Uncertainty Modeling of Radiological Risk Using Probability - Possibility Combination

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Abstract

Radiological risk analysis is an essential component for evaluating the performance criteria of nuclear power plant. Assessment of the radiological risk corresponding to the inhalation exposure finally guarantees that whether release is within limit or beyond limit, further dictating the performance of the system. However, all the parameters involved in the model used to evaluate the risk from various pathways of exposure are not possible to describe by the probability distribution. Parameters having insufficient knowledge are characterized by the possibility distribution. Possibility distribution of the parameter is addressed in terms of fuzzy set theory. The present paper proposed a probability-possibility combination in uncertainty modeling of the radiological risk keeping in mind that uncertainty analysis is an important issue for making any decision on radiological safety related problems. The paper describes the methodology of the probability-possibility combination. Methodology is illustrated with a case study of postulated release of radioactive iodine following the failure of the safety system.

Keywords: *Risk, possibility distribution, modeling, uncertainty.*

1. Introduction

Radiological risk is basically defined as the product of the consequence and likelihoods of these consequences. Consequences in case of radiological risk are measured in terms of exposures occurred from various pathways. Radiological risk analysis in case of any nuclear power plant is essential in the sense that risk analysis in this domain can provide a risk based operational guidelines of the plant. It can also provide a risk based monitoring system of the complete plant. Emergency preparedness of the plant can be designed on the basis of this risk analysis. Risk being a probabilistic measure, the parameters associated with the governing risk equation generally classified as uncertain and their uncertainties are expressed as specified random probability distributions. Usually the probabilistic paradigm is utilized to deal with uncertainty. In this context, reliability is identified with and measured by the probability that the system will perform its intended mission over a given period of time. The important part of the probabilistic analysis is the probabilistic information on input quantities. Extremely often such information is missing and safety analyst has to make far-reaching assumptions on the probabilistic information. This is perhaps one of the main reasons why the probabilistic methods do not yet enjoy wide acceptance in practice. Mathematician Wentzel [1] notes that the theory of probability is not a magic stick, which produces information from a void. These and other considerations led to the development of alternatives to the probabilistic paradigm [2]. According to Klir [3], three types of uncertainty and corresponding mathematical models can be distinguished:

(a) Uncertainty deriving from non-specificity of sets of equally possible alternatives measured through classical set approaches. Convex models of uncertainty were produced by Ben-Haim and Elishakoff [4], Elishakoff et al, [5] and they are an extension to the methods of interval analysis [6] or ellipsoidal modeling of uncertainty [7].

(b) Uncertainty deriving from conflict among the likelihood claims associated with many mutually exclusive alternatives, measured through classical probability theory.

(c) Uncertainty deriving from vagueness, namely imprecision of definition or linguistic terms in a natural or artificial language. Multivalued-logic, approximate reasoning techniques, and fuzzy logic provide us with tools for treating vague information [8].

In an analogous but independent discussion, these three extreme types of uncertainty were suggested by Elishakoff [9] as corners of an abstract triangle called uncertainty triangle. However, in practice all the uncertain parameters of a model are not possible to characterize by probability theory due to their insufficient information. The parameters having insufficient information are generally attributed as possibilistic distribution. Therefore, uncertainty modeling of risk from the various pathways of exposure is addressed here in this paper as a combination of probability and possibility. In risk analysis, the basic task consists of exploiting the mathematical model of some phenomenon, so as to predict its output when some inputs or parameters of the model are imprecisely known [10].

There are two basic reasons why such parameters or inputs cannot be assigned precise values. First, some quantities are subjected to intrinsic variability. For instance, during an inadvertent release when predicting the effect of radioactivity pollution on the health of people, it is clear that this effect depends on the particulars of individuals (their weight, for instance), and such characteristics differ from one individual to another. Another source of uncertainty is the lack of knowledge of meteorological parameters (wind speed, weather category). This lack of knowledge may stem from a partial lack of data, either because this data is impossible to collect, or too expensive to collect. This may be due to the limited precision of the measurement devices. Another possibility could be the imprecise knowledge from human experts. Baudrit and Dubois [11] have proposed the joint propagation of the probability and possibility in risk analysis. Slightly more restrictive is the theory of evidence, initiated by Dempster [12], an approach relying on the notion of random set, each set-valued realization representing a plainly incomplete information item. The set-functions generated in this mathematical framework were further exploited by Shafer [13] and Smets [14], within a purely subjectivist, non-statistical approach to uncertain evidence.

