MODELLING OF RANDOM ACTIVITY CONCENTRATION FIELDS IN AIR FOR PURPOSES OF PROBABILISTIC ESTIMATION OF RADIOLOGICAL BURDEN OF POPULATION

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KEYWORDS AND ABBREVIATIONS: ADM-Atmospheric Dispersion Model, FCM-Food Chain Model, GPM-Gaussian Plume Model, UA-Uncertainty analysis, SA-Sensitivity Analysis, UF-Uncertainty Factor, LHS-Latin Hypercube Sampling, DA-Data Assimilation

INTRODUCTION

The paper deals with the trend of transition from deterministic assessment of radiological consequences of radioactive releases into atmosphere towards the probabilistic approach. The first step of the analysis consists in modelling of fields of activity concentration in air, its time integrals, radioactivity deposition on the ground and its time integrals. Input parameters of the analysis involve uncertainties due to stochastic character, insufficient description of real physical processes by parametrization, incomplete knowledge of submodel parameters, uncertain release scenario, simplifications in computational procedure etc. It is evident that results of the modelling are of little value without accounting for the associated uncertainties.

The purpose of this paper is to describe procedure for evaluation of input uncertainties propagation within the model of radionuclides transfer through the living environment and to demonstrate practical approaches to the assessment of model reliability. The technique enables progress from former deterministic calculations towards the generation of probabilistic answers on assessment questions. Deterministic calculations did not comply with the inherent uncertain character of the problem and offer only single values of the output variables. It relates to a certain deterministic single set of input parameters based on the “best estimate” procedure or conservative “worst case” choice. On the other hand reliability codes introduce capability to define a measure of confidence in model predictions. Quantitative reliability statements can determine a level of confidence with regards to exceeding of postulated limits and then provide much firmer basis for qualitative statements in the field of emergency management (can support subjective inference of decision makers either “results are conservative” or “results are realistic”).

DEFINITION OF THE TASK

Within the frame of selected dispersion model, many uncertainties related to both conceptual model (parametrization errors, uncertain submodel parameters, stochastic nature of some measured input data,) and computational scheme (step of computation net, averaging land-use characteristics, averaging time for dispersion parameters etc) are involved. Let $\mathbf{X} \equiv \{X_1, X_2, \ldots, X_N\}$ denotes a vector of N input random parameters X_i with corresponding sequence of random distributions $D_1, D_2, \ldots, D_N$ which are usually selected (range, type of distribution, potential mutual dependencies) on the basis of commonly accepted agreement of experts. Reducing the analysis of uncertainty propagation only to a certain random scalar output variable Y, its dependency given by Gaussian plume model (GPM) can be schematically expressed as $Y = \Re^{GPM}(X_1, X_2, \ldots, X_N)$. Let us first restrict physical meaning of Y only to values of near ground radioactivity concentration in air or specific radioactivity deposition on the ground in a certain fixed point on terrain. Both variables and their time integrals are the main governing factors for further calculations of all required radiological consequences due to all pathways of radioactivity transport to human body.

In this study is analysed one specific meteorological situation given by short-time series of either real historical measurements or hourly forecasts on the next 48 hours that could be assumed as "best estimate" values. Only those uncertainties of meteorological fields are taken into account having character of measurement or definition errors interpreted as fluctuation in wind direction and mean plume velocity of advection and precipitation intensity. Variations of dispersion parameters are treated as well. Let us notice, that our aspirations do not head towards the extensive PSA-Level 3 projects reflecting the probability distribution of different atmospheric conditions based on meteorological sampling schemes. To bring evidence related to overall risk induced by nuclear industry is another approach of probabilistic safety analysis and is not our job.

UNCERTAINTY PROPAGATION THROUGH THE MODEL

The value of dimension N of input vector $\mathbf{X}$ is rather big. For example in COSYMA code the ADM analysis declares for the specific analysis 24 input random parameters. Further reduction of number N should be done because of two main reasons. Firstly, ADM is usually only the first part of the overall uncertainty analysis chain consisting of sequence of ADM $\rightarrow$ FCM $\rightarrow$ DOS subsystems (DOS – DOSe model for doses assessment) and then the overall number of input random parameters has to be reduced in general. Secondly, not all parameters have significant contribution to the variations of the model outcome. Sensitivity analysis techniques are used to classify the significance of each input parameter's partial contribution and enable ranking of inputs with regard to the contributions in the overall uncertainty.

