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Methods for the treatment of common cause failures in redundant systems

Keywords

nuclear power plant, probabilistic safety assessment, simulation, common cause failure, modelling

Abstract

Dependent failures are extremely important in reliability analysis and must be given adequate treatment so as to minimize gross underestimation of reliability. German regulatory guidance documents for PSA stipulate that model parameters used for calculating frequencies should be derived from operating experience in a transparent manner. Progress has been made with the process oriented simulation (POS) model for common cause failure (CCF) quantification. A number of applications are presented for which results obtained from established CCF models are available, focusing on cases with high degree of redundancy and small numbers of observed events.

1. Common cause failure analysis in the frame of probabilistic safety assessment

Design, operation and maintenance of systems are performed to minimize potential failures such as random, systematic and dependent failures. Dependent failures comprise secondary failures caused, e.g., by violation of operational conditions and so-called commanded failures like component fails due to violation of interface conditions. The residual part of the group of commanded failures is called common cause failures (CCF). To identify dependent failures, approaches have been extended to encompass potential interpendencies between systems or components. Secondary and commanded failures are supposed to be modelled explicitly as far as possible in fault tree models of the system whereas common cause failures are taken into account in probabilistic safety assessment implicitly by parametric models.

In general, the most important defence against accidental component or system failures is the implementation of principles such as separation, diversity and redundancy. However, experience has shown that redundancy itself is not sufficient to avoid undesired events just because of possible dependent failures.

CCF of redundant safety relevant systems have been of concern since quantitative estimation of the reliability of these systems was developed starting in the early 70ies because this type of failures affect significantly their availability and reliability leading – in the worst case – to a simultaneous loss of all redundancies.

Typical examples of CCF are miscalibration of sensors, incorrect maintenance, environmental impact on the field device and use of a not appropriate process fluid, which plugs valves in different redundancies.

Experience from numerous probabilistic safety assessments has shown that, especially for highly redundant systems in nuclear power plants, common cause failures tend to dominate the results of these assessments such as the core damage frequency or large early release frequency.

As a consequence of generally rather effective defence against common cause failures in place, the number of really observed events in nuclear power plants is limited, in particular with respect to events involving failures of all or at least many redundant components. However, the operational experience contains some information on potential common cause failures, i. e., partial failures that could have evolved into the complete failure- of the common cause component group within a short period of time. This in turn requires in one way or the other an extrapolation based on parametric models, which is extremely difficult to verify.

Despite of these difficulties significant progress has been made in the last years due to increasing operational experience, more systematic data collection and analysis, growing experience in probabilistic safety assessment and an enhanced exchange on data and methods both nationally and internationally.

Although the use of plant-specific data in probabilistic safety assessment is preferred, in case of lack of events or of information it is helpful to provide a generic data base taking into account all national experiences and appropriate international data. Data bases like the OECD/NEA International Common Cause Failure Data Exchange Project allows collecting and analysing data of a lot of different components such as valves, pumps and diesel generators. Results of the analysis of these data also enable to assess and improve the effectiveness of defences against common cause failure events. For that purpose, data and information related to events observed in the operational experience with sufficiently detailed content have to be provided.

In general, the treatment of common cause failures within probabilistic safety assessment requires four main steps: development of a system logic model, identification of common cause component groups, common cause modelling and data analysis as well as quantification and interpretation of the results. For the quantitative part of the common cause failure assessment, models have still to be further developed, in particular with respect to applicability to highly redundant systems, suitability and traceability.

2. German practice

Probabilistic safety analyses (PSA) have been performed for all operating German nuclear power plants. Experience has shown that CCF in many cases tends to dominate the results of the PSA. Therefore, methods and results of CCF analyses receive a lot of attention in the discussions between regulator, technical experts, utilities and analysts.

