The POS Model for Common Cause Failure Quantification

Fachbereich
Sicherheit in der Kerntechnik

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SUMMARY

The POS (Process-Oriented Simulation) model can be seen as an extension of the BFR (Binominal Failure Rate) model carried out to overcome some of the shortcomings of this approach. In contrast to the BFR model the POS model explicitly distinguishes between immediate and delayed failures of components, does not assume that in each CCF (Common Cause Failure) event all components share the CC (Common Cause) but assigns probabilities to the different degrees of “extension” of the cause and is based on clearly formulated stochastic assumptions. This broader approach implies a more complex structure, however, the price paid in terms of greater complexity pays off due to a larger range of applicability. In particular the POS model can be applied to systems with high degree of redundancy. Another important advantage is the possibility to generate failure events using the POS simulation code. Simulating with known model parameters and estimating these from the generated failure events offers the possibility to test the framework for parameter estimation and, in addition, to obtain the uncertainties of the model results. No further assumptions beyond the model itself and the estimation procedure need to be introduced. Last but not least, the test of the estimation procedure demonstrated that the POS model works already quite well with only a small number of events as a basis. This makes it a candidate for plant specific CCF applications.

In contrast to other approaches like MGL (Multiple Greek Letter) and Alpha Factor, the POS model comprises only a few parameters, beyond the frequency of CCEs (Common Cause Events) only three.

The applications of the POS model carried out so far indicate that it can readily be applied to practical cases. The results obtained by benchmark tests are no outliers but are rather consistent with the majority of existing analyses.

To summarize, the POS model represents an interesting alternative to established models with some new and unique model features. Looking ahead, two aspects are discussed and emphasized. The first is the still existing development potential of the model, the second is a proposal for the quantitative comparison between CCF models.

ZUSAMMENFASSUNG

Das POS-Modell stellt eine Erweiterung des BFR-Verfahrens mit dem Ziel dar, einige Schwächen und Nachteile des Letzteren zu vermeiden, es unterscheidet im Gegensatz zum BFR-Ansatz ausdrücklich zwischen sofortigem und verzögertem Komponentenausfall. Es geht auch nicht von der Annahme aus, dass bei jedem gemeinsam verursachten Ausfall (GVA) alle Komponenten vom gleichen Fehler befallen sind, sondern weist verschiedenen „Ausdehnungsgraden“ der Ursache separate Wahrscheinlichkeiten zu. Das Modell basiert zudem auf klar formulierten stochastischen Annahmen. Dieser breitere Ansatz führt notwendigerweise zu komplexeren Strukturen, dem steht jedoch ein deutlich weiterer Anwendungsbereich gegenüber: Das POS-Modell kann insbesondere auf Systeme mit einem hohen Redundanzgrad angewendet werden, ein weiterer Vorteil liegt in der Möglichkeit, Ausfallereignisse mit Hilfe des POS-Simulationscodes zu generieren. Die Simulation mit bekannten Modellparametern und deren Abschätzung aus den erzeugten Ausfallereignissen erlaubt es, den Rahmen für die Parameterabschätzung zu testen und darüber hinaus die Unsicherheitsbänder für die Modellergebnisse zu bestimmen. Neben dem Modell selbst und den Abschätzungsmechanismen müssen keine weiteren Annahmen eingeführt werden. Schließlich zeigte der Test der Abschätzungsverfahren, dass das POS-Modell bereits auf der Basis kleiner Ereigniszahlen gute Ergebnisse liefert. Es ist somit besonders für anlagenspezifische GVA-Analysen geeignet.

Im Gegensatz zu anderen Verfahren, wie dem MGL- und dem Alpha-Faktor-Modell umfasst das POS-Modell nur wenige Parameter. Es sind dies, neben der Häufigkeit von GVA-Ereignissen, nur drei.

Die bisher durchgeführten Anwendungen deuten darauf hin, dass das POS-Modell reif für die praktische Anwendung ist. Die bei Benchmark-Tests erzielten Ergebnisse sind keine „Ausreißer“, sondern weitgehend konsistent mit der Mehrzahl der vorliegenden Analyseergebnisse.

Zusammenfassend kann festgestellt werden, dass das POS-Modell eine interessante Alternative zu bestehenden Analyseverfahren darstellt und z.T. neue und einzigartige Eigenschaften aufweist. In der Vorrauschau werden zwei Aspekte betont und erörtert, zum einen das für das Modell weiterhin bestehende Entwicklungspotential, zum anderen wird ein mögliches Vorgehen für einen quantitativen Vergleich zwischen bestehenden GVA-Analysemodellen vorgeschlagen.

1. INTRODUCTION

1.1 THE ROLE OF PSA IN SAFETY ASSESSMENT

Traditional nuclear safety analysis is based on conservative deterministic modelling, primarily using realistic models with a conservative choice of parameters. Postulates like e.g. the single failure criterion have been introduced to define the range of failures that needs to be covered by the analyses. The overall approach is completed with the help of engineering judgement and experience. The probabilities of events are taken into account in indirect ways, typically by assumptions and postulates.

With the milestone study WASH-1400, also known as the Rasmussen Report [RAS 75], the method of probabilistic modelling appeared in nuclear safety assessment. Since then, it was used in many countries, frequently triggered by national risk studies like e.g. the German Risk Study [DRS 79]. With different pace, depending on specific national conditions, it became part of safety evaluation practice and regulatory frameworks.

Probabilistic Safety Assessment (PSA) has been shown to provide important safety insights in addition to those provided by deterministic analysis. PSA provides a methodological approach for identifying accident sequences that emerge from a broad range of initiating events and it includes the systematic and realistic determination of accident frequencies and consequences [BAL 01].

In international practice three levels of PSA are distinguished:

- Level 1 identifies the sequence of events that can lead to core damage, estimates the core damage frequency and provides insights into the strengths and weaknesses of the safety systems and procedures provided to prevent core damage.
- Level 2 identifies ways in which radionuclides releases from the plant can occur and estimates their magnitude and frequency. This analysis provides additional insights into the relative importance of accident prevention and mitigation measures such as the use of a reactor containment.
- Level 3 estimates public health and other societal risks such as the contamination of land or food subsequent to a spectrum of accident scenarios.

Level 1, level 2, and level 3 PSAs are sequential analyses, and the results of the previous level usually serve as a basis for the PSA of the next level. A level 1 PSA provides insights into design weaknesses and into ways of preventing the accidents leading to the nuclear core damage, which might be the precursor to accidents leading to major releases of radioactive substances with possibly severe health and environmental consequences. A level 2 PSA provides additional information concerning the relative importance of accident sequences leading to nuclear core damage in terms of the severity of the releases they might cause, and insight into weaknesses in and ways of improving the mitigation and management of accidents leading to the nuclear core damage. Finally, a level 3 PSA provides results pertaining to the relative importance of accident prevention and mitigation measures expressed in terms of the adverse consequences for the health of both plant workers and the public, and the contamination of land, air, water and foodstuff. In addition, a level 3 PSA provides insights into the relative effectiveness of aspects of accident management related to emergency response planning.

To date level 1 PSAs have been carried out for most nuclear power plants in operation worldwide. However, in recent years, the emerging standard is level 2 PSAs either completed or yet to be carried out for many types of nuclear power plants. To date, relatively few level 3 PSAs have been completed [BER 06B].

1.2 DEPENDENT FAILURES AND COMMON CAUSE FAILURES

PSAs have been performed for all operating German nuclear power plants. Experience has shown that in many cases Common Cause Failures (CCF) dominate the results of the PSA, one of the main reasons being the high degree of redundancy in the engineered safety systems.

A detailed overview on regulatory guidance for PSA in Germany is given in detail in [BER 06B]. According to the importance of CCF, it is addressed in the PSA guideline [BMU 05], moreover, dedicated chapters in the German regulatory guidance documents on PSA methods [FAK 05A] and data [FAK 05B] are devoted to

dependent failures. This category of failures comprises secondary failures caused by violation of operational or environmental conditions as well as so-called commanded failures - intact component failing due to violation of interface conditions, e.g. in the case of erroneous signals or failed energy supply. The residual part of the group of dependent failures are the Common Cause Failures mentioned before. Secondary and commanded failures are supposed to be modelled explicitly as far as possible in the fault tree models of the system. CCFs, on the other hand, are taken into account in PSA by parameter models.

The guidelines mentioned before do not prescribe specific CCF models. Rather, they require the parameters of any model used to be derived in a clearly described way from operating experience. Thus, in German PSA practice, a variety of models has been used to quantify CCFs of redundant components. The Basic Parameter Model, the Binomial Failure Rate Model, derivatives of the BFR model, the Multiple Greek Letter Model and the Alpha Factor model are the most frequently applied quantification methods. Key features of some of these models are addressed in the following chapter.

2. ESTABLISHED APPROACHES TO CCF QUANTIFICATION

2.1 COMMON CAUSE EVENTS

In the following, it is assumed that the Common Cause Component Group (CCCG) consists of r equal and redundant components. This – as it is often called – "symmetry assumption" is made for practically all cases in a PSA.

If two or more components share a Common Cause that can lead to failure of the component this is a Common Cause Event (CCE). The number of components that share the cause is denoted by m which can be equal to or smaller than r.

$$2 \le m \le r \tag{2.1-1}$$

Alternatively, this is expressed by stating that m components are affected by the cause.

The number of components actually failed in a given event is denoted by k.

$$0 \le k \le m \tag{2.1-2}$$

2.2 THE BINOMINAL FAILURE RATE MODEL

The BFR model has been used in CCF analyses for many years, it is described in detail in [MOS 98A & B]. The following assumptions define the BFR model:

- The CCCG is "hit" by two types of impacts, called lethal and non-lethal shocks. In the BFR model, it is assumed that both types of shocks hit all components ($m = r$).
- The lethal shocks lead to immediate failure of all components, they occur at a time-constant rate ω.
- The non-lethal shocks occur at a constant rate μ. They also affect all components, but in contrast to the lethal shocks these fail independently with a conditional probability $p < 1$.

These assumptions lead to the following rates of k-out-of-r failures:

$$R(r,r) = \omega + \mu \cdot p^r \tag{2.2-1}$$

$$R(k,r) = \mu \binom{r}{k} (1-p)^{r-k} p^k \quad \text{if } k < r \tag{2.2-2}$$

Division by the combinatorial factor yields the rate for failure of a specific set of components.

The BFR model is a simple, but by all means non-trivial stochastic model for CCFs. In [MOS 98B], it is described how to estimate the values of its 3 free parameters p, ω and μ from operating experience.

In the following, the practical value of this model and its limitations shall be addressed.

Firstly, there are conceptual limitations because the basic assumptions "all components are affected" and "components fail immediately after being hit by a shock" are not fulfilled in many events that are observed in operating experience.

Secondly, the BFR model has a practical difficulty, if not a shortcoming. When the model results based on events with limited degree of redundancy are extrapolated to highly redundant systems, the rate of complete system failure $R(r,r)$ is either constant for a sufficiently large degree of redundancy r or, if there are no lethal shocks, it decays with a power law to unrealistically low values. Chapter 4 gives an example for magnetically operated pilot valves (r = 22), which illustrates these problems.

With respect to these observations, however, it can rightly be answered that it is not necessary that all model assumptions are fulfilled. Rather, the failure behaviour predicted by the model using the parameter estimates obtained from operating history must be satisfactory. This is a key question: How to evaluate the prediction capabilities of CCF models? This point will be addressed in chapter 5.

2.3 MODIFICATIONS OF THE BFR MODEL

The deficiencies of the BFR model addressed above have triggered different efforts to modify it.

The first modification to be mentioned is the so-called Multi-Class BFR (MCBFR) model which has been suggested by Hauptmanns [HAU 96]. It is based on a separation of events into different technical classes, to which the BFR model is applied separately. An application of this model will be discussed in para. 4.1.

Another somewhat related approach is the modified BFR model (MBFR), which is based on the idea of assigning a coupling factor p_j to each individual event j and superpose the associated probabilities. According to [FAK 97, KRE 01A] the estimator of the CCF probability for an k-out-of-r failure is given by

$$W_{MBFR}(k,r) = \sum_{j=1}^{N} \frac{T_{CCF_j}}{T_{obs}} \cdot \binom{r}{k} p_j^k \left(1 - p_j\right)^{r-k} \tag{2.3-1}$$

The term T_{CCF_j} denotes the failure detection time and T_{obs} is related to the test interval. The factor T_{CCF_j} / T_{obs} can be interpreted as the probability that a multiple failure, caused by CCF phenomenon j, could occur in the specific component group, when the group is demanded. This appears attractive on first glance as the basic formulae of BFR can further be applied with some additional summing up. But there is an issue that should not be overlooked: the sum over all observed events would in the limit of many events mean a sum over the possible values of the coupling factor weighted with the probability that the coupling factor is observed in an event. Letting aside aspects like additional degraded components, according to [FAK 97] the coupling factor is given by

$$p_j = \frac{j}{r} \quad .$$

If $W(k,r)$ is the probability to observe a failure multiplicity k-out-of-r, then this method would finally lead to the following probability

$$W_{MBFR}(k,r) = \sum_{j=0}^{r} W(j,r) \cdot \binom{r}{k} \cdot \left(\frac{j}{r}\right)^k \left(1 - \frac{j}{r}\right)^{r-k} \tag{2.3-2}$$

to observe k-out-of-r failure. Depending on the CCF definition, the sum is in some cases restricted to $j > 0$. For simplicity here $j = 0$ is included, the general argument does apply also for the cases with $j > 0$.

In general, the $W_{MBFR}(k,r)$ will not be equal to the observed "true" $W(k,r)$. This is easily verified for the highly important special case k=r, the complete failure of all components

$$W_{MBFR}(r,r) = \sum_{j=0}^{r-1} W(j,r) \cdot \left(\frac{j}{r}\right)^r + W(r,r) > W(r,r) \tag{2.3-3}$$

which means that the method does systematically overestimate complete system failure.

To illustrate this behaviour, an example for a number of postulated "true" $W(k,r)$ with redundancy $r = 4$ will be given. In general, empirical information shows a decreasing $W(k,r)$ with increasing redundancy. Respecting this, generic values are chosen by $W(k,4) = 0.5^k / C_{norm}$ with $k = 0,1,\ldots,4$. This yields a "true" value of $W(4,4) = 0.032$. With the additional sum of formula (2.3-3) however, the MBFR model yields a value of $W_{MBFR}(4,4) = 0.062$. In this special example the probability of a total system loss is overestimated by a factor of 2.

Though a doubling is not very much in an area where uncertainty is high, the MBFR approach systematically overestimates the contribution of CCF to core damage frequency. This can be welcomed as a conservative feature, on the other hand it appears questionable, whether this type of modelling is a good starting point for a realistic risk estimate. It should further be noted that the discrepancy can be large in cases of stronger decline of the probability towards total system failure or for higher degrees of redundancy.

It is emphasized that the argument presented above using formula (2.3-3) can not be applied quantitatively to some of the approaches, in particular not to the so-called coupling model [KRE 01A], as it is based on a modified form of (2.3-2), involving a Bayesean estimate of the coupling factor. There are further aspects like applicability factors, which have not been considered here, but which play a role in practical applications.

