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Uncertainty Analysis with a View Towards Applications in Accident Consequence Assessments

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Unsicherheitsanalysen mit Anwendungen bei Unfallfolgenabschätzungen

Kurzfassung

Seit der Publikation der US-Reaktor-Sicherheitsstudie WASH-1400 hat das Interesse an probabilistischen Risikountersuchungen und Unfallfolgenrechnungen für kerntechnische Anlagen stark zugenommen. Methoden wurden entwickelt und angewandt, um Unsicherheiten der zugrundeliegenden Modelle quantifizieren und bewerten zu können. Forschung und Entwicklung werden motiviert durch die Tatsache, daß Industrie und Genehmigungsbehörden probabilistische Risikountersuchungen und Unfallfolgenrechnungen zunehmend im Rahmen von vergleichenden Studien und Entscheidungsfindungsprozessen einsetzen.

Der vorliegende Bericht gibt einen Überblick über die wesentlichen Methoden zur Durchführung von Sensitivitäts- und Unsicherheitsanalysen.

Erste Anwendungen der Methoden auf ein Teilmodell des Unfallfolgenmodells UFOMOD (KfK) werden präsentiert und die wichtigsten Parameter mit Hilfe von Sensitivitäts-/Unsicherheitsbetrachtungen für weitere Unsicherheitsanalysen identifiziert.

Diese Arbeit entstand in Kooperation mit der GRS (Garching) innerhalb des EG-Projekts CEC-MARIA.

Abstract

Since the publication of the US-Reactor Safety Study WASH-1400 there has been an increasing interest to develop and apply methods which allow to quantify the uncertainty inherent in probabilistic risk assessments (PRAs) and accident consequence assessments (ACAs) for installations of the nuclear fuel cycle. Research and development in this area is forced by the fact that PRA and ACA are more and more used for comparative, decicive and fact finding studies initiated by industry and regulatory commissions.

This report summarzies and reviews some of the main methods and gives some hints to do sensitivity and uncertainty analyses.

Some first investigations aiming at the application of the method mentioned above to a submodel of the ACA-code UFOMOD (KfK) are presented. Sensitivity analyses and some uncertainty studies an important submodel of UFOMOD are carried out to identify the relevant parameters for subsequent uncertainty calculations.

This work was performed within the scope of the CEC-contract on "Methods for Assessing the Radiological Impact of Accidents" (CEC-MARIA).

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1. Introduction

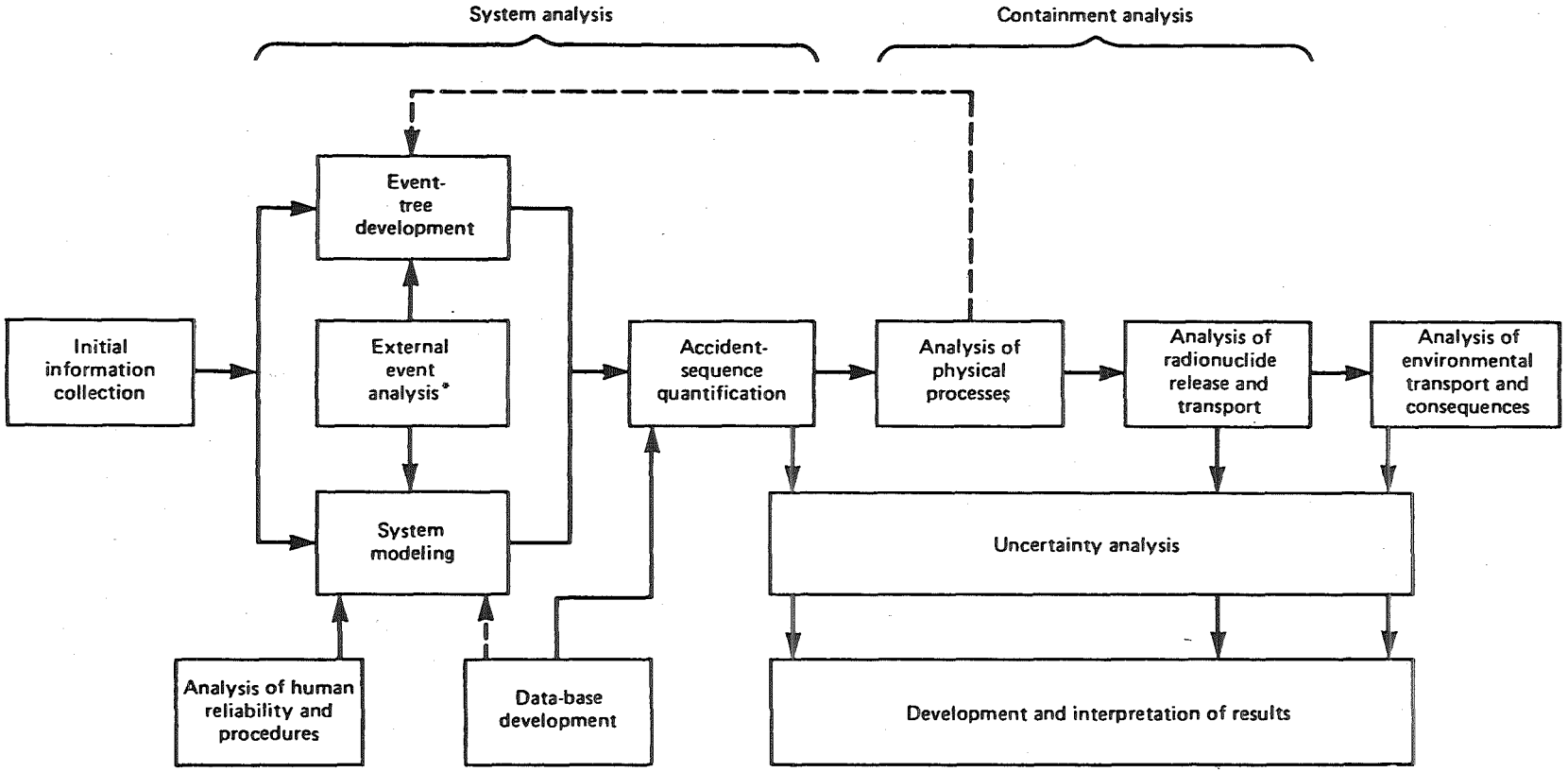
Probabilistic risk assessment (PRA) techniques have been becoming widerspread in the nuclear community since the completion of the US-Reactor Safety Study /1/ (WASH-1400) in 1975. In this study as well as in the German Risk Study /2/,/3/ conservative assumptions regarding the choice of input parameter values of calculational models have been made to eliminate to a certain degree the subject of uncertainty. By taking each of several parameters at its respective conservative limit, the results of the calculations have been considered to envelop all results expected to occur on a realistic or best estimate basis.

The increasing application of PRA within industry and the regulatory process requires turning away from conservative modelling to get realistic results for comparative and fact finding studies, which have been performed e.g. in the USA: ZION, LIMERICK, INDIAN POINT;, in the UK: SIZEWELL; and in West Germany: GERMAN RISK STUDY, RISK ORIENTED ANALYSIS OF THE SNR-300.

The exact role of PRA in the design and licensing processes is presently not clear, but there are several indicators that national governments and the European Community fund R&D activities in this area.

Risk studies for installations of the nuclear fuel cycle have been carried out to quantify and compare accident consequences and their frequencies. The most important steps of a probabilistic risk assessment (PRA) procedure are shown in Figure 1-1.

A serious aspect of a PRA is the assessment of accident consequences. For this purpose models and computer codes have been developed. Their structure results from the sequence of effects and is therefore nearly identical in all codes. For example the accident consequence model UFOMOD of the German Risk Study consists of the following main components:



*May or may not be included in the analysis

Figure 1-1: Risk-assessment procedure
(from /5/, Vol. 1, p. 2-5)

- atmospheric dispersion and deposition submodel
- protective action submodel
- dosimetric submodel
- health effects submodel

The flow scheme of the consequence model and its submodels is given in Figure 1-2.

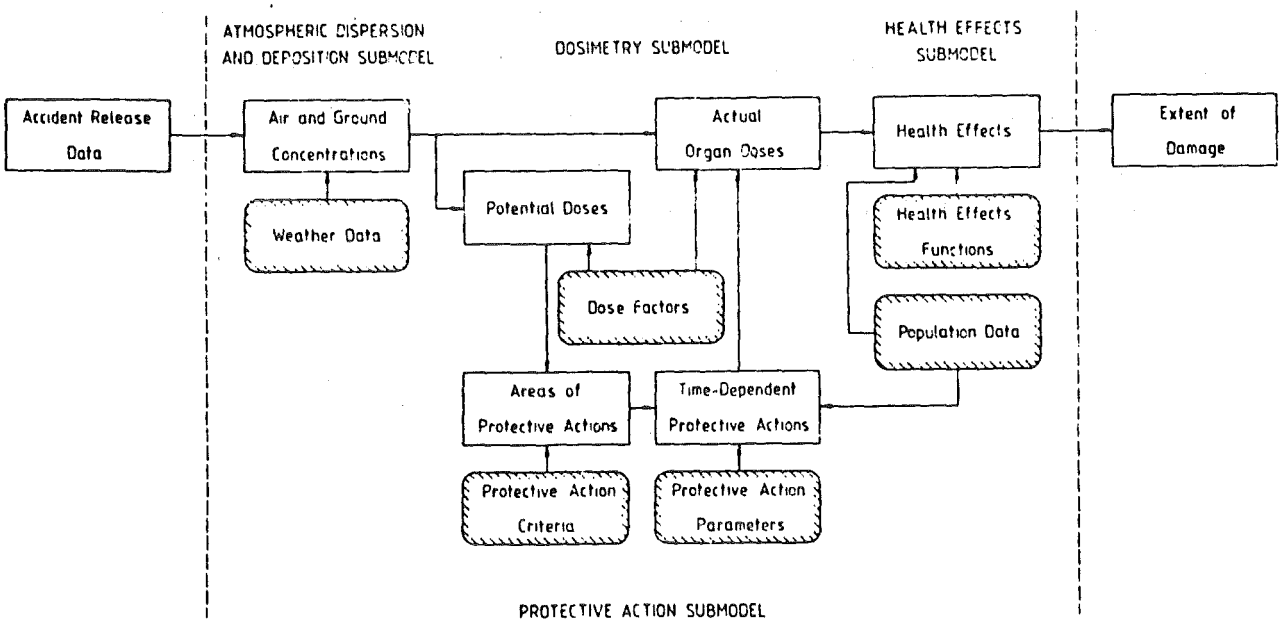


Figure 1-2: Flow schematic of the consequence model and its submodels (from BAYER et al /4/)

Due to its definition risk is composed of the two quantities consequences and expected frequencies.

Both quantities are linked with a certain degree of uncertainty, which results from the difficulty to predict very rare events and the imponderables associated with the behaviour of radioactive material after its release into the environment up to the impact on human health, respectively.

Therefore, the uncertainties of the input data and model parameters have to be propagated through an accident consequence model to quantify their influence on the output variables of interest.

With the application of PRA in decisive procedures, the uncertainty of the calculational results becomes a most important question. For this reason mathematical tools must be developed, tested and chosen for the estimation of the confidence in the different PRA results. The investigations performed within project 6 of the CEC-MARIA programme (*)are restricted to methods suited for uncertainty analysis of accident consequence calculations within the scope of risk studies for installations of the nuclear fuel cycle.

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*) CEC-MARIA: "Methods for Assessing the Radiological Impact of Accidents" within the CEC Radiation Protection Research Programme

2. Problem Formulation

An uncertainty analysis of the model predictions is a systematic procedure to quantify by means of mathematical statistics the imponderables in the results. The determination of the sources and the extent of uncertainties encompasses aspects of model development, analysis, data collection, and simulation.

The probabilistic accident consequence assessment(ACA) itself is in essence the propagation of the uncertainties associated with random variables through mathematical models, which describe the environmental processes. The random variables characterize the stochastic behaviour of the real world, e.g. changing wind direction and wind velocity. The formulas describing the various models (atmospheric dispersion up to the health effects) contain parameters with fixed values, which stem from experiments or more detailed calculations. These parameters are not varied within an ACA despite their variability in reality (e.g. dispersion and deposition parameters, transfer coefficients, dose conversion factors or risk coefficients). The choice of these parameter values may be "conservative" or "best-estimate".

This basic procedure of a probabilistic analysis may be illustrated by the following example. Classical "deterministic" dose calculations presume one well-defined atmospheric dispersion condition to calculate activity concentrations in the air and on ground surface. The input for the dose model consists of fixed values for e.g. wind velocity and dispersion category, as output, one single dose value is predicted for a given distance from the source. This often leads to the common misconception, that this single output value is "the" value to be expected under a given set of exposure conditions pretending an accuracy which does not exist. In contrast to this, probabilistic dose calculations are performed for a large number of measured real atmospheric dispersion

conditions, each of them linked with the probability of occurence. Consequently, not one single value results but a frequency distribution of dose values which best represent the perpetual variability in the environment.

In general, the results of an ACA (e.g. number of health effects and the corresponding expected frequencies) are presented in the form of complementary cumulative distribution functions (ccdf's). These frequency distributions demonstrate how the accident consequences depend on the various environmental conditions, which may exist with a certain probability during and after the radioactive release.

Due to imprecisions of the fixed parameter values in the accident consequence model and the modelling itself, the results of an ACA are uncertain as well. In addition, the random input variables may be erroneous due to errors in measurements or derived predictions.

There are different sources of uncertainty: (1) modelling uncertainties, (2) completeness uncertainties, (3) uncertainties in parameter values and input variables.

Modelling uncertainties may exist in the mathematical formulation of environmental and health phenomena because of the complexity of e.g. atmospheric dispersion, food chain bioaccumulation and human dosimetry. Inadequate descriptions of these processes may cause an undue estimation of probabilities and consequences.

Completeness uncertainties may result from the fact, that the contributions to risk have not been considered comprehensively. This may be caused by insufficient knowledge of the relevant processes or the inability of the analysts to recognize unforeseeable events.

Both types of uncertainty defy the quantification by presently available methodologies. Only qualitative assessments have been performed till now to show the influence on the final results of a PRA /5/. However this does not mean, that these uncertainties are considered to be of minor significance; on the contrary, the development of mathematical tools to quantify their influence on output accuracy is an important task of future investigations.

The uncertainties in parameter values and input variables can be devided into two classes (HOFER/KRZYKACZ /6/):

- "statistical uncertainties"
  are inherent in the complex to be analyzed. They represent possible variability in the complex and are due to the fact that repeated realizations of the same complex may show different outcomes. These uncertainties are modelled by random variables in a probabilistic analysis of the complex.

- "uncertainties in estimation"
  are inherent in the analysis of the complex. They represent possible variability in the analysis of the same realization of the complex and are due to inaccurate knowledge of model parameters. These uncertainties are modelled by random variation of the model parameters in a probabilistic uncertainty study of the analysis.

The influence on the results of an accident consequence assessment is quite different for both classes. While the first class of uncertainties (e.g. unknown weather conditions during release) leads actually to the desired results of the assessment (namely the distributions of consequences), the second class causes uncertainties in these results and is in general quantitatively expressed by (subjective) confidence intervals.

Unfortunately, in many probabilistic analyses, this difference is not regarded accurately, what leads to more or less erroneous interpretations of the results. On the other hand, it is not always easy to separate the two concepts. The complexity of the calculations and interdependency of phenomena sometimes forces analysts to combine both uncertainties into one measure.

Before going into some more details explaining probability concepts a short remark is given.

Remark*

The essential difference between 'statistical uncertainties' and 'uncertainties in estimation' is that an enlargement of the data base may improve precision in the second concept but cannot affect the fundamental random variability, although a numerical assessment of that variability can be made more precise (tolerance/ confidence intervals).

The distinction between these two concepts is important for decisionmaking because it indicates where, on the one hand, an increased effort in data gathering can improve the quality of decisionmaking by reducing uncertainty and, on the other hand, where it would be ineffective. □

To sum up:

The uncertainties that arise in accident consequence assessments (ACA's) are of three types:
- uncertainties in parameter values,
- uncertainty in modelling,
- uncertainty in the degree of completeness.

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* Remarks close with the sign " □ "

Having defined different classes and types of uncertainty the quantification of uncertainty (i.e. the use of measures of uncertainty) is categorized by

- the classical (frequentistic) statistical approach
- the Bayesian (subjectivistic) approach.

In the following section the basic probability concepts and their application to uncertainty analysis is introduced.

2.1 Some Discriminations in Probabilistic Uncertainty Analyses (+)

What do we mean by "probabilistic"? Briefly it says that our reasoning includes probability statements. Why are we interested in probability statements? Because we wish to express uncertainty in numbers to enable comparisons and to finally base decisions on these comparisons.

As far as our decisions are concerned, the question arises whether quantitatively equal uncertainties will always be equal from the qualitative point of view. A generally understandable and easily grasped example should explain this problem in detail. Later on, the relation to risk analyses will be pointed out.

Let us assume we had a fair die. The chances of "6" to come up in a throw would be 1 in 6. However, if we had a die showing the same number on each side, we would either always, or never, throw a "6". Let us assume this die were taken at random out of a box containing only dice which show the same number on each side, and for each of the numbers from 1 to 6 the box contained equally many dice. The chances of taking a die showing a "6" on each side would also be 1 in 6. If we cannot see the die so taken, i.e. if we always have to throw it blindly, would the uncertainty as to whether "6" comes up in a throw be of the same quality as that in the case of the fair die? Obviously not, since:

With a die showing the same (unknown) number on each side	With a fair die
- "6" will come up either always, or never.	- anyone of the numbers 1 to 6 will be equally possible.

(+) see HOFER/KRZYKACZ /7/

This means the result was determined the moment we took the die.

- The statement "there is a probability of 1/6 for '6' to appear in a throw" does not make any sense here in its classical interpretation. We could, however, (e.g. after evaluation of a sample from the box) claim that we are (1/6·100)% confident to always throw a "6" with the die at hand.

The result varies stochastically from throw to throw.

- Here, we can say that there is a probability of 1/6 for "6" to appear in a throw. Even the closest inspection of the fair die will not change this value.

This obvious qualitative difference in the uncertainty to be quantified and modelled probabilistically has consequences for the choice of the probability concept. There are two customary concepts:

A) "Probability" in its interpretation as limit of relative frequency (frequentistic concept).

B) "Probability" in its interpreation as degree of belief (subjectivistic concept).

Let us consider these concepts in a familiar framework and introduce some essential discriminations with respect to quantification basis:

To estimate the probability of a specified random experiment to result in a certain event, the experiment is repeated many (n-) times. If the event occurs in exactly $m \neq 0$ repetitions, the

relative frequency m/n serves as an estimate of the probability in its interpretation A (i.e. as an estimate of the limit of m/n for $n \to \infty$).

This estimate may be supplemented by confidence intervals at specific confidence levels. In statistics, the confidence level is knwon as the probability of a random sample to supply a range (confidence interval at the specified level) containing the appropriate value of the unknown probability. Given a confidence interval at a confidence level of e.g. 90%, based on sample evidence, the degree of belief is 90% that it contains the unknown probability value, although it deterministically either does or does not. This degree of belief is an example of the probability interpretation B.

In this specific case, the confidence level or the confidence interval, are derived from sample evidence. However, lacking random experiments under the specified conditions, they can also be based on random experiments conducted under other conditions combined with expertise and experience (expert judgment), or even solely on expert judgment. In such cases the confidence interval (resp. confidence level) is, however, to be called "subjective".

In the case of deterministic quantities like constants (e.g. the number of the unfair die above) and functional laws (fixed functional relationships) , the uncertainty due to inaccurate knowledge can only be quantified through probability interpretation B.

It is not only confidence intervals and confidence levels (for a probability value of interpretation A) that can be based on expert judgment, but also the estimate of the probability value as such. Consequently the estimate is a subjective estimate which, of course, has to satisfy the axioms of probability theory.

The attribute "subjective" is to say that the estimate is based on expert judgment rather than sample evidence ("objective" estimate).

To provide a better survey, these discriminations are illustrated schematically in Fig. 2.1-1.

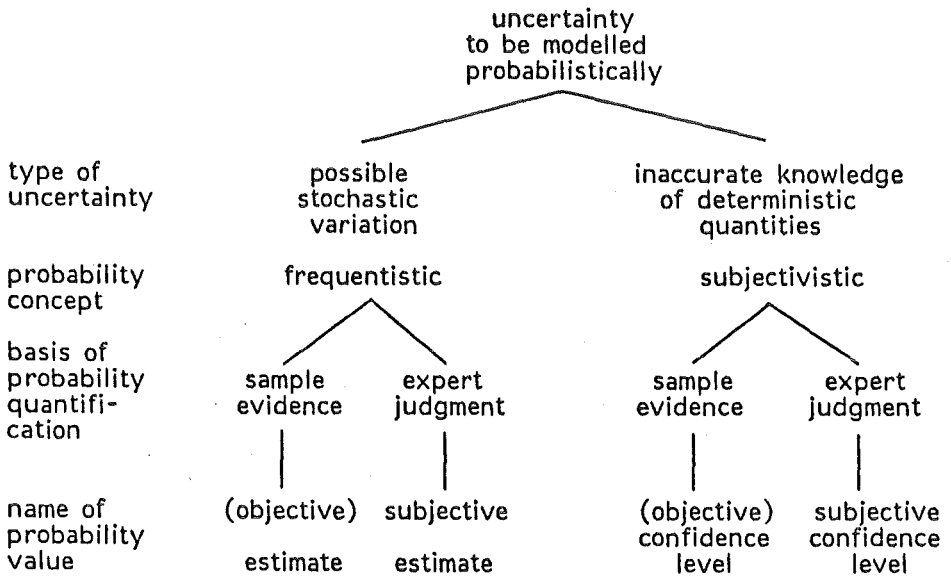

Figure 2.1-1 Some discriminations in probabilistic uncertainty analyses (see HOFER/KRZYKACZ /7/)

Uncertainty analyses generally have to cope with numerous quantities that are subject to uncertainty of the one and / or the other type. Thus, without a consistent discrimination already in the course of the analysis, it would not be possible to identify the resulting combined effect of the uncertainties of either type. However, the latter is indispensable for a meaningful interpretation of the analysis results, and as such, is essential for the decision-making process based on it. The necessity of a consistent discrimination becomes most obvious in

the case of risk studies. There, the uncertainty due to possible stochastic variation is of prime interest since it is one of the two components of the risk to be investigated. On the other hand, the uncertainty due to inaccurate knowledge of deterministic quantities in the risk computation entails that many alternative computational results have to be regarded as possibly correct values of the risk to be quantified. Although improved knowledge of these quantities and the associated narrowing down of their ranges of uncertainty leads to more realism in the quantitative assessment of the risk, it will not change the risk as such. It is thus obvious that probabilistic uncertainty analyses of risk assessments only deal with the uncertainty due to inaccurate knowledge of constants and fixed functional relationships of the computational assessment procedure. Therefore they can only work on the basis of the subjective probability concept (i.e. with subjective probabilities). That this need not be synonymous with the sole use of expert judgment follows from the second level of discrimination in Fig. 2.1-1. However, various reasons often prevent the supply of sample evidence as a quantification basis for subjective probabilities.

