The Effect of Conservatism on Identifying Influential Parameters

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ABSTRACT

Sensitivity analysis is an important component of any probabilistic risk assessment that provides the foundation for a risk-informed, performance-based approach for protecting public health or making an engineering decision. Results from sensitivity analysis are typically used to derive the risk significance of various aspects of the system being modeled (i.e., parameters, conceptual models, and assumptions). An implicit assumption for conducting sensitivity analysis is that the model and the associated parameters representing the system is realistic (i.e., neither overly pessimistic nor optimistic). However, making conservative assumptions on the values of the parameters (model conservatism) is unavoidable when modeling large and complex systems, such as a high-level radioactive waste disposal system, when the systems have a significant level of uncertainty. This paper presents a systematic investigation of the effects of model using conservative values on the identification and ranking of influential parameters when using sensitivity analysis. The three simple, nonlinear stochastic example problems in this paper clearly illustrate how the ranking of influential parameters changes with the level of assumed conservatism. Such changes could lead to erroneous conclusions that other parameters in the system model are more influential than the ones that are assumed to be conservative.

INTRODUCTION

Risk-informed, performance-based approach is increasingly being adopted by nuclear and non-nuclear industries (e.g., waste disposal, facility decommissioning, chemical process plant safety, and food safety) for safety evaluation and licensing. Quantitative risk assessment, which permits systematic investigation, quantification, and explanation of system safety, is essential to implementing the risk-informed, performance-based approach. A vital component of quantitative risk assessment is obtaining risk insights. Risks insights help (i) focus efforts on risk-significant events, processes, components, designs, and model limitations to identify areas for improvement, prioritize resource allocation, and develop action plans; (ii) reduce unnecessary regulatory burden on licensees; and (iii) drive development of a common understanding in multi-disciplinary environments. Sensitivity analysis is an important tool for identifying risk significant factors (e.g., conceptual models, parameters, and assumptions) from which risk insights are derived. An implicit assumption for sensitivity analysis is that the model on which sensitivity analysis is carried out is realistic (i.e., neither overly pessimistic nor optimistic). However, conservative assumptions are common in models for quantitative risk assessment. That model conservatism could affect sensitivity is not new. But literature survey reveals no efforts to systematically examine how model conservatism affects sensitivity analysis. The objective of this paper is to explore, through simple example calculations, the effects of conservatism on sensitivity analysis and the information derived from it. The paper provides a brief background on model conservatism and sensitivity analysis and then presents three examples to demonstrate the effects of conservatism on sensitivity analysis results.

Model Conservatism

In many situations, analysts are forced to make simplifying assumptions because of (i) paucity of data, (ii) complexity of the processes to be modeled, (iii) poorly developed understanding of the system during the early stage of modeling (e.g., screening-level calculations), and (iv) limited resources and time available to realistically model the system. For complex problems, the mathematical models are often simplified or idealized intentionally for simplification or to allow solution. When assessing large and complex systems such as a high-level radioactive waste disposal system, simplifying assumptions are unavoidable because the system has a significant level of uncertainty, primarily associated with the long performance period. Probabilistic assessment is needed to treat uncertainty, which puts demands on computational resources that, in turn, force the use of simplified models. In such problems, particularly those addressing protection of health and safety, simplifying assumptions are deliberately biased toward conservatism. Conservatism, in this context, implies underestimation of the performance of the system. Conservative choices, in risk/safety assessments that have regulatory compliance as one of the objectives, allow the use of limited resources to provide a solution in a reasonable time. Thus, there is a tradeoff between model realism and model conservatism, and the difference between the two is a function of model complexity, model uncertainty, available resources, and time to solve the problem. Quantifying this difference is important so that the safety margin in the system can be demonstrated more clearly to stakeholders. However, the need remains to address the effect of model conservatism on the calculation of quantitative risk and sensitivity analysis.

