UK Experience of Developing Alpha Factors for Use in Nuclear PRA Models

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Abstract: Modelling Common Cause Failures (CCFs) is an essential part of Probabilistic Risk Assessment (PRA). In the UK, the normal approach for the Advanced Gas-cooled Reactors (AGRs) is to use the beta factor approach with these parameters determined using the Unified Partial Method (UPM). However, there has been recent impetus to consider the feasibility of using a more detailed CCF approach for the AGRs such as the Alpha Factor method. The AGRs share some component types with water cooled reactors. For these it is possible to obtain alpha factors from international databases (such as the US Nuclear Regulatory Commission (NRC) CCF Parameter Estimates and the International Common-Cause Data Exchange (ICDE)). However, AGRs contain many unique components which are not listed in these databases. An additional difficulty is the small AGR fleet size and consequently a potential lack of operating experience. This paper presents the experience to date in deriving alpha factors for AGR components, and presents a Bayesian method which can be used in cases where comparative prior data is sparse. Insights and experiences from the process are discussed.

Keywords: Common Cause Failure, Nuclear, Alpha Factor method, Unified Partial Method, Bayesian

1. INTRODUCTION

Complex systems, such as nuclear power stations, have numerous interactions between different parts of the system. Some of these interactions are obvious while others are less apparent, but the net effect is that different parts do not act independently of one another. Phrased in a statistical sense this means that the probabilities of failure of any two components are not independent of one another. However, given the large number of components at a power station, the number of potential combinations and dependencies is vast. As a first approximation most risk models make the assumption that basic entities in the model are independent of one another. Redundancy is a key area where this first approximation needs to be revised in order to produce meaningful risk results. Redundancy of components is a core concept in the design of high reliability systems, providing protection against single failures of equipment, and also helping to provide protection against hazards by physically separating redundant trains. However, it is well known that the probability of multiple "identical" components failing simultaneously is significantly more probable than would be expected if failures were independent. Hence, independence of failures is not an appropriate assumption to maintain, and it is revised through the use of the concept of common cause failure (CCFs) probabilities. Estimating common cause failures can be thought of as a simplifying method which circumvents the need to estimate a full covariance matrix over all plant components which would not be practically possible, and would be unsupportable by data.

In order to gain a reasonable estimate of the reliability of systems with high redundancy, it is essential to estimate the effect of dependent failures by estimating CCF probabilities. CCFs can represent a large proportion of risk in NPPs and feature in many PRA minimal cutsets. In the nuclear industry the main three models used to model CCF are the Multiple Greek Letter (MGL) model, the Alpha Factor model, and the simpler Beta Factor model. These are parametric models, where the parameters are derived using statistical analysis of failures and degradations from operating experience.

The simplest of these methods is the beta factor approach. A beta factor is simply a proportion of observed failures which are CCF events. The use of beta factors is binary in the sense that either a

CCF event occurs and all redundant trains are affected, or there is no CCF. There are different ways of estimating beta factors, for example they can be estimated directly from data, and in the past this data driven approach has been used in the UK.
For the AGRs, the approach that has been used to determine the beta factors is the UPM [1]. A body of work has been conducted to determine the feasibility of moving to the Alpha Factor model for the AGRs. This paper presents the findings of this work and the issues found to date.

2. UNIFIED PARTIAL METHOD (UPM)

The UPM is driven by assessing the likelihood of CCFs on a system based level, using a scoring assessment across eight categories [2]. The scoring in these areas is used to estimate a beta factor. The categories are:

1. Redundancy/Diversity
2. Separation
3. Environmental testing
4. Analysis
5. Understanding
6. Safety Culture
7. Operator interaction
8. Environmental control

Based on the assigned scores, an overall beta factor (conditional probability of a CCF, given that a failure has occurred) is calculated. Note, deriving beta factors using the standard Beta Factor Method differs from the UPM in two significant respects. The first is that the standard Beta Factor Method uses operating experience to derive a single beta factor. The second is that in calculating the beta factors, no consideration is made for redundancy, and in particular whether there are more than 2 components is a particular system/group. Redundancy is considered when using the UPM to derive beta factors as one of the assessment categories.

