

Extending the Alpha Factor Model for Cause Based Treatment of Common Cause Failure Events in PRA and Event Assessment

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Abstract: Common Cause Failure modeling for Probability Safety Assessments has become standard practice in many industries. Of the numerous models proposed to include common cause, one of the most widely adopted has been the Alpha Factor Model, which is supported by the US Nuclear Regulatory Commission CCF database and software tools.

The Alpha Factor Model (AFM) uses an empirical ratio between the independent failures and CCF failures to quantify the model parameters. While this has been advantageous in allowing the prediction of system reliability with little or no data, it has been limiting in other applications such as modeling the characteristics of a system design or including the characteristics of failure when assessing the risk significance of a failure or degraded performance event (known as an event assessment).

This paper proposes a new CCF model called the Partial Alpha Factor Model (PAFM), which extends the AFM to allow the explicit modeling of coupling factors between components such as shared maintenance, or shared location. Using this more explicit modeling allows the model to be tailored depending on how far the system design defends against such dependencies. By using the principles of the AFM as the basis for this new model, its implementation may be feasible without modification to existing PRA software or significant changes in data collection requirements.

Keywords: Common Cause Failure, Alpha Factor Model, Partial Alpha Factor Model, Dependency Modelling.

1. INTRODUCTION

Common Cause Failures (CCFs) are ‘simultaneous’ failures of a two or more components due to a shared event. These types of failures have the ability to cut through multiple layers of redundancy and cause unforeseen coincidental events that will put safety critical systems in jeopardy. During the 1980s the PRA community first developed quantitative CCF models, however with CCF event data being so scarce, a consolidated effort by the nuclear industry established data collection methods to support the quantitative models. These data collection activities aligned themselves to quantitative method which used impact vectors such as the Alpha Factor Model (AFM). With software and data to support the use of the AFM it quickly became one of the most common CCF models to be used within the nuclear industry.

Since the AFM was first proposed, PRAs have gradually expanded as a management and decision tool beyond the simple quantification of system failure probabilities. In the nuclear industry, PRAs are increasingly used to support the following activities [1]:

- decisions on safety and performance improvement,
- evaluation of proposed modifications,
- assessment of new designs, and
- event assessment and significance determination.

Whilst the AFM allow for the quantification of soft dependencies at a system level, they are inadequate for providing further insight into the causes of CCF which are necessary to inform mitigation strategy

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development. Furthermore, without any cause information contained within the model, it cannot provide an accurate assessment of the system response to failure (also known as event assessments). It has become evident that the commonly accepted CCF modeling methodology [2] and corresponding tools need to be enhanced to meet these emerging PRA activities.

2. RATIO AND ALPHA FACTOR CCF MODELS

Ratio models are based on the hypothesis that system specific estimates for CCF can be made by combining generic average ratio parameters with system specific single/total failure rates [3]. This provides the advantage that ratio models can be estimated from specific data collection activities such as the Common Cause Failure Database [4] and applied to areas where CCF data may not exist. Popular ratio models include the Beta Factor Model, Alpha Factor Model and the Multiple Greek Letter Model.

Limitations of ratio models include:

- Assumes a transferable empirical ratio between failure rates and Common Cause Failure rate.
- Assumes component symmetry.
- Assumes all failure causes have the ability to propagate within the Common Cause Component Group (CCCG)
- No inference can be made given knowledge of the failure cause.
- The model cannot account for unique system architectures which may contribute or defend against CCF.
- Ambiguity in the interpretation of single failures being modeled as independent failures, particularly when applying impact mapping rules.

The alpha factor model (AFM) is a failure event ratio model that was first proposed by Mosleh and Siu in 1987 [3]. Each α_k factor is the probability that given a failure it will fail k components out of m components within the Common Cause Component Group (CCCG). The AFM parameters are defined and calculated as (Mosleh et al. 1998):

$$\alpha_k = \frac{n_k}{\sum_{k=1}^m n_k} \quad (1)$$

$m =$ the number of redundant components

$n_k =$ the number of failure events/frequency which resulted in k components failing within a common cause component group of size m , ($1 \leq k \leq m$).

$\alpha_k =$ the fraction of total failure events/frequency that occur in the system resulting in k out of m failures.

The main difference between the AFM and some other ratio models (such as the Beta Factor Model) is the ability for the AFM to model multiplicities of failure.