System models used in risk/safety assessments are typically multi-disciplinary. Subject matter experts from the various disciplines develop process-level detailed and abstracted conceptual and mathematical models and provide parameter ranges to represent uncertainty. The abstracted models are integrated to develop the system model. Although the level of conservatism should be ideally uniform across the abstracted process models, this is difficult to achieve (at least during the initial phase of a system model development) because the assessment of conservatism can vary among experts. Moreover, there can be discipline-specific or institutional bias in the degree of conservatism depending on whether the model is developed by an implementor, a regulator, or a stakeholder. As a result, the system model may have different degrees of conservatism in its components, and the effects of the conservative assumptions on sensitivity analyses may be significant. If all model components are equally conservative or optimistic, sensitivity analysis can give meaningful results. For unbalanced models, meaning that the influence of one or more components is amplified or attenuated relative to other components because of a mixture of conservative and optimistic assumptions, the results may be more unreliable.

Sensitivity Analysis

Sensitivity analysis identifies the factors in a system model that contribute most importantly to the system behavior. The model parameters responsible for the largest relative changes in model response are the most important or influential. Sensitivity analysis, generally, identifies where a small input perturbation has significant effect on system response. System response can be quantified as a sensitivity coefficient, which is the ratio of the fractional change in the model response caused by a change in the value of a particular input parameter (defined in the next section).

However, if the system model is stochastic, sensitivity analysis has a slightly different connotation. For stochastic modelling, sensitivity analysis also provides the response of the model to uncertainty in the input parameters. This is usually referred to as uncertainty importance. Uncertainty importance is the relative contribution of uncertainty in model input parameters to the overall model output uncertainty. The uncertainty importance of a parameter depends on (i) the sensitivity of the model output variable to the input parameter value and (ii) the actual uncertainty in the parameter value. Using this definition, the influence of a parameter is the greatest when the value of the parameter is relatively uncertain and the model output is sensitive to the parameter. Conversely, the importance of a parameter is low when either the model results are insensitive to the parameter value or the parameter has less uncertainty [1]. Therefore, the importance of parameters in this approach is not based on a single value for each parameter, but rather on an entire distribution that embodies all moments (e.g., mean, variance). In this case, the sensitivity coefficient is determined using the statistical characteristics of the distribution. For the purposes of this paper, no distinction is made between 'sensitivity analysis' and 'uncertainty importance analysis.' The next section presents the sensitivity analysis formalism used to investigate the effects of model conservatism on parameter ranking.

COMPUTING SENSITIVITY

Let the performance function (transfer or objective function) for risk/safety assessment be defined as [2]

$$y = f\ (x_1, x_2, \ldots, x_1; a_1, a_2, \ldots a_m) \tag{1}$$

where y, the model output variable, is a function of parameters x_i and model assumptions a_m. The model parameters represent the quantitative properties of the system (e.g., initial condition, time-invariant coefficients). In many risk assessment problems, y may be a vector (i.e., many output variables of interest), and f may be a set of differential equations with an implicit input-output relationship. For the purpose of this paper, the model output is considered to be a simple variable.

The first order local sensitivity of y to x_i can be defined as $\partial y / \partial x_i$, which is also called absolute sensitivity. Because parameters in the model have different units, the first order local sensitivity is normalized in the following manner.

$$S\,(y, x) = \frac{x_i \partial y}{y \partial x_i} \tag{2}$$

where $S(y, x_i)$ is the normalized sensitivity of y with respect to x_i, and $\partial y / \partial x_i$ is calculated at a specific value of x_i. Thus, the derivative of y is normalized by the model output variable and the model input parameter of interest to obtain a normalized non-dimensional sensitivity coefficient. The normalized sensitivity coefficient then measures the effect on y of perturbing parameter x_i by a fixed fraction. Normalized sensitivity is also referred to as relative sensitivity. This representation of the sensitivity coefficient makes the sensitivity comparisons more equitable.

The performance function represented by Eq. (1) is deterministic, and the corresponding sensitivity coefficients (Eq. 2) are deterministic (i.e., computed at a single point in the multidimensional parameter space). As mentioned earlier, risk/safety assessment problems invariably deal with uncertainty. Therefore, a probabilistic representation of the model to account for uncertainty can be achieved by associating probability distribution functions with the input parameters in Eq. (1), with the distribution functions representing the ranges of uncertainties.

