Application of Regionalized Sensitivity Analysis to a Performance Assessment Model of a High-Level Waste Repository

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***Abstract*—**The Regionalized Sensitivity Analysis (RSA) procedure is applied to a complex total-system performance assessment model of a geologic high-level radioactive waste repository. The analysis is designed to identify the constituent model parameters that influence the discrimination between model outputs above and below prescribed thresholds. The RSA procedure permits efficient identification of influential parameters at various model output thresholds. In this paper, model output thresholds set at five selected percentiles are used to investigate how parameter sensitivities may vary with repository performance criteria. Results identify four groups of parameters that (i) are most influential at all percentile thresholds, (ii) are more influential at high percentile thresholds, (iii) are less influential at high percentile thresholds, and (iv) show no pattern of influence with percentile thresholds. The strengths and limitations of the RSA procedure are discussed.

I. INTRODUCTION

In the United States, regulations governing a potential geologic repository for high-level radioactive waste at Yucca Mountain, Nevada, require that performance assessments be used in demonstrating compliance with postclosure public health and environmental standards. Performance assessment models are used to simulate the features, events and processes associated with the containment, release and transport of radionuclides in the geosphere, and to estimate future radiological exposures, doses and risk to an individual at the receptor location. The U.S. Nuclear Regulatory Commission (NRC) and the Center for Nuclear Waste Regulatory Analyses (CNWRA) have developed a computer code for conducting total-system performance assessments of the potential high-level waste repository at Yucca Mountain, Nevada [1]. This computer code is a tool that will assist NRC in evaluating the performance assessments conducted by the U.S. Department of Energy in support of any potential license application. The code contains hundreds of parameters with uncertainties represented by probability distributions. Monte Carlo simulation is used to propagate parameter uncertainties. Sensitivity analysis is performed on the model outputs to determine the influence of input parameters on the results. The objective of this paper is to apply the Regionalized Sensitivity Analysis (RSA) procedure to the total-system performance assessment code.

Section II provides a background and description of the RSA procedure. Section III highlights the application of the RSA procedure to results from the Total-system Performance Assessment (TPA) Version 4.1j code, independently developed by the NRC and CNWRA to conduct performance assessment of the potential Yucca Mountain repository. Section IV presents and discusses the results of the analysis, and Section V presents the conclusions. The analysis reported in this paper is limited to testing the applicability of the RSA procedure to the TPA code and comparing results obtained to that of other methods previously applied to the TPA code. Discussion and interpretation of the reasons for certain parameters being influential is beyond the scope of this paper.

II. RSA: BACKGROUND AND PROCEDURE

The RSA procedure was developed to identify key uncertainties in environmental systems [2]. The procedure was first applied to a water quality model of an estuary in Southwestern Australia to identify the biochemical processes driving the observed ecological behavior. By ranking the importance of parameters in the model, the procedure provided a basis for prioritizing future research to better understand the system and reduce uncertainties in model results. The RSA procedure has been applied to parameter estimation for hydrological models [3,4], structural identification and hypothesis screening of ecological models [5], and reliability assessment of multimedia environmental models [6]. Given its ubiquity in environmental systems applications, the RSA procedure is potentially beneficial to performance assessment models for nuclear waste disposal systems. When applied to performance assessment models, RSA could support the development of risk insights by identifying the most influential parameters for high-level radioactive waste repository performance. Because the sensitivity analysis is conditioned on a prescribed

performance level—say, a radiological dose threshold—the importance of a model parameter is determined by its role, relative to other parameters, in causing model output to exceed the threshold.

The RSA procedure is implemented as follows. Each realization from a set of p realizations obtained from sampled parameter values α_k, $1 \le k \le p$, is classified as acceptable (A) or unacceptable (U). An acceptable realization is obtained when the model output falls below the target threshold. Thus, for each parameter, two sets of sampled values are obtained—$\{\alpha_k|A\}$ in the acceptable realizations, and $\{\alpha_k|U\}$ in the unacceptable realizations. A Kolmogorov-Smirnov two-sample test is performed to assess the statistical difference between the sets of parameter values that gave acceptable and unacceptable realizations. The hypothesis test is stated formally as follows [7]:

$$H_0 : f_m(\alpha_k|A) = f_n(\alpha_k|U)$$
$$H_1 : f_m(\alpha_k|A) \neq f_n(\alpha_k|U) \qquad (1)$$
$$\text{Test statistic: } d_{m,n}(\alpha_k) = \max\left|F_m(\alpha_k|A) - F_n(\alpha_k|U)\right|$$

