Probabilistic Radiological Risk Assessments for Radiation Facilities with Vague Information

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Abstract: The objectives of this article are to provide streamlined technique, including the Delphi approach, Bayesian update and two-dimensional Monte Carlo analysis(2D MCA), and to provide information through the investigation of factors in risk model which supports risk assessment for the radiological risk assessment in operation of such radiation facilities with vague information. The scope of this study is restricted to risk assessment. Focus was placed on the framing of probabilistic risk assessment(PRA) procedure applicable to a system for which information on risk contributing factors is vagueness. Incorporation of the Delphi panel method and the Bayesian update into PRA for dealing very uncertain factors was addressed in particular. The PRA methodology established through this study for facilities with vague information on risk contributing factors was applied for risk assessment for field radiography. Task analysis was performed for operations and scenarios based on the risk ranking and relative frequency were constructed for each task in field radiography. The risks for the worker and the public member were estimated by dividing into the normal and accident situations.

Key words: Probabilistic radiological risk assessment, two-dimensional Monte Carlo analysis(2D MCA), Delphi method, Bayesian update, radiation facility

Introduction

Risk or safety analysis in reverse deals in nature with uncertain situations, conventional and deterministic assessments therefore employ conservatism both in the risk model and in setting safety criteria in relation with the estimated risk. However, under such situations dealing very uncertain events for which experiences are lack or limited, 'conservatism' itself carries uncertainties and should be affected by subjective judgments. The probabilistic risk assessment(PRA) methodology was expected to give better insights of risk, particularly for modern complex engineered systems like a nuclear power plant(NPP).

In accordance with advances in PRA methodologies and tools, and due to increase of radiation facilities of higher potential of radiological risk, the International Commission on Radiological Protection(ICRP) recommended consideration of PRA applications to relatively high risk practices involving radiation sources of high intensity[1]. The U.S. Nuclear Regulatory Commission (US NRC) conducted a study employing primitive PSA procedures with consideration of a probable rationality to identify regulatory options for a wide range use of nuclear byproduct materials[2]. Probabilistic assessment of radiological risk involves identification of exposure pathways or scenarios, evaluation of probabilities that such a pathway results, quantification of consequences by use of exposure models, and quantification of uncertainties in the estimates. The exposure model includes many variables like source term, exposure time and distance which are also uncertain. PRA applies the probability distributions for the variables in order to quantitatively characterize their variabilities and uncertainties. One of the prevailing methods in PRA is the Monte Carlo analysis (MCA), which is a procedure quantifying uncertainty of variability in a probabilistic framework using computer simulations. The MCA methodology, as well as its applications to risk analysis, has been reviewed and detailed in Cullen and Frey[3]. The two-dimensional Monte Carlo analysis(2D MCA), used to separate uncertainty and variability, are a natural extension of one-dimensional Monte Carlo analysis(1D MCA)[4, 5]. Experts can provide valuable information through his or her judgment/knowledge when the variable data are uncertain or restrictive[6]. Expert judgments have been widely applied to areas including nuclear engineering, aerospace, various types of forecasting(e.g. economic, technological, meteorological), military intelligence, and environmental risk from toxic chemicals[7]. In addition, applications of Bayesian inference are highly recommended for shaping and updating such uncertain variables[8].

Thus, it is of worth to establish a framework for an advanced procedure of risk analysis for the radiation facilities involving significant potential exposures, where information on risk contributing factors are vagueness, by encompassing the PRA approach and those new techniques in data production and improvement as well as in quantification of consequences and their uncertainties with MCA simulations.

Materials and methods

Risk Definition

In radiological risk assessments in general, risk analysis involve evaluation of the frequency(in event per year) of events and their conditional consequences(in mSv) associated with possible states of a system. The state of a system is a description of its physical condition and its environment. The status of all the barriers or control is anything that affects the potential radiological impact. Risk, in its broadest definition, is then a compilation of possible system states and the associated probabilities and consequences[2].