UPM offers some advantages over a purely data driven approach. It has a structured methodology based on engineering judgment to assess a system's propensity to CCF, providing an avenue for the insertion of engineering insight based on the realities of the system. The scoring methodology is relatively simple; the analyst must have an understanding of the system, but they need not be a system expert. Unlike the MGL and Alpha Factor methods, operating experience data is not required. This is a particular advantage for assessing AGR components, where operating experience is relatively scarce, due to small fleet size of UK AGRs, and the very low frequency of CCF events.

There are, however, criticisms of UPM. The weights used for different defenses were originally determined based on the analysis of electrical systems and discussions with engineers [3]. As such it is largely divorced from real operational experience. Changes in CCF probabilities with time are also not considered. It takes no account of differences between running and standby components. Additionally the discrete scoring scheme used does not differentiate between all levels of success criteria [4,5].

There has been some research into the shortcomings of UPM and comparisons to other methods. One study found that CCF probabilities calculated using UPM to be significantly higher compared to those derived using MGL, based on available plant data [6]. Another report recommended that three of UPM's weighting factors may need to be adjusted, based on analysis of data on emergency diesel generators (EDGs) and similar systems [7], and comparison with the results of other CCF estimation methods.

Considering these criticisms of the UPM (and the fact that it has limited use internationally), the current approach of using UPM in AGR PRA models could be improved by either:

- considering the feasibility to develop the UPM to address the shortcomings of the beta factor/UPM approach, and carry out such development work; or
- by replacing the beta factor/UPM approach with another CCF analysis method comparable with worldwide good practice.

EDF Energy, the operators of UK AGRs, have chosen to investigate the use of the Alpha Factor methodology within their PRA models, and commissioned a study to investigate how alpha factors can be used in their PSA models. The Alpha Factor method was chosen over the similar MGL method since uncertainty analysis is more straightforward with the Alpha Factor Method [8]. The study has been running for the past two years.

3. ALPHA FACTOR METHOD

The methodology of deriving alpha factors from operating experience is well defined. Both the NRC and the ICDE offer their own guidance [8, 9].

The calculation of CCF alpha factors requires impact vectors as an input. An impact vector is a numerical representation of a CCF event. It incorporates uncertainty as to whether or not an event was in fact a dependent failure event. For a Common Cause Component Group (CCCG) containing k components, the impact vector for that event will contain k+1 elements, where each element represents the number of coincident failures and one element is used to represent zero failures, as shown below:

$$\begin{pmatrix} 0 & 1 & 2 & \ldots & k \\ e_0 & e_1 & e_2 & \ldots & e_k \end{pmatrix}$$

An impact vector is created for each observed event, and the event is proportioned across the elements by considering three factors: a timing factor, a shared cause factor and a degradation state factor. The consideration of these factors results in a number between zero and one being assigned to each element in an impact vector. Appendix A gives summaries of the approach used to derive these factors, using NRC methodology, ICDE methodology and the methodology that has been used to analyze AGR operating experience, which in turn is based on the NRC and ICDE approaches.

The alpha factors represent the proportion of failure events which relate to a defined number of components (α_k is the probability that when a common cause basic event occurs in a CCCG, it involves the failure of k components). A point estimate of the alpha factors can be calculated as proportions based on the impact vectors.

4. A COMPARISON OF UPM AND ALPHA FACTOR METHODS

The experience outlined in Sections 2 and 3 is summarized in Table 1 below.