If the probability distribution functions are simple (e.g., uniform, log uniform), the model is explicit, and the problem is small, then the sensitivities in the stochastic problem can be obtained analytically. In reality, risk/safety assessment problems, especially ones that are physics based, are complex, and do not readily provide analytical solutions. Typically, these complex models are incorporated into a computer code, and finite element, finite difference, Green's function method, or other similar methods are used to solve the problem (i.e., obtain model output and sensitivity coefficient) semi-analytically or numerically. Therefore, rather than attempting to obtain sensitivity coefficients analytically, the Monte Carlo method is used. The Monte Carlo method allows a full mapping of the uncertainty in the model inputs (expressed as probability distribution functions) into the corresponding variability in the model output. This result can be expressed as a probability distribution.

In the probabilistic (stochastic) model, the sensitivity coefficient for each input parameter is computed at each sampled point in the multi-dimensional sample space. As a result, sensitivity $S(y, x_i)$, is now a distribution of points. For the purposes of this paper, only the first moment of the distribution of sensitivity coefficients (the mean) is used to represent sensitivity. This can be represented by

$$\overline{S_{x_i}} = \frac{1}{n}\sum_{j=1}^{n} S(y,x_{ij}) = \frac{1}{n}\sum_{j=1}^{n} \frac{\overline{x_{ij}}}{y_j}\frac{\partial y_i}{\partial x_{ij}} \tag{3}$$

where j represents the j-th Monte Carlo realization, y_j is the model response for the j-th realization, x_{ij} represents the elements of the input parameter vector in the jth realization, and n is the number of realizations.

A conservative result is generated by simply systematically moving the range of the desired parameter toward more conservative values. The nonconservative end of the distribution is adjusted while keeping the conservative end is fixed, as shown in Figure 1. Figure 1a shows increasing conservatism for the case in which the parameter has a direct relationship with the model output variable. Figure 1b shows increasing conservatism for the case in which the parameter has an inverse relationship with the model output variable. The Monte Carlo sampling is carried out, as described previously, corresponding to each conservative case. Each Monte Carlo run incorporates hundreds to thousands of realizations (each realization involving generation of a sampled parameter vector x_{ij} , i = 1,...I), computation of the performance function represented by Eq. (1), and computation of the partial derivative in Eq. (2) corresponding to each parameter and realization. The mean sensitivity is then obtained by Eq. (3) from the sensitivity corresponding to each realization.

EXAMPLE PROBLEMS

Three example problems are presented to illustrate the effects of conservatism in model parameters on the identification and ranking of influential parameters. Simple example problems are chosen so the effects of conservatism can be clearly demonstrated. The first example is a generic four-parameter, nonlinear analytic function that permits computation of the exact sensitivity analytically. The second and third examples are practical problems that have been highly simplified for illustration purposes. The second example illustrates the effects of conservatism when the model output has an inverse relationship with one of the key parameters of interest, and the third example illustrates the effects of conservatism when the model output has a direct relationship with one of the key parameters of interest. In all three cases, the parameters are sampled from assigned distributions.

Example 1: A Generic Function

This first example is an arbitrarily-chosen, four-parameter, non-linear function, $f(x, v, z, w)$ of stochastic variables x, v , z, and w, represented by

$$f(x,v,z,w) = \frac{x + zw}{v} \tag{4}$$

For simplicity, all input parameters are assigned uniform distributions with the following arbitrarily-chosen ranges: $0.34 \le x \le 0.57$, $0.01 \le v \le 0.18$, $1.2 \le z \le 2.4$, and $0.001 \le w \le 1{,}000$. The effect of conservatism in w is investigated.