Even more restrictive is the framework of possibility theory, where pieces of information take the form of fuzzy sets of possible values [15], which can be interpreted as consonant (nested) random sets. The merit of this framework with its great simplicity enables incomplete probabilistic information on the real line which can be encoded in the form of fuzzy intervals [16, 17]. Possibility distributions can also straightway accommodate linguistic information on quantitative scales.

Likelihoods are categorized as probabilistic and possibilistic. At this juncture, it is required to know that probabilistic parameters carry the aleatory part of the uncertainty and possibilistic parameters (fuzzy parameters) carry the epistemic uncertainty of the radiological risk. In order to demonstrate the probability-possibility combination for modeling uncertainty of radiological risk a case study is presented. In the case study, postulated scenario of release of radioiodine resulting inhalation risk to the members of the public and environment is presented.

The paper is organized in the following way. Section 2 describes the framework of probability-possibility combination. Section 3 and its subsections present the uncertainty modeling of radiological risk. Results of the case study and the necessary discussions are presented in section 4.Finally conclusions are presented in section 5.

2. Framework of Probability-Possibility Combination

Uncertainty analysis using the probability-possibility combination basically addresses the admixture of probability and possibility distribution of uncertain parameters of the model. The structure of the mathematical details of the probability- possibility combination is found elsewhere in [18-27]. However, as a documentary evidence to provide the support of the present task, it should be noted that the probabilistic uncertainty is due to randomness and possibilistic uncertainty is due to vagueness or imprecise information. The later one is also named as imprecise probability. Probabilistic uncertain parameters are generally addressed by their specified probability distribution such as normal, lognormal, beta, etc. But possibilistic uncertain parameters are addressed by possibilistic distribution (distribution of fuzzy random variable). If π_x denotes a possibility distribution function of Π_X, for a crisp set A as the subset of U, one can write

$$Poss\{x \in A\} \equiv \pi(A) \equiv \sup \pi_X(u), u \in A \qquad (1)$$

When *A* is a fuzzy subset of *U*, a more general definition of possibility measure can be given as follows,

$$Poss\{x \in A\} \equiv \pi(A) \equiv \sup\{\mu_A(u) \wedge \pi_X(u)\}, u \in U \qquad (2)$$

The dual measure of possibility is the *necessity measure*, which is defined as

$$Nec(A) = 1 - Poss(\overline{A}) \qquad (3)$$

where, $\overline{A}$ is the complement of A. *Necessity measure* has the properties that $Poss(A) \geq Nec(A)$. Any probability measure is always bounded by these two boundaries, that is to say that probability measure is greater than or *equal* to *necessity measure* and less than or equal to *possibility measure*. We can say that the classical probability theory and the possibility theory are subsets of the evidence theory as shown in Figure 1.

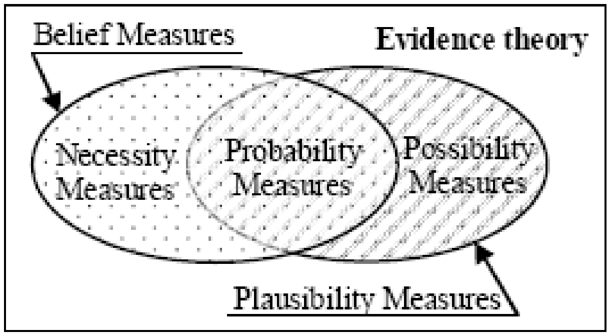

Figure 1 A pictorial description of uncertainty classification based on fuzzy measures

In the context of possibility measure, the membership function of a fuzzy set can be viewed as the possibility distribution of its singletons.

