating the consequences of the event and (b) to derive limits of safe operation of the plant, particularly with respect to the key operational and safety system parameters (i.e., to establish the Safe Operating Envelope). These objectives are most easily accomplished by placing all important operational and safety system parameters simultaneously at their safety limits.

LOE analysis, while suitable for confirming the adequacy of the plant parameters at their safety limits, leads to unrealistically conservative predictions of the actual safety margins available. The unrealistic predictions of available safety margins make it difficult to include the effects of modeling uncertainties and operating parameter variations on the analysis predictions. These unrealistic predictions when viewed outside of the context for which they are intended, can ultimately lead to apparently small safety margins, unnecessary restrictions in plant operating conditions, reductions in reactor power levels, and the implementation of design changes. Implementing such changes can result in significant increases in operational complexity. Moreover, operational and design changes dictated by very low frequency event sequences do not necessarily result in material improvements in overall plant safety when viewed in the context of a risk informed framework.

The apparently small safety margins resulting from LOE analysis stem largely from the extremely conservative and highly improbable configuration assumed in the analysis for the plant state. More realistic safety analysis methodologies are required to provide a realistic representation of the actual margins available.

The proposed alternative is known as the BEAU approach. It is based on the expectation that best estimate models of physical processes, best estimate (or operating centre) plant states, and most probable system configurations and failure events provide the most realistic representation of plant behaviour during an accident. Since deviations from these best estimate conditions can and do occur, uncertainties exist in the outcome of the best estimate analysis. To quantify the uncertainties, the contributing components are characterized, and their impact on safety consequences is assessed through the use of an integrated probabilistic approach.

The BEAU methodology is very similar to other statistically-based uncertainty analysis methods used elsewhere in the world. These include CSAU (Code Scaling, Applicability and Uncertainty), ASTRUM (Automated Statistical Treatment of Uncertainty Method) developed by Westinghouse, RLBLOCA (Realistic Large Break LOCA) developed by AREVA, and the KREM (Realistic Evaluation Methodology) developed by KEPRI. The combination of the conservative LOE methodology together with the more realistic BEAU methodology is similar to approved regulatory practices in the US and elsewhere. In these jurisdictions, conservative deterministic methods are used to demonstrate the adequacy of fuel cooling for all breaks up to a complete double-ended guillotine failure of the largest diameter piping. In traditional LOE methodology, the double-ended guillotine failure is assumed to occur "instantaneously" (typically within 0.01 ms). This is a significant and profound conservatism, as it results in an exaggeration of the predicted power pulse that follows a LBLOCA for CANDU reactors. In reality, breaks in large piping are expected to evolve over at least several seconds, even minutes. It is important to note that, in the present BEAU analysis, the conservative assumption of an "instantaneous" break opening is retained. However, these approaches also permit less restrictive, statistically-based uncertainty analysis methods to be used to provide a more realistic representation of the actual safety margins available. The use of BEAU methodology is also consistent with current Canadian regulations (i.e., G-144 and RD-310, respectively, [1] and [2]).

For CANDU reactors, the combination of natural uranium fuel and the heavy water moderated/heavy water cooled lattice results in a positive coolant void reactivity coefficient and, consequently, a positive reactor power excursion (i.e., a power pulse) following a large break LOCA. Although the fundamental objective of large break LOCA analysis is to demonstrate fuel channel integrity and acceptable dose consequences, the magnitude of the large break LOCA power pulse presents a unique challenge to the reactor shutdown systems. LOE analysis demonstrates that the shutdown systems are fully effective in terminating the power pulse, and the subsequent analysis of fuel cooling shows that fuel channel integrity is maintained throughout the transient.

This paper focuses on the determination of the expected variation in the metric most relevant to ensuring fuel channel integrity during the large break LOCA power pulse (fuel enthalpy) using the BEAU methodology.

2.0 Nomenclature

BEAU	Best Estimate Analysis and Uncertainty
CANDU	Canadian Deuterium Uranium
CNSC	Canadian Nuclear Safety Commission
CVR	Coolant void reactivity
FOM	Figure of Merit
FRS	Functional response surface
HBE	Hot bundle enthalpy
IUA	Integrated uncertainty analysis
(LB)LOCA	(Large Break) Loss of coolant accident
LOE	Limit of operating envelope
PIRT	Phenomena interaction and ranking table
PKPIRT	Phenomena key parameter interaction and ranking table
SOR	Shut-off Rod
RFSP	Reactor Fueling and simulation program
TUF	Two unequal fluids – the two-phase system thermal-hydraulics code used in analysis of CANDU reactors.

3.0 Analysis Methodology

The BEAU guidelines document [3] provides the basis for the application of the BEAU methodology to design basis accidents of CANDU reactors. The guidelines provide for the principles that should be applied to BEAU analyses, and are consistent with both the CNSC expectations as well as with international practice in these analyses. This section provides a brief overview of the method of application of the guidelines in this analysis.

