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A new safety assessment model for complex system based on the conditional generalized minimum variance and the belief rule base

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ABSTRACT

The safety assessment of complex system is important for implementing and fulfilling the policy of "safety first and prevention oriented". Most available approaches cannot combine historical data with expert knowledge or cannot handle vague and uncertain information efficiently. In this paper, a new safety assessment model for complex system based on the conditional generalized minimum variance (CGMV) and the belief rule base (BRB) is proposed. In the proposed model, to decrease the computation and improve the accuracy, the conditional generalized minimum variance is used to select the key features. Meanwhile, BRB is utilized to deal with both quantitative and qualitative information under uncertainty. Moreover, to improve the precision and efficiency of BRB, the referenced values for the antecedent attributes are optimized by the fuzzy subtractive clustering algorithm. Meanwhile, the belief degrees are calculated by the modified fuzzy c-means clustering. What's more, the differential evolution (DE) algorithm is used to identify the optimal BRB parameters. The new proposed model is applied to an actual engineering system, which is used to testify the validity of the new model. Compared with other approaches, the proposed model has shown superior accuracy and less computation complexity.

1. Introduction

The recent advances in engineering have been translated into large-scale and complicated system with longer lives and higher reliability. To accomplish these expectations, the safety assessment is fatal throughout the longtime running of complex system (Seifedine and Abdelkhalak, 2015). On one hand, the safety assessment of complex system is an important way to implement the policy of "safety first and prevention oriented" (Zhong et al., 2006). On the other hand, it can provide a pre-warning alarm to help engineers conduct proactive maintenance in advance (Hu et al., 2012).

Various approaches have been developed for the safety assessment of complex system such as nuclear power plants (Ciampoli and Ellingwood, 2002), aerospace (NASA, 2011), traffics (Zhang et al., 2014), and industries (Le Coze, 2013). Those assessment approaches could be summarized into three categories: the qualitative approaches, the quantitative approaches and the semi-quantitative approaches.

The common qualitative approaches include the event tree analysis (ETA) (Papazoglou, 1998), the fault tree analysis (FTA) (Wood, 1985), the Petri nets (Leveson and Stolzy, 1987), etc. They are simple, intuitive and easy to understand. However, in qualitative approaches, the mechanisms of the systems are needed to be acquainted by researchers and hard to implement in the safety assessment for complex system. The computational effort is too much and the precision is difficult to ensure (Zhang et al., 2015).

The popular quantitative approaches include the Monte Carlo simulation (MCS) (Metropolis and Ulam, 2012), the Bayesian Network (BN) (Jensen and Nielsen, 2007), etc. The quantitative approaches can perform the safety assessment in a more accurate way. The quantitative approaches use merely the measured signal to extract feature information or inference directly according to historical data (Liu et al., 2010). However, the results are sometimes inaccurate and hard to interpret (Zhou et al., 2013).

In practical engineering, there are qualitative, quantitative and uncertain information in the complex and nonlinear system (Si et al., 2010). The qualitative approaches and the quantitative

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approaches can fulfill the task of safety assessment from different angles but have difficulties in coping with the complicated status of complex system (Zhou et al., 2014).

Several semi-quantitative approaches have been introduced to combine historical data with expert knowledge. Analytic Hierarchy Process (AHP) (Fera and Macchiaroli, 2010), Delphi (Ferri et al., 2005), and Cross Validation (Kohavi, 2001) are all useful tools to solve problems like safety assessment. However, these semi-quantitative approaches can't handle vague and uncertain information efficiently.

Belief rule base (BRB) is an outstanding semi-quantitative approach that is capable of representing complicated causal relationships using different types of information under uncertainties (Zhou et al., 2015). BRB was developed by Yang et al. based on the traditional "IF-THEN" rules and the belief structure (Yang et al., 2006; Yang and Xu, 2013), which has shown excellent performance in many fields (Zhou et al., 2009; Chang et al., 2015). Therefore, it can be utilized for the safety assessment of complex system. The main work in this paper includes:

(1) The conditional generalized minimum variance method (CGMV) was used to select the most representative attributes and simplify the system model. It was an essential step in the assessment process of complex system. The computation complexity can reduce greatly and the accuracy can increase vastly.
(2) To construct a BRB in the appropriate size, the fuzzy subtractive clustering algorithm was adapted to optimize the number and the values of the referenced values for the antecedent attributes. The calculation difficulty was decreased further. Moreover, the belief degrees were calculated by the modified fuzzy c-means clustering. So, the size of BRB was further downsized.
(3) The differential evolution algorithm was employed as the optimization engine to train and optimize BRB parameters. As a result, the optimized BRB can reflect system's behavior accurately.
(4) The new CGMV-BRB-based model was proposed and applied to an actual engineering system, which was used to testify the validity of the new model. Compared with the other approaches, the proposed model has shown higher accuracy, efficiency and scalability.