CCF data collection activities such as the ICDE database make quantitative CCF modeling accessible to analysts. However these databases were designed around the concept of an impact vector which does not explicitly use information about the failure causes. Causal information has only been used to obtain insights into the CCF phenomena through qualitative analysis [5–9]. Since 2004 the failure causes for single failure data have also been recorded within the NRC CCFDB [10]. This has provided an opportunity to further conditionalize the Alpha Factor Model (AFM) parameters based on failure causes.

3. OBJECTIVE OF PARTIAL ALPHA FACTOR MODEL

The development of the Partial Alpha Factor Model (PAFM) is motivated by a need to conduct event assessments using knowledge of the failure cause, whilst minimizing changes to the popular AFM methodology. The PAFM will add consideration of failure cause as shown in Figure 1.

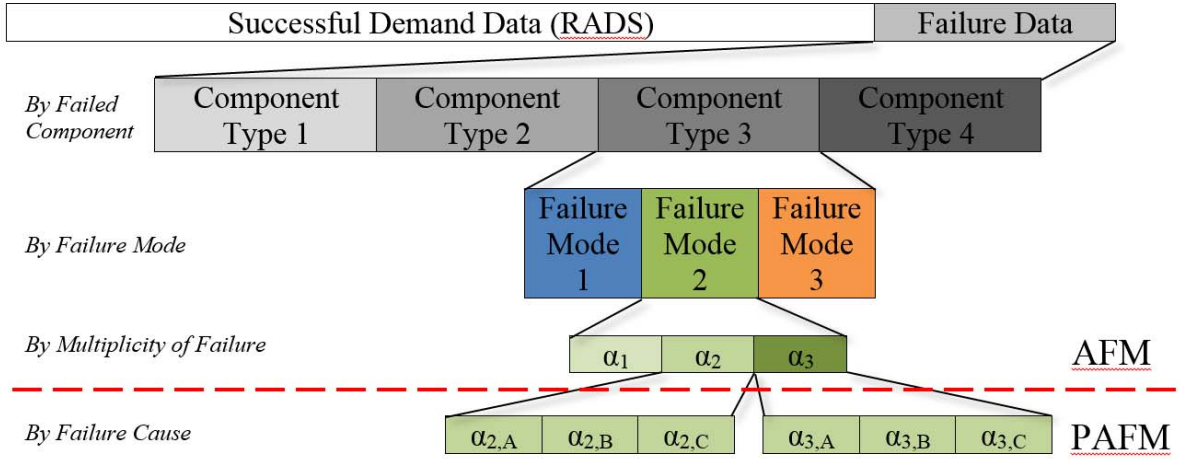


Figure 1: Failure Event Conditionalization

This conditionalization allows the use of the failure cause during event assessments and allows system specific coupling factor dependencies to be added or removed in the model. By dividing the data into a further category the estimates become more difficult when limited data is available. Despite this limitation, the total system failure probabilities will be no worse than using the AFM.

3. PARTIAL ALPHA FACTOR MODEL OVERVIEW

The PAFM follows the same basic principles as the Alpha Factor Model, that the quantification of CCFs is a ratio between the component failure rate and the quantity of CCF events. However the PAFM uses this concept for each possible failure cause. This introduces two parameter types.

- *Partial Alpha Factors* (PAF) which represent the propensity of a failure to propagate to other components through a particular coupling factor.
- *Gamma Factors* (GF) represent the portion of system failure which have the potential to propagate through the coupling factor.

An *Assessed Alpha Factor* is calculated using a combination of gamma factors and partial alpha factors. Assessed alpha factors can be used in exactly the same way as the AFM parameters. The AFM is a special case of the PAFM when the components within a Common Cause Component Group share all coupling factors.

With these revised definitions, the AFM CCF analysis procedure detailed in NUREG/CR-5485 [2] is modified to implement the PAFM:

1. *Qualitative Screening.* A component may be a member of multiple CCCGs based on its coupling factor with other components (noting that the component can only be in one CCCG for each coupling factor). For example, if pump 1 shares its maintenance team and location with pump 2 and shares its installation procedure with pump 3, pump 1 will be part of two common cause component groups: $CCCG_X = \{P_1, P_2\}$ and $CCCG_Y = \{P_1, P_3\}$.
2. *Identification of Common Cause Basic Events.* The CCCBEs will be constructed with consideration for all CCCGs which the component is a part of. E.g. $P_1 = P_{1,i} + X_{P_1P_2} + Y_{P_1P_3}$.
3. *Parameter Representation of CCBEs.* The CCBEs are quantified using the Basic Parameter which accounts for multiple CCCGs. For example $P(P_{1,i}) = Q_1^{(2)}$, $P(X_{P_1P_2}) = Q_2^{(2)[X]}$ and $P(Y_{AC}) = Q_2^{(2)[Y]}$