The radiation risk is the expected radiation exposure per unit time or mSv y^{-1}. The normal task is the exposure the receptor is expected to receive over the year for activities and/or conditions that are expected during the year. It would be the accumulated exposure indicated by personal dosimetry devices(plus any internal exposure not measured by the dosimetry). The 'accident' risk is determined for non-normal sequences of events that are relatively unlikely. Because of the infrequency of the accident sequences, the accident risk would be an average or expected exposure only if averaged over a period of time that is long compared to the time between events or over a large number of devices or activities. Although a single receptor would not be expected to see the exposure indicated by the accident risk in a given year, a single receptor does has a probability of receiving the estimated dose for any given postulated accident sequence in a year. While not something that can be measured, the product of probability and consequences(dose) is the mathematically 'expected' dose for the year and is a useful measure of total accident risk.

Structure of the PRA Model in This Study

To the extent possible, PRA models are hierarchical in nature. This provides a way of structuring the vase quantities of information that go into a risk analysis. In order to analyse statistically the behaviour of a system from the known behaviour of components or sub-components, the logical structure of the interdependency of the components must be determined. An essential idea in the analysis of logical structures is the concept of success or failure of the system, sub-system and component. In particular, two reliability analysis techniques are commonly used for quantifying the likelihood of an accident; fault tree and event tree[9, 10]. Also, a variety of different types of data needed to support PRA quantification. This includes data on initiating event frequencies(i.e., the frequency of departures from normal operation), component failure rates, common cause failure rates(i.e., the frequency with which two or more components fail during a short period of time for the same reason), component maintenance frequencies and durations, component fragilities(i.e., component failure probabilities as a function of exogenous stresses such as fires, earthquakes, or high temperatures), and human error rates. For most of these data needs, several different types of information may be available, including not only component-specific information(e.g., the number of observed failures of each component), but also expert opinion and data on the failure frequencies of similar components at other system. The process for assessing radiological risk on radiation facility with vague information shows Figure 1.

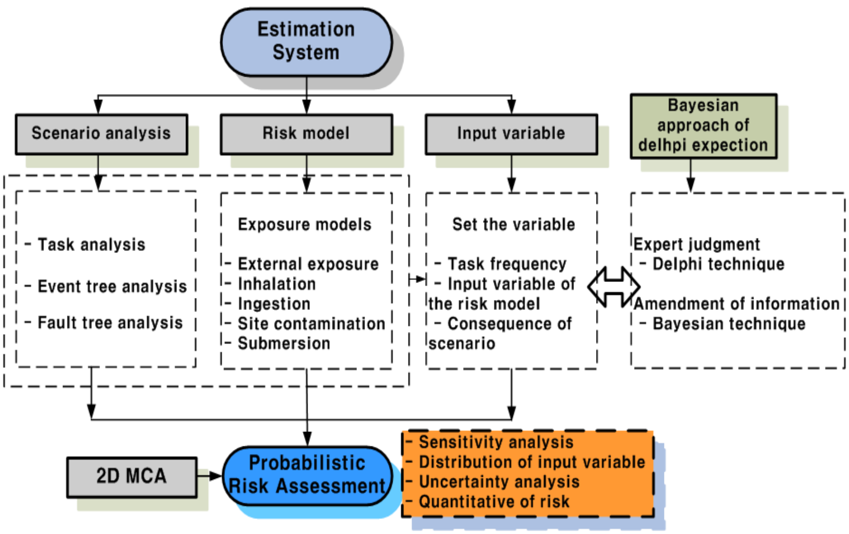


Figure 1. Brief flow chart showing the process of radiological risk assessment of radiation facility with vague information.

The methodology developed through this study is applied for risk assessments for field radiography(NDT). The risks for the worker and the public member have been estimated by dividing as the normal and accident situations. Potential scenarios have been derived through visiting workplace and investigating accidents in Korea, and the importance of safety functions required for deriving final scenarios been then perceived. So have been collected the risk model variable and distribution parameters. For drawing the expert opinions, three-round Delphi survey has been tried out and the panels have been designed for NDT.