Table 1: UPM Beta Factor - Alpha Factor Comparison Table

Criteria	UPM/Beta Factor	Alpha Factor method
Internationally recognised	Limited use internationally.	Widely used in nuclear industry
Based on operating experience	Method derived from engineering judgment interpretation of historical operating experience through workshops.	Yes.
System or component based	System.	Component.
Ease of use	Straight forward.	Straight forward.
Success criteria	Limited allowance for different success criteria.	Can be used to calculate CCF probabilities for all levels of success criteria.
Differences between running and standby components accounted for	No.	Potentially, if alpha factors are available for different failure modes.
Allows for variation in CCFs amongst different components	No.	Yes – different alpha factors can be used for different components.
Compatible with Bayesian techniques	Not without further development.	Yes.
Compatible with sensitivity modelling	No.	Yes – assuming PRA software has the facility to assign assumed distributions to alpha factors.

5. ALPHA FACTORS FOR UK PRA MODELS

CCF alpha factors for various components are published in the NRC database [10]. These have been derived using US operating experience. The ICDE database publishes impact vectors for various components from which alpha factors can be calculated [11]. This is based on operating experience gathered from a number of different participating countries. These databases could be used to provide alpha factors for UK AGR PRA models. However, AGRs contain a number of component types which are listed in the NRC or ICDE databases.

Alpha factors for these components could be derived from AGR operating experience. Indeed AGR operating experience is used to provide estimates of independent failure rates in UK PRA models. However, CCFs are much rarer than independent failures, so far more data is required to provide reliable estimates of CCF probabilities. Preliminary results of analysis across a number of components shows that the alpha factors calculated purely from AGR operating experience are zero for α_3 and above.

The NRC CCF database contains “No Data (Prior Only)” factors. These are the prior factors used to derive the component alpha factors in the NRC CCF database. NRC state that these CCF parameters may be used for those cases where there is no reasonable set of data to approximate the intended event [10]. The basis for how these prior factors are calculated is described in Reference 12.

The use of No Data (Prior Only) factors in AGR PSA models is currently being investigated. Updating these factors using Bayesian methodology (see Section 7) is an additional option, which provides a method to take account of operational experience from specific stations even in the case where there is limited applicable prior data available.

6. USING ALPHA FACTORS IN RISKSPECTRUM PSA SOFTWARE

The PRA modelling software currently used for AGR PRA models is RiskSpectrum v1.1.4.3.

RiskSpectrum has the facility to model CCFs by assigning alpha factors to CCF groups [13]. There are however two significant shortcomings with this approach, which are discussed below.

(i) Adjusting for "non staggered" alpha factors in RiskSpectrum

The alpha factors published in the NRC database are based on a staggered testing regime. However alpha factor modelling within RiskSpectrum uses formulae based on the assumption that the alpha factors were calculated under a non-staggered testing regime. The formulae for calculating CCF probabilities, from alpha factors are given below [8]:

a.) Alpha Factor method (non-staggered testing)

$$Q_k^{(m)\,NS} = \frac{k}{\binom{m-1}{k-1}}\left(\frac{\alpha_k^{(m)} Q_T}{\alpha_{tot}}\right) \qquad (1)$$

Where $Q_k^{(m)}$ is the probability of a common cause basic event involving k specific components in a CCCG size m, ($1 \le k \le m$), Q_T is the total failure probability of all m components, $\binom{m-1}{k-1}$ is the standard combinatorial term:

$$\binom{m-1}{k-1} = \frac{(m-1)!}{(k-1)!(m-k)!} \qquad (2)$$

And

$$\alpha_{tot} = \sum_{k=1}^{N} k\alpha_k \qquad (3)$$

b.) Alpha Factor method (staggered testing)

$$Q_k^{(m)\,S} = \frac{1}{\binom{m-1}{k-1}}\left(\alpha_k^{(m)} Q_T\right) \qquad (4)$$

where Q_T and $\binom{m-1}{k-1}$ are as above

It is possible to derive a formula to convert α factors from "staggered" to "non-staggered", however, a simpler substitution method can be used [14]. See Table 2 below:

Table 2: Calculation of the amended α-factors to input into RiskSpectrum PRA model