where $F_m(\alpha_k|A)$ and $F_n(\alpha_k|U)$ are the sample cumulative probability distribution functions for parameter α_k in the m acceptable realizations and n unacceptable realizations respectively, and $f_m(\alpha_k|A)$ and $f_n(\alpha_k|U)$ are corresponding probability density functions. The test statistic $d_{m,n}$ is the maximum vertical distance between the cumulative distributions. RSA is essentially a univariate method because the $d_{m,n}$ statistic is calculated independently for each model parameter. The influence of the parameters is determined by ranking their respective $d_{m,n}$ values. Parameters with larger $d_{m,n}$ values are more influential in discriminating between the acceptable and unacceptable model results. In other words, the values assumed for such parameters would strongly determine whether model results are above or below the threshold. On the other hand, parameters with smaller $d_{m,n}$ values are less influential because any sampled value is almost equally likely to produce results below or above the threshold.

III. RSA: APPLICATION TO THE TPA CODE

The RSA procedure is applied to the TPA code, which was developed for understanding the aspects of the repository system that are important to radiological safety [1]. The following is a brief description of the model implemented in the TPA Version 4.1j code.

The calculations for the nominal repository scenario involve (i) the degradation of waste packages containing high-level waste (e.g., spent nuclear fuel) approximately 300 meters below the surface of Yucca Mountain; (ii) the release of radionuclides when the water infiltrating the ground surface contacts exposed spent nuclear fuel; and (iii) vertical transport of radionuclides through the partially saturated geologic medium beneath the repository and horizontal transport in the saturated zone to a designated receptor.

The system level computations involve estimation of (i) time varying precipitation resulting from climate changes, water percolation from the land surface to the subsurface and subsequently into the emplacement drifts and onto the waste packages; (ii) the evolution of the chemical and physical processes (e.g. temperature, humidity, pH, ionic concentrations) affecting degradation of the engineered barriers including the waste packages and radionuclide releases; (iii) the time of failure and the number of waste packages failed based on corrosion phenomena and rockfalls; (iv) rockfalls induced by seismic events; (v) the rate of release of radionuclides from the engineered barrier system to the groundwater pathway as a function of time; (vi) the rate of flow and transport of radionuclides through the ground in the unsaturated and saturated zones; and (vii) radiation dose via groundwater pathways to a receptor with designated lifestyle characteristics.

In addition to estimating the nominal scenario, the TPA code also computes the processes that involve high-consequence, low-probability events including (i) waste package failure due to the displacement of yet unknown faults intersecting the repository; (ii) intrusive igneous activities (i.e., waste packages fail in place after coming in contact with a magmatic intrusion); and (iii) extrusive igneous activities (i.e., waste packages are disrupted and radionuclides become airborne). These events constitute the disruptive scenarios.

The TPA Version 4.lj code applies the Latin Hypercube sampling scheme to 330 specified input parameter distributions, several of which are correlated. The remaining parameters are assigned constant values. Because special calculations are needed to include dose from the disruptive scenarios in the total dose, only the results from the nominal scenario are analyzed in this paper.

The primary output of the TPA code is a time history of estimated radiological dose to receptors downstream of the potential repository. The RSA procedure is applied to the TPA code to evaluate the performance assessment model results against various dose thresholds and to determine the importance of the model parameters. Specifically, the analysis seeks to explore whether or not the same set of parameters appear to be influential in discriminating between acceptable and unacceptable model results for thresholds set at the 5th-, 25th-, 50th-, 75th-, and 95th-percentile doses. Model realizations are classified as acceptable or unacceptable based on dose

estimates at the time of the peak percentile dose. For each threshold, the model parameters are ranked according to their relative importance in discriminating between below-threshold and above-threshold model results. Two replicates of the RSA procedure are performed. In each replicate, the TPA code generates 4000 random model realizations from various distributions assigned to 330 input parameters.

IV. RESULTS AND DISCUSSION

Tables I and II present rankings of the parameters of the TPA code for the two RSA replicates. This ranking is based on the Kolmogorov-Smirnov statistic ($d_{m,n}$). The $d_{m,n}$ statistic depends on the sizes (m and n) of the two samples being compared. For each percentile dose threshold, a different set of acceptable and unacceptable realizations is obtained, resulting in $\{\alpha_k|A\}$ and $\{\alpha_k|U\}$ of different sizes. Tables I and II show, for example, that the 5th-percentile threshold gives 200 acceptable and 3800 unacceptable realizations, whereas the 75th-percentile threshold gives 3000 acceptable and 1000 unacceptable realizations. For an unbiased comparison of the parameter rankings across the percentile dose thresholds, the $d_{m,n}$ statistic is converted to the standard Kolmogorov-Smirnov variate (z_{KS}) as follows [7]:

