Common-Cause Failure Parameter Estimates with Causal Alpha Factor Model, Component-Specific Priors, and More

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Abstract: Common-cause failures (CCFs) are modeled in probabilistic risk assessments (PRAs) for commercial nuclear power plants as important risk contributors, predominantly using the Alpha Factor or Multiple Greek Letter (MGL) parametric models. The CCF alpha factor parameter estimations have been periodically updated since the early 2000s using the CCF database developed and maintained by Idaho National Laboratory for the U.S. Nuclear Regulatory Commission (NRC). Recently, two additional sets of CCF alpha factor parameter estimations were developed that could be used for the NRC's event and condition assessments (ECAs) or the Standardized Plant Analysis Risk (SPAR) models. This paper presents an overview of these new CCF developments—the causal alpha factor parameter estimates and the alpha factor parameter estimation using component-specific CCF priors. In addition, the paper provides a plan for periodic CCF parameter updates, provides suggestions on how the different sets of CCF parameters should be used in the SPAR models and ECAs, and discusses the potential issues or challenges in future CCF parameter estimations.

1. INTRODUCTION

Common-cause failures (CCFs) are modeled in probabilistic risk assessments (PRAs) for commercial nuclear power plants (NPPs) as important risk contributors, predominantly using the Alpha Factor or Multiple Greek Letter (MGL) parametric models, which were developed more than 30 years ago and described in the U.S. Nuclear Regulatory Commission (NRC) reports such as NUREG/CR-4780 [1] and NUREG/CR-5485 [2]. The CCF alpha factor parameters were first estimated in NUREG/CR-5497 [3] and periodically updated afterward using the CCF database [4] developed and maintained by Idaho National Laboratory (INL) for the NRC.

Since 2014, CCF-related research activities conducted by the NRC and INL have focused on the development of new, alternative CCF models and parameter estimates to reduce the uncertainties in the CCF parameters from the current practice [5, 6]. INL/EXT-21-33376 [7] evaluated alternative CCF models developed by University of Maryland [8] and recommended the Causal Alpha Factor Model (CAFM) as the alternative CCF model for the NRC event and condition assessments (ECAs). INL/EXT-21-43723 [9] developed CCF generic prior and causal CCF prior distributions using the new data available at the time. INL/EXT-21-65527 [10] developed component-specific CCF prior distributions for five component types—pump, valve, strainer, generator, and "other"—after the study conducted during the development of the new CCF prior distributions in Ref. [9] determined that different component types can have drastically different alpha factors and should thus be analyzed separately. Multiple sets of CCF parameter estimations using the same 2006–2020 data were developed consequently in the last few years that could be used for the NRC's Standardized Plant Analysis Risk (SPAR) models or ECAs: the classical alpha factors estimated using the generic CCF priors [11], the causal alpha factors estimated using the causal CCF priors [12], and the alpha factors estimated using the component-specific CCF priors [13].

This paper presents an overview of the causal alpha factor parameter estimates and the alpha factor parameter estimation using component-specific CCF priors. In addition, the paper provides a plan for future periodic CCF parameter update, provides suggestions on how the different sets of CCF parameters should be used in the SPAR models and ECAs, and discusses the potential issues or challenges in future CCF parameter estimations.

2. FROM ALPHA FACTOR MODEL TO CAUSAL ALPHA FACTOR MODEL

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2.1. Alpha Factor Model

The Alpha Factor Model (AFM) is a failure event ratio model that uses a set of alpha factors to represent the probability of failure for a specified number of components at the same time due to a shared cause. Each alpha factor, α_k, is the conditional probability that given a failure it will fail k components out of m components within the common cause component group (CCCG). For example, α_2 is the probability that exactly two items fail at the same time. α_3 is the probability that exactly three items fail at the same time. With $\alpha_k$being the number of failure events involving exactly k components failing within a CCCG of size m, α_k can be calculated as

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

in which k = the number of failed components; m = the number of redundant components in the CCCG; n_k = the number of failure events, which resulted in k components failing within a CCCG of size m due to the same cause.