Regulatory guidance is available in Germany for level 1+ PSA (a level 1+ analysis is understood to end at the onset of core damage but to take into account active containment functions) as part of periodic safety reviews of nuclear power plants. According to the importance of CCF, a chapter in the German regulatory guidance documents is dedicated to dependent failures [6]-[7]. These failures comprise secondary failures caused by violation of operational or environmental conditions as well as commanded failures - intact component failing due to violation of interface conditions, for example in the case of erroneous signals or failed energy supply. The residual part of the group of dependent failures is the common cause failures mentioned before. Secondary and commanded failures are to be modelled explicitly as far as possible in the fault tree models of the system. CCF, on the other hand, are taken into account in PSA by parameter models [2].

The guidelines mentioned before – they are currently undergoing final steps of revision in view of the fact that the Atomic Energy Act as amended in 2002 makes Periodic Safety Reviews (including PSA) mandatory – do not prescribe specific CCF models. Rather, they demand that the parameters of any model used are to be derived in a clearly described way from operating experience. Thus, in German PSA practice, a variety of models have been used [1], [9], [10].

3. A process oriented simulation model (POS) for CCF quantification

3.1. Rationale and objectives

The question can be raised whether an approach aiming at modelling the entire CCF process from the point in time of the root cause impact to failures taking effect or being detected in the common cause component group (CCCG) in a more mechanistic manner could support and complement the established modelling which is mostly aiming at failure probabilities. Such a process oriented modelling approach is described and discussed in this paper. It represents a further elaboration of the modelling stages described in [3]-[4].

3.2. Model description

The method of stochastic simulation offers a convenient way to describe the model and to quantify its results. The sequence of stochastic variables displayed in table 1 is supposed to adequately describe the CCF process.

Based on simulation of this sequence, the associated unavailability's can be calculated.

The following fixed-value parameters are used throughout a simulation sequence:

- operation time T_B
- number of components in the CCCG: r
- time between functional tests T_{FT}

The sequence of variables and calculations defines a single simulation of the common cause failure process. It is described how the variables are either derived from a stochastic assumption or are calculated deterministically.

The calculation of the probabilities *W(m,r)* for the event that the common cause impact will affect exactly *m* out of *r* components are calculated by a recursive scheme that is detailed in [3]. Here, only the formulae up to r = 4 are given. Model parameters are a and r_0.

$$W(2,2) = 1, \tag{1}$$

$$W(3,3) = a, \tag{2}$$

$$W(2,3) = 1 - a, \tag{3}$$

$$W(4,4) = a \cdot \left(a + (1-a)\cdot\left(1 - e^{-3/r_0}\right)\right), \tag{4}$$

$$W(2,4) = (1-a)^2, \tag{5}$$

$$W(3,4) = 1 - W(4,4) - W(2,4). \tag{6}$$

To facilitate handling of the necessary equations, model parameter r_0 is replaced by:

$$c = \exp(1/r_0). \tag{7}$$

In the applications presented here, a model version has been used that is based on a simplified assumption regarding the CCF identification. It is assumed that non-staggered testing is applied and that a CCF-event is identified at the functional test following the first component failure. It is well known that conditions in the field are more complex. To account for that from the information provided in the literature sources effective test intervals have been estimated for the POS-analyses. The model assumptions can be modified to account for other situations like staggered testing in a straightforward manner. As the prime purpose of this paper is to demonstrate key features of the POS model such refinements have been postponed.

3.3. Parameter estimation for the process oriented simulation model

The parameter estimation routine used here is closely related to the one described in [4]. It has, however, been simplified without significantly lowering its precision.

3.3.1. Frequency

The model has essentially four parameters that have to be estimated. The first is the frequency of CCF-events for which the usual estimator for failure rates is used.

