A guideline for sensitivity analysis of repository models

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To support the safety assessment of final repositories for radioactive waste, it is very helpful to do sensitivity analysis (SA). The applied numerical models, however, may exhibit a highly non-linear behaviour. For example, quasi-discontinuous behaviour may occur when barriers fail to function at some point in time, which can happen very fast. This can cause a two-split output distribution. In addition, the model output is dominantly very low and varies over many orders of magnitude, which may result in a steep and asymmetric distribution of the model output. Such distributions and model behaviours are challenges for performing proper SA.

All methods of SA have their specific advantages and disadvantages in view of the nature of the model under consideration, number of parameters, input distributions and available computational power. Furthermore, SA will also depend upon which questions need to be answered about the sensitivity of the system. Objectives of a guideline for SA are that the analyses produce unique and robust results as well as provide clear answers to the asked questions. The guideline presented in this talk is a recommendation based on the outcome of detailed experiments with different methods and sample sizes.

We generally recommend using a quasi-Monte Carlo sampling method for SA as it covers the parameter space more homogeneously and produces more robust results compared to random sampling and existing samples can be extended.

Although, from a radiological point of view, it may be sufficient to only analyse the peak values of all runs, we recommend performing a time-dependent analysis in addition, as it provides more insight into the system behaviour.

In general, the nature of the numerical model will not be fully known before the analysis. Therefore, a stepwise approach is advisable, starting with graphical SA and then advancing to more sophisticated methods. This approach may also allow detecting sensitivities which are not found with one type of method.

Graphical methods provide a visual insight into the model behaviour and sensitivity of the different parameters. They can be used as the first approach to identify potentially important parameters. Graphical SA is in particular useful when many parameters need to be considered. The number of parameters may be reduced in this first analysis which makes more advanced methods easier to use and less time-consuming in terms of required computational power. With the graphical methods Contribution to the Sample Mean (CSM) plot and scatterplots we obtained good results.

In the next step, regression- or correlation-based methods are suggested to be applied. This can be done on a value- or rank-basis. If nonlinear effects play a role, the rank-based version is often more adequate, but that has to be checked as the coefficient of determination (R^2) can even decrease under a rank transformation. We made good experience with the standard regression method SRC and standard rank regression method SRRC.

Variance-based methods of SA do not require linearity or monotonicity, which does, however, not automatically mean that they work better on a nonlinear model. As a first approach of this kind we recommend applying the EASI algorithm, which is numerically effective, can be used with any sample and seems to yield robust results. However, EASI can only compute the first-order effects. A low sum of all first-order sensitivity indices indicates poor significance of the first-order analysis. This can often be improved by applying an adequate transformation to the model output. Otherwise, an analysis of the higher orders is recommended in such cases.

If certain model properties are known or have been identified during the above analysis, it is recommended to add specifically designed investigations. For instance, influences of parameter correlations may be seen in the difference between the Partial Correlation Coefficients (PCC) and SRC results or Partial Rank Correlation Coefficients (PRCC) and SRRC results. Non-parameteric methods like the two-sample Smirnov test can also be helpful in specific cases.

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