NTHAS8: The Eighth Japan-Korea Symposium on Nuclear Thermal Hydraulics and Safety
Beppu, Japan, December 9-12, 2012

Paper Number N8P1115

QUANTITATIVE RISK ASSESSMENT OF COMMON CAUSE FAILURE INVOLVING THE DEGRADATION OF DEFENSE BARRIER AGAINST SEISMIC INDUCED INTERNAL FLOODING

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ABSTRACT

The degradation of defense barrier against common cause failure (CCF) is an important factor that affects probability distributions for system failures. The assessment of system-specific CCFs is necessary for reducing the uncertainty during the process of probabilistic risk assessment (PRA). α-decomposition method is an approach for the quantitative analysis of CCF modeling using Bayesian probability, in which the estimation of parameters is more accurate by combining the failure information from system, component and cause level. This article describes the application of α-decomposition method involving the degradation of defense barrier against seismic induced internal flooding. The Markov model for the degradation of defense barrier is applied for estimating time dependent CCF parameters. Examples are presented to demonstrate the calculation process and necessary databases are recommended to be built. As a result, the posterior distributions for CCF parameters (α-factors) are obtained at each time node, and the dynamic risk analysis of CCF for seismic induced internal flooding is estimated.

1. INTRODUCTION

In the probabilistic risk assessment (PRA) performed by nuclear safety analysts, the parameter estimation for common cause failure (CCF) is an important factor in obtaining more reliable probability distributions for system failures. Great achievements have been gained to improve understanding and modeling of CCF events. Basic parameter models (BPM) were developed by U.S. NRC (Mosleh A. et al., 1989; Mosleh A. et al., 1998). These are single or multiple parameter models for numerically estimating CCF risk for system failures and each parameter represents the failure risk including certain amount of components. Recent research reveals that the analysis of CCF has been expanded to failure cause inference (Wierman T.E. et al., 2003; Wierman T. E. et al., 2007). In order to reduce the uncertainty in CCF parameter estimation, it is necessary to combine the information of failure mechanism from cause level, component level and system level together. Based on traditional BPM for CCF analysis and cause analysis, α-decomposition method (Zheng X. et al., 2012) was proposed with the application of Bayesian probability to obtain posterior distributions for CCF parameters which can utilize different data sources and the result is of less uncertainty.

CCF events are system specific topics since the detailed design of systems vary from one system to another system. The BPM models can be treated as an average on all similar system and time because all CCF events are classified and collected without the consideration of causes and the detailed design of each system. There are main elements of CCF events including failure cause, coupling factor and defense barrier (a defense strategy). The failure cause is the initiating event why a CCF occurs. The coupling factor is the condition through which failures of multiple components are coupled. The defense barrier for the CCF system may be a functional barrier, physical barrier, etc. which is constructed primarily based on defending against the CCF coupling factors. Therefore, when the defense barrier against CCF events degrades for some certain reasons, the risk of CCF will increase and the failure probability of the system will change.

Following the Fukushima Dai-ichi nuclear power plant accident on March 11 2011, the Atomic Energy Society of Japan (AESJ) started to develop the standard of Tsunami PRA since May 2011. Research shows that the seismic-induced secondary events (e.g. seismic-induced flood, seismic-induced station blackout) should be considered and PRA standards for coupled phenomena of earthquake should be established (Yamaguchi A. et al., 2012). Recent research shows the Markov models for nuclear power plant piping systems can utilize different data sources and non-data information to reduce the evaluation uncertainty

(Fleming K.N., 2004). Similarly, this article proposes an alternative method to consider the failure probability of defense barrier against seismic induced internal flooding.

This paper is presented to conduct the quantitative risk analysis of CCF involving the degradation of defense barrier: (1) α-decomposition method is reviewed on the basis of α-factors model and cause inference. (2) Markov modeling for the degradation of defense barrier is introduced. (3) An example of Bayesian inference is exhibited to explain the application of α-decomposition method in consideration of defense barrier failure and databases are developed with necessary information.

2. α-DECOMPOSITION METHOD

2.1 α-factor model

The movement from single-parameter model to multi-parameter model is actually the decomposition from single lumped parameter to multiple lumped parameters at component-level. α-factor model is an event-based multi-parameter model. In other words, α-factor model is based on component failure and more directly related to the observable number of CCF events. Due to the lack of space in this paper, the simplest α-factor model is briefly reviewed and more specific introduction can be obtained in NUREG/CR-4780 (Mosleh A. et al., 1989) and NUREG/CR-5458 (Mosleh A. et al., 1998). Let us consider a system of three components A, B, and C, with a two-out-of-three success logic, so 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 common cause component group. The failure probability of component A is decomposed as:

$$P(A_t) = P(A_I) + P(C_{AB}) + P(C_{AC}) + P(C_{ABC}) \quad (1)$$

Here, A_t: all failures of component; A_I: failures of component A from independent causes; C_{AB}: failures of components A and B from common causes; C_{AC}: failures of components A and C from common causes; C_{ABC}: failures of components A, B and C from common causes; $P(X)$: probability of event X. And assume that:

$$P(A_I) = P(B_I) = P(C_I) = Q_1 \quad (2)$$

$$P(C_{AB}) = P(C_{AC}) = P(C_{BC}) = Q_2 \quad (3)$$

$$P(C_{ABC}) = Q_3 \quad (4)$$

And the component A failure probability is

$$Q_t = Q_1 + 2Q_2 + Q_3 \quad (5)$$

In this paper, the system is assumed as staggered testing scheme. The definition of α-factors (staggered testing scheme):

$$\alpha_1 = \frac{Q_1}{Q_t};\ \alpha_2 = \frac{2Q_2}{Q_t};\ \alpha_3 = \frac{Q_3}{Q_t} \quad (6)$$

2.2 α-decomposition method for CCF analysis

2.2.1 The definition of α-decomposition

For distinction, the α-factors in component level are named as global α-factors, and after decomposition, the α-factors in cause level are named as decomposed α-factors. In previous CCF analysis, the global α-factors are treated as distributions and the uncertainty in such distributions is always unknown and ignored. The uncertainty in basic events analysis will be propagated through PRA models, such as Fault Tree and Event Tree, and then the distributions for top events will be flattened. The global α-factors in α-factor model can be affected by observable or unobservable variables. Information about such variables can be used in Bayesian inference paradigm to obtain posterior distributions for parameters of less uncertainty.