Of course, subjective estimates are probabilities in the mathematical sense and can be treated according to the rules of probability theory only if they comply with the axioms of this theory. While it may frequently be easy to check for this condition there are situations where dependences complicate matters de FINETTI /8/, NAU /9/. However, compliance with the axioms is not yet an indication of good quality. Numerous publications (KAHNEMAN/TVERSKY/10/, JUNGERMANN/de ZEEUW /11/ as well as contributions and quotations contained therein) deal with the typical causes of bias in subjective estimates. The scope of the literature undoubtedly reflects their significance for many important applications. At the same time, however, it clearly demonstrates how necessary it is to ear-mark probability values based on expert judgment rather than sample evidence. It seems that many disputes, such as e.g. in ABRAMSON /12/ could be avoided if the

discriminations in Fig. 2.1-1 were observed by all those interested in probabilistic analyses and particularly in risk assessments.

The discriminations in Fig. 2.1-1 have the following consequences for the presentation and interpretation of the results of probabilistic analyses:

- Discrimination with respect to type of uncertainty

  On the one hand there is a probability distribution of the quantity of interest (accident consequences of a specific type, for instance) because of the possible stochastic variation and its probabilistic modelling in the frequentistic probability concept.

  On the other hand there is a family of distributions and associated degrees of belief. This is due to the inaccurate knowledge of deterministic quantities in the computation of the distribution and its probabilistic modelling in the subjectivistic probability concept.

Figure 2.1-2 is to illustrate this in more detail. In this figure Z_1, Z_2 and Z_3 are input quantities of a computational risk assessment (life time of a component of a technical safety system etc.).They are subject to possible stochastic variation. The computation may account for this stochastic variation via Monte Carlo simulation using $Z_{1,i}, Z_{2,i}, Z_{3,i}, i=1,2,\ldots,n$ as realizations from the associated random laws (frequentistic concept) obtained in n Monte Carlo runs.

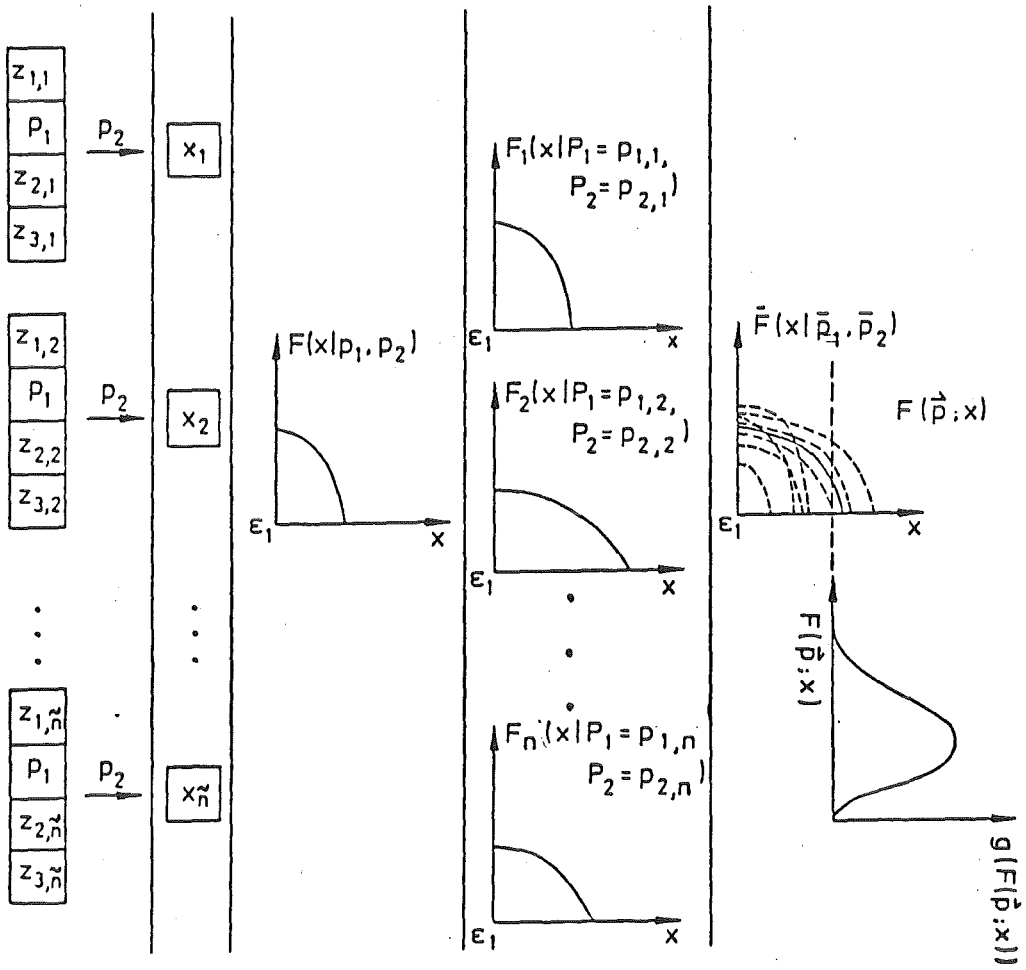

Figure 2.1-2 Schematic of the relation between the resulting ccfd of a PRA and the outcome of the supplementing uncertainty analysis
(see HOFER/KRZYKACZ /7/)

On the other hand, P_1 and P_2 stand for inaccurately known deterministic quantities of the computational assessment procedure. P_1 may be the parameter of the random law modelling the stochastic variation of the component life time above while P_2 may represent a fixed but inaccurately known functional relationship between the input quantities Z_1, Z_2 and Z_3 and the outcome (accident consequences, for instance). The outcomes of all n Monte Carlo runs are generally presented in form of a ccfd (complementary cumulative frequency distribution - see column 3 of Fig. 2.1-2)giving the expected frequency per year (ordinate) of accidents with consequence magnitude $\geq x$ under the condition that the specific value p_1 and relationship p_2 used for P_1 and P_2 in all n Monte Carlo runs are correct.

Quite frequently risk assessments end here with the condition above stated only implicitly. Exactly this condition and the thereby expressed uncertainty about the appropriateness of the computationally obtained ccfd are the starting point of a supplementing uncertainty analysis. While the set of possibly correct pairs (p_1, p_2) in the twodimensional parameter space may be very large there are generally subsets of clearly differing degree of belief. To see the corresponding alternative ccfds in proper perspective the uncertainty analysis too is therefore performed probabilistically, employing the subjectivistic probability concept. This enables the analysist to utilize the well established rules and methods from probability calculus to arrive in a logically consistent way at degrees of belief for the alternative ccfds. So, for the purpose of the uncertainty analysis of the risk assessment P_1 and P_2 too will be seen as random variables,and m realizations $p_{1,j}$, $p_{2,j}$, $j=1,2,\ldots,$ n may be obtained from the corresponding random laws (now expressing degrees of belief). The corresponding n conditional ccfds (column 4 of Fig. 2.1-2) may be obtained by repeating the computational risk assessment procedure for these m pairs of parameter values. In the end there will be n expected fre-

quencies $F_j(x/P_1=p_{1,j}, P_2=p_{2,j})$, $j=1,2,\ldots,n$ at given consequence magnitude x. The degree of belief for the correct expected frequency F(x) to be below a given value $\tilde{F}$ may be derived from their empirical distribution (indicated in column 5 of Fig. 2.1-2).

- Discriminations with respect to quantification basis.
  Should a decisive measure of expert judgment have entered the quantifications in both probability concepts above we may only speak of subjective confidence levels (respectively intervals and limits) and any ccfd obtained from these quantifications and serving as result (point "value") of the risk assessment is to be called a subjective estimate of the correct ccfd.

Keep in mind: the discrimination of probability concepts is an important task to avoid serious ambiguities and misunderstandings. If necessary further clarifications concerning this subject will be given in the text.

2.2 Key Problems

Some aspects of PRA have been described which show the necessity to do an uncertainty analysis.

Before starting the uncertainty analysis for accident consequence models some absolutely necessary tasks for evaluating uncertainties in a PRA (see /5/, vol. 2, p. 2-36 and 2-37) will be pointed out:

1. Determine level of analysis to be performed. Uncertainty analyses can be performed either qualitatively or quantitatively. It is usually preferable to quantify uncertainties, but the selection of the analysis level depends on the objectives of the PRA, what is feasible for a particular risk assessment, and the preference of the analyst.

2. Select treatment and depth of analysis for the uncertainties to be included.

3. Identify sources of uncertainty.

4. Decide on statistical framework. Decide where to use classical and/or Bayesian methods.

5. (Optionally) perform sensitivity analysis. Before performing an uncertainty analysis, the analyst may wish to evaluate sensitivities to obtain some insight into what is important in controlling the output of the risk analyses. This process can help in deciding what should be included in an uncertainty analysis.

6. Estimate input uncertainties.

7. Propagate input uncertainties through risk analyses.

8. Combine intermediate uncertainties.

9. Display uncertainties in risk results.

Remark:

It should be noted that an uncertainty analysis cannot be performed simply by following the tasks listed above step by step. Some iteration among steps is likely to be needed, and in some cases it may not be possible to perform each step completely. □

From these tasks the first steps can be extracted:

In the problem definition phase some preliminary decisions must be made:

- decisions on the aim of the sensitivity and uncertainty analysis,
- definition of input parameters and output (response),
- ranges and probability distributions (if possible) for input parameters, collection of data.

With other words the following questions must be answered:

- What is the definition of responses?
- Which and how many input parameters do you have, especially those which have some inherent uncertainty?
- Which input parameters can be combined, omitted from further considerations, or are correlated?
- Is there statistical information about the input parameters?

Then some key problems can be formulated:

1) Which set of input values should be used to run the accident analysis code to generate analytical functions that approximate the output data (i.e. accident consequences)?

2) Which are the suitable fitting functions for the approximation of these output data?

3) How can the probability distributions of the output and their dependence on the distributions of the input parameters be estimated ?

OLIVI /13/ made an important remark:
Approximation procedures to model the system output cannot be used to interpret the system internal mechanisms producing the output. Even if the modelling might synthesize a quite complex situation in a mathematical relationship, any attached physical interpretation could be misleading. It has to be remembered that an approximative model (for instance response surface model) provides a purely descriptive reduction of the data and should be used very carefully to make any inference about the physical behaviour of the underlying system.

3. Design, Sensitivity, Uncertainty

Some key problems and necessary tasks have been defined as an inevitable framework for sensitivity and uncertainty analysis.

Following IMAN/HELTON /14/, large accident consequence models such as UFOMOD are too complex to permit a simple examination of uncertainty in its entirety. Therefore it seems necessary to use some carefully designed procedure to determine the impact of individual submodels of the ACA, and then to study the impact of uncertainty on the entire accident consequence model under consideration.

As it has been indicated in Chap. 2.1 it is convenient to think of the ACA computer model as a function of parameters some of which

- are uncertain subject to possible stochastic variation, and/or
- are representing fixed but inaccurately known functional relationships between input quantities and output of the code because of

  . insufficient knowledge of physical processes,
  . model simplifications,
  . lack of data,
  etc.

Examples from accident consequence assessments are the weather data at the time of release on one hand and the dry deposition velocities (as model constants) and plume rise relationship on the other.

The second class of input quantities are called in the following "uncertain parameters" and their uncertainty is described by subjective probability distributions.

Uncertainty analysis can be defined to be the determination of the variation or imprecision in the output of the code that results from the collective variation in the uncertain input parameters. Summarizing and displaying the uncertainty is a serious task since there are many quetions of potential interest characterizing the output behaviour.

A convenient tool for providing answers to these questions is the estimated cummulative distribution function of the output.

Sensitivity analysis is closely related to uncertainty analysis. The importance of sensitivity analysis lies in the guidance it provides with respect to the identification of the important contributors to uncertainty in output. Sensitivity analysis can be defined to be the determination of the change in the 'response' of an ACA-code to changes in uncertain input parameters. Thus, sensitivity analysis can be used to identify the main contributors to the variation or imprecision in the output.

Remark: (see HOFER/KRZYKACZ /7/):

Some analysts prefer to restrict themselves to sensitivity analysis without modelling uncertainties probabilistically. However, unless all combinations of the various alternatives are investigated in the course of the analysis they will have little to say about the combined influence of the uncertainties on the output of the computational model. For complex computational models it is often not even possible to deliberately select a worst(or nearly worst) case parameter combination and if the analysis is to be restricted to a few combinations what is the rational for their choice?

It seems unrealistic to weight all conceivable alternatives alike if there are good reasons to prefer some to others.

The models to which uncertainty and sensitivity analyses are applied (e.g. ACA-code UFOMOD) are often large, complex and longrunning.

Therefore, it is reasonable to have a plan for selection of the specific input parameter values to run the original ACA-code. The aim is to get informative statements on sensitivity and uncertainty with a number of necessary ACA-code runs as least as possible.

Such plans (strategies) for the selection of sets of input parameters values are called experimental designs.

There are various studies treating sensitivity/uncertainty problems within PRA for nuclear power plants (e.g.: compare the papers of MAZUMDAR et al /15 /, /16/, STECK et al /17/, /18/, MARSHALL et al /19/, /20/.)

In the meantime some of the methods have been refined and generalized, some new methods have been developed.

Which of the various concepts and methods seems best suited for application in accident consequence modelling depends on the information available, the objective of the analysis, the cost of the analysis and last but not least on the decision maker.

This chapter will give some hints on sensitivity/uncertainty analysis methods without claiming to be complete. The methods which have been (will be) used for sensitivity/uncertainty analyses of the ACA-code UFOMOD will be given a little bit more detailed.

To facilitate understanding, methods and concepts are reviewed without going into deep formal and detailed descriptions. The interested reader is refered to the Appendix and the References.

3.1 Design

As already indicated, in studying sensitivity/uncertainty there is an urgent need to have suitable plans (designs) for input parameter value selection before starting longrunning and cost-intensive ACA-code runs.

Designs embrace instructions

- how much ACA code runs are necessary and
- which runs (depending on specific values of uncertain input parameters) have to be selected

to get informative sensitivity and uncertainty results.

There are many ways to perform such a design, changing the uncertain input parameters one at a time, up to all at a time.

In a one-at-a-time-design each uncertain input parameter is varied seperately within its range, all other parameters are fixed at their nominal value (usually 50%-fractiles), thus quantifying the relative effect on the model output. If two (or four) values other than the choosen nominal value are used, then the total number of points in this design is 2m+1 (resp. 4m+1) for m uncertain input parameters.

This method is an easy but somewhat doubtful course to treat sensitivity/uncertainty: Wrong conclusions may be drawn if the uncertain input parameters are not independent or if interactions between these parameters are suspected.

In these cases more sophisticated designs should be used.

A factorial design utilizes two or more fixed values (i.e. levels) to represent each parameter under consideration. Thus, if there are m uncertain input parameters and if two levels are used for each parameter, then there exist 2^m possible combinations of the m parameters while 3^m combinations are possible with three levels, or in general r^m combinations are possible with r levels.

Factorial designs are used

- to check the effect of many input parameters in a limited range,
- to check whether certain input parameters influence on effects of other parameters (i.e. interactions between parameters),
- to determine in some code runs, which parameters have to be investigated successively for further considerations.

To get an impression of the number of runs necessary to do a two (three) level m-factorial see Table 3.1.1 - 1 below:

m	2^m	3^m
3	8	27
4	16	81
5	32	243
6	64	729
7	128	2,187
8	256	6,561
9	712	19,683
10	1024	59,049

Table 3.1.1-1: Number of Runs in Two- and Three-level m-Factor Factorials

An advantage of both design methods is that the results can be saved and used as a basis for the construction of fitted response surfaces.

The number of computer runs necessary to do these designs become quite large even for a small number of input parameters. That may be a problem if the ACA-codes are long-running.

But there are some features in the context of factorial designs (e.g. central composite designs factorials with resolution R or fractional factorials) that allows for a reduction in the number of input paramter combinations.

In fractional factorial designs only some fraction of the total number of input parameter combinations is used.

That is, for each of the m parameters at r = 2 levels some fraction $(1/2)^k$, $k \leq m$, of the total number of input paramters combinations is used. The number of required runs of the ACA-code would equal the number of input parameter combinations.

Following IMAN/HELTON /14/, as k (the degree of fractionation) increases, the effects of some individual uncertain input parameters cannot be estimated because of confounding with interactions among input parameters. Thus, the selection of the degree of fractionation and input parameter combinations must be done with great care, keeping in mind which parameter effects and interactions are of greatest interest.

For a more detailed discussion see BOX/HUNTER/HUNTER /21/, OLIVI /13/, MAZUMDAR/15/.

Factorial designs possibly may not give a global representation of the uncertain input parameters, because they lay too much emphasis on the endpoints of the parameter ranges (i.e. they do not adequately represent the middle of the ranges).

Possible alternatives to the previous mentioned designs are Latin hypercube sampling (LHS) and the tolerance limit design (TLD) using random sampling techniques.

The LHS-technique, as originally described in McKAY/CONOVER/BECKMAN /22/, operates in the following manner: n different values from each of the m uncertain input parameters are selected. The range of each paramter is divided into n nonoverlapping intervals on the basis of equal width or equal probability. One value from each interval is selected at random. For intervals based on equal probability, random sampling means sampling without replacement and random with respect

to the probability density in the interval. The n values thus obtained for parameter P_1 are paired in a random manner (equally likely combinations) with the n values of P_2. These n pairs are combined in a random manner with the n values of P_3 to form n triplets, and so on, until n m-tupels are formed.

McKAY/CONOVER/BECKMAN /22/ did the input value selections independently for each input parameter so that the input selections are uncorrelated. IMAN/CONOVER /23/ have extended the sampling to include cases were the inputs are correlated.

We will not give here a complete description of the LHS-method (for details see McKAY/CONOVER/BECKMAN /22/, IMAN/HELTON/CAMPBELL /24/, /25/, IMAN/CONOVER /26/, IMAN/HELTON /27/; some catchwords are sketched in the Appendix).

Following ALPERT/HELTON /28/ it can be summarized, that the LHS-design

- uses input from any multivariate structure and can be modified to incorporate correlations between uncertain input parameters,
- the entire range of each input parameter is utilized, which is important if there are thresholds or discontinuities in output,
- directly produces estimates of output distribution functions,
- permits a variety of sensitivity analysis techniques (e.g. stepwise regression, partial correlation),
- does not require extensive modification of the ACA-model under analysis,
- is constructed to make efficient use of the number of ACA-code runs required.

For applications in sensitivity/uncertainty analysis the number of code runs using LHS should be greater than the number of uncertain input parameters.

The LHS-design has been described roughly as a type of stratified Monte-Carlo sampling providing estimates for the output distributions with an adequate number of code runs.

The tolerance limit approach is a method of direct Monte-Carlo-sampling, which

- gives an estimation of the output distributions and
- provides "upper limits" (so-called upper statistical tolerance limits) for the output distributions

with a relative small number of necessary ACA-code runs to get reasonable results.

Tolerance limits give the degree of precision (confidence) that the probability/consequence predictions lie within the indicated range and are effected by the nature and extend of the available data.

To be a little bit more precise:

A tolerance confidence interval for a random variable X, at confidence level γ and for a tolerance coefficient α ($\alpha,\gamma \in (o,1)$), is a random interval such that the probability is γ that the interval selected at random covers at least a specified proportion $\alpha \in (o,1)$ of the distribution G(x) of X.
The endpoints of this random interval are called upper (lower) (α,γ)-tolerance limits. The simplest case of such tolerance limits can be determined from ordered samples. They do not require any distributional assumptions on the function G(x);it therefore will be called distribution-free tolerance limits.

A Monte-Carlo-simulation of the uncertain input parameters is performed according to their subjective probability distributions, for instance with sample size n = 59 and α=0.95, γ=0.95.

Then a run of the ACA-code is performed for each of the 59 input data sets. The resulting 59 values of the output concerned may be regarded as a random sample ($X_1, \ldots, X_{59}$) from a certain distribution G (G is the unknown distribution of the output resulting from the input parameters); several output quantities may be considered simultaneously.

Then the (0.95, 0.95)-tolerance limit, L, is

$$L = X_{j_{59}} = \max (X_1, \ldots, X_{59})$$

It may be interpreted in the following way:

95 % of the mass of the distribution of output X lie below the tolerance limit L with probability at least 0.95, or when the tolerance limit L is already determined: we are at least 95 % confident that 95 % of the distribution of the output X lie below the calculated value L.

The number n = 59 is justified by the theory of order statistics to get a distribution-free (0.95, 0.95)-tolerance limit (for details see Appendix).

Remark:

For use of tolerance-limit design in sensitivity analysis the number of ACA-runs should be greater than the number of uncertain input parameters; for use in uncertainty analysis the number may be less than the number of input parameters.

□

3.2 Sensitivity

A large number of uncertain input parameters could potentially be selected from accident consequence models (e.g. like UFOMOD (KfK) and MARC (NRPB) for the purpose of evaluating the uncertainties in radioactivity concentrations, organ doses, and health effects.
We follow IMAN/HELTON/CAMPBELL /24/,/25/ that due to the possibly significant expense of running accident consequence models and the often much greater expense of collecting appropriate data for use as model input, a reduction of problem complexity is indispensable.

Therefore it is important to have efficient techniques to examine and assess the influence of model input on model output. The benefits of such undertaking include:

- an indication whether the model operates as intended,
- an identification of unimportant uncertain input parameters or unnecessary model complexity,
- an assessment of relative input parameter importance for guidance in data collection by determination of some measures of dependence between the specific output and input parameters. (These measures of dependence serve to rank the input parameters according to their degree of importance for the output considered).

By intensive variational studies, model deficiencies can be detected and subsequently corrected. If an (accident consequence) model survives a vigorous sensitivity analysis, its credibility as a relevant forecasting tool is increased (see McKAY/BOLSTAD/WHITEMAN /29/).

In Chap. 2.2 the principles of sensitivity/uncertainty investigations are mentioned: partition of the study in some procedure steps to get insight into models and methods on submodel basis.