However, the principle argument raised here remains valid. Checks as performed in the example above should be carried out to assess the significance, especially for a potential contribution to model uncertainty.

2.4 THE ALPHA FACTOR MODEL

In the Alpha Factor model, independent and Common Cause Failures are treated in one combined assessment. The fundamental definition is that of the alpha factor [MOS 98A], [MOS 98B]:

$\alpha(k,r)$: fraction of the total frequency of failure events that occur in the system and involve the failure of k-out-of-r components due to a Common Cause

$Q(k,r)$: probability of a CCE involving k specific components in a CCCG of size r ($1 \le k \le r$)

Q_t: total failure frequency of each component due to independent and Common Cause failures

The estimation of the quantities $\alpha(k,r)$ is based on the following maximum likelihood estimator:

$$\alpha(k,r) = \frac{n_k}{\sum n_k} \tag{2.4-1}$$

n_k denotes the number of events with a CCF of exactly k-out-of-r components.

A β-distribution is assumed for uncertainty analysis.

The alpha factors are obviously taken directly from operating experience. In cases where no events of type (k,r) have been observed, this brings zero values for $\alpha(k,r)$ which in general – if the corresponding event can not be excluded – can not be accepted as a reasonable estimate. Therefore, in addition to the parameter estimates, procedures for mapping up and down are introduced, which support the extrapolation between different degrees of redundancies. This may lead to desired results in practical terms, but from the point of model building systematics it presents an additional assumption.

The algorithm given in [MOS 98B] provides the relation between $Q(k,r)$ and $\alpha(k,r)$ for different testing schemes:

Staggered testing:

$$Q(k,r) = \alpha(k,r)\frac{Q_t}{\binom{r-1}{k-1}} \tag{2.4-2}$$

Non-staggered testing:

$$Q(k,r) = \alpha(k,r)\cdot(k/\alpha_t)\frac{Q_t}{\binom{r-1}{k-1}} \tag{2.4-3}$$

$$\alpha_t = \sum l \cdot \alpha(l,r)$$

In figure 2-1, for 4 different types of components the alpha factors according to [MOS 98B] for a degree of redundancy 6 are displayed. In all cases, $\alpha(1,6)$ is close to 1. This implies that, in addition to the independent events, a major fraction of the CCEs are identified, when just one component has failed. The data in figure 2-1 are based on 17 independent and 16 dependent failure events.

It shall, moreover, be pointed to two aspects. Firstly, in some cases $\alpha(6,6)$ is greater than $\alpha(5,6)$. This is not an artificial feature created by modelling, as the data are largely empirically based. This issue is addressed here, as in discussions on CCF it is often argued that there should generally be a strong and monotone decrease. This view is not shared, as it is opposed to operating experience. Secondly, the approach used in [MOS 98B] creates 0 values for $\alpha(6,6)$, which indicates that the extrapolation to multiplicities not observed might require improvement.

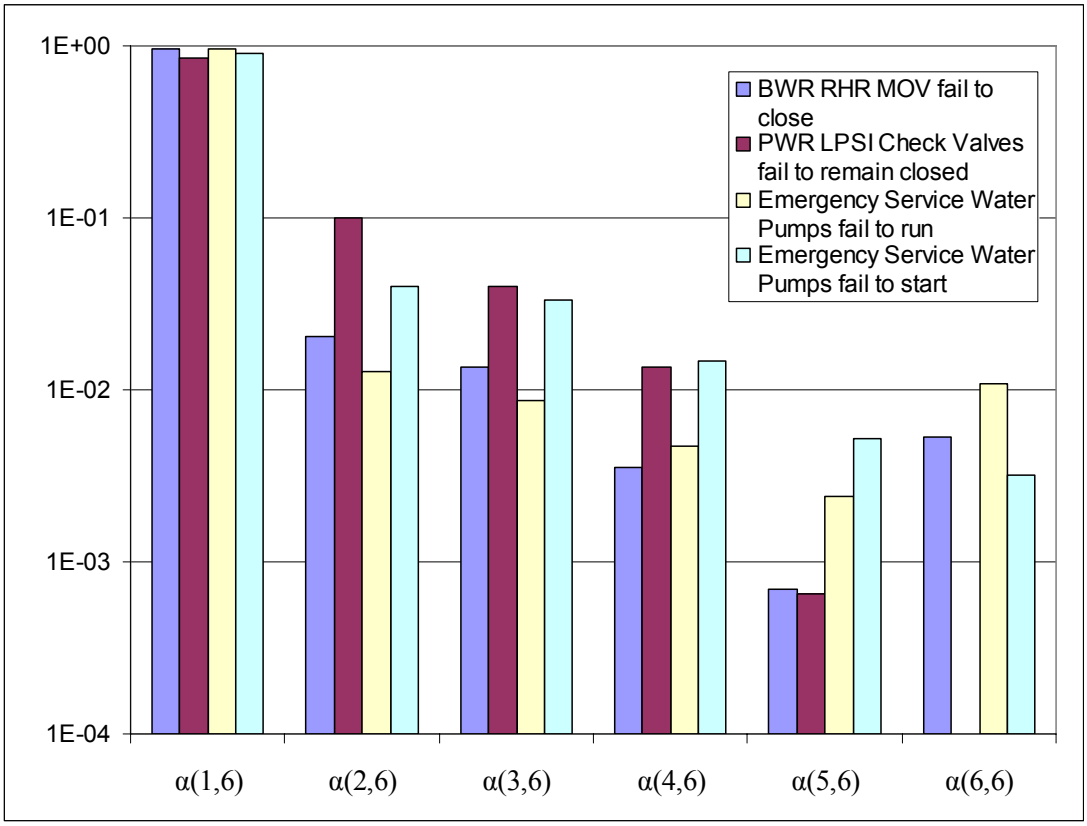

Figure 2-1: Alpha factors for 4 different types of components according to [MOS 98B].

2.5 THE MULTIPLE GREEK LETTER MODEL

The Multiple Greek Letter (MGL) model has a structure similar to that of the Alpha Factor model. The Greek letters and the alpha factors can be converted into each other [MOS 98A], therefore, no discussion of the MGL model is given here.

Both approaches are not based on a stochastic model with a few parameters, like in the case of the BFR model as described in para. 2.2, from which the multitude of factors for the different failure combinations can be obtained.

3 THE PROCESS-ORIENTED SIMULATION MODEL

Model features and some applications of the Process-Oriented Simulation (POS) model have been described in various publications [BER 02, BER 06 A&C, BER 07], which are reflected in this comprehensive report.

3.1 OBJECTIVES OF MODEL DEVELOPMENT

The objectives of the POS model development can be extracted directly from the survey of the weak points of the models presently used in PSA practice. They are:

- The model should – unlike the MGL and the Alpha Factor models – only comprise a limited number of free parameters.
- The model should be capable of a credible extrapolation to high degrees of redundancy without automatically exhibiting a drop to unrealistically low values, which e.g. is the case for the BFR model.
- The model should explicitly distinguish between immediate and delayed failures with respect to the occurrence of the Common Cause.
- The model should include the possibility that not all redundant components share the cause, which implies that the number of components sharing the cause is taken into account as a stochastic variable.
- From the beginning the model equations should comprise different degrees of redundancy, so that no additional assumptions – like e.g. those for mapping up and down in the Alpha Factor model – are needed in applications involving systems with different degrees of redundancy.

This list of objectives implies that it can not be expected to find a model showing the different features and being analytically solvable in a straightforward way. The stochastic simulations have in many cases demonstrated their capabilities in providing results for complicated models. Therefore, this approach is also applied here.

3.2 MODEL EQUATIONS AND THE RATIONALE BEHIND

3.2.1 RATE OF COMMON CAUSE EVENTS

A Common Cause Event is one in which 2 or more equal redundant components are hit by a cause that can lead to a failure of the components sharing the cause. It is assumed that these events occur at a constant rate R_{cc} during the operation period T_{OP} of the system.

R_{cc} is assumed to be so small that the mean number of CCEs is small during the operation period. For this report T_{OP} has been set to 40 years as default value.

3.2.2 TIME WHEN THE COMMON CAUSE HITS THE SYSTEM

It is assumed that the cause impacts the components at a certain point in time t_{CCE}. Due to the assumptions on the rate of events this quantity can be assumed to be homogeneously distributed throughout the operation period T_{OP}.

3.2.3 NUMBER OF COMPONENTS SHARING THE CAUSE

The stochastic variable m has already been introduced in section 2.1. $W(m,r)$ shall denote the conditional probability – given that a Common Cause has occurred - that in a system of degree r exactly m components share the Common Cause.

A model describing dependent failures requires m to be greater than 1. For r = 2 this leads necessarily to

$$W(2,2) = 1 \tag{3.2-1}$$

as a CCE needs at least two redundant components.

For 2 < m < r the event "a Common Cause on the system affects exactly m-out-of-r components" implies that in any subsystem consisting of r-1 components either m or m-1 components are affected. The probabilities for these mutually exclusive sets of events are $W(m,r\text{-}1)$ and $W(m\text{-}1,r\text{-}1)$, respectively. By multiplying these probabilities with the conditional probabilities $F(m\text{-}1,r\text{-}1)$ that component r is affected and 1- $F(m,r\text{-}1)$ that it is not affected, respectively, one obtains:

$$\begin{aligned} W(m,r) = {} & W(m-1,r-1)\cdot F(m-1,r-1) \\ & + W(m,r-1)\cdot\left(1-F(m,r-1)\right) \end{aligned} \tag{3.2-2}$$

For 2 < m = r this reduces to

$$W(r,r) = W(r-1,r-1)\cdot F(r-1,r-1), \tag{3.2-3}$$

because an impact on all components of a system implies that all components in all subsystems are affected as well.

From the normalization of the probabilities $W(2,r)$, $W(3,r)$, $W(4,r)$,...,$W(r,r)$ it can be concluded that

$$W(2,r) = 1 - \sum_{l=3}^{r} W(l,r) \tag{3.2-4}$$

The system of equations (3.2-1) through (3.2-4) can be solved for all $W(m,r)$ by simple recursion, provided $F(m,r)$ is known for the corresponding values of m and r.

This offers the possibility to define a stochastic model for the number of components affected by the Common Cause, by making assumptions on the conditional probabilities $F(m,r)$. The following set of assumptions shall be considered and some of the resulting model features shall be derived.

$$m \geq 2, r > 2: \qquad F(m,r) = a + b\cdot\frac{m-2}{r-2} \tag{3.2-5}$$

$$b = (1-a)\cdot\left(1-\exp(-r/r_0)\right) \tag{3.2-6}$$

$$r = 2: \qquad F(2,2) = a \tag{3.2-7}$$

a and r_0 are free model parameters.

The assumption (3.2-5) can be interpreted as a linear dependence of F from the number of components that have already been identified as impacted. This is the most simple dependence beyond the assumption of a constant F, which can easily be verified as too restrictive for adequately describing the available operating experience.

For r = 3 and r = 4 the resulting probabilities are as follows:

$$W(3,3) = a \tag{3.2-8}$$

$$W(2,3) = 1-a \tag{3.2-9}$$

$$W(4,4) = a\cdot(a+(1-a)\cdot(1-e^{-3/r_0})) \tag{3.2-10}$$

$$W(2,4) = (1-a)^2 \tag{3.2-11}$$

$$W(3,4) = 1 - W(4,4) - W(2,4) \tag{3.2-12}$$

3.2.4 TYPE OF COMMON CAUSE

Like in the BFR model, 2 types of causes are distinguished: those which cause immediate failure of the components and those which make the affected components fail in a delayed manner. Let W_{inst} denote the fraction of causes leading to immediate failure.

Accordingly, with complementary probability 1 – W_{inst} the failures occur in a delayed manner.

3.2.5 TIMES TO FAILURE

According to W_{inst} the m components fail either instantaneously or delayed. The delayed failures are assumed to occur independently according to a failure rate which is assumed to be logarithmically equally distributed in the interval R_{MIN} to R_{MAX}. The two quantities R_{MIN} and R_{MAX} are considered as fixed quantities and not as free parameters. Their values are chosen as:

$$R_{MIN} = 0.001 \frac{1}{\text{year}}$$

$$R_{MAX} = 100 \frac{1}{\text{year}}$$

The rate R_{MAX} limits the spectrum of possible failure rates and thus implicitly defines what an immediate failure. R_{MIN}, on the other hand, cuts off processes which would not contribute to times of unavailability in an operation period of typically 40 years. It is known that the wide spectrum of CCF processes comprises both very fast mechanisms, like some maintenance errors and very slow ones, e.g. corrosion.

The assumption of a flat distribution in this interval reflects the absence of detailed technical information, which might justify a more specific assumption.

3.2.6 COMMON CAUSE EVENT IDENTIFICATION

Most of the CCEs are identified during testing. In addition, there are cases – especially actual demands or visual inspections – where other measures lead to CCE identification. It is assumed that the major part of CCE-induced unavailability is identified by testing.

Depending on the testing scheme – staggered or non-staggered – assumptions have to be introduced as to when the CCE is identified. In this report, a very simple assumption is used that could easily be extended. It is assumed that the event is identified during the first test after the first component has failed and that all components which share the CC are immediately repaired and as good as new. Obviously, this has to be modified for certain applications with different testing or maintenance procedures.

3.2.7 CALCULATION OF UNAVAILABILITIES

According to the assumptions set out in para. 3.2.6, the system exhibits unavailabilities from the time of failure of the first component up to the first following test. It must be noted that there is a significant difference between causes leading to immediate or delayed failures.

In the first case, there will be a m-out-of-r unavailability until testing. In the latter case, there will be at first only one component which has failed, later there will possibly be two up to m-out-of-r failed components. As the event might be identified early after the failure of the first component, there might be only a contribution to the 1-out-of-r- unavailability.

3.2.8 CODE FOR SIMULATION OF THE POS MODEL

To work practically with the model, a computer simulation code of the sequence of stochastic variables has been written. Summing up the explanations above this sequence is:

1. Time of occurrence of the Common Cause
2. Numbers of redundant components sharing the cause
3. Immediate or delayed failure
4. Times of failure of the components
5. Time of CCF identification

As this sequence represents all relevant stages of the full CCF process, the model has been called Process-Oriented Simulation model (POS).

From the times of failure of the components and the time at which the CCF is identified, the times of unavailability for the failure multiplicities involved are calculated. Multiple repetition of the sequence yields the distribution of the unavailability from which the mean value and the relevant percentiles can be obtained.

The code extends over a few hundred lines. It would certainly be possible to arrive at some analytical results for the unavailabilities. However, this has not been pursued, because experience has shown that a code can more easily be modified if changes to the assumptions are to be assessed.

3.3 POS MODEL FEATURES

3.3.1 SOME ANALYTICAL RESULTS

From equations (3.2-2) and (3.2-7), it can be concluded that

$$W(2,r+1) = w(2,r)\cdot(1-F(2,r)) = W(2,r)\cdot(1-a) \tag{3.3-1}$$

and hence

$$W(2,r) = (1-a)^{r-2} \tag{3.3-2}$$

This exact result for all values of r will be used for estimating parameter a.

