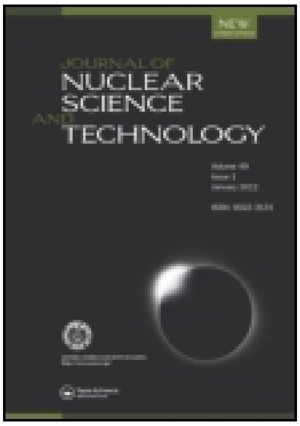

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Probabilistic common cause failure modeling for auxiliary feedwater system after the introduction of flood barriers

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ARTICLE

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Causal inference is capable of assessing common cause failure (CCF) events from the viewpoint of causes' risk significance. Authors proposed the alpha decomposition method for probabilistic CCF analysis, in which the classical alpha factor model and causal inference are integrated to conduct a quantitative assessment of causes' CCF risk significance. The alpha decomposition method includes a hybrid Bayesian network for revealing the relationship between component failures and potential causes, and a regression model in which CCF parameters (global alpha factors) are expressed by explanatory variables (causes' occurrence frequencies) and parameters (decomposed alpha factors). This article applies this method and associated databases needed to predict CCF parameters of auxiliary feedwater (AFW) system when defense barriers against internal flood are introduced. There is scarce operation data for functionally modified safety systems and the utilization of generic CCF databases is of unknown uncertainty. The alpha decomposition method has the potential of analyzing the CCF risk of modified AFW system reasonably based on generic CCF databases. Moreover, the sources of uncertainty in parameter estimation can be studied. An example is presented to demonstrate the process of applying Bayesian inference in the alpha decomposition process. The results show that the system-specific posterior distributions for CCF parameters can be predicted.

Keywords: ***common cause failure; alpha decomposition method; Bayesian theory; flood barrier; probabilistic risk assessment; auxiliary feedwater system***

1. Introduction

In the probabilistic risk assessment (PRA) performed by nuclear safety analysts, the identification and quantification of common cause failure (CCF) risk are essential parts in analyzing the probability distributions for redundant system failures. The basic parameter models (BPMs including beta factor models, multiple Greek letter model and alpha factor model) had been proposed by Karl Fleming and Ali Mosleh et al. for mathematically modeling the CCF risk of one system with redundant components [1,2]. There are limitations of the BPM with respect to the calculation of lumped parameters, which are determined by generic operation data and encompass all possible causes' information. Because of rarity of CCF events on a plant- and system-specific basis, plant-specific PRA has to rely on the generic operation database, which means the assessment of much unknown uncertainty [3]. The traditional CCF modeling approaches cannot provide cause-specific quantitative insights to engineers to help them focus on their efforts at reducing CCF [4]. To model systems more reasonably and reduce uncertainties in the estimation of probability distributions for lumped parameters, it is necessary to combine the CCF information from cause level with system fault tree analysis. Usually, there are three main elements (the failure cause, coupling factor and defense strategy) that determine the occurrence of one CCF event [5]. Since 1998, the US Nuclear Regulatory Commission's Office of Nuclear Regulatory Research and the Idaho National Laboratory have been developing a generic CCF database for the US commercial nuclear power industry [6]. However, the utilization of generic database for CCF analysis will inevitably generate uncertainties in results as the three elements of CCF events are system specific.

The alpha factor model is one of the most widely used BPMs for CCF analysis. The parameter vector is denoted as $(\alpha_1, \alpha_2, \ldots, \alpha_m)$, each of which represents the

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failure probability fraction with certain amount of components. The alpha factors are integrated parameters determined by possible causes' occurrence frequency and causes' abilities of triggering CCF events. A cause's ability of triggering CCF events is determined by the cause's characteristics and the defense strategy applied in systems against the failure mechanism. The alpha decomposition method is an approach developed by authors to decompose alpha factors [7,8]. This method is capable of evaluating CCF risk significances of different causes and uncertainties in parameter estimation.