Corresponding to the commonly justified practice 'to start somewhere' one may try to study the effects of varying a single uncertain input parameter at a time only as a prelude to the study of varying several factors simultaneously.

Therefore, follwing MAZUMDAR et al /16/, the one-at-a-time design is favoured as the simplest way to get some sort of visual appreciation of the input - output dependency.

E.g., each input is evaluated at its nominal value (50%-fractile), then at its Min., 10%-fractile, 90%-fractile, Max. This necessitates (4m+1) runs, which would be impractically if the number of uncertain input parameters is large and the ACA-code is complex and long-running. The information from the one-at-a-time-design can be used to rank the input parameters as to their effect on the output. Ranking can be done due to an importance-criterion, which measures the distance of the target values resulting from the two cases

- input parameter is at one of its four levels,
- input parameter is at its 50%-fractile level.

Large values of the distance measure indicate a marked effect whereas small values indicate little or no effect on the output (for details see Appendix).

The determination of the most important input parameters by using factorial designs is done in the context of trying to find those input parameters that should be taken into account in constructing an approximation function (response surface) for the ACA-code. Following MAZUMDAR et al/15/, the coefficients of the approximation function can be taken as measures of the sensitivity of the computer code to the terms in the fitted expression. If these terms representing the input parameters (or some suitable functions thereof) have been suitably scaled or standardized (being divided by their respective standard deviations) the values of the respective coefficients in the fitted expression will provide a ranking of the importance of the uncertain input parameters and of combinations thereof.

McKAY et al /22/ and IMAN/CONOVER /30/suggested that Latin hypercube sampling may be used to conduct sensitivity analysis.

Following DOWNING et al /31/, the LHS-method of Iman/Conover uses partial rank correlation analysis to indicate the sensitivity of the output of each of the uncertain input parameters. The method operates with ranks to reduce the influence of extreme observations on the calculations and to give a better measure of the strength of the nonlinear relationship between an uncertain input parameter and output. Therefore using ranks means measuring of monotonicity rather than linearity as is done with raw data.

Partial rank correlation is a measure of correlation between two variables removing the effect of the other variables. Partial rank correlations with absolute value near 1 indicate strong monotonic relationships. These can be used to indicate which inputs have a strong monotonic effect on the output. (See the computer-code described in IMAN/SHORTENCARIER/JOHNSON /32/).

A drawback of this technique is that the ranking makes it difficult to distinguish between the relative sensitivity of two input parameters when the response is a plane with no interaction but the rate of increase in one direction is markedly greater than the rate of increase in the other. Those two input parameters would appear to have equal sensitivities with regard to the output when indeed they are different. When either random sampling or Latin hypercube sampling is used, the partial rank correlation will reflect the true sensitivities with regard to the input parameter's effect on the output. The approach may be run on the raw data as well as the ranked data and compared. Large discrepancies between the two analysis might indicate departures from linearity. If the partial rank correlation is high while the partial correlation is low this would indicate a nonlinear relationship between the input and output.

Remark:

Following IMAN/HELTON/CAMPBELL /24/,/25/, once a set of potentially important uncertain input parameters is selected by some of the above mentioned 'screening techniques', it is desired to select a 'best set' of important input parameters by using regression techniques to fit a response surface for the model output. That is, those input parameters should be selected that predict well both for the input parameter vector from which the surfaces was constructed and for additional input vectors selected from the ranges of the uncertain input parameters. Examples of such regression techniques are stepwise regression and rank regression. These methods are very well described in HELTON/IMAN/BROWN /33/. □

In the tolerance limit approach, Monte-Carlo sampling is used to get n input parameter vectors; a corresponding number of ACA code runs are performed which give estimates of the unknown output distribution.

The parameter ranking indicating the input parameter importance on output is done in a way similar to the Latin hypercube sampling method.

The rankings of the uncertain parameters are derived from measures of correlation between output distribution and each of the uncertain input parameters at selected argument values. While partial correlation coefficients are generally preferred as indicators of the degree of linear relationship, partial rank correlation coefficients are able to handle nonlinearity and measure monotonic relationships between output and each input parameter (for details see HOFER/KRZYKACZ /7/.

It should be noted that the parameter ranking are dependent upon the uncertainty quantification as well as the probabilistic modelling given by the submodel experts. They may be considered adequate if all uncertainties not quantified may be neglected.

Each of the procedures has its merits and limitations. Without going into a judging discussion the following guidelines may be appropriate:

- Reduce entire model complexity by starting on submodel basis.
- Invoke engineering skill to reduce the number of uncertain input parameters requiring further considerations. Use group screening techniques or the simple one-at-a-time-design to get a preliminary sensitivity analysis.
- Use suitable and cost-effective design methods in consideration of

  . distributional aspects
  . interdependencies of input parameters

to identify and rank sensitive uncertain input parameters.

Which method is the best for your purpose depends on the concrete problem you have.

Remark:

We only mention other sensitivity methods which are seen by some authors as an alternative to statistical design techniques like LHS. The so-called differential sensitivity approach is based on a Taylor series expansion and the associated partial derivatives. The results are dependent on the assumption of linearity. (For discussion see DOWNING/GARDNER/HOFFMAN /31/, HARPER/GUPTA /34/ and IMAN/HELTON /14/).A rigorous method for sensitivity is the so-called adjoint method using differential equations. These equations yield exact sensitivities. But it is difficult to obtain the adjoint equations and in practice the nonlinear aspects are usually ignored (see OBLOW /35/ and THOMAS /36/).

□

3.3 Uncertainty

Various possible ways of uncertainty propagation through complex computational models, differing in computational effort and quality of results are at disposal. In practical problems the choice will depend upon the

- complexity of the computational model to be investigated,
- desired quality of the final uncertainty statements,
- means (CPU-time etc.) at hand.

Therefore different methods may be applied for different parts of a computational risk assessment procedure.

The general problem is how

- to achieve uncertainty propagation from input to output,
- to quantify output uncertainty.

The output quantity, say Y, is a function, say h, of the uncertain input parameters $P_1,..,P_m$

$$Y = h\ (P_1,...,P_m),$$

which is not known explicitely and usually is described only by the ACA-code.

The output quantity itself is an uncertain (random) variable which has an "uncertainty distribution", which depends on the ACA-code and the distributions of the uncertain input parameters.

Example

An accident consequence model is applied to compute the probabilities that radioactivity concentrations, organ doses or number of health effects exceed a certain quantity.

In the atmospheric dispersion submodel of an ACA-code the uncertain input parameters are radioactive plume rise due to thermal energies, time-dependent turbulence of the atmosphere, depletion of the radioactive plume as a result of dry and wet deposition etc.

□

Various methods have been developed to treat and propagate uncertainty in PRA or ACA.

Following the PRA-Procedures Guide /5/ there is a classification in

- integration methods and
- various techniques based on moments ("moment matching").

The former methods include

- analytical integration,
- numerical integration (discrete probability distribution method),
- Monte-Carlo-simulation,

while the latter include

- the method of moments,
- Taylor expansion approximation,
- response surface approximation.

3.3.1 Bird's Eye View on Methods

The analytical integration presumes the joint probability density function of the uncertain input parameters to be konwn. The integration of this function leads to an analytical expression for the probability density function of the output variable, if the input-output function or an approximating equivalent is known.

In the discrete probability distribution method the input uncertainties are characterized by a discrete probability distribution of input values. Suppose the output y is a function of the input parameters $p_1,\ldots,p_m$.

$$y = h\ (p_1,\ldots p_i,\ldots,p_m)$$

Let $p_{i1},\ldots,p_{ik}$ denote a set of discrete values of p_i and let $s_{i1},\ldots,s_{ik}$ be the probabilities associated with these values such that $\Sigma s_{ij} = 1$. The discrete probability distribution is defined as the set

$$((s_{i1},p_{i1}),\ldots,(s_{ik},p_{ik})) \qquad i = 1,\ldots,m$$

that approximates the p_i-continuous probability density function.

The corresponding discrete probability distribution for the model output y is given by the set:

$$(t_{r_1,\ldots,r_m},\ y_{r_1,\ldots,r_m})$$

where

$t_{r_1,\ldots,r_m}$ is the product of the probabilities associated with the p_i-values, if the p_i are independent,

and

$y_{r_1,\ldots,r_m}$ is functionally related to the p_i-values by the given function h.

If the number, m, of the input parameters is large or the function h is complicated then this approach becomes computationally burdensome.
For details see KAPLAN/APOSTOLAKIS /37/ or AHMED et al /38/.

Then another approach becomes more feasible.

Under the Monte-Carlo-technique, sets of uncertain input parameters are sampled randomly from their assumed joint probability distribution and the model output is determined at these input values. This yields a set of random outputs which can then be analyzed by statistical methods. For example, estimates of moments or percentiles of the output distribution can be obtained.

Monte-Carlo-techniques can be used to run the actual model. The aim is to obtain an empirical distribution of the output, to obtain moments of the output, and to get statements about the precision of the results (confidence statements).

Remark:

The motivation to mention confidence arguments under the headline 'Monte-Carlo-sampling' is the following:

By direct Monte-Carlo-sampling, sensitivity and confidence considerations can be combined effectively (see HOFER et al /39/).

□

Moment methods are applicable when sufficient information is available to generate estimates of the first few moments of the uncertain input parameters. This information is used to generate estimates of the corresponding moments for the output quantity. Unfortunately, sufficient information is usually not available to define the joint probability density function of the input parameters and therefore difficulties arise to get estimates of the first few moments of the output.

The Taylor expansion method can be used if there are more complex dependencies of the output y to the input parameters $(p_1,\ldots,p_m)$. This method provides a good procedure to approximate the mean and variance of output, by expanding the input-output function $y = h(p_1,\ldots,p_m)$ about a nominal point up to the second derivative. However, in cases where h is highly non-linear, higher-order expansions will be needed.

To construct a response surface model, the p most important input prarameters selected from the m original uncertain input parameters must be fit to some approximation function, usually a second order polynomial, that adequately describes the unknown input-output function h. The existence of strong nonlinearities can cause the second order polynomials to be inadequate for a valid uncertainty analysis unless they are expanded to include higher-order terms.

It should be noted that the ability of a response surface to represent well a complex computer code could possibly be improved by using a representation other than polynomial functions.

For details, critizisms of these methods and some ways out of the limitations and possible extensions we refer to MAZUMDAR et al /15/, DOWNING et al /31/.

Remark:

We discussed methods for evaluating function uncertainty when the argument uncertainties are expressed as distributions. If data based estimates of function arguments are available, some of the classical statistical methods for estimating output sampling distributions can be used e.g.: the 'bootstrap'-, the Taylor series-, the 'jackknife'-method; we refer to the PRA-Procedures Guide /5/ Chap. 12.4.3.3 and in more detail to EASTERLING /40/.

3.3.2 Confidence Considerations

Statements about output uncertainties are statements about "output uncertainty distributions".
We now try to characterize output uncertainty.

As the outcome of the quantification of input uncertainties and their propagation through the code using the methods of the calculus of probability, families of (complementary) frequency distributions are obtained, each of which must be regarded as possibly the correct one. A range could be specified therefore in a (damage-scale-frequency)-diagram in which the correct frequency distribution lies with, for example, a certainty of 95 %. This would be a global subjective 95 % confidence interval.

It is also possible, however, to specify subjective confidence intervals, which can be described as "local", on straight lines parallel to the frequency-axis or damage axis. This form of representation of the influence of input uncertainties is entirely adequate for the purposes of the complementary frequency distributions and was adopted in the GERMAN RISK STUDY (DRS) /2/,/3/ and BAYER et al /4/. Often one-sided uncertainty intervals are used which give upper (lower) uncertainty bounds (subjective confidence limits).

Let us paraphrase the problem a little bit more formally corresponding to Chap. 2.1.

Following HOFER/KRZYKACZ /7/ and /41/ we state that in the case of PRA's or ACA's the interest focusses on complementary cummulative distributions $\bar{F}(x)$, with $\vec{F}(x)$ the probability of the annual accident consequences to exceed x. Let $\vec{P}$ be the vector of uncertain parameters of the computational risk assessment procedure and $k(\vec{p})$ their joint subjective probability density function (pdf);

then $\bar{F}(x|\vec{P})$ is also assigned a subjective pdf. The uncertainty of ccdf's is customarily investigated locally, at fixed argument values x, which means that the distributed quantity $\bar{F}(x|\vec{P})$ is investigated. The computational model of the ACA transforms the joint pdf $k(\vec{p})$ into the distribution $G(\bar{F}(x|\vec{P}))$ with its 95 % fractile $F^*:= \bar{F}_{95}(x)$ usually serving as a quantitative measure of the output uncertainty (i.e. as an estimate of the resulting local (at x) upper 95 % confidence limit for the distribution to be assessed).

F^* satisfies:

$$G(F^*): = \text{Prob}\left\{\vec{P} : \bar{F}(x|\vec{P}) \leq F^*\right\} = 0{,}95 \ .$$

"Prob" stands for subjective probability ("probability" interpreted as degree of belief).

$I_{90}(x): = (\bar{F}_5(x), \bar{F}_{95}(x))$, on the other hand, may serve as an estimate of the resulting local symmetric 90 % confidence interval. To narrow down the $I_{90}(x)$ for a given power plant and site is thus required to reduce the inaccuracy in the knowledge of the deterministic items $\vec{P}$ while for given $\vec{P}=\vec{p}$ [1] the ccdf $\bar{F}\ (x|\vec{P} = \vec{p})$ may only be changed via modifications to the plant or to the relevant site characteristics.

The ideal procedure to get confidence bands would be to simulate the output ccdf by Monte-Carlo-simulation of the input parameter distributions and running the ACA-code. The results would be estimates of the output distribution and some estimates of its quantiles.

In general, this way is impossible because ACA-codes are long-running and Monte-Carlo-simulation requires a lot of runs to get sufficient results.

---

1) $\vec{P} = \vec{p}$ means: $\vec{p}$ is a realization of the random vector $\vec{P}$.

Therefore now the modified problem is to construct confidence bands for the output quantity by using design methods and their results, which require only a restricted (small) number of ACA-code runs.

3.3.3 Hints on Uncertainty Evaluation Procedures Based on Special Designs

Let us indicate here some procedure steps to get uncertainty statements by using the designs mentioned in Chap. 3.1.

1. One-At-A-Time-, (Fractional) Factorial-, LHS-Design

   The distribution function for the output cannot be estimated directly from the set of output values resulting from input based on the two first mentioned designs since the selection procedure used with the input values is not random.

   Therefore it is necessary to use a response surface replacement for the ACA-model and to use Monte-Carlo simulation with the response surface to estimate a distribution function and its quantiles for the output. This will lead in general only to approximate confidence intervals, because the output is usually non-normally distributed.

2. Tolerance Limit-Design

   W i t h o u t using an ACA-code approximation:

   Determination of a certain estimation of the desired output quantiles (for instance: 95%-quantile).

   The results are distribution-free confidence intervals (example: for the 95 %-quantile) of the output distribution with confidence level, for example, 95 %. These bands are called one-sided (95 %, 95 %)-tolerance intervals for the output distribution.

1.1 One-At-A-Time Design

The construction of an interpolating response surface is as follows.

Two cases:

a) For each input parameter two values are chosen (usually 10%- and 90%-quantile) and the reference case (all input parameters are at their nominal value), i.e. there are (2p + 1) ACA-code runs. ($p \prec m$ is number of important input parameters).

   Elementary geometric considerations (right and left-sided difference quotients) lead to an interpolating response surface which is continuous (but in general not differentiable) and linear within each quadrant.

b) For each input parameter four values are chosen (usually Min, 10%-quantile, 90%-quantile, Max) and the reference case, which give 4p + 1 ACA-code runs (see Chap. 4 and Appendix).

   Similar geometric considerations as in case 1a) lead to an interpolating response surface which is segmentwise continuous (i.g. not differentiable) and segmentwise linear (1 quadrant = 4 segments).

   Remark:

   In case 1b) the code approximation is more precise than in 1a), because there are more difference quotients.

   There is a need to do some adequacy checks, i.e. the response surface should not underestimate the ACA-code in those parts of the input parameter space which contribute to the (90%, 95%, 99%)-quantiles of the output.

1.2 (Fractional) Factorial Design

Usually you have to construct a response surface which is linear in the parameters or in terms of parameters (functions of input parameters). The unknown coefficients of the response surface have to be estimated by the method of least squares.

But be careful, the "fractionizing" forces dropping or including of parameter terms into the response surface equation (for details see MAZUMDAR et al /15/, /16/ and VAURIO/MUELLER /42/).

Often linear or polynomial response surfaces are used,built up by the input parameters or transformations of them. But it is possible that these functions may not be controllable outside the design points.

1.3 Latin Hypercube-Sampling Design

Due to the probabilistic nature of LHS, it is possible to estimate the distribution function and the variance for the particular output under consideration directly from the model output associated with the LHS-sample. Quantiles of the output distributions can also be obtained and approximate confidence intervals be determined. (see McKAY/CONOVER/BECKMAN /22/ and IMAN/CONOVER /30/).

Remark:

The distribution function for the output could also be estimated indirectly by fitting a response surface to the model input-output based on LHS and then proceeding as with factorial designs.

Linear and polynomial terms or transforms of input parameters form the response surface function. Response surface construction can be initiated by using stepwise regression to build a model based on a linear combination of the independent input parameters. If some indicators reveal the existence of nonlinear relationships, then

some approach other than linear regression on raw data should be considered for response surface construction (regression on ranks).

□

IMAN/HELTON/CAMPBELL /24/, /25/ give an excellent overview on LHS and its properties.

2. Tolerance-Limit Design

Here it is possible to get uncertainty statements, so-called tolerance-limits, about the output quantity without using a response surface.

Performing a TL-design to get a $\alpha \cdot 100\%$-upper statistical tolerance limit with confidence level $\gamma \cdot 100\%$ gives an output sample

$$(Y_1, \ldots, Y_{59}) \qquad (\alpha, \gamma) = (0.95, 0.95)$$

from the unknown output distribution. Then the (0.95, 0.95)-tolerance limit is

$$L = Y_{(59)} = \max (Y_1, \ldots, Y_{59}) \qquad \text{(see Chap. 2.1)}$$

$(-\infty, Y_{(59)})$ is an 95%-confidence interval for the 95%-quantile of the output distribution, i.e. the interval is a kind of'upper estimator' for the 95%-uncertainty band which we are interested in.

This type of design has been used for uncertainty studies to treat the German atmospheric dispersion model of UFOMOD, and the MARC-submodels (atmosph. dispersion, food chain) in the United Kingdom.

(For details see HOFER/KRZYKACZ /7/)

3.3.4 Display of Results

Following IMAN/HELTON /27/, there exists a number of ways in which sensitivity and uncertainty may be displayed at various stages in an ACA or PRA.

Parametric studies for sensitivity show the results of varying one or a few parameters at a time; however it is hard to investigate the relative effects of a large number of variables with this technique.

Many sensitivity analysis methods involve generating partial derivatives or regression coefficients for dependent parameters of interest. In turn, various normalizations provide inside into relative parameter importance. Further for analyses based on stepwise regression, R^2 values and the order in which individual parameters enter a regression model provide insight with respect to variable importance. Ordinary and partial correlation coefficients and fractional contribution to variance can also be used to indicate parameter importance.
To display uncertainty, one of the simplest ways is to present a range of possible values. Such a range may result from a propagation of ranges obtained from assessments of expert opinion for a number of individual independent parameters. Similarly, if distributions are given for the independent parameters, then distributions can be estimated for the outcome quantities. When the quantity of interest is itself a distribution, this results in a family of distributions.

However, it must be recognized that the quality of such distributions depends on the quality of the distributions which we propagated. Confidence intervals of the output distribution can also be given.

In the German Risk Study /2/,/3/ as in various other studies the method of displaying the uncertainties in the results of an ACA or PRA has been to present a series of complementary cumulative distribution functions. These different ccdf's could represent, for instance, the best estimate and an upper and lower bound.

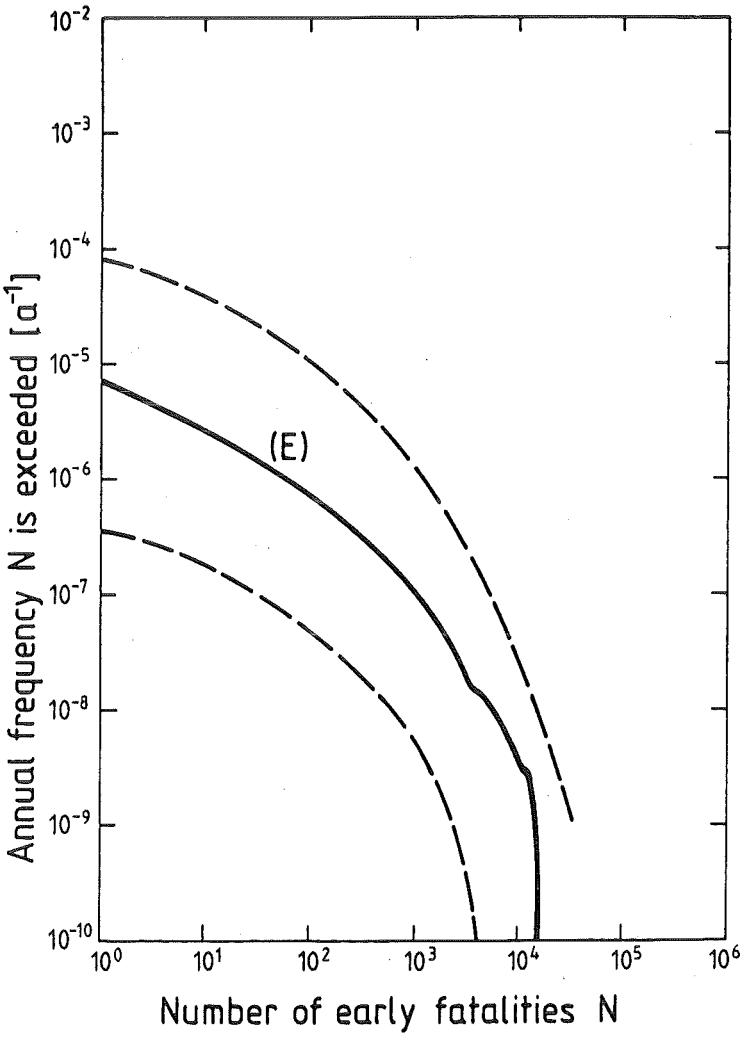

Fig. 3.3.4-1 Local subjective confidence interval for "early fatalities"(applied to the reference curve and "smoothed") /2/

Figure 3.3.4-1 shows as a typical result a reference curve (E) for "early fatalities", determined with the "best-estimate" values for the input parameters. The lower (upper) broken line is the 5% (95%)-confidence curve; i.e. for a fixed number of health effects it denotes the range of expected frequencies in which, with 90%-confidence, the expected frequency (per year of accidents) of exceeding this number of effects lies (see GERMAN RISK STUDY /2/, /3/). (The totality of the local subjective confidence intervals has been joined by a smoothed trend-curve.)