Expert judgment for vague information and Bayesian Approaches

The Delphi method originated in a series of studies that the RAND corporation conducted in the 1950s [11,12]. Researchers have applied the Delphi method to a wide variety of situations as a tool for expert problem solving. One of aims in this study is for an investigation of factors in the risk model which supports risk assessment of radiation facility with vague information.

The flow chart of Bayesian update in this study is shown in Figure 2. The process of combining these distributions can be mathematically difficult. The problem is the assessment of the likelihood function $L(x_1, \cdots, x_n|\theta)$. This function amounts to a probabilistic model for the information $x_1, \cdots, x_n$ and as such it must capture the interrelationships among θ and $x_1, \cdots, x_n$. In particular, it must account for the precision and bias of the individual x_i and it must also be able to model dependence among the x_i. Therefore, the Markov Chain Monte Carlo(MCMC) simulation approach was used in calculating the posterior result with aid of the Crystalball's batch fit function, which provides optimized distributions of variables using the goodness-of-fit statistic. The WinBUGS package based on the MCMC method was used for deriving the posterior distribution. Gibbs sampler was used to generate the posterior distribution of the unknown parameters.

The first Delphi survey is provided for constructing the major factors for scenarios, deciding their importance and designing inputs, for example, frequency, time and distance. The second survey is provided for revision and supplementation for the factors obtained through the first survey, and collection of the input variables. The third survey is designed for final revision and supplementation for the factors and final collection of the input variables by feedback of the first and second surveys. The final event trees for NDT have been constructed through the safety functions derived by Delphi surveys. All of the data obtained through Delphi surveys are needed to determine their optimized probabilistic distributions, and 'Batch Fit' function in CrystallBall program and ProUCL provided by NCRP (National Council on Radiation Protection and Measurements) are used for determining the optimized distributions.[13] The inputs in this risk model have been quantified for satisfying the scenarios, and the model variables such as dose reduction factor are applied by referring US NRC(U.S. Nuclear Regulatory Commission; US NRC) information. Posterior distributions for the model parameter and distribution parameter have been obtained by Bayesian inference using Markov Chain Monte Carlo method and WinBUGS package is used as tool obtaining posterior distributions[14].

