ABSTRACT

Uncertainty analysis of any physical model is always an essential task from the point of decision making analysis. Two kinds of uncertainties exist: (1) aleatory uncertainty which is due to randomness of the parameters of models of interest and (2) the epistemic uncertainty which is due to fuzziness of the parameters of the same models. So far both these uncertainties are addressed independently; however since in any practical problem both the types of uncertain variables present, it is required to address them jointly. In order to solve practical problems on uncertainty modeling, it is required to replace the abstract definition of hybrid set by fuzzy random set. Since uncertainty modeling using fuzzy random set has not been carried out so far, the present chapter will address the utility of fuzzy random set for uncertainty modeling on geotechnical and hydrological applications. This chapter will present the fundamentals of fuzzy random set and their application in uncertainty analysis.

1. INTRODUCTION

In any scientific investigation, the relationship between data and theoretical models is very important. Which comes first is not always clear, since the collection, storage and retrieval of large data files is a more or less vague concept. Theoretical models are not expected to represent the data exactly, but at the very least they act as a sorting device that directs the data analyst to efficient ways of extracting information. When a model has a component of randomness in it, there is an extra, although exploitable, source of inexactness (Datta, 2009). By definition, two realizations of the same random phenomenon will not be exactly the same. However, the parameters estimated from two such realizations should be stable. If the realization is large, the the estimates of two parameter become close to each other. The statistical and probabilistic techniques ensure the existence of stochastic models and efficient estimation of their parameters are very well developed for data that are modeled as independent and identically distributed random variables. On the other hand, if any model has a component which is imprecise or vague due to

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the lack of information or insufficient knowledge of that component, the component is known to have fuzziness or simply the component is fuzzy. Modeling of such quantity is completely different from the component that has randomness. Uncertainty quantification of a model having both these components is a challenging task. Several researchers have expressed their expertise in this direction. For example, uncertainty analysis of a model having random component is generally carried out by Monte Carlo simulation (Binder & Heerman, 1992) with either simple random sampling (SRS) or Latin hypercube sampling (LHS), whereas uncertainty analysis of a model having fuzzy components is carried out by using fuzzy vertex theory (Klir & Yaun, 1995). The uncertainty of a model having random component is categorized as variability or probabilistic or stochastic uncertainty and the uncertainty of a model having fuzzy component is categorized as epistemic uncertainty (Ayyub & Klir, 2006; Datta & Kushwaha, 2009). However, in general, any model for scientific and engineering investigation contains both these components. It is required to make an effort to bring them under same umbrella and then develop a reasonably approximate efficient technique for quantification of the uncertainty of the models. So, what should be that instrument and how we should device that? Soft computing is an important basis for hybridizing these two different platforms as one uncertain component. Before proceeding further, let us investigate as an example the following scenario from the domain of health or environmental risk.

We know that preventive approaches to mitigate the risk to the environment from any industry concentrate on eliminating waste and pollution at the source. Managing risk means finding ways to reduce, mitigate, or simply learning to live with risks. How this is done it depends often on acceptability of the risk. The acceptability can be decided by regulators or public. Regulator criteria of acceptability are driven by scientific evidences or public perceptions. The public considers some risk unacceptable risks and the society is prepared to pay a high cost to avoid such risks. Some of the main factors affecting social perception towards risk are credibility of risk assessment process and communication of risk. However to regulators, it’s all about a well informed decision making process. Basic criteria for “good” decision making are efficiency, effectiveness and equity. A further criterion specific to environmental decision making is flexibility. In the context of environmental risk management, efficiency can be interpreted as good process (rather than economic efficiency), and effectiveness as good outcomes. Ideally, if outcomes can be predicted with reasonable certainty, then good process should lead to good outcomes. In practice, the concept of a “good” decision depends on a combination of good process and good outcomes, and, according to the circumstances, different weights may be given to different aspects. In environmental situations, long lead time between action and outcome means that deducing effect from cause is not always possible; a decision maker must rely on judgment. Improving decision making therefore requires looking for ways of improving the quality of the judgment of the decision maker. Study related to trend in risk analysis away from single summary estimates risk towards comprehensive risk characterization that is based on a probabilistic or possibilistic estimate of risk. The range of risks spanned by these estimates encompasses both uncertainty in the factors affecting risk, as well as variability in exposure or susceptibility within the population of interest. For example body weight, which is pertinent to a number of health risks, varies considerably among individuals even of the same age and sex, but is subject to little uncertainty. On the other hand, levels of exposure to dietary risk factors such as food contaminants can be both highly variable and highly uncertain. Most risk factors will be subject to varying degrees of both variability and uncertainty and the assessment of risk requires consideration of all of the possible factors that may influence risk.