3.4 Conclusions

We have sketched to a certain extent some of the rationale, the connections and tools when doing sensitivity and uncertainty studies.

We follow DOWNING et al /31/ that the methodology for performing sensitivity and uncertainty analysis for complicated computer codes is still under development. Many of the methods in use today are based on computer codes and have been used successfully on probabilistic risk assessment in nuclear safety, and related areas.

One way is to follow the route of screening uncertain input parameters, fitting a response-surface model to the output, varying only the "important" parameters from the screening, then calculating the moments of this response model (either exactly or using Monte Carlo or Latin hypercube sampling method to obtain sample estimates), and fitting an output distribution. The pitfalls in this approach are several. The uncertainty that we selected the most important input parameters especially when interactions cannot be neglected, is a major problem in this approach. After selecting the important parameters and fitting a response surface to the output varying only these variables, one must ask this question: What is the cumulative effect on the output for those variables that were held fixed? This cumulative effect may be large when working with a computer code containing several hundred parameters input. The fitting of a response-surface model is not as straightforward as many contributors to the literature lead us to believe. It is still very much on an art; with highly nonlinear functional forms, the second-order response-surface model may not be an acceptable approximation except over a very limited range. In addition there is always the question of what is an acceptable fit to the output. Finally, if we accept the response-surface model as representative of the output, then we can use it to obtain the first four moments and fit a distribution to it.

In contrast to the preceding course of action is the method to use a tolerance limit approach (MAZUMDAR et al /15/, Chap. 4.2 and HOFER/KRZYKACZ /7/) or the LHS-method. IMAN/CONOVER /30/ used the Latin hypercube sampling methodology to obtain an estimate of the ccdf of the output. The Latin hypercube sampling allows a representative sample of the input variables to be selected and in this way yields a more complete description of the model behavior. Using the empirical ccdf, one can then obtain estimates of the percentile points of the output. This methodology is straightforward and does not suffer the pitfalls mentioned earlier. It can be used to screen input parameters, in the sense of forming a hierarchy of most important to least important, and no parameters need be dropped from the analysis. Moreover, the use of Latin hypercube sampling and partial rank order correlation can uncover strong monotonic (highly nonlinear) relationships better than standard techniques.

Both approaches offer different insights to the input-output relationships of the computer code. Few studies exist that indicate the superiority of one approach over the other.

In general, it appears that uncertainty analysis requires a good approximation to the code over the complete set of possible input values. Response-surface approximations are designed to be local in nature and, therefore, do not perform well in uncertainty analysis. They are more suited to situations where local behavior of the code is of interest. Sensitivity analysis is a good example of this type of application. In some applications qualitative informations about the relationship of Y to the inputs is all that is required. In such cases, the approximations provided by fitting a response surface to Y is adequate. More work needs to be done in assessing the strengths and weaknesses of the two approaches in the areas of sensitivity and uncertainty analysis.

4. Some Applications of Methods to the Atmospheric Dispersion and Deposition Submodel of UFOMOD (*)

Within the framework of the CEC-MARIA programme some sensitivity and uncertainty studies were carried out at GRS and KfK.

It was suggested to

- investigate the specifics of probabilistic uncertainty analyses of accident consequence models for nuclear power plants and to suggest practical approaches;
- investigate the relevant characteristics of important submodels of the accident consequence model and to utilize the gained insights for the probabilistic uncertainty propagation through these submodels;
- perform exemplificative probabilistic uncertainty analyses for some ready-to-run submodels after an a priori compilation of relevant uncertain parameters (including typefication and quantification) was set up together with the model experts.

Before going into sophisticated methodological treatments and expensive computer runs some work was done to decide on the level of sensitivity and uncertainty analyses: Operating on submodels or on the complete models.

(*): see FISCHER/EHRHARDT /43/, FISCHER/EHRHARDT/MEDER /44/ and HOFER /KRZYKACZ / 7 /, HOFER et al /39/

- Operating on submodels

Generally the accident consequence model exhibits a structure suggesting the uncertainty analysis to operate on individual submodels. To this end the data transfered between the submodels is to be identified. The analysis is to propagate the uncertainties through the respective submodel to the output to others, thereby proceeding from submodel to submodel. This way the selection of the propagation procedures may take account of the individual submodel characteristics (number of relevant uncertain parameters, running time, specific functional relationship between uncertain parameters and output to other submodels etc.).

- Advantages:

Submodels without relevant uncertain parameters need only be run once;
submodels that need relatively little CPU-time per run but are subject to numerous and severe uncertainties may receive treatment with methods selected with emphasis on accuracy;
CPU-intensive submodels with, however, only few relevant uncertain parameters may permit elaborate treatment with respect to these parameters;
knowledge of the functional submodel characteristics may enter the formulation of the propagation expression;
in effect, insights may be gained comparable to those from a number of accident consequence model runs larger than the number that could possibly ever be afforded with the full model;
subsequent changes in the probabilistic modelling of the parameter uncertainties (within limits, however) may be taken into account at relatively low cost.

- Disadvantages:

  Inaccuracy of the propagation procedures chosen for the various submodels (especially beyond the design points) is difficult to quantify;
  CPU-time needed for the analysis is strongly dependent on the number of relevant uncertain parameters in CPU-intensive submodels with output uncertainties of overall importance;
  discontinuities with respect to the uncertain parameters may be hard to take care of properly;
  correlations between relevant uncertain parameters of different submodels require specific attention;
  overall sensitivity analysis (individual contributions to the resulting combined uncertainty in the consequences) will have to be performed in submodel steps.

- Operating on the complete model

  Here the propagation procedure is selected with respect to the complete accident consequence model and its characteristics. The resulting uncertainties in the conditional ccdf of the consequences (given an accidental release of a specific category and at a specific site) are the immediate objective of the uncertainty propagation.

- Advantages of a response surface approach for the complete model:

  knowledge of consequence model characteristics may enter the response surface formulation;
  no merging into scenarios at submodel interfaces;
  no isolation of submodels necessary (data storage at submodel interfaces may, however, be recommendable to reduce CPU-time);
  overall sensitivity analysis is a by-product;
  changes in the probabilistic modelling of the parameter uncertainties (within limits, however) may be taken into account at relatively low cost.

- Disadvantages

  CPU-time (≙ number of consquence model runs) is strongly dependent on the number of relevant uncertain parameters and terms in the response surface (data storage at submodel interfaces may help to reduce CPU-time dependent on the experimental design);
  extrapolation beyond the design points is not encouraged;
  discontinuities with respect to the uncertain parameters are hard to take care of properly;
  measure of accuracy of the uncertainty analysis is problematic (check of adequacy of the response surface).

For the following reasons it was decided to start to operate on submodels:

- the large number of uncertain parameters may profitably be reduced already on the submodel level,
- the insights gained from the analysis of the submodels will be most useful for the analysis of complete accident consequence models,
- various alternative analysis techniques may be explored within a restricted computer budget.

The following procedure steps have been adopted:

- the objectives of investigation were defined.
- relevant uncertain parameters were identified and typefied and data collection was done in discussion with submodel experts;
- a compilation of these parameters was set up by the experts including uncertainty quantification and probabilistic modelling as well as indication of correlations between the quantified uncertainties:

  . for preliminary 'important parameter' selection and sensitivity analysis an one-at-a-time-design was used;

- on the other hand, in the tolerance-limit design, both uncertainties and sensitivity were evaluated for the atmospheric dispersion submodel.

4.1 The Atmospheric Dispersion and Deposition Submodel and its Parameters

4.1.1 General Description

As a consequence of an accident in an installation of the nuclear fuel cycle, there is a certain probability that radioactive material is released into the atomsphere from the containment or the exhaust air stack. The radioactive plume travels away from the source of emission according to the actual wind direction and velocity. In general the radionuclide concentrations in air decrease continuously in the course of this movement, mainly due to turbulence in the atomosphere, dry deposition and washout by precipitation, if any.

The atomospheric dispersion and deposition submodel of UFOMOD is based on the 'Gaussion diffusion model', which has been modified and extended to avoid completely unrealistic results under real release conditions. A detailed description of the model is given in GERMAN RISK STUDY /3/, the most important characteristics are summarized in the following condensed description.

A general view of the phenomena considered in the model and a schematic view of its structure are shown in Figs. 4.1.1-1 and 4.1.1-2. The basic formula for the calculation of ground level concentrations C_A at the receiving point P (x,y,0) under the assumption of total reflection at the earth's surface is given by

$$C_A(x,y,0,h_{eff}) =$$

$$= \frac{\dot{A}}{\pi\, \sigma_y(x)\sigma_z(x)\, \bar{u}} \cdot \exp\left\{-\left(\frac{y^2}{2\sigma_y^2} + \frac{h_{eff}^2}{2\sigma_z^2}\right)\right\} \qquad (4.1.1.1)$$

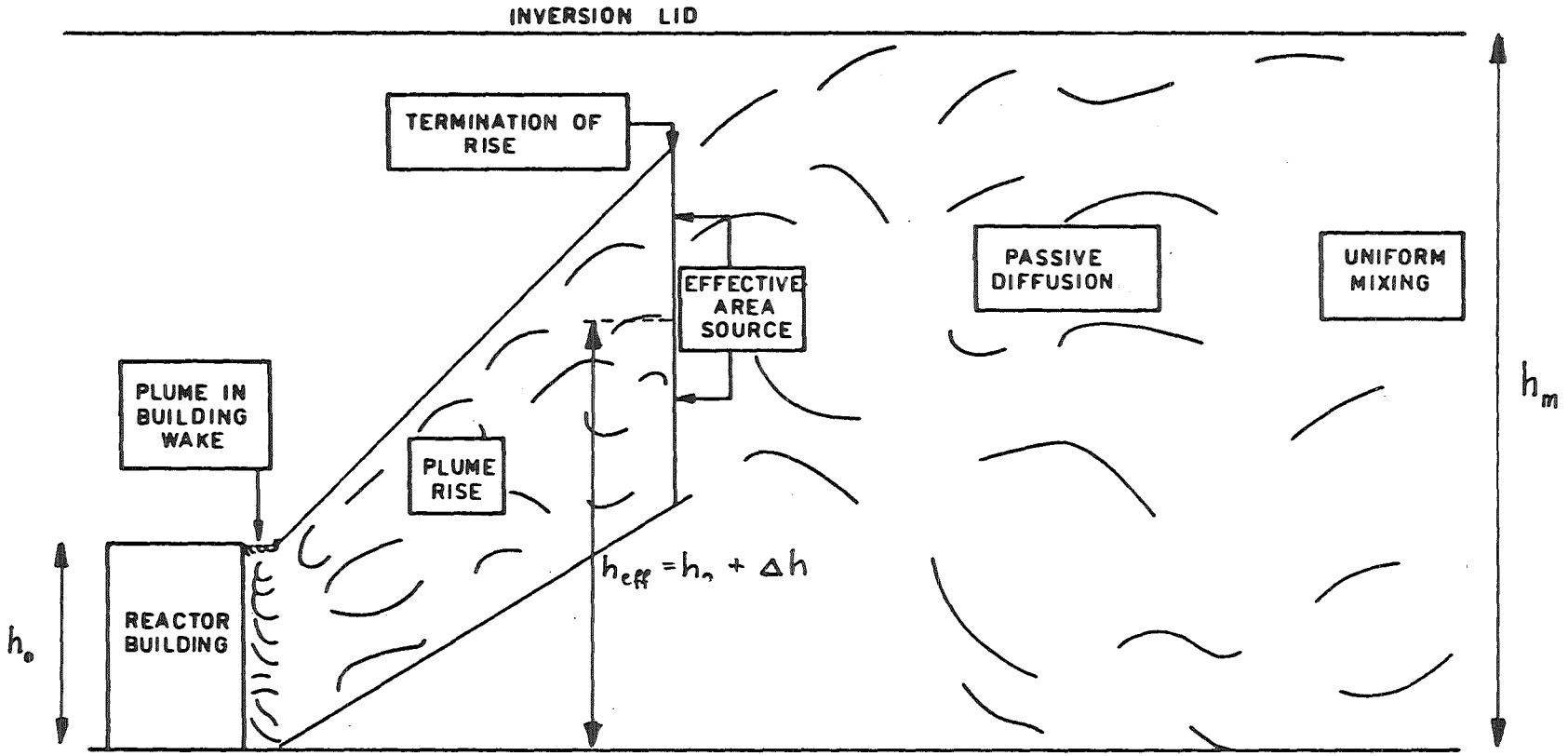

Fig. 4.1.1-1: Typical history of plume behaviour
(according to /45/, p. 1-43)

where

$\dot{A}$	activity release rate of the source
$\sigma_y(x)$	horizontal and vertical dispersion
$\sigma_z(x)$	parameters respectively
$\bar{u}$	mean wind speed
h_{eff}	effective height of emission

The dispersion parameters $\sigma_y(x)$ and $\sigma_z(x)$ are expressed by the following power functions

$$\sigma_y(x) = \sigma_{y_o} \cdot x^{p_y} \qquad (4.1.1.2)$$

$$\sigma_z(x) = \sigma_{z_o} \cdot x^{p_z} \qquad (4.1.1.3)$$

The coefficients σ_{z_o}, p_z and σ_{y_o}, p_y are determined by approximation of equation (4.1.1.1) to concentration values resulting from tracer experiments carried out at KfK /3/. They are dependent on roughness length, which was found in the neighbourhood of KfK to be Z_o = 1,5 m (roughness grade III).

Corresponding to the mixing height concept, in which a barrier layer stops turbulent exchange at greater heights, the vertical dispersion parameter is kept constant on reaching the value, $\sigma_{z,max}$. This value is linked with the mixing height h_m by the expression

$$\sigma_{z,max} = \sqrt{\frac{2}{\pi}} \cdot h_m = 0.8 \cdot h_m \qquad (4.1.1.4)$$

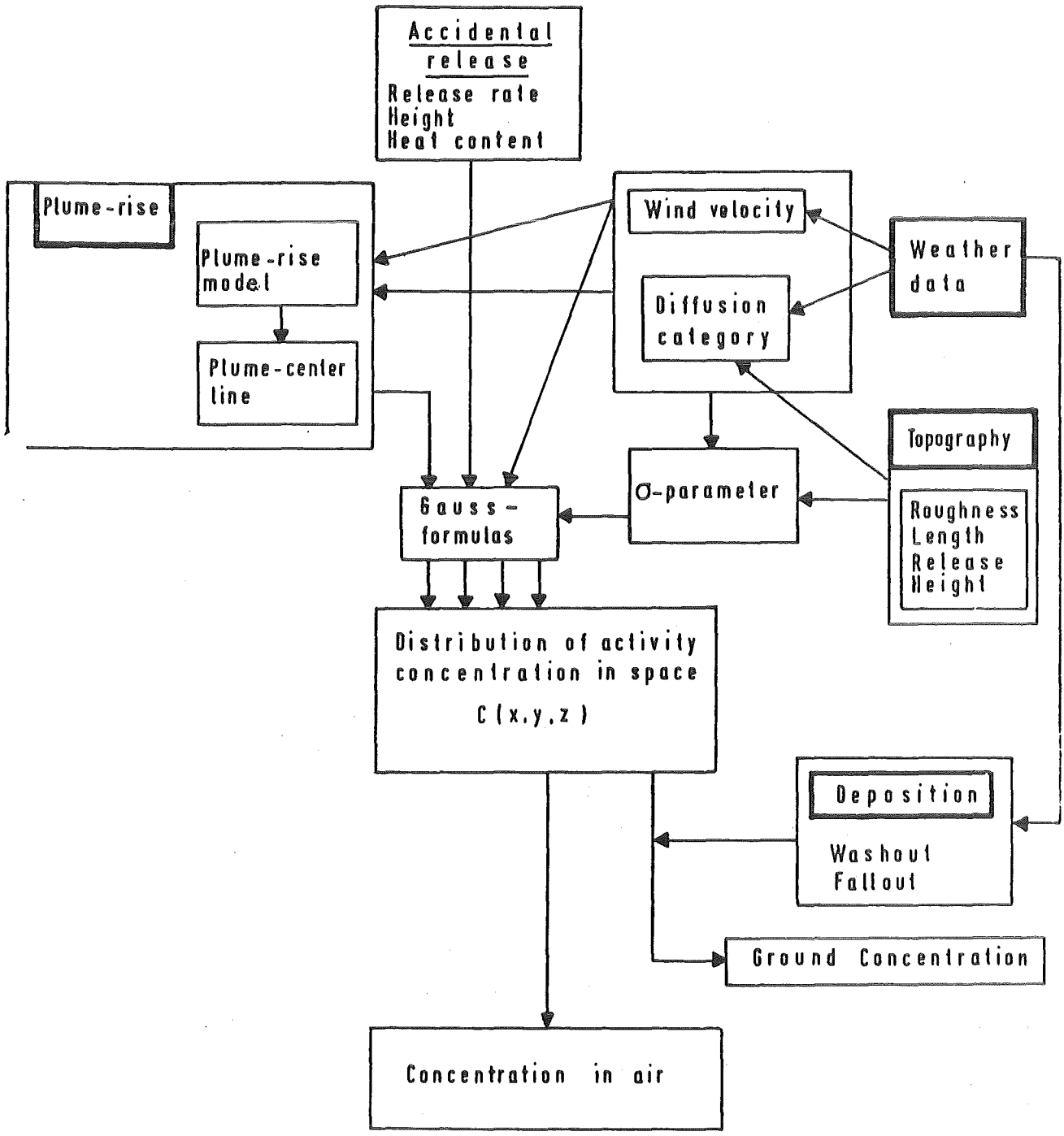

Fig. 4.1.1-2: Basic structure of the atmospheric dispersion and deposition submodel of UFOMOD/B3

The radioactive material may leave a nuclear facility in one of several ways, e.g. from a stack or leaking from the face of the building. In the case of a stack release, the source is effectively an isolated point and has negligible influence on the dispersion process. Radioactivity emerging from the building however, may be swept down into a turbulent building wake where it will be diluted before it travels further downwind. This increased dilution is taken into account as follows:

$$\frac{C_A \cdot \bar{u}}{A} = \qquad (4.1.1.5)$$

$$= \left[\pi \cdot \sigma_y(x) \cdot \sigma_z(x) + C \cdot F\right]^{-1} \cdot \exp\left\{-\left(\frac{y^2}{2\sigma_y^2} + \frac{h_{eff}^2}{2\sigma_z^2}\right)\right\}$$

with F representative building area flowed to

$$C = \begin{cases} C_1 & \text{when } h_{eff} < 20 \text{ m} \\ 0 & \text{when } h_{eff} > 20 \text{ m} \end{cases}$$

The effective emission height h_{eff} in the equations (4.1.1.1) and (4.1.1.5) consists of the geometric release height h_o and the increase in height Δh caused by a buoyant, rising plume:

$$h_{eff} = h_o + \Delta h \qquad (4.1.1.6)$$

As the only reason for plume rise, a release of thermal energy is considered; the possibility of a high upward momentum is neglected. To calculate Δh, the following modified BRIGG's formulas are used:

for dispersion categories A to D:

$$\Delta h = \left(D_A^{\,3} + f_{PR}^{\,3} \cdot \frac{F^* \cdot x^2}{\bar{u}^3} \right)^{\frac{1}{3}} - D_A \qquad (4.1.1.7)$$

for dispersion categories E and F:

$$\Delta h = \left(D_A^{\,3} + f_{PR}^{\,3} \cdot \frac{F^*}{\bar{u} \cdot s} \right)^{\frac{1}{3}} - D_A \qquad (4.1.1.8)$$

where

D_A quantity to correct plume rise (area source instead of point source)

$f_{PR} = \begin{cases} 1{,}6 \text{ for A to D} \\ 2{,}9 \text{ for E,F} \end{cases}$

$F^* = 8.84 \left[\frac{m^4/s^3}{MW} \right] \cdot Q$ emission coefficient

Q heat content released with the activity plume [MW]

$\bar{u}$ mean wind speed

S stability parameter

x distance from point of release

For further details see /3/.

To determine the mean wind speed $\bar{u}$, the wind profile

$$u(z) = u_o \left(\frac{z}{h_o} \right)^p \qquad (4.1.1.9)$$

is averaged over the effective height of emission h_{eff}.

$$\bar{u} = \frac{1}{h_{eff}} \int_{o}^{h_{eff}} u(z)dz = \frac{u(h_{eff})}{1+p} \qquad (4.1.1.10)$$

where

$u(h_{eff})$	wind speed at the effective emission height h_{eff}
u_o	wind speed at anemometer height h_o
p	wind profile exponent

If $\bar{u}$ is calculated less than 1 m/s, then the value 1 m/s is used.

During the dispersion process, aerosols and iodine are removed from the atomsphere by dry deposition ("fallout") or in the case of precipitation by wet deposition ("washout"). To calculate dry deposition, the so-called "source depletion" model is applied, which assumes proportionality between deposition rate and instantaneous air concentration near ground surface. This ratio is called the deposition velocity v_d. The activity inventory of the plume is reduced by the amount deposited.

Wet deposition is modelled by the washout coefficient λ and treated similar to dry deposition. The component of activity remaining in the plume is

$$f_w = e^{-\lambda \Delta t} \qquad (4.1.1.11)$$

where Δt gives the duration of rain. Noble gases are neither wet nor dry deposited.

The meteorological data used to calculate the radioactivity concentrations of the air and the contamination of the soil, namely wind speed, diffusion category and information about precipitation, are adapted at hourly intervals to the measured real weather patterns. The meteorological parameters measured on the site are assumed to have the same values over all distances at the same time. This is done for 115 weather sequences whose starting times are equidistantly shifted (three days plus five hours difference) over the time span of one year.

A straight line transport of the exhaust air plume is assumed. This model of straight line diffusion is applied up to a distance of 540 km. The area enclosed by this circle is roughly correspondent to the area of Central Europe.

4.1.2 Parameter Values and Their Distribution

The above mentioned equations (4.1.1.1) to (4.1.1.11) represent the mathematical formulation of the atmospheric dispersion and deposition submodel of UFOMOD. They contain various input quantities, whose actual values are uncertain (i.e. not known exactly) due to

- insufficient knowledge of physical processes
- model simplifications
- lack of data base etc.