From equations (3.2-1), (3.2-3), and (3.2-7) the probabilities that all components share the cause can be calculated.

$$W(r,r) = a\cdot F(3,3)\cdot F(4,4)\cdot\ldots\cdot F(r-1,r-1) \tag{3.3-3}$$

As $F(r\text{-}1,r\text{-}1)$ is approaching 1 for large values of r, there is only little further decline of $W(r,r)$ for $r >> r_o$. Therefore, there is no strong decline to unrealistic low values of the unavailabilities as, e.g. for the BFR model. This is a key feature of the POS model.

In the other asymptotic case $r_o >> r$ the following solution can be obtained:

$$W(m,r) = \binom{m-2}{r-2}\cdot a^{m-2}\cdot(1-a)^{r-m} \quad . \tag{3.3-4}$$

The mean for this binomial type distribution is:

$$\langle m\rangle = 2 + a\cdot(r-2) \quad . \tag{3.3-5}$$

This indicates that parameter a is closely related to the average number of components sharing the Common Cause.

3.3.2 ON THE INTERPRETATION OF THE MODEL PARAMETERS AND THEIR IMPACT ON THE RESULTS

To provide a first rough idea of the interpretation of the model parameters a, r_0 and W_{inst}, as well as their impact on the results, the following set of parameters is used as a reference case:

r = 4

r_{cc} = 10^{-2} years

a = 0.35

r_0 = 3.48

W_{inst} = 0.25

T_{FK} = 12 months (non-staggered testing, CC identification at the first test after the first failure occurred)

T_{OP} = 40 years

Figure 3-1 shows the unavailability for the reference case and varied values of parameter α. Parameter α influences the number of impacted components, as already pointed out in section 3.3.1. In the limiting case α = 0 it can be directly seen from equation (3.3-2) that W(2,4) = 1, which means that there are no events with 3 or 4 affected components. For the opposed limiting case α = 1, one obtains from equation (3.2-10) W(4,4) = 1, which means that all components are affected for all events. The variations of parameter α quantified in figure 3-1 are close to these limiting cases and hence the displayed changes of unavailabilties are plausible.

Figure 3-2 shows the corresponding results for W_{inst}. The interpretation of this parameter is self-explaining. As the immediate failure events do not contribute to 1-out-of-4 unavailability, increasing W_{inst} leads to enhanced multiple failures, low values of W_{inst} work towards the opposite direction.

The impacts of the variation of r_o are displayed in figure 3-3. They are consequences of equations (3.2-10), (3.2-11) and (3.2-12). Equation (3.2-11) shows that W(2,4) does not depend on r_0. Therefore it is not surprising that there are no great changes in the associated unavailability. According to equation (3.2-10), W(4,4) is monotonously decreasing with r_0. Equation (3.2-12) shows that the opposite is true for W(3,4). These observations explain the changes for the 3-out-of-4 and 4-out-of-4 unavailabilities in figure 3-3. An application providing insights on the role of parameter r_0 with respect to highly redundant systems is provided in chapter 4.

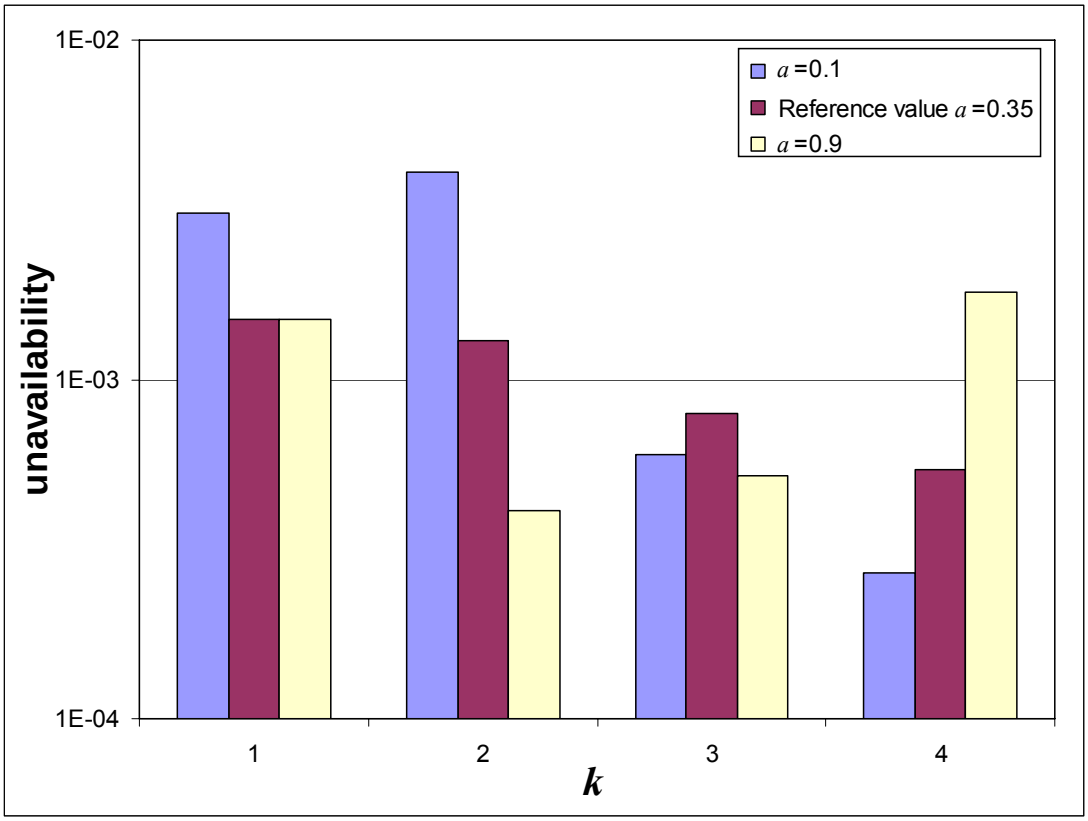

Figure 3-1: Unavailability for the reference case and varied values of parameter α.

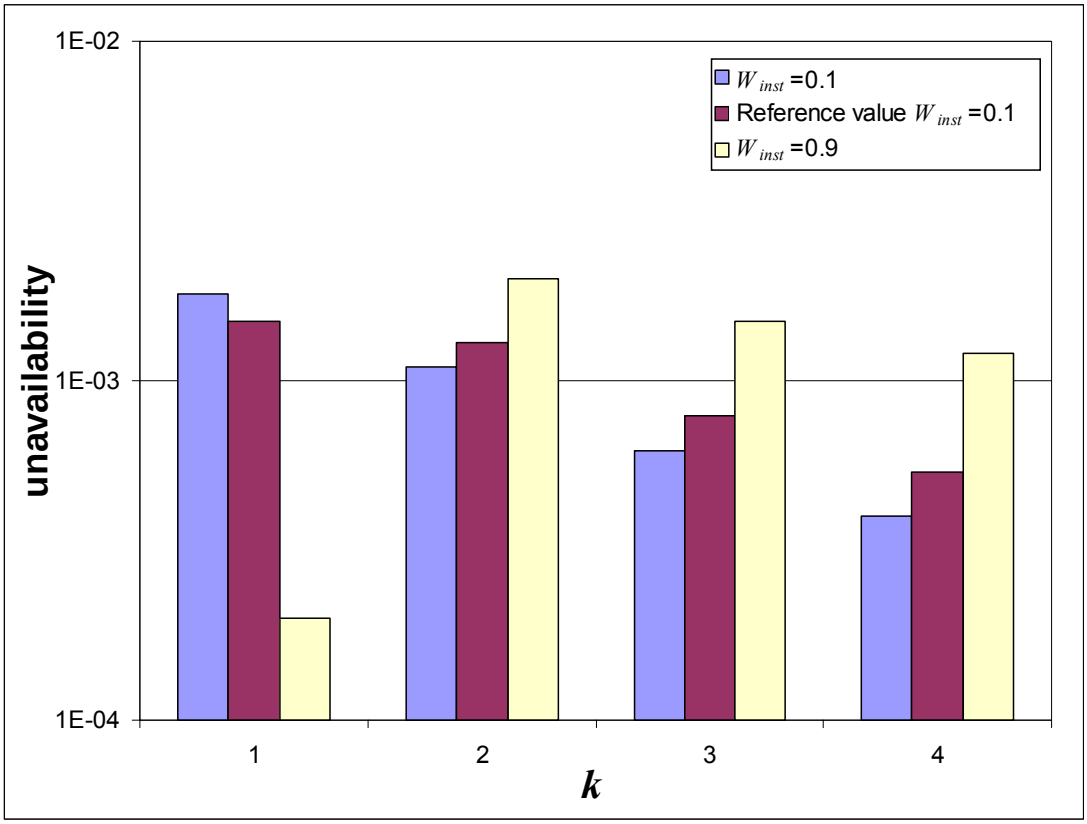

Figure 3-2: Unavailability for the reference case and varied values of parameter W_{inst}.

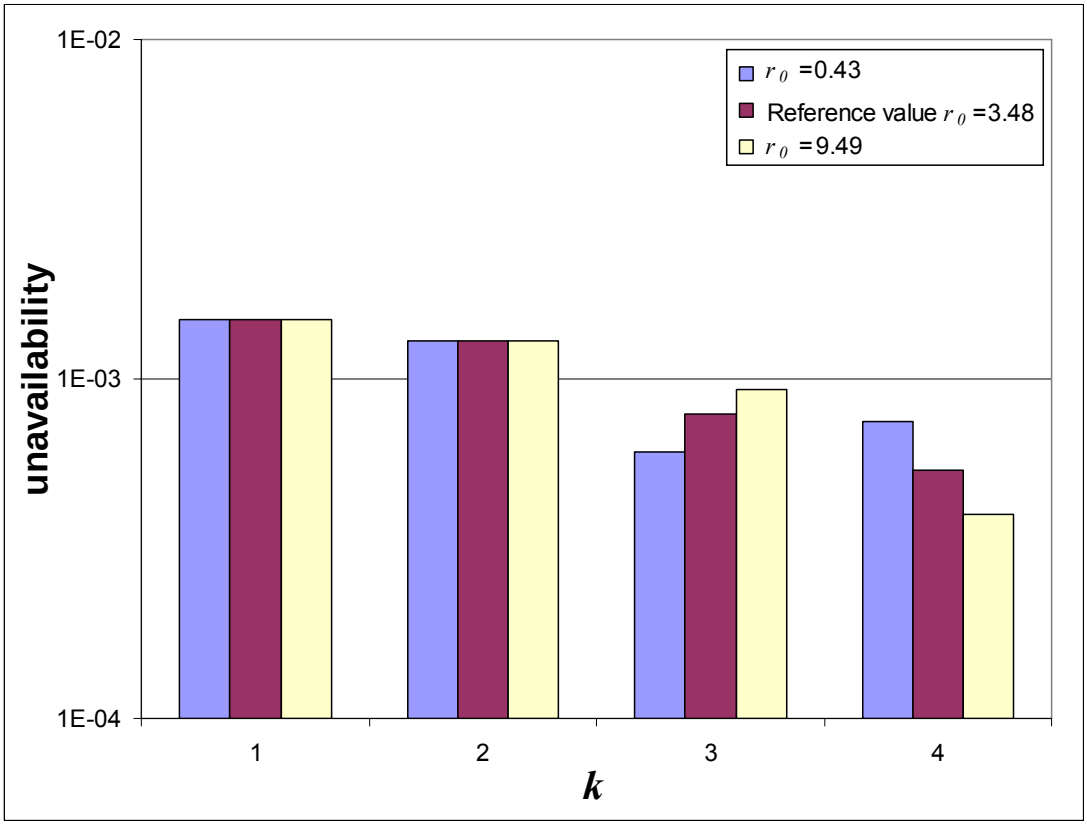

Figure 3-3: Unavailability for the reference case and varied values of parameter r_0.

3.3.3 THE CAPABILITY OF THE POS MODEL TO SIMULATE CCE

As the POS model comprises all relevant stages of the CCF process it can be explicitly used to generate artificial failure data. In appendix 2 a set of examples is presented, which firstly illustrate this capability and secondly can foster the understanding of the model itself.

This feature will be utilized in para. 3.5.2 to test parameter estimating schemes. CCF data are simulated with known POS parameter values. On the basis of the simulated failure data, parameter values are estimated which can be compared to the "true" values. On this basis uncertainty distributions will be obtained.

3.4 PARAMETER ESTIMATION

3.4.1 OVERVIEW

Any parameter estimation requires a set of events that has been observed in operating experience. The information needed is summed up in the following.

For a given degree of redundancy r the total observation time T_{tot} is required, possibly split up in periods belonging to different times for CCF identification, in most cases CCCG with different test intervals T_{FK}.

The observed CCE ought to be characterized by the number m of components "hit" and by the number k of failed components.

As an intermediate result the distribution of the number of affected components $W(m,r)$ is estimated as follows:

$$W(m,r) = \frac{1}{C_{norm}}\left(n(m,r) + \frac{1}{r-1}\right) \tag{3.4-1}$$

C_{norm} is a constant establishing the normalization. For given CCCG size $1/(r\text{-}1)$ is a constant term, which avoids zero probability estimates. For large numbers of observed events the influence of this term disappears.

The rate of CCEs is estimated in the usual way:

$$R_{CC} = (N_{CCE} + 0.5)/T_{tot} \tag{3.4-2}$$

In the following, the estimation of the three parameters W_{inst}, a and r_0 is described. The approach described is based on separate estimates for each CCCG of size r. The values obtained for the different CCCG sizes are averaged weighted with the number of CCEs observed for each degree of redundancy.

The parameter W_{instT} is estimated first. It is the probability that due to a CC the affected components fail immediately. It does not depend on the number of affected components and can therefore be estimated independently. Events for all CCCG sizes $r \geq 2$ carry information on this parameter.

As for $r = 2$ for a CCE necessarily both components are affected, information on the two parameters a and r_0 are obtained from events in CCCG with $r > 2$ only. As can be derived from equations (3.3-2) and (3.3-5), only parameter a is relevant for $r = 3$, whereas dependencies on r_0 are given for $r \geq 4$ (see eq.3.2-10).

The approach described here has been selected, as it is straightforward and carried out easily. As the tests in para. 3.5, show it is effective as well. It can be refined for greater accuracy, but this is beyond the scope of this report, whose key objective is to completely describe the POS model with its key features and to outline how it can be applied.

3.4.2 ESTIMATE OF PARAMETER W_{inst}

Let N_{tot} denote the number of events where all components sharing the cause have failed. N_{inc} is the fraction of failures with at least one affected component not having failed.

$$N_{\mathrm{CCE}} = N_{\mathrm{tot}} + N_{\mathrm{inc}} \tag{3.4-3}$$

The N_{inc} events obviously have been caused by processes leading to delayed failures. N_{tot}, however, can consist of both immediate and delayed failures. For the estimation of the contribution of the delayed failures, events are “fractionated” in the following way:.

$$N_{tot} = \left(\sum W_{del} / \left(1 + W_{del}\right)\right) + X_{tot} \tag{3.4-4}$$

W_{del} denotes the probability that for an event with m-out-of-r affected components all these components fail.

If N_{tot} = 0 then the two terms on the right-hand side are 0 as well.