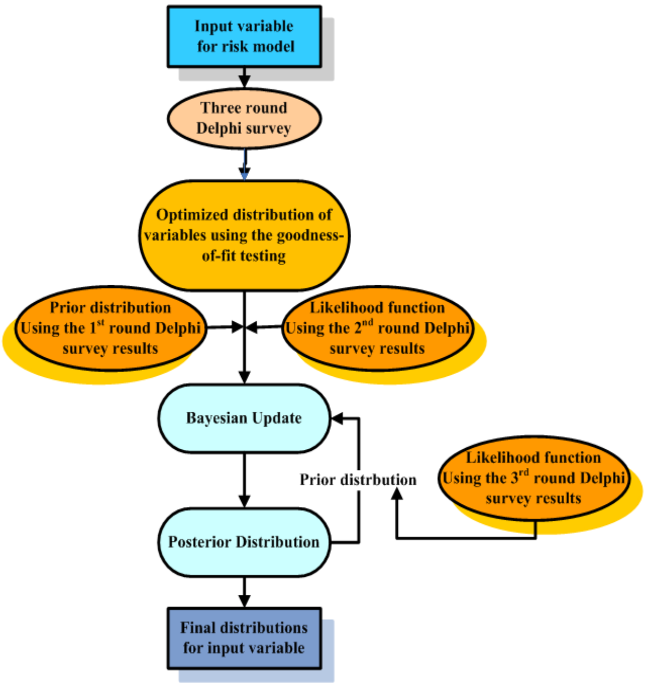


Figure 2. Flow chart for the Bayesian update in this study

Two-Dimensional Monte Carlo Technique

A two-Dimensional(or second-order) Monte Carlo analysis(2D MCA) was proposed to estimates the uncertainty in the risk estimates stemming from parameter uncertainty[15]. A 2D MCA is a Monte Carlo simulation where the distributions reflecting variability and uncertainty are sampled separately in the Monte Carlo simulation framework, so that variability and uncertainty in the output may be estimated separately[16]. The 2D MCA was performed using the PDFs of V-type(variability) and U-type(uncertainty). The flow chart for the 2D MCA process and illustration of 2D Monte Carlo simulation are presented in Figures 3. A total of 250 cumulative distribution functions(CDFs) were generated using the software packages CrystalBall. For example, the exposure frequency is modeled as normally distributed random variable with various mean and standard deviation combinations selected from triangular or other distributions. In this study, 250 different mean and standard deviation combinations are generated for the exposure frequency. For each mean and standard deviations combination 10,000 Monte Carlo simulations are conducted to generate one CDF. The number of runs was 10,000 for the inner loop and 250 for the outer loop. The resulting risks are expressed in terms of annual radiation dose.

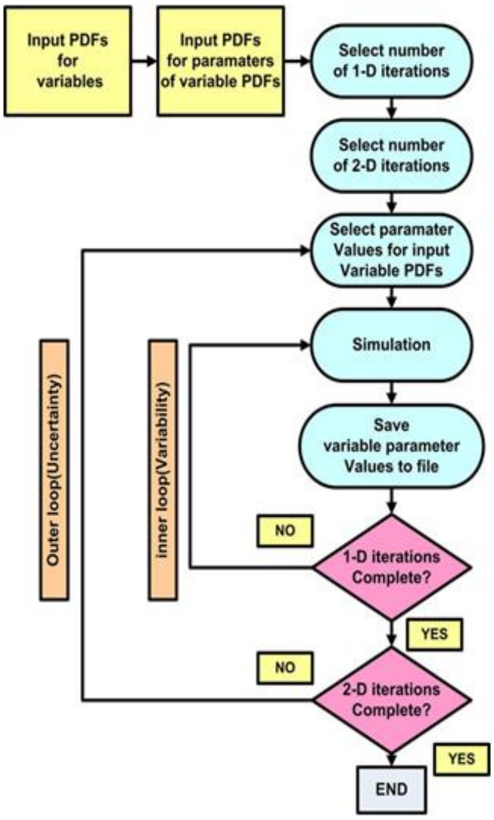


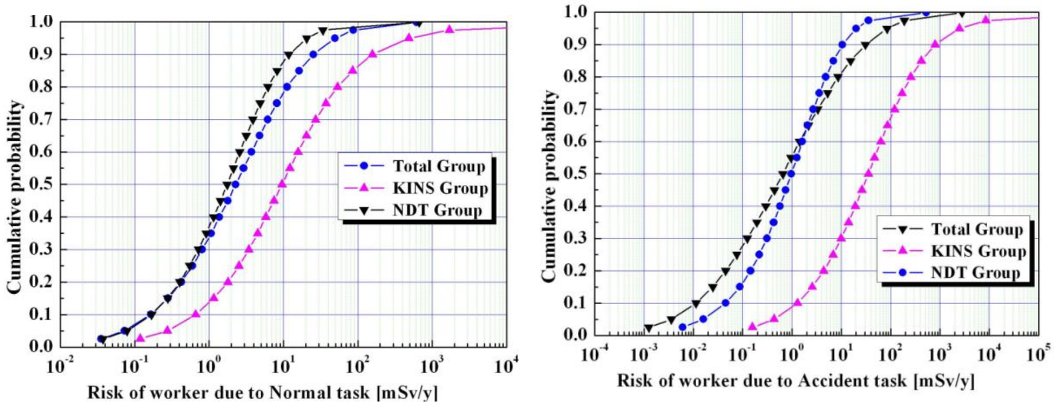
Figure 3. Schematic flowchart for 2D MCA.

Results and Discussion

Selection of Model Variable

The results of risk estimates based on 1D MCA using the Delphi panel responses for tasks in field radiography(using task) were shown in Figure 4. Generally, conservative risk evaluations were obtained with model variables from experts in the regulatory organization(KINS) compared with those with model variables from experts in NDT companies. Since the updated model variables have significant effects on final risk results, three risk results have been compared and analyzed each other. Through these comparison and analysis, the model variables for final risk assessment have been then determined. The overall risks by the Bayesian updating of the model variables are compared with both those without updating (3rd Delphi survey) and those resulted from the estimation employing data within the 95% confidence interval at the third-round Delphi survey, as depicted in Figure 5.