4. *Alpha Factor Model Parameterization.* The new AFs are quantified using a combination of PAFs. E.g. $Q_2^{(2)[X]} = \left(\frac{m_X - 1}{k_X - 1} \right)^{-1} \cdot \alpha_k^{[X]} \cdot Q_t$.
5. *Parameter Estimation – Impact Vectors.* The system total impact vectors are calculated for each failure cause within the database.
6. *Parameter Estimation – Partial Alpha Factor Model.* The PAFs for each failure cause are calculated. The GF representing the frequency of each cause is calculated. The alpha factor for each CCCG (i.e. $\alpha_2^{[Y]}$) is calculated.
7. *System Quantification and Results Interpretation.* The remainder of the CCF analysis process is identical to using the AFM.

4. PARAMETER ESTIMATION

NUREG/CR-6823 [4] discusses a number of methods for conducting data analysis and parameter assessments, however this section will use two formulations of parameter estimation, a classical (frequentist) interpretation using Maximum Likelihood Estimates and Bayesian methodology with conjugate priors. The following estimates have been formulated with the assumption that only one cause could propagate through one coupling factor. Estimates have been developed when this is not the case and will be presented in future papers.

4.1. Partial Alpha Factor Estimation

The maximum likelihood estimate for the PAF is:

$$\alpha_{k,i} = E \left[\frac{n_{k,i}}{\sum_{k=1}^m n_{k,i}} \right] = E \left[\frac{n_{k,i}}{n_{t,i}} \right] \quad (2)$$

$\alpha_{k,i}$ = a partial alpha factor which represents the portion of system failure events which resulted in k components failing within a common cause component group of size m , ($1 \leq k \leq m$) when there was a potential for failure propagation through coupling factor i where $i \in \{1,2,3,\dots,w\}$

$n_{k,i}$ = the number of failure events which resulted in k components failing within a common cause component group of size m , ($1 \leq k \leq m$) of coupling factor i where $i \in \{1,2,3,\dots,w\}$

$n_{t,i}$ = the total number of common cause failure events for coupling factor/cause i where $i \in \{1,2,3,\dots,w\}$.

The Bayesian estimates for PAF are:

$$\alpha_i \sim \text{Dirichlet}_m\{\psi_i\} \quad (3)$$

α_i = the portion of failure events for each multiplicity of failure [$\alpha_{1,i}, \alpha_{2,i}, \dots, \alpha_{m,i}$] for failure cause i .

ψ_i = the equivalent count of failure events for each multiplicity of failure with cause i [$\psi_{1,i}, \psi_{2,i}, \dots, \psi_{m,i}$]

The parameter α_i , which is the unknown of interest (UOI), can be estimated using Bayes' rule:

$$f(\alpha_i | \mathbf{n}_i) = \frac{f(\alpha_i) L(\mathbf{n}_i | \alpha_i)}{\sum_{j=1}^m L(\mathbf{n}_i | \alpha_{j,i}) f(\alpha_{j,i})} \quad (4)$$

$f(\alpha_i)$ = is the prior distribution of the parameter α_i

$L(\mathbf{n}_i | \alpha_i)$ = is the likelihood equation for observing the evidence \mathbf{n}_i given the parameters α_i .

$f(\boldsymbol{\alpha}_i|\mathbf{n}_i)$ = the posterior distribution of $\boldsymbol{\alpha}_i$ given the evidence \mathbf{n}_i
 \mathbf{n}_i = the number of failure events for each multiplicity of failure $[n_{1,i}, n_{2,i}, \dots, n_{m,i}]$ for failure cause i .
 $\boldsymbol{\alpha}_i$ = the portion of failure events for each multiplicity of failure $[\alpha_{1,i}, \alpha_{2,i}, \dots, \alpha_{m,i}]$ for failure cause i .