The estimator for W_{inst} is derived from the following relation:

$$\frac{W_{inst}}{\left(1 - W_{inst}\right)} = \left(X_{tot} + 0.5\right) / \left(N_{inc} + \sum \frac{W_{del}}{\left(1 + W_{del}\right)} + 0.5 \right) =: q \tag{3.4-5}$$

$$W_{inst} = \frac{q}{\left(1 + q\right)} \tag{3.4-6}$$

3.4.3 ESTIMATE OF PARAMETER *a*

The estimate of parameter a can then be based on the exact relation

$$W\left(2, r\right) = \left(1 - a\right)^{r-2} \tag{3.4-7}$$

which suggests

$$a = 1 - W\left(2, r\right)^{\left(1/(r-2)\right)} \tag{3.4-8}$$

3.4.4 ESTIMATE OF PARAMETER r_0

With given estimates for parameter a and W(4,4) the following relation seems to suggest an estimator of r_o:

$$W\left(4,4\right) = a \cdot \left(a + \left(1 - a\right) \cdot \left[1 - \exp\left(-3 / r_o\right)\right]\right) \tag{3.4-9}$$

A positive value, however, is only obtained if the following condition is fulfilled:

$$a^2 < W\left(4,4\right) < a \tag{3.4-10}$$

If, for example, we have

$$W(4,4) = (a + a^2)/2 = g \tag{3.4-11}$$

The corresponding value according to equation (3.4-9) is

$$r_0 = -3/\ln(1-(1/2)) \tag{3.4-12}$$

Using

$$D = 1 + \frac{2}{\pi} \arctan\left[\left(W(4,4) - g\right) \cdot \left(\frac{1}{W(4,4)} + \frac{1}{1 - W(4,4)} \right) \right] \tag{3.4-13}$$

the estimation of r_0 is based on

$$r_0 = -\frac{3}{\ln\left(1 - D\right)} \tag{3.4-14}$$

For estimation of r_0 , events in CCCG sizes of 4 or more are needed. If these are not available, generic data should be used with large uncertainty bands. This can be achieved by adding an artificial r = 4 event with n(2,4) = n(3,4) = n(4,4) = 1. The choice of this event can be seen as trying to be unbiased with respect to the number of affected components.

Information from CCCG sizes r > 4 can be used in the following way: It should first be noted that parameters a and W_{inst} can be obtained before r_0 is estimated. They are available for the estimate of r_0. In particular,

$W(2,4)$ can be calculated according to formula (3.4-7). Using the numbers $n(m,r)$ as introduced in formula (3.4-1) an artificial set of numbers $n(m,4)$ is constructed for the range $r > 4$. In a first step, a fraction of the number of events observed for CCCG = r is accordingly assigned to $n(2,4)$, the integer closest to N_{CCE} * $W(2,4)$. $n(4,4)$ consists of $n(r,r)$ plus half of the residual numbers, which are divided between $n(3,4)$ and $n(4,4)$. If the residual number is odd, $n(3,4)$ gets one more.

Though this approach is very much heuristic, it is working surprisingly well in the practically relevant parameter ranges, as shown by the tests described in para. 3.5.1.

3.5 TESTING THE PARAMETER ESTIMATION APPROACH

3.5.1 CONCEPT

The approach to estimating the model parameters from operating experience can be tested in a way that is specific for the POS model. Due to its complex, process-oriented structure each simulation run produces all significant aspects characterising a CCE. Examples for such sequences of key quantities are displayed in appendix 2.

This offers the following opportunity for testing the parameter estimation approach:

1. Firstly, for a given set of model parameters CCEs are simulated, comprising, amongst the key quantities described in para 3.2.8, in particular the observation time of the CCCG, the number of affected components, the number of failed components and the functional test interval.
2. Using the formulae set out in 3.4, in a second step the model parameters are estimated from the simulated data.
3. Finally, the estimated model parameters are compared to the “true” parameters, where the degree of deviation is based on key model output like the probability of complete system failure. By generating a sufficiently large number of simulated events, the uncertainty distribution of the model results can be obtained as a function of the number of simulated events.

3.5.2 SIMULATION OF FAILURE EVENTS

The results presented here refer to the “true” data set already considered in 3.3.2.:

$r = 4$

$r_{CC} = 10^{-2}$ / year

$a = 0.35$

$r_0 = 3.48$

$W_{inst} = 0.25$

T_{FK} = 12 months (non-staggered testing, CCE identification at the first test after the first failure)

T_{OP} = 40 years

In figure 3.4, the probabilities are given that exactly k-out-of-4 components fail, under the condition that a CCF is observed. For comparison, the same quantities calculated from the estimated parameters are shown. The expectation values are based on more than 100 simulated events, which were combined into groups of three. The degree of agreement is more than satisfactory. This indicates that the POS model does not need many events to arrive at reasonable estimates and, moreover, that the estimation procedure is working well.

Of course, the tests of parameter estimation have been carried out for other sets of parameters, in particular for different degrees of redundancy.

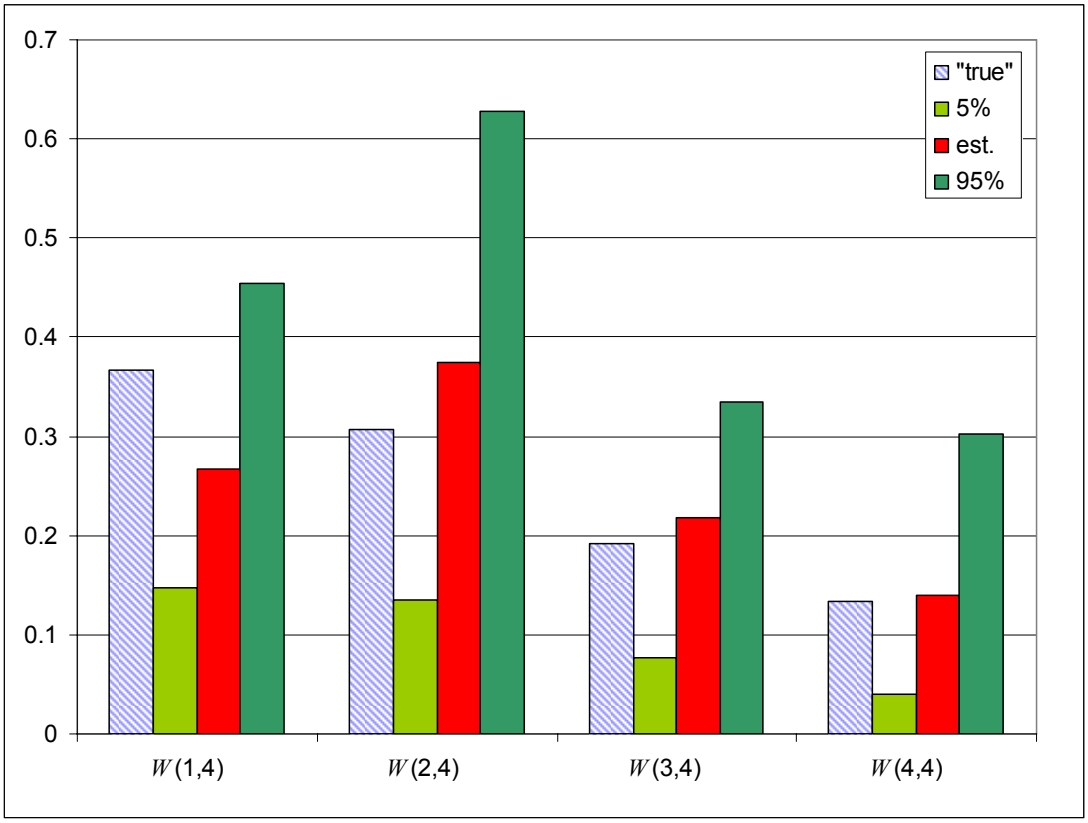

Figure 3-4: Comparison of "true" unavailabilities with those based on estimated parameters.

The uncertainty due to the rate of CCEs has not been included here, as this contribution is well known and can be handled according to an established framework.

The results of the test show that there is a slight overestimation of the higher failure multiplicities. This indicates that notwithstanding the good results, there is still some room for further improvement of the estimation procedure. First analyses to explore this potential have shown that by removing the 0.5 both from nominator and denominator in equation 3.4-5, a slightly better result in the estimation of W_{inst} is obtained.

4 APPLICATIONS OF THE POS MODEL

4.1 MAGNETIC PILOT VALVES

The first application to be discussed deals with magnetically operated pilot valves in German nuclear power plants. Hauptmanns [HAU 96] has published the data from operating experience shown in table 4-1. In figure 4-1 POS results are compared to results obtained with approaches using the BFR model and a Multi-Class BFR model introduced by Hauptmanns. Obviously, the component group size is high and the BFR model exhibits an unreasonably strong drop of unavailability towards larger failure multiplicities. The Multi-Class BFR approach requires a separation of events into different classes in order to avoid this drop. The POS results shown for comparison do not show this strong decrease without any need to categorize events.

In contrast to the two other free parameters a and W_{inst} the meaning of r_0 is less obvious. As set out already in para. 3.3.1, r_0 is decisive for the behaviour of $W(m,r)$ for large degrees of redundancy. To illustrate this feature, a sensitivity analysis with respect to this parameter is presented in figure 4-2. With the parameter set given in figure 4-1 for the magnetic pilot valves r_0, has been enhanced and lowered. The larger value shows a substantially different behaviour. Instead of stabilizing the values of $W(m,r)$, they continue to decrease to lower values. This decrease would be stopped at higher values of r.

The feature that $W(r,r)$ is higher than $W(r\text{-}1,r)$ is worth being explained. Two points shall be made in this regard. Firstly, some empirical data exhibit this feature, as the Alpha Factors displayed in figure 2-1 show. Secondly, there is a plausibility argument. If all but one component of a highly redundant system have been tested and practically all were found to be affected, one would expect a conditional probability close to 1 that the last one is affected as well. This option has been built into the POS model. However, as figure 4-2 shows, it is not a necessary result, but only a possibility. Operating experience is decisive, which of the different behaviours displayed in figure 4-2 is selected in the estimation process for the application under consideration. A CCF model should comprise these different behaviours as they all correspond to data from operating experience.

k	*r*	*m*
2	9	2
6	8	8
2	22	2
2	8	2
1	16	16
2	16	7
2	12	12
7	8	8
1	14	14
1	6	2
2	12	8
2	4	2

Table 4-1: Observed CCF events of magnetically operated pilot valves in German NPPs according to [HAU 96].

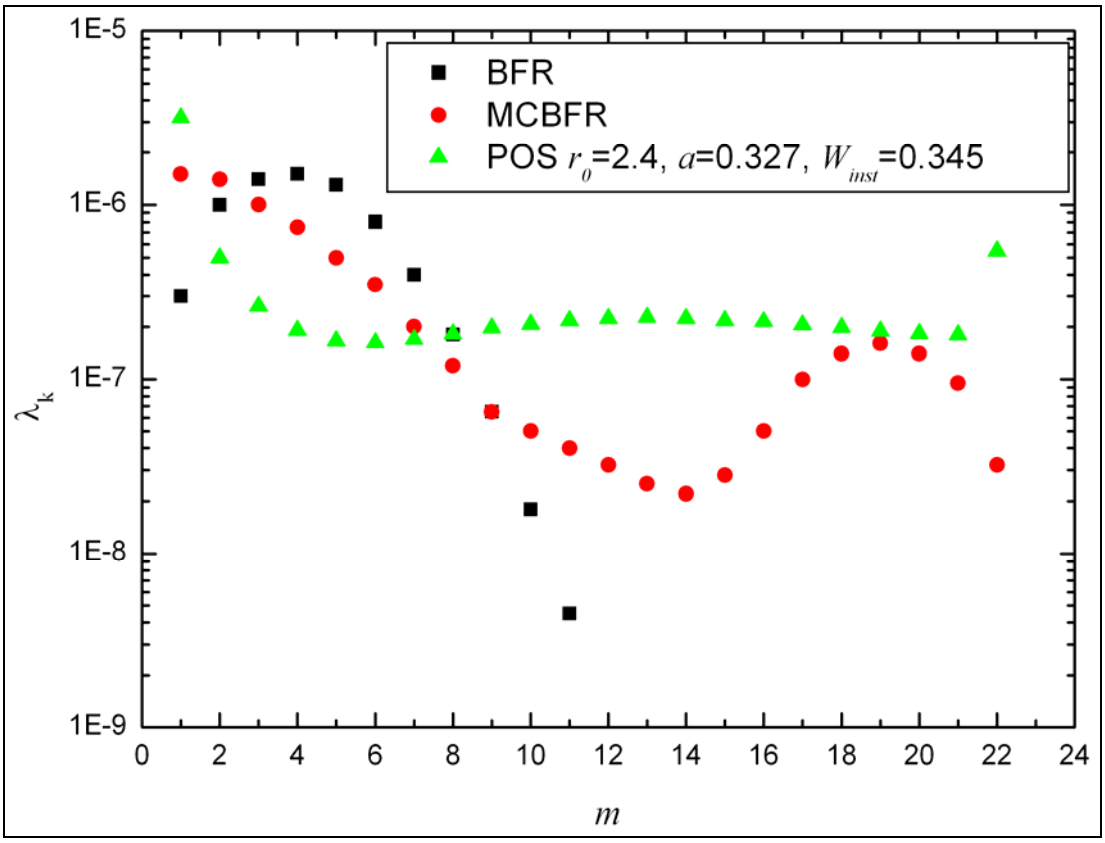

Figure 4-1: CCF analyses for magnetically operated pilot valves in German NPP using the BFR, a Multi-Class BFR and the POS model for r = 22 [HAU 96]. λ_k denotes the failure rate for m-out-of-22.

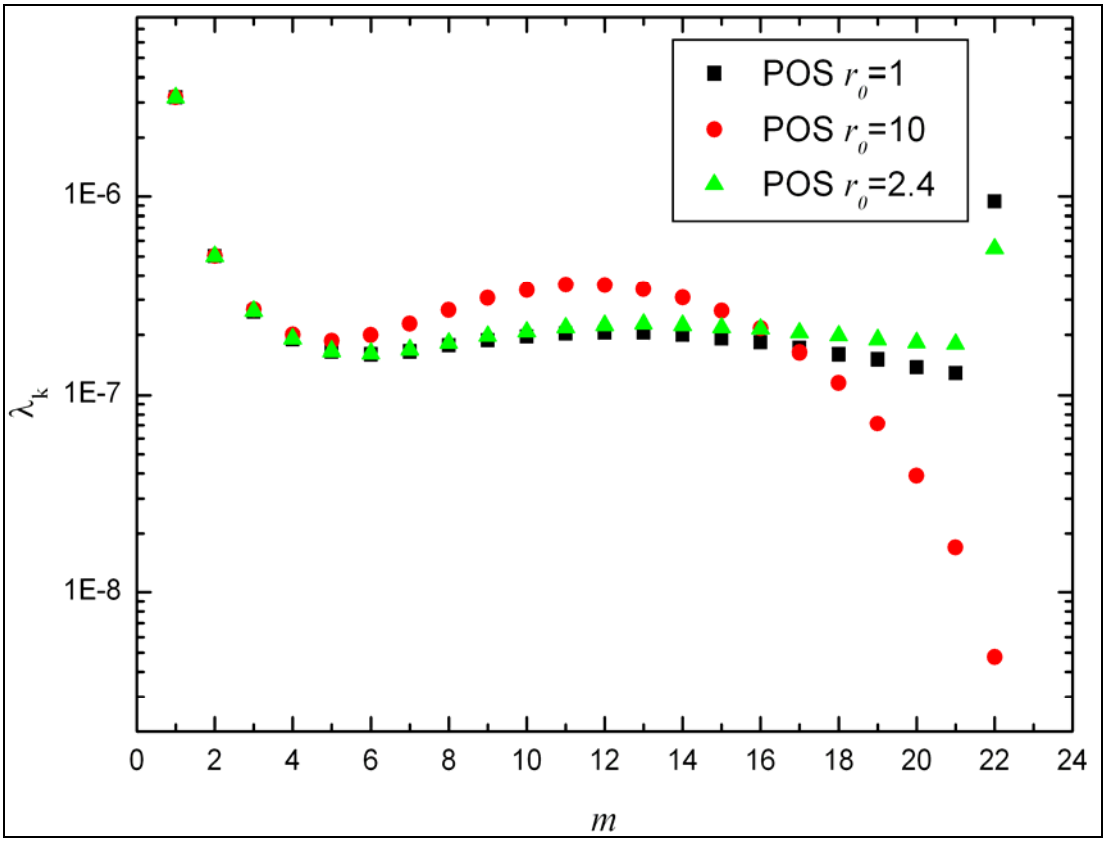

Figure 4-2: Sensitivity analysis with respect to parameter r_0. Parameters a and W_{inst} according to figure 4-1.