In Table 4.1.2-1(a) (b) the parameters, their current values used in UFOMOD/B3 and the assigned distribution function with the characteristic quantities minimum, 10%-, 50%-, 90%-fractile and maximum are listed. The distributions express our judgment of the lack of precision in the 'best estimate' of a parameter's value as input to UFOMOD. They do not represent actual variability in the data. Furthermore, for the present exercise, the choice of source term parameters is based on the assumption of release category FK2 of the German Risk Study /3/.

The following explanatory remarks refer to the choice of parameter values and their variations:

Explanatory Remarks to Tables 4.1.2-1 (a)(b)

1. The thermal energy Q is released in three subsequent puffs each of one hour duration due to the UFOMOD modelling of release category FK2.

2. The wind speed data u_o (see Equ. 4.1.1.9) are measured values, taken from hourly recorded weather data on magnetic tape. Their uncertainty is taken into account by

$$u = (1 + 0.1 * r)\ u_o + 0.5 * r$$

   The quantity r is an uncertain parameter uniformly distributed between -1 and +1.

3. The effective plume height $h_{eff} = h_o + \Delta h$ is given by the geometric height of the source h_o and the plume rise Δh. The geometrical height of the source h_o is uncertain due to the unknown location of the failure of the containment.

4. The quantities f_{PR} and D_A to describe plume rise have been chosen according to expert judgment, as well as the atmospheric dilution parameter C_1 in Equ. 4.1.1.5).

5. The mixing height h_m for the diffusion categories A to F are valid for roughness length 1.5 m (roughness grade III).

6. The uncertainty of the horizontal and vertical dispersion parameters was assigned to the parameter σ_{yo} and σ_{zo} respectively (see Equs. 4.1.1.2 and 4.1.1.3) .

7. Dry and wet deposition parameters are specified for iodine and aerosols. The 50%-fractiles of the washout-coefficients stem from reference /5/.

8. There is a certain correlation, in uncertainty between the elements x_i of the following parameter groups G_r (r=1,...,5):

G_1 =	$\{x_8,\ldots,x_{13}\}$	mixing height for diffusion categories A to F
G_2 =	$\{x_{14},\ldots,x_{19}\}$	horizontal dispersion parameters for diffusion categories A to F
G_3 =	$\{x_{20},\ldots,x_{25}\}$	vertical dispersion parameters for diffusion categories A to F
G_4 =	$\{x_{32},x_{34},x_{36},x_{38}\}$	dry and wet deposition parameters for iodine
G_5 =	$\{x_{33},x_{35},x_{37},x_{39}\}$	dry and wet deposition parameters for aerosols

The correlation coefficient within each group G_r (r=1,...,5) has been assumed to be k = 0.5. Parameter uncertainties of different groups are not assumed correlated.

9. The lognormal distributions have been truncated at their 10%- and 90%-fractiles.

   A variate X is lognormally distributed if y = log X has a normal distribution $N(\mu,\sigma)$ where μ = log m and m = 50%-fractile of the distribution of X.

   Symbolized by L: μ,σ

10. HOFER/KRZYKACZ /7/ used essentially the same distribution list of Tables 4.1.2-1(a)(b) with some slight changes.

Number of variable		List of parameters	Unit	Best estimate or current value in UFOMOD	Minimum	10%	50% percentiles	90%	Maximum	Type of distribution	Notes
1	Q	thermal energy released in three hours	[MWh]	12.5	0.84	1.3	4.2	11.5	16.8	lognormal (truncated)	Note No. 1, 9 Note No. 10
2	r	quantity to describe error in wind speed		0	-1	-0.80	0	0.80	1	uniform	Note No. 2
3	h(Q)	height of source	[m]	10	0	5	10	20	30	lognormal	
4	fPR(A-B)	factor to describe plume rise for different DC		DC=A,B 1.6 C,D	1.1	1.2	1.6	2.0	2.1	uniform	Note No. 3, 4
5	fPR(E-F)			DC=E,F 2.9	1.65	1.9	2.9	3.9	4.15		
6	D(A)	quantity to correct plume rise	[m]	45	7.5	10	20	30	32.5	uniform	Note No. 4
7	C(1)	atmospheric dilution parameters for lee-eddies of reactor building		1.5	0.25	0.5	1.5	2.5	2.75	uniform	Note No. 4
8	h_m	mixing height for category A-F and roughness-length > 1 m	[m]	DC=A 2500	1000	1200	2000	2800	3000	uniform	Note No. 5, 8
9				DC=B 1875	750	900	1500	2100	2250		
10				DC=C 1250	500	600	1000	1400	1500		
11				DC=D 1250	350	420	700	980	1050		
12				DC=E 1250	200	240	400	560	600		
13				DC=F 1250	125	150	250	350	375		

Table 4.1.2-1(a): Atmospheric dispersion submodel parameters for uncertainty (DC = diffusion category A, B, C, D, E, F)

Number of variable		List of parameters	Unit	Best estimate or current value in UFOMOD	Minimum	10%	50%	90%	Maximum	Type of distribution	Notes
14	σy_o	horizontal dispersion parameter for different DC		DC=A 0.65	0.325	0.4	0.65	1.05	1.3		
15				DC=B 0.65	0.325	0.4	0.65	1.05	1.3		
16				DC=C 0.43	0.215	0.265	0.43	0.7	0.86	lognormal	Note No.6,
17				DC=D 0.34	0.17	0.21	0.34	0.56	0.68	(truncated)	8,9
18				DC=E 0.34	0.17	0.21	0.34	0.56	0.68		10
19				DC=F 0.34	0.17	0.21	0.34	0.56	0.68		
20	σz_o	vertical dispersion parameter for different DC		DC=A 0.039	0.0195	0.024	0.039	0.065	0.078		
21				DC=B 0.020	0.010	0.0125	0.020	0.033	0.04		
22				DC=C 0.052	0.026	0.032	0.052	0.086	0.104	lognormal	Note No.6,
23				DC=D 0.100	0.05	0.061	0.100	0.165	0.2	(truncated)	8,9
24				DC=E 0.66	0.33	0.4	0.66	1.05	1.32		10
25				DC=F 1.30	0.65	0.8	1.30	2.15	2.6		
26	P	wind profile exponent for different DC		DC=A 0.07							
27				DC=B 0.13							
28				DC=C 0.21							
29				DC=D 0.34	-50%	-40%	current values	+40%	+50%	uniform	
30				DC=E 0.44							
31				DC=F 0.44							
	v(d)	dry deposition velocity	[m/s]								
32		iodine		0.01	$1.2 \cdot 10^{-4}$	0.002	0.01	0.05	0.84	lognormal	Note No.7,
33		aerosols		0.001	$2.5 \cdot 10^{-5}$	0.0004	0.002	0.01	0.165		8
	Λ	washout-coefficient for precipitation rates	[1/s]								
34		0-1mm/s iodine		$3.7 \cdot 10^{-5}$	$5 \cdot 10^{-7}$	$8.4 \cdot 10^{-6}$	$4.2 \cdot 10^{-5}$	$2.1 \cdot 10^{-4}$	$3.5 \cdot 10^{-3}$		
35		aerosols		$2.9 \cdot 10^{-5}$	$4.2 \cdot 10^{-7}$	$6.8 \cdot 10^{-6}$	$3.4 \cdot 10^{-5}$	$1.7 \cdot 10^{-4}$	$2.9 \cdot 10^{-3}$		
36		1-3mm/s iodine		$1.1 \cdot 10^{-4}$	$1.35 \cdot 10^{-6}$	$2.1 \cdot 10^{-5}$	$1.06 \cdot 10^{-4}$	$5.3 \cdot 10^{-4}$	$8.5 \cdot 10^{-3}$		
37		aerosols		$1.22 \cdot 10^{-4}$	$1.4 \cdot 10^{-6}$	$2.3 \cdot 10^{-5}$	$1.17 \cdot 10^{-4}$	$5.85 \cdot 10^{-4}$	$1 \cdot 10^{-2}$	lognormal	Note No.7, 8
38		>3mm/s iodine		$2.37 \cdot 10^{-4}$	$2.7 \cdot 10^{-6}$	$4.6 \cdot 10^{-5}$	$2.31 \cdot 10^{-4}$	$1.16 \cdot 10^{-3}$	$1.9 \cdot 10^{-2}$		
39		aerosols		$3.4 \cdot 10^{-4}$	$4 \cdot 10^{-6}$	$6.6 \cdot 10^{-5}$	$3.29 \cdot 10^{-4}$	$1.65 \cdot 10^{-3}$	$2.5 \cdot 10^{-2}$		

Table 4.4.2-1(b): Atmospheric dispersion submodel parameters for uncertainty analysis
(DC = diffusion category A, B, C, D, E, F)

4.2 Main Results of the One-At-A-Time-Design

In Chap. 4.1.2 a list of 39 uncertain input parameters has been presented, which have certain effects on the output in the atmospheric dispersion and deposition submodel (UFOMOD).

The aim was to reduce the number of relevant input parameters to the most sensitive ones, say 14 out of 39. This was done by the one-at-a-time-design due to a certain distance criterion (see Appendix). The number fourteen is motivated by the fact that in certain design cases the number of computer runs of the ACA-codes resulting from 10-15 uncertain input parameters can still be managed within time and cost limits.

157 UFOMOD runs have been performed, each based on a set of 115 weather sequences. The evaluation of the resulting concentration fields in the air and on ground surface have been restricted to the mean values under the centerline of the plume, i.e. 157 concentration values each averaged over 115 weather situations.

To perform sensitivity and uncertainty analysis, the two nuclides

(1) iodine-131 ($T_{1/2}$ = 8d)
(2) caesium-137 ($T_{1/2}$ = $1.2 \cdot 10^4$ d = 30 y)

have been chosen as representatives for isotopes with short and long radioactive half-lifes. They are also important contributors to early (1) and latent cancer (2) fatalities. Additionally the influence of different depositions velocities for iodine and aerosols can be investigated.

The resulting concentration fields in the plume, in the air and on ground surface up to 540 km from the site have been analyzed with respect to the variability of the mean concentration values at the four distance intervals:

. 0.2 km ÷ 0.5 km
. 0.8 km ÷ 1.2 km
. 8 km ÷ 12 km
. 80 km ÷ 120 km

representative for the microscale and near, mean and far distances.

In the following a series of tables are listed which give the 14 most important input variables for each of the 24 combinations (nuclide, distance, concentration type):

Nuclides: · Iodine ÷ 131
· Caesium ÷ 137

Distances: 0.2 km ÷ 0.5 km
0.8 km ÷ 1.2 km
8 km ÷ 12 km
80 km ÷ 120 km

Concentration types: · plume
· air near ground (1-m-height)
· ground surface

A complete and detailed phenomenological interpretation of all results is neither the aim of this report nor a meaningful task, because the one-at-a-time design does not allow quantitative conclusions with respect to the overall importance of each parameter. For this reason, the most remarkable findings of the results will be shortly and qualitatively discussed and interpreted exemplarily for

- iodine concentration in air, 1m above ground surface (Tables 4.2-1.2(a)-(d) and 4.2-3(a))
- iodine concentration on ground surface (Tables 4.2-1.3(a)-(d) and 4.2-3(b))
- caesium concentration on ground surface (Tables 4.2-2.3(a)-(d) and 4.2-3(e))

1. The maximum relative deviations of mean air concentrations occur in close vicinity to the sites. This is due to the fact that FK2 releases contain thermal energy which causes plume rise. Therefore variation of the thermal energy Q has a very strong influence on the air concentrations near ground surface; this influence decreases with growing distance, since after termination of plume rise, the radioactive material is transported back to the lower regions of the atmosphere by diffusion (see Fig. 4.1.1-1). The parameter Q is the most important one up to the second distance band (0.8km ÷ 1.2km). In the third distance band (8km ÷ 12km) it causes smaller deviations (rank 15 for iodine and rank 12 for caesium).

2. The maximum relative deviation of mean ground concentrations is much higher than for the air concentration, especially in distances up to some 10 km. This is due to the variation of the dry and wet deposition parameters, which are most important in this distance range. Since in all calculations, the mean concentration under the centerline plume, averaged over 115 weather sequences, is considered, dry deposition has rank 1 (wet deposition occurs with lower frequency). With increasing distance form the site, the variation of deposition parameters leads to smaller deviations of ground concentrations due to the source depletion. At distances beyond 100 km, the dispersion parameters σ_y are responsible for the highest deviations.

3. The effect of parameters describing the influence of the reactor building on plume behaviour is relatively small. Only f_{PR} and D_A appear up to 1 km within the 14 most important parameters. All other quantities (h_o,C_1) have minor influence on uncertainty of mean concentration values.

4. Variation of the mixing height gives significant contributions only at far distances (> 50km), where the deviations are small anyhow. This is due to the modeling of vertical dispersion, which stops at h_m (see Fig. 4.1.1-1). At distances beyond some 10 km, the vertical Gaussian profile has changed and a constant axial concentration results. Consequently, the concentration dependent on the mixing height and σ_y.

5. Due to the model characteristic described in point 4. above, the influence of the dispersion parameters σ_y and σ_z is dependent on the distance range considered. At far distances, the concentrations are only a function of σ_y. In close vicinity to the site, σ_z is responsible for activity concentrations above and on ground surface in particular when plume rise occurs.

6. The results show, that beyond some kilometers, variations of the air and ground concentrations of iodine and caesium higher than 20% are caused by variations of the same 10 parameters of σy ,v_d and Λ. This result simplifies the future uncertainty analyses.

7. It must be pointed out, that the results of this sensitivity study are valid only for the assumed release category FK2. This concerns especially all results in the vicinity of the sites up to 10 kilometers. Other releases, e.g. without or higher thermal energy or stack releases can lead to other sensitivities in this distance range.

To sum up:

The most important parameters identified by the one-at-a-time-design are:

- released thermal energy; Q
- dry deposition velocities for iodine and aerosols; v_d
- washout-coefficients for iodine and aerosols for various rainfall rates; Λ
- horizontal and vertical dispersion parameters for various diffusion categories; σ_{y_o}, σ_{z_o}

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-1.1(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-2.1(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)

TABLE 4.2-1.1(8) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)

TABLE 4.2-2.1(8) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
MIXING HEIGHT DC=D	HM(D)	X(11)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
MIXING HEIGHT DC=C	HM(C)	X(10)

TABLE 4.2-1.1(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : PLUME

MEANING	PHYS. SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
MIXING HEIGHT DC=D	HM(D)	X(11)
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)

TABLE 4.2-2.1(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : PLUME

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
MIXING HEIGHT DC=C	HM(C)	X(10)
MIXING HEIGHT DC=B	HM(B)	X(9)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=A	HM(A)	X(8)
MIXING HEIGHT DC=E	HM(E)	X(12)
MIXING HEIGHT DC=F	HM(F)	X(13)
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)

TABLE 4.2-1.1(d) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : PLUME

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
MIXING HEIGHT DC=C	HM(C)	X(10)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=B	HM(B)	X(9)
MIXING HEIGHT DC=A	HM(A)	X(8)
MIXING HEIGHT DC=F	HM(F)	X(13)
MIXING HEIGHT DC=E	HM(E)	X(12)
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)

TABLE 4.2-2.1(d) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : AIR

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-1.2(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : AIR

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-2.2(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : AIR

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-1.2(B) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : AIR

MEANING	PHYS. SYMBOL	VARIABLE
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)

TABLE 4.2-2.2(B) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : AIR

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)

TABLE 4.2-1.2(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : AIR

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
THERMAL ENERGY	Q	X(1)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)

TABLE 4.2 -2.2(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : AIR

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=C	HM(C)	X(10)
MIXING HEIGHT DC=B	HM(B)	X(9)
MIXING HEIGHT DC=A	HM(A)	X(8)

TABLE 4.2 - 1.2(d) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : AIR

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=C	HM(C)	X(10)
MIXING HEIGHT DC=B	HM(B)	X(9)
MIXING HEIGHT DC=E	HM(E)	X(12)

TABLE 4.2 - 2.2(d) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)

TABLE 4.2.1.3(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.2 - 0.5 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
THERMAL ENERGY	Q	X(1)
PLUME RISE FACTOR DC=A,B,C,D	FPR(A-D)	X(4)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=B	SIGZ(B)	X(21)
VERTICAL DISPERSION DC=A	SIGZ(A)	X(20)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)

TABLE 4.2-2.3(a) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
THERMAL ENERGY	Q	X(1)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
VERTICAL DISPERSION DC=C	SIGZ(C)	X(22)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
QUANTITY TO CORRECT PLUME RISE	DA	X(6)

TABLE 4.2-13(6) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 0.8 - 1.2 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
THERMAL ENERGY	Q	X(1)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)

TABLE 4.2-2,3(6) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)
VERTICAL DISPERSION DC=D	SIGZ(D)	X(23)

TABLE 4.2 - 1.3(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 8.0 - 12.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
THERMAL ENERGY	Q	X(1)
VERTICAL DISPERSION DC=E	SIGZ(E)	X(24)
VERTICAL DISPERSION DC=F	SIGZ(F)	X(25)

TABLE 4.2 - 2.3(c) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : IODINE
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
DRY DEPOSITION VELOCITY IODINE	VD(IO)	X(32)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
WASHOUT COEFFICIENT IODINE 0-1MM/S	LAMB(IO,0-1)	X(34)
WASHOUT COEFFICIENT IODINE 1-3MM/S	LAMB(IO,1-3)	X(36)
WASHOUT COEFFICIENT IODINE >3MM/S	LAMB(IO,>3)	X(38)
MIXING HEIGHT DC=C	HM(C)	X(10)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=B	HM(B)	X(9)
MIXING HEIGHT DC=A	HM(A)	X(8)

TABLE 4.2 - 1.3(d) LIST OF 14 MOST IMPORTANT VARIABLES

RELEASE CATEGORY : FK2
DISTANCE : 80.0 - 120.0 KM
NUCLIDE : CAESIUM
CONCENTRATION CLASS : GROUND

MEANING	PHYS.SYMBOL	VARIABLE
DRY DEPOSITION VELOCITY AEROSOLS	VD(AE)	X(33)
WASHOUT COEFFICIENT AEROSOLS 0-1MM/S	LAMB(AE,0-1)	X(35)
HORIZONTAL DISPERSION DC=D	SIGY(D)	X(17)
WASHOUT COEFFICIENT AEROSOLS 1-3MM/S	LAMB(AE,1-3)	X(37)
WASHOUT COEFFICIENT AEROSOLS >3MM/S	LAMB(AE,>3)	X(39)
HORIZONTAL DISPERSION DC=E	SIGY(E)	X(18)
HORIZONTAL DISPERSION DC=C	SIGY(C)	X(16)
HORIZONTAL DISPERSION DC=F	SIGY(F)	X(19)
HORIZONTAL DISPERSION DC=B	SIGY(B)	X(15)
HORIZONTAL DISPERSION DC=A	SIGY(A)	X(14)
MIXING HEIGHT DC=D	HM(D)	X(11)
MIXING HEIGHT DC=C	HM(C)	X(10)
QUANTITY TO DESCRIBE ERRORR IN WIND SPEED	R	X(2)
MIXING HEIGHT DC=B	HM(B)	X(9)

TABLE 4.2 - 2.3(d) LIST OF 14 MOST IMPORTANT VARIABLES

****
* IODINE (AIR) *
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	164.47	70.69	147.69	16.38	19.97	20.19
0.8 - 1.2 KM	147.17	61.75	121.86	18.64	13.82	17.37
8.0 - 12.0 KM	35.65	45.16	43.88	9.74	13.18	12.88
80.0 -120.0 KM	80.36	80.12	74.65	13.60	11.53	13.17

TABLE 4.2-3(a) : MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

****
* IODINE (GROUND) *
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	143.33	365.35	1813.05	19.97	22.35	23.14
0.8 - 1.2 KM	136.27	368.47	1396.30	22.62	24.02	26.04
8.0 - 12.0 KM	73.61	167.44	121.19	9.62	12.15	12.18
80.0 -120.0 KM	80.95	51.73	75.09	10.98	9.18	10.68

TABLE 4.2.-3(b): MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

****
* IODINE (PLUME) *
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	66.90	39.24	61.55	16.39	18.12	18.23
0.8 - 1.2 KM	72.05	43.02	63.03	11.68	11.59	13.20
8.0 - 12.0 KM	67.79	47.06	63.44	8.94	9.65	9.98
80.0 - 120.0 KM	1489.09	136.50	1302.66	16.98	46.62	44.82

TABLE 4.2-3(c): MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

****
CAESIUM (AIR)
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	165.03	71.00	148.23	16.38	19.97	20.20
0.8 - 1.2 KM	149.61	61.86	123.92	18.99	13.95	17.65
8.0 - 12.0 KM	36.28	28.61	36.13	8.52	13.29	13.73
80.0 -120.0 KM	81.97	52.86	76.12	7.69	15.03	20.15

TABLE 4.2-3 (d): MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

****
CAESIUM (GROUND)
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	95.52	306.88	1729.47	18.76	21.56	22.39
0.8 - 1.2 KM	107.51	330.58	1721.12	18.63	19.65	20.31
8.0 - 12.0 KM	66.91	273.04	299.63	7.90	9.94	9.83
80.0 -120.0 KM	84.15	147.05	105.40	14.08	9.45	12.75

TABLE 4.2-3 (e): MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

****
CAESIUM (PLUME)
****

	MAXIMUM RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE CALCULATED AT 10%- RESP. 90%-LEVEL OR DUE TO THE CRITERION			REMAINING RELATIVE VARIATION OF CONCENTRATION FROM CENTRAL VALUE WITH 14 MOST SENSITIVE VARIABLES AT CENTRAL VALUE		
	10%	90%	CRITERION	10%	90%	CRITERION
0.2 - 0.5 KM	67.37	39.24	61.91	16.44	18.27	18.35
0.8 - 1.2 KM	73.74	43.20	64.33	11.82	11.71	13.33
8.0 - 12.0 KM	70.39	47.50	65.60	8.64	7.71	11.56
80.0 -120.0 KM	1713.99	138.52	1503.61	7.39	19.71	30.96