The BEAU process consists of 15 steps, arranged into three elements. The elements, and applicable associated steps, are:

Table 1: BEAU Elements and Steps

Element	Step
1	1: Technical Basis
	2: PIRT
	3: PKPIRT
	4: Code Applicability Assessment
2	5: Computer Code Uncertainty
	6: Representational Uncertainty
	7: Deterministic Assumptions
	8: Plant Parameter Uncertainties
	9: Independence/Correlation of Parameters
3	10: best Estimate Case
	11: Determination of Margin Parameter Calculation Method
	12b: Quantitative Parameter ranking/Final PKPIRT
	13b: Devise/Validate Surrogate
	14b: Margin Parameter Distribution
	15: Comparison with integral test results
	16: Additional bias for unaccounted uncertainties
	17: Determine safety margin

3.1 Element 1

In the first element, all the phenomena that are important to the accident scenario and the figure of merit that is assessed are identified and ranked. A PIRT process was undertaken for this analysis.

Once the important phenomena are known, the key parameters that model these phenomena need to be identified and ranked. This forms the initial parameter ranking table (PKPIRT – Phenomena, Key Parameter Identification and Ranking Table). This identification and ranking of key parameters is a key interfacial activity between identification of relevant phenomena and their use in analyses. The term 'initial' PKPIRT is used as it represents the judgement of the subject matter experts and constitutes the basis for sensitivity studies that are performed to quantitatively rank the parameters' influence on the Figure of Merit (FOM). Once the quantitative parameter ranks are established, a 'final' PKPIRT is derived that is used in the Integrated Uncertainty Analysis (IUA). An a priori decision in this analysis was to retain all high and medium ranked parameters from the initial PKPIRT process, regardless of their ranking in the sensitivity analysis. This was possible due to the relatively small number of significant parameters identified.

For both the reactor physics code used (RFSP) and the system thermal-hydraulics code (TUF) a code applicability assessment was performed and documented for the scenario being analysed.

3.2 Element 2

The second element of the BEAU process consists of the quantification of the uncertainties to be applied in the analysis. For the modeling parameters, the uncertainties were obtained from either the available experimental information specific to CANDU or available literature. Examples of the CANDU-specific sources of experimental data are the RD-14M and ZED-2 facilities. In each case the uncertainty was described by the distribution (e.g., normal or beta) as well as any parameters required by the distribution (e.g., mean and variance).

The uncertainties for each of the plant parameters were determined using operational data. For each parameter, data spanning several operational years was obtained and analyzed. The uncertainty was then determined as well as any additional measurement uncertainty. In some cases a parametric distribution could not be assigned to the data. For those parameters, the Monte Carlo analysis was performed using the empirical data in a sample with replacement approach.

3.3 Element 3

3.3.1 Sensitivity Studies

As provided in the BEAU guidelines, sensitivity studies must be performed in order to obtain the final PKPIRT from the initial PKPIRT. The sensitivity studies serve to reject parameters for inclusion in the integrated uncertainty analysis based on the sensitivity of the FOM to the parameter. In addition, sensitivity studies provide additional information that is useful in understanding both the results of the Integrated Uncertainty Analysis as well as the system behavior and the relative importance of the governing phenomena. Additional benefits of a sensitivity analysis include determination of those parameters whose uncertainty contributes significantly to the uncertainty in the FOM.

In short, there are two types of questions that a sensitivity study can attempt to answer:

- By how much is the output changed by a change in an input parameter?
- By how much is the uncertainty in the output influenced by the uncertainty in an input parameter?

These questions can be answered through the appropriate sensitivity studies. The first question is generally addressed through linear response, regression, ranked regression, or through the Morris [4] method. The latter questions can be addressed through such means as the Sobol' [5] method, or FAST [6] analysis. In this analysis the methods employed were:

- Linear response through regression
- Rank correlation coefficients
- Morris Method
- Sobol' Method

Sensitivity studies can be classified into two categories: local and global. Local sensitivity studies concentrate on the local properties of the figure of merit and provide data over a local range. The commonly used linear response is an example of a local sensitivity measure. Global measures, on the other hand, provide information regarding the global behavior of the figure of merit. In the current analysis both local and global sensitivity tests were performed.

The local sensitivity was evaluated using a variant on the commonly used linear response. The linear response was determined using several values of each parameter centered on the best estimate value. A least squares regression was performed in order to estimate the linear contribution of the parameter to the change in the figure of merit. The measure was normalized to the full range of the parameter in order that the effects of parameters with different characteristics can be assessed.

The global sensitivity studies requires more information than the local sensitivity studies. This information can be obtained either through the execution of the computer codes at many points in the parameter space, or through the use of a surrogate to the codes. In the global sensitivity analyses performed in this analysis both methods were employed.

This analysis used a functional response surface as a surrogate in the Integrated Uncertainty Analysis. The generation of this surrogate requires the execution of at least 128 separate computer simulations. This case matrix provided a means to examine the impact of the parameters on the FOM. Using the regression data, Pearson and Spearman correlation coefficients were used to assess the parameter sensitivity.

Two other global sensitivity tests were conducted using a different surrogate to the simulation codes. The surrogate used in these cases was not the functional response surface used in the BEAU analysis. As the response surface is a linear combination of the parameters (whether first or second order), the resultant uncertainty measures could be influenced by this characterization of the response. Thus, an interpolation function was used instead. In this analysis, a Kriging [7] surface was used.

Morris provided a method of sampling that was an efficient means of determining the linear and non-linear response of a computer model to its inputs. This method was improved [8] and this later method was the one employed in this analysis.

