

A SENSITIVITY ANALYSIS TECHNIQUE FOR APPLICATION TO DETERMINISTIC MODELS*

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The characterization of severe accident source terms for light water reactors should include consideration of uncertainties.¹

An important element of any uncertainty analysis consists of evaluating the sensitivity of the output uncertainty distributions to the input assumptions. These sensitivity analyses require extensive information regarding mathematical correlations between input and output variables which are generally obtained through repeated computer runs of a physical model. However, in predicting uncertainties associated with severe accident source terms using contemporary methods, techniques must be devised which reduce the need for extensive computation using large computer codes.

Historically, Response Surface Methods (RSM) were developed to replace physical models using, for example, regression techniques, with simplified models² for extensive calculations.

The purpose of the current paper is to propose a new method for sensitivity analysis which does not utilize RSM, but instead relies directly on the results obtained from the original computer code calculations.

RSM is most readily used to obtain the sensitivity of the outputs to inputs with respect to the regression-based surrogate and not to the actual model. A small sample sensitivity analysis technique using the Latin Hyper-

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cube Sampling (LHS) approach has been proposed by Iman et al.³ The currently proposed technique, which bears similarity to that of Iman, comprises the following steps.

- (1) A set of LH input samples are generated:

$$\bar{x}_i = (x_{1i}, x_{2i}, \dots, x_{Li}), i = 1, 2, \dots, N \quad (1)$$

Here, the N samples correspond to N combinations of values for the L parameter inputs. The input \bar{x}_i yields the output y_i from the computer code where, for simplicity, just one output is considered.

- (2) Based on the analysis of partial correlation coefficients (PCCs) or standardized regression coefficients (SRCs), important input variables x_1, x_2, \dots, x_K ($K < L$), for the reference output variable y , are determined.

- (3) Another set of randomly sampled input vectors,

$$\bar{x}_j = (x_{1j}, x_{2j}, \dots, x_{Lj}), j = 1, 2, \dots, M \quad (2)$$

is generated. These samples are obtained with respect to the new input probability density functions (PDFs), the effects of which upon the output distributions are to be ascertained.

- (4) The output value Y_j corresponding to the randomly sampled input vector \bar{x}_j is approximated by the LHS output value y_s whose corresponding LHS input vector \bar{x}_s is "closest" to the vector \bar{x}_j . That is, the original LH sample point \bar{x}_s^* that minimizes the quantity

$$\sum_{k=1}^K a_k^2 (x_{ks}^* - x_{kj}^*)^2 \quad (3)$$

is ascertained. Then the corresponding original output y_s is used to approximate the output Y_j . Here a_k is a weight that reflects the importance of the k -th input variable (e.g., as measured by the PCC), and x_{ks}^* and X_{kj}^* are the standardized (dimensionless) values of x_{ks} and X_{kj} . Hence M random output values are approximated by the nearest of the N Latin Hypercube Sample output values.

The merits of this approach are demonstrated by application of the proposed method to the SPARC (Suppression Pool Aerosol Removal) code and the results are compared with those obtained by sensitivity analysis with (a) the code itself, (b) a regression model, and (c) Iman's method.

In the SPARC uncertainty analysis, six inputs are considered and are each assigned a uniform probability distribution. The sensitivity assessment involves the alteration of one of these distributions to a normal form.

Figure 1 shows a comparison of the sensitivity analysis results based upon the various methods for estimating output cumulative distribution functions. The output considered is the suppression pool integral decontamination factor (DF) for CsI associated with an ATWS initiated BWR core melt scenario. It is found that the new method shows good agreement with the direct SPARC sensitivity results, as does the regression model. Iman's method shows the least agreement for the methods considered. Similar conclusions were reached for the other SPARC output variables.

In conclusion, the new method is implementable for detailed sensitivity analyses. It is emphasized that the method does not resort to response surface techniques and relies on data generated by the original computer model. Hence, when the regression models fail to provide a good surrogate for the model under consideration, the proposed approach is anticipated to constitute a superior basis for sensitivity analysis.

References

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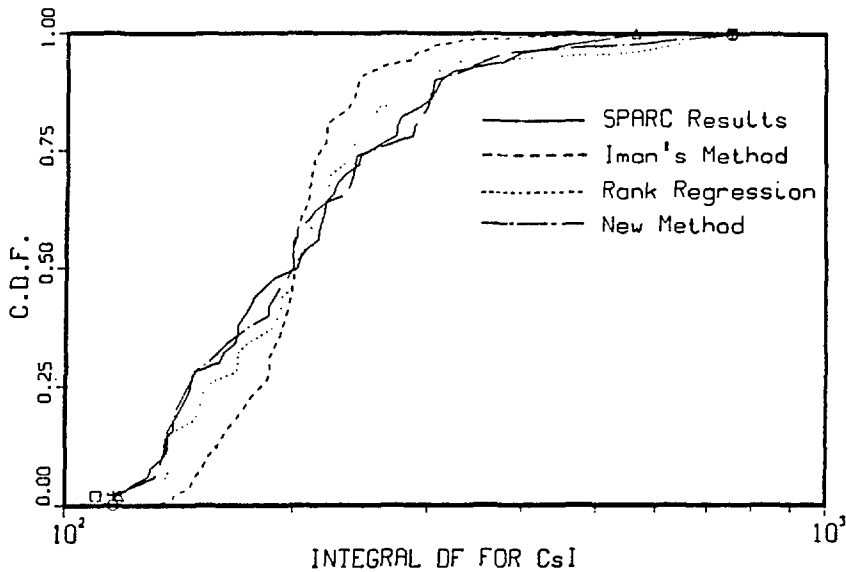


FIGURE 1 Comparison of Cumulative Distribution Functions (CDFs) for the Integral DF for CsI in the Case Where the Probability Density Function (PDF) of VSWARM (Bubble Swarm Rise Velocity) is Changed From Uniform to Normal Distribution

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