2.2. Causal Alpha Factor Model

Although the AFM is one of the most commonly utilized CCF models in PRAs with its ability to calculate its parameters directly from the CCF event data, industry has expressed concerns that the AFM does not explicitly incorporate the failure causes into the model; therefore, using conditional CCF probabilities with the AFM in ECA would include all causes in the CCF probabilities, including causes that did not result in the observed failure(s). The argument is that if the cause of an event or condition was environment (for example), the cause from human or component design should not be accounted for in the ECA. To address this issue, the NRC investigated potential alternative CCF models and identified the CAFM as the potential new model to replace the AFM in Ref. [7].
CAFM is an extension of AFM with the alpha factors broken into different failure causes to provide additional insights and support ECAs. CAFM uses the same equations as the AFM but calculates a different alpha factor (i.e., causal alpha factor) for each failure cause

$$\alpha_{k,i} = \frac{n_{k,i}}{\sum_{j=1}^{m} n_{j,i}} = \frac{n_{k,i}}{n_{t,i}} \quad (2)$$

in which, i = the i^{th} failure cause, $i \in r$ with r different failure causes; $n_{k,i}$ = the number of failure events, which resulted in k components failing within a CCCG of size m due the i^{th} failure cause; $n_{t,i}$ = the total number of failure events due the i^{th} failure cause.
Five failure cause groups in the existing NRC CCF database [4] are used to estimate causal alpha factors: component, design, environment, human, and "other." Table I shows the failure cause code, cause, and description included within each cause group as categorized in the NRC CCF database.

With the introduction of gamma factor (γ_i) that is a weighting factor that represents the strength of the correlation among the identified failure causes, the assessed alpha factor in CAFM (α'_k) equals to the generic alpha factor (α_k) in AFM.

$$\gamma_i = \frac{n_{t,i}}{n_t} \tag{3}$$

$$\alpha'_k = \sum_{i\in r} \gamma_i \alpha_{k,i} = \sum_{i\in r} \frac{n_{t,i}}{n_t} * \frac{n_{k,i}}{n_{t,i}} = \sum_{i\in r} \frac{n_{k,i}}{n_t} = \frac{n_k}{n_t} = \alpha_k \tag{4}$$

Table 1: Five Failure Cause Groups Used for Causal Alpha Factor Estimation

Cause Group	Cause Code	Cause	Description
Component	IC	Internal to component; piece part	A failure results from a failure internal to the component that failed due to reasons other than aging or wear; this applies to erosion/corrosion, equipment fatigue, and internal contamination.
	IQ	Setpoint drift	A failure results from setpoint drift or adjustment.
	IW	Age or wear	A failure results from a failure internal to the component that failed due to aging or wear.
Design	DC	Construction or installation error or inadequacy	A construction or installation error was made during the original or modification installation (e.g., installation of an incorrect component or material, or specifying an incorrect component or material).
	DE	Design error or inadequacy	A design error was made.
	DM	Manufacturing error or inadequacy	A manufacturing error was made when manufacturing the component.
Environment	EA	Ambient environmental stress	A failure results from an environmental condition at the component location; this applies to: • Chemical reactions • Electromagnetic interference • Fire/smoke • Impact loads • Acts of nature • Radiation (irradiation) • Temperature (abnormally high or low) • Vibration loads (excluding seismic events).
	EE	Extreme environmental stress	A failure results from an environmental condition that is transitory in nature and places a higher-than-expected load on the equipment.
	IE	Internal environment	A failure results from an internal environment condition; this applies to: • Debris • Foreign material • Operating medium chemistry issue.
Human	HA	Accidental human action	A human error incurred when performing an operational activity results in an unintentional or undesired action.
	HM	Inadequate maintenance	A human error occurred when performing a maintenance activity results in an unintentional or undesired action.

Cause Group	Cause Code	Cause	Description
	HP	Human action procedure	The correct procedure was not followed; this applies to: • Calibration/test staff • Construction/installation/modification staff • Maintenance staff • Operations staff • Other plant staff.
	PA	Inadequate procedure	A failure results from an inadequate procedure; this applies to: • Calibration/test procedures • Construction/installation/modification procedures • Maintenance procedures • Operational procedures • Administrative procedures • Other procedures.
Other	EC	State of another component	A failure results from a component state not associated with the component that failed. One example would be that the diesel generator failed due to having no fuel in the fuel storage tanks.
	OT	Other	The failure cause is provided but does not meet any one of these descriptions.
	OK	Unknown	The failure cause is not known.