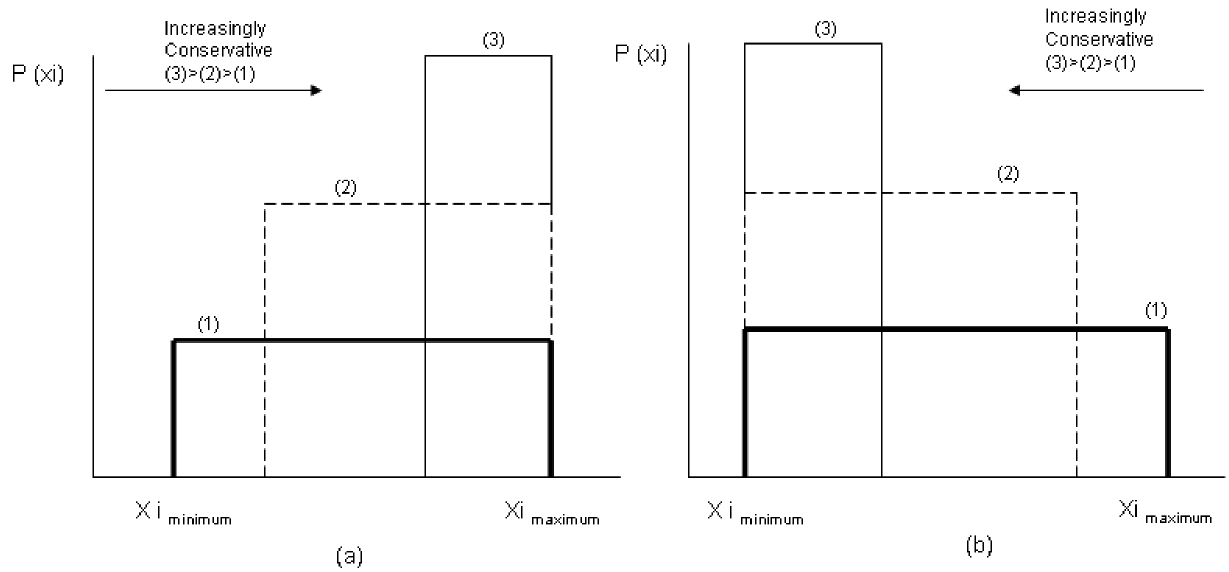

Figure 1. Generation of Conservative Results by Decreasing the Range and Biasing the Distribution Function Toward Conservative Values of X_i. The Nominal Case Distribution Function is Indicated by the Thick Solid Line. In Figure (a), the Output Varies Directly with the Parameter of Interest X_i, while in Figure (b), Output Varies Inversely.

Example 2: Drinking Water Dose Example Problem

The second example is a highly-simplified model for estimating the radiation to a dose receptor from groundwater ingestion. All fixed parameters in the detailed model are lumped into one factor, *C*, to develop a simplified model based on [3] represented by

$$D = C \times \frac{\rho_b C_s I^{\frac{2b+2}{2b+3}}}{(\frac{n}{n_e} + \frac{\rho_b K_d}{n_e})n} \tag{5}$$

where D is radiation dose to the receptor [mrem/yr], ρ_b is the bulk density of the contaminated zone in g/cm^3 [1 g/cm^3 = 0.58 oz/in^3], C_s is the radionuclide concentration in soil in the contaminated zone in pCi/g [1 pCi/g = 28 pCi/oz], I is the infiltration rate in m/yr [1 m/yr = 3.0 ft/yr], n and n_e are total porosity and effective porosity of the contaminated zone [unitless], respectively. K_d is the sorption coefficient of the radionuclide in water in cm^3/g [1 cm^3/g = 1.7 in^3/oz], and b is a soil-specific parameter [unitless]. In this equation, D is a function of radionuclide leaching and transport to the water table from the contaminated soil. The leaching and transport are modeled as a function of infiltration and radionuclide retardation factor (the denominator in Eq. 4). Retardation factor depends on n, ρ_b , and K_d. The function b in the numerator results from the leaching rate, which is linear function of I, and saturation rate, which depends on I as $I^{1/(2b+3)}$ [3].