The likelihood equation of observing the number of failures in each failure cause category, $\mathbf{n}_i = [n_{1,i}, n_{2,i}, \dots, n_{m,i}]$ is distributed as a multinomial distribution with parameters $\boldsymbol{\alpha}_i = [\alpha_{1,i}, \alpha_{2,i}, \dots, \alpha_{m,i}]$.

$$\mathbf{n}_i \sim \text{Multinomial}_m\{n_{t,i}, \boldsymbol{\alpha}_i\} \quad (5)$$

(6)

Therefore the hyper parameters, $\boldsymbol{\psi}_i$, for the posterior $\boldsymbol{\alpha}_i$ given evidence \mathbf{n}_i using a Dirichlet prior with parameters, $\boldsymbol{\psi}_{i,0}$, is:

$$\boldsymbol{\psi}_i = \boldsymbol{\psi}_{i,0} + \mathbf{n}_i \quad (7)$$

The choice of a prior distribution parameters, $\boldsymbol{\psi}_{i,0}$, depends on the availability of data as discussed in detail by Siu and Kelly [11].

4.1. Gamma Factor Estimation

The maximum likelihood estimate for the GF is:

$$\gamma_i = E \left[\frac{n_{t,i}}{\sum_{i=1}^w n_{t,i}} \right] = E \left[\frac{n_{t,i}}{n_t} \right] \quad (8)$$

γ_i = the portion of failure events which had the potential to propagate through coupling factor i where $i \in \{1, 2, 3, \dots, w\}$
 n_t = the total number of failure events/frequency.

The Bayesian estimates for GF is:

$$\boldsymbol{\gamma} \sim \text{Dirichlet}_w\{\boldsymbol{\varphi}\} \quad (9)$$

$\boldsymbol{\gamma}$ = the portion of failure events for each cause $[\gamma_1, \gamma_2, \dots, \gamma_w]$
 $\boldsymbol{\varphi}$ = the equivalent count of failure events for each cause $[\varphi_1, \varphi_2, \dots, \varphi_w]$

The point estimates for each gamma factor can be obtained using:

$$\hat{\gamma}_i = \frac{\varphi_i}{\sum_{i=1}^w \varphi_i} \quad (10)$$

The parameter $\boldsymbol{\gamma}$, which is the unknown of interest (UOI), can be estimated using Bayes' rule:

$$f(\boldsymbol{\gamma}|\mathbf{n}_t) = \frac{f(\boldsymbol{\gamma})L(\mathbf{n}_t|\boldsymbol{\gamma})}{\sum_{j=1}^w L(\mathbf{n}_t|\boldsymbol{\gamma}_j)f(\boldsymbol{\gamma}_j)} \quad (11)$$

$f(\boldsymbol{\gamma})$ = is the prior distribution of the parameter $\boldsymbol{\gamma}$
 $L(\mathbf{n}_t|\boldsymbol{\gamma})$ = is the likelihood equation for observing the evidence
 $f(\boldsymbol{\gamma}|\mathbf{n}_t)$ = the posterior distribution of $\boldsymbol{\gamma}$ given the evidence \mathbf{n}_t
 \mathbf{n}_t = the number of failure events for each cause $[n_{t,1}, n_{t,2}, \dots, n_{t,w}]$
 $\boldsymbol{\gamma}$ = the portion of failure events for each cause $[\gamma_1, \gamma_2, \dots, \gamma_w]$

The likelihood equation of observing the number of failures in each failure cause category, $\mathbf{n}_t = [n_{t,1}, n_{t,2}, \dots, n_{t,w}]$ is distributed as a multinomial distribution with parameters $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, \dots, \gamma_w]$.

$$\mathbf{n}_t \sim \text{Multinomial}_w\{n_t, \boldsymbol{\gamma}\} \quad (12)$$

Therefore the hyper parameters, $\boldsymbol{\varphi}$, for the posterior $\boldsymbol{\gamma}$ given evidence \mathbf{n}_t using a Dirichlet prior with parameters, $\boldsymbol{\varphi}_0$, is:

$$\boldsymbol{\varphi} = \boldsymbol{\varphi}_0 + \mathbf{n}_t \quad (13)$$

The choice of a prior distribution parameters, φ_0 , depends on the availability of data as discussed in detail by Siu and Kelly [11].

5. EXAMPLE

A cooling systems objective is to provide water to a cooling system using three pumps and two generators. Only one pump needs to be running in order to provide sufficient water. A pump requires power from only one generator to operate. The failure probability for each generator is also assumed to be $Q_t^{[E]} = 0.006$ and the failure probability for a pump is assumed to be $Q_t^{[P]} = 0.002$. The fault tree with the system failure rate is shown in Figure 2.

