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Modeling uncertainty in risk assessment: An integrated approach with fuzzy set theory and Monte Carlo simulation

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ABSTRACT

Modeling uncertainty during risk assessment is a vital component for effective decision making. Unfortunately, most of the risk assessment studies suffer from uncertainty analysis. The development of tools and techniques for capturing uncertainty in risk assessment is ongoing and there has been a substantial growth in this respect in health risk assessment. In this study, the cross-disciplinary approaches for uncertainty analyses are identified and a modified approach suitable for industrial safety risk assessment is proposed using fuzzy set theory and Monte Carlo simulation. The proposed method is applied to a benzene extraction unit (BEU) of a chemical plant. The case study results show that the proposed method provides better measure of uncertainty than the existing methods as unlike traditional risk analysis method this approach takes into account both variability and uncertainty of information into risk calculation, and instead of a single risk value this approach provides interval value of risk values for a given percentile of risk. The implications of these results in terms of risk control and regulatory compliances are also discussed.

1. Introduction

As risk assessments have become important aids in the decision making process related to the management of sources of undesired events, the issue of uncertainty is of primary importance. The risk involved in industries is related to many factors such as physical and chemical properties of the materials, likelihood of incidents, propagation of incidents occurred, location, activity, and effects on human and environment. Many of these factors pose sparse and imprecise information. In these situations, uncertainty evaluation cannot be neglected. In addition to this, decision-making based on risk are more effective when the risk is realistic and accurate characterization of uncertainty have been done. But in practice, the uncertainty is irreducible from the data and models. This uncertainty arises from input data, inappropriate structure and erroneous calibration of the model (Lowell and Benke, 2006). Therefore, it is necessary to consider the impact of uncertainty over decision making based on risk assessment models. To facilitate proper decisions, quality of the risk analysis should be enhanced. Insignificant risk source, vague risk analysis approach, and ambiguous results lead to unacceptable safety levels. Backlund and Hannu (2002) identified the factors affecting quality of risk analysis and evaluated the risk analysis approaches. Pasman et al. (2009) discusses the problem of the present status of quantitative risk assessment techniques (QRA). It says that a large amount of variability is observed in the output results while applying different risk assessment techniques for particular hazardous events. Pasman et al. (2009) also provides some information about the sources of variability which gives rise to the large differences in output results namely, variety in scenario description which includes human judgment and the mathematical formulas used to model the real life complex systems. Assessment of frequency of failure is also a major contributor which gives rise to the variability. The authors also suggest that the effect of domino effect should be taken into consideration while conducting any QRA.

The hazard identification, initial consequence analysis, risk estimation, and analysis of results are very important steps to be considered for risk assessment for effective decision making (Backlund and Hannu, 2002; Arunraj and Maiti, 2007; Khanzode et al., 2011, 2012). The uncertainty analysis in risk assessment was performed by various studies in different applications (McCauley and Badiru, 1992 and Vadeby, 2004 – injury risk; Ferson and Kuhn, 1992 and Hobday et al., 2011a,b ecological risk; Quelch and Cameron, 1994 – chemical consequence risk; Lees, 1996 – software development risk; Boncivini et al., 1998 and Koornneef et al., 2010 – transportation risk; Chauhan and Bowles, 2003 – dam safety risk; Kentel and Aral, 2004 and Kumar and Xagoraraki, 2010 – human health risk; Davidson et al., 2006 – microbial risk; Karirmi et al., 2007 – earthquake risk; Wang and Elhag, 2007 – bridge risk; Zavadskas et al., 2010; Van der Pas et al., 2012; Badri et al., 2012 and Pinto et al., 2012 – construction projects). The uncertainties in risk

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assessment are represented in various forms such as probability density functions, fuzzy numbers, and arithmetic intervals. Many researchers have addressed uncertainty using either one or other of these forms to characterize. For example, Chang et al. (1985) considered probability density functions to characterize the uncertainty. Quelch and Cameron (1994), Boncivini et al. (1998), and Davidson et al. (2006) presented the applications of fuzzy theory to characterize uncertainty, and Kumar and Maiti (2012) analytic network process (ANP) to characterize uncertainty in a chemical plant. Button and Reilly (2000) criticized the approaches of quantifying uncertainties in terms of sensitivity analysis and confidence intervals and provided a methodology using probability distribution.

Other alternative approaches for risk analysis are decision analytic framework, control banding and Bayesian Network analysis. Bunn (1984) explains the basic underlying process in the decision analytic framework. The framework starts with decomposing the problem into several component structures, analyzing each component and subsequently recomposing the components to provide overall insights and recommendations on the original problem. The first of the three underlying phases is called as the problem structuring phase. The second phase is called as the construction phase where the process of developing the preference model is done; it involves mainly evaluation and comparison of performances of the alternatives. The third phase involves performing sensitivity analyses for checking the robustness of the model thus developed. The framework can be seen as iterative and explanatory in nature, as iterations are made both among the steps in the three different phases and also of the complete cycle as a whole. The control banding methodology is mainly used for the purpose of qualitative risk assessment. It involves clustering risk situation into control bands, which takes into account the effect of hazard of a situation and its corresponding exposure information. They are not meant to be used as predictive exposure model. Bayesian methods or Bayesian network are also known as probabilistic directed acyclic graphical model which is mainly used to represent a set of random variables formed by nodes of the graph, and their conditional dependencies are represented as arcs of a directed acyclic graph. Bayesian methods are favored by many authors in cases where subjective information such as expert opinion or personal judgments of analyst is to be considered for quantification of risk. Dubois and Prade (1992) criticized the use of Bayesian methods in uncertainty analysis as the method somehow considers an unique distribution even if detailed information is not available to support the assumed unique distribution.