For simplicity, all parameters in Eq. (4) are assigned uniform probability distribution functions with the following arbitrarily-chosen ranges: n : 0.34 ≤ n ≤ 0.57, 0.001 ≤ n_e ≤ 0.18, 1.2 ≤ ρ_b ≤ 2.4, 0.0 ≤ K_d ≤ 5.0, 0.0 ≤ I ≤

1.0, and $0.0 \leq C_s \leq 1.0$. This example was selected to illustrate the effects of conservatism on sensitivity when the model output is inversely proportional to a key parameter (in this case, K_d, which in many cases, is poorly known because of its dependence on radionuclide, soil type, pH, and other factors). K_d is the ratio of radionuclide concentration in soil to the radionuclide concentration in water. Therefore, in groundwater pathway dose calculations, a conservative approach is to assume that the distribution coefficient is zero. Distribution coefficients of zero imply no radionuclide retardation (i.e., the radionuclides move at the velocity of water), which is a highly conservative assumption for radionuclides that are known to absorb on rock surfaces. Modelers often use ranges of K_d values biased toward conservative values.

Example 3**: **External Exposure Dose Example Problem

The third example is a model to calculate external dose from a layer of soil contaminated by radionuclides. In this model, the equivalent dose D [mrem/yr] received by an individual exposed to external radiation from a layer of contaminated soil can be given by [3]

$$D = C \times DCF_{\infty}\left[1 - Ae^{-K_A \rho d} - Be^{-K_B \rho d}\right] \times \theta \tag{6}$$

where C is the radionuclide concentration in the contaminated layer [pCi/g]; d is the contaminated layer thickness [cm]; θ is the fraction of the time the receptor is exposed to external radiation [unitless]; DCF_{∞} is the dose conversion factor for an infinitely thick contaminated layer in mremyr^{-1}/pCig^{-1} [mrem yr^{-1}/pCig^{-1} = 0.036 mrem yr^{-1}/pCi oz^{-1}]; ρ is density of the contaminated soil layer [g/cm^3]; and A, B, K_A, and K_B are the fitting parameters: K_A, K_B have dimensions of cm^2/g, and A and B are dimensionless.

Parameters C, Δd, and θ in this example are assigned uniform probability distribution functions, with the following arbitrarily assigned ranges: $0.001 \leq C \leq 1{,}000$, $10 \leq \Delta d \leq 140$; and $0.01 \leq \theta \leq 0.4$. Other parameters are arbitrarily assigned fixed values: $A = 0.9235$, $B = 0.0765$, $K_A = 0.0783$ cm^2/g [2.2 in^2/oz], $K_B = 1.263$ cm^2/g [0.93 oz/in^3], $\rho = 1.6$ g/cm^3, and $DCF_{\infty} = 16.2$ mremyr^{-1}/pCig^{-1} [0.58 mrem yr^{-1}/pCi oz^{-1}] [3]. The model applies to a wide range of contaminated soil thicknesses, including nearly zero thickness (i.e., surface distribution of radionuclides). The model shows a non-linear dependence of D on the contaminated soil layer thickness. This example was selected to illustrate the effects of model conservatism on sensitivity when the model output is directly proportional to the key parameter (in this case, d, the thickness of the contaminated soil layer). The model becomes more conservative when d approaches the upper limit of its range.

ASSUMPTIONS

The analysis techniques and approach used in this paper use the following assumptions.

- The analyses are conducted using local sensitivity analysis. Local sensitivity analysis assumes that there are no model parameter interactions. To investigate the interaction effects, global sensitivity analysis methods can be used. However, the general conclusions in this paper are not anticipated to change.

- The example problems do not consider any correlation among the input parameters. Care must be taken in interpreting the outcome of the sensitivity analysis because the ranking of non-conservative parameter could be influenced by the rank of conservative parameters.

- Model conservatism is introduced by simply adjusting parameter ranges so the model output will be pesimistic. However, conservative biases may have been built into the models at the conceptualization stage by excluding processes contributing beneficially to system safety. Such conservative biases cannot be compensated for in parametric sensitivity analysis unless explicit provisions have been established at the model development stage.