For definition of the limited group of input random parameter group and their ranking we have accepted the results of extensive literature review of the analogous codes (UFOMOD, COSYMA, MARC-2A, OSCAAR, NPK-PUFF). At the same time, the random characteristics were selected under attempt to follow recommendation from elicitation procedures of experts. Due to strong dependency on scenario type and subjective expert's opinion, the selections from the following Table 1 used here for UA serve only for demonstration purposes.

Sampling-based method for UA and SA consists in multiple repetition of calculations of outputs successively for each specific sample of random input vector, specifically:

- Generation of a particular i-th sample of input vector $\mathbf{x}^{\mathbf{i}} \equiv \{x_1^{\,i}, x_2^{\,i}, \dots, x_N^{\,i}\}$ where $x_j^{\,i}$ are realisation of input random parameters X_j (successively i=1,2,…,K)
- Propagation of the sample <u>i</u> through the model, it means calculation of the corresponding resulting realisation y^i of random output value Y when running the model $y^i = \Re^{GPM}(x_1^{\,i}, x_2^{\,i}, \dots, x_N^{\,i})$

Adopted scheme of Monte Carlo modelling uses stratified sampling procedure LHS. Code HARP comprise interactive subsystem for generation of K LHS samples for various types of random distributions D_j of input vector components X_j (j=1, … , N). A certain technique for correlation control between input components X_j is included. Resultant mapping of pairs $[y^i;\mathbf{x}^i]$, (i=1, … , K) provides bases for:

- <u>Uncertainty analysis</u> – statistical processing of the pairs can determine extent of the uncertainty on predicted consequences and yield various statistics such sample mean and variance, percentiles of the uncertainty distribution on the quantity given, uncertainty factors, reference uncertainty coefficients etc.

- Sensitivity analysis – its strategies are applied depending on the settings *Saltelli A., K. Chan and E. M. Scott(2001)* with further discrimination as factor screening (one-at-a-time experiments), local SA (partial derivations at a local point) and global SA (using typically sampling approach). Various techniques can be used providing different measures of sensitivity (scatterplots, regression and correlation analysis, rank transformations etc.).

UNCERTAINTY ANALYSIS USING THE HARP CODE

Mathematical models only approximate complicated real situation during an accidental radioactive release. Simplifications are done on both levels of conceptual and computational model selection. Necessary reduction of the input random vector dimension N can be demonstrated on the scheme:

$$Y = \Re^{GPM}(X_1, X_2, \ldots, X_N) \;\rightarrow\; Y = \Re^{GPM}(X_1, X_2, \ldots, X_M; x^b_{M+1}, x^b_{M+2}, \ldots, x^b_N)$$

Only the first M parameters are assumed to be random and the rest of N-M are substituted by their single best estimate values x^b. As was stated, the number M should be selected on the bases of compromise between complexity of the problem and intentions to include all parameters with significant contribution to the output value fluctuations. The results of UA depend on the type of release scenario, its dynamics and release source characteristics.

Simplified best estimate (expected) input data are selected here for a certain LB-LOCA scenario (Large Break - Loss Of Coolant Accident). Let us only notice, that release height is 45 m, mixing height is 200 m for Pasquill category F, u_{10}=1m/s, dispersion coefficients are calculated using KFK-Jűlich model for rough terrain, near-standing building effect on initial plume broadening is assumed. Severe 1-hour radionuclides release was restricted to 3 nuclides: Sr-90=1.0E+15 Bq, I-131=2.2E+16 Bq, I-131=3.3E+17 Bq. Input random parameter group is truncated to M=12 and random characteristics were selected on the basis of literature review. The options are shown in Table 1.

Table 1. Input random parameter estimates for UA of code HARP – atm. dispersion submodel

param. id. and meaning	min	mean	max	pdf_type	σ
ADM1: fraction release intensity		1.0		normal-3σ trunc	0.20
ADM2: fraction σ_y dispersion		1.0		normal-3σ trunc	0.13
ADM3: horizontal wind fluct. (*)	-5	0	+5	uniform discrete	
ADM4: fraction dry depo-elem I	0.41		1.60	uniform	
ADM5: fraction dry depo-aerosol	0.41		1.60	uniform	
ADM6: fraction scavening coef. elem I	1/5		5	log-uniform	
ADM7: fraction scavening coef. aer.	1/5		5	log-uniform	
ADM8: mean wind speed correction(**)	-1	0	+1	uniform	
ADM9: fraction wind profile exp.	0.5	1	1.50	uniform	
ADM10: fraction σ_z dispersion		1.0		normal-3σ trunc	0.13
ADM11: mixing height correction	0.6		1.6	uniform	
ADM12: thermal energy correrction	0		1	uniform	

