Combining Bayesian Networks into the Risk Analysis of Passive Systems Given under Altered Evolution Scenarios

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1. Introduction

A lot of risk analyses have been performed to actually estimate a risk profile from both uncertain future states of hazard sources and undesirable scenarios. These risk prediction would require a systematic process for the scenarios. The scenario in the risk analysis can be defined as a propagating feature of specific initiating event which can go to a wide range of undesirable consequences, which answers to the question, "What can go wrong?"

In terms of treating scenarios, we can classify states of systems with two – active and passive. First, the state of system is called 'active' if an event can be directly controlled according to its happening simultaneously, whose risk has been easily assessed using a traditional probabilistic risk assessment (PRA) technique. The operating risk from nuclear power plants is categorized into this case. Next, on the other hand, the state of system is called 'passive' if any event cannot be directly controlled according to its happening, whose risk then scarcely has assessed via the traditional PRA technique. The future risk from, for example, radioactive waste disposal systems will be categorized into this case. In this case, with natural hazards being considered, the risk under any of the scenarios should be estimated.

Since the system performance in the passive state is very sensitive depending on a variety of scenarios, a temporal evolution by change in environmental conditions becomes a fundamental factor in estimating the risk. However, usually there are no direct methods of assuring the credibility of the evolution. In order to consider the effects owing to the evolution of environmental conditions of passive systems, this paper proposes a quantitative assessment framework combining an inference process of Bayesian network (BN) into a traditional risk analysis.

2. BNs for the PRA of a passive system

2.1. General Structuring

We attempted to represent a general structure model for the application. Figure 1 shows a fully-specified BN corresponding with an actual inference problem. For the purpose of showing an illustration, a multiply-connected network with 4 query nodes is outlined. The logic in Figure 1 is explained in detail. In the figure, we introduce some random variables which can give a system response *R* following after the *instantiation* (it commonly means that a random variable becomes a true state) of triggering; therefore, let a random variable X_k an actual system performance indicator corresponding to a domain variable *k* under the dependency of initiating events. E_i in a root node represents the happening of an initiating event *i* which affects physical domain variables of given system. A random variable *V* denotes a trigger (a kind of filtering interaction) reflecting the fact that any input cannot always produce the output. As a descendant node is affected by different trigger nodes, diverse connections from any *j-th* node of *V* (V_j) to any *k-th* node of *X* (X_k) exist depending on their causal characteristics. As far as *R* from an instantiation of X_k is concerned, we may define it as an adverse impact on the system or any other consequential measure of the system.

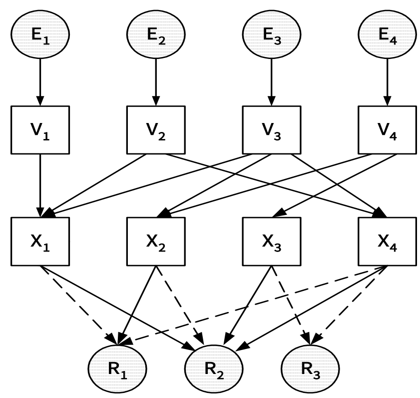

Figure 1. A BN with fully treating causal relationships in PRA

2.2. Approaches for a probabilistic inference

The probability of each instantiation can be simply calculated as the product of the conditional probabilities of its predecessors. Therefore, we need specifying a joint probability distribution over all the random variables. In functional and logical determinations, the state values of the descendant node are wholly determined by the values of the parent nodes.

A key point of practical reasoning is to take the evidence propagation by computing the answer probabilistically for particular queries about the domain, which is generally referred to as a probabilistic inference. Therefore, in order to obtain an adequate solution on the reasoning with parameter fitting, it is necessary to consider an appropriate probabilistic inference algorithm [1]. Finding a sufficient and effective inference algorithm in static BNs is desirable with a computing efficiency of simulation considered. Since general marginalization using joint probabilities requires exponential time in the probabilistic inference, we had to consider more efficient methods. To meet the above demands, we finally selected the best out of a lot of inference algorithms, i.e. likelihood weighting algorithm [2].

3. An example application to a passive system

3.1. Characteristics of a passive system given scenarios

The application involves an example for estimating the risk in a passive system, particularly in association with a radiological waste disposal repository. A basic mechanism governing the release in underground media is the mass transfer in a porous medium. After an elapse of a delay period, the groundwater system becomes an important part of pathway for radionuclide transfer. The degree of saturation of medium, flow of the groundwater system, and chemical properties of radionuclides may be key uncertain elements in determining the release rate.

We introduce the concept of ‘altered evolution scenarios (AESs)’ here as one of extreme and special types of the scenarios. For convenience’ sake, AESs are defined as unusual happenings that can cause significant alteration or momentary changes of underground geochemical, hydrological, and/or mechanical properties which are directly linked with the system performance.

3.2. Supporting evaluation models

Instead of choosing insufficient empirical data, the frequency about AES likelihood is just estimated based on the subjective engineering judgment which uses a concept of categorized selection criterion. Also, we adopted a so-named ‘mixture prior’ concept. By introducing the ‘mixture prior’ we can articulate the effects of uncertain parameters under the occurrence of AESs. The ‘mixture prior’ shows a mixing status of a normal prior and the ‘contaminated prior’.

First, we define an arbitrary prior set Γ to elicit a linear estimator of an uncertain parameter θ. Next, the priors $\pi(\theta)$ ‘close’ to a single normal prior $\pi_0(\theta)$ can be realized with a class of possible ‘contamination’ [3]:

$$\Gamma = \{\pi : \pi(\theta) = (1-\varphi)\pi_0(\theta) + \varphi q(\theta), q \in \Psi\}, \quad (1)$$

where Ψ is a class of possible ‘contamination,’ and φ is an adjustable correction factor with $0 \le \varphi < 1$ which reflects how π closes to π_0.

4. Results of an application

Based on current knowledge of the relationship between domain variables and scenarios which are usually gathered from relevant experts, we can prepare specific information on the conditional probability tables (CPTs) used in the inference program. We had primarily considered the dependencies between 4 domain variables and 4 AESs. In preparing a simulation input for CPTs, we defined a dependency matrix with an ad hoc basis, where the dependency relationships with 4 grades – high, medium, low, and zero – were assumed. All the random variables were simulated concurrently with each AES. The simulation easily reached a stable state except initial transitions. With the acceptance of this simulation, therefore, we can provide the solutions of the query random variables depending on each AES. We also got some remarkable insights, acquired in the simulation results, on the relationship between random variables used in BN and various AESs.

5. Conclusions

Since BNs can contribute to identify the causality of an uncertain system’s behaviour, we introduced its inference process estimating the dependency between stochastic scenarios and affected domain variables of the system. A general approach combining the BN concept into the nuclear PRA was illustratively demonstrated. After simplifying the network corresponding with a problem-specific structure, we developed and verified an approximate probabilistic inference program using an appropriate algorithm, finally shown to be adequate in the verification test for clarifying the dependency relationships under different problem queries.

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