- The parameter distribution (i.e., the uncertainty range) in the basecase is realistic. In many problems, a conservative choice may involve a single value that subsumes the entire uncertainty range. In other problems, the entire distribution may have been shifted toward conservative values. In either case, model output may be insensitive to this parameter.

RESULTS

Monte Carlo random sampling was implemented using Mathematica® to sample model input parameter values.

One thousand realizations per Monte Carlo run were found adequate for obtaining a stable mean of the model output values. Sensitivity coefficients were obtained analytically, but the forms of these coefficients are not shown in this paper.

Example 1: A Generic Function

Figure 2 shows the sensitivity of model output (i.e., the generic-function) to *w* and *x* changes when *w* changes toward conservative values. In this example, model output is sensitive to all four parameters although sensitivity to only two parameters is shown for illustration purposes. Figure 2 demonstrates that sensitivity changes non-linearly with conservatism in *w*. When Δw (i.e., the range of *w*) varies, the sensitivity of the function to *x* also varies non-linearly. This sensitivity must not be confused with the basecase sensitivity, which is only one case of Δw (i.e., $0.001 \leq w \leq 1{,}000$). The notation S_w (Δw) implies S_w sensitivity when Δw is varied. Likewise, the notation S_x (Δw) implies S_x sensitivity when Δw is varied. It should be noted that the ranges of *x, v, and z* in Eq. (4) are maintained at the basecase ranges when Δw is varied. Figure 2 also shows that, at low Δw values (i.e., biased toward conservatively higher *w* values) , $\overline{S_w}$ (Δw) approaches zero, while $\overline{S_x}$ (Δw) dominates, implying that *x* is more important than *w*. At high Δw values (i.e., biased toward the nominal case range), $\overline{S_x}$ (Δw) sensitivity approaches zero and $\overline{S_w}$ (Δw) sensitivity dominates, implying that *x* is more important than *w*. The switch from $\overline{S_x}$ (Δw) to $\overline{S_w}$ (Δw) domination occurs at $\Delta w \approx 0.5$.

Example 2:Drinking Water Dose Example Problem

Figure 3 shows the sensitivity of the model output variable *D* to various parameters K_d, *I, S, n*, n_e, and ρ_b [i.e., $\overline{S_{K_d}}$ *(*ΔK_d*)*, $\overline{S_I}$ *(*ΔK_d*)*, $\overline{S_S}$ *(*ΔK_d*)*, $\overline{S_n}$ *(*ΔK_d*)*, $\overline{S_{n_e}}$ *(*ΔK_d*)*, and $\overline{S_{\rho_b}}$ *(*ΔK_d*)]* when ΔK_d changes toward conservative values. The negative values on the y-axis reflect inverse proportionality between output variable and the input parameter, while a positive value indicates direct proportionality. While $\overline{S_I}$ *(*ΔK_d*)* and $\overline{S_S}$ *(*ΔK_d*)* are large, they do not vary with the choice of ΔK_d. However, the choice of ΔK_d influences $\overline{S_{K_d}}$ *(*ΔK_d*)*, $\overline{S_n}$ *(*ΔK_d*)*, and $\overline{S_{\rho_b}}$ *(*ΔK_d*)*. $\overline{S_{K_d}}$ *(*ΔK_d*)* approaches a small value at lower ΔK_d values. $\overline{S_{\rho_b}}$ does not vary with the choice of ΔK_d at lower values of ΔK_d, whereas at ΔK_d > ~4.5, it increases with increasing ΔK_d, approaching 0.4 at large ΔK_d values. At lower values of ΔK_d, (e.g., $\Delta K_d = 1$), the sensitivity is approximately ± 1.0 in the case of *S*, n_e *I, n*, and K_d; and the sensitivity to ρ_b is approximately 0.1. At $\Delta K_d < 4$ the model is more sensitive to *n* than to ΔK_d. However, at higher values of ΔK_d, (e.g., $\Delta K_d > 4$), the model becomes more sensitive to K_d than to *n*.