Definition 1 (α-decomposition): The global α-factors are decomposed with explanatory variables, such as occurrence frequencies and CCF triggering abilities (decomposed α-factors) of potential causes. The Bayesian network is applied to represent the relationship of global α-factors and decomposed α-factors.

2.2.2 The hybrid Bayesian network (HBN) for α-decomposition process

To infer the mathematical model of α-decomposition process, two kinds of relationships are considered: the relationship between system failures and component failures; the relationship between component failures and causes. Hybrid Bayesian network (HBN) is applied to express both relationships. A hybrid network means to use a combination of two or more topologies, and here the HBN is a combination of Fault Tree (FT) and Bayesian network. Let's consider a system of three components A, B, and C. In standard α-factor model, all components of one system are assumed identically. For the simplest consideration, it is also assumed that all of three components, A, B, and C are identical and that there are three potential causes, C1, C2, and C3 that will possibly lead to the component failure (as shown in Fig.1).

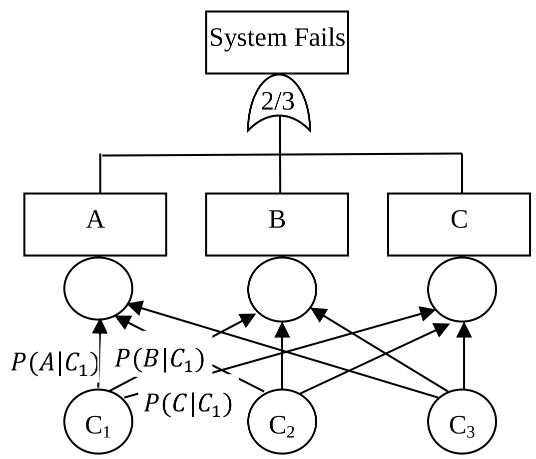

Fig. 1 HBN for CCF analysis

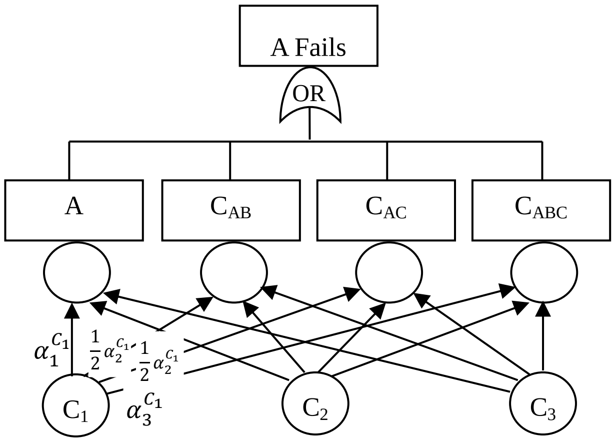

Fig. 2 α-decomposition for CCF analysis with HBN

The conditional probabilities of component failure and system failure are expressed in Fig.1. Take component A as an example:

$$P(A) = \sum_{i=1}^{3} P(A|C_i)P(C_i) \tag{7}$$

The process of α-decomposition method is illustrated in Fig.2, and the mechanism of Cause i is operated by generating independent A failure; A and B failures; A and C failures; A, B and C failures:

$$P(A|C_i) = P(A_I|C_i) + P(AB|C_i) + P(AC|C_i) + P(ABC|C_i) \tag{8}$$

Both sides of equation are divided by $P(A|C_i)$:

$$1 = \alpha_1^{C_i} + \alpha_2^{C_i} + \alpha_3^{C_i} \tag{9}$$

Here, $\alpha_1^{C_i} = \frac{P(A_I|C_i)}{P(A|C_i)}$; $\alpha_2^{C_i} = \frac{P(AB|C_i)}{P(A|C_i)} + \frac{P(AC|C_i)}{P(A|C_i)}$; $\alpha_3^{C_i} = \frac{P(ABC|C_i)}{P(A|C_i)}$. On the purpose of distinguishing the difference between two kinds of α-factors, in this paper, we named the α_j $(j = 1,2,3)$ as global α-factors, and named the $\alpha_j^{C_i}$ $(i, j = 1,2,3)$ as causes' α-factors. The independent failure of component is affected by Cause 1, Cause 2 and Cause 3, and according to Fig.2, the relationship is expressed as:

$$P(A_I) = \sum_{i=1}^{3} P(A_I|C_i)P(C_i) \tag{10}$$

Replace the independent part of probability with $\alpha_1^{C_i}$ elements as follows,

$$P(A_I) = \sum_{i=1}^{3} \alpha_1^{C_i} P(A|C_i)P(C_i) \tag{11}$$

Both sides of equation are divided by P(A) and because $\frac{P(A_I)}{P(A)} = \alpha_1$, so we get as follows,

$$\alpha_1 = \sum_{i=1}^{3} \alpha_1^{C_i} \frac{P(A|C_i)P(C_i)}{P(A)} \tag{12}$$