Class I equipment (safety-related) in pressurized water reactor (PWR), safeguards alley compartments, is affected by the failure of non-Class I systems in the turbine building. For instance, the random or seismically induced ruptures of pipe or tank will result in severe flooding or excessive steam release to the extent that the auxiliary feedwater (AFW) pumps' function will be impaired [9]. According to the accident management measures taken by many utilities for nuclear power plants (NPPs), flood barriers are recommended to be built in the turbine building. The CCF risk of the AFW pump system will be changed after the construction of flood barriers. Based on associated databases, this article applies the alpha decomposition method to quantitatively evaluate the change of CCF risk for the AFW pump system after the flood barriers are built.

2. Alpha decomposition method with hybrid Bayesian network

2.1. Review of alpha factor model

The alpha factor model defines CCF probabilities from a set of failure frequency ratios and the total component failure frequency, Q_t. Compared with the beta factor model using one single parameter to express CCF risk, the alpha factor model uses multiple parameters to express different CCF risks for failures including certain amount of components, respectively. The development of CCF modeling from the beta factor model to the alpha factor model can be treated as the decomposition based on the failure information from component level. The estimation of alpha factors is of less uncertainty than that of beta factors. Due to the lack of space in the current article, the alpha factor model is simply reviewed and more detailed introduction can be obtained from previously published references [1,2]. Let us consider a two-out-of-three system of three redundant components A, B and C. The failure probability of component A is given by

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

Here $P(X)$ is the probability of event X, A_t is the total failure of A from all causes, A_I is the independent failure of component A, C_{XY} is the failure of components X and Y from common causes and C_{ABC} is the failure of components A, B and C from common causes. The probabilities in the above equation are typically assumed to be

$$P(A_I) = Q_1 \tag{2}$$

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

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

The testing scheme to which the common cause component group is subjected has an impact on the mathematical form of models. In the case of staggered testing scheme, only one component is tested in a test episode. When the test result is a failure, the rest of the components will be tested. In contrast, in the case of non-staggered testing scheme, all components are tested in a test episode. According to the two different testing schemes, there are two estimates of the CCF probabilities differed by factors, but both of them are reasonable. Different assumptions for two testing episodes are usually necessary because of the lack of success data in the database. It is assumed as staggered testing scheme in this article. The alpha factors for staggered testing scheme are written as

$$\alpha_1 = \frac{Q_1}{Q_t} \tag{5}$$

$$\alpha_2 = \frac{2Q_2}{Q_t} \tag{6}$$

$$\alpha_3 = \frac{Q_3}{Q_t}. \tag{7}$$

2.2. Alpha decomposition method for CCF analysis

Since the authors proposed the alpha decomposition method in previously published papers, the method is simply reviewed in the current article. For distinction, the alpha factors in the alpha factor model are named as global alpha factors, and after the process of decomposition, the alpha factors at the cause level are named as decomposed alpha factors. As introduced before, the global alpha factors are lumped parameters, which are the integrated reflection of a variety of causes' CCF risk significance. The causes' risk performance can be affected by two variables that are shown in **Figure 1**. The occurrence frequency and CCF triggering ability (parameterized as decomposed alpha factors) of one possible cause decide the cause's potential CCF risk. Figure 1 roughly explains how the cause's CCF risk significance is decided by occurrence frequencies and CCF triggering abilities. The black diamond, black triangle and black circle represent three potential causes. They are of different CCF risk significance because of different occurrence frequencies and CCF triggering ability. The black diamond is of similar occurrence frequency compared

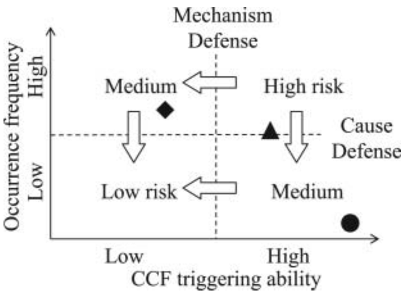

Figure 1. Two elements of causes' CCF risk significance.

with the black triangle, but the CCF triggering ability is weaker than that of the black triangle. Hence, the CCF risk of the black diamond is less than that of the black triangle. This article assumed the two-out-of-three system is affected by three possible causes, so the regression models relating global alpha factors to a function of occurrence frequencies and decomposed alpha factors are given by

$$\alpha_1 = \alpha_1^{C_1} r_1 + \alpha_1^{C_2} r_2 + \alpha_1^{C_3} r_3 \tag{8}$$

$$\alpha_2 = \alpha_2^{C_1} r_1 + \alpha_2^{C_2} r_2 + \alpha_2^{C_3} r_3 \tag{9}$$

$$\alpha_3 = \alpha_3^{C_1} r_1 + \alpha_3^{C_2} r_2 + \alpha_3^{C_3} r_3. \tag{10}$$