(*) … *horizontal wind direction fluctuation $\Delta\varphi$ = ADM3*2π/80 (rad)*

(**) …*UFOMOD: uncertain wind speed $u=(1+0.1*ADM8)*u_0 + 0.5*ADM8$; u_0 measured*

Additional uncertainty measures gives Table 2, where "uncertainty factor" UF is defined as the ratio of the 95^{th} to 5^{th} percentiles of the distribution of deposited radioactivity of I-131 in a certain distance from the source under the nominal plume axis and "reference uncertainty coefficient" RUC means the ratio of the 95^{th} percentile of the uncertainty distribution to the expected value (all inputs have their best estimate values) of the I-131 activity deposition.

Table 2. Extent of uncertainties on the consequences predicted by code HARP

consequence	distance	expected_value	sample_mean	sample_var.	UF	RUC
I-131 depo on ground	4.5km	$4.74E+8^{(*)}$	$3.71E+8^{(*)}$	$2.07E+8^{(*)}$	8.35	1.64
	52.5km	$1.09E+7^{(*)}$	$4.44E+6^{(*)}$	$4.06E+6^{(*)}$	32.4	1.34
Annual eff. dose-child	4.5km	$4.93E+1^{(**)}$	$5.69E+1^{(**)}$	$3.02E+1^{(**)}$	5.23	2.23
	52.5km	$5.84E+0^{(**)}$	$5.60E+0^{(**)}$	$2.94E+0^{(**)}$	5.87	1.97

$^{(*)}$ in Bq/m^2; $^{(**)}$ in Sv/year

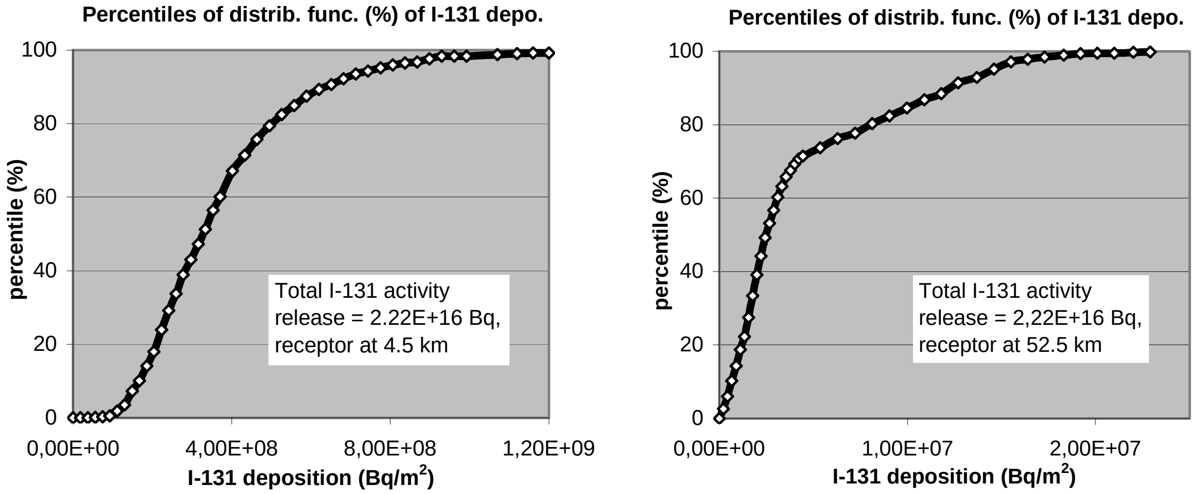

Fig. 1; Uncertainty analysis results for endpoint values of I-131 deposition on the ground