TABLE 4.2-3 (f): MAXIMAL RELATIVE VARIATIONS OF CONCENTRATION

4.3 Main Results of the Uncertainty Analysis Using the Tolerance-Limit-Approach (+)

As already indicated the relevant output of the atmospheric dispersion and deposition submodel of UFOMOD are three types of concentration (plume, ground, air), of all nuclides considered, in all mesh-cells of the spatial grid (20 radial distances, 36 angular sectors) following a specific accidental release. An FK2 release (see /2/) was assumed for the present uncertainty analysis. Since the Gaussian distribution (modeling the plume) is represented by a 7-step function in cross-wind direction its superposition with the spatial grid leads to an even finer spatial representation of the concentrations. Four different ways of analyzing the resulting bulk of output data were considered:

i) Limitation to the centerline concentration of each type and nuclide at four selected distances and averaged over 115 weather sequences;
ii) Limitation to the ccdf of the centerline concentration of each type and nuclide at the same four distance;
iii) Limitation to the area exhibiting a concentration of a given type, nuclide and class (> 1Ci/m^2 etc.) and averaged over 115 weather sequences.
IV) ccdf of the area exhibiting a concentration of a given type, nuclide and class (>1 Ci/m^2 etc.) This aggregation is very close to the customary presentation of the final ACA results, namely the ccfs of the consequences.

i) Averaged centerline concentrations:

The analysis results are presented in Table 4.3-1. For all three types of concentration of each of the two nuclides the table shows at four selected distances under the plume centerline

- the minimum (averaged) concentration from the 59 parameter vectors $\vec{p}_j$ (the associated index j is given in the table);

(+) see HOFER/KRZYKACZ /7/ , HOFER et al /39/

Distance (km)	0.2 - 0.5		0.8 - 1.2		8 - 12		80 - 120	
Concentration:	Plume (1)				Nuclide:		I-131 (1)	
run j Conc.								
Min.	45	30.6	10	11.7	16	0.5	16	2.E-5
Ref.		130.3		72.1		4.1		1.E-2
Max.	41	457.4	39	192.9	56	11.1	56	4.E-1
par. i "P_i" $t_{C,i-k\neq i}$	1 Q	-0.52	1 Q	-0.56	17 $\sigma_{y_o,D}$	-0.29	16 $\sigma_{y_o,C}$	-0.32
	23 $\sigma_{z_o,D}$	0.17	17 $\sigma_{y_o,D}$	-0.20	18 ,E	-0.27	17 ,D	-0.28
	6 D_A	0.15	2 r	-0.15	11 $h_{m,D}$	-0.17	18 ,E	-0.21
	17 $\sigma_{y_o,D}$	-0.13	6 D_A	0.11	16 $\sigma_{y_o,C}$	-0.17	15 ,B	-0.15
	21 $\sigma_{z_o,B}$	0.13	9 $h_{m,B}$	0.09	2 r	-0.15	9 $h_{m,B}$	0.14
Concentration:	Plume (1)				Nuclide:		Cs-137 (2)	
run j Conc.								
Min.	45	1.5	10	0.6	45	5.E-2	16	1.E-5
Ref.		6.3		3.5		2.E-1		7.E-4
Max.	41	22.6	39	9.5	32	3.E-1	56	3.E-2
par. i "P_i" $t_{C,i-k\neq i}$	1 Q	-0.52	1 Q	-0.55	17 $\sigma_{y_o,D}$	-0.38	17 $\sigma_{y_o,D}$	-0.33
	23 $\sigma_{z_o,D}$	0.17	17 $\sigma_{y_o,D}$	-0.20	18 ,E	-0.27	16 ,C	-0.29
	6 D_A	0.15	2 r	-0.15	2 r	-0.24	18 ,E	-0.25
	17 $\sigma_{y_o,D}$	-0.14	6 D_A	0.10	19 $\sigma_{y_o,F}$	-0.23	19 ,F	-0.23
	21 $\sigma_{z_o,B}$	0.13	21 $\sigma_{z_o,B}$	0.10	1 Q	-0.15	2 r	-0.12

Distance (km)	0.2 - 0.5		0.8 - 1.2		8 - 12		80 - 120	
Concentration:	Air (1 m above ground surface) (3)				Nuclide:		I-131 (1)	
run j Conc.								
Min.	27	1.8	27	4.1	8	1.0	8	7.E-4
Ref. Ci/m³		145.9		102.7		9.7		3.E-1
Max.	41	1264.	41	469.7	22	20.6	56	1.2
par. i "P_i" $t_{C,i-k\neq i}$	1 Q	-0.51	1 Q	-0.63	32 $V_{d,I}$	-0.25	32 $V_{d,I}$	-0.44
	23 $\sigma_{z_o,D}$	0.21	17 $\sigma_{y_o,D}$	-0.16	1 Q	-0.24	17 $\sigma_{y_o,D}$	-0.20
	6 D_A	0.15	9 $h_{m,B}$	0.15	18 $\sigma_{y_o,E}$	-0.20	18 ,E	-0.13
	4 $f_{PR,A-D}$	-0.12	39 $\Lambda_{3,A}$	-0.10	11 $h_{m,D}$	-0.19	16 ,C	-0.12
	21 $\sigma_{z_o,B}$	0.11	2 r	-0.09	24 $\sigma_{z_o,E}$	-0.17	10 $h_{m,C}$	-0.11
Concentration:	Air (1 m above ground surface) (3)				Nuclide:		Cs-137 (2)	
run j Conc.								
Min.	27	9.E-2	27	2.E-1	45	1.E-1	42	5.E-3
Ref. Ci/m³		7.1		5.0		5.E-1		3.E-2
Max.	41	62.5	41	24.3	56	1.0	57	9.E-2
par. i "P_i" $t_{C,i-k\neq i}$	1 Q	-0.51	1 Q	-0.63	1 Q	-0.31	17 $\sigma_{y_o,D}$	-0.37
	23 $\sigma_{z_o,D}$	0.21	17 $\sigma_{y_o,D}$	-0.16	18 $\sigma_{y_o,E}$	-0.22	33 $V_{d,A}$	-0.23
	6 D_A	0.15	9 $h_{m,B}$	0.14	2 r	-0.17	18 $\sigma_{y_o,E}$	-0.21
	4 $f_{PR,A-D}$	-0.12	2 r	-0.09	17 $\sigma_{y_o,D}$	-0.16	15 ,B	-0.16
	21 $\sigma_{z_o,B}$	0.11	39 $\Lambda_{3,A}$	-0.09	6 D_A	0.15	19 ,F	-0.14

Distance (km)	0.2 - 0.5		0.8 - 1.2		8 - 12		80 - 120	
Concentration:	Ground Surface (2)				Nuclide:		I-131 (1)	
run j Conc.								
Min.	45	6.E-2	45	5.E-2	45	1.E-2	8	2.E-4
Ref. Ci/m²		1.7		1.1		1.E-1		4.E-3
Max.	8	63.3	8	35.6	3	5.E-1	57	1.E-2
par. i "P_i" $t_{C,i-k\neq i}$	32 $V_{d,I}$	0.38	32 $V_{d,I}$	0.44	32 $V_{d,I}$	0.60	17 $\sigma_{y_o,D}$	-0.24
	1 Q	-0.32	1 Q	-0.33	34 $\Lambda_{1,I}$	0.14	16 ,C	-0.23
	38 $\Lambda_{3,I}$	0.17	38 $\Lambda_{3,I}$	0.15	24 $\sigma_{z_o,E}$	-0.12	18 ,E	-0.22
	23 $\sigma_{z_o,D}$	0.16	23 $\sigma_{z_o,D}$	0.10	38 $\Lambda_{3,I}$	0.11	32 $V_{d,I}$	0.22
	3 h_Q	-0.10	34 $\Lambda_{1,I}$	0.10	18 $\sigma_{y_o,E}$	-0.10	15 $\sigma_{y_o,B}$	-0.15
Concentration:	Ground Surface (2)				Nuclide:		Cs-137 (2)	
run j Conc.								
Min.	34	1.E-3	2	8.E-4	34	7.E-5	2	5.E-6
Ref. Ci/m²		3.E-2		1.E-2		2.E-3		8.E-5
Max.	42	6.E-1	42	4.E-1	3	2.E-2	3	4.E-4
par. i "P_i" $t_{C,i-k\neq i}$	33 $V_{d,A}$	0.37	33 $V_{d,A}$	0.46	33 $V_{d,A}$	0.68	33 $V_{d,A}$	0.45
	1 Q	-0.30	1 Q	-0.35	35 $\Lambda_{1,A}$	0.16	17 $\sigma_{y_o,B}$	-0.24
	37 $\Lambda_{2,A}$	0.20	35 $\Lambda_{1,A}$	0.16	37 $\Lambda_{2,A}$	0.16	16 ,C	-0.19
	35 $\Lambda_{1,A}$	0.20	17 $\sigma_{y_o,D}$	-0.12	1 Q	-0.15	35 $\Lambda_{1,A}$	0.16
	23 $\sigma_{z_o,D}$	0.18	37 $\Lambda_{2,A}$	0.12	3 h_Q	-0.09	10 $h_{m,C}$	-0.15

Table 4..3-1: Statistical tolerance confidence limits and partial rank correlation coefficients.

- the (averaged) concentration assessed with the reference values of the uncertain parameters p_i;
- the maximum (averaged) concentration from the 59 parameter vectors $\vec{p}_j$.

All the concentrations are averages over the 115 weather sequences.

The uncertainty statement reads:

> At a subjective confidence level of 95% the averaged[1]) concentration of the respective type and nuclide at the respective distance under the plume centerline is below the given maximum[2]) value.

Subsequently the parameter ranking provided by the partial rank correlation coeffcients derived from Kendalls τ is presented. Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in Table 4.1.2-1 of paragraph 4.1.2 and its meaning in the context of the atmospheric dispersion model is explained in /3/. It should be noted that coefficients of small absolute value are lacking statistical significance with respect to the case of independence.

The table applies to centerline concentrations averaged over 115 weather sequences (FK2 release). It provides for three concentration types, two nuclides and four distances the indices j of those parameter vectors $\vec{p}_j$ (or submodel runs) that led to the extreme (Min., Max.) concentration values among the 59 runs. Additionally the respective averaged concentration values are shown together with those (Ref.) obtained for the reference values of the uncertain parameters. Subsequently the indices i of the parameters with the empirical partial rank correlation coefficients (Kendall) $t_{C,i\cdot k\neq i}$ of largest absolute

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1) Average over the specific sample of 115 weather sequences basic to this investigation

2) Statistical tolerance limit

value are listed together with the parameter symbol (cf. Table 4.1.2-1 for details) and the value of $t_{C,i \cdot k \neq i}$. Coefficients of small absolute value are lacking statistical significance.

The partial rank correlation coefficients in Table 4.3-1 reveal interesting connections between the assessed concentrations of a specific type, nuclide and at a specific distance on one hand and the parameter uncertainties on the other hand. Some of these connections will now discussed:

- Plume, I-131:
  Distance 1: The uncertainty in the best value of the released thermal energy Q seems to be the most important parameter uncertainty. The negative sign of the coefficient indicates a counter-current influence on the concentration (large best value Q: small concentration). Q is followed by the vertical dispersion parameter σ_z [1]) for diffusion category D and the plume rise correction D_A for area sources, both acting in the same direction (large parameter value: large concentration). It should be noted that the influence of the latter would not be revealed so well by a separate effect sensitivity analysis based on a one-at-a-time design since the effect of D_A on the concentration is more pronounced for large Q.

  Distance 2: Still Q seems to be most influential followed, however, by the also counter-current influence of the uncertainty in the horizontal dispersion parameter σ_y [2]) for diffusion category D. D_A received a lower ranking at this distance.

  Distance 3: Here the uncertainties in the horizontal dispersion parameters σ_y for diffusion categories D and E seem to be most important followed by the mixing height for diffusion category D, all acting in a counter-current manner on the concentration.

---

1) more precisely the constant coefficient σ_{z_o} in the expression for σ_z (see Sec. 4.1.1)

2) more precisely the constant coefficient σ_{y_o} in the expression for σ_y (see Sec. 4.1.1)

Distance 4: Clearly the uncertainties in the horizontal dispersion parameters σ_y for various diffusion categories are dominant here.

Cs-137:
Principally the same conclusions seem to hold for the nuclide Cs-137 except for the parameter r (to correct wind speed data) appearing in the list instead of the mixing height at distance 3 and $\sigma_{y,F}$ receiving some higher ranking at distances 3 and 4.

Ground Surface, I-131 :
Distance 1: The uncertainty in the dry deposition velocity of iodine $v_{d,I}$ seems to be most influential, acting concurrently (large $v_{d,I}$: large concentration on the ground surface). It is immediately followed by Q, again acting counter-currently, and by the iodine wash-out coefficient $\Lambda_{3,I}$ for rainrate class 3 being influential in the same direction as $v_{d,I}$.

Distance 2: Still $v_{d,I}$ seems most influential again followed by Q and $\Lambda_{3,I}$.
Distance 3: The influence of the uncertainty in $v_{d,I}$ seems to be even more pronounced here, now followed by the iodine wash-out coefficient for rainrate class 1.

Distance 4: As in the case of the concentration in the plume the uncertainties in the horizontal dispersion parameters are dominant at this distance - $v_{d,I}$ is still of importance.

Cs-137:
Similar conclusions seem to hold for Cs-137, of course, with $v_{d,I}$ and $\Lambda_{.,I}$ replaced by the respective parameters for aerosols. A major difference is to be observed at distance 4 where the dry deposition velocity $v_{d,A}$ still seems to dominate.

Air, I-131:
Distance 1: As in the case of the concentration in the plume Q is the leading parameter uncertainty here, followed by $\sigma_{z_o,D}$ and D_A.

Distance 2: Much the same picture as for the concentration in the plume.

Distance 3: In contrast to the concentration in the plume the uncertainty in the dry deposition velocity $v_{d,I}$ is of importance here. It acts counter-currently while in the case of the concentration on the ground surface it acted concurrently. $V_{d,I}$ is followed by Q, $\sigma_{y_o,E}$ and $h_{m,D}$.

Distance 4: Still the uncertainty in $v_{d,I}$ is important now followed by the horizontal dispersion parameters acting, as in all other cases, in a counter-current manner.

Cs-137:
Much the same picture for distances 1,2 and 4. Otherwise the main difference lies in the ranking of $v_{d,A}$, the dry deposition velocity of aerosols.

From this probabilistic uncertainty analysis of concentrations under the plume centerline at selected distances and averaged over 115 weather sequences it may be concluded that the parameter uncertainties, most important to these concentrations, are those in

- Q best value of the released thermal energy,
- v_d dry deposition velocities for iodine and aerosols,
- Λ wash-out coefficients for iodine and aerosoles for various rainfall rates,
- σ_y horizontal dispersion parameters for various diffusion categories,
- σ_z vertical dispersion parameters for various diffusion categories.

ii) ccdf of the centerline concentration at a specific distance

The analysis results are illustrated by Figs. 4.3-1 to 4.3-4. The figures present for the ground surface concentration of I-131 at the selected distance the ccdf of the concentration under the plume centerline, as it is assessed with the reference values of the uncertain parameters (solid line). Additionally a continous connection of the maximum ccdf values from the 59 parameter vectors $\vec{p}_j$ is shown (dashed line).

The uncertainty statement reads:

> At a subjective confidence level of 95% the conditional probability[1] for the concentration (of the respective type, nuclide and at the respective distance under the plume centerline) to exceed x is below the ordinate value at x of the dashed curve[2].

The figure captions present the parameter ranking provided by the partial rank correlation coefficients $t_{F,i\cdot k\neq i}$, derived from Kendall's τ, for one or two selected argument values x of the ccdf. Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in Table 4.1.2.-1 of section 2.2.1 and its meaning in the context of the atmospheric dispersion model is explained in Chap. 4.1.1. It should be noted that coefficients of small absolute value are lacking statistical significance with respect

---

1) Derived from the specific sample of 115 weather sequences basic to this investigation and conditional on a FK2 release.

2) Statistical tolerance confidence limit - the possible error in estimating the required 95% fractile from a limited sample (n=59) is accounted for.

to the case of independence. The partial rank correlation coefficients reveal interesting connections between the assessed ccdf-value at x and the parameter uncertainties. To give an example some of these connections in Fig.4.3.-1 will now be discussed:

- At x = 0.01 $[Ci/m^2]$:
  The uncertainty in the best value of the released thermal energy Q seems to be the most important parameter uncertainty. The negative sign of the coefficient $t_{F,1\cdot k\neq 1}$ indicates a counter-current influence (Larger Q: Smaller probability for concentrations > x = 0.01). Q is followed by the uncertainties in vertical dispersion parameters, which seem to act concurrently.

- At x = 1 $[Ci/m^2]$:
  Still the uncertainty in Q receives the highest ranking but, different to the situation at x = 0.01, it is now immediately followed by the uncertainty in the dry deposition velocity of iodine. The larger this parameter the larger the probability for concentrations > x = 1. This parameter ranking for the ccdf value at x = 1 happens to be very similar to the one given in Table 4.3-1 for the ground surface concentration of I-131 at 0.2-0.5 km averaged over the 115 weather sequences. However, as the example shows, rankings at other argument values x may differ remarkably. The study of the rankings at different argument values of the ccdf provides a more detailled indication of the influence of the parameter uncertainties as compared to the study of rankings for averaged concentrations.

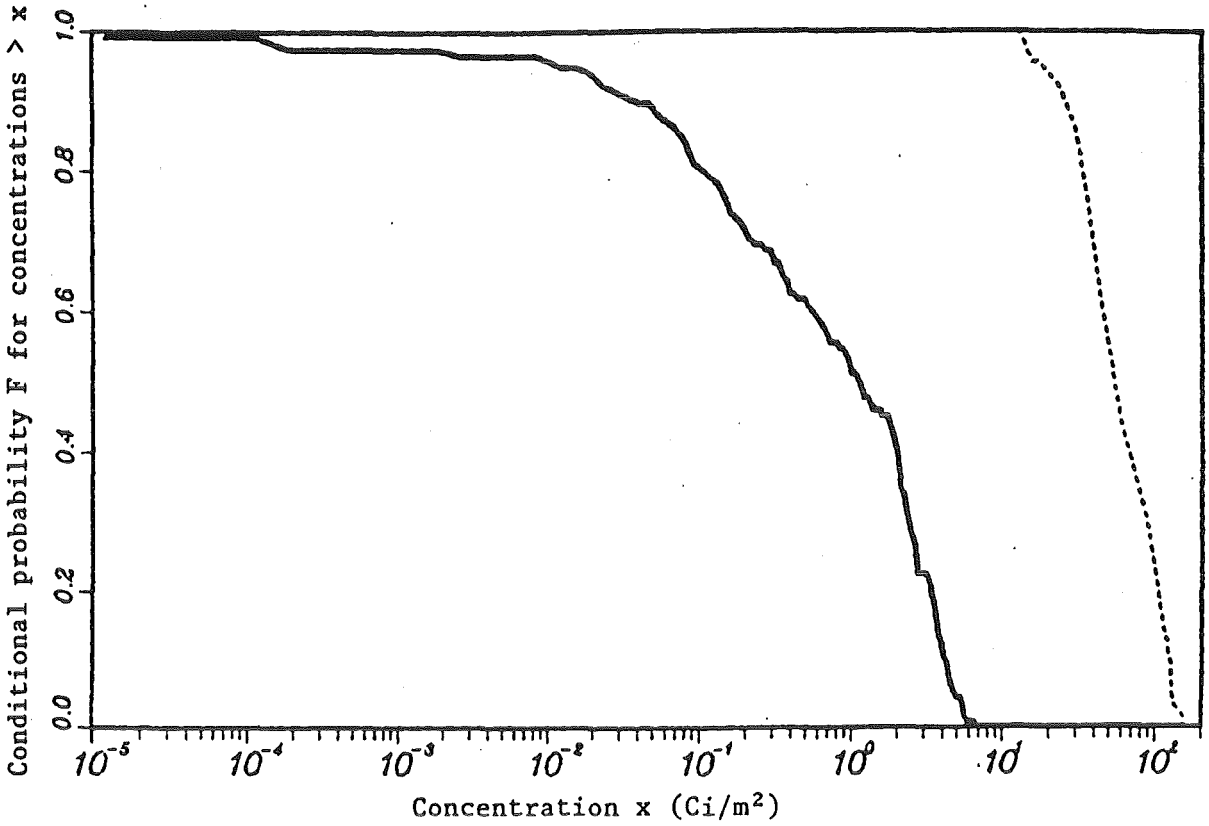

Figure 4.3-1: Complementary cumulative distribution function (conditional on a FK2 release) of the concentration under the plume centerline for

- conc. type: Ground surface
- nuclide: I-131
- distance: 0.2-0.5 km.

Solid line: ccdf assessed with the reference values of the uncertain parameters

Dashed line: Subjective 95% confidence limit of the ccdf value at x.

Parameter ranking:

At x = 1 $[Ci/m^2]$:

i	symb.	$t_{F,i \cdot k \neq i}$
1	Q	-0.40
32	$V_{d,I}$	0.31
23	$\sigma^{zo,D}$	0.19
38	$\Lambda^{3,1}$	0.14
3	h_Q	-0.14

At x = 0.01 $[Ci/m^2]$:

i	symb.	$t_{F,i \cdot k \neq i}$
1	Q	-0.45
23	$\sigma_{zo,D}$	0.18
24	$\sigma^{zo,E}$	0.15
13	$h^{zo,F}$	0.12
25	$\sigma^{m,F}_{zo,F}$	0.12

Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in table 4.1.2-1 of paragraph 4.1.2. Coefficients of small absolute value are lacking statistical significance.