The regression model Equations (8)–(10) can be proved by hybrid Bayesian network and the theory of condition probability, and the detailed derivation can be obtained from references [7,8]. Here, α_j $(j = 1, 2, 3)$ is the global alpha factor involving the failure of *j* components, $\alpha_j^{C_i}$ $(i, j = 1, 2, 3)$ is the decomposed alpha factor involving the failure of *j* components due to the common cause *i* and r_i $(i = 1, 2, 3)$ is the occurrence frequency of the common cause *i*, which can be calculated by

$$r_i = \frac{P(A|\,C_i)\,P(C_i)}{P(A)} = P(C_i\,|A)\,. \tag{11}$$

3. Additional flood barriers in turbine building

There is safety-related equipment (American Nuclear Society safety Class I) in the PWR AFW system, for instance, AFW pumps, emergency diesel generators and safe shutdown panel. The Class I equipment's function can be impaired for the occurrence of severe common cause. Previous inspection found that there was inadequate design control to ensure Class I equipment protected against internal flood [9]. The internal flood results from the failure of non-Class I water system piping and equipment, for instance, circulating water system, firewater pipes, feedwater pipes and reactor makeup water storage tanks. Random or seismically induced failures of non-Class I systems in the turbine building will generate severe flood water.

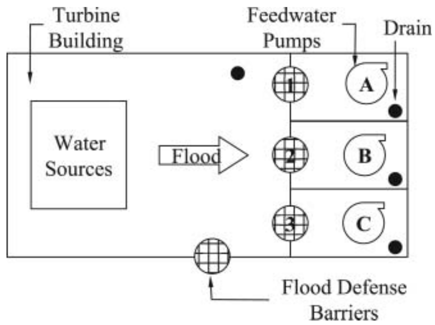

Figure 2. Additional flood barriers in turbine building.

The flood water will flow into the safeguards alley compartments where the identified Class I equipment is located. Therefore, internal flood is an important common cause for the Class I equipment at the safeguards alley.

Flood barriers are recommended to be built into PWR turbine building. However, the current available CCF parameter database is the generic database without consideration of the specific defense design of each turbine building. Thus, after the flood barriers are constructed in the turbine building, it is necessary to analyze the change of CCF risk for Class I systems. This article focuses on the risk assessment of the PWR AFW pump system. The simplified layout diagram of the PWR AFW pump system with recommended flood barriers is shown in **Figure 2**. Usually, this system has two identical motor-driven pumps and one steam turbine-driven pump. For the simplest consideration, as shown in Figure 2, it is assumed that there are three identical water pumps A, B and C in AFW system. The grid circles are recommended physical barriers to protect the AFW pumps from internal flood. The water source in the turbine building might be circulating water, service water, fire protection water, etc.

The hybrid Bayesian network for the modified AFW pump system's causal inference is shown in **Figure 3**. There are three possible causes assumed, which will result in CCF events in the system and Cause 1 (internal flood) is the common cause of interest. In Figure 3,

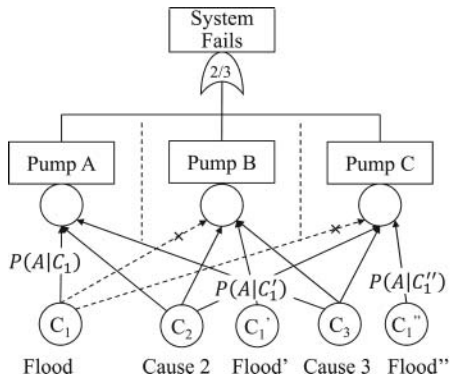

Figure 3. Causal inference for the system with flood barrier.