3. Uncertainty Modeling of Radiological Risk

Radiological risk presented here basically concerns about the risk from the radiation exposure in the event of reactor accidents or any inadvertent release of radioactive material in the atmospheric environment during any mal operation or failure of the passive safety systems. Mathematically, risk in this case is defined as the sum total of the consequences and the corresponding likelihoods or probabilities. Consequences are measured in terms of doses. Finally dose to risk conversion factor transforms the dose expression into a risk expression. Exposure to the members of the public or radiation worker causing from the release of the radioactive material in the event of mal operation or failure of the safety systems is modeled by considering various pathways which are (1) direct plume submersion (cloudshine), (2) inhalation of the contaminant plume, (3) deposited activity on the ground (groundshine) and (4) ingestion of contaminated food due to this deposited activity.

So, the radiological risk model is two folded, viz., (a) a model that computes the time integrated air concentration (TIC) using an atmospheric dispersion model, and (b) the model that transforms the air concentration into the risk for the specific pathways of exposure. The paper describes the risk model and the associated uncertainty due to inhalation exposure pathway. Specifically, in the event of nuclear accident inhalation may occur due to the release of radioactive iodine (half life = 8 days). Radioactive iodine (I-131) is a fission product produced during the nuclear fission of uranium (U-235 nuclide. Exposure due to inhalation is modeled by multiplying the TIC (unit: Bq sec/m^3) with the breathing rate (unit: m^3/s) and the dose conversion factor (unit: Sv/Bq). Therefore, risk is modeled as the product of the exposure (Sv) and the exposure to risk conversion factor (per year per Sv). Probabilistic definition of the risk in this paradigm is signified as the probability of occurrence of the death of the number of people due to radiogenic cancer [22]. For example, if the risk is estimated as 1.0e-6, it means that for a population size of 10^6, only one people will be dead due to cancer.

The frequent question is that why there will be an uncertainty in this risk model? If uncertainty really exists, can that be quantified using complete probability theory. The answer is no, uncertainty in the risk model cannot be quantified completely by probability theory because parameters such as breathing rate, exit velocity of the hot effluent cannot be described by probability theory due to either lack of information or imprecise nature of those data. That is the reason a new platform has been chosen to address the uncertainty quantification in the risk model using probability-possibility combination. In the present risk model breathing rate is considered as possibilistic parameter (fuzzy set characterized by triangular membership function for the convenience of computation) to estimate the uncertainty of the inhalation risk model.

3.1 Time Integrated Air Concentration Model

Time integrated air concentration is main physical entity to quantify the inhalation exposure deterministically. A large number of atmospheric dispersion models exist to estimate the time integrated air concentration (TIC). Every model has their merits and demerits. However, for understanding the approach of probability-possibility combination, simple Gaussian plume model [23] has been selected for computing the TIC. Gaussian plume model is applied for monitoring the environmental consequences of routine discharge of nuclear power plant. Here, in this model, air concentration is a function of source strength, Q (unit: Bq), wind speed, u (unit: m/s), horizontal and vertical dispersion coefficient, σ_y and σ_z (unit: m), effective stack height, h_{eff} (unit:m); Effective stack height (H_{eff}) is sum total of physical stack height (H) and the plume rise (ΔH). The plume rise is further function of many parameters such as the exit velocity of the effluent released from the stack, stack diameter, temperature of the released effluent and the ambient temperature. Among all these parameters, wind speed and ambient temperature are assumed as probabilistic uncertain parameter due to their sufficient experimental evidences. So, in effect, the TIC is turned out to be probabilistic uncertain quantity. Horizontal and vertical dispersion coefficients are function of spatial distance (downwind distance) and weather category and therefore they are estimated using standard Pasquill-Gifford (P-G) model [23]. The mathematical expression used for estimating the ground level plume centerline TIC in presence of plume rise is given by

$$C(x,0,0) = \frac{Q}{\pi\, u\, \sigma_y\, \sigma_z} \exp\left(-\frac{H_{eff}^2}{2\sigma_z^2}\right) \tag{4}$$