1.1. Description of uncertainty

The most commonly used equation for risk arising from the occurrence of an undesired event is:

$$R = P(Uc_i) \times M(Uc_i) \quad (1)$$

where $P(Uci)$ represents the probability of undesirable consequences and $M(Uc_i)$ is the magnitude of the loss to undesirable consequences.

The uncertainty in the estimate of risk can be calculated from an estimate of uncertainty of each of the parameters used in the risk assessment equations. This approach is sometimes referred to as a "parameter uncertainty analysis" (IAEA, 1989). The technique of parameter uncertainty analysis provides a quantitative way to estimate the uncertainty in the model result assuming the structure of the model is correct. The risk related to an activity is often formulated as the spectrum of consequences C, discrete outcomes from undesirable events during the activity, and the associated probabilities P, i.e., (C_1,P_1), (C_2,P_2), . . ., (C_n,P_n).

The factors affecting uncertainty in risk assessment are of various types and arise from different sources. Oberkampf et al. (2004) and Helton (1993) referred uncertainties into two broad categories namely, aleatory or stochastic and subjective or epistemic uncertainty. Stochastic uncertainty is due to the randomness that is heterogeneity or diversity in a population of some type (Frey and Rubin, 1992; Helton, 1993; Quelch and Cameron, 1994; U.S. EPA, 2001; Zonouz and Miremadi, 2006). For example, the frequency of failure may not be same for all equipment. Stochastic uncertainty refers to the different failure frequency values for different equipment. In this case, the frequency distribution helps to reflect the difference between equipment and to segregate the equipment population into homogeneous smaller groups.

The second type of uncertainty (subjective uncertainty) is mainly due to the lack of knowledge, measurement error, vagueness, ambiguity, under-specificity, indeterminacy, and subjective judgment (Arunraj and Maiti, 2009a; Frey and Rubin, 1992; Helton, 1993; Quelch and Cameron, 1994; U.S. EPA, 2001; Zonouz and Miremadi, 2006; Van der Pas et al., 2012). The stochastic uncertainty is irreducible, as it is inherent nature of the system under study. The subjective uncertainty cannot be reduced due to inherent limits on human capacity to process information, but to account for this uncertainty fuzzy set theory is used. Vose (2000) divided total uncertainty into variability and uncertainty. He proposed a term *verity* (combined term for variability and uncertainty) to represent the total uncertainty. Based on the review, taxonomy for uncertainty is developed (Fig. 1) to illustrate the types and sources of uncertainty.

1.2. Existing methods in uncertainty analysis

This section describes methods to quantify uncertainty in risk assessment. The methods evolve from analytical equations for simple models to numerical approaches. A brief summary of crisp, probabilistic, possibilistic, and hybrid approaches that are used in risk assessment studies are described below.

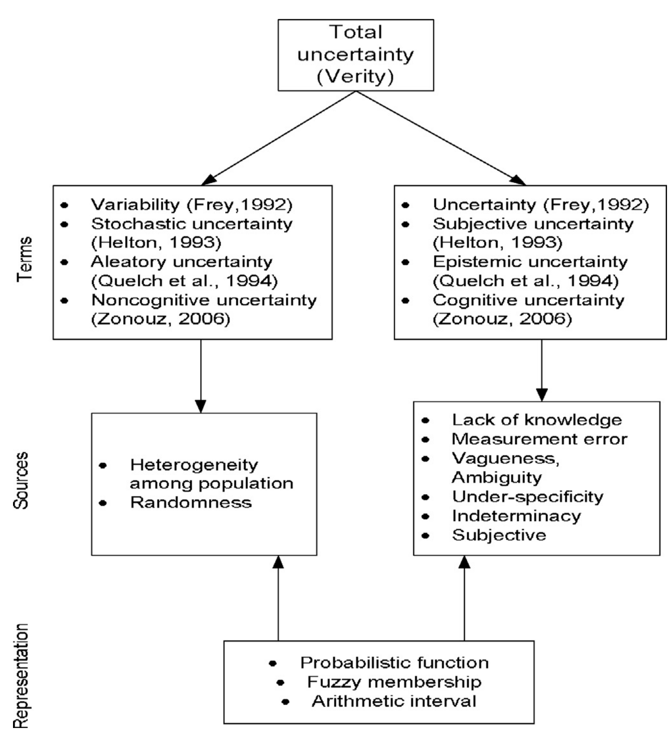

Fig. 1. Classification of total uncertainty.