The Morris Method considers the effects of single parameter variations taken one at a time. Morris defines an elementary effect as:

$$EE_i = \frac{f(x_1, x_2 \ldots x_{i-1}, x_i + \Delta, x_{i+1}, \ldots x_n)}{\Delta}$$

The parameters of interest are the mean of the absolute values of the elementary effects, and their standard deviations.

Parameters which have a relatively large mean are those whose contributions are linear; those with high standard deviations are more non-linear. The results are shown in a plot with the abscissa being the mean and the ordinate the standard deviation.

While the original Morris approach was to be used as a screening tool using the actual analysis codes, in this implementation a Kriging surrogate was used. This allowed for significant numbers of code trials to be executed with the results being based on several thousand executions of the surrogate. The Kriging surface was designed using the 128 cases in the case matrix.

The Sobol' method is a global, variance based method that also takes into account interaction effects between input parameters. Homma and Saltelli [9] used a 'total' sensitivity measure that is related to the Sobol' sensitivity measure. This latter measure was used in this analysis. In order to evaluate the Sobol' measure a Monte Carlo approach was used employing the same Kriging surface as that used in the Morris approach as a surrogate for the analysis codes. Parameters with a high sensitivity are those parameters whose variance is a significant contributor to the variance of the FOM. In this respect, the Sobol' measure differs from the other sensitivity measures used.

3.3.2 Integrated Uncertainty Analysis

There are three general approaches that can be taken in order to perform an integrated uncertainty analysis. These methods are:

- Application of output parameter uncertainties
- Use of Wilk's formula
- Use of a code surrogate

Each of these methods has benefits and disadvantages. A summary of the first two methods can be found in References [10] and [11]. For this analysis a code surrogate was used.

3.3.2.1 Development of Functional Response Surface Surrogate

The code surrogate used must be able to reproduce the behavior of the actual safety analysis codes with reasonable fidelity over the range of application. As well, the surface should be continuous and, in order to achieve the benefit of the use of a surrogate, must be sufficiently faster to execute than the codes so that a significant efficiency is achieved.

The response surface that was used in the integrated uncertainty analysis was a second order polynomial potentially containing all cross terms:

$$M = \beta_0 + \sum_{i=1}^{k} \beta_i P_i + \sum_{j=1}^{k} \sum_{i \geq j}^{k} \beta_{ij} P_i P_j$$

In order that the effects of all parameters were considered, all linear terms were included in the response surface. However, as the number of terms in the response surface model varies as the square of the number of parameters, with 40 parameters the number of terms in a full second order model becomes prohibitive.

For 40 parameters, there would be 2^{860} possible response surfaces (assuming a constant term in each). Thus, a means of selecting a surrogate from this large set of possible surrogates was required. This problem is generally referred to as a 'model selection' problem. A number of methods are available to select the parameters for inclusion in the response surface; the method used in this analysis was a genetic algorithm.

Regardless of the means through which the surrogate is selected, a set of data representing the behaviour of the FOM given the selected input parameters was required. This set of data was chosen to cover the range of each of the parameters and to be sufficiently robust that the fitting errors were minimized. This set of parameter values is referred to as the Case Matrix. The parameter values were all derived from the operating and modeling parameter ranges.

The result of these considerations is that the response surface is defined for a finite domain. This domain is sufficiently large so that the contribution to the overall IUA of values that fall outside of the domain is small.

The case matrix is generated as a Latin hypercube, fractional block design as defined in Reference [12]. This formulation provides an efficient coverage of the parameter space and allows for a reduced number of independent cases to be executed for the same number of parameters in the resulting response surface. The resulting case matrix is centered on the best estimate point.

As discussed previously, the surrogate is selected from the potential surrogates using a genetic algorithm [13]. A genetic algorithm is a means of optimizing a non-linear system that is based on a Darwinian selection paradigm. The basis of the methodology is the concept of a gene and fitness function. The gene determines the characteristic of the solution to the problem, and the fitness function its suitability. For the model selection problem, the gene consists of a bit sequence in which a 1 signifies the presence of a term, and 0 its absence from the response surface model. Thus, 11101… would have the first three and fifth terms included in the response surface and the fourth excluded.

Each potential model was determined by a least squares fit to the case matrix data for the terms included in the model. These models were then assessed through the use of a fitness function. The fitness function used was intended to judge the suitability of each of the potential models. There are several possible fitness functions, however they all have the same basic constituents: a measure of the deviation from the values to be fit, and a means of ensuring that the minimum number of terms be in the fit. The fitness function selected for use in this analysis is the sum of squares of the residuals divided by the square of the number of free parameters:

$$F = \frac{\sum_{i=1:N} (y_i - r(x))^2}{(N-m)^2}$$

Here N is the total number of samples (rows) in the case matrix and m is the number of terms in the response surface model. Effectively, this penalizes models with a higher number of terms.

3.3.2.2 Validation of Response Surface Surrogate

The measure of fitness that is used in determination of the response surface model was based on the residuals of the fit. As such, the use of these residuals in determination of the response surface fitting error would result in an artificially low value. This is the result of the fact that the models selected are effectively those that minimize the residuals in the case matrix. However, the case matrix values are only representative of the actual set of all possible combinations of parameters. Thus, a separate set of validation cases must be executed and the resulting residuals used to determine the fitting error. This is generally referred to as a predictive error, as the cases used in determining the error were not used in the creation of the response surface, and as a result the error is related to the ability of the resulting model to predict the FOM for other parameter combinations. In this analysis a separate set of 68 cases was executed to allow for determination of the prediction error.