The expression for the effective stack height is written as

$$H_{eff} = H + \frac{\left(1.6 * \exp\left(\frac{\ln f_0}{3}\right) * \exp\left(\frac{2 * \ln(3.5 * x_0)}{3}\right)\right)}{u} \tag{5}$$

where, f_0 and x_0 are given by the following expressions

$$f_0 = 3.12 * 0.785 * \nu_0 * d^2 * \left(\frac{t_0 - t_1}{t_0}\right) \tag{6}$$

and

$$\begin{aligned} &if\ f_0 > 55, \text{ then } x_0 = 34 * \exp(0.4 * \ln(f_0)) \\ &if\ f_0 \le 55, \text{ then } x_0 = 14 * \exp(0.625 * \ln(f_0)) \end{aligned}$$

where, ν_0 = exit velocity of the effluent (m/s), d = stack diameter (m), t_0 = effluent exit temperature (in degree Kelvin), t_1 = ambient temperature (in degree Kelvin)

Therefore, the second component of equation (5) provides the expression for plume rise, ΔH. The uncertainty of the parameter u is represented by the normal probability distribution. The parameters ν_0 , t_0 and t_1 of the equation (6) though uncertain due to their randomness but in the present paper these parameters are treated as deterministic from the point of simplicity.

3.2 Breathing Rate and Inhalation Dose to Risk Coefficients

In order to compute the inhalation dose, TIC, is multiplied by the breathing rate and the product results the quantity of the activity inhaled by the members of the public. Inhaled activity can be converted into the corresponding dose by multiplying the activity by the activity to dose conversion coefficient. Inhalation dose is converted into the corresponding risk by multiplying the dose with dose to risk coefficient. However, one can obtain the inhalation risk directly from the inhaled activity just by multiplying the activity to inhalation risk coefficient (unit: /Bq per year). Breathing rate of child or adult is an average imprecise estimate and therefore this parameter is treated as possibilistic uncertain parameter. Breathing rate is modeled as triangular fuzzy number.

3.3 Uncertainty Modeling

Uncertainty of the probabilistic parameter is modeled using Monte-Carlo simulation [24]. Latin hypercube sampling scheme [24] is applied for generating the sample values of the wind speed (probabilistic uncertain parameter). Possibilistic uncertain parameter is discretized at various alpha cuts. Each sample value of the resulting uncertain TIC is multiplied with left and right bound of the breathing rate at every alpha cut level. Probability of these resulting values of the inhaled activity is computed by 1/(sample size * number of alpha cuts). So, if the sample size for probabilistic uncertain parameters is taken as 500 and if the number of alpha cuts is 10 then the probability of occurrence of one sample value of the risk is 1/5000. Cumulative probability distribution of each of these bounds of the resulting inhalation risk is separately generated. The lower bound of the cumulative probability plot of the inhalation risk can be used to estimate the belief and the upper bound of the cumulative probability plot of the inhalation risk can be used to quantify the plausibility. Belief and the plausibility are the two bounds of the estimated risk. Uncertainty of any quantity under the probabilistic and possibilistic combination is expressed by the belief and plausibility [25].

4. Results and Discussion

The probability-possibility combination method of uncertainty modelling of radiological risk described in section 2 is illustrated with a case study of risk estimation from inhalation exposure due to a postulated scenario of an inadvertent release of radioactive iodine. First the inhalation risk is estimated deterministically to show that what could be the acceptance level of the inhalation risk. As per the methodology of obtaining the deterministic value of the TIC and the inhalation risk, the input values of the deterministic parameters mentioned for the postulated scenario are as follows: release rate of the source term in Curies/sec is assumed as 15000, wind speed (m/s) recorded from the recorder as 3.57, weather category is observed as ‘F’ (Extremely stable), height of the stack (m) is 100, exit velocity (m/s) of the effluent is 11.8, stack diameter (m) is taken as 4.0, effluent exit temperature (in degrees Kelvin) is 355, and ambient temperature (in degrees Kelvin) is 276.8. Horizontal and vertical dispersion coefficient calculations for all weather categories (A-F) are shown in figures 2 and 3.