$$z_{KS} = d_{m,n} \cdot [m \cdot n/(m+n)]^{0.5} \qquad (2)$$

Tables I and II also show the values of z_{KS} obtained for the selected percentile thresholds in each replicate of the RSA procedure. For this analysis, a 5% significance level is adopted as the criterion for determining the most influential parameters of the model. The 5% significance level corresponds to z_{KS} = 1.36 in the Kolmogorov-Smirnov distribution. Tables I and II show the parameters with z_{KS} values that exceed 1.36. In the first replicate (Table I), the number of influential parameters obtained ranges from 9 to 14, while the second replicate produced 13 to 15 influential parameters. This represents 2.7% to 4.5% of the sampled parameters in the TPA code. Thus, to the extent that the number of influential parameters varies little with percentile threshold, the TPA code seems to have performed consistently in both replicates of the RSA procedure.

Another aspect of the results is the composition of influential parameters. In Tables I and II, three groups of parameters exhibit distinct patterns of variation across the percentile thresholds. The first group are parameters that are most influential at all the percentile thresholds. This group includes the mean areal average infiltration into the subsurface at the start of the simulation (*AAMAI@S*), the fraction of waste packages in the repository wetted by infiltrating water (*SbArWt%*), the passive current density associated with waste package corrosion (a corrosion rate,

Table I. Ranking of the Influential Parameters in the First Regionalized Sensitivity Analysis Replicate*

	5th-percentile		25th-percentile		50th-percentile		75th-percentile		95th-percentile	
r	a	z_{KS}	a	z_{KS}	a	z_{KS}	α	z_{KS}	α	z_{KS}
1	InvMPerm	6.272	AA_1_1	7.869	AA_1_1	9.234	PSFDM1	9.339	PSFDM1	8.884
2	AAMAI@S	4.933	SbArWt%	7.376	PSFDM1	9.060	AA_1_1	7.431	SbArWt%	4.840
3	SbArWt%	4.498	PSFDM1	5.852	SbArWt%	7.020	SbArWt%	5.623	AAMAI@S	3.820
4	AA_1_1	4.012	AAMAI@S	5.258	AAMAI@S	4.649	DTFFAVIF	5.039	AA_1_1	3.608
5	MAPM@GM	2.249	MPrm_TSw	4.090	DTFFAVIF	4.396	AAMAI@S	4.674	DTFFAVIF	2.588
6	ARDSAVNp	2.028	ARDSAVPu	3.706	ARDSAVPu	4.396	ARDSAVPu	3.998	ARDSAVPu	1.658
7	ARDSAVPu	1.531	InvMPerm	3.661	MPrm_TSw	3.984	MPrm_TSw	3.469	MPrm_TSw	1.629
8	WP-Def%	1.455	DTFFAVIF	2.775	ARDSAVNp	2.893	ARDSAVNp	2.638	gen_ifi	1.586
9	MKDCHvNi	1.451	ARDSAVNp	2.729	InvMPerm	2.688	SFWFC1	1.424	MKDUCFCs	1.567
10			WP-Def%	2.045	SFWFC1	1.581	SFWt%I5	1.424	FOCTR	1.400
11			APrs_SAV	1.643	SFWt%C2	1.423	genpfitC	1.388		
12			gen_ifi	1.515	VEi/e-R#	1.407				
13			MAPM@GM	1.461						
14			SFWt%16	1.424						
	m	200		1000		2000		3000		3800
	n	3800		3000		2000		1000		200

* r – rank; α – parameter abbreviation; z_{KS} – Kolmogorov-Smirnov variate

Table II. Ranking of the Influential Parameters in the Second Regionalized Sensitivity Analysis Replicate*