Once the prediction error was determined, inclusion in the integrated uncertainty analysis was through the addition of a random value sampled from this distribution.

3.3.3 Integrated Uncertainty Analysis

The BEAU methodology allows for the estimation of the distribution of the FOM based on a Monte Carlo sampling of the input distributions, using a functional response surface as a surrogate. Thus, the fundamental calculations in the Integrated Uncertainty Analysis consist of a Monte Carlo simulation of the parameter uncertainty propagation. The Monte Carlo consisted of 300,000 calculations using the FRS surrogate with each parameter sampled from their respective distribution and any associated measurement error included. The FRS prediction error was added to each result, sampling from its distribution. The 95th percentile was determined from the resulting order statistics, with a correspondingly high confidence.

4.0 Results

4.1 Parameter Identification and Uncertainty Estimation

The figure of merit for this analysis was chosen to be the Hot Bundle Enthalpy (HBE), calculated at 5 seconds after the break initiation. The Hot Bundle Enthalpy is the highest enthalpy in the limiting fuel element. It is comprised of two terms; the first being the initial enthalpy present in the fuel at the start of the transient, and the second related to the energy deposited during the transient. An adiabatic deposition is assumed.

The PIRT and PKPIRT process identified 41 parameters that were either High or Medium ranked. These parameters were divided between reactor physics related (13 plant and 9 modeling) and thermal-hydraulic (3 plant and 16 modeling). Each of these parameters was assessed and an uncertainty assigned. In the case of the plant parameters, measurement uncertainty was also assessed and quantified. The parameters were assigned unique identifiers for use in the sensitivity studies; all identifiers began with the letter ‘S’ and at least one following character (e.g., S4, CVR bias; SX, interfacial drag coefficient, Sb, 2 phase multiplier).

4.2 Sensitivity Analyses

4.2.1 Local Sensitivity and parameter Ranking

Figure 1 to Figure 3 show the sensitivity results for selected parameters included in the sensitivity analysis. For each parameter, the figures show the resulting least squares fit as well as the 95% confidence bounds on the slope.

It was found that many of the slopes are essentially zero. That is, the confidence interval on the calculated slope includes zero. For these parameters, the HBE is effectively insensitive to local variations in these parameters. Other parameters, such as CVR bias (S4, Figure 1) exhibit significant sensitivity.

In most cases, the parameters appear to be essentially linear; however, the Interfacial Drag Coefficient (SX) appeared to be non-linear, Figure 3. As the curve is concave downward, the estimated sensitivity is higher than the actual sensitivity and as such, the effect of this parameter may be over estimated in the sensitivity studies.

Table 2 shows an extract from the final parameter ranking table. Shown are the top nine parameters with their calculated slopes and relative ranking. The relative rank is calculated as the absolute value of the ratio of the slope of the parameter to the maximum slope.

The parameter ranks are consistent with the experts’ initial ranks, with parameters that directly influence voiding, reactivity resulting from voiding, and initial and transient energy deposition being the highest ranked parameters. The first timing gate of the SOR relates to the speed at which the Shutoff Rods (the active shutdown mechanism in the simulation) become effective after a trip is received. Q1 and Q2 are coefficients relating deposited energy to fuel enthalpy.

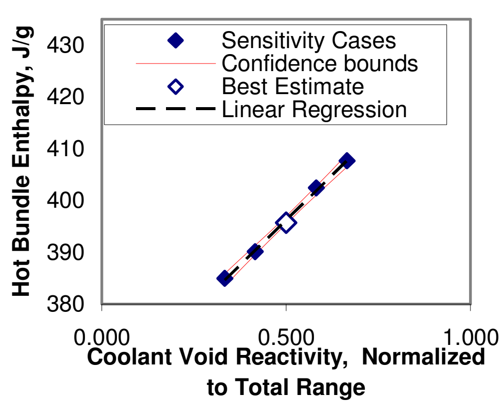

Figure 1: Sensitivity to CVR Bias (S4)

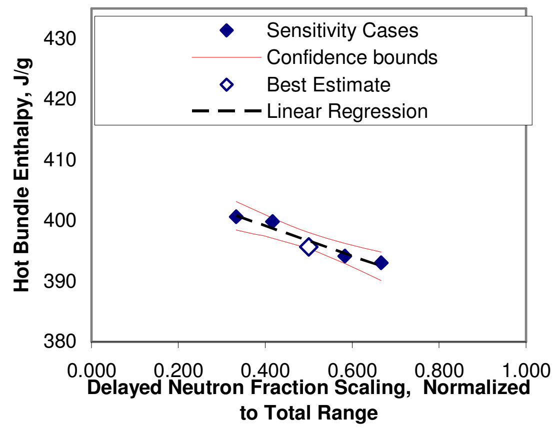

Figure 2: Sensitivity to Delayed Neutron Fraction (S9)