3.3.2. Number of impacted components

The approach selected consists of an estimation of the distribution of the number of impacted components based on the observed events:

$$W_{est}(m,r) = \frac{N_m + 1/(r-1)}{K}. \tag{8}$$

The constant term 1/(r-1) is introduced into the estimator to avoid vanishing probabilities, which in practice are not expected. K serves for normalization. N_m is the number of events for CCCG size r and with number of impacted components m.
On the other hand, the probabilities can be calculated as functions of the model parameters. It can be shown that

$$W(2,r) = (1-a)^{r-2}. \tag{9}$$

Table 1. Overview of the POS model

Sequence of stochastic variables	Modelling assumptions for the stochastic variables Model parameter	Assumption
Time t_{CCI} of common cause impact	Rate of common cause impacts r_{CCI}	Equally distributed in T_B, $r_{CCI} \cdot T_B << 1$,
Number $m < r + 1$ of impacted components	a, r_o	Probability $W(m, r)$, see formulae (1) to (6) and [3]
Failure rate R of the impacted components	Probability of instantaneous failure of all impacted components W_{inst}, interval for rates of non- instantaneous failures R_{MIN} to R_{MAX}	According to W_{inst} the m components fail either instantaneously or are logarithmic equally distributed in the interval R_{MIN} to R_{MAX}
Times of failure of the impacted components	$t_F(m)$	Either all impacted components fail at t_{CCI} or the times of failure are exponentially distributed with rate R
Identification of CCF-process by the functional test	—	For times > $t_F(i)$ the failure and the common cause process are identified, the components are immediately repaired and as good as new
Time of CCF identification t_{ID}	T_{FT}	The functional tests are performed at intervals T_{FT}. The first test time after the first failure occurring at the minimum of the $t_F(m)$ is equal to t_{ID}
Finally, from the failure times $t_F(i)$ $(i = 1, ..., m)$ in the time interval between t_{CCI} and t_{ID} the time periods are calculated in which zero, one, two, ... up to at most m components are failed: $\Delta(i)$ $(i = 0,1,2,..,m)$		
The average of $\Delta(i) / T_B$ $(i \geq 1)$ for many simulations is the unavailability.		

This relation suggests the following estimator:

$$a_{est}(2,r) = 1 - W_{est}^{1/(r-2)}. \tag{10}$$

In a second step, parameter c is estimated based on the mean of m:

$$< m >_{est} = \sum_{m=2}^{r} m \cdot W_{est}(m,r). \tag{11}$$

Again, the mean of m can be calculated as a function y of the model parameters a and c

$$< m >= y(a,c). \tag{12}$$

This can be used to estimate c based on the estimates a_{est} and $W_{est}(m,r)$ already obtained

$$c_{est} = y^{-1}(a_{est}, < m >_{est}). \tag{13}$$

Here, y^{-1} denotes function $y(a,c)$ inverted with respect to c.

There are, however, cases in which the non-linear equation (13) for c_{est} does not have a meaningful solution. This is avoided by applying the following transformation to the estimated $<m>_{est}$:

$$< m >'_{est} = y(a_{est},0) \cdot \left(\frac{< m >_{est} - 2}{r-2} \right) + y(a_{est},1) \cdot \left(\frac{r - < m >_{est}}{r-2} \right). \tag{14}$$

The following estimator does always lead to meaning-full results:

$$c_{est} = y^{-1}(a_{est}, < m >'_{est}). \tag{15}$$

3.3.3. Fraction of impacts leading to immediate failure

The last parameter to be estimated is the fraction of events that lead to failure of all impacted components immediately, W_{inst}. It can – in some cases – be derived from the event reports in a straightforward manner.

A quantity sensitive to this parameter is the ratio of the number of events N_f in which all impacted components failed to the number of all events N_{total}

$$f = N_f / N_{total}. \tag{16}$$

For the mean value of this parameter holds

$$< f >= W_{inst} + (1 - W_{inst}) \cdot F_{cont}, \tag{17}$$

F_{cont} denotes the probability that in case of a non-instantaneous failure event all impacted components fail. This quantity obviously depends on the time of CCF detection. The identity serves as motivation for the following estimator

$$W_{inst} = \max\{(1 / 2 \cdot N_{total}), (f - F_{cont})/(1 - F_{cont})\}. \tag{18}$$

The estimation procedure described here is easier to handle than the approach described in [4] which is based on minimization of Kullback's information measure [11].
The rationale for the estimation procedure is rather of heuristic nature and not supported by rigorous proof. It is therefore necessary to assess its appropriateness using a simulation test outlined in the following.