2.3. Causal Alpha Factor Parameter Estimates

The causal alpha factor parameter estimation in general follows the classical alpha factor estimation process with the CCF event impact vector, mapping methodology, and Bayesian update [2, 4, 12], except an additional normalization process must be introduced to ensure Eq. (4) is satisfied after the Bayesian update process for both causal alpha factors and generic alpha factors. While Ref. [7] provides a detailed description of the causal alpha factor estimation process and results, the key insights are presented below:

- The CAFM is a natural extension of the AFM. With its combined or assessed alpha factor being equal to the generic alpha factor as seen in Eq. (4), the base SPAR models can continue to use the generic alpha factors developed in Ref. [11], while the causal alpha factors developed in Ref. [12] can be used in the NRC ECAs.
- A comparison of the causal and generic priors of the mean values of the alpha factors (e.g., $\alpha 2$ in the CCCG size of two; $\alpha 2$ and $\alpha 3$ in the CCCG size of three) shows that
    - The component causal priors are about 50% lower than the generic priors
    - The design causal priors are about 40–80% higher than the generic priors
    - The environment causal priors are about 2–3 times higher than the generic priors
    - The human causal CCF priors are about 25% (or less) lower than the generic priors
    - The “other” causal CCF priors are about 80% lower than the generic priors.
- A comparison of the posterior mean values of $\alpha 2$ for CCCG size of two for the CCF templates shows that depending on the observed data in specific CCF templates

- The component causal alpha factors could range from approximately 90% lower to 20% higher than the generic alpha factors
- The design causal alpha factors could range from approximately 90% lower to 230% higher than the generic alpha factors
- The environment causal alpha factors could range from approximately 0% to 1500% higher than the generic alpha factors
- The human causal alpha factors could range from approximately 90% lower to 100% higher than the generic alpha factors
- The "other" causal alpha factors could range from approximately 0% to 100% lower than the generic alpha factors.

- A common question when comparing causal alpha factors against their corresponding generic alpha factor values is why an individual causal alpha factor could be larger than the generic alpha factor. For example, the generic alpha factor α2 for the CCF template ALL-MDP-FS is 1.07E-2, but three of its five causal alpha factors are higher (i.e., design 1.52E-2, environment 3.47E-2, and human 1.94E-2) are higher than the generic alpha factor 1.07E-2. The answer to this question is that alpha factors are estimated as the ratio of the number of CCF events to the total number of failure events. When the number of CCF events is split into several different causal groups, the number of total events becomes split as well. Thus, we would have

$$\frac{n_{CCF,1}+n_{CCF,2}+n_{CCF,3}+n_{CCF,4}+n_{CCF,5}}{n_{t,1}+n_{t,2}+n_{t,3}+n_{t,4}+n_{t,5}} \neq \frac{n_{CCF,1}}{n_{t,1}}+\frac{n_{CCF,2}}{n_{t,2}}+\frac{n_{CCF,3}}{n_{t,3}}+\frac{n_{CCF,4}}{n_{t,4}}+\frac{n_{CCF,5}}{n_{t,5}} \tag{5}$$

$$\sum_{i=1}^{5} \hat{\alpha}_{2,i} \neq \hat{\alpha}_2 \tag{6}$$

- The CAFM and the causal alpha factors could better characterize the potential CCF risk impact in ECAs by focusing on a specific failure cause as result of the licensee performance deficiency (PD).
- However, using the causal alpha factors also has the following limitations
  - The failure cause categories in the NRC CCF database do not often align well with the licensee PDs being evaluated in the ECAs

Causal alpha factors include data of dissimilar components and failure modes, which increases the uncertainties (refer to INL/EXT-21-65527 [10] for component-specific CCF prior development).

3. ALPHA FACTOR PARAMETER ESTIMATE USING COMPONENT-SPECIFIC PRIORS

During the development of the new CCF prior distributions in Ref. [9], a study found that different component types can have drastically different alpha factors and should be analyzed separately. Component-specific CCF prior distributions for five component types—pump, valve, strainer, generator, and "other"—were developed in Ref. [10], and new sets of alpha factor parameters were estimated and published in Ref. [13]. The study found that:

- The alpha factor mean values vary significantly between the component-specific and generic priors
  - The alpha factor prior mean values for the pump, generator, and "other" component types are about 40–70% lower than the generic prior mean values
  - The alpha factor prior mean values for the valve component type are about 20–100% higher than the generic prior mean values

    - The alpha factor prior mean values for the strainer component type are about 2–3 times higher than the generic prior mean values.
- The differences between component-specific and generic posteriors are usually smaller than the differences between the priors. The abundance of observed data (or "evidence") determines the level of discrepancy between a posterior delta and a prior delta.
    - The alpha factor posterior mean values for the pump-, generator-, and "other"-related CCF templates are about 10–70% lower than those obtained using generic priors.
    - The alpha factor posterior mean values for the valve-related CCF templates are about 20% lower to 100% higher than those obtained using generic priors.