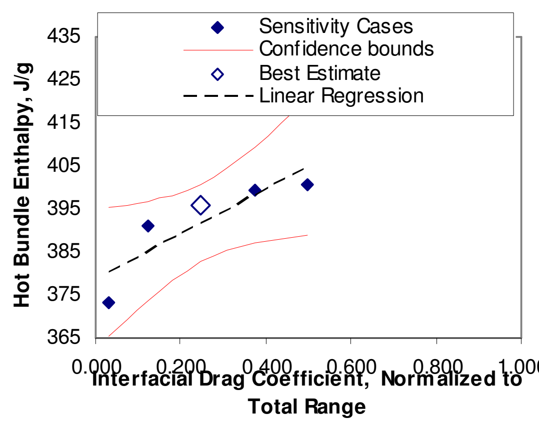

Figure 3: Sensitivity to Interfacial Drag Coefficient (SX)

Table 2: Abridged Parameter Ranking Table

Parameter	ID	Slope (J/g/Fraction of Range)	Ranking
Coolant void reactivity	S4	69.5	100.0
‘Interfacial Drag Coefficient’	SX	52.0	74.8
Initial Fuel/Sheath Heat Transfer Coefficient	Sd	34.7	49.9
Total delayed neutron fraction	S9	-25.0	36.0
Limit on Initial Bundle Power (kW)	S1	24.7	35.6
Q1 and Q2 scaling factor	Si	23.7	34.1
First timing gate of SOR	SE	19.3	27.8
Transient Bundle Power Scaling Factor	SK	15.2	21.9
Φ2 (two phase multiplier)	Sb	14.8	21.3

4.2.2 Additional Sensitivity Studies

Global sensitivity studies were performed using the Morris and Sobol' methods. Figure 4 shows a comparison of the results of these studies. The results of the Spearman rank correlation are shown in Figure 5. The order of the top ranked parameters is the same as the order of the top ranked parameters in the local, Morris, and Sobol' studies. This demonstrates that the selection of important parameters is relatively independent of the method used to perform the selection.

The coolant void reactivity response as calculated by the response surface to be used as a surrogate for the code was essentially the same as that calculated by single parameter variation at the best estimate point. This provides additional confirmation of the suitability of the response surface formulation, Figure 6.

Finally, a separate sensitivity study conducted at a non-best estimate point representative of the 95% of the FOM (based on the case matrix results) resulted in a parameter ranking that was consistent with that obtained at the best estimate point. This provides confirmation of the fact that by ranking the parameters based on a local measure centered at the best estimate point will not result in the rejection of parameters that are sensitive at the 95th percentile. This comparison is shown in Figure 7.