Process Description	**Relevant Parameters and Equations**
Step 1: input data (from the CCF database)	$\alpha_2, \alpha_3, \alpha_4$
Step 2: calculate α_1 and α_t	$\alpha_1 = 1 - \alpha_2 - \alpha_3 - \alpha_4$ $\alpha_t = \alpha_1 + 2\alpha_2 + 3\alpha_3 + 4\alpha_4$
Step 3: calculate α_{2a}, α_{3a} and α_{4a}	$\alpha_{2a} = \alpha_2\alpha_t / 2$ $\alpha_{3a} = \alpha_3\alpha_t / 3$ $\alpha_{4a} = \alpha_4\alpha_t / 4$

Step 4: calculate α_{1a} and α_{ta}	$\alpha_{1a} = 1 - \alpha_{2a} - \alpha_{3a} - \alpha_{4a}$ $\alpha_{ta} = \alpha_{1a} + 2\alpha_{2a} + 3\alpha_{3a} + 4\alpha_{4a}$
Step 5: calculate α_{2aa}, α_{3aa} and α_{4aa} (which provides the input to RiskSpectrum)	$\alpha_{2aa} = \frac{\alpha_{2a}\alpha_{ta}}{\alpha_t}$ $\alpha_{3aa} = \frac{\alpha_{3a}\alpha_{ta}}{\alpha_t}$ $\alpha_{4aa} = \frac{\alpha_{4a}\alpha_{ta}}{\alpha_t}$
Output: CCF parameters for input into RiskSpectrum	$\alpha_{2aa}, \alpha_{3aa}, \alpha_{4aa}$

A simpler (though approximate) method to convert "staggered" alpha factors for use in RiskSpectrum is to divide each alpha factor by its number. I.e. divide α_2 by 2; α_3 by 3 etc. Using the "No data prior" NRC alpha factors for a CCCG size 4 [10] and this approximation, the error in the Q values is around 1.5%.

(ii) Using alpha factors for CCCGs with more than 4 components within RiskSpectrum

The general formula is given in equation (1). RiskSpectrum v1.1.4.3 only has the facility to input values for up to α_4. This is also true of the latest version v1.2.0. For component groups of size x (where x>4) then RiskSpectrum uses the value entered for α_4 as the value for α_x when calculating the value of Q_x (CCF of all components). For the purposes of calculation it assumes that $\alpha_4 \ldots \alpha_{x-1}$ are all zero.

This means that the value RiskSpectrum gives to CCF of all components is not correct, though the error is small, where $\alpha_4 \ldots \alpha_{x-1}$ are all small, which is normally the case.

Using NRC "no data prior" alpha factors (with no adjustment for staggered testing) and entering the α_8 value as α_4 in RiskSpectrum, Q_8 is around 2.6% higher than the correct value.

Using higher values of alpha factors (α_2 and greater all 0.02), the RiskSpectrum calculated value of Q_8 is 30% higher than the correct value. However it is worth noting that the alpha factors used in the model are not expected to have values this high.
For CCCGs with more than 4 components, where the success criteria is for one or more components to function successfully, then the alpha factor modelling within RiskSpectrum can be used. The errors due to RiskSpectrum limitations will only be small.

Where different levels of redundancy are required for CCCGs with 5 or more components, then the alpha factor modelling within RiskSpectrum is conservative. (RiskSpectrum can only model CCFs involving up to 3 components or CCF of all components within a CCCG.)

6. BAYESIAN METHODOLOGY

In some instances there is very little or no observed data, in the form of impact vector values, for CCFs involving large numbers of components. This is particularly challenging for systems that are specific to one facility. In these cases it can become desirable to use Bayesian updating to attempt to use all available data to provide the best possible estimate. This section describes a method for the implementation of Bayesian updating of alpha factors.