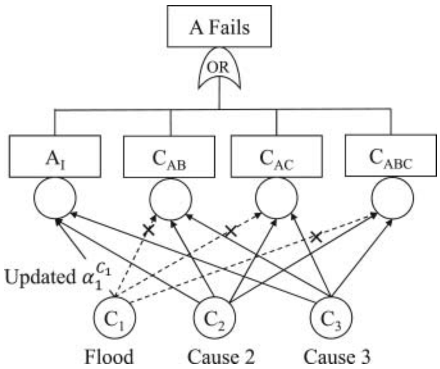

Figure 4. Causal inference for ump A after the construction of flood barrier.

Causes 1, 2 and 3 are notated as C_1, C_2 and C_3, respectively. The dashed lines mean the introduced flood barriers. When the flood barriers are applied in the turbine building, all three pumps are separated since the flood flow paths among compartments are blocked. When a random failure of a defense barrier (such as Barrier 1 in Figure 2) occurs, the internal flood from turbine building is an independent cause, which only affects Pump A. Therefore, the three pumps are influenced by three independent floods, which are determined by whether the random failure of respective defense barrier happens. If all three flood barriers (Barriers 1, 2 and 3 in Figure 2) fail, the internal flood from turbine building will upgrade to a common cause, which affects all components. This scenario is the same as the system without flood barrier. As illustrated in Figure 3, after the construction of defense barriers, the CCF risk of flood is changed, which is depended on the physical states of flood barrier.

4. Analysis of flood risk for modified AFW system with decomposed alpha factors

The construction of flood barrier in AFW pump system will protect the pumps from random or seismically induced failures of non-Class I water system in the turbine building. This section takes the Pump A as an example as all three pumps are assumed as identical. **Figure 4** depicts all four failure types involving Pump A. When the flood barriers are constructed in turbine building, the Pump A will be influenced by the flood if there is a random failure of the flood Barrier 1. The CCFs of three flood barriers (e.g. seismically induced barrier failure and flood-induced barrier failure) are discussed by authors in [10]. Therefore, the internal flood is an independent failure when only flood Barrier 1 has a random failure, as shown in Figure 4. The flood (C_1) results in the independent failure of Pump A. There is no defense mechanism applied to protect AFW pump system against the Cause 2 and Cause 3, so the Cause 2 and Cause 3 are still probable to result in CCF events. Based on the theory of conditional probability, this transformation of CCF risk can be expressed as

$$P\left(C_{AB} \cup C_{AC} \cup C_{ABC} \,|\text{Flood}\right) \rightarrow P\left(A_I^* \,|\text{Flood}\right). \quad (12)$$

Here, Equation (12) demonstrates the degradation of CCF events to independent failure. In the current article, parameters with the asterisk mark are the CCF parameters for the modified AFW pump system after the introduction of additional flood barriers. The random failure of the flood Barrier 1 only results in the independent failure. The flood Barriers 2 and 3 are effective to separate the Pumps 2 and 3 from Pump 1 so that the AFW pump system is still available (two-out-of-three systems). The decomposed alpha factors for flood (Cause 1) represent the CCF triggering abilities. Thus, the updated decomposed alpha factors after the introduction of flood barriers can be expressed as

$$\text{updated } \alpha_1^{C_1{}^*} = 1 \quad (13)$$

$$\text{updated } \alpha_2^{C_1{}^*} = 0 \quad (14)$$

$$\text{updated } \alpha_3^{C_1{}^*} = 0. \quad (15)$$

Here, $\alpha_1^{C_1{}^*}$ represents the ability of internal flood to trigger an independent failure. $\alpha_2^{C_1{}^*}$ and $\alpha_3^{C_1{}^*}$ represent the abilities of internal flood to trigger CCF events involving two and three pumps, respectively. Equations (13)–(15) indicate that when the flood barriers are constructed in AFW pump system, the internal flood generated from turbine building will only trigger independent failure based on the assumption that only random failures of flood barriers happen.

5. Bayesian inference for alpha decomposition process

5.1. *Hierarchical Bayesian modeling*

In traditional CCF parameter estimation, the vector of global alpha factors is usually assumed as a Dirichlet distribution, which is conjugate to the multinomial distribution. The multinomial distribution always serves as an aleatory model for failure of a group of redundant components. Therefore, the estimation of posterior global alpha factors can be conducted by Bayesian inference. A noninformative prior distribution for the multinomial likelihood is a Dirichlet distribution with each parameter equaling 1 [11–13].