The alpha factor posterior mean values for the strainer component type are about 1.0–1.3 times higher than those obtained using generic priors.

4. ISSUES AND OTHER THOUGHTS FOR FUTURE CCF PARAMETER ESTIMATES

4.1. Use of Different Sets of Alpha Factors

With multiple sets of alpha factors available for the same 2006–2020 data, analysts may wonder which set of alpha factors should be used in SPAR models and ECAs. Currently there is agreement on the use of alpha factor parameters derived from component-specific priors released in Ref. [13] over the use of the existing generic alpha factors released in Ref. [11]. As for the causal alpha factors developed in Ref. [12], the uncertainties associated with the use of CCF data from dissimilar components and failure modes, and the matching of failure cause categories with the license PDs being evaluated in ECAs are considered larger than the alpha factors derived from component-specific priors. Therefore, the overall preference would be to replace the existing generic alpha factors with the new alpha factors from component-specific priors in Ref. [13] until the next parameter updates.

4.2. Future CCF Parameter Update

NRC/INL is currently updating component reliability and CCF parameters every 5 years. The last parameter update uses the 2006–2020 data [11, 14], and the next update plans to use the 2011–2025 data and will be conducted in 2026 when the 2025 industry data is available. For the 2025 CCF parameter update, component-specific priors will be used instead of the generic priors. The results will be used to update the CCF data in SPAR base models.

4.3. Issues and Challenges in Future CCF Parameter Estimates

One of the biggest issues and challenges for the future CCF parameter estimates is the decreasing number of CCF events. Figure 1 and Table II, adapted from Ref. [11], show the apparent decreasing trend over the years. With the use of the 15-year-rolling data period, the CCF prior development process, and the CCF parameter Bayesian update method, CCF parameter estimates will become more and more difficult due to the lack of failure data. A new methodology or process may need to be developed to provide meaningful parameter estimates.

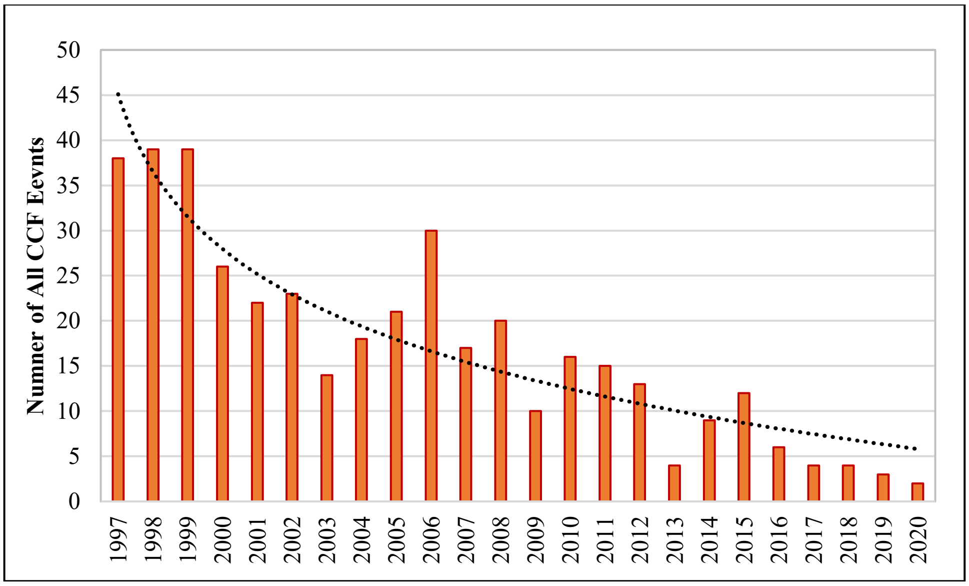

Figure 1. Number of CCF Events from 1997 to 2020

Table 2. Number of CCF Events by 5-Year Period

5–Year Period	1997–2001		2002–2006		2007–2011		2012–2016		2017–2020	
	Total	Per Year	Total	Per Year	Total	Per Year	Total	Per Year	Total	Per Year
All CCF Events	164	32.8	106	21.2	78	15.6	44	8.8	13	3.3
Complete CCF	25	5.0	23	4.6	14	2.8	5	1.0	2	0.5