Considering the release category as elevated release, time integrated air concentrations for the same weather category at various downwind distances with and without plume rise have been calculated and their plots at various downwind distances are presented in figures 4 and 5 respectively. Deterministic value of the breathing rate used in the computation as 1.2 m^3/h and the corresponding risk coefficient of I-131 for inhalation pathway for an infant is used as 6.41×10^{-10} /Bq. Variation of the computed inhalation risk with downwind distances is presented in figure 6. Uncertainty of the estimated risk at downwind distance of 1.6 km is expressed as an interval corresponding to 5^{th} and 95^{th} percentile which are computed from figure 7 as [0.1992, 0.2782] x 10^{-6}.

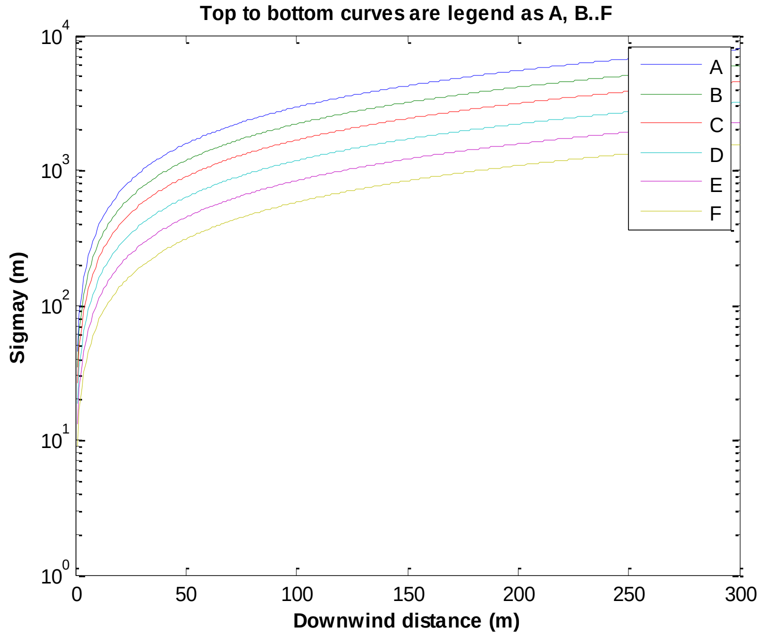

Figure 2. Horizontal Dispersion Coefficient (σ_y)

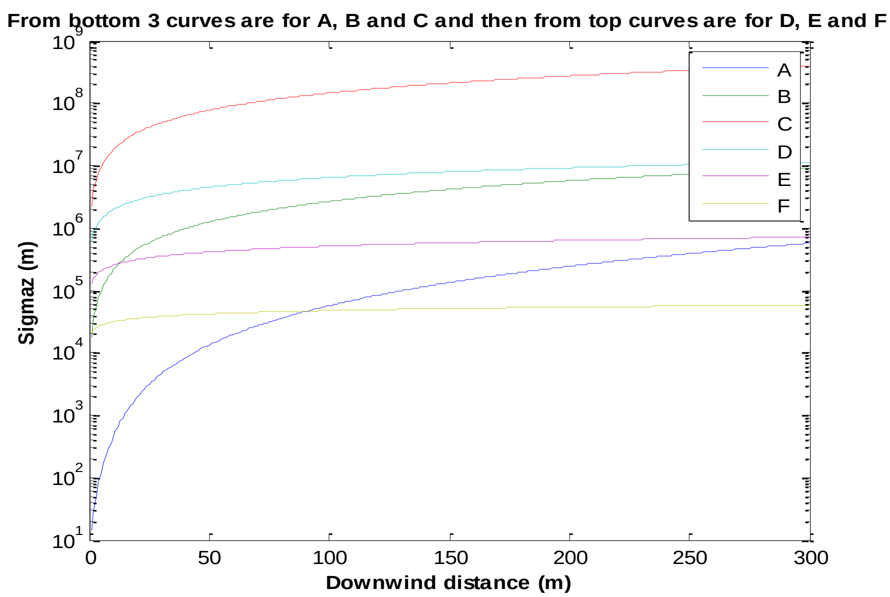

Figure 3 Vertical Dispersion Coefficient (σ_z)