3.4. Test for the estimation procedure

The estimation procedure is seen as a practical approach that is not underpinned by sophisticated mathematics but rather by direct testing. The latter is possible because the POS model can be used to generate fictitious failure data which can than be subjected to parameter estimation. Comparing the estimated parameters with the "true" parameters used in the simulation will display the balance of the strengths and weaknesses of the estimation procedure. The possibility to carry out such a test is a further advantage of simulation modelling.

3.4.1. Failure data and comparison to estimated parameters

From the data given *Table 2*, a set of 30 simulated CCF event data sets was produced, comprising on average some three CCF events each.

Table 2. 'True' parameters and derived CCF failure multiplicities (assuming CCF rate of 0,075 a^{-1}) used for the model test

Parameters	a = 0,5	c = 2,0	W_{inst} = 0,1
Failure multiplicities	2-out-of-4	3-out-of-4	4-out-of-4
Failure probabilities	$1,3 \cdot 10^{-4}$ a^{-1}	$8,3 \cdot 10^{-5}$ a^{-1}	$9,7 \cdot 10^{-5}$ a^{-1}

This exercise representing a straightforward test of principle, all simulated failure events were supposed to affect CCCG of size r = 4. The low number of simulated events corresponds to the well-known fact that CCF events as such are rather scarce. For the parameter estimation, only the number of CCF events, the number of failed and the number of affected – but not failed – components in each event were used, together with the supposed observation time, given in component group years. To assess the predictive power of the model, the parameters estimated for each of the 30 data sets were used to predict a 4-out-of-4 failure probability which was compared to the 'fictitious reality' as given in *Table 2*.

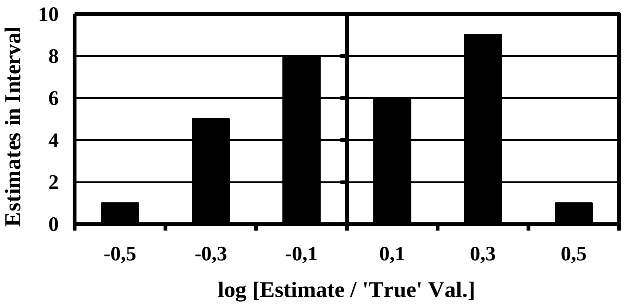

Figure 1. 'True' vs. estimated CCF probabilities for 4-out-of-4 failures

The result is shown in *Figure 1* above. In all cases, a CCF-detection time of 1.5 months has been assumed.

Obviously, the estimation procedure gives rather satisfactory results. The conservatism introduced by the heuristic assumption of eqn. (18) results in a very moderate overestimation of the true value.

3.4.2. Data base and quality of prediction

In order to test the POS model's performance in case of a scarce data base, the estimation procedure as detailed above was repeated, this time using a data set of simulated CCF events based on a CCF impact rate corresponding, on the average, to one event in the observation period. Obviously, a data set with zero events does not make sense; therefore, in such cases the fictitious observation time was extended until an event was simulated.

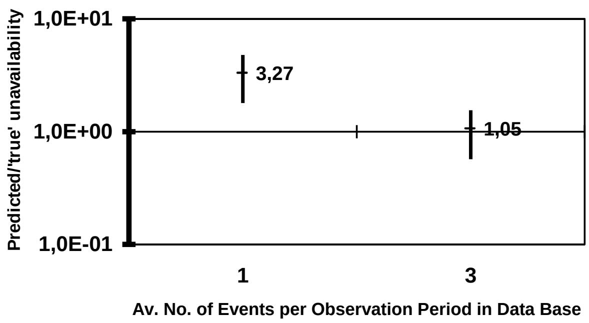

Figure 2. Comparison of predicted vs. 'true' unavailability's for 4-out-of-4 CCF on the basis of, on average, one or three events per database. Medians and standard error bars are given based on ten data sets for each case.