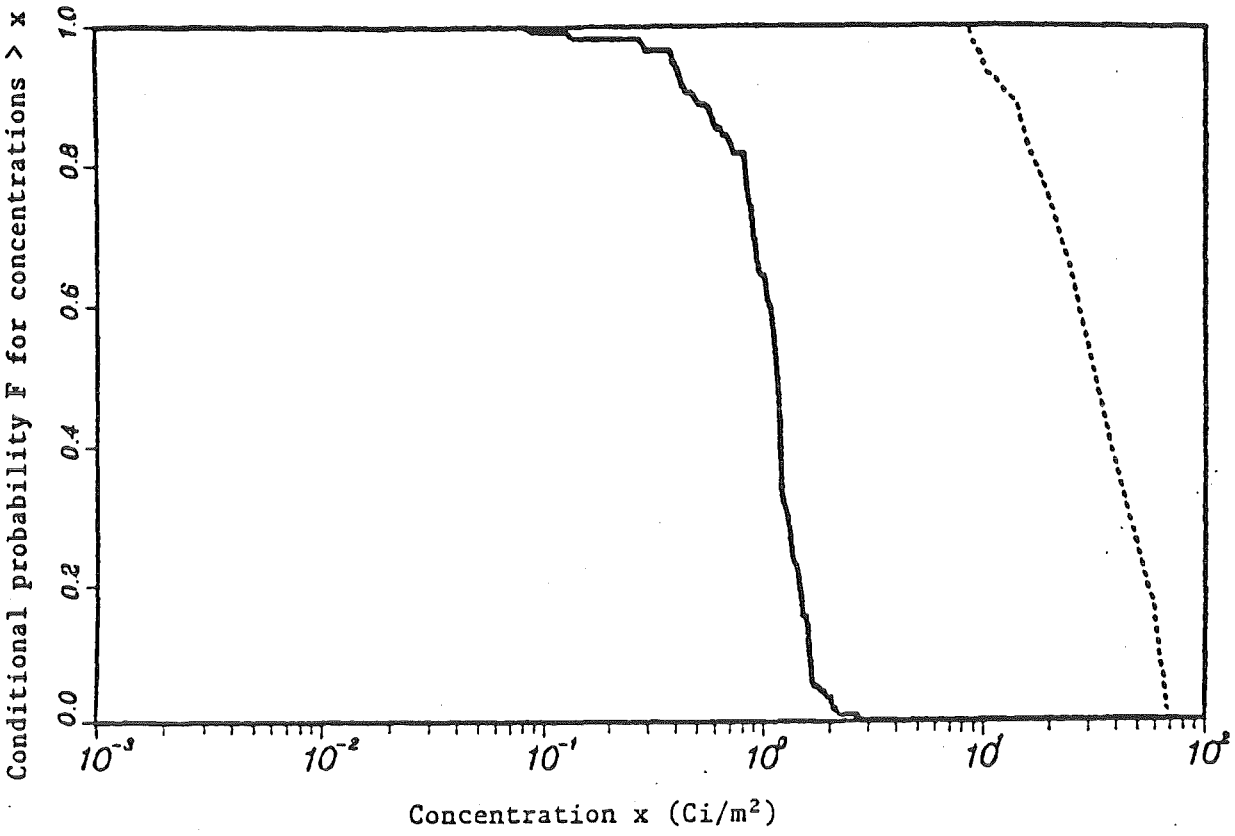

Figure 4.3-2: Complementary cumulative distribution function (conditional on an FK2 release) of the concentration under the plume centerline for

- conc. type: Ground surface
- nuclide: I-131
- distance: 0.8-1.2 km.

Solid line: ccdf assessed with the reference values of the uncertain parameters

Dashed line: Subjective 95% confidence limit of the ccdf value at x.

Parameter ranking at x = 0.5 $\left[\mathrm{Ci/m^2}\right]$:

i	symb.	$t_{F,i\cdot k\neq i}$
1	Q	-0.40
32	$V_{d,I}$	0.38
38	$\Lambda_{3,I}$	0.15
28	p_C	-0.10
23	$\sigma_{zo,D}$	0.09

Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in table 4.1.2-1 of paragraph 4.1.2. Coefficients of small absolute value are lacking statistical significance.

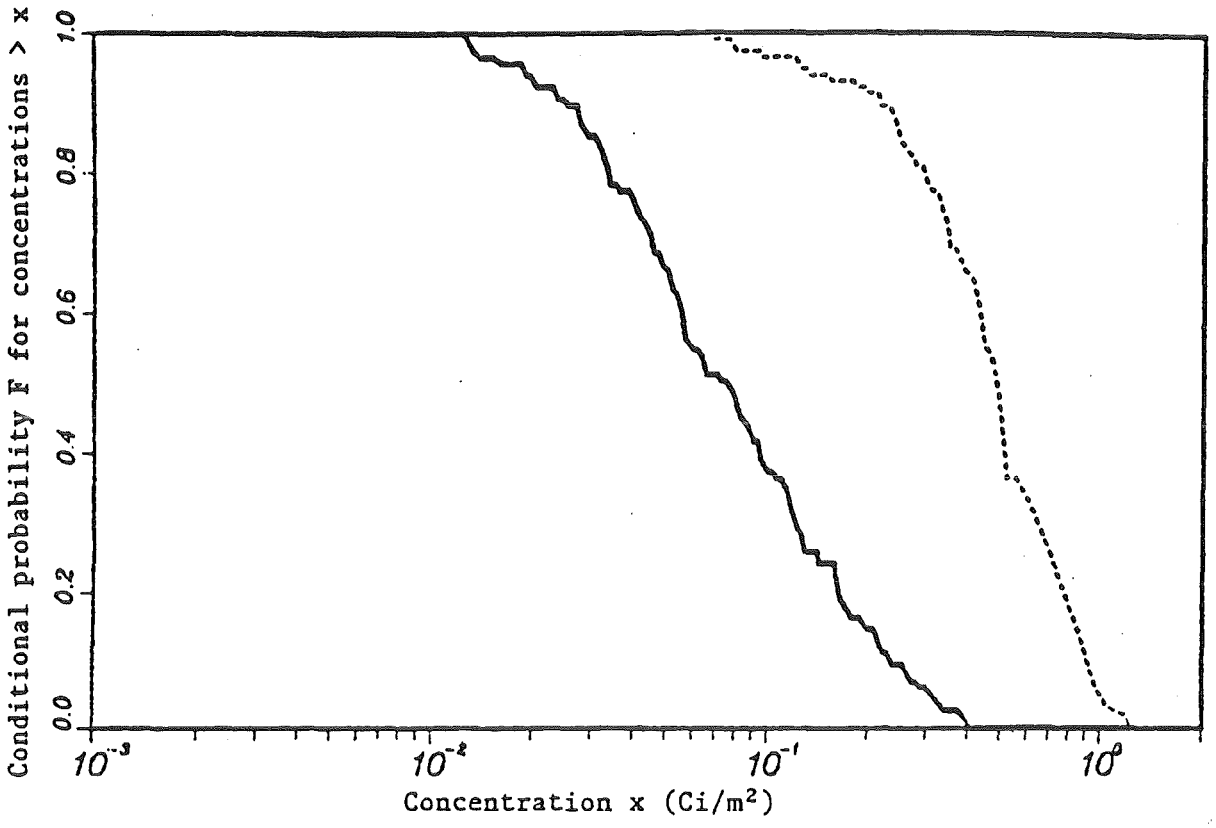

Figure 4.3-3: Complementary cumulative distribution function (conditional on a FK2 release) of the concentration under the plume centerline for

- conc. type: Ground surface
- nuclide: I-131
- distance: 8-12 km.

Solid line: ccdf assessed with the reference values of the uncertain parameters

Dashed line: Subjective 95% confidence limit of the ccdf value at x.

Parameter ranking at x = 0.1 $\left[Ci/m^2\right]$:

i	symb.	$t_{F,i\cdot k\neq i}$
32	$V_{}$	0.63
34	$\Lambda^{d,I}_{1}$	0.16
17	$\sigma^{1,I}$	-0.14
24	$\sigma^{yo,D}$	-0.11
38	$\Lambda^{zo,E}_{3,I}$	0.10

Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in table 4.1.2-1 of paragraph 4.1.2. Coefficients of small absolute value are lacking statistical significance.

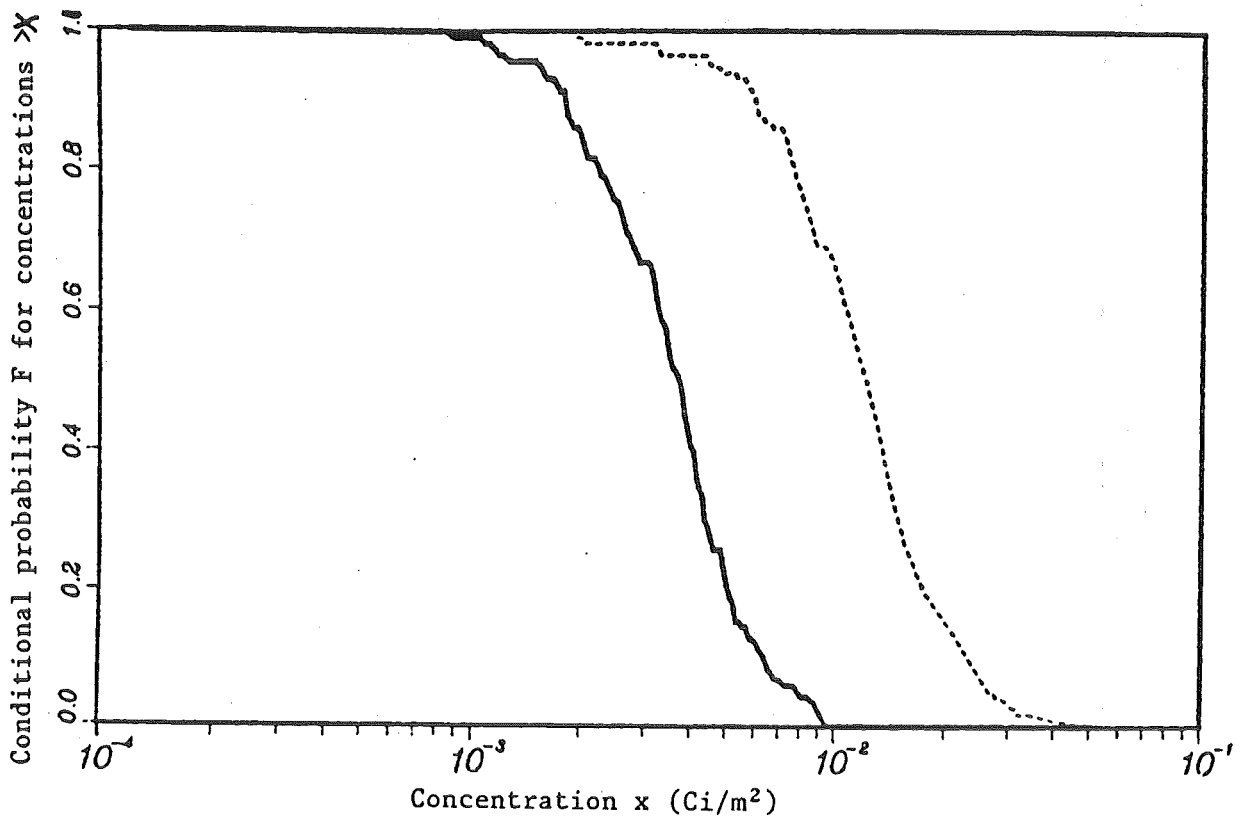

Figure 4.3-4: Complementary cumulative distribution function (conditional on a FK2 release) of the concentration under the plume centerline for

- conc. type: Ground surface
- nuclide: I-131
- distance: 80-120 km.

Solid line: ccdf assessed with the reference values of the uncertain parameters

Dashed line: Subjective 95% confidence limit of the ccdf value at x.

Parameter ranking at x = 0.001 $[Ci/m^2]$:

i	symb.	$t_{F,i \cdot k \neq i}$
16	σ	-0.23
15	$\sigma^{yo,C}$	-0.20
12	$h^{yo,B}$	0.16
32	$V_d^{m,E}$	0.15
31	$p_F^{d,I}$	-0.15

Only the five coefficients of largest absolute value are listed together with the corresponding parameter index i. The actual parameter name may be found in table 4.1.2-1 of paragraph 4.1.2. Coefficients of small absolute value are lacking statistical significance.

(iii) Average area exhibiting concentration values from a specific interval

For the ground surface concentration of I-131 from four intervals the minimum (Min.) and maximum (Max.) area from the 59 parameter vectors $\vec{p}_j$ as well as the area (Ref.) assessed with the reference values of the uncertain parameters p_i are presented below. All the areas are averages over the 115 weather sequences.

The corresponding uncertainty statement reads:

> At a subjective confidence level of 95% the average area exhibiting a ground surface concentration of I-131 from the respective interval is below the given maximum value.

The PRCC[1] reveal connections between the assessed averaged land area exhibiting a ground surface concentration of I-131 from a specific interval on the one hand and the parameter uncertainties on the other hand. To give an example some of these connections are now discussed for the intervals of lowest and highest concentration values:

- $<10^{-4}$ Ci/m^2: {Min., Ref., Max.} = {9200, 29300, 366600} km^2
  The uncertainty in the horizontal dispersion parameters acts on the uncertainty in the averaged land area with concentrations from this interval in a concurrent manner. However, as indicated above, it shows counter-current influence on the (averaged) centerline concentration at 80-120 km. This agrees very well since the counter-current influence indicates larger areas exhibiting small concentrations if σ_{y_o} is increased.
- >1Ci/m^2: {Min., Ref., Max.} = {$6.7 \cdot 10^{-5}$, 0.34, 5.3} km^2
  The uncertainty in the averaged land area with concentrations from this interval is influenced concurrently by the uncertainty in the dry deposition velocity of iodine ($v_{d,I}$) and counter-currently by the uncertainty in the

1) PRCC = Partial rank correlation coefficient

"best value" to be used for released thermal energy (Q). Again, this agrees with the information obtained for the averaged centerline concentrations at smaller distances (related to the area of highest concentration values).

(iv) CCDF of the area exhibiting concentration values from given intervals

Figure 4.3-5 presents for the ground surface concentration of I-131 and four intervals of concentration values the ccdf of the respective area of land, as it is assessed with the reference values of the uncertain parameters (solid line). Additionally a continuous connection of the maximum ccdf values from the 59 parameter vectors $\vec{p}_j$ is shown (dashed line).

The uncertainty statement reads:

> At a subjective confidence level of 95% the conditional probability[1)] for an area larger than x km^2 to exhibit a ground surface concentration of I-131 from the respective interval is below the ordinate value at x of the dashed curve.

The PRCCs now reveal connections between the assessed ccdf value at x and the parameter uncertainties. To give an example some of these connections in Fig. 4.3-5c are discussed:

- At x = 100 km^2 the uncertainty in the probability for an area larger than 100 km^2 to exhibit a ground surface concentration of I-131 between 0.02 and 1.0 Ci/m^2 is dominated by the uncertainty in the dry deposition velocity of iodine $v_{d,1}$.
- At x = 250 km^2 the uncertainty in $v_{d,1}$ is less influential, but still dominant and followed by the uncertainty in the wash-out coefficient for the third class of rainfall rates.

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1) Derived from the specific sample of 115 weather sequences basic to this investigation and conditional on a FK2 release.

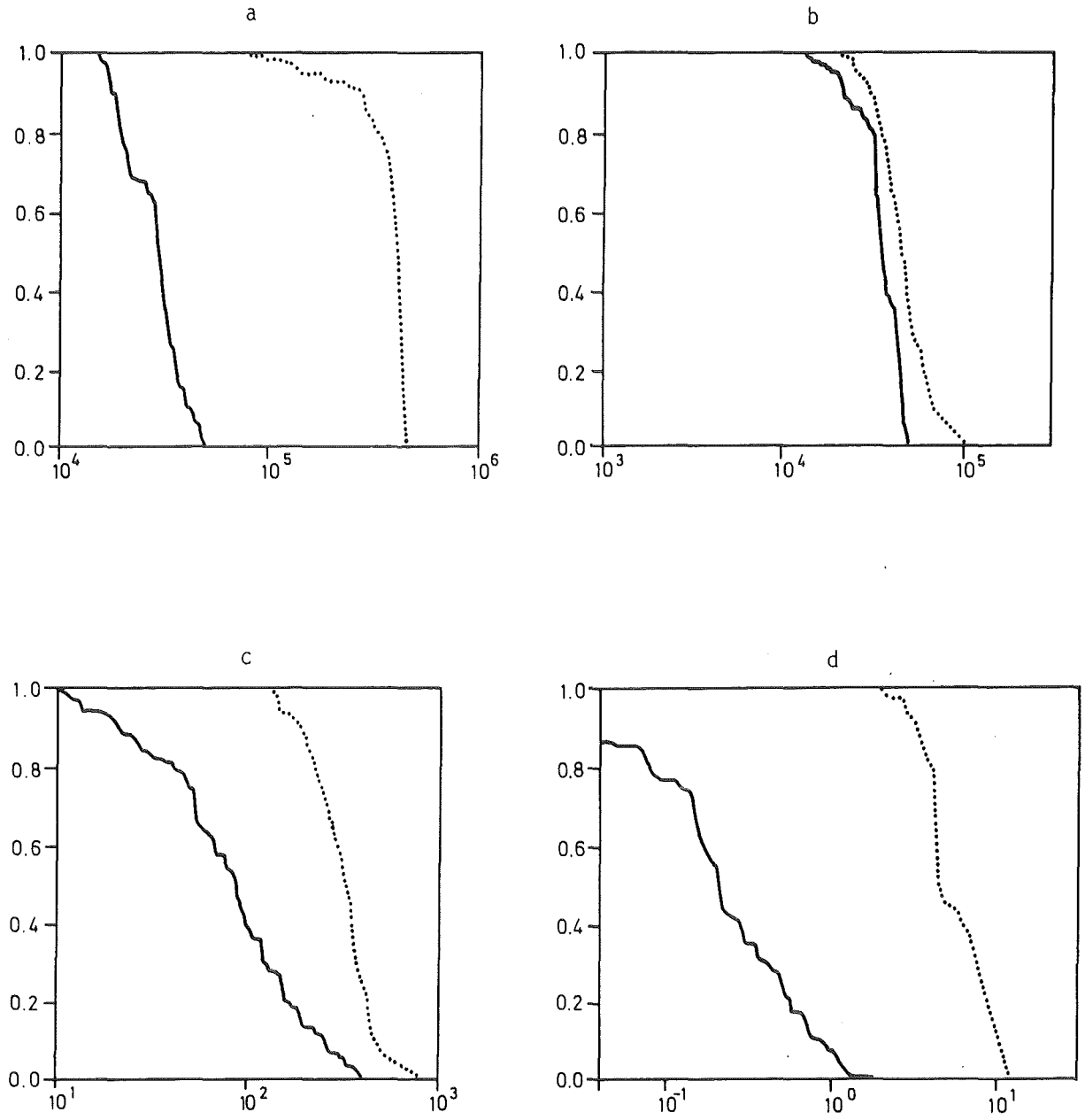

Figure 4.3-5: Complementary cumulative distribution function (conditional on a FK2 release) of the area exhibiting a ground surface concentration of I-131 from the interval (Ci/m^2): (+)

(a) $< 10^{-4}$, (b) 10^{-4}-$2 \cdot 10^{-2}$, (c) $2 \cdot 10^{-2}$-1, (d) > 1.

Horizontal axis: Area x $[km^2]$
Vertical axis : Conditional probability F for areas > x
Solid line: ccdf assessed with the reference values of the uncertain parameters
Dashed line: Subjective 95% confidence limit of the ccdf value at x.

(+) see HOFER et al /39/

From the probabilistic uncertainty analysis of land areas with concentration values from different intervals as well as center-line concentrations at selected distances it may be concluded that the most important parameter uncertainties, are those in

- Q best value of the released thermal energy
- v_d dry deposition velocities for iodine and aerosols
- Λ wash-out coefficients for iodine and aerosols for various rainfall rates
- σ_y horizontal dispersion parameters for various diffusion categories
- σ_z vertical dispersion parameters for various diffusion categories
- f_{PR} factor to describe plume rise for different diffusion categories
- r quantity to describe error in wind speed

The latter two parameters received a high ranking in the study of areas for one type of nuclide and one medium interval of concentration values only.

These conclusions as well as the uncertainty statements above (subjective 95% confidence limits) are, of course, highly dependent upon the uncertainty quantifications and their probabilistic modeling as given by the submodel experts. Needless to say, that only the influence of the quantified uncertainties can show up in the uncertainty statements and parameter rankings given above. The latter may be considered appropriate if the influence of all uncertainties not quantified may be neglected.

Remark:

Some details on correlation coefficients and the modelling of dependence between input parameters (for MC-simulation of dependent parameters in the tolerance-limit design) are given in HOFER/KRZYKACZ /7/.

□

A. APPENDIX

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A.1. One-At-A-Time-Design

Procedure steps

- Consider k input uncertain parameters but one as constants at some central value. (e.g. 50%-fractile)
- Select two (resp. four) other values of this one parameter . (e.g. Min.,Max.resp.; Min.,10%-fractile, 90%-fractile, Max.)
- Perform two (resp. four) computer runs (accident consequence code) with k-1 parameters at their central value and one parameter at these two (resp. four) selected values.
- Repeat this procedure for all k variables, i.e. 2k + 1 (resp. 4k + 1) computer runs.

For the UFOMOD accident consequence code we have:

$$k = 39 \Longrightarrow 4k + 1 = 157 \text{ UFOMOD runs}$$

D-Criterion for importance

As criterion for importance the distance of the target values (concentrations) resulting from the two cases

- input variable is at one of its four levels
- input variable is at its central level

was chosen.

The distance measure is defined as:

$$D_j := \sum_{i=1}^{4} P_i (C^* - C_{ij})^2 \qquad j=1,\ldots,39$$

whereby the levels i depict the cases

i = 1: variable x_j at Min
i = 2: variable x_j at 10%-fractile
i = 3: variable x_j at 90%-fractile
i = 4: variable x_j at Max

$P_1 = 0.1$
$P_2 = 0.4$
$P_3 = 0.4$
$P_4 = 0.1$

are the weighting factors for the squared difference between C^* and C_{ij},

C^* 'central value' of concentrations (all input variables at 50%-fractile)

and C_{ij} concentration value, if variable x_j is at level i (all other variables at central value)

Remark

The choice of the weights is motivated by the fact that due to the probability of occurence the attention is focussed rather on the central part of the input parameter distributions than on their tails.

□

Criticism and Limitations of a One-At-A-Time-Design

In Chap. 2.2 the principles of uncertainty investigations are mentioned:

- Partition of the study in some procedure steps to get insight into models and methods on submodel basis.

- Corresponding to the commonly justified practice 'to start somewhere' we have tried to study the effects of varying a single input parameter at a time only as a prelude to the study of varying several factors simultaneously.

- Moreover, following MAZUMDAR et al. /16/, this type of design is favoured as the simplest way to get some sort of visual appreciation of the form of input-output dependency.

- Following BOX/HUNTER/HUNTER /21/ there is the statement:

"The one-at-a-time design method provides an estimate of the effect of a single parameter at selected fixed conditions of the other parameters . However for such an estimate to have general relevance it is necessary to assume that the effect would be the same at other settings of the other parameters - that, over the ranges of current interest, the parameters act on the response additively."

A.2 Modelling Remarks to Tolerance Limit-Design

(see HOFER/KRZYKACZ /7/)

Generally a large number of evaluation points $\vec{p}_j$, $j=1,2,\ldots,n$ (parameter vectors, with components $p_{i,j}$, $i=1,2,\ldots,k$) is selected at random from the (subjective) joint probability distribution employed to model the uncertainties in the parameters P_i of the computational PRA models (for instance, the accident consequence model).