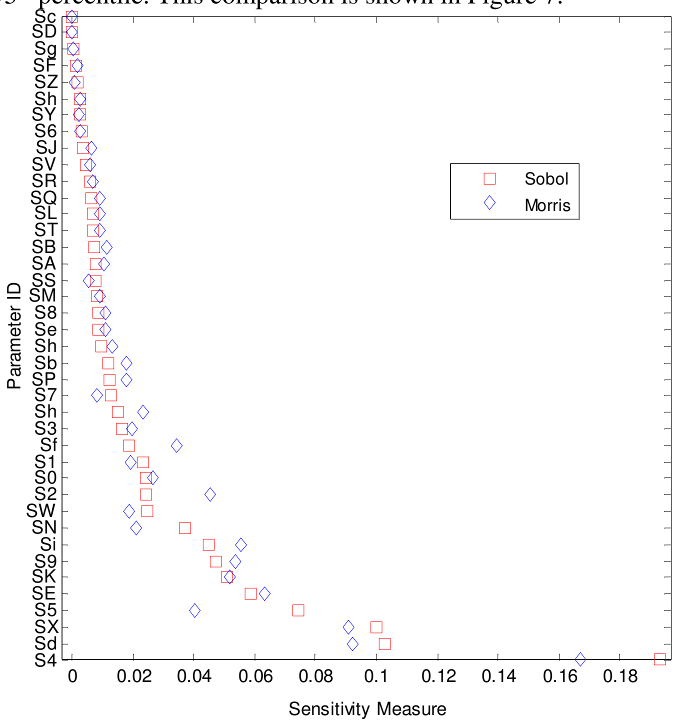

Figure 4: Comparison of Morris and Sobol' Ranks

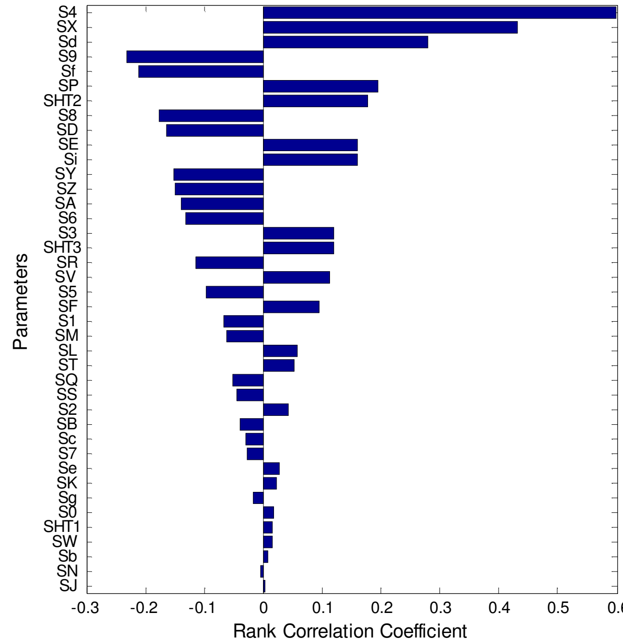

Figure 5: Spearman Correlation Coefficient Ranking

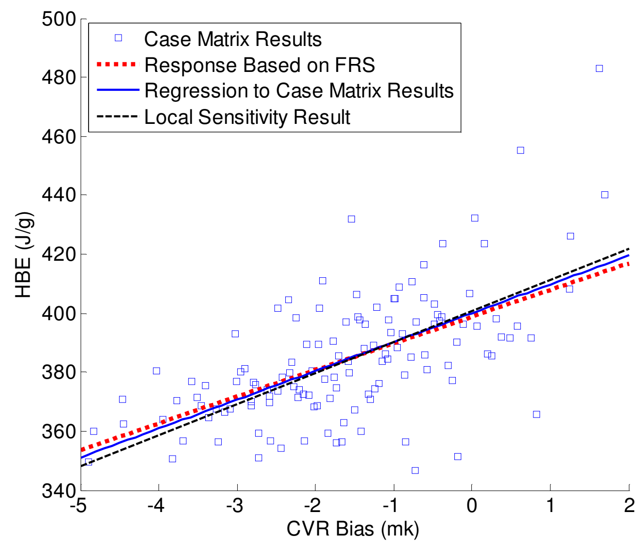

Figure 6: Comparison of FRS and Case Matrix Sensitivity to CVR

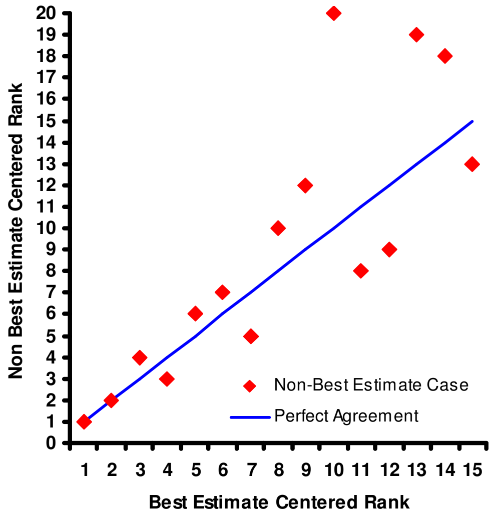

Figure 7: Comparison of Best Estimate and non-Best Estimate Ranking

4.3 Integrated Uncertainty Analysis

4.3.1 Response Surface Generation and Validation

Figure 8 shows the power amplitude that resulted from execution of the case matrix. Also shown is the best estimate case (in red). As shown, the amplitudes resulting from execution of the 128 cases are of similar shape and general characteristic, and the best estimate case is centered within the distribution of amplitudes.

Figure 9 shows the reactivities that result from the execution of the power pulse case matrix. As with the amplitude results, the reactivity transient for the best estimate case is centered within the distribution of the reactivity transients.

The case matrix results for the HBE are shown in Figure 10.

Both the Case Matrix and Validation Case Matrix results stem from the application of a set of randomly generated parameter values, and as such are themselves stochastic quantities. In order to asses the suitability of the validation case matrix to represent the response surface error, it is important that the validation cases be consistent with the cases used to generate the response surfaces. In order to demonstrate that the validation and case matrix results come from the same distribution, a Kolmogorov-Smirnov test was performed for the power pulse case matrix and validation matrix HBE. The Kolmogorov-Smirnov test is a hypothesis test that has the null hypothesis that the two sets of values come from the same distribution, against the alternate hypothesis that they come from different distributions. This test is based on the empirical cumulative distributions. The Empirical Cumulative Distribution Function (ECDF) for the case matrix and validation matrix is shown in Figure 11. The ECDF for the validation cases is seen to be similar to that for the case matrix. The Kolmogorov-Smirnov p-value was 0.7533. This indicates that the hypothesis that the validation and case matrix results come from the same distribution cannot be rejected. Thus, the validation cases serve as a suitable set of cases to use to obtain the response surface error.

Figure 12 compares the response surface results to those from the case matrix and validation cases. The response surface provides a good fit to the data. As expected, the 'scatter' resulting from the validation cases is larger than that resulting from the case matrix. This results from the fact that the response surface was selected by minimizing the residual error from the case matrix. This emphasizes the fact that the error for the response surface must be obtained using the prediction error that results from the validation cases.

Table 3 provides the residual errors and the mean predictive errors for the HBE. As discussed previously, the predictive errors were used as the response surface error in the integrated uncertainty analysis.

Table 3: Response Surface Errors

# Cases	Residual Error		Prediction Error	
	Mean (J/g)	Standard Deviation (J/g)	Mean (J/g)	Standard Deviation (J/g)
68	0	7.01	7.87	23.28