Extrapolate the α_1 to any α_j, and we get very simple form of α_j-decomposition; and deduced from Fig.1, it is known that failure of A is generated by three parts, and we notate these three parts as fractions or rates;

$$\alpha_j = \alpha_j^{C_1} r_1 + \alpha_j^{C_2} r_2 + \alpha_j^{C_3} r_3;\ (j = 1,2,3) \tag{13}$$

$$r_i = \frac{P(A|C_i)P(C_i)}{P(A)} = P(C_i|A);\ (i = 1,2,3) \tag{14}$$

The $\alpha_j^{C_i}, r_i (i, j = 1,2,3)$ have practical engineering meanings: The $\alpha_j^{C_i}$ means the ability of Cause i to lead to the j components failure; the r_i means that among all failures, totally there are $r_i \times 100\%$ failures generated by cause i. In other words, r_i is the occurrence rate over the occurrence of all effective causes. (Effective cause means the cause really triggers a failure whether independent or dependent and oppositely, if a cause happens but no failure is generated, it is not an effective cause.) For example, if Cause 1 happens much more frequently than other causes, the global α_j will tend to be $\alpha_j^{C_1}$; on the other side, if Cause 2 happens rarely with low $\alpha_j^{C_2}$, it means that risk-significance of Cause 2 is negligible.

3. DEGRADATION OF DEFENSE BARRIER

3.1 Markov model for states of defense barrier against internal flooding

Various secondary dependent events may be caused by an earthquake, and such secondary events may be the proximate causes of failures. Generally, secondary events could be a non-safety-related pipe break caused by an earthquake which is the water source of a flood, or seismic-induced fire, or seismic-induced station blackout, etc. In the current paper, it is assumed that there is no direct failure for safety concerned components caused by the earthquake but the risk of CCF will be affected by the shock. The reason is that the defense barrier against CCF proximate causes will degrade as a result of the seismic shock. The defense barrier against internal flooding is taken as an example to illustrate the calculation process. It should be cautioned that the detailed failure mechanism of defense barriers might be not identical to the example proposed, but the consideration of defense barrier in probabilistic CCF analysis is important to reduce the parameter estimation uncertainty reasonably. Further study on the physical failure mechanism of defense barrier should be conducted to establish Tsunami PRA Standards. The degradation of defense barrier against internal flooding is assumed as propagating among four states: success, flaw, partial failure and failure. There are dynamic probabilities for states over time. If the transition parameters can be determined, the dynamic probability distribution over each state can be estimated correctly. As shown in Fig.3, Markov model is proposed to simulate the degradation of defense barrier and the transition parameter between two states is assumed based on databases or expert experience.

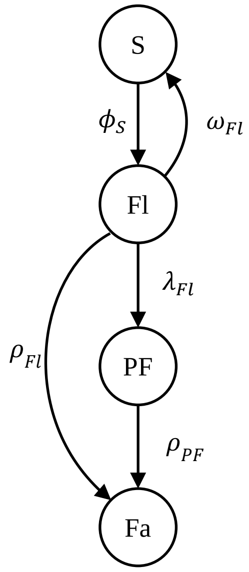

Fig. 3 Markov model for degradation of defense barrier

Four states of defense barrier are notated as: S - Success; Fl - Flaw; PF - Partial Failure; Fa - Failure. The transition probability between states are expressed as: ϕ_S - Flaw occurrence probability; ω_{Fl} - Repair probability for flaw; λ_{Fl} - Partial failure probability given flaw; ρ_{PF} - Failure probability given partial failure; ρ_{Fl} - Failure probability given flaw.

In order to compute probabilities over four states, differential equations should be defined.

$$\frac{dP_{(S)}}{dt} = -\phi_S P_{(S)} + \omega_{Fl} P_{(Fl)} \quad (15)$$

$$\frac{dP_{(Fl)}}{dt} = \phi_S P_{(S)} - (\omega_{Fl} + \rho_{Fl} + \lambda_{Fl}) P_{(Fl)} \quad (16)$$

$$\frac{dP_{(PF)}}{dt} = \lambda_{Fl} P_{(Fl)} - \rho_{PF} P_{(PF)} \quad (17)$$

$$\frac{dP_{(Fa)}}{dt} = \rho_{Fl} P_{(Fl)} + \rho_{PF} P_{(PF)} \quad (18)$$

So the Markov model can be described by a set of four coupled linear first-order ordinary differential equations (ODEs). At any time t there is a sum-to-one constraint for four probabilities, so the sum of initiating values for all state probability should be 1. Usually, the set of initiating values is assumed as $(1,0,0,0)^T$.

$$P_{(S)} + P_{(Fl)} + P_{(PF)} + P_{(Fa)} = 1 \quad (19)$$

Therefore, the solutions of equations (15) ~ (18) can be computed at each time point based on all known parameters $(\phi_S, \omega_{Fl}, \lambda_{Fl}, \rho_{Fl}, \rho_{Fa})$. The transition parameters associated with failure propagation are provided in Table 1.