4.4. Cross-Unit CCF

Some SPAR models and licensee PRA models may include cross-unit CCF modeling of emergency diesel generators (EDGs) and/or service water (SW) motor-driven pumps (MDPs), which could be significant risk contributor in some ECAs. However, since the current CCF parameters are estimated based on the CCF events in the NRC CCF database that are collected on a per-unit basis, extending the usage of these CCF parameters to the cross-unit CCF modeling raised the concern that the results would be too conservative with the belief that the coupling strength among cross-unit equipment is likely weaker in most cases than those among single-unit equipment. After discussion with the NRC, INL plans to conduct a limited scope cross-unit CCF study to (1) expand the current CCF event search process from per-unit basis to per-site basis for EDGs, SW MDPs, and SW strainers/traveling screens and (2) estimate cross-unit CCF parameters for EDGs, SW MDPs, and SW strainers/traveling screens. The results will be presented after the study is completed.

4.5. Digital Instrumentation and Control (DI&C) CCF

DI&C systems leverage advanced digital technologies that could enable more reliable, safe, and efficient operation of modern NPPs. However, adopting DI&C systems also introduces new challenges including the DI&C component reliability and CCF analysis, as well as the DI&C risk impact analysis. In fiscal year 2024, INL was tasked by the NRC to explore the possibility of estimating DI&C component and system reliability and CCF parameters using relevant nuclear industry OpE (operating experience) data. For DI&C CCF, we should first distinguish between the two different types of CCF:

- DI&C Internal CCF: CCFs occurred in redundant trains of a DI&C system, e.g., redundant software that fulfills the same function.

- DI&C External CCF: CCFs caused by the DI&C failure that impacts multiple components, potentially across multiple systems, for the same or different functions.

Note that the DI&C external CCF defined above does not correspond to the traditional definition of CCF (i.e., the simultaneous failure of redundant components due to a shared cause). Rather, it refers to intrinsic dependencies that are typically modeled explicitly within the system logic model. However, this type of dependencies is sometimes perceived as the CCF of concern when applying DI&C technology. To distinguish it from DI&C internal CCF—where redundant DI&C trains or components fail simultaneously due to the same cause—the term "DI&C external CCF" is used here to distinguish it from the "DI&C internal CCF".

The regulatory requirements for redundant and diverse DI&C system design and implementation are primarily aimed at mitigating the potential risks of multiple component or function failures due to a single DI&C failure or the DI&C external CCF risk. The treatment of this kind of CCFs would differ from the classical CCF parametric modeling approach for hardware. The functional dependencies among a DI&C system and its impacting systems should be explicitly modeled in PRA for DI&C risk assessment. More results from the NRC/INL DI&C study will be provided after it is completed

5. CONCLUSION

CCFs are modeled in PRAs for commercial NPPs as important risk contributors, predominantly using the Alpha Factor or MGL parametric models, which were developed more than 30 years ago. Since 2014, CCF-related research activities conducted by the NRC and INL have focused on the development of new, alternative CCF models and parameter estimates to reduce the uncertainties in the CCF parameters from the current practice. CCF generic prior and causal CCF prior distributions using the new data available at the time were developed. Causal alpha factors were subsequently developed for five cause groups—component, design, environment, human, and "other". In addition, component-specific CCF prior distributions and alpha factors for five component types—pump, valve, strainer, generator, and "other"—were developed. The result is multiple sets of CCF parameter estimations using the same 2006–2020 data were developed and could be used for the NRC's SPAR models and/or ECAs.

This paper provides an overview of the causal alpha factor parameter estimates and the alpha factor parameter estimates using component-specific CCF priors. These new sets of alpha factor parameters are compared with the existing generic alpha factors. The comparisons led to the following observations:

- The comparison results between causal priors and generic priors were observed to vary by failure cause. The priors associated with component, human, and "other" causes are generally lower than the generic priors, while the priors associated with design and environment causes are generally higher.
  The posterior comparison results were observed to vary by both failure cause and CCF template. For example, even within the same design cause group, the design causal alpha factors (α_2 for CCCG size of two) for different CCF templates ranged from 90% lower to 230% higher than the corresponding generic alpha factors.
- The comparison results between component-specific priors and generic priors were observed to vary by component type. The priors for pump, generator, and "other" component types are generally lower than the generic priors, while the priors for valves and strainers are generally higher than the generic priors.
  The posterior comparison results were generally consistent with the prior comparison results for each component type. For example, as the pump prior is lower than the generic prior, the resulting pump alpha factors are also lower than the generic alpha factors.
- When comparing causal- or component-type-specific mean values to generic values, no consistent trends should be expected (i.e., not consistently higher or lower than the generic

values). The use of causal- or component-type-specific values is intended to better reflect the performance of each specific group than the corresponding generic values.