	5th-percentile		25th-percentile		50th-percentile		75th-percentile		95th-percentile	
r	α	z_{KS}	α	z_{KS}	α	z_{KS}	α	z_{KS}	α	z_{KS}
1	InvMPerm	5.833	AA_1_1	8.170	AA_1_1	9.977	PSFDM1	9.704	PSFDM1	8.811
2	AAMAI@S	4.422	SbArWt%	6.381	PSFDM1	9.345	AA_1_1	7.458	SbArWt%	4.920
3	AA_1_1	4.088	PSFDM1	6.144	SbArWt%	7.004	SbArWt%	5.377	AAMAI@S	3.984
4	SbArWt%	3.482	AAMAI@S	5.578	AAMAI@S	5.423	DTFFAVIF	5.222	AA_1_1	3.462
5	ARDSAVPu	2.398	InvMPerm	3.469	DTFFAVIF	4.775	AAMAI@S	4.610	Solbl-Np	2.521
6	WP-Def%	2.100	DTFFAVIF	3.469	ARDSAVPu	3.874	ARDSAVPu	3.898	MPrm_TSw	2.504
7	SSMO-JS2	1.643	ARDSAVPu	3.368	MPrm_TSw	3.257	MPrm_TSw	2.775	DTFFAVIF	2.369
8	gen_lirP	1.636	WP-Def%	2.739	ARDSAVNp	2.957	ARDSAVNp	2.675	ARDSAVPu	2.026
9	ARDSAVNp	1.592	ARDSAVNp	2.620	InvMPerm	2.245	VC-Dia	1.616	SFWt%C9	1.932
10	SSMOV202	1.523	MPrm_TSw	2.593	InitRSFP	1.755	SFWt%C2	1.534	SFWt%S35	1.706
11	gen_hfgt	1.451	gen_hirP	1.470	SFWt%C2	1.676	SFWt%S49	1.461	MKDCHvNi	1.626
12	SSMOV402	1.378	MKDPPwNi	1.378	APrs_SAV	1.550	gen_girC	1.424	SFWt%S32	1.626
13	FOCTR	1.378			gen_ifi	1.470			SFWt%C6	1.494
14					WP-Def%	1.455				
15					SFWFSEI6	1.423				
	m	200		1000		2000		3000		3800
	n	3800		3000		2000		1000		200

* r – rank; α – parameter abbreviation; z_{KS} – Kolmogorov-Smirnov variate

AA_1_1), and the matrix retardation factor for Plutonium in the alluvium portion of the saturated zone (*ARDSAVPu*). These parameters are consistent with the influential parameters identified in previous studies that applied various other sensitivity analysis techniques to the TPA code [8,9,10][1]. These previous studies had subsequently contributed to the development of risk insights related to postclosure performance of a potential geologic repository at Yucca Mountain [11]. The second group of parameters are less influential at higher percentile thresholds. This group includes the fraction of the total waste packages that are defective at the start of the simulation (*WP-Def%*) and the matrix retardation factor for Neptunium in the alluvium portion of the saturated zone (*ARDSAVNp*). The third group of parameters are more influential at the higher percentile thresholds. These include the distance from the repository to the interface between the volcanic tuff and alluvium portions of the saturated zone (*DTFFAVIF*), and the matrix permeability of the Topopah Spring-welded stratigraphic unit of the unsaturated zone (*MPrm_TSw*). The second and third groups of parameters complement the first group by identifying attributes of the repository performance that could distinguish risk information for different repository performance criteria.

A few model parameters, such as *gen_ifi*, *SFWt%C2*, and *FOCTR*, show no pattern of change in influence with the percentile threshold. The full description of these and other parameters listed in Tables I and II is provided in Table III. Most of the remaining model parameters consistently rank below the 5% significance criterion at all percentile thresholds. For reasons discussed later, the RSA procedure cannot confirm that these parameters are not influential.

In the TPA Version 4.1j code, 22 pairs of correlated parameters are specified in the input distributions. The correlations involve *SbArWt%*, *AAMAI@S*, *MPrm_TSw*, the matrix retardation factors for selected radionuclides in the alluvium portion of the saturated zone, and the matrix sorption coefficients for selected radionuclides in the stratigraphic units of the unsaturated zone. Of these, only three pairs of parameters rank above the 5% criterion {*SbArWt%*, *AAMAI@S*}, {*SbArWt%*, *MPrm_TSw*}, and {*ARDSAVPu*, *ARDSAVNp*}. Correlation is one form of interaction among model parameters [12]. Parameter interaction could result in several combinations of parameter values giving identical model results. In general, there are two kinds of parameter

[1]In previous studies, the well pumping rate for the residential receptor group was identified as an influential parameter. The well pumping rate parameter was excluded from this analysis.