The alpha factors can be modelled using a multinomial distribution [8]. The conjugate distribution to the multinomial distribution is the Dirichlet distribution. The Dirichlet distribution is the multi-variate generalisation of the Beta distribution. The joint multinomial likelihood distribution for the alpha factors has the following form:

$$P(X \mid \alpha_1, \alpha_2, \alpha_3, \alpha_4) = \frac{(\sum_i x_i)!}{\prod_i x_i!} \alpha_1^{x1} \alpha_2^{x2} \alpha_3^{x3} \alpha_4^{x4} \qquad (5)$$

Where X represents the data vector, α_i is the i[th] alpha factor, and x_i is the i[th] observed number of data points. Note also, that the values of α_i are constrained by:

$$\sum_i \alpha_i = 1 \qquad (6)$$

Note also that the following expression:

$$\sum_i x_i \qquad (7)$$

is the total number of observed failure events. It is also worth noting that, since the observed data is fixed, the combinatorial term at the start of the equation can be omitted for the purposes of calculating a posterior.

The application of Bayes' theorem can then be used with an appropriately chosen prior (such as the Dirichlet distribution) to provide the posterior distribution. However, a full multi-dimensional prior and solution is particularly complex. The use of CCFs themselves can be thought of as a method to avoid using multi-dimensional parameters and estimating covariances in the main model. With this viewpoint in mind, if there were an effort to introduce multi-dimensionality into commercial risk models, then CCFs would be a counter-intuitive place to start. Hence, one possibility is to reduce the problem into several one dimensional problems; in the example above there would be four one-dimensional estimation problems.

Using this simpler method, the problem is reduced to several uni-dimensional problems, rather than a single multi-dimensional problem. A beta distribution could be used as the prior over each parameter in turn, and using a binomial likelihood. In this case we can view all other parameters as taking the "1-p" probability of the binomial distribution. For example if we are seeking to update alpha 2, then we can look at the probability that an event occurs affecting two components, and the probability that an event occurs which affects a different number of components to two. In this case we have simplified the problem sufficiently that validated software such as R-DAT can be used to perform the analysis. It should be noted that to perform multivariate analysis, alternative software such as BUGS is needed. The simplified Beta distribution method has numerous attractive properties. However, it is not clear from inspection what impact this simplification will have on the overall results. For this, a comparison between the simplified Beta distribution method and the full Dirichlet distribution approach is required.

This comparison is carried out for a simple example case below, in which it is assumed that there is some available data from the specific plant of interest but no data with which to form a prior:

Table 3: Hypothetical (Simplified) Data

Failures of 1 component (α_1)	Failures of 2 component (α_2)	Failures of 3 component (α_3)	Failures of 4 component (α_4)
11	2	1	0

The observed data in Table 3 is used together with non-informative beta and Dirichlet priors (all parameters set to one). The *only* difference in the priors under this selection of distribution parameters is that the beta distribution considers each parameter individually, while the Dirichlet is a multivariate distribution, and hence permits the use of a multivariate multinomial likelihood distribution for the observed failures. The idea behind this selection is to choose the simplest case in which to evaluate the effect of considering the dimensions individually or combined. The analysis was carried out using WinBUGS1.4.3. For each analysis case three chains were used each with a different, user specified, initialisation. 100,000 update iterations were run to generate the posterior distribution estimate. The results are presented in Table 4 below.