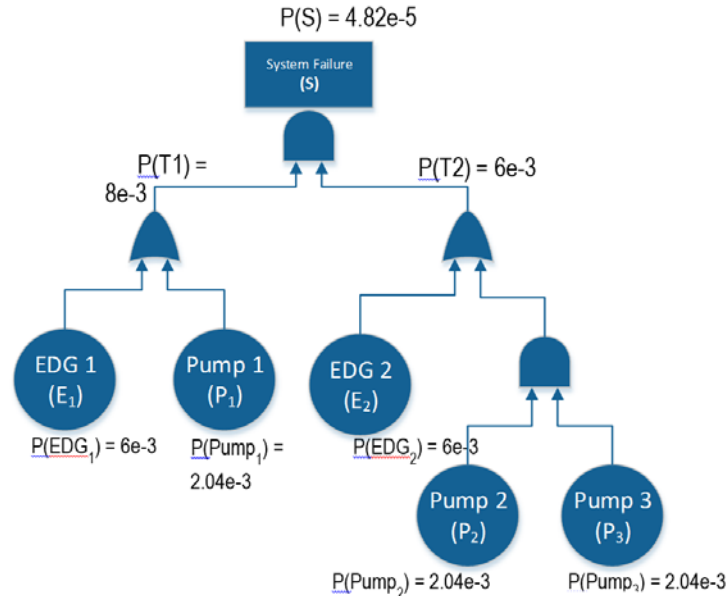


Figure 2: Fault tree for example 2 – Two train Emergency Diesel Generator and pump system

The minimal cut sets for the second example system are:

$$\{E_1, E_2\}; \{P_1, E_2\}; \{P_1, P_2, P_3\}; \{E_1, P_2, P_3\}$$

5.1. Qualitative Analysis

Qualitative analysis involves finding CFs that can help define CCCGs. This is achieved by finding qualitative dependencies between components as illustrated in Table 1.

Table 1: Qualitative dependency assessment

Component	Install Procedure	Maintenance Staff	Location
EDG 1 (E1)	EDG	Team X	Room Y
EDG 2 (E2)	EDG	Team X	Room Y
Pump 1 (P1)	Pump V1.1	Team X	Room Y
Pump 2 (P2)	Pump V2.8	Team X	Room Y
Pump 3 (P3)	Pump V1.1	Team Y	Room X

While the EDGs are symmetrical (in that they share all CFs), pumps 1 and 2 only share the same maintenance team and location (two coupling factors). Pumps 1 and 3 share an installation procedure only (one coupling factor). Note that as per the AFM, CCCGs can only formed with like components. Therefore the following Common Cause Component Groups Exist:

$$CCCG_X = \{E_1, E_2\}, CCCG_Z = \{P_1, P_2\}, CCCG_Y = \{P_1, P_3\}.$$

5.2. Identification of Common Cause Basic Events

The CCBEs will be constructed with consideration for all CCCGs which the component is a part of. If a component belongs in multiple CCCGs, then the CCBEs for both CCCGs would be added. The CCBE events for the example system are shown in Table 2.

Table 2: CCBE for example system

Component	Common Cause Basic Events
EDG 1 (E_1)	$E_{1,i}, X_{E_1,E_2}$
EDG 2 (E_2)	$E_{2,i}, X_{E_1,E_2}$
Pump 1 (P_1)	$P_{1,i}, Z_{P_1,P_2}, Y_{P_1,P_3}$
Pump 2 (P_2)	$P_{2,i}, Z_{P_1,P_2}$
Pump 3 (P_3)	$P_{3,i}, Y_{P_1,P_3}$

5.3. Fault Tree Development

The CCBEs are incorporated into the fault tree as basic events. The fault tree for the example after substitution of CCBEs is shown in Figure 3.