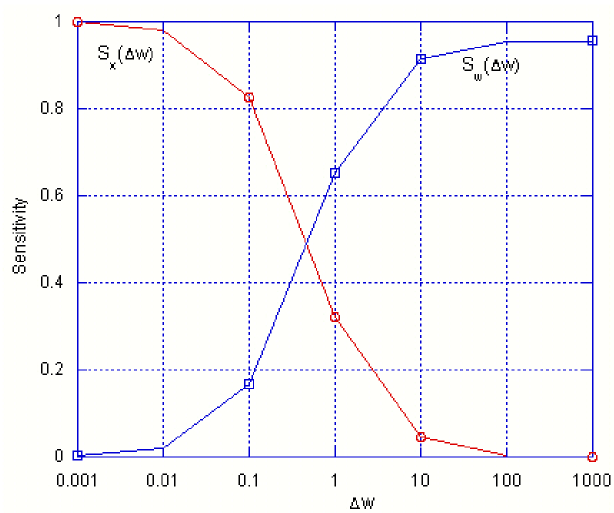

Figure 2. Sensitivity of Function f With Respect to *x* [i.e., $\overline{S_x}$ (Δw)] and *w* [i.e., $\overline{S_w}$ *(Δw)*] When *Δw* is Increasingly Biased Toward Conservative Values (i.e., From *Δw* = 1,000 Toward *Δw* = 0.001)

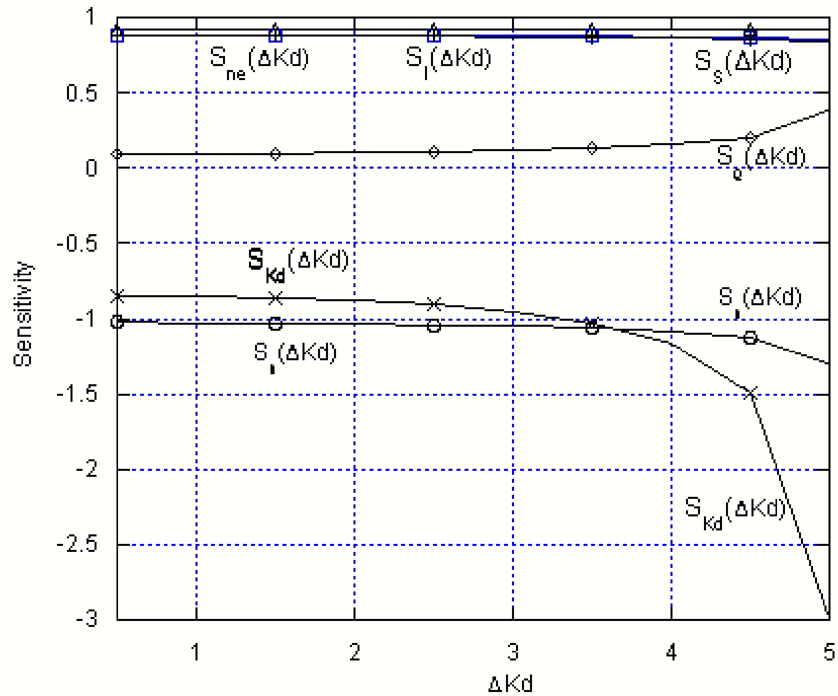

Figure 3. Sensitivity of *D* With Respect to Various Stochastic Parameters When ΔK_d is Assigned Conservative Values

Example 3: External Exposure Dose Example Problem

Figure 4 shows the sensitivity of model output variable *D* to *C*, θ, and d [i.e., $\overline{S_\theta}$ *(Δd)*, $\overline{S_C}$ *(Δd)*, and $\overline{S_d}$ *(Δd)*]. Sensitivity coefficients are computed for all parameters; however, these coefficients are analyzed only when parameter *d* has been varied toward conservative values. In this problem, *D* varies directly with *d*, so higher values of *d* give conservative estimates of dose. The figure shows that the sensitivity of *D* to *C* and θ does not change with Δ*d*, while the sensitivity of *D* to Δ*d* changes significantly. At the lower end of Δ*d*, $\overline{S_d}$ (Δd) is comparable to $\overline{S_C}$ *(Δd)* and $\overline{S_\theta}$ *(Δd)*. However, $\overline{S_d}$ *(Δd)* drops non-linearly from 0.78 at Δ*d* = 10 cm [4.0 in] to 0.53 at Δ*d* = 140 cm [55 in].