As the alpha decomposition method estimates CCF parameters based on the failure information from cause level and component level, the prior distribution in the traditional CCF Bayesian models should be specified in multiple stages. The graphical representation of the multi-state hierarchical Bayesian modeling is shown in **Figure 5**. Oval nodes refer to stochastic components of the model, and squared nodes refer to constant parameters. Solid arrows indicate the stochastic dependence

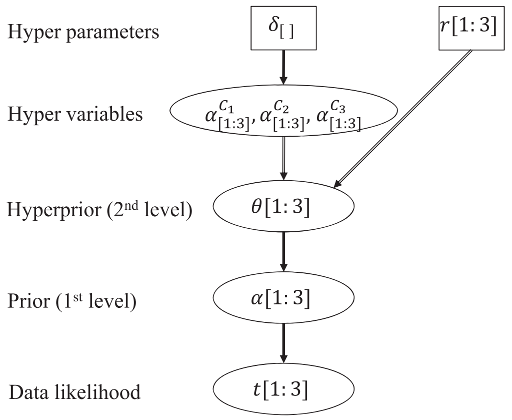

Figure 5. Directed acyclic graph for Bayesian inference.

while hollow arrows indicate logical functions. The node ($t\,[1:3]$) is the operation data of failure events, which is assumed as multinomial distribution as introduced before. Here, the size of redundant AFW pump is assumed as three, so failure events ($t\,[1:3]$) may involve one, two or three redundant components. The failure data can be used to estimate the global alpha factors ($\alpha\,[1:3]$), which are assumed as Dirichlet distribution. According to Equations (8)–(10), the parameters ($\theta\,[1:3]$) in the prior Dirichlet distribution can be repressed by decomposed alpha factors $\left(\alpha^{C_1}_{[1:3]}, \alpha^{C_3}_{[1:3]}, \alpha^{C_3}_{[1:3]}\right)$ and causes' occurrence frequencies ($r\,[1:3]$). The parameters $\left(\delta_{[]}\right)$ in the prior distributions of decomposed alpha factors are named as hyper parameters. The prior distributions of decomposed alpha factors are assumed as noninformative Dirichlet. The causes' occurrence frequencies ($r\,[1:3]$) can be obtained from generic CCF database. Usually, $P\,(\boldsymbol{t}\,|\boldsymbol{\alpha}\,)$ is called prior distribution (first level), and $P\left(\theta\,\left|\boldsymbol{\alpha}^{C_{[]}}_{[]}, \boldsymbol{r}\right.\right)$ is called hyperprior (second level). If parameters in the hyperprior were all constant, the related Bayesian model would be named as two-stage Bayesian hierarchical model. However, since all decomposed alpha factors are uncertain variables assumed as Dirichlet distributions, the current model is simply noted as multistage Bayesian hierarchical model.

The estimation of decomposed alpha factors can be written by Bayes' theorem,

$$P\left(\alpha^{C_i}_j\middle|\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right) = \frac{P\left(\alpha^{C_i}_j, \boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right)}{P\left(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right)} = \frac{P\left(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\middle|\alpha^{C_i}_j\right) P\left(\alpha^{C_i}_j\right)}{P\left(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right)}, \quad (16)$$

Here, $P\left(\alpha^{C_i}_j\right)$ is the prior distribution for decomposed alpha factors and $P\left(\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\middle|\alpha^{C_i}_j\right)$ is the likelihood of parameters. It is noted that all bold letters are vectors of a group of parameters. Therefore, according to the chain rule of conditional probability and the independence between parameters, the posterior distribution of decomposed alpha factors can be written as

$$\pi_2\left(\alpha^{C_i}_j\middle|\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right) \propto f_t\left(\boldsymbol{t}\,|\boldsymbol{\alpha}\right) f_\alpha\left(\boldsymbol{\alpha}\,|\boldsymbol{\theta}\right) \times f_\theta\left(\theta\middle|\alpha^{C_i}_j, \boldsymbol{r}\right) \pi_1\left(\alpha^{C_i}_j\right). \quad (17)$$