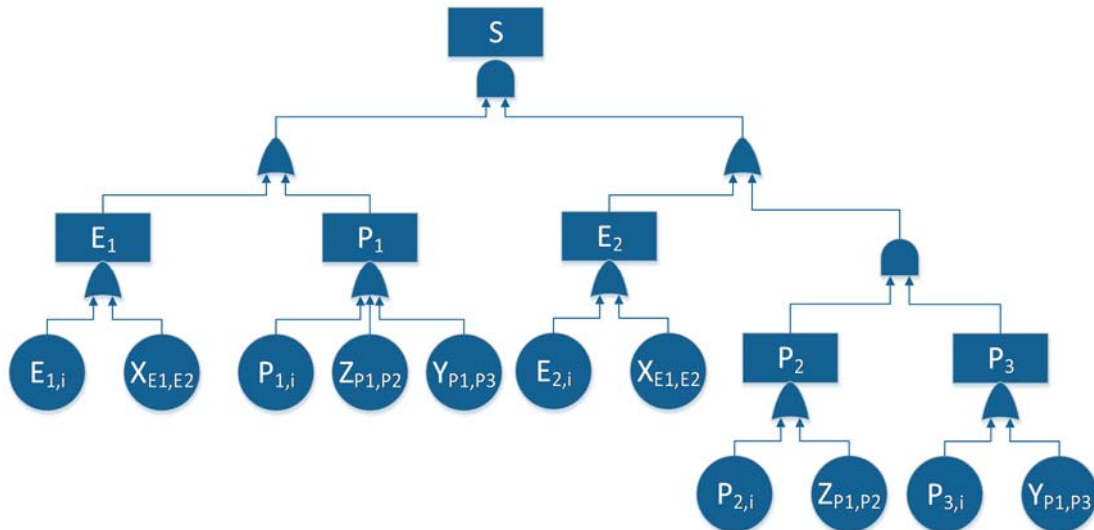


Figure 3: Fault tree for example with CCBEs

The cut sets with CCBEs are:

$$\begin{aligned} & \{E_{1,i}, E_{2,i}\}; \{P_{1,i}, E_{2,i}\}; \{P_{1,i}, P_{2,i}, P_{3,i}\}; \{E_{1,i}, P_{2,i}, P_{3,i}\}; \\ & \{P_{3,i}, Z_{P_1,P_2}\}; \{E_{2,i}, Z_{P_1,P_2}\}; \{P_{2,i}, Y_{P_1,P_3}\}; \{E_{2,i}, Y_{P_1,P_3}\}; \\ & \{Z_{P_1,P_2}, Y_{P_1,P_3}\}; \{X_{E_1,E_2}\} \end{aligned}$$

Note that the cut set $\{Z_{P_1,P_2}, Y_{P_1,P_3}\}$ treats the failure of a single component due to different causes in separate CCCGs as independent, not mutually exclusive. This is the same assumption used to separate individual and common cause basic events. Generally, as CCBEs are treated as independent events (not mutually exclusive), this may produce a lower estimate of the component failure rates.

5.4. Parameter Representation of CCBEs

For the example system, the CCBEs are equal to:

$$\begin{aligned} P(E_{1,i}) &= P(E_{2,i}) = Q_1^{(2)[E]} \\ P(X_{E_1,E_2}) &= Q_2^{(2)[X]} \\ P(P_{1,i}) &= Q_1^{(2)[P_1]}, P(P_{2,i}) = Q_1^{(2)[P_2]}, P(P_{3,i}) = Q_1^{(2)[P_3]} \end{aligned} \quad (14)$$

$$P(Z_{P_1, P_2}) = Q_2^{(2)[Z]}, \quad P(Y_{P_1, P_3}) = Q_2^{(2)[Y]}$$

In comparison to the AFM, the pumps are not symmetrical and so:

$$Q_1^{(2)[P_1]} \neq Q_1^{(2)[P_2]} \neq Q_1^{(2)[P_3]} \quad (15)$$

Using rare event approximation, the system equation is now:

$$\begin{aligned} P(S) &= (Q_1^{(2)[E]})^2 + Q_1^{(2)[P_1]} Q_1^{(2)[E]} + Q_1^{(2)[P_1]} Q_1^{(2)[P_2]} Q_1^{(2)[P_3]} \\ &+ Q_1^{(2)[E]} Q_1^{(2)[P_2]} Q_1^{(2)[P_3]} + Q_1^{(2)[P_3]} Q_2^{(2)[Z]} + Q_1^{(2)[E]} Q_2^{(2)[Z]} + Q_1^{(2)[P_2]} Q_2^{(2)[Y]} \\ &+ Q_1^{(2)[E]} Q_2^{(2)[Y]} + Q_2^{(2)[Z]} Q_2^{(2)[Y]} + Q_2^{(2)[X]} \end{aligned} \quad (16)$$

5.5. Partial Alpha Factor Model Parameterization

The Basic Parameter values are quantified using assessed AFs which add the contribution from the relevant dependencies. The CCBEs are quantified using assessed alpha factors.