Table 4: Beta vs Dirichlet Priors

	Percentile	Using Beta Prior	Using Dirichlet Prior
α_1 Posterior Distribution	5^{th}	5.605E-01	4.77E-01
	25^{th}	6.833E-01	5.95E-01
	50^{th}	7.603E-01	6.73E-01
	75^{th}	8.28 E-01	7.45E-01
	95^{th}	9.032 E-01	8.33E-01
	Mean	7.5E-01	6.67E-01
α_2 Posterior Distribution	5^{th}	5.696 E-02	4.98E-02
	25^{th}	1.161 E-01	1.02E-01
	50^{th}	1.741 E-01	1.54E-01
	75^{th}	2.449 E-01	2.18E-01
	95^{th}	3.637 E-01	3.26E-01
	Mean	1.87E-01	1.67E-01
α_3 Posterior Distribution	5^{th}	2.427 E-02	2.13E-02
	25^{th}	6.42 E-02	5.66E-02
	50^{th}	1.091 E-01	9.68E-02
	75^{th}	1.695 E-01	1.51E-01
	95^{th}	2.783 E-01	2.51E-01
	Mean	1.25E-01	1.11E-01
α_4 Posterior Distribution	5^{th}	3.402 E-03	3.03E-03
	25^{th}	1.894 E-02	1.68E-02
	50^{th}	4.498 E-02	3.98E-02
	75^{th}	8.801 E-02	7.79E-02
	95^{th}	1.807 E-01	1.61E-01
	Mean	6.23E-02	5.54E-02

Intuitively one of the main benefits of using a Dirichlet distribution is to ensure that the constraint that the sum of all the alpha factors equals one is not violated. It is worth noting that the sum of the means is 1.12. Intuitively, the results using the Dirichlet distribution are “forced” to account for effects such as that the best estimate for α_4 is not zero, while the beta distribution approach enforces no such strict accounting. Despite this justification of the results, this is a greater than expected violation of the constraint in the beta distribution case, and it is an area for further investigation. It is acknowledged that other selections of the parameters may cause a greater difference in the analysis results, and this could form the subject of additional work. However, note that in instances where there is little prior information in the form of either operational experience data or expert judgment, that the prior will be diffuse, and the results are likely to be of a similar form to that presented above.

7. CONCLUSIONS

A comparison of the UPM and the Alpha Factor method for estimating CCFs has been presented. The main advantage of the Alpha Factor method over the UPM is that alpha factors are more clearly data driven compared to beta factors calculated using the UPM. That is, the estimates for each alpha factor are based on observed operational experience. However, it must be noted that there is still an element of subjectivity in this apparently data driven process. The derivation of the shared cause, timing and degradation factors used to derive the impact vector for each observed event is prescribed by guide tables, as shown in Appendix A, the interpretation of which necessarily has a subjective component. So the use of the Alpha Factor method does not completely remove the subjective nature of CCF assessment. However, the focus changes from judgments about the properties of safety systems which affect CCF, to judgments about the meaning of operating events and the potential for them to lead to CCF of two or more components. Given the rarity and complexity of CCF events, it is not entirely clear that complete removal of subjective assessment is even desirable.

Overall the Alpha Factor method has a good grounding in operational data, which provides greater confidence in the estimates being used. As noted, the complexity of CCF events merits the input of human judgment. Future work could explore the value of using the important factors assessed under the UPM as modifying factors for alpha factor estimates. This would allow “sensible” modifications of the factors based on the realities and idiosyncrasies of individual power stations.

A simplified method for conducting Bayesian analysis for the Alpha Factor method in no data prior cases has also been presented. Analysis supporting this simplification has been presented, but further cases should also be analysed to provide greater confidence in the validity of the simplification. Ultimately it should be noted that the purpose of CCF analysis should not be mathematical purity, but rather obtaining practical and reasonable estimates. This is especially true given the perspective that the use of CCFs itself is a significant mathematical simplification of the full dependency problem, albeit a very necessary one.

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APPENDIX A – ASSESSMENT TABLE FOR IMPACT VECTORS [8, 9]