The posterior distribution $\pi_2\left(\alpha^{C_i}_j\middle|\boldsymbol{r}, \boldsymbol{\theta}, \boldsymbol{\alpha}, \boldsymbol{t}\right)$ can be obtained by the evidence of CCF operation data, causes' information and the prior distribution $\pi_1\left(\alpha^{C_i}_j\right)$. Therefore, based on the generic CCF databases, the updated decomposed alpha factors of possible causes can be determined and the relationship between causes and global alpha factors can be determined as well. When the flood barriers are constructed in turbine building, the probability distribution for global alpha factors can be calculated according to the updated decomposed alpha factors of internal flood and the posterior distributions for all other decomposed alpha factors.

5.2. *An example for AFW pump system with flood barrier*

As shown in **Table 1**, a hypothetical generic CCF database for Pump A is assumed to demonstrate the numerical computation of CCF risk. All the databases and results in the current article are for illustration only and do not represent the actual CCF risk of flood. Based on the assessment of the risk of causes, the updated alpha factors can be obtained when the flood barriers are constructed in turbine building. The process of Bayesian inference has been conducted by OpenBUGS version 3.2.2. Bayesian inference has been widely applied in the context of nuclear PRA [14,15]. The numerical simulation of Bayes' theorem is possible using Markov chain Monte Carlo (MCMC) [16]. OpenBUGS is a free and useful tool to realize the computation in a relatively easy manner, especially when the calculation of Dirichlet distribution is involved [11]. In Table 1, two groups of important CCF data are recorded and collected for parameter estimation. One is the record of CCF events and the other is the occurrence of failure causes. Totally, three causes are assumed. To consider the problem simply, the Cause 1 is flood and the other two causes are not named. CCF events include independent single failure, partial CCF involving two pumps and complete CCF involving all three pumps. It is recorded as the operation data of 16 AFW pump systems. Because CCF data is scarce, the generic database is always applied for the PRA analysis. This example can show how to reasonably utilize the hypothetical generic database for specific system, which is an AFW pump system with additional flood barrier.

As introduced in the last section, there are three redundant pumps in the analyzed AFW system. The multinomial distributions serve as the aleatory model for CCF events, and the prior distributions for global

Table 1. Hypothetical CCF database for Pump A.

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

alpha factors are assumed as Dirichlet distributions. The noninformative prior for decomposed alpha factors of one cause is Dirichlet distribution with each parameter $\delta_i[\,] = 1$. The likelihood function and prior distribution can be written as

$$t\,[k, 1:3] \sim \text{dmulti}\ (\alpha\,[k, 1:3]\,, T\,[k]) \tag{18}$$

$$\alpha\,[k, 1:3] \sim \text{ddirich}\ (\theta\,[k, 1]\,, \theta\,[k, 2]\,, \theta\,[k, 3]) \tag{19}$$

$$\alpha^{C_i}\,[1:3] \sim \text{ddirich}\ (\delta_i\,[1]\,, \delta_i\,[2]\,, \delta_i\,[3])\,. \tag{20}$$

Here, $t\,[k, 1:3]$ is the record of failure events for AFW pump system k, $T\,[k]$ is the total number of failure events for AFW pump system k, $\alpha\,[k, 1:3]$ is the estimate of the global alpha factors for AFW pump system k and $\alpha^{C_i}\,[1:3]$ is the estimate of the decomposed alpha factors for three causes.

Therefore, the posterior distributions for decomposed alpha factors and for global alpha factors can be obtained by Bayesian inference. The estimation of decomposed alpha factors is based on the generic database, which is the record of AFW pump systems without flood barrier. The estimation of CCF parameters for system with flood barrier should combine the updated decomposed alpha factors introduced in Section 4. The graphical model of parameter estimation for modified system by alpha decomposition process is provided in **Figure 6**. It is illustrated that the global and decomposed alpha factors are updated based on the failure data ($t\,[k, 1:3]$) and causes' occurrence data ($r\,[k, 1:3]$). After the construction of flood barrier, the CCF risk generated by internal flood is changed. The updated decomposed alpha factors of flood $\left(\alpha^{C_1}\,[1:3]^*\right)$ are used to update the global alpha factors ($\alpha\,[k, 1:3]^*$) for modified AFW pump systems with additional flood barriers. The random failure probability of the flood barrier is assumed