4.2 GERMAN CCF BENCHMARK

In the frame of a benchmark test on CCF, published in 1997 [KNI 98A, KNI 98B], different German institutions – mainly TSOs - demonstrated and justified their interpretations of CCEs and their methods and models for analyzing such effects. The task was to analyze two typical groups of motor operated valves in German NPPs, starting from the assessment of a large number of event reports, which may or may not indicate a CCF type of event. The data and results referring to the second phase of the benchmark were used as a reference for the demonstration calculations presented here.

It appeared that, after identification and evaluation of individual failure events as being a relevant CCE or not, the next most important factors influencing the quantitative results of the participants were the modelling uncertainties in extrapolating a narrow statistical base of observed component failures to different compositions of component groups and the modelling of the identification of CCFs and of the time of identification.

Figure 4.3 shows the results of the benchmark for plate valves. The results are based on a reference evaluation of the event reports provided by the benchmark organizer. Without the reference evaluation the scatter between the outcomes of the benchmark participants had been substantially larger. For comparison, the POS results have been included. Being close to the “center of mass” of the results they fit well into the overall picture and are by no means outliers.

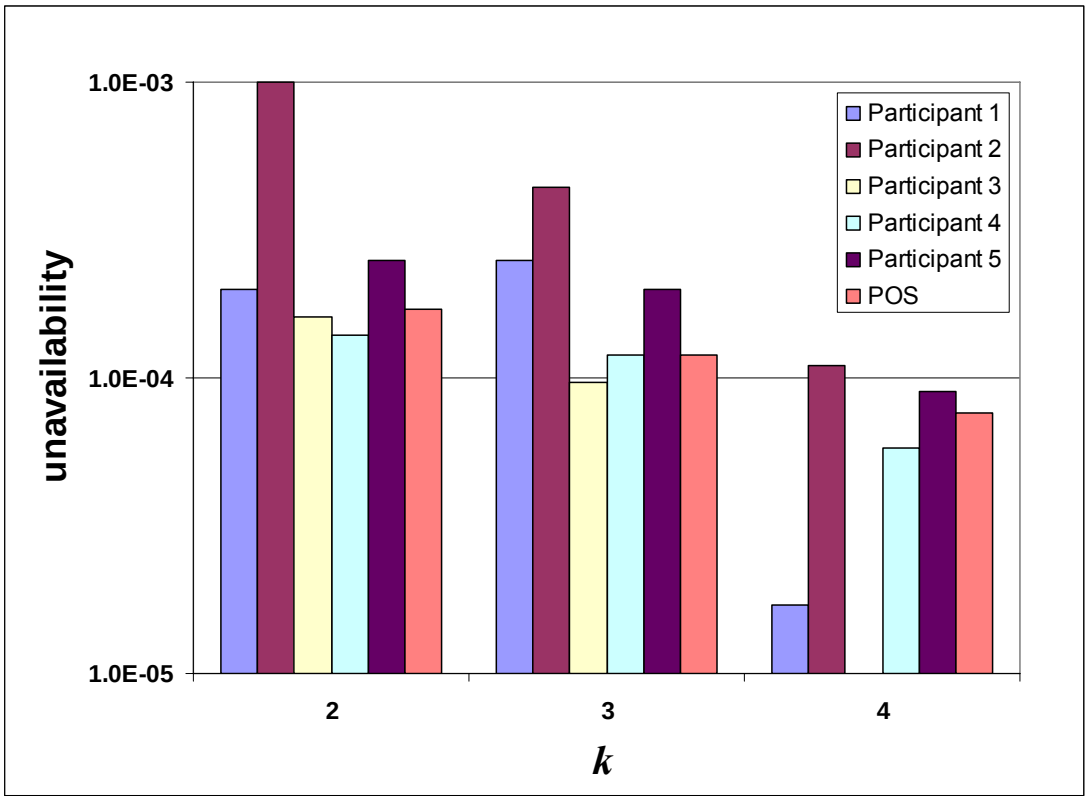

Figure 4-3: Unavailabilities due to CCF for a group of 4 redundant plate valves resulting from 2-out-of-4, 3-out-of-4 and 4-out-of-4 failures, respectively, based on a benchmark test. The parameter values used were as follows: $\alpha = 0.37$, $r_0 = 4.59$, $T_{FK} = 3$ months.

4.3 EXPERT INTERPRETATION OF CCE

In many cases, a classification of a CCE can not be given easily. Due to different states of damage, the determination of the number m of affected components and the number k of failed components is ambiguous. An internationally acknowledged approach to find these numbers was suggested in [NUR 98]. In the German regulatory guidance PSA method document it is described and used in calculating generic CCF probabilities [FAK 05A].

Starting point for this approach is a grading system for the damaged components. An expert assigns the state of each component of the CCCG into one of the following 5 damage categories:

Damage category	Damage value
Failure	1
Heavy damage	0.5
Low damage	0.1
Very low damage	0.01
No damage	0

The associated damage values are interpreted as subjective probability estimates that in case of a demand the component would not perform its intended function. For details of the method, the references given above should be consulted.

Here, as a simple example, it is demonstrated that the POS model can be adapted to this type of damage categorization. An expert has analyzed two CCEs in a system of redundancy 4 and arrived at the following association to the damage categories:

	Event 1	Event 2
Failure	1	0
Heavy damage	1	1
Low damage	1	0
Very low damage	0	1
No damage	1	2

The total observation time is 1000 years, the test interval 1 year. In the terms of the POS model, all components with any damage are interpreted as affected. That is m = 3 for event 1 and m = 2 for event 2.

With the probability interpretation of the damage value, the probabilities for the number of failed components can be calculated:

No. failed	Event 1	Event 2
k = 0	0	0.495
k = 1	0.45	0.5
k = 2	0.5	0.005
k = 3	0.05	0
k = 4	0	0

To map this to POS, there are 3x3 combinations of nontrivial events for which a parameter set has to be estimated. Subsequently, these are averaged weighted with their probabilities. The parameter estimation for the POS model does currently not account for events without failures. That is for combinations including event 2 with k = 0, the values for k = 1 were taken. The resulting parameter set is:

a	=	0.333
r_0	=	11.4
W_{inst}	=	0.181

4.4 ALPHA FACTOR CONSIDERATIONS

As the POS model comprises a full picture of the CCF process, it is possible to assess quantities required for other CCF approaches. For beta factors, this has been published in [BER 07]. It is also possible to calculate alpha factors. Nevertheless, as these comprise independent failures as well, there are two ways to overcome

this complication. One could extend the POS model as described here to include independent failures, which is in principle possible, but has not been done up to now. Alternatively, one can make reasonable assumptions on the contribution of the independent failures and combine these with the POS results. This has been done for published alpha factors. However, this was done in a very limited approach to underline the possibility to create such data in cases where the POS parameters have been determined. Appendix 4 comprises these considerations.

5 COMPARISON OF THE PREDICTIVE STRENGTH OF CCF MODELS

5.1 GENERAL

The difficulties associated with quantitative CCF analyses – that has been clearly observed in benchmark tests like e.g. [KNI 98A] and [KNI 98B] – are rooted to a substantial degree in problems with identifying CCEs and interpreting event records and plant documentation. The question of evaluation of CCEs with respect to their applicability to a target system to be analyzed has to be seen in this very context. In recent years progress has been made with respect to these difficulties by improving data collection and exchange, both on the national and international scale.

The role of the CCF model used, however, has not yet been addressed in quantitative terms. This situation should be improved as the influence of the selected model can be significant. In this chapter, a way to achieve such a comparison is set out.

The basic idea is to split available operating experience and to use one part as a basis for estimating model parameters and make predictions of unavailabilities. These predictions can then be checked against the evidence in the complementary part of operating experience.

5.2 BFR VERSUS POS AS AN EXAMPLE

In this paragraph an example is provided, how the comparison addressed in general terms in para. 5.1 can be implemented.

Magnetic pilot valves and the associated operating experience as displayed in table 4-1 have been selected. From the 12 events the first 3 have been split. For this triple of events, model parameters have been estimated for the BFR model (without lethal shocks) and the POS model. With both models the probability to find the events with the observed failure multiplicities can be calculated as product of the probabilities for the individual events. This exercise was also carried out for events 4 to 6, 7 to 9 and 10 to 12 as basis for parameter estimation.

In figure 5-1, the results are displayed in terms of the conditional probabilities obtained for the POS model compared to those obtained by the BFR model. Based on the discussion in para. 2.1, it is not a great surprise that the comparison is very much in favour of the POS model.

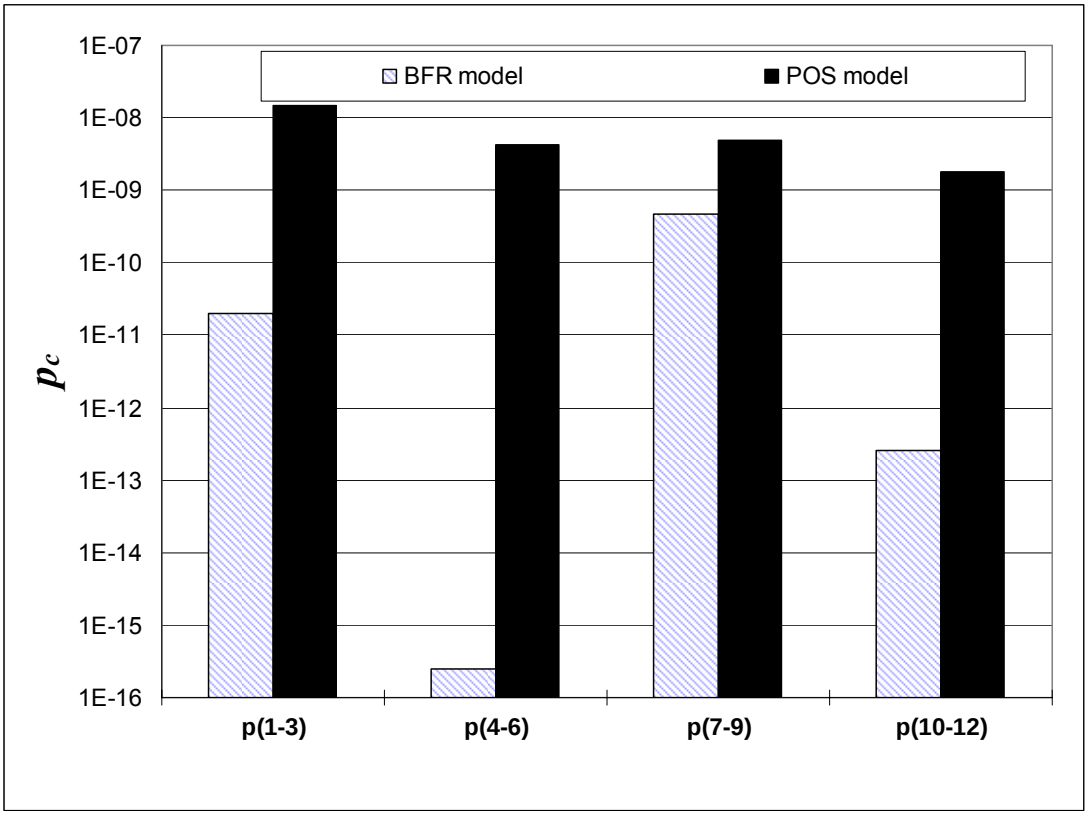

Figure 5-1: Comparison of the predictive capabilities of the POS and the BFR model, based on different splits of operating experience for magnetic pilot valves. p_c denotes the conditional probability for the CCF multiplicities in the components used.

5.3 EVALUATION AND POTENTIAL FURTHER DEVELOPMENT

Though this report is devoted to the POS model, the purpose of the little exercise carried out in 5.2 was not to establish its superiority. Rather, the objective was to demonstrate that a quantitative model comparison can be achieved without unreasonable effort.

To arrive at conclusions, however, the approach should certainly comprise more operating experience including other types of components and other CCF modelling approaches. The question on which quantities the comparison should be based should be further explored. For example, as an alternative to the probability of observing a certain pattern of failures, more sophisticated approaches based on measures used in information theory could be envisaged.

The type of comparison introduced here should certainly be pursued with some development effort in view of its potential to further narrow the uncertainties associated with CCF analyses.

6 DISCUSSION AND OUTLOOK

The POS model can be seen as an extension of the BFR model, carried out to overcome some of the shortcomings of this approach. In contrast to the BFR model the POS model explicitly distinguishes between immediate and delayed failures of components, does not assume that in each CCF event all components share the Common Cause, but assigns probabilities to the different degrees of “extension” of the cause and is based on clearly formulated stochastic assumptions. This broader approach implies a more complex structure. Nevertheless, within this more complex frame the assumptions are kept as simple as compatible with the modelling objectives. No simple analytical expression is obtained for the probabilities of failed components. Instead, these results have to be obtained from a simulation code. The code, however, has a clear structure and can be produced with limited effort.

The price paid in terms of greater complexity pays off due to a larger range of applicability. In particular the POS model can be applied to systems with high degree of redundancy. Another important advantage is the possibility to generate failure events using the POS simulation code. Simulating with known parameters and estimating parameters from the generated failure events offers the possibility to test the framework for parameter estimation and, in addition, to obtain the uncertainties of the model results. No further assumptions beyond the model itself and the estimation procedure need to be introduced. Last, but not least, the test of the estimation procedure demonstrated that the POS model works already quite well with only a small number of events as a basis. This makes it a candidate for plant-specific CCF applications.

In contrast to other approaches like MGL and Alpha Factor model the POS model comprises only a few parameters, beyond the frequency of CCEs only three.

The applications of the POS model carried out so far indicate that it can readily be applied to practical cases. The results produced in cases of benchmark tests are no outliers, but are rather consistent with the majority of existing analyses.

To summarize, the POS model represents an interesting alternative to established models with some new and unique model features.