As can be expected, the conservative assumption implicit in equation (18) takes more effect in this case. *Figure 2* gives a comparison of predicted vs. 'true' failure rates for 4-out-of-4 CCF. As is evident from the comparison, the predictions based on scarce data tend somewhat to the conservative side.

On the other hand, it is demonstrated in *Figure 3* how the estimation is improved if more events are included in the database for a representative example. The parameter W_{inst} being rather sensitive to failure of all components is overestimated in the upper part of figure 3 based on 3 events in the average in the data set. In the lower part of figure 3, it can be seen how the enhanced number of events improves the estimate.

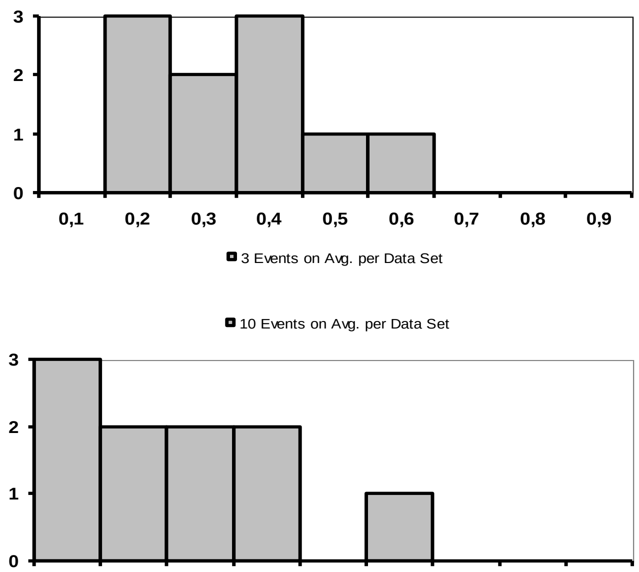

Figure 3. Dependency of parameter estimation quality on the number of events in the database. Estimated parameter: W_{inst}; true value: W_{inst} = 0.1 (cf. *Table 2*).

Upper diagram corresponds to 3 events on average, lower diagram corresponds to 10 events on average, showing improved estimation.

4. Analysis of a highly redundant system with the POS model

Hauptmanns [8] has published a challenging case study on a highly redundant CCCG. It concerns the combined impulse pilot valves which in German nuclear power plants govern the function of pilot operated safety or relief valves. For German Boiling Water Reactors (BWR), there are up to 22 such impulse pilot valves governing the function of the automatic depressurisation system (ADS).

CF quantification for such highly redundant systems is demanding, due to the sparse base of observed events, which, in addition, will mostly consist of events with only a limited number of failed components. Even in Hauptmanns' case, where the database consists of twelve events, there are only two cases with more than half of the CCCG actually failed (cf. *Table 3* below).

In [8], Hauptmanns compares CCF rates predicted for 1-out-of-22 through 22-out-of 22 failure multiplicities using the classical binomial failure rate (BFR) model to those predicted with his improved multi-class binomial failure rate (MCBFR) model. For the latter, the events in the database are sorted into different classes according to engineering judgement, and attempts to estimate individual coupling factors p for all of the defined event classes. Detailed information on the models and the calculation method are in [8].

Table 3. Observed CCF and degradations for combined impulse pilot valves (failure mode: does not open); adapted* from [8]

Event No.	No. failed components	No. degraded components	CCCG size *r*	Operation time T_B *[a]*
1	2	0	9	9
2	6	2	8	10
3	2	0	22	7
5*	1	15	16	9
6	2	5	16	7
7	2	10	12	6
8	7	1	8	10
9	1[a]	13[a]	14	9
11*	2	6	12	6
12	2	0	4	9

* H's events # 4 and 10 were omitted because with 1 failed and 0 degraded but not failed components they do not correspond to the definition of a CCF used in this paper, which is based on at least two components impacted by the common cause.

[a] In H's event # 9, one of the 14 components found degraded is assumed failed, because the analyses with the POS model presented here do not handle 'zero failure' events.

In case there is at least one CCF event in the database where all or nearly all components of the CCCG were failed, the MCBFR model can be expected to yield less unrealistic failure rates for high failure multiplicities than the classical BFR model.