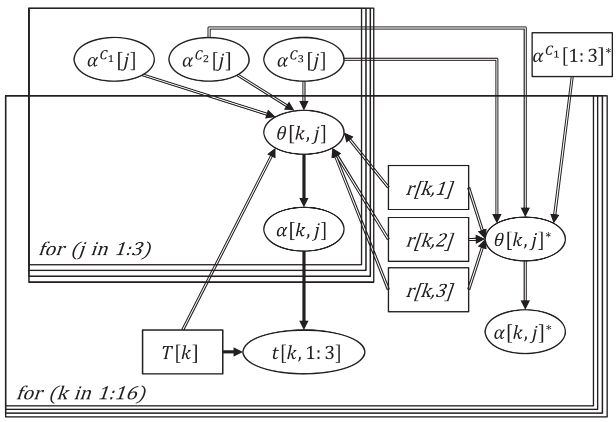

Figure 6. Graph model for CCF parameter estimation.

as 0.1. The failure probability will affect the failures caused by flood and change the occurrence rate of failure causes, so this factor is important to predict the global alpha factor. If a flood occurs, no accompanying failure happens as the flood barrier is available, so no CCF event induced by the flood will be recorded.

Based on the Bayesian inference with MCMC Gibbs sampling (via the tool of OpenBUGS), the posterior distributions can be obtained, both for CCF parameters of systems without and with flood barriers constructed. The summary of posterior distributions for decomposed alpha factors is shown in **Table 2**. The decomposed alpha factors represent the CCF risk of causes before the flood barriers are installed. When the flood barriers are installed, the decomposed alpha factors of flood (Cause 1) can be updated according to Equations (13)–(15). Decomposed alpha factors represent the CCF triggering abilities of causes. For instance, compared with the Cause 2 and Cause 3, the Cause 1 (flood) tends to trigger complete CCF most probably since $\alpha_3^{C_1} > \alpha_3^{C_3} > \alpha_3^{C_2}$. **Figure 7** shows the probability density

Table 2. Summary of posterior distributions for decomposed alpha factors.

Parameters		Mean	95% interval
Cause 1 (flood)	$\alpha_1^{C_1}$	8.17E−1	(6.28E−1, 9.62E−1)
	$\alpha_2^{C_1}$	9.71E−2	(4.30E−3, 2.55E−1)
	$\alpha_3^{C_1}$	8.61E−2	(5.07E−3, 2.13E−1)
Cause 2	$\alpha_1^{C_2}$	9.06E−1	(8.22E−1, 9.78E−1)
	$\alpha_2^{C_2}$	7.62E−2	(1.01E−2, 1.57E−1)
	$\alpha_3^{C_2}$	1.76E−2	(5.06E−4, 5.81E−2)
Cause 3	$\alpha_1^{C_3}$	8.23E−1	(6.92E−1, 9.41E−1)
	$\alpha_2^{C_3}$	1.08E−1	(1.31E−2, 2.16E−1)
	$\alpha_3^{C_3}$	6.90E−2	(4.52E−3, 1.50E−1)

curves of decomposed alpha factors of flood. Because all three decomposed alpha factors do not equal to 0, it means that flood can trigger both independent failures and CCF. It indicates that there is an innate ability of the cause that can decide how many components can be influenced as it happens.

The summary of posterior distributions for global alpha factors of AFW Pump System 1 is shown in **Table 3** and global alpha factors of other systems can be

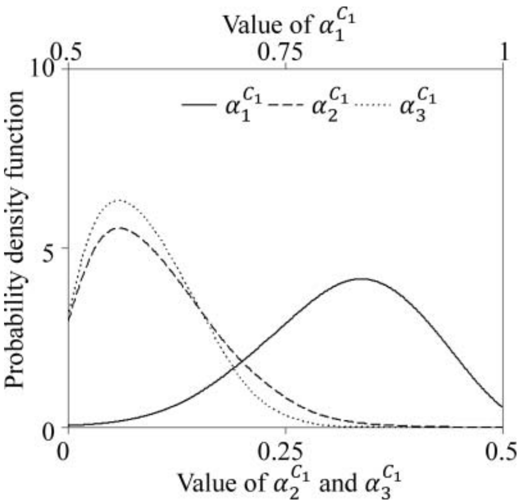

Figure 7. Posterior distributions for decomposed alpha factors.