Table 1 Distributions for transition parameters

Parameter symbol	Definition
ϕ_S	ϕ_S: Flaw occurrence probability. The recorded detectable flaw occurrence rate is assumed as Poisson distribution with the parameter λ, so the total flaw occurrence is a multiple of the detectable flaw rate. m_{Fl} is the flaw to detectable flaw ratio, which is assumed as Beta distribution based on expert judgment. (m_{Fl}: Lower bound – 1; Upper bound – 10; Alpha – 1; Beta – 2; Mean – 4) $$\phi_S = m_{Fl}\lambda$$
ω_{Fl}	ω_{Fl}: Repair probability for flaws. P_R is the repair rate for a detectable flaw, which is assumed as Beta distribution based on service data. (P_R: Lower bound – 0.1; Upper bound – 0.3; Alpha – 1; Beta – 2; Mean – 0.17) $$\omega_{Fl} = \frac{P_R}{m_{Fl}}$$
λ_{Fl}	λ_{Fl}: Partial failure probability given flaw. Distribution for λ_{Fl} is assumed as Lognormal distribution. (λ_{Fl}: Mean – 0.04; Range factor – 3) $$\lambda_{Fl} \sim Lognormal(\mu_{\lambda.Fl}, \sigma^2_{\lambda.Fl})$$
ρ_{PF}	ρ_{PF}: Failure probability given partial failure. Distribution for ρ_{PF} is assumed as Lognormal distribution. (ρ_{PF}: Mean – 0.02; Range factor – 3) $$\rho_{PF} \sim Lognormal(\mu_{\rho.PF}, \sigma^2_{\rho.PF})$$
ρ_{Fl}	ρ_{Fl}: Failure probability given flaw. P_F is the failure probability, whose prior distribution is always assumed as Lognormal distribution for each failure mode and there is always great uncertainty in this estimation. m_{Fa} is the factor of failure affected by aftershock, which is assumed as Beta distribution based on expert judgment. (m_{Fa}: Lower bound – 1; Upper bound – 3; Alpha – 1; Beta – 2; Mean – 1.67) $$\rho_{Fl} = m_{Fa}P_F$$

Since the degradation mechanism for defense barrier against internal flooding needs to be well established and limited information is available, the definition refers to the definition of parameters for pipe failure (Fleming

K.N. et al., 2010). It should be noted that the aim of current paper is to explain the method conceptually. The essential process of Markov model is that the stationary failure data is applied to estimate the transition parameters based on Bayesian theory and then the ODEs are resolved at each time step.

3.2 CCF modeling involving defense barrier

A coupling factor is a term to explain how a shared cause propagates to involve multiple equipment items, which is defined as the condition or mechanism through which failures of multiple components are coupled, e.g. quality-based couplings, design-based couplings and environment-based couplings, etc. It is a design-based coupling that redundant components that are of same design will fail because of the same design error. Hence, there are two methods to protect systems from CCF: one is to defend against the possible shared cause, for example, improve the safety factor in design, and the other is to defend against the coupling factor, for example, adopt the concept of diversity to avoid same design error. The defense barrier for internal flooding is to limit the flood at one location to avoid other locations affected by the flood. As shown in Fig.4, in turbine building where three feedwater pumps (A&B&C) are located and potential alternative flood water sources exist. Green circles are flood defense barriers adopted to protect safety-related feedwater pumps from flood. Basically, if the defense barrier is effective constantly, the internal flood at one location will only affect components at one location. To some extent, an effective defense barrier will protect the system by converting the shared causes to independent causes. Therefore, the state of defense barriers affect the CCF parameters distribution.

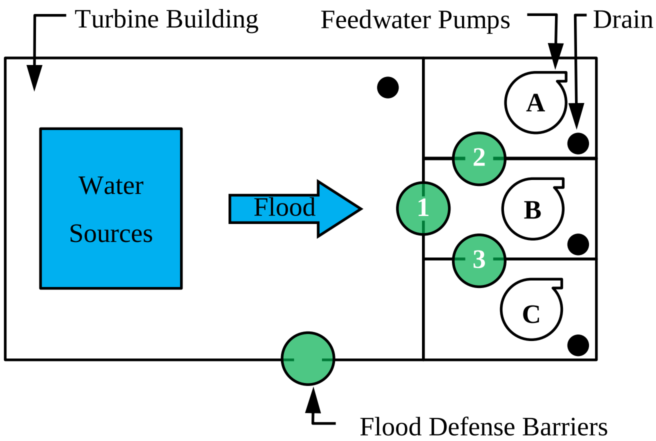

Fig. 4 Additional flood defense barriers in turbine building

As shown in Fig.5, the red lines represent the defense barriers for Cause 1 (internal flood), and the internal flood is relatively an independent cause that only affects the respective component at one location. Compared with a system without defense barrier for internal flooding, the CCF risk for the current protected system is lower. Such difference is not considered in previous α-factor model, and the estimation of such system with defense barrier will be of unpredicted uncertainty. Especially, once that there is an earthquake happens and then the defense barrier is damaged or in the state of damage propagation, it is necessary to evaluate the time-dependent CCF risk.

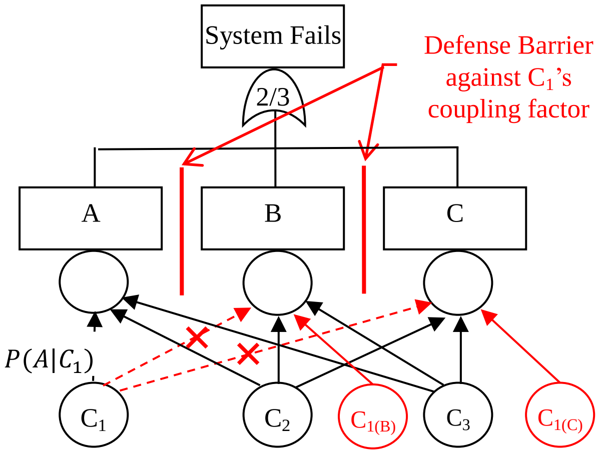

Fig. 5 CCF modeling involving a defense barrier against one shared cause's coupling factor

3.3 α-decomposition method for systems with barrier degradation

Based on the analysis in Section 2, decomposed α-factors represent the ability of one cause to trigger independent failures and dependent failures. To the system with defense barrier against internal flooding, the internal flooding tends to affect single component at one location, so the $\alpha_1^{C_1}$ is near to 1. With the damage propagation of defense mechanism against internal flooding, the risk of internal flooding becomes more common and tends to triggering CCF other than an independent failure. Therefore, the application of α-decomposition method aims to quantitatively compute the dynamic CCF risk of system.