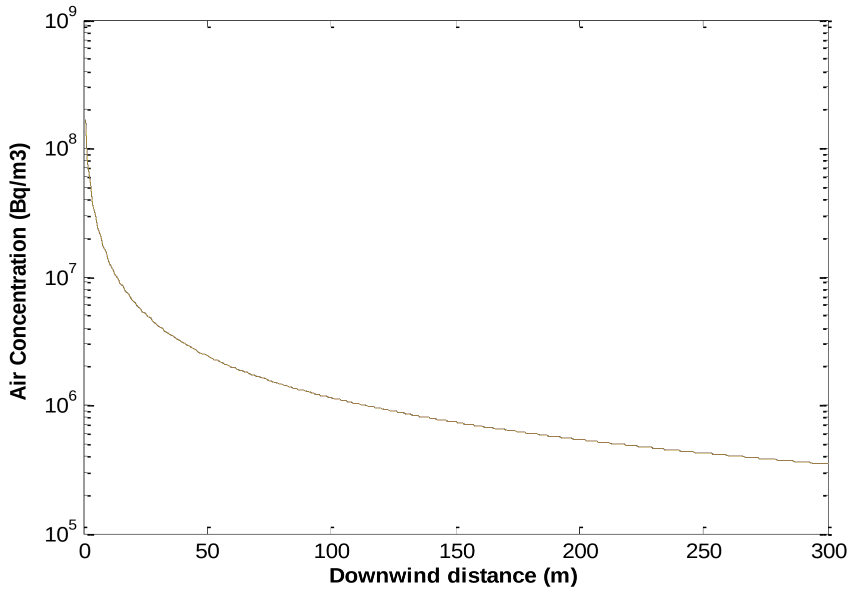

Figure 4. Time Integrated Air Concentration for an Elevated Release and without Plume Rise for Weather Category 'F'

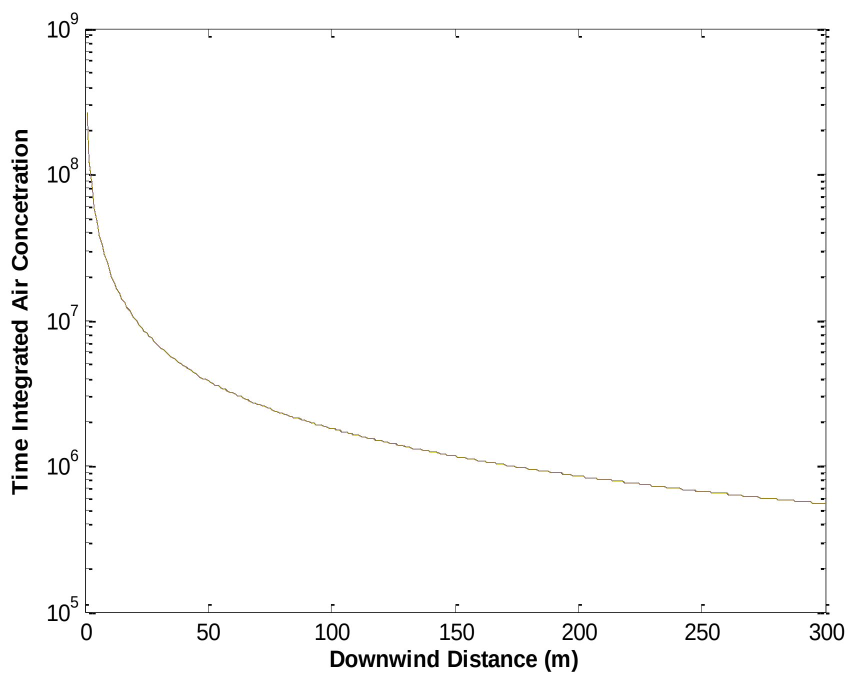

Figure 5. Time Integrated Air Concentration for an Elevated Release and with Plume Rise for Weather Category 'F'