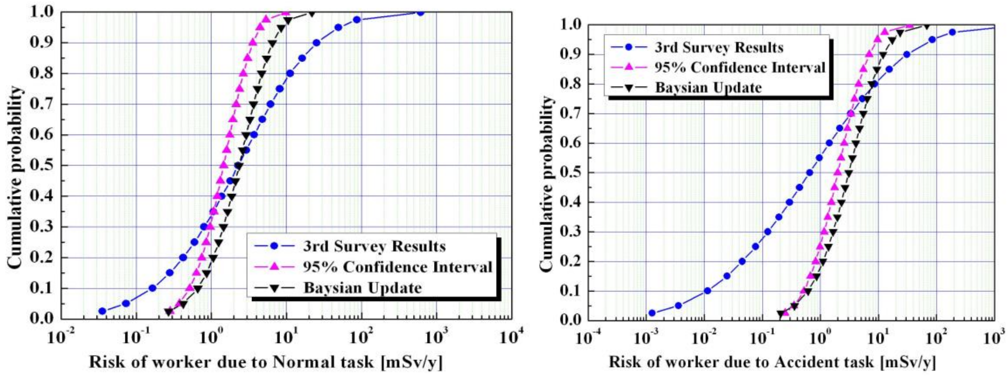
It is noted in Figure 5 that the CDFs without updating show unrealistically low and high values of dose in the lower and upper tails. On the other hand, the risks applying the Bayesian updating well agree with the risk reflecting 95% confidence interval. The later, however, suffers arbitrary rejection of some collected data. Consequently, the radiological risk assessment in order to uncertainty analysis was performed using the Bayesian updated input variable for the system.



(a) Normal task(using) (b) Accident(using)

Figure 4. Distribution of risk from 1D MCA using Delphi panel response for field radiography due to normal task(a) and accident(b) for worker.

Since the updated inputs have significant effects on final risk results, three risk results have been compared and analyzed each other. The overall risks by the Bayesian updating of the inputs are compared with both those without updating(3rd round Delphi survey) and those resulted from the estimation employing data within the 95% confidence interval at the third-round Delphi survey. Through these comparison and analysis, the inputs for final risk assessment have been then determined. For final risk assessment, the model variable and distribution parameter have been divided as U and V-type, and the uncertainties for the risks are quantitatively analyzed by applying 2D MCA.

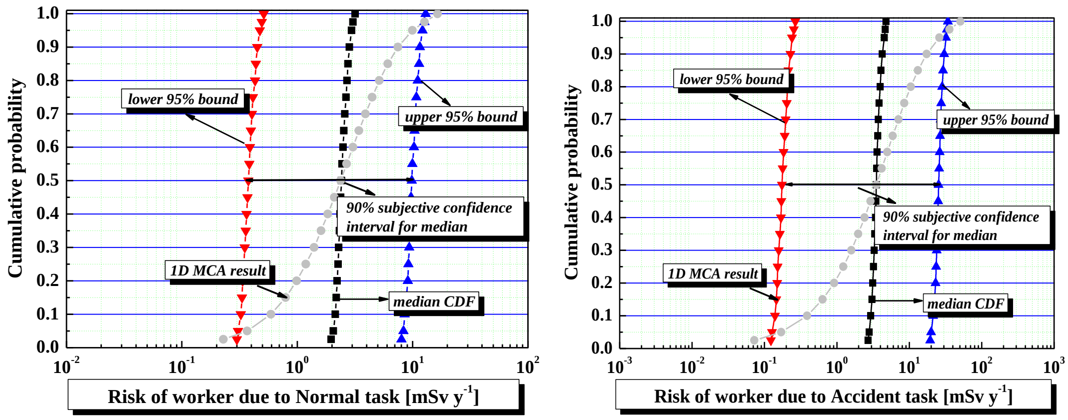


(a) Normal task(using) (b) Accident(using)

Figure 5. Risks distributions from different characterizing methods of input variable for field radiography due to normal task(a) and accident(b) for worker.