The paper also provides some thoughts on the use of different sets of alpha factors in risk analysis, the plan for the future CCF parameter updates, and introduces the cross-unit CCF and DI&C CCF tasks that INL is undertaking for the NRC.

- It is recommended to replace the existing generic alpha factors in the SPAR models with the new alpha factors using component-specific priors during the next CCF parameter update. Alpha factors using component-specific priors are also recommended to be used instead of the causal alpha factors in ECAs. The potential future use of causal alpha factors in ECAs is still being evaluated; however, no additional research is planned currently.
- A decreasing number of CCF events pose challenges to future CCF parameter estimations resulting in the need for innovative, new solutions.
- Exploratory CCF studies are underway to conduct a limited scope of cross-unit CCF study for EDGs, service water MDPs, and service water strainers/travelling screens, and the DI&C component and system reliability and CCF parameter estimate.

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References

[1] A. Mosleh, K. N. Fleming, G. W. Parry, H. M. Paula, D. H. Worledge, D. M. Rasmuson, “Procedures for treating common cause failures in safety and reliability studies: Volume 1, Procedural framework and examples: Final report,” United States Nuclear Regulatory Commission, NUREG/CR-4780, EPRI NP-5613, 1988.

[2] A. Mosleh, D. M. Rasmuson, F. M. Marshall, “Guidelines on Modeling Common Cause Failures in Probabilistic Risk Assessment,” United States Nuclear Regulatory Commission, NUREG/CR-5485, 1998.

[3] F. M. Marshall, D. M. Rasmuson, A. Mosleh, “Common Cause Failure Parameter Estimations,” United States Nuclear Regulatory Commission, NUREG/CR-5497, 1998.

[4] T. E. Wierman, D. M. Rasmuson, A. Mosleh, “Common Cause Failure Database and Analysis System: Event Data Collection, Classification, and Coding,” United States Nuclear Regulatory Commission, NUREG/CR-6268, Revision 1, 2007.

[5] C. Hunter, C. Ng, M. R. Fard, Z. Ma, S. Zhang. “Research Activities Associated with the Treatment of Potential Common-Cause Failures in Event and Condition Assessment,” in *Proc. 2021 International Topical Meeting on Probabilistic Safety Assessment and Analysis (PSA 2021)*, Virtual Meeting, 2021.

[6] Z. Ma. “Summary of 2020 Common-Cause Failure Parameter Update for U.S. Commercial Operating Nuclear Power Plants,” in *Proc. ANS Winter Meeting*, Phoenix, AZ, 2022.

[7] Z. Ma, J. Knudsen, J. Schroeder, C. Smith, "Feasibility Study of Developing Alternative Common-Cause Failure Model for Event Assessment," Idaho National Laboratory, INL/EXT-21-33376, Rev. 1, 2021.
[8] A. O'Connor, A. Mosleh, "A general cause based methodology for analysis of common cause and dependent failures in system risk and reliability assessments," *Reliability Engineering & System Safety*, Vol. 145, pp. 341-350, 2016.
[9] Z. Ma, J. Schroeder, C. Smith, "Developing Generic Prior Distributions for Common Cause Failure Alpha Factors and Causal Alpha Factors," Idaho National Laboratory, INL/EXT-21-43723, INL/LTD 17 43723, Rev. 001, 2021.
[10] S. Zhang, Z. Ma, "Developing Component-Specific Prior Distributions for Common Cause Failure Alpha Factors," Idaho National Laboratory, INL/EXT-21-65527, Rev. 1, 2023.
[11] Z. Ma, K. J. Kvarfordt, "CCF Parameter Estimations, 2020 Update," Idaho National Laboratory, INL/EXT-21-62940, Rev. 1, 2021.
[12] Z. Ma, K. J. Kvarfordt, "Causal CCF Parameter Estimations, 2020 Update," Idaho National Laboratory, INL/RPT-23-72728, 2023.
[13] NRC Reactor Operational Experience Results and Databases. *CCF Parameter Estimates using Component-Specific Priors Spreadsheet 2020* [Online]. Available: https://nrcoe.inl.gov/ccf_pe/.
[14] Z. Ma, T. E. Wierman, K. J. Kvarfordt, "Industry-Average Performance for Components and Initiating Events at U.S. Commercial Nuclear Power Plants: 2020 Update," Idaho National Laboratory, INL/EXT-21-65055, 2021.