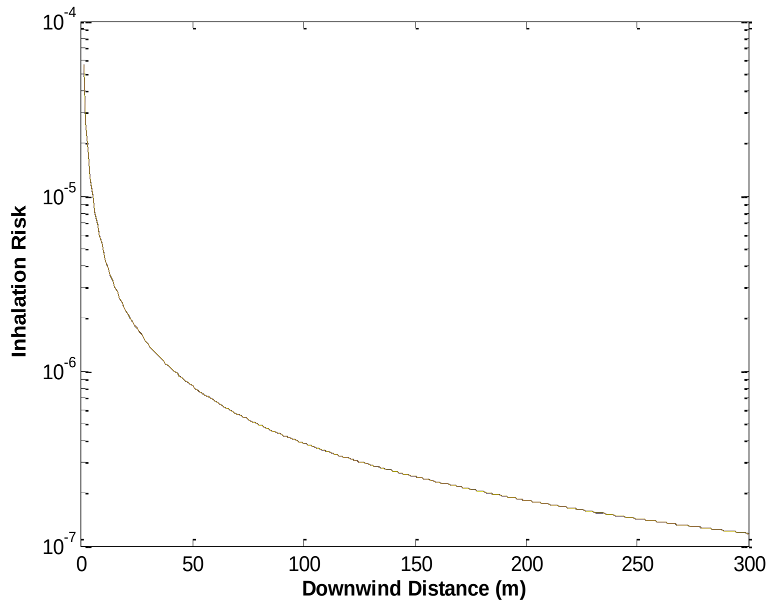

Figure 6. Inhalation Risk at Various Downwind Distances with Elevated Release and Plume Rise for Weather Category 'F'

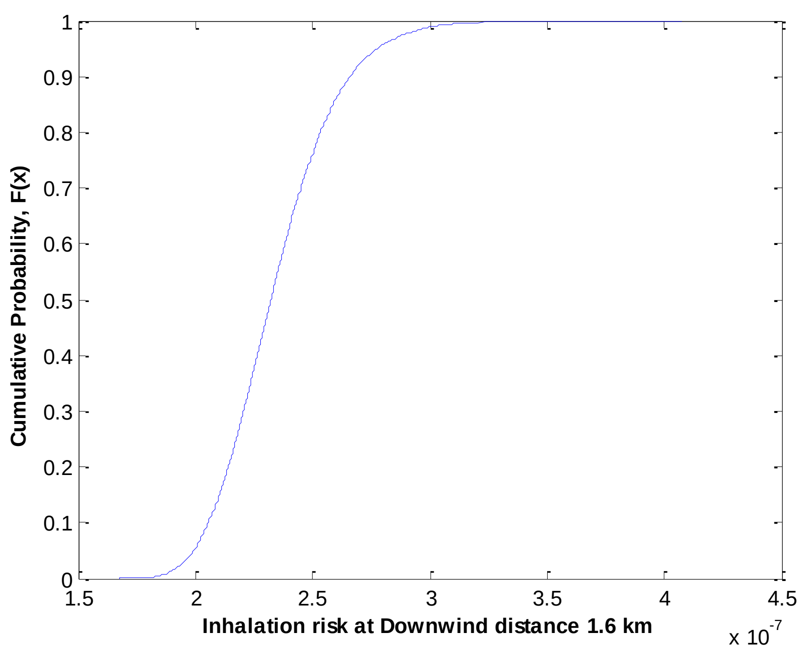

Figure 7. Cumulative Probability of Inhalation Risk with Elevated Release and Plume Rise for Weather Category 'F'

Breathing rate is now treated as fuzzy number having the most likely value as 1.2 m^3/h, lower bound as 1 m^3/h and the upper bound as 1.4 m^3/h. The membership function of this fuzzy set is as shown in figure 8. Computation of inhalation risk with the wind speed as probabilistic parameter and breathing rate as fuzzy parameter is carried out and the estimates of the lower and upper bound of inhalation risk at any specific alpha cut say 0.5 are plotted as cumulative probability and shown in figure 9. It can be envisaged from figure 9 that possibilistic uncertain parameter as fuzzy number characterizes the bounds of the risk as fuzzy but the presence of large number of samples of the probabilistic uncertain parameter express the risk bounds as cumulative probability.