obtained similarly. There are two groups of posterior distributions in Table 3. One group is the CCF parameters of AFW systems before the flood barriers are installed, and the other group is the CCF parameters of respective AFW systems after the flood barriers are installed. It is demonstrated in Table 3 that the system with flood barrier is of less CCF risk than the system without flood barrier. Successful flood barriers will protect pumps from the CCF by separating them. However, if the flood barriers fail together for serious external events (e.g. an earthquake or the internal flood) the assumption of random failure is no longer available. This topic is discussed by authors in other publications [10]. **Figure 8** illustrates the update of global alpha factors after the construction of flood barriers. The gray curves are alpha factors of the system without flood barriers and the black curves are alpha factors of the system with flood barriers. After the process of Bayesian update, the posterior dashed curve of alpha-2 and the dotted curve of alpha-3 move leftward, and by contrast, the posterior solid curve of alpha-1 moves rightward. The CCF risk of the redundant AFW pump system has been reduced. However, the predictive uncertainty in the result is larger than previous alpha factors. The estimation of previous alpha factors is based on the operation data of system without flood barriers. The prediction of alpha factors for systems with flood barriers is based on the estimation of causes' CCF risk (decomposed alpha factors). Thus,

Table 3. Summary of posterior distributions for global alpha factors of AFW pump system 1.

Parameters		Mean	95% interval
Without flood barriers	α_1	8.65E−1	(8.12E−1, 9.10E−1)
	α_2	9.23E−2	(5.57E−2, 1.38E−1)
	α_3	4.30E−2	(1.86E−2, 7.52E−2)
With flood barriers	α_1^*	8.99E−1	(7.64E−1, 9.83E−1)
	α_2^*	7.53E−2	(6.66E−3, 1.99E−1)
	α_3^*	2.55E−2	(1.75E−5, 1.02E−1)

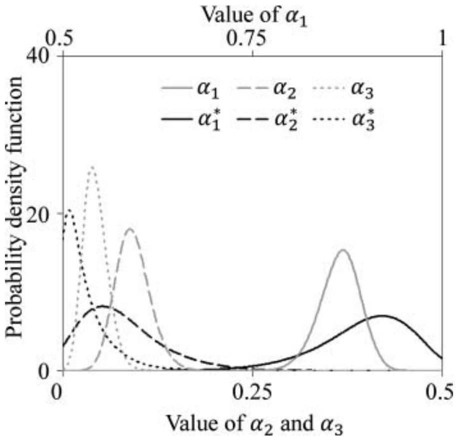

Figure 8. Posterior distributions for global alpha factors of AFW pump system 1.

the uncertainty has been propagated by the process of prediction.

6. Conclusion

When flood barriers are constructed to protect the AFW pumps from internal flood, the changed internal flood-induced CCF risk has been analyzed in this article by the alpha decomposition method, hypothetical databases and the modeling of recommended flood barriers. The following conclusions could be obtained from the current article and supporting references:

(1) The alpha decomposition method is demonstrated to be useful to evaluate the CCF parameters by combining the information from causal inference. It is recommended to build a generic database for CCF parameter estimation, which contains the record of component failures and cause occurrence.

(2) The proposed regression model reveals that the traditional CCF parameters (global alpha factors) are encompassing all failures from a variety of causes. This method can be used to evaluate each cause's CCF triggering ability (decomposed alpha factors), which is useful to find the potential cause of significant hazard.

(3) According to accident mitigation measures taken by many utilities for NPPs, additional flood barriers have been recommended to be built to protect the AFW pumps from the risk of internal flooding. The CCF analysis of the modified AFW system is a system-specific topic. This article has showed how to use alpha decomposition method to evaluate the risk of internal flood on AFW system and how to predict the CCF parameters for system after the introduction of flood barriers. The flood barriers can block the water flow paths to protect the pumps from flood water. Moreover, the results show that flood barriers could separate the redundant pumps, so the potential CCF events can be transformed to independent failures.

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