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α-Decomposition for estimating parameters in common cause failure modeling based on causal inference

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A R T I C L E I N F O

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A B S T R A C T

The traditional α-factor model has focused on the occurrence frequencies of common cause failure (CCF) events. Global α-factors in the α-factor model are defined as fractions of failure probability for particular groups of components. However, there are unknown uncertainties in the CCF parameters estimation for the scarcity of available failure data. Joint distributions of CCF parameters are actually determined by a set of possible causes, which are characterized by CCF-triggering abilities and occurrence frequencies. In the present paper, the process of α-decomposition (Kelly-CCF method) is developed to learn about sources of uncertainty in CCF parameter estimation. Moreover, it aims to evaluate CCF risk significances of different causes, which are named as decomposed α-factors. Firstly, a Hybrid Bayesian Network is adopted to reveal the relationship between potential causes and failures. Secondly, because all potential causes have different occurrence frequencies and abilities to trigger dependent failures or independent failures, a regression model is provided and proved by conditional probability. Global α-factors are expressed by explanatory variables (causes' occurrence frequencies) and parameters (decomposed α-factors). At last, an example is provided to illustrate the process of hierarchical Bayesian inference for the α-decomposition process. This study shows that the α-decomposition method can integrate failure information from cause, component and system level. It can parameterize the CCF risk significance of possible causes and can update probability distributions of global α-factors. Besides, it can provide a reliable way to evaluate uncertainty sources and reduce the uncertainty in probabilistic risk assessment. It is recommended to build databases including CCF parameters and corresponding causes' occurrence frequency of each targeted system.

1. Introduction

As a conclusion from probabilistic risk assessment (PRA) for nuclear power plants (NPPs), common cause failures (CCFs) are significant challenges to the availability of safety systems with redundant components. WASH-1400 defined common mode failure as multiple failures that result from a single event. The single event can be any one of a number of possibilities: a common property, process, environment, or external event [1]. NUREG/CR-4780 defined common cause events as a subset of dependent events in which two or more component fault states exist at the same time, or in short intervals, and are direct results of a shared cause [2].

In past years, great achievements are gained to understand and model the mathematical mechanism of CCF. Fleming [3] introduced the most widely used single parameter model to be applied to CCF analysis, which is known as the β-factor model. Thereafter, for a more accurate analysis of systems with higher level of redundancy, Fleming and Kalinowski [4] extended the β-factor model to Multiple Greek Letter model (MGL). The α-factor model was developed by Mosleh and Siu [5], which can be applied to multi-component system by using total component failure probability and the fractions of CCF probability. NUREG/CR-4780 [2] and NUREG/CR-5485 [6] provided basic principles, models and guidance for analysts performing CCF analysis. Noticeably, NUREG/CR-5485 proposed generic prior distributions of α-factors for various system sizes. Therefore, a question would be asked that how could analysts update the distributions of CCF parameters, since α-factors of every system differ from each other and from time to time.

Along with the development of CCF modeling methodology and database, the understanding of CCF occurring-mechanism is progressing. United States Nuclear Regulatory Commission (U.S. NRC) has been endeavoring to develop a database for CCF parameters estimation [7]. NUREG/CR-5497 provided the parameter estimation employing two quantitative models: MGL model and α-factor model [8]. Furthermore, since 21st century, the emphasis of CCF analysis has been converted from simple mathematical models to

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more complicated event assessment. Based on U.S. commercial NPPs event data, NUREG/CR-6819 illustrated further understanding of CCF insights for emergency diesel generators, motor-operated valves, pumps, and circuit breakers [9]. Updated version of NUREG/CR-6268 presented the process of event data collection and grouped the hierarchy of proximate failure causes, which provided a way to gain further understanding of the CCF events' occurring [10].

Rasmuson et al. extended the previous work on the treatment of CCF in event assessment. Fully expanded fault trees were used, and it is specifically showed that all terms in the basic parameter model (BPM) for each failure model. They quantified the conditional probability of CCF, given independent failures or failures with common-cause potential, and the asymmetry within a common-cause component group (CCCG) is considered [11]. Kelly et al. proposed the preliminary framework of a causality-based model via Bayesian networks which has the potential to overcome limitations of BPM. This model aimed to tell the conditional failure probability of remaining equipment given observed equipment failures and associated causes. Furthermore, it aimed to provide cause-specific quantitative insights into likely causes of failures [12].

As one family of graphical representation of distributions, Bayesian network uses a directed graph (where the edges have a source and a target) to represent a set of independencies and to factorize a distributions [13,14]. This advantage of probabilistic graphical models can promote the visual analysis of CCF. Besides, Bayesian statistical inference provides a way of formalizing the process of learning from data to update beliefs in accord with recent notions of knowledge synthesis [15].