There are four states of the defense barrier against the internal flooding, success, detective flaw, partial failure and failure. For states of success and detective flaw, the defense barrier is effective to protect the system from CCF caused by internal flooding, so the major type of failure is independent. For the state of partial failure, the defense barrier is thought as partially effective. For the state of failure, the system is treated the same as the system without defense barrier, when the CCF part caused by internal flooding is largest. Therefore, based on the failure data for the system without defense mechanism, all decomposed α-factors can be calculated. Afterwards, with the consideration of the introduction and degradation of defense barrier, the change of α-factors can be evaluated. At a certain time step t_k , the decomposed α-factors $\left(\alpha_{1(t_k)}^{C_1}, \alpha_{2(t_k)}^{C_1}, \alpha_{3(t_k)}^{C_1}\right)^T$ of internal flooding (Cause 1) can be expressed by equations (20) ~ (22). $\left(\alpha_1^{C_1}, \alpha_2^{C_1}, \alpha_3^{C_1}\right)^T$ is the set of decomposed α-factors of system without defense barrier against internal flooding. It numerically explains that the effectiveness of defense barrier will reduce the CCF risk of system. With the degradation of defense barrier, the probability over states (success and flaw) will reduce and the probability over states (partial failure and failure) will increase, so the risk of partial and complete CCF will increase.

$$\alpha_{1(t_k)}^{C_1} = \alpha_1^{C_1} + \left(P_{(S)(t_k)} + P_{(Fl)(t_k)}\right)\left(\alpha_2^{C_1} + \alpha_3^{C_1}\right) \quad (20)$$

$$\alpha_{2(t_k)}^{C_1} = \alpha_2^{C_1} - \left(P_{(S)(t_k)} + P_{(Fl)(t_k)}\right)\alpha_2^{C_1} + P_{(PF)(t_k)}\alpha_3^{C_1} \quad (21)$$

$$\alpha_{3(t_k)}^{C_1} = \alpha_3^{C_1} - \left(P_{(S)(t_k)} + P_{(Fl)(t_k)} + P_{(PF)(t_k)}\right)\alpha_3^{C_1} \quad (22)$$

4. BAYESIAN INFERENCE FOR PARAMETERS

4.1 Hierarchical Bayesian modeling

This section shows how to calculate the posterior distributions for CCF parameters (global α-factors and decomposed α-factors) based on available operational database. In traditional CCF parameter estimation, the vector of global α-factors is almost always assumed to be a Dirichlet distribution, which is conjugate to the multinomial likelihood. Moreover, the failure distributions for CCF events are always assumed as Multinomial distribution, so the estimation of global α-factors can be conducted by Bayesian inference. Usually, in the Bayesian inference for CCF parameters, parameters in prior distribution are set as constant, for example, the noninformative prior for global α-factors, which is a Dirichlet distribution with all parameters equal to 1 (Kelly D.L. et al., 2009).

Considering CCF parameter estimation based on the information from cause level, the prior in the previous model should be specified in multiple stages. The graphical representation of a multi-stage hierarchical Bayesian modeling is shown in Fig.6. Oval nodes refer to stochastic components of the model, and squared nodes refer to constant parameters. Solid arrows indicate a stochastic dependence while hollow arrows indicate a logical function. The node ($\mathrm{t}[1:3]$) is the data of CCF events, which is assumed as Multinomial distribution. This value is affected by the node global α-factors ($\alpha[1:3]$) and the distribution of global α-factors is assumed as Dirichlet distribution. The node ($\theta[1:3]$) represses parameters in prior distribution of node ($\alpha[1:3]$), which is affected by hyper variables. Hyper variables are decomposed α-factors and causes' occurrence frequencies. The distribution of global α-factors is affected by these two sets of variables. Decomposed α-factors are called hyper variables since they are uncertain variables. Other constant values are called as hyper parameters. Usually, $\mathrm{P}(\mathbf{t}|\boldsymbol{\alpha})$ is called likelihood, $\mathrm{P}(\boldsymbol{\alpha}|\boldsymbol{\theta})$ is called prior distribution (1st level), and $\mathrm{P}\left(\boldsymbol{\theta}\middle|\boldsymbol{\alpha}_{[\,]}^{\mathbf{C_1}}, \boldsymbol{\alpha}_{[\,]}^{\mathbf{C_2}}, \boldsymbol{\alpha}_{[\,]}^{\mathbf{C_3}}, \mathbf{r}\right)$ is called hyperprior (2nd level). If parameters in the hyperprior were all constant, such kind of model would be called two-stage Bayesian hierarchical model. However, since all decomposed α-factors are treated as uncertain variables, this model is simply named as multi-stage Bayesian hierarchical model.

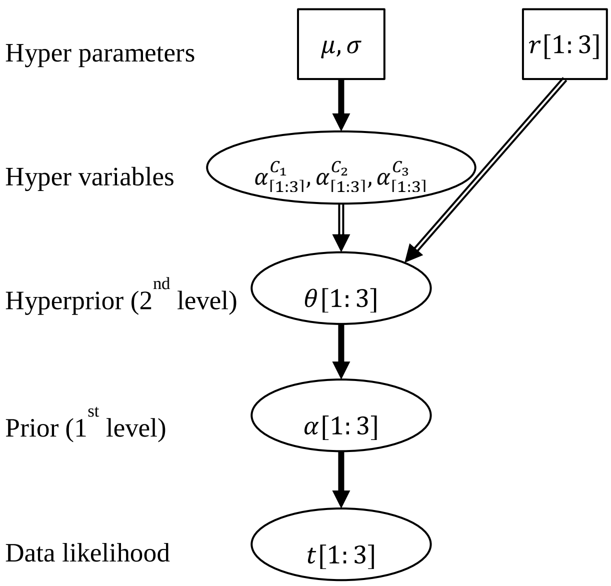

Fig. 6 Directed acyclic graph for Bayesian inference

Bayes' theorem provides an expression for the conditional probability of global α-factors and causes' α-factors given the rates of causes' occurrence, which is shown as:

$$P\left(\alpha_j^{C_i}\middle|\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right) = \frac{P\left(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\middle|\alpha_j^{C_i}\right)P(\alpha_j^{C_i})}{P(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t})} \quad (23)$$