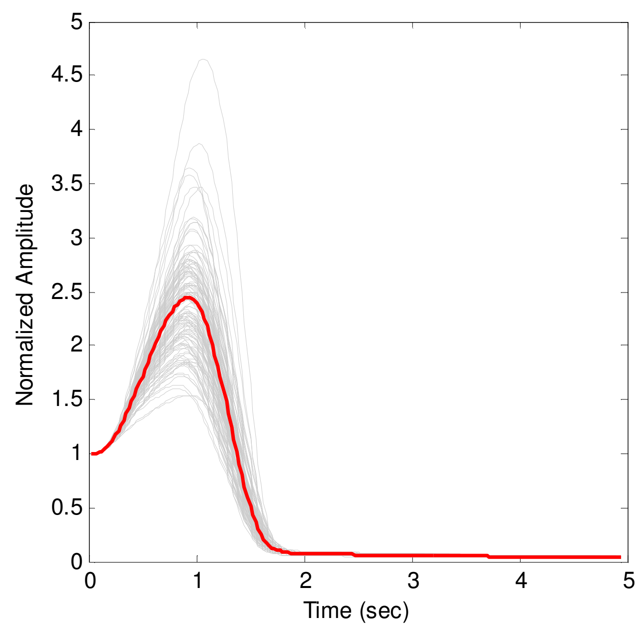

Figure 8: Normalized Reactor Power

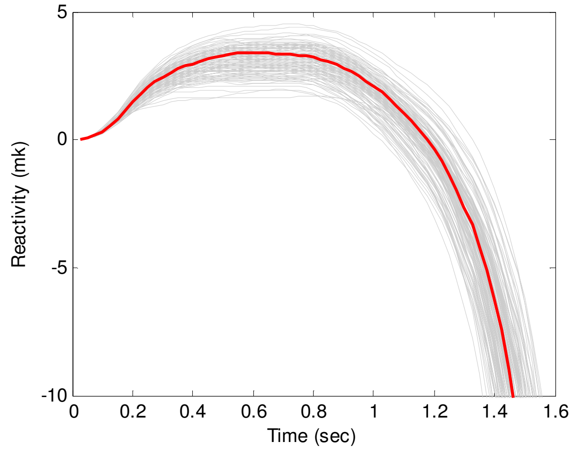

Figure 9: Reactivity Transient (first 1.6 sec)

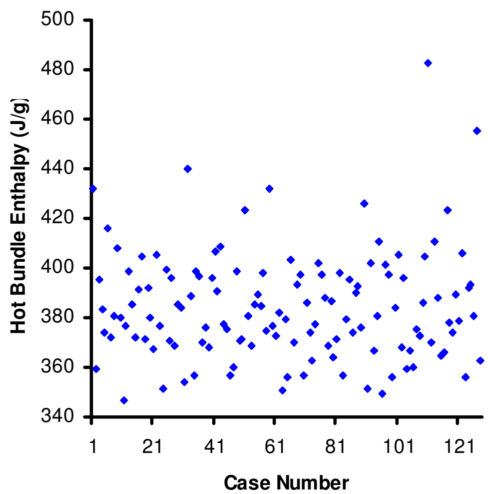

Figure 10: Case Matrix Results

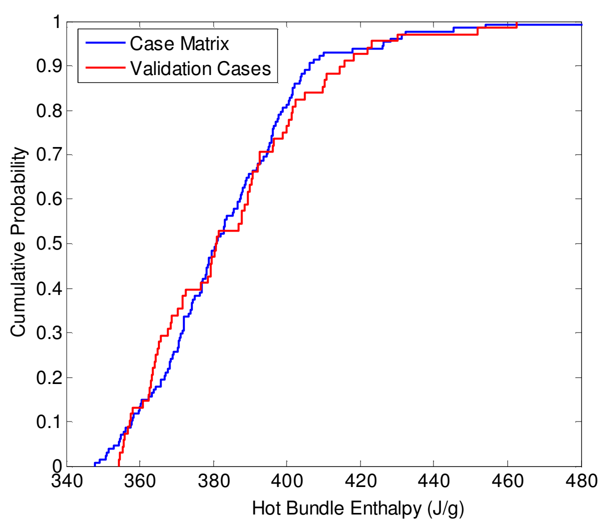

Figure 11: Comparison of ECDF of Case Matrix and Validation Cases

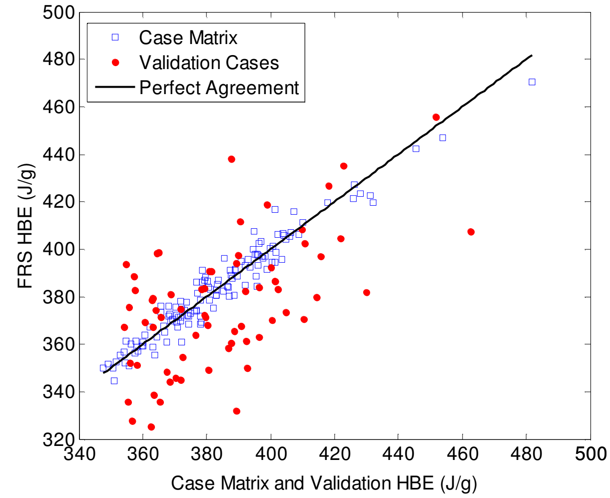

Figure 12: Comparison of FRS and Validation Case Results

4.3.2 Integrated Uncertainty Analysis

Figure 13 shows the results of the uncertainty calculations for the hot bundle enthalpy for a LBLOCA. For this analysis, 300,000 Monte Carlo simulations were performed. The distribution function include the propagation of all input uncertainties, measurement uncertainties, and the inclusion of the response surface prediction error.