Based on the frequentist probability, the widely applied BPM (β-factor model, MGL model, α-factor model, etc.) enables the uncomplicated evaluation of CCF probability. However, there are unknown uncertainties in the parameter estimation, limitations to identify the risk of potential causes and it is impossible to arrive at posterior distribution as a result of sparse failure data or data-missing problem. Recent research reveals that CCF analysis is transferring from pure mathematical modeling to causality-based analysis. In order to reduce the uncertainty in CCF parameter estimation, Bayesian regression models can be applied to combine difference data sources of CCF failure events and cause occurrence. Therefore, posterior distributions of less uncertainty can be obtained.

In this paper, the authors propose the α-decomposition process to estimate CCF parameters. The α-decomposition process is named as Kelly-CCF method since Dana Kelly firstly proposed the preliminary framework of a causality-based Bayesian network for CCF analysis: (a) based on the causal inference for CCF, global α-factors are decomposed as a regression model with explanatory variables (causes' occurrence frequencies) and parameters (decomposed α-factors); (b) Bayesian inference is applied to arrive at posterior distributions for global α-factors and decomposed α-factors, which quantitatively represent the CCF risk on component level and cause level, respectively; (c) a hypothetical database is constructed and recommended to be built for the α-decomposition analysis. This database must include causes occurrence frequencies and either α-factors or CCF event records for specific systems.

2. α-factor model for standard CCF analysis

Before the introduction of the α-decomposition process, a review of the standard α-factor model is necessary for the purpose of easy understanding of the notation. As shown in Fig. 1, let us consider a system of three identical components A, B, and C from the perspective of a two-out-of-three success logic [6]. The common-cause component group (CCCG) is A, B, and C. There, a group of components identified in the process of CCF analysis is called as a CCCG. The minimal cutsets of this system failure are:

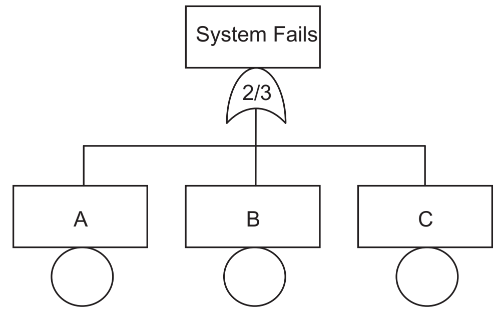

Fig. 1. Component-level fault tree of system.

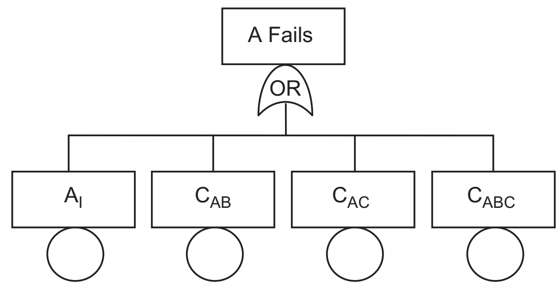

Fig. 2. Expanded CCBE fault tree for component A.

$\{A,B\}; \{A,C\}; \{B,C\}; \{A,B,C\}$

For the consideration of CCF, the fault tree is expanded to include corresponding common-cause basic event (CCBE). Take component A as an example as shown in Fig. 2.

The cutsets of component A are

$\{A_I\}; \{C_{AB}\}; \{C_{AC}\}; \{C_{ABC}\}$

Similarly, the cutsets of component B failure are

$\{B_I\}; \{C_{AB}\}; \{C_{BC}\}; \{C_{ABC}\}$

The cutsets of component C failure are

$\{C_I\}; \{C_{AC}\}; \{C_{BC}\}; \{C_{ABC}\}$

Here, A_I is the failures of component A from independent causes, B_I is the failures of component B from independent causes, C_I is the failures of component C from independent causes; C_{AB} is the failures of components A and B from common causes, C_{AC} is the failures of components A and C from common causes, C_{BC} is the failures of components B and C from common causes and C_{ABC} is the failures of components A, B and C from common causes.

Using the rare event approximation, the system failure probability of the two-out-of-three system is given by

$$P(S) \cong P(A_I)P(B_I)+P(A_I)P(C_I)+P(B_I)P(C_I)+P(C_{AB})+P(C_{AC})+P(C_{BC})+P(C_{ABC}) \tag{1}$$

In Eq. (1), the rare event approximation is defined as that the probability of the simultaneous occurrence of two independent failures is assumed as zero. It can be written as

$$P(a+b)=P(a)+P(b)-P(a \cdot b) \cong P(a)+P(b) \tag{2}$$

The failure probability of component A is decomposed as

$$P(A_t)=P(A_I)+P(C_{AB})+P(C_{AC})+P(C_{ABC}) \tag{3}$$

Here, A_t is the all failures of component A, and $P_{(X)}$ is the probability of event X.