Table III. Description of Influential Parameters

Short name	Description
AA_1_1	Passive electric current density for the waste package outer overpack
AAMAI@S	Mean areal average infiltration into the subsurface at the start of the simulation
APrs_SAV	Amargosa Valley alluvium saturated zone matrix porosity
ARDSAVNp	Matrix retardation for Neptunium in the saturated zone of the Amargosa Valley alluvium
ARDSAVPu	Matrix retardation for Plutonium in the saturated zone of the Amargosa Valley alluvium
DTFFAVIF	Distance traveled in tuff
FOCTR	Fraction of water condensate moving towards the repository
gen_girC	Grain irrigation rate for current biosphere
gen_hfgt	Egg-laying hen feed growing time
gen_hirP	Residential irrigation rate for pluvial biosphere
gen_ifi	Irrigation interception fraction
gen_lirP	Leafy vegetable irrigation rate for pluvial biosphere
genpfitC	Poultry feed irrigation time for current biosphere
InitRSFP	Initial radius of spent fuel particle
InvMPerm	Matrix permeability of the invert
MAPM@GM	Mean annual precipitation increase at glacial maximum
MKDCHvNi	Matrix sorption coefficient for Calico Hills-nonwelded vitric layer for Nickel
MKDPPwNi	Matrix sorption coefficient for Prow Pass-welded layer for Nickel
MKDUCFCs	Matrix sorption coefficient for Upper Crater Flat layer for Cesium
MPrm_TSw	Matrix permeability for Topopah Spring-welded layer
PSFDM1	Preexponential factor for spent nuclear fuel dissolution model
SbArWt%	Subarea wet fraction
SFWFC1	Spent nuclear fuel wet fraction for corrosion failures in subarea 8
SFWFSEI6	Spent nuclear fuel wet fraction for seismic failures for seismic interval 3 in subarea 8
SFWt%C2	Spent nuclear fuel wet fraction for corrosion failures in subarea 2
SFWt%C6	Spent nuclear fuel wet fraction for corrosion failures in subarea 6
SFWt%C9	Spent nuclear fuel wet fraction for corrosion failures in subarea 9
SFWt%I5	Spent nuclear fuel wet fraction for initial failures in subarea 5
SFWt%S16	Spent nuclear fuel wet fraction for seismic failures for seismic interval 1 in subarea 6
SFWt%S32	Spent nuclear fuel wet fraction for seismic failures for seismic interval 3 in subarea 2
SFWt%S35	Spent nuclear fuel wet fraction for seismic failures for seismic interval 3 in subarea 5
SFWt%S49	Spent nuclear fuel wet fraction for seismic failures for seismic interval 4 in subarea 9
Solbl-Np	Solubility limit for Neptunium
SSMO-JS2	Joint spacing for rock condition 2
SSMOV202	Vertical extent of rock fall for rock condition 2 and ground acceleration 0.10g
SSMOV402	Vertical extent of rock fall for rock condition 4 and ground acceleration 0.10g
VC-Dia	Diameter of volcanic cone
VEi/e-R#	Random number to determine type of volcanic event (extrusive or intrusive)
WP-Def%	Fraction of initially defective waste packages in a subarea

interactions—direct and indirect [13]. Direct interactions occur among parameters that appear in the same mathematical expression. For example, in a function that includes the product of two sampled parameters, the sampled values that produce identical results are inversely correlated. Indirect interactions occur through the model structure and can only be detected by an evaluation of the conceptual structure of the model. The correlations specified among the matrix sorption coefficients and alluvium retardation factors in the TPA code are the result of prior conceptual knowledge of indirect interactions. In general, when correlated parameters are involved in sensitivity analyses, the resulting sensitivity coefficients do not properly indicate the influence of these parameters [14]. In the case of the RSA procedure, the sensitivity coefficient—the Kolmogorov-Smirnov ($d_{m,n}$) statistic—is derived by examining the multidimensional parameter space one parameter at a time [15]. Therefore, the ranking of parameters only indicates their individual influence and parameter correlations are ignored. Another reason is that

correlated parameters do not partition well under the binary classification of the RSA procedure. In other words, because correlated parameters could compensate one another in order to produce similar results, it is often difficult to clearly distinguish between their values in the $\{\alpha_k|A\}$ and $\{\alpha_k|U\}$ partitions of the parameter space. Thus, the influence of parameter correlations cannot be assessed properly on the basis of the univariate $d_{m,n}$ statistic alone. Additional multivariate analyses must be performed on the $\{\alpha_k|A\}$ and $\{\alpha_k|U\}$ sets to determine the influence of parameter correlations.

V. CONCLUSIONS

Regionalized Sensitivity Analysis (RSA) provides a conditional approach to sensitivity analysis because the influence of a model parameter is determined by its role in discriminating whether or not the model result matches a prescribed performance level. In this study, the RSA procedure was applied to the TPA Version 4.1j code to identify parameters that influence the discrimination between performance above or below five prescribed percentile dose thresholds. The results showed that very few of the sampled parameters were influential at all percentile thresholds and at high or low thresholds. Many parameters showed no consistent pattern of variation in influence with threshold. The RSA procedure identified influential parameters consistent with those of previous sensitivity studies using various other methods. This suggests that the RSA procedure can be beneficial for screening influential model parameters, building confidence in performance assessment models, and may provide support for risk-informing regulation of nuclear waste repositories.

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