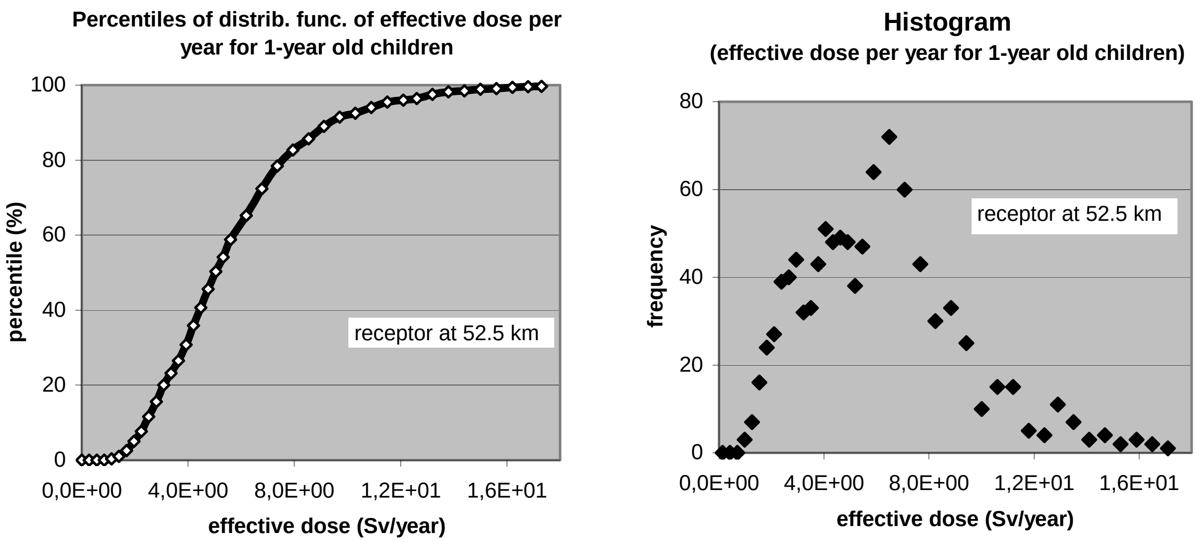

Fig. 2; Probabilistic estimation of consequences of irradiation: effective dose for children

The results presented here relate to output values at selected fixed receptor points at a certain distances from the source (located under the plume axis corresponding to the nominal wind direction, i.e. ADM3=0). Two sampling-based procedures were executed:

<u>Case 1</u>: ADM uncertainty modelling (1000 realisations) for target values of I-131 deposition that are shown on Figure 1 and other statistics are given in the first two rows of Table 2.

<u>Case 2</u>: Separate Monte Carlo procedure was realised from the same beginning for joint chain of ADM→FCM uncertainty analysis for target value of annual effective committed

dose for children. In this second procedure the Table 1 was used again for the new ADM sample generation (K=1000) with one exception, when the range of ADM3 fluctuations was reduced to uniformly distributed discrete values (-1; 0; 1). As for successive FCM uncertainty generation we refer to detailed description in our working materials. In brief, 16 most important (recommended) uncertain input parameters have been used and K=1000 LHS samples entered overall analysis of endpoint values of the effective doses. FCM dynamic model assumes July 1 as a day of radioactive fallout which is within the vegetation periods of the most of plants taken into consideration. The results are presented in the Figure 2 and other uncertainty measures are given in the Table 2, row 3 and 4. All consequences were generated using dispersion formulas for rural-type of terrain roughness (SCK/CEN), the same set of results was obtained for rough urban-type surface (severalfold decrease under the plume axis).

CONCLUSION

Computational code HARP for reliability assessment uses traditional Gaussian plume type model for ADM based on Pasquill stability categories. Its segmented version enables to respect hourly changes of meteorological situation. Even though the concept is rather simple, quick and easy Gaussian plume empirical approach meets the basic requirement on sufficient speed of Monte-Carlo computations. The probabilistic code is designed for two purposes:

UA and SA – provide both generation of probabilistic answers on assessment questions and identification and ranking the input components of a model that are potentially important contributors to predicted uncertainty of consequences. Some results were presented here.

Data assimilation – improvement of reliability of predictions by means of minimisation of uncertainties in the model results using observed data. So far only first step was realised when code HARP is capable to include sparse measurements on terrain (not real data, but provisionally a certain random "simulation" by model) for purposes of "sequential data assimilation" when available observations are used for updating of model forecast. Algorithms of direct search are used in the optimisation process when effect of selected random parameter fluctuations have clear physical meaning with regards to handling of Gaussian-shape of respond surface over the terrain (its translation, rotation, horizontal squeezing and longitudinal gradient). Perfect convergence to the "simulated" measurements will be shown during oral presentations. Extension of this method to segmented GPM is in progress and our objective is to generate "probabilistic trajectories" of the segments and to find their optimum position with regards to observed values. However, the methods are simple approach of solution of complicated data assimilation problem and still have rather character of Gaussian response surface fitting.

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