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Review

Using Evidence Credibility Decay Model for dependence assessment in human reliability analysis

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ABSTRACT

Dependence assessment among human errors plays an important role in human reliability analysis. When dependence between two sequent tasks exists in human reliability analysis, if the preceding task fails, the failure probability of the following task is higher than success. Typically, three major factors are considered: "Closeness in Time" (CT), "Task Relatedness" (TR) and "Similarity of Performers" (SP). Assume TR is not changed, both SP and CT influence the degree of dependence level and SP is discounted by the time as the result of combine two factors in this paper. In this paper, a new computational model is proposed based on the Dempster–Shafer Evidence Theory (DSET) and Evidence Credibility Decay Model (ECDM) to assess the dependence between tasks in human reliability analysis. First, the influenced factors among human tasks are identified and the basic belief assignments (BBAs) of each factor are constructed based on expert evaluation. Then, the BBA of SP is discounted as the result of combining two factors and reconstructed by using the ECDM, the factors are integrated into a fused BBA. Finally, the dependence level is calculated based on fused BBA. Experimental results demonstrate that the proposed model not only quantitatively describe the fact that the input factors influence the dependence level, but also exactly show how the dependence level regular changes with different situations of input factors.

Contents

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1. Introduction

Recently human error paid much attention to the design and risk assessment of large complex systems, especially when the human is an important factor of the system, such as nuclear power plant operations, air traffic control, and grounding of oil tankers (Martins and Maturana, 2010; Li et al., 2012; Paté-Cornell, 2012). Human Reliability Analysis (HRA) is a crucial part in the Probabilistic Safety Assessment (PSA) of the technological system, which includes the process of evaluation of human performance and associated impacts on structures, system, and components for a complex facility (Čepin, 2008). Many methods have been proposed based on the HRA (Reer, 2008a,b; French et al., 2011; Marseguerra et al., 2007). An important activity within HRA is the assessment of dependence among human failure events (Swain and Guttman, 1983).

Dependence analysis within HRA refers to evaluating the influence of the failure of the operator to perform one task on the failure probabilities of subsequent tasks (Swain and Guttman, 1983). When dependence between two sequent tasks exists in human reliability analysis, if the preceding task fails, the failure probability of the following task is higher than the success probability (Zio et al., 2009). Thus, an appropriate assessment of dependence is proposed in order to avoid underestimation of the risk. The result of dependence assessment which means a Conditional Human Error Probability (CHEP), given failure on the preceding task (Zio et al., 2009).

Several works have been done for the dependence assessment between Human Failure Events (HFEs) in HRA. The most widely used method is the Technique for Human Error Rate Prediction (THERP) dependence method. THERP introduces five different levels of dependence corresponding to different values of CHEPs and it suggests some of factors that may influence the dependence level. The THERP model refers to five main factors: spatial relatedness, time relationship, functional relatedness, stress, and similarities among the personnel performing the tasks (Podofillini et al., 2010), but it limited these factors on how these factors effect on. Therefore, the assessment requires considerable amount of expert judgment, on identifying which factors are important and on how these factors influence the dependence level, a highly subjective process that may be insufficient traceability and reproducibility.

To overcome this limitation, Decision Trees (DTs) method (Gertman et al., 2005; Čepin, 2008; Grobbelaar et al., 2005) and Fuzzy Expert System (FES) (Zio et al., 2009; Podofillini et al., 2010) have been extended for the THERP dependence model. The central idea of DTs is that the input factors should have less subjective quantities than the dependence level, as the analyst has to give evaluation on the input factors, but it is not required to draw conclusions on the dependence level. In the FES method, analysts are asked to give judgements on the input factors. The input judgements are converted into fuzzy numbers and through a set of rules output the dependence level.

For the ability to represent complex influencing factors relationship and combine different sources of information potentially allows developing HRA models with a stronger basis on cognitive theory and empirical data, applications of Bayesian Belief Networks (BBNs) to HRA are receiving much attention (Mkrtchyan et al., 2015; Baraldi et al., 2015, 2009). Applications of Bayesian Belief Networks (BBNs) to HRA was proposed by Baraldi et al. (2009). A BBN with "ranked nodes" has first been adopted with respect to the dependence assessment model in this paper. Then, two Conditional Probability Tables (CPTs) have to be defined for the TR node (intermediate) and "dependence level" node (final) in order to model the relationship among the input and output factors of the dependence assessment model. This model is also requires an expert system, of which CPTs are constructed by using the historical data, expert judgement or inferred from other expert system.

Based on the above review, they have some limitations which include:

- Lack of theoretical and stronger empirical basis for the key ingredients and fundamental assumptions of the models;
- Lack of sufficient model to deal with uncertainty in the analysts' judgments;
- Methods were insufficiently structured to prevent significant analyst-to-analyst variability of the results generated, stronger subjectivity in capturing the relationships between the judgments of the input factors and output dependence levels.

Considered these issues, a computational model based on the Dempster–Shafer evidence theory (DSET) and the analytic hierarchy process (AHP) method was proposed (Su et al., 2015). It was using the DSET as the framework for representing uncertainty in the analyst's judgment and aggregating the uncertain judgments. The proposed DSET-AHP method could represent the analyst's judgment in a more flexible way: not only the ambiguity but also the confidence of the judgment is considered. Also, this proposed method provides the conditional human error probability (CHEP) among human tasks using a computational model, which reduces the subjectivity in capturing the relationships between the values of the input factors and output result.

However, the DSET-AHP method did not consider the time factor and simply constructed the BBA of "Closeness in Time". It is not appropriate fuzzy the time for the time is a precious concept. Such as, compare the interval time of two sequent tasks 5 min to 10 min, it is obvious that the influence on dependence level is not same in the HRA. When fuzzy the time, the 5 min and 10 min maybe are all "low dependence" (LD) and the influence to dependence level is same in the HRA. Obviously in the DSET-AHP method, it is not appropriate to construct the BBA of CT. The experts are not appropriate to evaluate the interval time.

The relationship among the input factors was not considered in the DSET-AHP method, for that the relationship among the input factors is equal and then combine them. This method make a negative result that it can not control the input factors. Such as, assume the factors TR and SP are not changed, this method can not display how it influence the dependence level that the factor CT as the interval time of two sequent tasks is changed.

In this paper, the DSET is used to quantitate the uncertain judgement and combine the analysts evaluate. It was first proposed by Dempster (1967), and developed further by Shafer (1976). The reasons for selecting DSET in the proposed method were: (1) The DEST is an objective model for it can reduce the influence among the subjective factors; (2) It is a powerful mathematical tool for modeling both uncertainty and imprecision, and can effectively deal with missing information and ignorance; (3) It is a computation model and provide a combination rule to deal with the information relationship among many factors. In this article, the DEST is used to deal with the relationships among the input factors.

In this paper, we use the Evidence Credibility Decay Model to analysis how the time model influence the evidence credibility and dependence level. The Evidence Credibility Decay Model (ECDM) in temporal evidence combination was proposed by Song et al. (2015). The reasons why we use the ECDM are as follows: (1) In time domain, the BBAs are collected sequentially one by one and the evidence credibility of a certain BBA is decaying over the time. Consider the factor of "SP" is changing by the time, like the evidence credibility of the BBA of SP is decaying. The ECDM is used to discount the BBA of SP. (2) The ECDM is an objective model, for it can effective reduce the influence of subjective factors.