Looking ahead, two aspects are emphasized. The first is the still existing development potential of the model, the second is the quantitative comparison between CCF models.

The development potential comprises the parameter estimation procedure, which still can be improved, and the development of an user-friendly software covering both the simulation and associated presentation of results, as well as the estimation procedure and the fit of distributions to the simulated results.

The concept for a quantitative comparison between different CCF models has been set out in chapter 5. As already pointed out there, such a comparison can be achieved and should be prepared by optimizing the concept. Such a more advanced type of benchmark should certainly include the POS model.

REFERENCES

[BAL 01] *Balfanz, H.-P., Berg, H. P. and Steininger, U.:* Comparison of Plant-Specific Probabilistic Safety Assessments and Lessons Learned, *Kerntechnik 66 (2001) No. 5-6, 242*

[BER 02] *Berg, H.-P., Görtz, R., and Schimetschka, E.,:* A Process Oriented Simulation Model for common cause failures, *Kerntechnik 67 (2002) No. 2-3, 72*

[BER 05] *Berg, H.-P., Görtz, R., and Schimetschka, E.,:* Process Oriented Simulation Model: theoretical basis and practical applications, *Proc. . ICOSSAR'05, Rome, June 19 – 23, 2005,* 3671

[BER 06A] *Berg, H.-P., Fröhmel, T., Görtz, R., Kesten, J. and Weil, L*. ICDE-Results on Complete Common Cause Failures in the Light of Results Obtained with the POS Model. *Kerntechnik, Vol. 71, No. 5-6, p. 306 – 309*, Carl Hanser Verlag, 2006

[BER 06B] *Berg, H. P., Fröhmel, T.,Görtz, R., and Schimetschka, E.:* Updated Requirements on PSA Methods and Data for Comprehensive Safety Reviews in Germany, *Kerntechnik , Vol 71, No. 1, p.9*, Carl Hanser Verlag, 2006

[BER 06C] *Berg, H.P., Görtz, R., and Schimetschka, E.:* A Model for Common Cause Failures in Systems of Redundant Components and Applications, Proceedings of the 8th *Internat. Conf. on Probabilistic Safety Assessment and Management PSAM '8, New Orleans,* May 23 – 27, 2006, (to be published)

[BER 07] *Berg, H.-P., Fröhmel, T., Görtz, R., Kesten, J. and Weil, L*. Calculating Generic ß-Factors for Common Cause Failure Analysis with the POS Model. *Compacts der Jahrestagung Kerntechnik. Karlsruhe,* May 2007 (to be published)

[BLO 06] *Blombach, J., Bordihn, S. & Kollasko*, CCF Analysis for New Reactor Designs. *Kerntechnik Vol. 71, No. 1-2, p. 29,* Carl Hanser Verlag, 2006

[BMU 05] Bekanntmachung des Leitfadens zur Durchführung der „Sicherheitsüberprüfung gemäß §19a des Atomgesetzes - Leitfaden Probabilistische Sicherheitsanalyse -" für Kernkraftwerke in der Bundesrepublik Deutschland, *BAnz-Nr. 207a, 3. 11.* 2005

[DRS 79] *Der Bundesminister für Forschung und Technologie (Hrsg.*), Deutsche Risikostudie Kernkraftwerke, *Verlag TÜV Rheinland*, Köln, 1979

[FAK 97] *Facharbeitskreis Probabilistische Sicherheitsanalyse für Kernkraftwerke:* Methoden zur probabilistischen Sicherheitsanalyse für Kernkraftwerke, *BfS-KT-16/97*, June 1997

[FAK 05A] *Facharbeitskreis Probabilistische Sicherheitsanalyse für Kernkraftwerke:* Methoden zur probabilistischen Sicherheitsanalyse für Kernkraftwerke, *BfS-SCHR-37/05*, October 2005

[FAK 05B] *Facharbeitskreis Probabilistische Sicherheitsanalyse für Kernkraftwerke*: Daten zur probabilistischen Sicherheitsanalyse für Kernkraftwerke, *BfS-SCHR-38/05*, October 2005

[GÖR 08] *Rudolf Görtz, Heinz P. Berg, and Jan Mahlke*: The POS Model For Common Cause Failure Quantification: Progress In Parameter Estimation And Comprehensive Documentation *Proceedings of PSAM 9,* Hong Kong, May 2008 (to be published)

[HAU 96] *Hauptmanns, U*.: The Multi-Class Binomial Failure Rate model. *Reliability Engineering and System Safety, Vol. 53 (No.1), 85 – 90*, 1996

[KNI 98A] *Knips, K. and Kreuser, A.:* Bewertung der Ergebnisse des Benchmarks zu GVA, *Schriftenreihe Reaktorsicherheit und Strahlenschutz, BMU-1998-514, Oct 1997*, ISSN 0724-3316

[KNI 98B] *Knips, K. and Kreuser, A.:* GVA-Benchmark, *Schriftenreihe Reaktorsicherheit und Strahlenschutz, BMU-1998-515, Nov 1997*, ISSN 0724-3316

[KRE 01] *Kreuser, A. and Peschke, J.:* Coupling Model: A Common-Cause-Failure-Model with Consideration of Interpretation Uncertainties, *Nuclear Technology, VOL. 136*, 2001

[KRE 06] *Kreuser, A., Peschke, J. and Stiller, J. C.:* Further Development of the Coupling Model, *Kerntechnik, 71*, 2006.

[MOS 98A] *Mosleh, A., Rasmuson, D.M., and Marshall, F.M.:* Guidelines on Modelling Common - Cause Failures in Probabilistic Risk Assessment. *NUREG/CR – 5485, US Nuclear Regulatory Commission, Washington DC*, 1998

[MOS 98B] *Mosleh, A., Rasmuson, D.M., and Marshall, F.M.:* Common - Cause Failure Parameter Estimations. *NUREG/CR – 5497, US Nuclear Regulatory Commission*, Washington DC, 1998

[RAS 75] *Rasmussen, N.C.*: Reactor Safety Study – An Assessment of Accident Risks in US Commercial Nuclear Power Plants, *US Nuclear Regulatory Commission, WASH-1400 (NUREG-75/014)*, October 1975

[STI 08] *Stiller, J.C., Kreuser, A., and Verstegen, C.*: Consideration of Additional Uncertainties in the Coupling Model for the Estimation of Unavailabilities due to Common Cause Failures, *Proceedings of PSAM 9, Hong Kong*, May 2008 (to be published)

APPENDIX 1: ORIENTATIONAL THOUGHTS SUPPORTING THE MODELLING APPROACH FOR THE NUMBER OF REDUNDANT COMPONENTS SHARING THE CAUSE

The POS model calculates the probability that exactly *m*-out-of-*r* redundant components share the cause based on an assumption on the conditional probability $F(m,r)$, as introduced in para. 3.2.

$F(m,r_s)$: Given that there are *m* redundant components in a subsystem of size r_s that share a certain failure cause, then $F(m,r_s)$ is the probability that a specific component r_s +1 not in the subsystem is as well sharing this cause.

The special process considered here is supporting the choice made when a parametric model had been set up for $F(m,r_s)$. Let us consider a system of $r > r_s$ redundant components, which is subject to two types of causes that differ with respect to the number of components affected. They are both assumed to be of binomial type, but with different parameters p_1 and p_2. They are further supposed to occur with different rates r_1 and r_2.

Now, the following situation shall be considered: A CCE of one of the two types has occurred. A subsystem of size r_s has been checked and *m* components were found to be affected.

$$m \geq 2,\ r_s \geq m$$

We can now calculate the conditional probability $F(m,r_s)$ that a given further component is affected by the cause as well.

Three events are introduced:

B: *m*-out-of-r_s components share the same cause

E1: The cause is of type 1

E2: The cause is of type 2

Obviously, F is given by

$$F(m,r_s) = p_1 \cdot \mathrm{P}(\mathrm{E1}|\mathrm{B}) + p_2 \cdot \mathrm{P}(\mathrm{E2}|\mathrm{B})$$

The Bayes theorem can be used to express the conditional probabilities

$$\mathrm{P}(\mathrm{E1}|\mathrm{B}) = \frac{\mathrm{P}(\mathrm{B}|\mathrm{E1}) \cdot w_1}{\mathrm{P}(\mathrm{B}|\mathrm{E1}) \cdot w_1 \ + \ \mathrm{P}(\mathrm{B}|\mathrm{E2}) \cdot w_2}$$

in terms of the probabilities for the evidence conditional to the cause type which can be calculated to be

$$\mathrm{P}(\mathrm{B}|\mathrm{Ei}) = \binom{r_s}{m} p_i^{\,m} (1-p_i)^{r_s - m}$$

$$w_1 = \frac{r_1}{r_1 + r_2}, \quad w_2 = \frac{r_2}{r_1 + r_2}$$

This is true because the components in the subsystem share the cause independent of the events in the rest of the system.

This finally yields

$$F(m,r) = p_1 \cdot \frac{X(1)}{X(1) \ + \ X(2)} + p_2 \cdot \frac{X(2)}{X(1) \ + \ X(2)}$$

where

$$X(i) = w_i \cdot p_i^{\,m} \cdot (1-p_i)^{r\text{-}m}, \qquad i \ = \ 1,\ 2$$

In the special case

r = 8

w_1 = w_2 = 0.5

p_1 = 0.1, p_2 = 0.9

the following numerical results are obtained:

F(2,8) = 0.1001

F(3,8) = 0.1097

F(4,8) = 0.4999

F(5,8) = 0.8902

F(6,8) = 0.8998

F(7,8) = 0.8999

F(8,8) = 0.8999

Firstly, a significant dependence of $F(m,r)$ on m is observed. Trying to keep the analysis simple by assuming a constant value for *F* is not encouraged by this special case. Starting at values close to p_1, F is increasing to end up close to p_2. The transition is following a power law in r.

In a more realistic case, one would certainly have to expect a superposition of more than two types of causes. Including causes with p = 1, on which the BFR model is exclusively based, one obtains a model, which comprises the feature that $F(r,r)$ approaches 1 for large r. The following assumption fulfills this requirement:

$$F(2,2) = a$$

$$F(m,r) = a + b \cdot \frac{m-2}{r-2} \quad , \quad r > 3$$

$$b = (1-a)(1-\mathrm{e}^{-\frac{r}{r_0}})$$

This assumption comprises a simple linear dependence on m, the most simple one beyond a constant.

It should further be noted that for the central question, how many components are affected in the model, the two free parameters a and r_0 are available to adjust the model to the pattern found in operating experience.

APPENDIX 2: EXAMPLES OF CCE SEQUENCES SIMULATED WITH THE POS MODEL

As described in chapter 3, the POS model is based on a sequence of stochastic variables, which are explained in para. 3.2 in some detail. To get a better understanding of the model, a couple of randomly generated examples for these sequences are presented here.

All times are given in years after beginning of operation. An operating time of 40 years has been assumed. As before, m denotes the number of affected components. Functional testing is assumed to occur at the end of each year, the CCE is assumed to be identified and repaired at the first test after the first failure.

Example 1:

- Time of Common Cause impact: 25.07 years
- Affected components m: 3-out-of-4
- Type of impact: delayed
- Times of failure of the impacted components: 429, 665 and 1505 years
- Time of CC identification: not identified within 40 years
- Times of unavailability: none

This example comprises a very slow process which would lead to failure long after final plant shut-down. No contribution to unavailability is encountered.

Example 2:

- Time of Common Cause impact: 4.5 years
- Affected components m: 2-out-of-4
- Type of impact: instantly
- Times of failure of the impacted components: instantly
- Time of CC identification: after 5 years
- Times of unavailability:
    - 1 out-of 4: -
    - 2 out-of 4: 0.5 years
    - 3 out-of 4: -
    - 4 out-of 4: -

This example comprises a CCE, in which 2 components are affected and fail instantly. 2-out-of-4 components are unavailable for half a year.

Example 3:

- Time of Common Cause impact: 0.56 years
- Affected components m: 4-out-of-4
- Type of impact: delayed
- Times of failure of the impacted components: 23.2, 62.9, 46.1, 4.1 years
- Time of CC identification: after 5 years
- Times of unavailability:
    - 1 out-of 4: 0.9 years
    - 2 out-of 4: -
    - 3 out-of 4: -
    - 4 out-of 4: -

This example comprises a slow CCE, which occurs early after plant operation is started. All components are affected and the first component fails after 4.1 years. Undiscovered for nearly a year, the component is unavailable. Hopefully discovered as a CCE, as assumed in the model, the other components are repaired/replaced as well, otherwise an additional failure occurs after 23.2 years.

Example 4:

- Time of Common Cause impact: 24.78 years
- Affected components m: 3-out-of-4
- Type of impact: delayed
- Times of failure of the impacted components: 24.785, 24.791, 24.790 years
- Time of CC identification: after 25 years
- Times of unavailability:
    - 1 out-of 4: 0.06 years
    - 2 out-of 4: 0.01 years

- 3 out-of 4: 0.19 years
- 4 out-of 4: -

This example comprises a fast CCE, in which 3 components are affected towards the end of the 24th year. They all fail within 48 days and are unavailable for the remaining fifth of the year.

APPENDIX 3: ALTERNATIVE SCHEMES OF CCF IDENTIFICATION

As pointed out in paragraph 3.2.6, the POS results presented in this report are based on the assumption of a non-staggered functional testing interval. That means all components of a CCCG are tested at the same time. Moreover, it is assumed that the CCE is identified as soon as the first failed component is tested. Of course, this is a simple limiting case, which can not be expected in practical applications. In this chapter the influence of staggered testing will be examined. For staggered testing, each component of a CCCG might be inspected at different times in the testing interval, so that each component is tested once in the full testing interval.

In addition to staggered testing schemes, the CCE might not be identified before the second failed component is tested or – on the other hand – the CCE might be identified before a failure occurs e.g. by inspection. Due to the modelling of both immediate and delayed failures, these complications can easily be taken into account with the POS model. The case of staggered testing will be briefly addressed in the following.

A 4-fold redundant system shall be considered with the data and model parameters according to the reference case introduced in 3.3.2. The two cases of non-staggered yearly testing and staggered testing with 3 months test interval shall be compared. The results for the first case were already displayed in Figure 3-1. For the staggered testing every 3 months one of the 4 components is tested until all have been inspected at the end of the year.

To quantify the second case, immediate and delayed failures have to be distinguished. The different contributions to the unavailability are split up in table A3-1.

The case of immediate failures can be handled in a straightforward manner. The failures simply occur at independent rates. The factors to adapt the reference case results to staggered testing can be obtained from simple combinatorial considerations.

	Contributions to the unavailability					
	immediate failure			delayed failure		
	m=2	m=3	m=4	m=2	m=3	m=4
1-out-of-4				$6.6\cdot10^{-4}$ (1)	$4.7\cdot10^{-4}$ (1.1)	$3.7\cdot10^{-4}$ (1.3)
2-out-of-4	$5.2\cdot10^{-4}$ (0.575)			$5.0\cdot10^{-4}$ (0.5)	$1.3\cdot10^{-4}$ (0.8)	$9.7\cdot10^{-5}$ (0.7)
3-out-of-4		$4\cdot10^{-4}$ (0.375)			$3.1\cdot10^{-4}$ (0.4)	$7.1\cdot10^{-5}$ (0.4)
4-out-of-4			$3.2\cdot10^{-4}$ (0.25)			$2.2\cdot10^{-4}$ (0.3)

Table A3-1: Contributions to the unavailability of an r = 4 system from immediate and delayed failures and different values of m (number of components sharing the Common Cause). Testing: yearly, non staggered. POS input data as in chapter 3.3.2. Values in parentheses are the adapting factors to obtain the corresponding values for 3-month-staggered testing.