In equation (23), $\mathrm{P}(\alpha_j^{C_i})$ is the prior distribution of decomposed α-factors, and $\mathrm{P}\left(\mathbf{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \mathbf{t}\middle|\alpha_j^{C_i}\right)$ is defined as the likelihood of parameters. Therefore, according to the chain rule of conditional probability and the independence between some parameters, the posterior distribution can be written as

$$\pi_2\left(\alpha_j^{C_i}\middle|\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right) \propto f_t(\boldsymbol{t}|\boldsymbol{\alpha}) f_\alpha(\boldsymbol{\alpha}|\boldsymbol{\theta}) f_\theta\left(\boldsymbol{\theta}\middle|\alpha_j^{C_i}, \boldsymbol{r}\right)\pi_1(\alpha_j^{C_i}) \quad (24)$$

Here, all bold letters mean vectors of respective parameters. Therefore, the posterior distribution $\pi_2\left(\alpha_j^{C_i}\middle|\mathbf{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \mathbf{t}\right)$ can be obtained by the deduction on the basis of prior distribution $\pi_1(\alpha_j^{C_i})$ and the likelihood functions. The CCF parameters for system without defense barrier can be well established according to the operation record of CCF events and the statistical computation. Combining the analysis in Section 3.3, the dynamic analysis for CCF parameters can be conducted. In the next part, an example is proposed to explain the calculation process.

4.2 An example of Bayesian inference for system with degraded defense barrier

The following example is proposed to explain how to evaluate CCF parameters for system with degraded defense barrier combining the time-dependent factor. It should be cautioned that the developed database used in current paper are not from real database and is for illustration only. The Bayesian calculation is conducted by OpenBUGS version 3.2.2.

Table 2 describes the data used for the Bayesian updating of Markov parameters. 2 hypothetical experiments are assumed to be conducted to obtain the occurrence rate of flaw after the defense barrier receives a seismic shock. Such as for Experiment 1, after the shock happens, there is 8 detectable flaws are discovered but no direct failure. The failure will be propagated according to the failure mechanism. Therefore, based on the evidence database and the assumption of transition parameters, the posterior distributions for transition parameters can be obtained.

Table 2 Flaw and failure occurrence rate

	Experiment 1	Experiment 2
Detectable Flaw	8	10
Failure	0	0

Table 3 lists the hypothetical database with the record of the occurrence of causes and CCF events. The recorded system is without the applying of defense barrier against internal flooding. The aim of this analysis is to reveal the change of CCF parameter after the introduction and the degradation of effective defense barrier against internal flooding. Three causes are assumed in Table 1. The Cause 1 is assumed as Internal Flooding, the Cause 2 as Seismic and the Cause 3 as Others. Components A, B, and C are assumed as safety-related components which is seismically qualified. Meanwhile, the water sources (e.g. high energy pipe lines and fire sprinklers, etc.) and defense barriers are generally not safety qualified. It is reasonable that safety-related components do not fail for an earthquake but fail for seismic induced flood. Table 3 lists the data of internal flood and earthquake which are not totally dependent since there are other causes (e.g. random breaks of feed water pipe or tank, steam line breaks causing fire protection system actuation, etc.) which will lead to internal floods.

As introduced before, for a single system with 3 redundant components, the Multinomial distribution serves as the aleatory model for CCF events, and the prior distributions for global α-factors are assumed as Dirichlet distribution.

$$t[1{:}m] \sim dmulti(\alpha[1{:}m], T) \tag{25}$$

$$\alpha[1{:}m] \sim ddirich(\theta[\,]) \tag{26}$$

Similarly, the prior distributions of decomposed α-factors are assumed as Dirichlet distribution. A noninformative prior is a Dirichlet distribution with each parameter $\delta_i[\,] = 1$.

$$\alpha^{C_i}[1{:}m] \sim ddirich(\delta_i[\,]) \tag{27}$$

On the basis of equations (13) and (14), the parameters of global α-factors can be expressed with decomposed α-factors as well as occurrence rate:

$$\theta[i] = \left(\sum_{i=1}^{3} \alpha_j^{C_i} \times r_i\right) \times T \tag{28}$$

Thus,

$$Posterior\ \alpha_j^{C_i} \propto Prior\ \alpha_j^{C_i} \times Likelihood\left(r, t \middle| \alpha_2^{C_i}\right) \tag{29}$$

Table 3 Hypothetical database of CCF events recording

	Common causes' occurrence				Independent and CCF event		
	Cause 1 (Internal flooding)	Cause 2 (Seismic)	Cause 3 (Others)	Total	Single (1/3)	Partial (2/3)	Complete (3/3)
System 1	32(25.20%)	28(22.00%)	67(52.80%)	127	113	11	3
System 2	17(16.00%)	78(73.60%)	11(10.40%)	106	98	7	1
System 3	18(20.70%)	19(21.80%)	50(57.50%)	87	73	9	5
System 4	29(43.90%)	6(9.10%)	31(47.00%)	66	53	5	8
System 5	7(14.00%)	33(66.00%)	10(20.00%)	50	45	4	1
System 6	15(36.60%)	9(22.00%)	17(41.40%)	41	33	3	5
System 7	12(35.30%)	15(44.10%)	7(20.60%)	34	32	2	0
System 8	2(6.50%)	22(71.00%)	7(22.50%)	31	29	2	0
System 9	7(31.80%)	4(18.20%)	11(50.00%)	22	20	2	0
System 10	10(47.60%)	8(38.10%)	3(14.30%)	21	20	1	0
System 11	3(15.80%)	6(31.60%)	10(52.60%)	19	16	2	1
System 12	7(43.80%)	3(18.80%)	6(37.40%)	16	14	1	1
System 13	3(20.00%)	5(33.33%)	7(46.67%)	15	13	1	1
System 14	5(33.30%)	3(20.00%)	7(46.70%)	15	12	1	2
System 15	4(36.40%)	5(45.50%)	2(18.10%)	11	9	1	1
System 16	1(11.10%)	6(66.70%)	2(22.20%)	9	7	1	1