- Let $F(\vec{p};x)$ be the value of the ccfd at x for a given parameter vector $\vec{p}$.
- Order the $F_j := F(\vec{p}_j;x)$, $j=1,2,\ldots,n$ (n=1000, for instance) so that $F_{j_1} \leq F_{j_2} \leq \cdots \leq F_{j_{1000}}$
- Use $F_{j_{950}}$ as an estimate of the local (at x) subjective 95% confidence limit of $F(\vec{p}^*;x)$ where $\vec{p}^*$ is the appropriate parameter vector.
- Confidence limits to this fractile (other customary names: percentile, quantile) estimate of $G(F(\vec{p};x))$ may be obtained from order statistics.
- $F_{j_{950}}$ may serve as a local subjective 95% confidence limit of $F(x)$ (the value at x of the appropriate ccfd) provided all uncertainties not quantified may be neglected.

We may say:

The expected frequency per year (or per year and y reactors etc.) of accidents with consequence magnitude large than x is below $F_{j_{950}}$ at a subjective confidence level of 95% provided all uncertainties not quantified may be neglected.

- The meaning in consequence direction:
  The consequence magnitude x per accident, exceeded with the expected frequency w per year (or per year and y reactors) lies below $x_{j_{950}}$ at a subjective confidence level of 95% provided ...
  Here we assign x_j locally (at w) to $\vec{p}_j$ if $F(\vec{p}_j;x_j) = w$ and order the x_j so that $x_{j_1} \leq x_{j_2} \leq \cdots \leq x_{j_{1000}}$.

However: It is generally infeasible, for practical reasons, to have 1000 ccfds by direct MC simulation.

Therefore: Statistical tolerance limits may serve as a satisfactory alternative.

We observe ($F(\vec{p};x)$ assumed to be continuous) from order statistics STECK et al /17/ GIBBONS /46/ that for quite modest $n(<<1000)$ F_{j_n} can be used as a γ% confidence limit of the α% fractile of the (unknown subjective) probability distribution $G(F(\vec{p};x))$, i.e.

$$\text{Prob}\{G(F_{j_n}) \geq \frac{\alpha}{100}\} \geq \frac{\gamma}{100}$$

Required values of n for F_{j_n} to be an upper γ% confidence limit of the α% fractile:

$\frac{\alpha}{100}$ \ $\frac{\gamma}{100}$	0.90	0.95	0.99	0.995
0.50	4	5	7	8
0.90	22	29	44	51
0.95	45	59	90	104
0.99	230	299	459	528
0.995	460	598	919	1058

Table A.4-1: Necessary runs for (α, γ)-tolerance limits

The simplest case of a tolerance limit can be determined from the ordered sample. Since it is based only on order statistics of the sample and does not require any distributional assumptions on G it will be called distribution-free tolerance limit.

Let $Y_1,\ldots Y_n$ be a sample from an arbitrary distribution G (not necessarily assumed to be continuous!) and let $Y^*=Y_{j_n} := \max\{Y_1,\ldots,Y_n\}$

Using some well known properties of order statistics it may easily be shown that $G(Y_{j_n})$ is a random variable with the property:

$$p(G(Y_{j_n})<z) \leqq z^n \quad (z \in [0,1])$$

(equality holds for continuous distribution G!).

Let $\vec{U(Y)}$ be defined by

$$L(\vec{Y}) := Y_{j_n} = Y^*$$

where n is the smallest integer satisfying

$$1 - \alpha^n \geqq \gamma.$$

Then

$$\begin{aligned} p(G(L(\vec{Y})) \geqq \alpha) &= p(G(Y^*) \geqq \alpha) \\ &= 1 - p(G(Y^*)<\alpha) \\ &\geqq 1 - \alpha^n \\ &\geqq \gamma \end{aligned}$$

i.e. Y^* is a (α,γ)-tolerance limit.

The table shows the numerical values of $n=n(\alpha,\gamma)=\left(\frac{\ln(1-\gamma)}{\ln \alpha}\right)$.

So: 59 runs (giving 59 ccfds) would render a (γ=) 95% upper confidence limit of the (α=) 95% fractile of $G(\vec{p};x)$ which is the local subjective upper (α=) 95% confidence limit of $F(\vec{p}^{*};x)$.

- 59 runs may still require too much CPU;
- More than 59 runs will be needed if the sensitivity to distribution type, chosen for the p_i, is to be studied.

A.3 Catchwords for Latin Hypercube Sampling

- Sampling

  · Random sampling may result in a selection of k-tupel $(X_1,\ldots,X_k)$ where the full range of the uncertain input parameters X_i (i=1,...k) is not covered.

  · In stratified random sampling all areas of the sample space S of the parameter vector $\vec{X} = (X_1,\ldots,X_k)$ are represented by input parameters. But one might randomly select the corners of the input parameters range, say X_i, and thus not adequately represent the middle of the X_i-input parameter range.

  (To do stratified sampling one has to partition the sample space S of the parameter vector $\vec{X} = (X_1,\ldots,X_k)$ into M disjoint strata S_i, where $p_i = \text{Prob}(\vec{X} \in S_i)$. Get a random sample X_{ij} ((j=1,...,n_i), n_i=k) from S_i. If i=1 one has the case of random sampling.)

  · Latin Hypercube sampling
  If we wish to ensure that each of the parameters X_i (i=1,...,k) has all portions of its distribution represented by input parameters, a partition of the range of each parameter into N strata (generally with equal probability) is required. The components of the 'partioned' X_i are matched randomly without replacement. If there are only two input parameters this method of sampling is called Latin square sampling. LHS can be viewed as a k-dimensional extension of Latin square sampling. One has k^N 'partition elements' (cells) which cover the sample space of $X = (\vec{X}_1,\ldots,X_k)$.

(Note: A LHS-plan for response surfaces construction uses the same number of intervals for each input parameter as the number of computer runs!(see McKAY/CONOVER/WHITEMAN /47/. A user-friendly FORTRAN 77-code for LHS is given in IMAN/SHORTENCARIER /48/.

Although LHS has certain advantages this parameter selection technique makes it difficult to ascertain relationships that may exist between individual independent inputs and dependent output. This difficulty arises from the concurrent variation of input parameters which results from LHS. Therefore one has to determine the effects of individual inputs on output with the effects of other parameters removed. The partial (rank) correlation coefficient can be used and treated as a measure of sensitivity.

- Partial (rank) correlation coefficient

A good sampling for selecting input parameters should permit an assessment of the relative importance of each input parameter. It is usually (in the case of linear models) measured using the partial correlation coefficient. In most nuclear codes the relationships are usually not linear. It is nevertheless reasonable to assume that the relationships between input and output are monotonous. This is more meaningful than testing linearity.

Following McKAY/BOLSTAD/WHITEMAN /29/, therefore partial rank correlation coefficients (PRCC) provide a good means for measuring monotonicity.

The PRCC is the partial correlation coefficient (PCC) evaluated using rank transformed data. The PCC measures the degree of linear association between two parameters from a multivariate structure after adjusting for the linear effects of the remaining parameters.

The PRCC measures the degree of monotonous association in the same way that the PCC measures linear association ($-1 \leq PRCC \leq 1$).

A.4 Response Surface Techniques

(see HOFER /41/)

The problem:
Certain fractiles of $G(F(\vec{p};x))$ are needed. The "random variable" $F(\vec{P};x)$ is a function of "random variables" P_i with given joint pdf. The analytical functional expression is unknown and each evaluation (real or numerical experiment) is very expensive:
Given (as computer code) the transformations

$$\pi_1 : \vec{P} \to Y := F(\vec{P};x) \quad \Rightarrow \quad \pi_2 : k(\vec{p}) \to g(F(\vec{p};x))$$

Needed:
- Not primarily a good approximation of the response surface $F(\vec{p};x)$
- Not primarily a good approximation of its subjective pdf $g(F(\vec{p};x))$

But good approximations of y_1 and y_2 with

$$\int_{-\infty}^{y_1} g(y)dy = \int_{y_2}^{\infty} g(y)dy = 0.05, \text{ for instance.}$$

A.4.1 Fitted Response Surfaces (Regression)

Principle:
- Points $\vec{p}_j$, $j = 1,2,\ldots,n$ selected (at will) from the parameter space
- Corresponding n runs of the computational model give the responses $F_j := F(\vec{p}_j;x)$
- Determine the coefficients in the set $B := \{\beta_k \mid k = 0,1,\ldots, q; q+1 < n\}$ such that
  $F(B,\vec{p};x) = \beta_0 + \beta_1\phi_1(\vec{p}) + \ldots + \beta_q\phi_q(\vec{p})$
  approximates the unknown response surface satisfactorily.
  The functions ϕ_k indicate the possibility of transformations.

- Obtain the set B by the least squares principle

$$\text{SSE: } \sum_{j=1}^{n} \left[F_j - \left(\beta_o + \sum_{k=1}^{q} \beta_k \phi_k(\vec{p}_j)\right)\right]^2 \stackrel{!}{=} \text{Min.}$$

- Obtain estimate of $F_{95}(x)$ from MC[1] - simulation with $\hat{F}(B,\vec{p};x)$.

Stepwise procedures are available in standard mathematical subroutine libraries.
Inverse polynomials may in some situations be of advantage OLIVI/PIKE /49/. Switches in the computational model are a matter of concern.

Adequacy checks are sometimes performed via:
- the empirical multiple correlation coefficient $\hat{r}(\hat{F},F)$;
  $100 \cdot \hat{r}^2$ is an estimate of the "coefficient of determination" (percentage)
  $\hat{r}^2 = SSR/(SSR+SSE)$ with $SSR = \sum_j (\hat{F}_j - \bar{F})^2$

  $SSE = \sum_j (\hat{F}_j - F_j)^2$

  so $\hat{r}$ close to 1 is good but does not guarantee mode adequacy;
- the residuals
  - residual sum of squares (SSE)
  $-(F_{jmax}-F_{jmin})/(R_{jmax}-R_{jmin})$; $R_j = \hat{F}_j - F_j$
  - empirical distribution shows the requested properties?
    - mean value close to 0
    - standard deviation small
    - pdf symmetric
    - pdf peaked at 0.
  - confidence intervals and significance levels (F-Test).
    These quantities are problematic here since F_j is identical for identical $\vec{p}_j$.

for details see IMAN/HELTON/CAMPBELL /24/,/25/, IMAN/HELTON/BROWN /33/, IMAN/HELTON /14/.

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[1] MC = Monte-Carlo

A.4.2 Fitted Response Surfaces (Interpolation) (+)

Principle:

- Select at set S of points $\vec{p}_j$ (at will) in the parameter space
- Perform the function evaluations $F(\vec{p}_j;x)$
- Determine set C of coefficients such that $\hat{F}(C,\vec{p}_j;x) = F(\vec{p}_j;x)$ for $\vec{p}_j \in S$.
- Obtain estimate of $F_{95}(x)$ from MC simulation with $\hat{F}(C,\vec{p};x)$.

Specific realization:

$$\hat{F}(C,\vec{p};x)=A + \sum_{i=1}^{m}{}' \{ B_i + C_i(p_i-\bar{p}_i) + \sum_{k=i+1}^{m} D_{i,k}(p_k-\bar{p}_k) \quad (p_i-\bar{p}_i)\}$$

$M = 1 + 2m + m(m-1)/2$ runs are needed for this second degree fitted surface. $\hat{F}$ may be formed regionwise (over each quadrant) and continuously connected. $M = 1 + 2m$ if a regionwise linear fitted surface is used (19).

Transformations of the P_i (logarithms, exponentials, powers etc.) may permit the use of a structurally simple fitted surface in the transformed variables rather than a complex one in the original P_i.

Switches in the computational model may lead to discontinuities of $F(\vec{p};x)$ and are therefore a matter of concern. Adquacy checks of the fitted response surface need to be performed. There are several possibly expensive ways suggested.

(for details see VAURIO/MUELLER /42/ and VAURIO /50/)

+ see HOFER /41/

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References

/1/ N.C. Rasmussen
Reactor Safety Study. An assessment of accident risks in US commercial nuclear power plants
US Nuclear Regulatory Commission, Washington, October 1975
NUREG-75/014, WASH 1400

/2/ Deutsche Risikostudie Kernkraftwerke (DRS)
Gesellschaft für Reaktorsicherheit (Ed.)
Verlag TÜV Rheinland, Köln, 1981
(main report and eight technical appendices)
English translation of main report by EPRI
(EPRI-NP-1804-SR (1981))

/3/ Deutsche Risikostudie Kernkraftwerke (DRS)
Fachband 8: Unfallfolgenrechnungen und Risikoergebnisse
Verlag TÜV Rheinland, Köln,1981
English translation of Appendix 8 'Analysis of accident consequences and risks' by UKAEA Northern Division (Risley Trans 4496)

/4/ A. Bayer et al
German risk study: Accident consequence model and the results of the study
Nuclear Technology
59 (1982), p. 20-50

/5/ PRA - Procedures Guide
A guide to the performance of probabilistic risk assessment for nuclear power plants
US Nuclear Regulatory Commission
NUREG/CR-2300 Vol. 1 and Vol. 2
Jan 1983

/6/ E. Hofer, B. Krzykacz
Modelling and propagation of uncertainties in the German risk study
Proceedings of the International ANS/ENS Topical Meeting of Probabilistic Risk Assessment, Port Chester, New York, Sept. 20 - 24, (1981), p. 1342 - 1354.

/7/ E. Hofer, B. Krzykacz
Uncertainty analysis of the computational assessment of the radiological consequences of nuclear accidents
CEC Study Contract, Final Report
January 1985

/8/ B. de Finetti
Theory of probability, John Wiley & Sons (1974)

/9/ R.F. Nau
Coherent assessment of subjective probability, ORC 81-5, University of California, Berkeley (March 1981)

/10/ D. Kahnemann and A. Tversky
Judgment under undertainty, Cambridge University Press (May 1982)

/11/ H. Jungermann and G. de Zeeuw (eds.)
Decision making and change in human affairs, D. Reidl Publ. Comp. (1977)

/12/ L.R. Abramson
Some misconceptions about the foundation of risk analysis
S. Kaplan and B.J. Garrick
Some misconceptions about misconceptions: A response to Abramson
L.R. Abramson
A rejoinder to Kaplan and Garrick
Letters to the Editor, Risk Analysis, Vol. 1, No. 4 (1981)

/13/ L. Olivi
Response surface methodology - handbook for nuclear reactor safety, CEC-Joint Research Center, ISPRA Establishment published by the CEC, Luxembourg Report No. EUR 9600 EN 1984.

/14/ R.L. Iman, J.C. Helton
A comparison of uncertainty and sensitivity analysis techniques for computer models
Sandia National Laboratories , Albuquerque,
New Mexico (USA), March 1985
SAND 84 - 1461
NUREG/CR - 3904

/15/ M. Mazumdar et al
Review of the methodology for statistical evaluation of reactor safety analysis
Research Project 309 (WCAO-8555) Key Phase Report,
Electric Power Research Institute (EPRI), Palo Alto, Ca,
September 1975.

/16/ M. Mazumdar et al
Methodology development for statistical evaluation of reactor safety analysis
NP 194 (Research Project 309), Final Report,
Electric Power Research Institute (EPRI), Palo Alto, Ca,
July 1976.

/17/ G.P. Steck et al
Statistical analysis of LOCA
FY 1975 Report, December 1975
SAND 75 - 0653

/18/ G.P. Steck et al
Probabilistic analysis of LOCA
Annual Report for FY 1976, December 1976
SAND 76 - 0535

/19/ J.A. Marshall et al
Additional methodology development for statistical evaluation of reactor safety analyses
NP 483 (Research Project 768-1)
Electric Power Research Institute (EPRI), Palo Alto, Ca, March 1977

/20/ J.A. Marshall et al
Application of statistical evaluation methodology to the RELAP-code
NP 1053 (Research Project 768)
Electric Power Research Institute (EPRI), Palo Alto, Ca, April 1979

/21/ G.E.P. Box, W.G. Hunter, J.S. Hunter
Statistics for experimenters
An introduction into design, data analysis and model building
J. Wiley and Sons, New York, (1978)

/22/ M.D. McKay, W.J. Conover, R.J. Beckman
A comparison of three methods for selecting values of input variables in the analysis of output from a computer code
Technometrics 2 (1979), p. 239-245

/23/ R.L. Iman, W.J. Conover
A distribution-free approach to inducing rank correlation among input variables
Comm. Statist. - Simulat. Computat., 11 (1982), p. 311-334.

/24/ R.L. Iman, J.C. Helton, J.E. Campbell
An approach to sensitivity analysis of computer models: Part I
Introduction, input variable selection and preliminary variable assessment
Journal of Quality Control, 13 (1981), p. 174-183

/25/ R.L. Iman, J.C. Helton, J.E. Cambell
An approach to sensitivity analysis of computer models: Part II
Ranking of input variables, response surface validation, distribution effect and technique synopsis,
Journal of Quality Control, 13 (1981), p. 232-240

/26/ R.L. Iman, W.J. Conover
Sensitivity analysis techniques: Self-teaching curriculum
Sandia National Laboratories, Albuquerque,
New Mexico (USA), June 1982
SAND 81 - 1978
NUREG/CR-2350

/27/ R.L. Iman, J.C. Helton
Overview of methods for uncertainty analysis and sensitivity analysis in probabilistic risk assessment
Paper presented at ANS/ENS topical meeting on Probabilistic safety methods and applications, February 24 - 28, 1985, San Francisco
SAND 84 - 1811 C

/28/ D.J. Alpert, J.C. Helton
Uncertainty and sensitivity analysis for reactor accident consequence models
in Proceedings of "Workshop on methods for assessing the off-site radiological consequences of nuclear accidents",
CEC, Luxembourg, April 15-19, 1985
SAND-0885 C

/29/ M.D. McKay, J.W. Bolstad, D.E. Whiteman
An application of statistical techniques to the analysis of reactor safety codes,
Proceedings of the topical meeting on Probabilistic Analysis of Nuclear Reactor Safety
May 8 - 10, 1978, Los Angeles
p. II.9.1 - 9.12

/30/ R.L. Iman, W.J. Conover
Small sample sensitivity analysis techniques for computer models, with an application to risk assessment
Comm. Statist. - Theor. Meth., A9 (17), (1980), p. 1749 - 1842
Rejoinder to comments: 9 (1980), p. 1863 - 1874

/31/ D.J. Downing, R.H. Gardner, F.O. Hoffman
An examination of response-surface methodologies for uncertainty analysis in assessment models.
Technometrics, 27 (1985), p. 151-163

/32/ R.L. Iman, M.J. Shortencarier, J.D. Johnson
A FORTRAN 77 program and user's guide for the calculation of partial correlation and standardized regression coefficients
June 1985
SANDIA 85 - 0044 RG
NUREG/CR - 4122

/33/ J.C. Helton, R.L. Iman, J.B. Brown
Sensitivity analysis of the asymptotic behavior of a model for the environmental movement of radionuclides, March 1985
SAND 82 - 0600J
to appear in Ecol. Modelling

/34/ W.V. Harper, S.V. Gupta
Sensitivity/Uncertainty analysis of a borehole scenario comparing Latin hypercube sampling and deterministic sensitivity approaches
Battelle Memorial Institute, Columbus, Ohio (USA)
October 1983
Report BMI/ONWI - 516

/35/ E.M. Oblow
Sensitivity theory for general nonlinear algebraic equations with constraints
Nuclear Science and Engineering, 65 (1978),
p. 187 - 191

/36/ R.E. Thomas
Uncertainty analysis
Battelle Memorial Institute, Columbus, Ohio (USA)
March 1982
Report BMI/ONWI - 318

/37/ S. Kaplan, G. Apostolakis et al
Methodology for probabilistic risk assessment of nuclear power plants
Pickard, Lowe and Garric Inc
Irvine, California, June 1981, Report PLG-0209

/38/ S. Ahmed, R.E. Clark, D.R. Metcalf
A method for propagating uncertainty in probabilistic risk assessment
Nuclear Technology 59 (1982), 238 - 245

/39/ E. Hofer, B. Krzykacz; J. Ehrhardt, F. Fischer; M.J. Crick, G.N. Kelley
Uncertainty and sensitivity analysis of accident consequence submodels
Paper presented at ANS/ENS topical meeting on Probabilistic safety methods and applications,
February 24-28, 1985, San Francisco

/40/ R.G. Easterling
Methods for statistical uncertainty analysis in PRA's, in:
Advances in Reactor Computations
Proceedings of a topical meeting, Salt Lake City,
March 28-31, 1983, p. 540-554
CONF-83 0304--13
SAND-82-2832C

/41/ E. Hofer
Probabilistic uncertainty analysis;
Methods and their applications
in:
Proceedings of "Workshop on methods for assessing
the off-site radiological consequences of nuclear
accidents"
CEC, Luxembourg, April 15-19, 1985

/42/ J.K. Vaurio and C. Mueller
Probabilistic analysis of LMFBR accident consequences with
response surface techniques
Nucl. Science & Eng. 65 (1978), p. 401-403

/43/ F. Fischer, J. Ehrhardt
Private communication
January 1984

/44/ F. Fischer, J. Ehrhardt, E. Meder
Private communication
July 1984

/45/ B.Y. Underwood, P.J. Cooper, N.J. Holloway, G.D. Kaiser,
W. Nixon
Review of specific effects in atmospheric dispersion
calculation, Volume 1
Final Report XII/917/83-EN, (1983)
Safety and Reliability Directorate, UKAEA,
United Kingdon

/46/ J.D. Gibbons
Nonparametric statistical inference
MC Graw Hill Inc, New York, (1971)

/47/ M.D. McKay, W.J. Conover, D.E. Whiteman
Report on the application of statistical techniques to the analysis of computer codes
Los Alamos Scientific Laboratory, Los Alamos, Sept. (Oct.) 1976
(LA-6479-MS) (LA-NUREG-6526-MS)

/48/ R.L. Iman, M.J. Shortencarier
A FORTRAN 77 program and user's guide for the generation of Latin hypercube and random samples for use with computer models
Sandia National Laboratories, Albuquerque,
New Mexiko (USA), March 1984
SAND 83 - 2365
NUREG/CR - 3624

/49/ L. Olivi, D.J. Pike
Response surface methodology for the analysis of reactor safety: Methodology, development and implementation
Proceedings of the Internat. ANS/ENS Topical Meeting of Probabilistic Risk Assessment, Port Chester, New York, Sept. 20-24, 1981, p.943-952

/50/ J.K. Vaurio
PROSA-2: A probabilistic response - surface analysis and simulation code.
Argonne National Laboratory, Argonne, Ill. (USA),
May 1981
ANL-81-33 or NEA-Data Base No. NESC 0778/02