Timing Factor

Factor	NRC approach	ICDE definition (Failure to run/operate)	Proposed definition for WOC and AR review
1.0	The component events are separated by no more than the PRA mission time (announced failures). During the time interval between the degradation events of components 1 and 2, there was no successful challenge to component 2 (unannounced failures).	Multiple component impairment occurring within PRA mission time.	The component events are separated by no more than the test interval for that component (stand-by components) or within one month (for operating components).
0.5	The component events did not occur within the PRA mission time and two times the PRA mission time (announced failures). During the time interval between the degradation events of components 1 and 2, there was one and only one successful challenge of component 2 (unannounced failures).	Multiple component impairment occurring outside PRA mission time, but within a one month's period (for operating components) or within double mission time (for stand-by components).	The component events occurred between one and two test intervals times apart (stand-by components). One to two months apart (operating components).
0.1	The component events are separated by more than two times the PRA mission time and less than three times the PRA mission time (announced failures). During the time interval between the degradation events of components 1 and 2, there were two and only two successful challenges of component 2 (unannounced failures).	Multiple component impairment occurring more than one month apart (for operating components) or more than double mission time (for stand-by components).	The component events occurred between two and three test intervals times apart (stand-by components). Two to three months apart (operating components).

Shared Cause Factor

Factor	NRC approach (Announced Failures)	ICDE definition (Failure to run/operate)	Proposed definition for WOC and AR review
1.0	Used when the analyst believes that the cause of the multiple failures is the same, often resulting in the same failure/degradation mechanism and affecting the same piece-parts in each of the components. The corrective action(s) taken for each of the components involved in the event is (are) also typically the same.	This code is used when the analyst believes that the cause of the multiple impairments is the same, regardless of the cause. A shared-cause factor code “High” implies multiple impairments from the same root cause of impairment, often resulting in the same failure/degradation mechanism and affecting the same piece-parts of each of the multiple components. The corrective action(s) taken for each of the multiple components involved in the event typically is (are) identical.	As NRC and ICDE approach.
0.5	This value is used when the event description does not directly indicate that multiple failures resulted from the same cause, involved the same failure mechanism, or affected the same piece-parts, but there is evidence that the	This code is used when the event description does not directly indicate that multiple impairments resulted from the same cause, involving the same failure mechanism, or affected the same	As NRC and ICDE approach.

	underlying root cause of the multiple failures is the same.	piece-parts, but there is strong evidence that the underlying root cause of the multiple impairments is the same.	
0.1	This value is used when the event description indicates that the multiple failures resulted from different causes, involved different failure mechanisms, or affected different piece-parts, but there is still some evidence that the underlying root cause of the multiple failures is the same.	This code is used when the event description indicates that multiple impairments resulted from different causes, involved different failure mechanisms, or affected different piece parts, but there is still some evidence that the underlying root cause of the multiple impairments is the same.	As NRC and ICDE approach.

Degradation Factor

Factor	NRC approach (Announced Failures)	ICDE definition (Failure to run/operate)	Proposed definition for WOC and AR review
1.0	The component has completely failed and will not perform its specific function. For example, if a pump will not start, the pump has completely failed, and degradation is complete.	The component has completely failed and will not perform its function. For example, if the cause prevented a pump from starting, the pump has completely failed and impairment would be complete. If the description is vague this code is assigned in order to be conservative.	As NRC and ICDE approach.
0.5	The component is capable of performing some portion of the safety function and is only partially degraded. For example, high bearing temperatures on a pump will not completely disable a pump but will increase the potential for failing within the duration of the PRA mission.	The component is capable of performing the major portion of the safety function, but parts of it are degraded. For example, high bearing temperatures on a pump will not completely disable a pump, but it increases the potential for failing within the duration of its mission.	As NRC and ICDE approach.
0.1	The component is only slightly degraded but component safety function is impacted. An example would be a safety valve with setpoint drift in excess of technical specification but still within the bounds of the plant safety analyses. This also includes incipient failures where some degradation or a degradation mechanism has become apparent, has not yet impacted component function, but has caused failures in other components.	The component is capable of performing the safety function, but parts of it are in a state that - if not corrected - would lead to a degraded state. For example, a pump-packing leak, that does not prevent the pump from performing its function, but could develop to a significant leak.	As NRC and ICDE approach.
0.01	The component was considered inoperable in the failure report; however, the failure was so slight that failure did not seriously affect component function. An example would be a pump packing leak that would not prevent the pump from performing its function.	Not used	Not used

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