Using the raw data as given in [8] with the exception of omitting events #4 and #10 and assigning event #9 one failed and 13 affected components instead of 0 failed and 14 affected, cf. table 3 – the CCF rates for a CCCG of size 22 were calculated. Total operation time of 165 component group years was used in estimating the CCF rate.

The results obtained with the POS model do not exhibit the unrealistic low failure rates for higher multiplicities. They do not coincide with the MCBFR results but are comparable especially in the range of higher failure multiplicities. Key difference to the MCBFR approach is that for the POS application no decomposition of the event base had to be performed. The approach is integral. It can be concluded that the POS model is a candidate for CCF analyses of highly redundant systems.

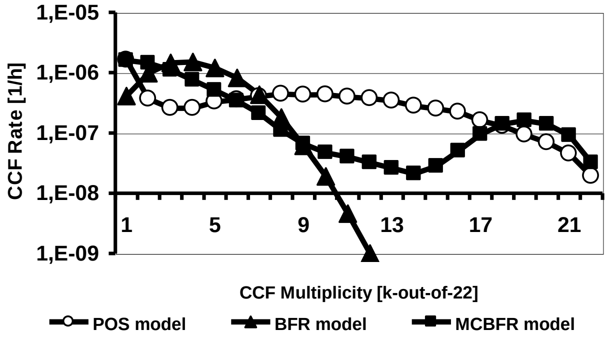

Figure 4. CCF-rates for pilot valves in German NPP according to Hauptmanns for the (BFR) and the (MCBFR) model. The results with the POS model have been obtained with the parameter estimation procedure described in this paper.

5. Calculating alpha-factors with the POS model

In [13], approaches to CCF quantification are outlined, especially the use of parametric models. In the report [12], common cause failure parameter estimations have been provided for some 40 different component types, various failure modes and common cause component group sizes from two up to six. One of the models for which parameter distributions have been derived is the Alpha-Factor Model. From the point of view of demonstrating the usefulness of the POS model, this large amount of systematically derived information was seen as a possibility to apply POS and compare to results obtained with established methods.

As pointed out before, for the POS parameter estimation information is required on the number of components, which are affected by the event. This kind of information is not available in [12]. Therefore, for this exercise a simplified approach has been selected [5].

The alpha factor $\alpha(k,l)$ is by definition the probability that in a CCF component group of size l exactly k components have failed as consequence of a CCF basic event. Hence, the quantities are normalized with respect to the failure multiplicity k = 1,2, ...l. The first simplifying assumption is that the failures with k equal to 2 and greater are determined by dependent failures only. The conditional probabilities w(k,l) for these events are calculated with the POS model. In [7], the numbers of independent and dependent events are given and thus the ratio q of dependent to total number of events is at hand. The alpha factors than can be calculated as follows:

$$\alpha(k,l) = w(k,l) \cdot q + (1 - q) \cdot \delta(k,1) \quad (19)$$

$$\delta(k,1) = 0 \text{ for } k > 1 \text{ and } \delta(1,1) = 1 \quad (20)$$

The selection of POS-parameters is – as pointed out before – simplified. The values of W_{inst} = 0.1 and of r_0 = 3 are taken as default values throughout the exercise. These values are typical values based on other applications. Parameter a is the fitted such that α(4,4) is equal to the value tabulated in [12] for the component type and failure mode under consideration.
This program has been carried out for six different combinations of components and failure modes. These were selected primarily based on large numbers of dependent failures to make sure that the comparison has a solid statistical basis. Furthermore, a mix of technically different components has been chosen. Furthermore, only those components were included for which CCF group sizes up to 6 are covered in [12].
For the comparison with the empirical data from [12] a metric for the deviation of the quantities is required. In [12], the mean, but also the 5-, the 50- and the 95-percentile of the alpha factor distributions are displayed. This suggested to use the logarithm of the ratio of the alpha factor derived from the POS model to the 50-percentile from [12], divided by logarithm of the ratio of the values of the 95-percentile to the 50-percentile. This means a deviation X = 1 if the calculated value equals the value of the 95-percentile

$$X = \log(\alpha_{POS} / \alpha_{50}) / \log(\alpha_{95} / \alpha_{50}). \quad (21)$$