Based on the assumption in Table 1 as well as flaw and failure data in Table 2, results for the transition parameters of Markov model are shown in Table 4 which is computed by OpenBUGS.

Table 4 Results for Markov parameters

Symbol	Mean	90% interval
ϕ_S	2.13E-01	(6.37E-02, 5.95E-01)
ω_{Fl}	7.91E-02	(2.00E-02, 1.89E-01)
λ_{Fl}	4.05E-02	(8.55E-03, 1.21E-01)
ρ_{PF}	4.04E-02	(5.46E-03, 1.41E-01)
ρ_{Fl}	2.01E-02	(4.35E-03, 5.99E-02)

For system without the defense barrier, the results for CCF parameters (global and decomposed α-factors) are shown in Table 5. It is obvious that causes have different abilities to trigger CCF events, so the posterior distributions for decomposed α-factors are different from each other. Moreover, the global α-factors for each system can be obtained with less uncertainty than that of previous α-factor modeling (Zheng X. et al., 2012). Here, the global α-factors for System 1 are listed for illustration.

Therefore, the time-dependent results for CCF parameters can be evaluated by combing the Markov model with the α-decomposition method. It can be predicted that the CCF risk for the system without defense barrier is highest. On the other hand, the system with effective defense barrier is of the lowest CCF risk. Within the degradation process of the defense barrier, the CCF risk is between the maximum and minimum. Curves in Fig.7 and Fig.8 explain the trend of CCF parameters over the time factor. The calculation is conducted from initiating seismic shock until 100 hours and the time step is 1 hour. Fig.7 shows the trend of CCF risk of Cause 1 (internal flooding). Values of decomposed α-factors ($\alpha_2^{C_1}$ and $\alpha_3^{C_1}$) increase from 0 to maximum and the value of $\alpha_1^{C_1}$ decreases from 1 to minimum. It means after the earthquake the CCF risk of internal flood increase and the independent failure will upgrade to failures involving more components. In other words, before the occurring of the earthquake, the defense barrier against internal flooding is effective and the internal flooding is an independent cause which only affects the components at one location. With the degradation of defense barrier, the flood will affect components at other locations, so the CCF risk of internal flood will increase.

Table 5 Posterior distributions for CCF parameters

CCF parameter	Mean	90% interval
$\alpha_1^{C_1}$	8.14E-01	(6.15E-01, 9.64E-01)
$\alpha_2^{C_1}$	1.03E-01	(5.24E-03, 2.71E-01)
$\alpha_3^{C_1}$	8.39E-02	(4.53E-03, 2.03E-01)
$\alpha_1^{C_2}$	9.09E-01	(8.24E-01, 9.77E-01)
$\alpha_2^{C_2}$	7.34E-02	(9.91E-03, 1.54E-01)
$\alpha_3^{C_2}$	1.77E-02	(5.08E-04, 5.64E-02)
$\alpha_1^{C_3}$	8.20E-01	(6.78E-01, 9.45E-01)
$\alpha_2^{C_3}$	1.10E-01	(1.05E-02, 2.27E-01)
$\alpha_3^{C_3}$	7.05E-02	(5.71E-03, 1.50E-01)
α_1 (Sys.1)	8.64E-01	(8.12E-01, 9.09E-01)
α_2 (Sys.1)	9.34E-02	(5.67E-02, 1.38E-01)
α_3 (Sys.1)	4.28E-02	(1.86E-02, 7.53E-02)