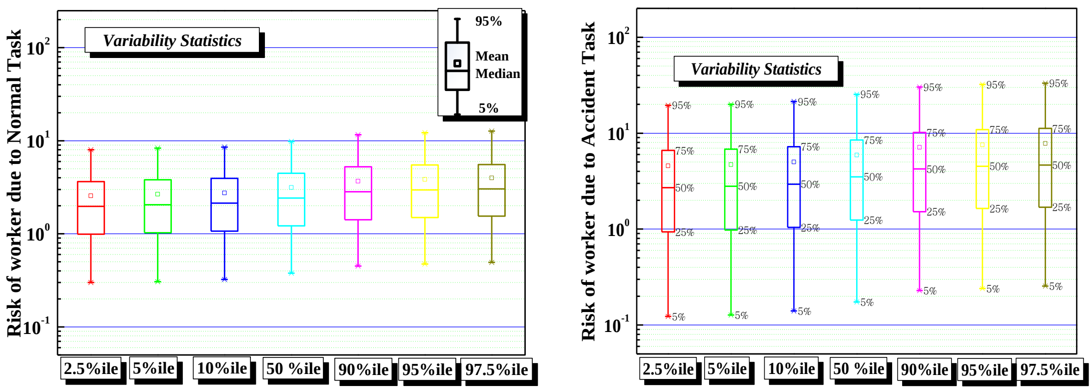
2D MCA Result of Field Radiography

Risk assessments of the field radiography for the worker as example divide into normal operation and accident were performed based on the probabilistic risk assessment methodology. Figures 6 and 7 shows that 90% confidence interval and the statistic summary for variability of risk for using task from 2D MCA and 1D MCA results in field radiography were presented for risk of the worker due to normal task and accident. In case of normal task, expected annual dose maximally for the worker was estimated as 12.7mSvy^{-1}(97.5th percentile of 95% value) which is presented lower than annual dose limit(20mSv). In the case of accident for the worker, the confidence intervals of risk for median are estimated as [0.174, 25.4]mSvy^{-1}. Table 1 given the results of the range of expected annual dose for using task.



(a) Normal task (b)Accident

Figure 6. 90% confidence interval of risk for using task from 2D MCA and 1D MCA results in field radiography due to normal task(a) and accident(b).



(a) Normal task (b) Accident

Figure 7. Statistical summary for variability of radiological risk from 2D MCA due to normal task(a) and accident(b) in using task. The presented are 90% confidence intervals for each percentile.

2D MCA percentiles	Range of expected annual dose[mSv y^{-1}]					1D MCA
	Receptor	5%	Mean	Median	95%	
Risk of normal task						
2.5%ile	Worker	3.00E-01	2.78E+00	1.97E+00	8.02E+00	2.29E-01

	Public	4.36E-06	4.53E-05	3.24E-05	1.29E-04	3.30E-06
50%ile	Worker	3.78E-01	3.42E+00	2.42E+00	9.85E+00	2.38E+00
	Public	5.94E-06	5.92E-05	4.32E-05	1.66E-04	4.34E-05
97.5%ile	Worker	4.94E-01	4.31E+00	3.04E+00	1.27E+01	1.27E+01
	Public	8.13E-06	7.55E-05	5.43E-05	2.12E-04	2.13E-04
Risk of accident						
2.5%ile	Worker	1.23E-01	5.42E+00	2.70E+00	1.95E+01	7.26E-02
	Public	1.92E-04	1.76E-02	6.72E-03	6.98E-02	1.12E-04
50%ile	Worker	1.74E-01	7.01E+00	3.50E+00	2.54E+01	3.50E+00
	Public	2.98E-04	2.34E-02	9.27E-03	9.12E-02	9.22E-03
97.5%ile	Worker	2.55E-01	9.16E+00	4.65E+00	3.33E+01	3.59E+01
	Public	4.55E-04	3.09E-02	1.25E-02	1.19E-01	1.35E-01

Table 1. Summary of 2D MCA and 1D MCA for radiological risk of using task in field radiography.