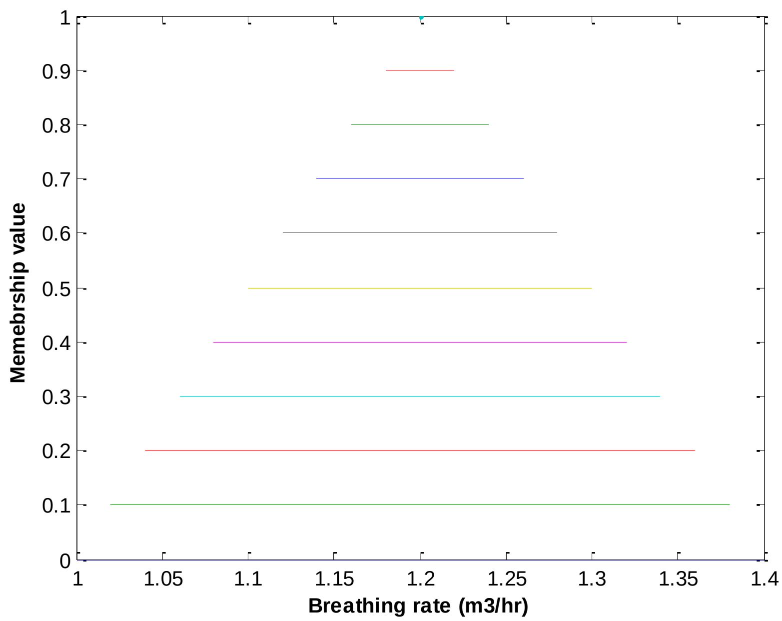

Figure 8 Membership Function of Breathing Rate as Fuzzy Uncertain Parameter

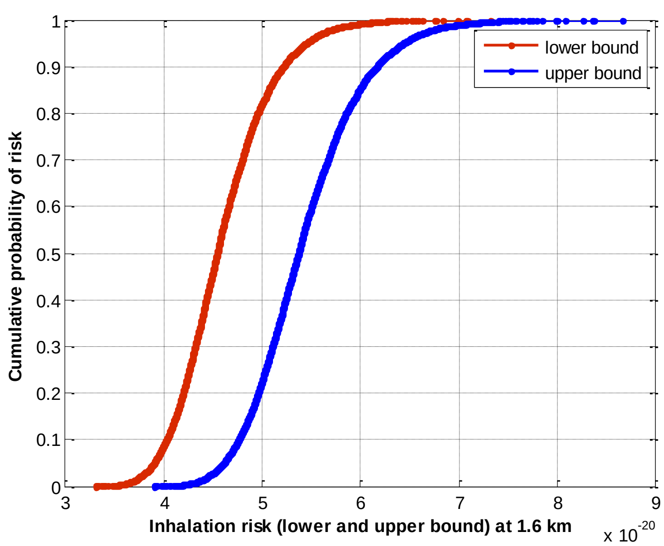

Figure 9. Upper and Lower Bounds of the Estimated Risk

5. Conclusions

The paper proposes a computation method of uncertainty of the radiological risk in presence of both the probabilistic and possibilistic uncertain parameters. Probabilistic simulation is carried out using standard Monte Carlo method. Possibilistic parameter is addressed by fuzzy sets. Fuzzy variable is simulated using the alpha cut representation of the appropriate membership function (for example, in the paper, triangular membership function is used). For a specified alpha cut singleton (focal element) of fuzzy variable is constructed. Each singleton is used in Monte Carlo simulation to have simulation of fuzzy random variable. Usage of probability-possibility combination technique is used at this stage. Uncertainty of the inhalation risk only is demonstrated. Risk from other pathways also can be calculated and the sum total of risk bounds can be obtained by addition of respective bounds. Presence of more than one possibilistic parameter can be tackled with fuzzy vertex method. Computation shows that risk from the inhalation risk for the postulated scenario is very low in comparison with the limit of the same stipulated by the radiation protection community. Upper and lower cumulative probabilities provide the uncertainty in terms of belief and plausibility. Lower cumulative probability curve represents the belief measure whereas the upper cumulative probability curve presents the plausibility measure. Traditional estimate of probability lies between these two bounds belief and plausibility. Thus, we have belief < probability < plausibility and uncertainty is expressed as [belief, plausibility].

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