$$Q_k^{(m)} = \alpha_k Q_t (k-1)^{-1} \quad (17)$$

For the example, the basic events for each component are:

$$Q_1^{(2)[P]} = \alpha_1^{[P]} Q_t^{[P]}, \quad Q_2^{(2)[P]} = \alpha_2^{[P]} \cdot Q_t^{[P]} \quad (18)$$

The EDGs are symmetrical and therefore the basic events are:

$$Q_1^{(2)[E]} = \alpha_1^{[E]} Q_t^{[E]}, \quad Q_2^{(2)[X]} = \alpha_2^{[X]} \cdot Q_t^{[E]} \quad (19)$$

$$\alpha_2^{[X]} = \sum_{i=\{IP, MH, EE\}} \gamma_i^{[E]} \alpha_{2,i}^{[E]} \quad (20)$$

$$\alpha_1^{[E]} = 1 - \alpha_2^{[X]} \quad (21)$$

The pumps in $CCCG_Z$ only share the maintenance team and external environment. The assessed alpha factors will not include the contribution from installation procedures.

$$Q_2^{(2)[Z]} = \alpha_2^{[Z]} \cdot Q_t^{[P]} \quad (22)$$

$$\alpha_2^{[Z]} = \sum_{i=\{MH, EE\}} \gamma_i^{[P]} \alpha_{2,i}^{[P]} \quad (23)$$

The pumps in $CCCG_Y$ only share installation procedure and the assessed alpha factor will not include the contribution from maintenance team and external environment.

$$Q_2^{(2)[Y]} = \alpha_2^{[Y]} \cdot Q_t^{[P]} \quad (24)$$

$$\alpha_2^{[Y]} = \sum_{i=\{IP\}} \gamma_i^{[P]} \alpha_{2,i}^{[P]} \quad (25)$$

The assessed alpha factors for each pump may now be calculated as the remaining failure events.

$$\begin{aligned} Q_1^{(2)[P_1]} &= \alpha_1^{[P_1]} \cdot Q_t^{[P]}, & \alpha_1^{[P_1]} &= 1 - \alpha_2^{[Z]} - \alpha_2^{[Y]} \\ Q_1^{(2)[P_2]} &= \alpha_1^{[P_2]} \cdot Q_t^{[P]}, & \alpha_1^{[P_2]} &= 1 - \alpha_2^{[Z]} \\ Q_1^{(2)[P_3]} &= \alpha_1^{[P_3]} \cdot Q_t^{[P]}, & \alpha_1^{[P_3]} &= 1 - \alpha_2^{[Y]} \end{aligned} \quad (26)$$

5.6. Parameter Estimation – Impact Vectors

Impact vectors are calculated for each CCF in accordance with NUREG/CR-5485 [2]. The primary difference is that the average impact vectors are calculated for each cause. Assume for this example that the sum of the EDG average impact vectors, for each cause is:

$$\begin{aligned} n_{\Omega,IP}^{[E]} &= [0, 172.2, 2.8] \\ n_{\Omega,MH}^{[E]} &= [0, 154.35, 3.15] \\ n_{\Omega,EE}^{[E]} &= [0, 16.45, 1.05] \\ n_0^{[E]} &= 29400 \end{aligned} \quad (27)$$

The sum of the pump average impact vectors for each cause is:

$$\begin{aligned} n_{\Omega,IP}^{[P]} &= [0, 26.0663, 0.1838] \\ n_{\Omega,MH}^{[P]} &= [0, 59.4125, 1.838] \\ n_{\Omega,EE}^{[P]} &= [0, 82.5213, 4.9788] \\ n_0^{[P]} &= 44433 \end{aligned} \quad (28)$$

5.7. Parameter Estimation – Partial Alpha Factor Model

In order to calculate the assessed alpha factors, the partial alpha factors and gamma factors must be calculated. For the example, the PAFs and GFs can be calculated as:

$$\begin{aligned} \alpha_{2,IP}^{[P]} &= \frac{0.18375}{26.06625 + 0.18375} = 0.007 & \gamma_{IP}^{[P]} &= \frac{26.25}{26.25 + 61.25 + 87.5} = 0.15 \\ \alpha_{2,MH}^{[P]} &= \frac{1.8375}{59.4125 + 1.8375} = 0.03 & \gamma_{MH}^{[P]} &= \frac{61.25}{26.25 + 61.25 + 87.5} = 0.35 \\ \alpha_{2,EE}^{[P]} &= \frac{4.97875}{82.52125 + 4.97875} = 0.0569 & \gamma_{EE}^{[P]} &= \frac{87.5}{26.25 + 61.25 + 87.5} = 0.50 \end{aligned} \quad (29)$$