Using these error distributions, the resultant 95th percentile can be calculated. This value represents the 95th percentile of the HBE including all uncertainties in modeling, plant and FRS prediction. Table 4 presents these results. The estimate of the 95th percentile of the HBE is found to be 437.9 J/g. This table also provides the associated safety limit. The safety margin for the BEAU result demonstrated a 200% improvement compared with the LOE approach.

For the power pulse, the HBE at the 95th percentile is significantly smaller than the acceptance criterion of 965 J/g demonstrating that the results of a postulated LBLOCA will not challenge fuel integrity. Further, the peak amplitudes for the power pulse are relatively small, demonstrating that the large amplitudes found in LOE analyses are the result of the excessive conservatisms present in LOE analysis.

Table 4: Results of Integrated Uncertainty Analysis

$HBE_{95\%}$ (J/g)	Safety Limit (J/g)
437.9	965

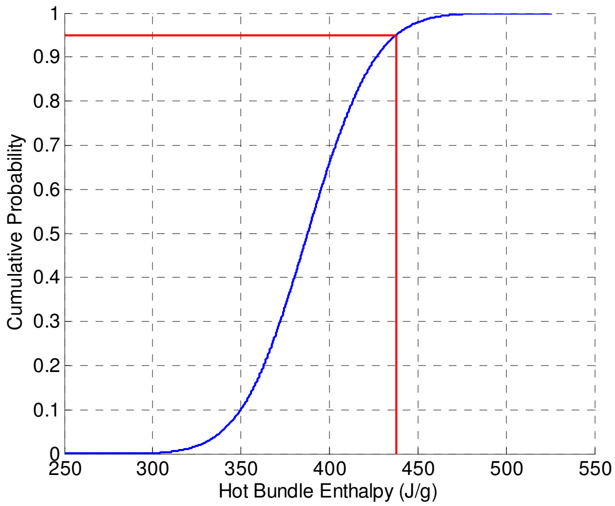

Figure 13: HBE Cumulative Distribution

5.0 Summary and Conclusions

Several sensitivity studies were performed to better understand the sensitivity of the HBE to parameters of importance in postulated LOCA scenarios. The results of these studies were largely consistent, with the top ranked parameters having essentially the same rank. While there may be some slight changes in the relative ranking, the actual parameters that were deemed most significant were found to be the same. The significant parameters were found to be those related to voiding, void induced reactivity, and initial enthalpy.

The 95th percentile of the HBE was found to be 437.9 J/g. This result is significantly smaller than LOE results. The results of this analysis also show that the HBE safety margin for Pickering B under a hypothetical LBLOCA is 527.1 J/g under normal operating conditions. This demonstrates that significantly larger margin is available when compared with the results of LOE analyses. Thus, the consequences that have been observed in LOE analyses in which a significant power pulse occurs are due to the limiting assumptions used. When realistic assumptions accounting for all operational and modeling uncertainties of significance are considered (while retaining conservatisms such as the assumption of an instantaneous double-sided guillotine break), the power pulse resulting from a hypothetical LBLOCA is significantly more benign.

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7.0 References

1. Canadian Regulatory Guide, "Trip Parameter Acceptance Criteria for the Safety Analysis of CANDU Nuclear Power Plants", G-144, May 2006, Canadian Nuclear Safety Commission.
2. Regulatory Document, "Safety Analysis for Nuclear Power Plants," RD-310, February 2008, Canadian Nuclear Safety Commission.
3. R. G. Huget and A. Abdul-Razzak, "Guidelines for Application of the Best Estimate Analysis and Uncertainty (BEAU) Methodology for Design Basis Accident (DBA) Licensing Analysis," COG-06-9012, November 2006.
4. M. D. Morris, "Factorial Sampling Plans for Preliminary Computational Experiments," Technometrics, Vol. 33, 1991.
5. I. M. Sobol', "Sensitivity Estimates for Non-Linear Mathematical Models," Matematicheskoe Modelirovanie, Vol. 2, 1990.
6. K. Chan, A. Saltelli, and S. Tarantola, "Sensitivity Analysis of Model Output: Variance-Based Methods Make the Difference," Proceedings of the 1997 Winter Simulation Conference, 1997.
7. D. G. Krige, "A statistical approach to some mine valuations and allied problems at the Witwatersrand," Master's thesis, University of Witwatersrand, 1951.
8. F. Campolongo, J. Cariboni, A. Saltelli, and W. Schoutens, "Enhancing the Morris Method," Sensitivity Analysis of Model Output (K. Hanson and F. Hernez, eds.), 2005, Los Alamos National Laboratory.
9. T. Homma and A. Saltelli, "Importance Measures in Global Sensitivity Analysis of Non-Linear Models," Reliability Engineering and System Safety, Vol. 52, 1996.
10. F. D' Auria, et. al., "State of the Art in Using Best Estimate Calculation Tools in Nuclear Technology," Nuclear Eng. And Tech., Vol. 38, No. 1, February 2006.
11. S. S. Wilks, "Statistical Prediction with Special Reference to the Problem of Tolerance Limits," Ann. Math. Statist. Volume 13, No. 4, 1942.
12. T.H. Andres, "Sampling Methods and Sensitivity Analysis for Large Sample Sets," Journal of Statistical Computation and Simulation, Vol. 57:1, 1997.
13. Haupt R. L. and, Haupt S. E., "Practical Genetic Algorithms", Wiley-Interscience Publication, 1998.