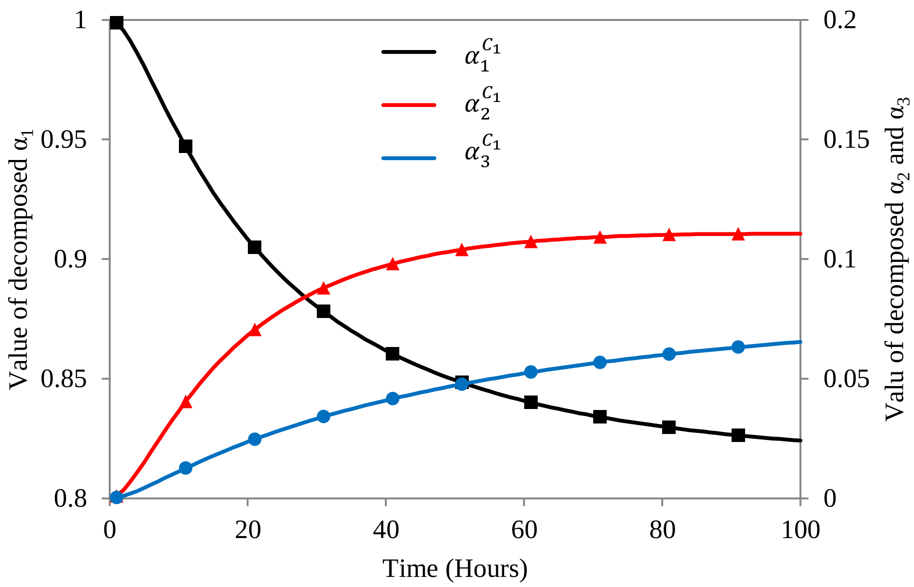

Fig. 7 Decomposed α-factors of internal flooding

Fig.7 shows the CCF risk change of possible cause, and Fig.8 shows the CCF risk change of System 1 over time. Because the internal flood is one possible cause for System 1 to fail, the CCF triggering ability of internal flood is one important factor to determine the failure distributions for System 1. The risk trend for System 1 accords to that of Cause 1 (internal flooding). When the defense barrier starts to degrade after the seismic shock, the independent part (α_1) tends to decrease and the α-factors representing the dependent failures tend to increase. There are other possible causes to generate CCF events, so the initiating values of α_2 and α_3 are not 0. It should be noted that curves in Fig.8 are not smooth is because the mean value at each time node for System 1 is generated by stochastic modeling, which is assumed as Dirichlet distribution. Parameters of Disrichlet distribution are calculated by decomposed α-factors. Therefore, the mean values of dynamic global α-factors are of aleatory uncertainty which cause the fluctuation of curves.

The Bayesian inference in this part shows how to quantitatively evaluate the CCF risk for the introduction and degradation of defense barrier against internal flooding. The physical separation of components is an effective way to reduce CCF risk, and on the other hand, the degradation of such defense strategy will enlarge the influence area of internal flooding. The Markov failure model is utilized in the analysis of CCF parameters, and it is proved that the time factor in CCF analysis can be conducted. The calculation challenges the traditional assumption in PRA research that the parameters of CCF modeling are assumed to be constant in time. The average values of CCF parameter over tremendous operation data is of unknown uncertainty, and the operation conditions for systems are different especially under the circumstance of site-specific external events. The application of Bayesian theory can utilize both data and non-data information from multiple sources, so the uncertainty in estimates can be reduced.

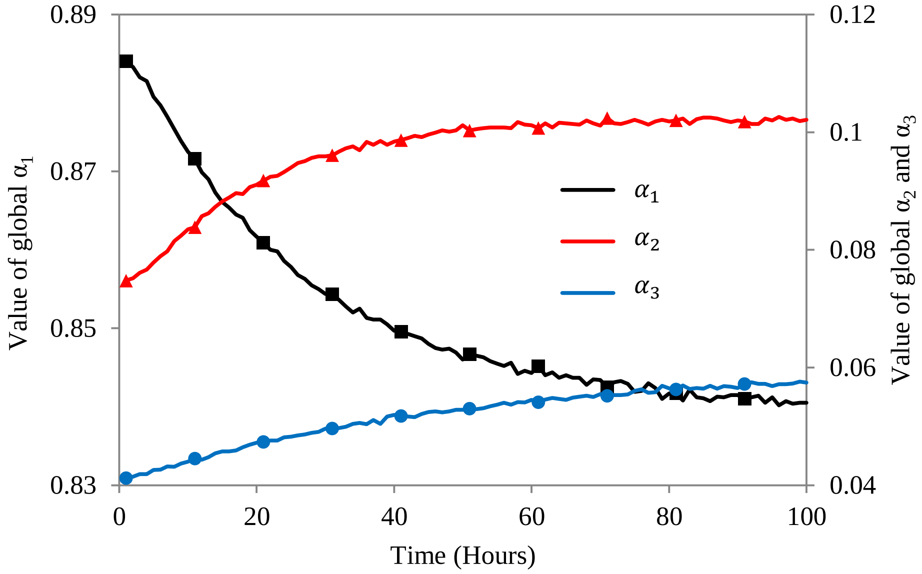

Fig. 8 Global α-factors of System 1

5. CONCLUSIONS

The α-decomposition method proposed by authors in current paper and in the supporting references is able to parameterize the common cause failure (CCF) risk significance of possible causes, which is named as decomposed α-factors. The defense strategy or mechanism against CCF is an effective way to protect system from CCF risk. The following conclusions are supported by the quantitative analysis of CCF risk involving the degradation of defense barrier against seismic induced internal flooding in current paper:

- Based on α-factor model and the cause inference for CCF events, the α-decomposition method has been introduced. The CCF occurring mechanism is recognized as hierarchical network. The first level is system failure, the second level is components failure and the third level is possible causes. A hybrid Bayesian network is applied to reveal the relationship among different levels and a regression model is proved by the theory of conditional probability. The CCF risk of components is notated as global α-factors and the CCF triggering ability of causes is notated as decomposed α-factors.
- The Markov modeling for the failure mechanism of defense barrier against internal flooding is demonstrated. Reasonable transition parameters of the failure propagation process are recommended to be defined based on operation data and expert opinion. This model is capable of estimating the time dependent probability distributions for all four states after the happening of an earthquake. Experiments in performance assessment for defense barrier are recommended to be conducted and the occurrence rate of flaws and failures are valuable data to evaluate the probability distributions for propagation states.
- The state of defense barrier is an important factor to affect the CCF failure distributions for a system with redundant components. The relationship between decomposed α-factors and the probability of each state is evaluated, which quantitatively shows how the state of barrier affects the influence area of internal flood.
- The Bayesian inference with MCMC method is introduced to obtain the posterior distribution of benchmark parameters on the basis of databases and assumptions. The database combing CCF events and

the occurrence rate of causes are recommended to be built. The results show that according to the state of defense barrier (success, flaw, partial failure and failure), the CCF parameters are time dependent. At the early period after the seismic shock, the risk of internal flooding appears the characteristic of independent failure triggering. When the failure rate of defense barrier increases, the risk of internal flooding tends to include more redundant components at different locations. It is concluded that CCF parameters (α-factors) of one system should not be assumed constant over time. The CCF events are system-specific and time-dependent. The application of Bayesian probability allows to combine different data sources and to reduce the uncertainty in results.

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