The assessed alpha factors can now be calculated as:

$$\begin{aligned} \alpha_2'^{[X]} &= \sum_{i=\{IP,MH,EE\}} \gamma_i^{[E]} \alpha_{2,i}^{[E]} = 0.02 \\ \alpha_2'^{[Z]} &= \sum_{i=\{MH,EE\}} \gamma_i^{[P]} \alpha_{2,i}^{[P]} = 0.03895 \\ \alpha_2'^{[Y]} &= \sum_{i=\{IP\}} \gamma_i^{[P]} \alpha_{2,i}^{[P]} = 0.00105 \\ \alpha_1'^{[P_1]} &= 1 - \alpha_2'^{[Z]} - \alpha_2'^{[Y]} = 0.96 \\ \alpha_1'^{[P_2]} &= 1 - \alpha_2'^{[Z]} = 0.96105 \\ \alpha_1'^{[P_3]} &= 1 - \alpha_2'^{[Y]} = 0.99895 \end{aligned} \quad (30)$$

5.8. System Quantification and Results Interpretation

The parameter estimates may now be substituted back into the system equations. Instead of calculating the system probability of failure using the system equation, the following quantities can be placed into the fault tree for calculation:

$$\begin{aligned} P(E_{1,i}) &= P(E_{2,i}) = Q_1^{(2)[E]} = \alpha_1'^{[E]} Q_t^{[E]} = 5.88e-3 \\ P(X_{E1,E2}) &= Q_2^{(2)[X]} = \alpha_2'^{[X]} \cdot Q_t^{[E]} = 1.2e-4 \\ P(P_{1,i}) &= Q_1^{(2)[P_1]} = \alpha_1'^{[P_1]} \cdot Q_t^{[P]} = 1.9584e-3 \\ P(P_{2,i}) &= Q_1^{(2)[P_2]} = \alpha_1'^{[P_2]} \cdot Q_t^{[P]} = 1.9605e-3 \\ P(P_{3,i}) &= Q_1^{(2)[P_3]} = \alpha_1'^{[P_3]} \cdot Q_t^{[P]} = 2.0379e-3 \end{aligned} \quad (31)$$

$$P(Z_{P1,P2}) = Q_2^{(2)[Z]} = \alpha_2'^{[Z]} \cdot Q_t^{[P]} = 7.95e-5$$

$$P(Y_{P1,P3}) = Q_2^{(2)[Y]} = \alpha_2'^{[Y]} \cdot Q_t^{[P]} = 2.1e-6$$

Substitution back into the system equation gives:

$$\begin{aligned}
P(S) &= \left(Q_1^{(2)[E]}\right)^2 + Q_1^{(2)[P1]}Q_1^{(2)[E]} + Q_1^{(2)[P1]}Q_1^{(2)[P2]}Q_1^{(2)[P3]} \\
&+ Q_1^{(2)[E]}Q_1^{(2)[P2]}Q_1^{(2)[P3]} + Q_1^{(2)[P3]}Q_2^{(2)[Z]} + Q_1^{(2)[E]}Q_2^{(2)[Z]} + Q_1^{(2)[P2]}Q_2^{(2)[Y]} \\
&+ Q_1^{(2)[E]}Q_2^{(2)[Y]} + Q_2^{(2)[Z]}Q_2^{(2)[Y]} + Q_2^{(2)[X]} \\
&= 1.668e-4
\end{aligned} \tag{32}$$

The system failure probability is calculated as 1.668e-4.

6. CONCLUSION

The PAFM aims to provide a cause-based CCF model which uses the same analysis methodology and data sources as the popular AFM. While minimized increases in complexity, the PAFM has the ability to create quantitative models using impact vectors, recognize efforts to create coupling factor defenses, and allow more sophisticated event assessments based on the observed failure cause. The PAFM does however use the same empirical ratio methods of the AFM and therefore most of the issues which exist with the current methodology remain.

The PAFM is quantified using two parameters, the partial alpha factors ($\alpha_{k,i}$) and the gamma factors (γ_i). The partial alpha factors represent the multiplicity of failures in a common cause component group, given a failure has occurred from cause i . The gamma factors represent the portion of failure events which are due to cause i . These two parameters can be combined to provide an 'assessed' alpha factor which may be implemented in an identical way to the AFM for system modelling.

8. ACKNOWLEDGEMENTS

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