In the case of delayed failures, the assessment is more complicated. A sufficient number of simulated events (examples see appendix 2) are analysed with respect to the differences in times of unavailability between staggered and non-staggered testing. This has to be done separately for the combinations of m and k. Finally, the results are to be added up with the appropriate weighting factors, which account for the fractions of immediate versus delayed failures (measured by W_{inst}) and the fractions associated with different values of m (measured by $W(m,4)$ depending on model parameters a and r_0).

Results for the k-out-of-4 unavailabilities are listed in table A3-1 and illustrated in figure A3-1. From these data it can be easily seen that the POS model is capable of respecting the testing method used. The POS model also allows to distinguish between immediate and delayed failures. This example shows that the contribution of the delayed failures can not generally be neglected.

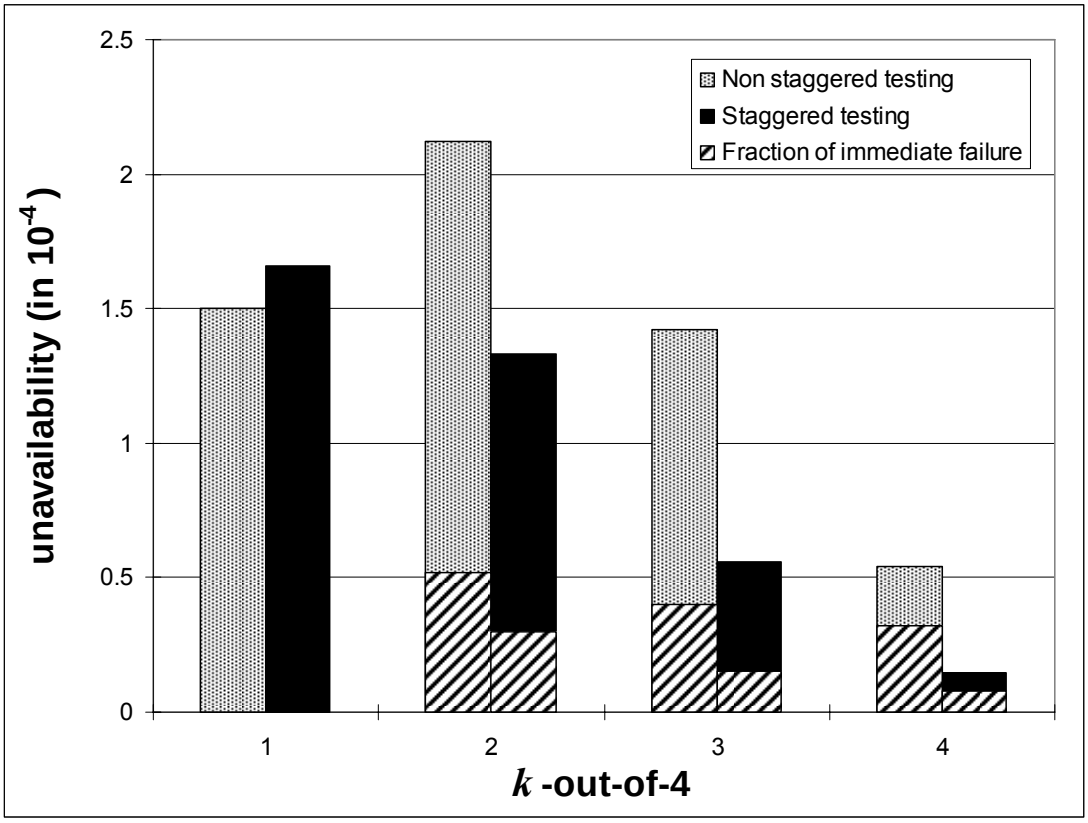

Figure A3-1: Contribution to the unavailability according to table A3-1. The values displayed are the sums for each value of k.

In the frame of a modelling perception, which denies delayed failures and comprises rates of immediate failures, only the analysis is much simpler. The POS model includes delayed failures and hence has to carry the burden of a more complicated analysis. This is more than compensated by the fact that delayed failures are a reality and thus the POS model provides a more realistic approach. With this remark the existence of areas where the rate approach is an excellent approximation shall not be denied.

APPENDIX 4: CALCULATION OF ALPHA FACTORS

A 4.1 OVERVIEW

In [MOS98A] approaches to CCF quantification are outlined, especially the use of parametric models. In the report [MOS98B] CCF parameter estimations have been provided for some 40 different component types, various failure modes and CCCG sizes from 2 up to 6. One of the models for which parameter distributions have been derived is the Alpha Factor model.

As pointed out before, for the POS parameter estimation described in [BER02], information is required on the number of components, which are affected by the event. This kind of information is not available in [MOS98B].

Two approaches have been caried out to overcome this lack of information. The first was already published [BER 06C] and is primarily based on a simplified fit of POS parameters to $\alpha(4,4)$. Only parameter a has been fitted, whereas for parameters W_{inst} and r_0 default values were taken. The approach is described in details in paragraph A4.2.

The second approach is described in A4.3. It is based on a fit to $\alpha(1,4)$ and a generic set of POS parameters.

In both cases, there is a considerably good agreement between the alpha factors obtained from the POS model and the tabulated data. In the second approach the POS results are tied to $\alpha(1,4)$ only, which corresponds to single failures. Therefore, the good agreement with respect to higher failure multiplicities is seen as the more remarkable outcome.

The prime objective, however, was to demonstrate that the POS model can be used to calculate alpha factors rather than highlighting the reasonable agreement of calculated quantities.

A 4.2 SURVEY OF THE APPROACH DESCRIBED IN [BER 06C]

The alpha factor $\alpha(k,r)$ is, by definition, the probability that in a CCCG of size r exactly k components have failed due to a CC. Hence, the quantities are normalized with respect to the failure multiplicity k = 1,2,...r. The first simplifying assumption is that the failures with $k \geq 2$ are determined by dependent failures only. The conditional probabilities $W(k,r)$ for these events are calculated with the POS model. In [MOS98B], 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 then can be calculated as follows:

$$\alpha(k,r) = W(k,r) \cdot q + (1-q) \cdot \delta(k,1) \qquad \text{(A4-1)}$$

using

$$\delta(k,1) = 0 \text{ for } k = 1 \qquad \text{(A4-2)}$$

and

$$\delta(1,1) = 1 \qquad \text{(A4-3).}$$

The selection of POS parameters is – as explained above – simplified. The values W_{inst} = 0.1 and r_0 = 3 are taken as default values throughout the exercise. These values are typical values, based on other applications. Parameter a is fitted in such a way that $\alpha(4,4)$ is equal to the value provided in [MOS98B] for the component type and failure mode under consideration. This choice has been taken because, as one can see from equations (3.2-1) and (3.2-8) to (3.2-10), this is the “lowest” combination of failure multiplicity and CCCG size, which is influenced by all 3 parameters.

This programme has been carried out for six different combinations of components and failure modes that were selected primarily based on large numbers of dependent failures, to make sure that the comparison has a solid statistical basis and on having a good mix of technically different components. Furthermore, only those components were included, for which CCCG sizes up to 6 are covered in [MOS98B].

In a first step, with the POS parameters as described, $\alpha(k,6)$ (k = 1,2,...,6) have been calculated. For the comparison with the empirical data from [MOS98B], a metric for the deviation of the quantities is required. In [MOS98B], not only 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 [MOS98B], divided by logarithm of the ratio of the values of the 95-percentile to the 50-percentile.

$$X = \frac{\log(\frac{\alpha_{POS}}{\alpha_{50}})}{\log(\frac{\alpha_{95}}{\alpha_{50}})} \qquad \text{(A4-4)}$$

This means a deviation X = 1 if the calculated value equals the value of the 95-percentile.

Equation A4-4 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.

In table A4-1, the deviations X are displayed for 5 different components and two different failure modes of one component. For failure multiplicities larger than 3, there seems to be a good agreement. For values of 3 and lower, the number of deviations with $|X| > 1$ is higher, especially for multiplicity 2. Due to normalization, a strong deviation for multiplicity 2 in many cases implies one for multiplicity 1. They are not independent.

Component / Failure Mode	$\alpha(1,6)$	$\alpha(2,6)$	$\alpha(3,6)$	$\alpha(4,6)$	$\alpha(5,6)$	$\alpha(6,6)$
BWR RHR MOV / Fail to Close	-0.2	0.09	-0.01	0. 8	1	-0.05
Emergency Service Water Pumps / Fail to Run	0.8	-1.1	-1.2	-0.09	0.4	0.8
Emergency Service Water Pumps / Fail to Start	1.91	-1	-2	-0.8	-0.6	0.2
PWR AFW Check Valves / Fail to Remain Closed	-0.9	1.2	-0.01	0.4	0.6	0.06
DC Power Battery Chargers / No Voltage	2	-1	-0.9	-0.2	0.9	-0.8
SG Injection Flow Control Valves / Fail to Open	-0.8	1.1	0.4	0.3	0.01	-0.2

Table A4-1: Deviation X of the alpha factors $\alpha(k,6)$ calculated with the POS model from values tabled in [MOS98B].

A similar picture is obtained by considering failure of all components. This is displayed in table A4-2. It is not surprising that the agreement is good for $\alpha(5,5)$ and $\alpha(3,3)$, as the parameter adjustment was done for $\alpha(4,4)$. For small sizes of the component group the deviations are larger, probably due to the same reasons as in table A4-1. Especially the assumption that the failure multiplicities > 1 are due to dependent failures only might be wrong here.

Component / Failure Mode	α(5,5)	α(4,4)	α(3,3)	α(2,2)
BWR RHR MOV / Fail to Close	0.001	0	0.6	0.4
Emergency Service Water Pumps / Fail to Run	-0.3	0	-0.5	-1.1
Emergency Service Water Pumps / Fail to Start	0.8	0	0.02	0.5
PWR AFW Check Valves / Fail to Remain Closed	0.5	0	0.2	1.1
DC Power Battery Chargers / No Voltage	0.2	0	0.1	0.05
SG Injection Flow Control Valves / Fail to Open	-0.07	0	0.04	0.7

Table A4-2: Deviation X of the alpha factors $\alpha(k=r,r)$ calculated with the POS-model from values tabled in [MOS98B].

A 4.3 FITTING TO $\alpha(1,r)$

The alpha factor $\alpha(1,r)$ is, by definition, the probability that in a CCCG of size r exactly 1 component has failed. Single failures can occur both as consequences of CCEs and independent failures. The POS model does not comprise independent failures. This advocates an alternative approach to the one described in A4.2. $\alpha(k,r)$ are now calculated with the POS model for values of $k \geq 2$, whereas $\alpha(1,r)$ is taken from [MOS 98B]. For the POS calculations the reference data set given in 3.3.2 is used with a single modification. Parameter a has been adjusted to 0.34, which corresponds to a fit to $\alpha(4,4)$ for only one of the components, the "BWR RHR MOV / fail to close" listed in table 30-17 of [MOS98B]. The results are shown in tables A4-3 and A4-4. Figures A4-1 and A4-2 illustrate the same results.

Component / Failure Mode	α(2,4)	α(3,4)	α(4,4)
BWR RHR MOV / Fail to Close	-0.17	0.62	0.07
Emergency Water Service Pumps / Fail to Run	0.58	1.1	-2.07
Emergency Service Water Pumps / Fail to Start	-1.17	1.17	0.83
PWR AFW Check Valves / Fail to Remain Closed	0.11	0.49	-0.13
DC Power Battery Chargers / No Voltage	-0.34	0.06	0.82

Table A4-3: Deviation X of the alpha factors $\alpha(k,4)$ calculated with the POS model from values tabled in [MOS98B].

Component / Failure Mode	$\alpha(2,6)$	$\alpha(3,6)$	$\alpha(4,6)$	$\alpha(5,6)$	$\alpha(6,6)$
BWR RHR MOV / Fail to Close	-1.16	-0.78	0.33	0.75	-0.56
Emergency Service Water Pumps / Fail to Run	0.006	0.26	0.79	1.14	-2.13
Emergency Service Water Pumps / Fail to Start	-0.65	-0.86	0.4	1.13	1.11
PWR AFW Check Valves / Fail to Remain Closed	-0.45	0.37	0.31	0.97	-0.15
DC Power Battery Chargers / No Voltage	-0.61	0.16	0.43	0.42	0.42

Table A4-4: Deviation X of the alpha factors $\alpha(k,6)$ calculated with the POS model from values tabled in [MOS98B].

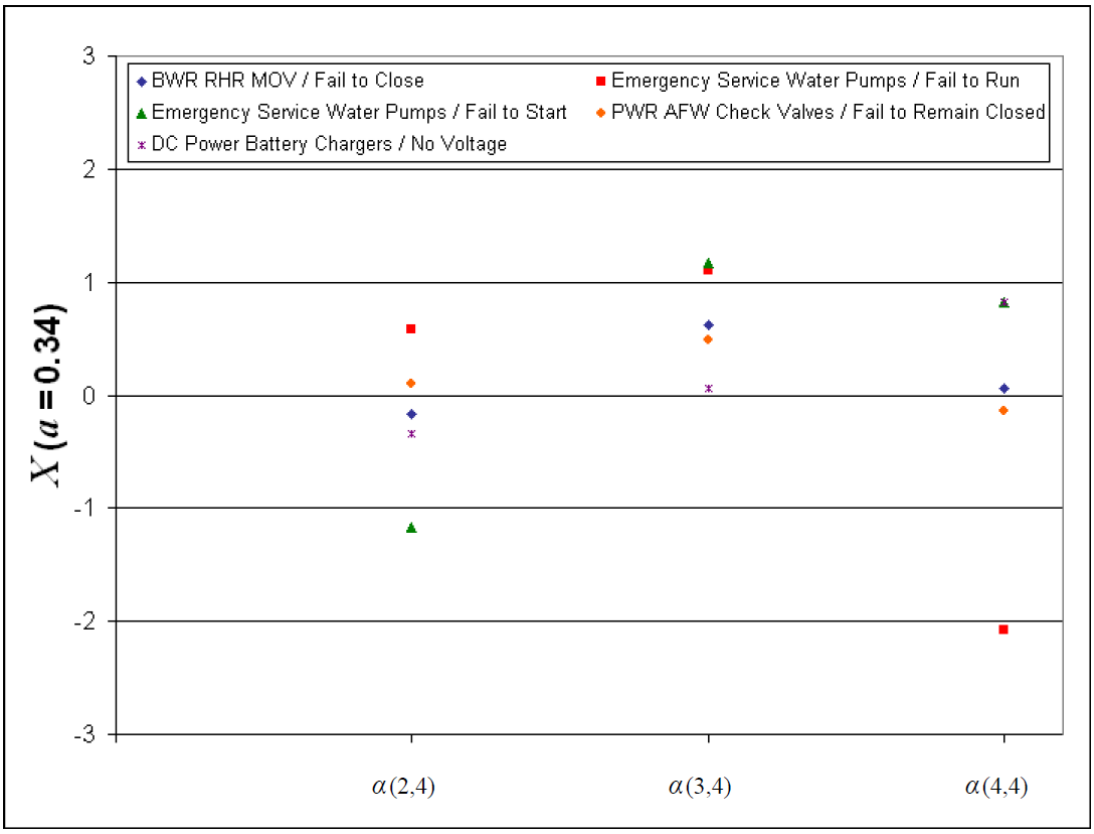

Figure A4-1: Deviation X of $\alpha(k,4)$. Data as in table A4-3.