The example shows that if *d* is conservatively biased toward high values, the analyst may conclude that *d* is unimportant, possibly recommending no characterization of soil thickness. Whereas, if *d* were low, sensitivity analysis would suggest soil thickness characterization would be needed. Clearly, such a conservative assumption could render sensitivity analysis inapplicable to identifying truly important parameters. If the range and standard deviation of *d* were changed to assess sensitivity, the same conclusion could be drawn.

CONCLUSIONS

The three examples presented in the paper illustrate the effects of model conservatism, represented as conservatism in model parameters, on the identification and ranking of influential parameters. All three example problems are nonlinear, analytic functions that allow analytical computation of sensitivity coefficients. The first example, a generic four-parameter model, illustrates the approach. The other two examples are simple environmental health risk problems. The first of these illustrates the effects of conservatism when the model output (dose from ingested well water) is inversely proportional to the parameter of interest (radionuclide sorption coefficient). The second (dose from a contaminated layer of soil) illustrates the effects of conservatism when the model output is directly proportional to the parameter of interest (the physical thickness of the contaminated layer). The sensitivity of model output changes nonlinearly with the conservatism built into the model through the conservative assumptions for parameter values. This non-linearity is a function of the structure of the performance function. Over the uncertainty range of a parameter, the model output sensitivity to the parameter could vary from being insensitive to highly sensitive depending on the level of conservatism assumed. The sensitivity-based ranking of influential parameters changes non-monotonically with the

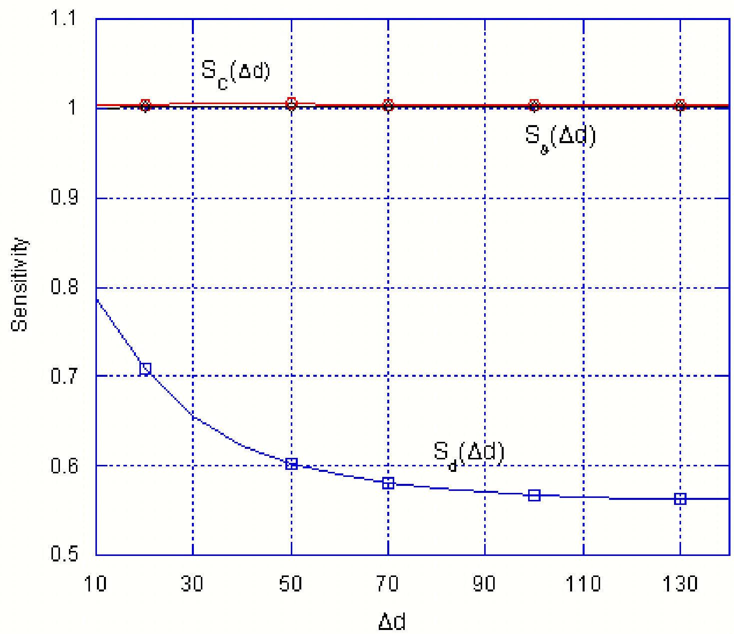

Figure 4. Sensitivity of *D* With Respect to Various Stochastic Parameters When Δ*d* is Assigned Conservative Values

assumed level of conservatism, depending on the model structure. Such dependence of the ranking of influential parameters on conservative assumptions could lead an analyst to conclude that other parameters are more influential. Because conservatism in safety analysis models with large uncertainties is unavoidable, analysts should evaluate the effects of the assumed degree of conservatism or the use alternative methods (e.g., component sensitivity analysis) [4] to ensure that influential parameters are correctly identified.

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