Performance of Six Sampling Methods for Global Sensitivity Analysis on the Basis of a Performance Assessment Model for a Generic High Level Radioactive Waste Repository in Clay

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Introduction

To prove long-term safety of a geological repository for radioactive waste, it is essential to deal adequately with the various uncertainties

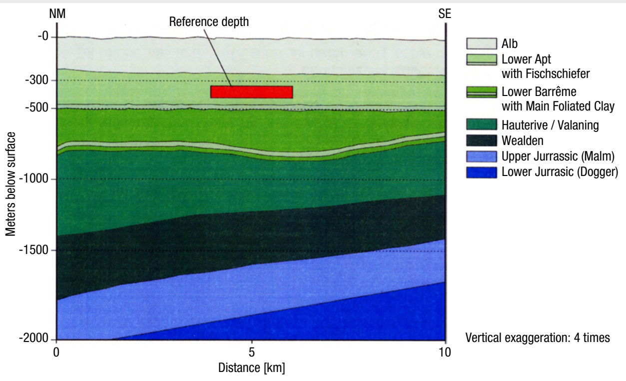
Can low-discrepancy sequence sampling schemes give more robust sensitivity measures with a lower number of simulations than other sampling methods?

Description of the Performance Assessment Model

Generic repository for high level waste in a consolidated clay host rock formation in Northern Germany

Behaves relatively smoothly

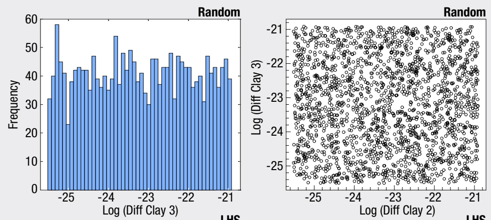
Its model output, i.e. annual effective dose to man, is skewed and tailed. Most of the output values are very low. Test case is monotonic and does not include (quasi-) discrete parameters



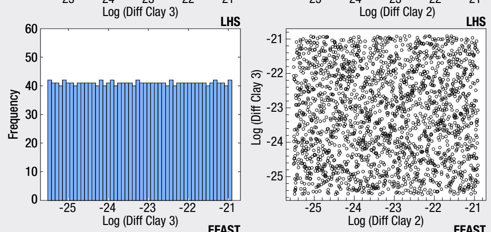
Cross-section of the Lower Cretaceous Clay Formation sequence

Investigated sampling methods

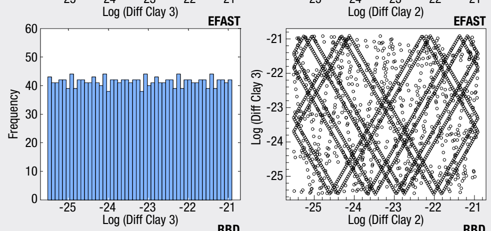
Random: points chosen randomly following given probabilistic density functions (pdf's) of the parameters



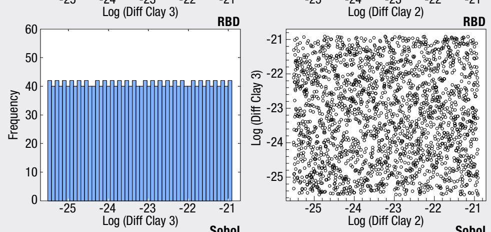
Latin Hypercube Sampling (LHS): statistical distribution divided in N equally probable intervals; within each interval, a random value selected according to the pdf's of the parameters



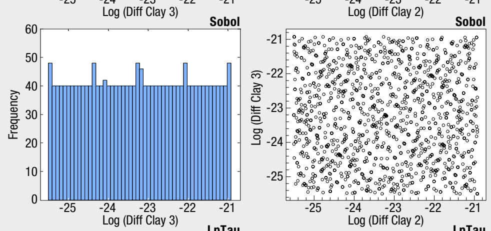
EFAST: parameter space explored periodically with interference-free frequencies



Random Balance Design (RBD): similar to EFAST but parameter space explored with only one frequency and random permutations following given seed to obtain points for each parameter



Sobol: replicated version of low-discrepancy sequences (see below)



Low-discrepancy sequences:
LpTau: parameter space explored by means of partitions of the parameter ranges on the base of two

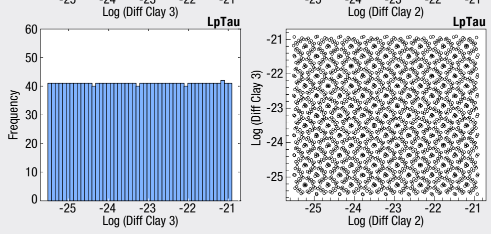
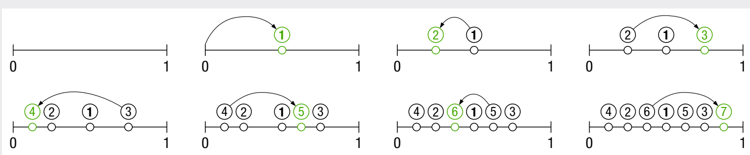


Illustration of basic idea of low-discrepancy sequences using base 2 in [0,1] (Niederreiter, 1987; Schwuchow, 2009)



Description of the samples

Parameter set	Sampling method	# samples	Sample sizes (Number of simulations)
6	Random	5	512, 2048, 4096, 8192 and 16384
	LHS	5	512, 2048, 4096, 8192 and 16384
	EFAST	4	2070, 4086, 8214 and 16374
	RBD	3	4096, 8192 and 16384
	Sobol	3	4096, 8192 and 16384
	LpTau	1	512, 1024, 2048 and 4096
13	LpTau	1	512, 1024, 2048 and 4096