Eq. (21) holds for values of α_{POS} larger than the median of the distribution, the analogous measure is used for α_{POS} smaller than the median. In that case, the deviation X = -1 is obtained if the calculated value equals the value of the 5-percentile.
A similar picture is obtained by considering complete CCFs (failure of all components). This is displayed in *Figure 5*. It is not surprising that the agreement is better for α(5,5) and α(3,3) than for α(2,2) as the parameter adjustment was done for α(4,4). For small sizes of the component group the deviations are larger. The assumption that the failure multiplicities > 1 are due to dependent failures only might here be wrong and thus lead to greater deviations.
Considering the severe simplifications that were made in the exercise, the results obtained with the POS model adjusting only one of three possible parameters are satisfactory especially for high failure multiplicities.

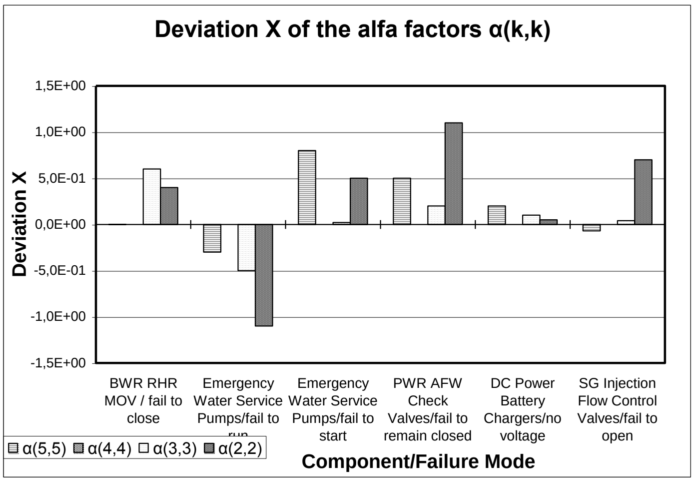

Figure 5. Deviation X of the alfa factors α(k,k) calculated with the POS-model from values tabled in [13].

6. Summary, conclusions and outlook

The POS model for CCF quantification is based on the following model structure:

- Time of CCF impact, simulated with a constant CCF impact rate,
- Number of components of the CCCG affected by the impact and subsequently failing immediately or time-delayed,
- Times of failure of the impacted components, and
- Time of detection of the CCF process by inspection or functional testing.

As a last step to prepare practical application of the model, a procedure for estimating the four free model parameters – rate of CCF impact, parameters a and c determining the probabilities of the number of impacted components and fraction of instantaneous failures – has been suggested and tested.
The POS model can be used to generate fictitious failure data which can than be subjected to parameter estimation. Comparing the estimated parameters with the “true” parameters used in the simulation gave a good agreement with a slightly conservative tendency. The low number of events – roughly three on the average – on which the estimation has been based, makes this observation remarkable. In situations with even less events the conservative overestimate of the unavailability becomes more visible but still results are not totally out of bounds.
CCF analyses for pilot valves in German nuclear power plants present a real challenge as component group seizes range up to 22. The POS application has no problem whatsoever with this situation. It does not show the totally unrealistic behaviour predicted by the BFR-model. The results show some agreement with a multi-class-BFR approach suggested by Hauptmanns

without the need to decompose the observed events into different technical classes.

As a bottom line, the results obtained increase the confidence into the model and the parameter estimation procedure. The next steps will be directed towards enhancing the number of applications. This work will be directed to areas of application where CCF failure data covering many component types and a larger range of component group sizes have been produced with well established models, [12] cf. e. g. In such cases, parameter estimates can be obtained from data derived from events in component group sizes up to 4 and extrapolated to higher degrees of redundancy. This will constitute a real test of the model and the parameter estimation procedure.

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