Conclusions

A streamlined procedure including Delphi method, Bayesian update and two-dimensional Monte Carlo analysis was established for the probabilistic radiological risk assessment of radiation facilities where information on risk contribution factors is often vague. The Delphi method was confirmed as a useful research tool for elicitation of expert opinions and the model variables for use in PRA were obtained through the three-round Delphi survey. The approach characterizing model variable and distribution parameters using the Bayesian inference provided improved risk estimates while avoiding intentional rejection of certain data. Bayesian updating of distributions of uncertain model variables also showed a plausible capacity in shaping those variables used in the successive risk calculations. The 2D MCA provided a quantitative measure of the confidence in the fraction of the population with a risk exceeding a particular level, which is sometimes referred to as a vertical or horizontal confidence interval(or credible interval). By separately characterizing variability and uncertainty, it will facilitate to understand and communicate of the PRA results. It is expected that the procedures established in this study, with certain refinements, will open the way leading to quantification of risks and their uncertainties in similar systems with vague risk information, particularly in radiation facilities of other type.

References

1. ICRP, *Protection from Potential Exposures-Application to Selected Radiation Sources*, ICRP Publication 76, (1997).
2. U.S. *Nuclear Regulatory Commission, Risk Analysis and Evaluation of Regulatory Options for Nuclear Byproduct Material Systems*, NUREG /CR-6642, (2000).

3. Cullen C.A. and Frey H.C., “Probabilistic Techniques in Exposure Assess ment; A Handbook for Dealing with Variability and Uncertainty in Models and Inputs,” New York: Plenum press, (1999).
4. Lester R.R., Green L.C. and Igor Linkov, “Site-Specific Application of Probabilistic Health Risk Assessment: Review of the Literature Since 2000,” Risk Analysis, 27(3), (2007) 635-654.
5. David L. Macintosh, Glenn W. Suter II, and F. Owen Hoffman, “Uses of Probabilistic Exposure Models in Ecological Risk Assessments of Contaminated Sites,” Risk Analysis, 14(4), (1994) 405-419
6. Mary A. Meyer, Jane M. Booker, *Eliciting and Analyzing Expert Judgment: A Practical Guide, ASA-SIAM Series on Statistics and Applied Probability*, ASA-SIAM, (2001).
7. Clemen R.T. and Winkler R.L., “Combining probability Distribution from Expert in Risk Analysis,” *Risk Analysis*, **19**(2), (1999)
8. Kahneman D. and Tversky A., “Subjective Probability: A Judgment of Representativeness Judgment Under Uncertainty: Heuristics and Biases,” Cambridge, Massachusetts: Cambridge University Press, (1982).
9. Vlasta Molak, “Fundamentals of Risk Analysis and Risk Management,” CR C Press LLC, 1997.
10. International Electrotechnical Commission, International Standard: Risk Management-Risk Assessment techniques, IEC/ISO 31010, (2009).
11. Dalkey N., Helmer O., “An Experimental Application of the Delphi Method to the Use of Experts,” *Management Science*, **9**(3), (1963) 458-467.
12. Schmidt R.C., “Managing Delphi Surveys Using Non-parametric Statistical Techniques,” *Decision Sciences*, **28**(3), (1997) 763-774.
13. NCRP, *Uncertainties in the Measurement and Dosimetry of External Radiation, National Council on Radiation Protection and Measurements*, NCRP Report No. 158, (2007).
14. Spiegelhalter D., Thomas A., Best N., Lunn D., WinBUGS User Manual, Ver 1.4, (2003). http://www.mrc-bsu.cam.ac.uk/bugs/
15. MacIntosh DL, Xue J, Ozkaynak H, Spengler JD, Ryan PB, “A Population based Exposure Model for Benzene,” *JEAEE*, **5**(3), (1995) 375-403.
16. Han-Ki Jang, Joo-Yeon Kim and Jai-Ki Lee, “Radiological Risk Assessment for Field Radiography Based on Two Dimension Monte Carlo analysis,” *Applied Radiation and Isotopes*, **67**, (2009) 1521-1525.

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