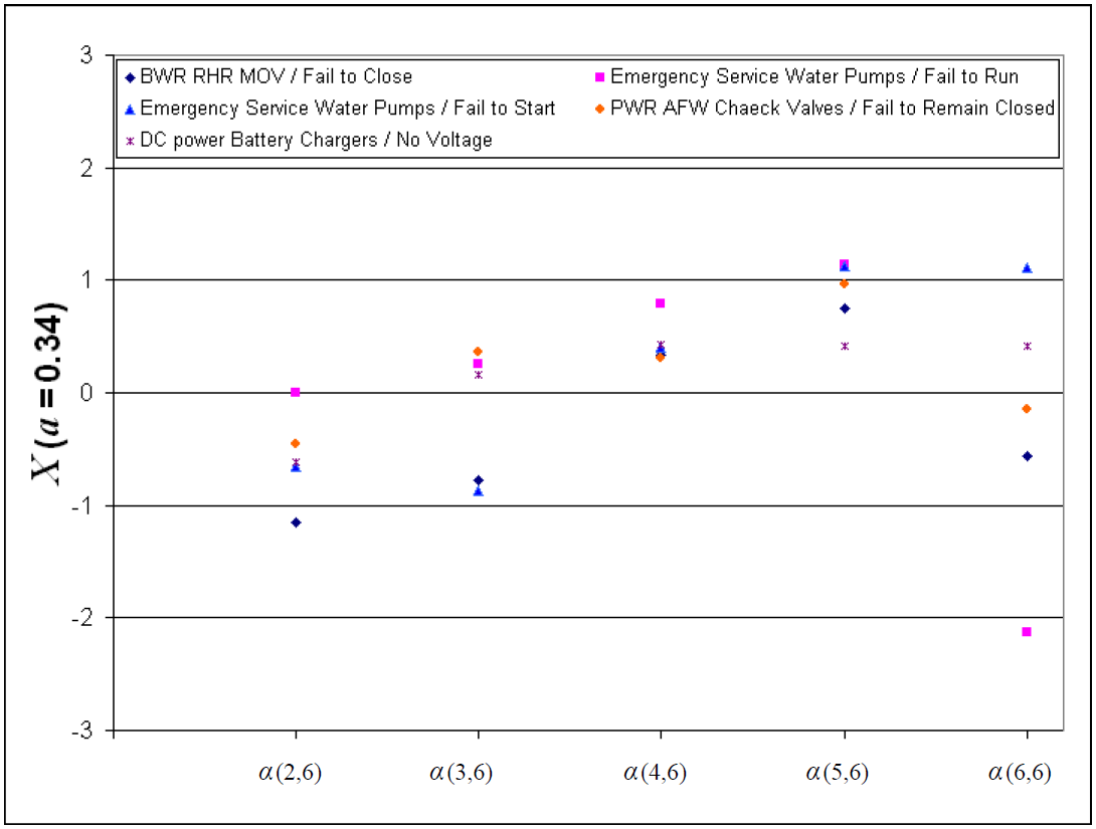

Figure A4-2: Deviation X of $\alpha(k,6)$. Data as in table A4-4.

LIST OF ABBREVIATIONS

AFW	Auxiliary Feedwater
BFR	Binominal Failure Rate
BWR	Boiling Water Reactor
CC	Common Cause
CCCG	Common Cause Component Group
CCE	Common Cause Event
CCF	Common Cause Failure
LPSI	Low Pressure Safety Injection
MBFR	Modified Binominal Failure Rate
MCBFR	Multi-Class Binominal Failure Rate
MGL	Multiple Greek Letter
MOV	Motor Operated Valve
NPP	Nuclear Power Plant
OP	Operation Period
POS	Process-Oriented Simulation
PSA	Probabilistic Safety Assessment
PWR	Power Water Reactor
RHR	Residual Heat Removal
SG	Steam Generator
TSO	Technical Support Organization

Bisher erschienene BfS-SK-Berichte (vorher BfS-KT-Berichte)

BfS-KT-1/92
Gersinska, R.; Hennig, R.; Kociok, B. (Hrsg.)
Zweites Expertengespräch zum BMU/BfS-Konzept Mensch-Maschine-Wechselwirkung in Kernkraftwerken am 5. und 6. März 1992 beim Bundesamt für Strahlenschutz in Salzgitter.
Salzgitter, April 1992

BfS-KT-2/92
Berg, H.P.; Schott, H.
Stand von Wissenschaft und Technik auf dem Gebiet der Quantifizierung der menschlichen Zuverlässigkeit - Dezember 1991 -.
Salzgitter, Februar 1992

BfS-KT-3/92
Berg, H.P.; Schott, H.
Probabilistische Sicherheitsanalysen. Aktueller Status, Weiterentwicklung von Methoden und Modellen, Anwendungen.
Salzgitter, Dezember 1992

BfS-KT-3/92-REV-1
Berg, H.P.; Schott, H.
Probabilistische Sicherheitsanalysen. Aktueller Status, Weiterentwicklung von Methoden und Modellen, Anwendungen.
Salzgitter, April 1993

BfS-KT-4/93
Ziegenhagen, J.
Zusammenstellung der Genehmigungswerte für Ableitungen radioaktiver Stoffe mit der Fortluft und dem Abwasser aus den Kernkraftwerken der Bundesrepublik Deutschland. Dezember 1992.
Salzgitter, April 1993

BfS-KT-5/93
Philippczyk, F.; Ziegenhagen, J.
Stand und Entwicklung der Kernenergienutzung in der Bundesrepublik Deutschland. Stand: Mai 1993.
Salzgitter, Mai 1993

BfS-5/93-REV-1
Philippczyk, F.; Ziegenhagen, J.
Stand und Entwicklung der Kernenergienutzung in der Bundesrepublik Deutschland. Stand: Mai 1993.
Salzgitter, Juli 1993

BfS-5/93-REV-2
Philippczyk, F.; Ziegenhagen, J.
Stand und Entwicklung der Kernenergienutzung in der Bundesrepublik Deutschland. Stand: Mai 1993.
Salzgitter, Oktober 1993

BfS-5/93-REV-3
Philippczyk, F.; Ziegenhagen, J.
Stand und Entwicklung der Kernenergienutzung in der Bundesrepublik Deutschland. Stand: Mai 1993.
Salzgitter, Mai 1994

BfS-KT-6/93
KT/KTA-Winterseminar 1993.
28. und 29. Januar 1993 in Salzgitter.
Kerntechnik in der Bundesrepublik Deutschland im Jahre 1993. Aufgaben, Probleme, Perspektiven aus der Sicht der Beteiligten.
Salzgitter, Juli 1993

Bisher erschienene BfS-SK-Berichte (vorher BfS-KT-Berichte)

BfS-KT-7/94
Gersinska, R.; Hennig, R.; Kociok, B.
Drittes Expertengespräch zum BMU/BfS-Konzept "Mensch-Maschine-Wechselwirkung in Kernkraftwerken" am 28. und 29. April 1994 beim Bundesamt für Strahlenschutz in Salzgitter.
Salzgitter, April 1994

BfS-KT-8/94
2. KT/KTA-Winterseminar 20. und 21. Januar 1994 in Salzgitter
Erhaltung und Verbesserung der Reaktorsicherheit.
Salzgitter, Juli 1994

BfS-KT-9/95
Meldepflichtige Ereignisse in der Wiederaufarbeitungsanlage Karlsruhe im Zeitraum 1. Januar bis 31. Dezember 1993.
Salzgitter, März 1995

BfS-KT-10/95
Philippczyk, F.; Hutter, J.
Stand und Entwicklung der Kernenergienutzung 1994 in der Bundesrepublik Deutschland.
Salzgitter, Mai 1995

BfS-KT-11/95
3. KT/KTA-Winterseminar. 19. und 20. Januar 1995 in Salzgitter.
EDV in der Kerntechnik.
Salzgitter, Juli 1995

BfS-KT-12/96
Krüger, F.W.
Quality assurance of a regulatory body.
Salzgitter, April 1996

BfS-KT-13/96
4. KT/KTA-Winterseminar. 25. und 26. Januar 1996 in Salzgitter.
Alterungsmanagement in Kernkraftwerken.
Salzgitter, Mai 1996

BfS-KT-14/96
Philippczyk, F, Hutter, J.
Stand und Entwicklung der Kernenergienutzung 1995 in der Bundesrepublik Deutschland.
Salzgitter, Juni 1996

BfS-KT-15/96
Berg, H.P., Görtz, R., Schaefer, T., Schott, H.
Quantitative probabilistische Sicherheitskriterien für Genehmigung und Betrieb kerntechnischer Anlagen: Status und Entwicklung im internationalen Vergleich.
Salzgitter, September 1996

BfS-KT-16/97
Facharbeitskreis Probabilistische Sicherheitsanalyse.
Methoden zur probabilistischen Sicherheitsanalyse für Kernkraftwerke. Dezember 1996.
Salzgitter, Juni 1997

BfS-KT-17/97
Arbeitsgruppe Schutzzielkonzept.
Schutzzielorientierte Gliederung des kerntechnischen Regelwerks. Übersicht über die übergeordneten Anforderungen, Dezember 1996.
Salzgitter, Juni 1997

Bisher erschienene BfS-SK-Berichte (vorher BfS-KT-Berichte)

BfS-KT-18/97
Facharbeitskreis Probabilistische Sicherheitsanalyse.
Daten zur Quantifizierung von Ereignisablaufdiagrammen und Fehlerbäumen. März 1997.
Salzgitter, Juni 1997

BfS-KT-19/97
Gelfort, E.; Krüger, F.W.
Wiederaufarbeitungsanlagen für Kernbrennstoff in der Russischen Föderation.
Salzgitter, Juni 1997

BfS-KT-19/97-REV-1
Gelfort, E.; Krüger, F.W.
Wiederaufarbeitungsanlagen für Kernbrennstoff in der Russischen Föderation.
- Statusbericht 1999 -
Salzgitter, November 1999

BfS-KT-20/97
Philippczyk, F.; Hutter, J.
Stand und Entwicklung der Kernenergienutzung 1996 in der Bundesrepublik Deutschland.
Salzgitter, Juni 1997 ***(nicht im Internet)***

BfS-KT-21/98
Philippczyk, F.; Hutter, J.
Stand und Entwicklung der Kernenergienutzung 1997 in der Bundesrepublik Deutschland.
Salzgitter, April 1998 ***(nicht im Internet)***

BfS-KT-22/99
Engel, K.; Gersinska, R.; Kociok, B.
Viertes Expertengespräch zum BMU/BfS-Konzept "Mensch-Maschine-Wechselwirkung in Kernkraftwerken" am 14. und 15. April 1999 beim Bundesamt für Strahlenschutz in Salzgitter.
Salzgitter, April 1999

BfS-KT-23/99
Berg, H.P.; Schaefer, Th.
Current Level 1 PSA.
Practices in Germany.
Salzgitter, Oktober 1999

BfS-KT-24/00
Krüger, F.-W.; Spoden, E.
Untersuchungen über den Luftmassentransport von Standorten Kerntechnischer Anlagen Ost nach Deutschland.
Salzgitter, Mai 2000

BfS-KT-25/00
Klonk, H.; Hutter, J.; Philippczyk, F.; Wittwer, C.
Zusammenstellung der Genehmigungswerte für Ableitungen radioaktiver Stoffe mit der Fortluft und dem Abwasser aus kerntechnischen Anlagen der Bundesrepublik Deutschland (Stand Juli 2000).
Salzgitter, Oktober 2000

BfS-KT-26/01
Philippczyk, F.; Hutter, J.; Schmidt, I.
Statusbericht zur Kernenergie in der Bundesrepublik Deutschland 2000.
Salzgitter, Mai 2001

Bisher erschienene BfS-SK-Berichte (vorher BfS-KT-Berichte)

BfS-KT-27/02
Philippczyk, F.; Hutter, J.; Schneider,M.
Statusbericht zur Kernenergie in der Bundesrepublik Deutschland 2001.
Salzgitter, Oktober 2002

Ab 1. Februar 2003 SK

BfS-SK-01/03
Berg, H.-P.; Fröhmel,T.; Görtz, R.; Schimetschka, E.; Schott, H.
Quantitative probabilistische Sicherheitskriterien für Genehmigung und Betrieb kerntechnischer Anlagen:
Status und Entwicklung im internationalen Vergleich.
Salzgitter, Juni 2003

BfS-SK-02/03
Philippczyk, F.; Hutter, J.; Schneider,M.
Statusbericht zur Kernenergie in der Bundesrepublik Deutschland 2001.
Salzgitter, November 2003

BfS-SK-03/03
Berg, H.-P.; Görtz, R.; Schimetschka, E.
Quantitative Probabilistic Safety Criteria for Licensing and Operation of Nuclear Plants
Comparsion of the International Status and Development.
Salzgitter, November 2003

BfS-SK-04/04
Philippczyk, F.; Hutter, J.; Rehs, B.; Schneider, M.
Statusbericht zur Kernenergienutzung in der Bundesrepublik Deutschland 2003
Salzgitter, August 2004

BfS-SK-05/05
Philippczyk, F.; Borrmann, F.; Hutter, J.; Schneider, M.
Statusbericht zur Kernenergienutzung in der Bundesrepublik Deutschland 2004
Salzgitter, Juli 2005

BfS-SK-06/06
Bredberg, I.; Borrmann, F.; Hutter, J.; Schell, H.; Schneider, M.; Wähning, R.; Hund, W.
Statusbericht zur Kernenergienutzung in der Bundesrepublik Deutschland 2005
Salzgitter, August 2006

BfS-SK-07/07
Bredberg, I.; Hutter, J.; Schell, H.; Schneider, M.; Wähning, R.
Statusbericht zur Kernenergienutzung in der Bundesrepublik Deutschland 2006
Salzgitter, Juli 2007

BfS-SK-08/08
Görtz, R.
An Identity on Alternating Sums of Squares of Binomial Coefficients
Salzgitter, Februar 2008

BfS-SK-09/08
Bredberg, I.; Hutter, J.; Schell, H.; Schneider, M.; Wähning, R.
Statusbericht zur Kernenergienutzung in der Bundesrepublik Deutschland 2007
Salzgitter, August 2008

Bisher erschienene BfS-SK-Berichte (vorher BfS-KT-Berichte)

BfS-SK-10/08
Berg, H.P.: Görtz, R.; Mahlke, J.; Reckers, J.; Scheib, P.; Weil, L.
The POS Model for Common Cause Failure Quantification
Fachbereich Sicherheit in der Kerntechnik
Salzgitter, November 2008

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