The rest of this paper is organized as follows. In Section 2, the problem is formulated. In Section 3, a new safety assessment model for complex system based on the CGMV and the BRB is proposed. In Section 4, the diesel engine is chosen as a numerical example to validate the efficiency of the new proposed model. Conclusions are provided in Section 5.

2. Problem formulation for the safety assessment of complex system

A large number of complex features are included in the safety assessment of complex system. In fact, only a small fraction of features is significant and relevant to their properties. For example, the performance of an air fighter or a submarine is influenced by hundreds of features. However, only certain features that are called the Key Performance Parameters (KPPs) are critical to its overall property (Mcchrystal, 2009). Hence, the task of feature selection is to select the KPPs to guarantee high accuracy, efficiency and scalability for the safety assessment (Han et al., 2011).

Once the KPPs have been selected, it is necessary to integrate all the information of the KPPs into a unified result. In this paper, the mathematical formulation of the problem is given in the following section.

Assumptions are given as follows:

(1) t denotes the moment when samples data are collected.
(2) $q_i(t)(i = 1, 2, \ldots, M)$ denotes the value of the ith safety feature which is collected at time instant t.
(3) $y(t)$ denotes the result of safety assessment at the t moment.

Based on the above discussion, the following problems should be solved to assess the safety level of complex system:

Problem 1. Suppose that the input matrix Q is tabled as N samples and M features. Here M is very large. The task of feature selection is to identify a subspace of m features from the M-dimensional observation space that "optimally" characterizes the system performances (Crystal, 2014). Therefore, Problem 1 mainly focuses on how to find the subset X which satisfies Eq. (1):

$$E = \min_A ||Q - XA||^2 \tag{1}$$

where Q is the input matrix, the coefficients matrix A is of size $m \times M$, $X \subset Q$.

Problem 2. To obtain a comprehensive assessment result, multiple safety features should be fused into the result of the safety assessment. Thus, Problem 2 mainly focuses on how to develop the aggregation scheme to obtain the system's safety level. In other words, the following model should be established:

$$O(y(t)) = \{(D_s, \beta_s), s = 1, \ldots, S\} = F(x_1, \ldots, x_m, \psi) \tag{2}$$

where the aggregation scheme F is a nonlinear function. x_i is the value of the safety feature. ψ is the parameter vector in the F function. D_s is the system's state. β_s is the belief degree assessed to D_s, $\beta_s \in [0, 1]$.

For example, there are three different states of a system, namely Normal, Medium fault and Serious fault, which could be expressed as:

$$D = \{Normal(D_1), Medium\ fault(D_2), Serious\ fault(D_3)\}$$

If the system is in normal state, then belief distribution can be expressed as:

$$\{(D, \beta)\} = \{(D_1, 1), (D_2, 0), (D_3, 0)\}$$

Problem 3. The parameter vector ψ in Eq. (2) are usually determined by experts' knowledge. So it should be optimized or adjusted to improve the precision and efficiency of the model. Therefore, Problem 3 mainly focuses on how to find ψ^* which satisfies the following:

$$e = \min(O(y(t)) - \overline{y(t)}) = \min(F(x_1, \ldots, x_m, \psi^*) - \overline{y(t)}) \tag{3}$$

where $\overline{y(t)}$ is the actual result of the system's safety level. ψ_i^* is the optimized parameter vector.

To solve the above three problems, a safety assessment model for complex system based on the conditional generalized minimum variance (CGMV) and the belief rule base (BRB) is proposed in the following sections.

3. A new CGMV-BRB-based model for the safety assessment of complex system

Fig. 1 shows the structure of the newly proposed CGMV-BRB-based model which is composed of four parts. The first part is feature selection which is completed by the CGMV method. The second part is the BRB inference method where the BRB is used to