Analysing methods

Graphical: Contribution to the Sample Mean (CSM) plots

Rank regression-based: Standardised Rank Regression Coefficients (SRRC) method

Non-parametric: Smirnov test

Variance-based: Extended Fourier Amplitude Sensitivity Test (EFAST), Sobol and Random Balance Design (RBD) method

Metamodel: State-Dependent Parameter (SDP) method

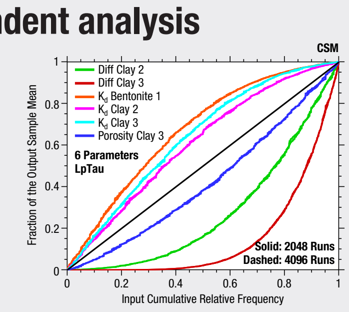
Software packages

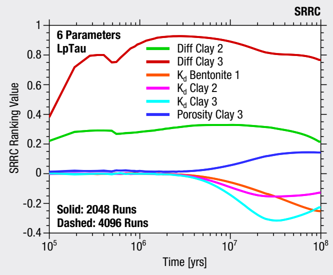
EMOS (Buhmann, 1999)

SIMLAB 3 within MATLAB environment from Joint Research Centre (JRC)
SDP software within MATLAB environment from Ratto et al. (2007)

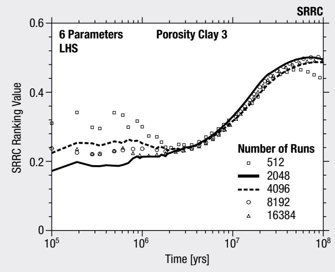
Results – time-dependent analysis

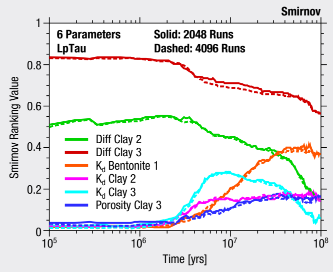
LpTau, CSM and SRRC: good convergence reached with 2048 runs





LHS, random, EFAST, CSM and SRRC: for obtaining a nearly comparable agreement of the curves with 6 parameters in general a factor of at least 4 more simulations are required compared to the LpTau sampling techniques

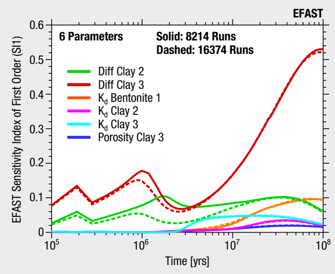


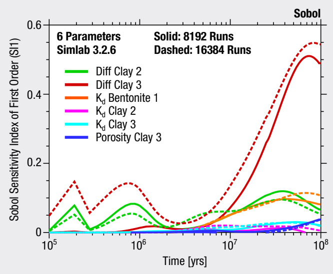


LpTau and Smirnov: convergence not quite obtained with 2048 runs

Random, LHS, EFAST and Smirnov: for some cases, no close agreement

EFAST and Sobol: convergence not reached with 16374/16384 runs

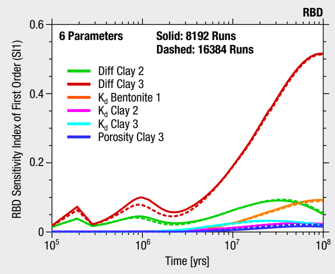


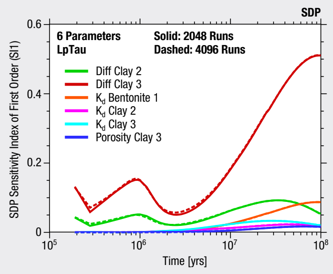


RBD: convergence not quite obtained with 8192 runs

LpTau and SDP: good convergence reached with 2048 runs

LHS, random, EFAST and SDP: for obtaining a nearly comparable agreement of the SI1 curves with 6 parameters a factor of at least 8 more simulations are required compared to the LpTau sampling technique





Summary – preliminary results

Sampling/ analysing method	Random	LHS	EFAST	RBD	Sobol	LpTau
CSM plots	+	+	+			+++
SRRC	+	+	+			+++
Smirnov	-	-	-			+
EFAST	NP	NP	-	NP	NP	NP
RBD	NP	NP	NP	0	NP	NP
Sobol	NP	NP	NP	NP	--	NP
SDP	0	0	0			+++

NP = Not Possible

The LpTau sampling performed best (except for the Smirnov test), as it yielded converging results with by a factor of 4-8 smaller sample sizes compared to the other methods

Acknowledgements

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References

Buhmann D. (1999). Das Programmpaket EMOS. Ein Instrumentarium zur Analyse der Langzeitsicherheit von Endlagern. GRS-159, ISBN 3-931995-21-6

Niederreiter H. (1987). Point sets and sequences with low discrepancy. Monatsheft fuer Mathematik, 104, pp. 273

Ratto M., Pagano A. and Young P. (2007). State Dependent Parameter Metamodelling and Sensitivity Analysis. Computer Physics Communications, 177, 863–876

Schwuchow R. (2009). Probabilistische Zuverlässigkeits- und Sensitivitätsanalysen für schlanke Stahlbetonstützen auf Basis der Quasi-Monte Carlo Methode. PhD Thesis, Technical University of Cottbus, Germany