Further Development of the GRS Common Cause Failure Quantification Method

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Abstract: For the quantification of common cause failures (CCF), GRS has developed the coupling model. This model has two important features: Firstly, estimation uncertainties which arise from different sources, e.g. statistical uncertainties, uncertainties of expert judgments or uncertainties due to inhomogeneities of statistical populations, are taken into account in a consistent way. Secondly, it automatically allows for the extrapolation of CCF events two groups of different sizes ("mapping"). This feature has been very important since for most component types groups of several different sizes can be found in German NPP. The model assumptions necessary to allow for this feature, however, also lead to undesirable convergence properties when a large amount of operating experience is available. Therefore GRS has started a project to research possible improvements of CCF modeling with respect to this aspect including the development of models that avoid making use of the restrictive modeling assumptions, which allow a comprehensive treatment of uncertainties, and which are applicable to data available in the German CCF data pool which does not contain information on single failures. Two different models have been developed, including a conservative mapping procedure. Comparisons of the results of the new estimation procedures and the coupling model show that the results are compatible.

Keywords: PRA, CCF, Quantification, Uncertainty Analysis

1. INTRODUCTION

Common cause failures (CCF) contribute to a large extent to the unavailability of redundant systems, especially for highly redundant systems. Probabilistic safety assessments (PSA) have shown that these unavailabilities may make a significant or even dominant contribution to the estimate of the core damage frequency of a nuclear power plant. Therefore an appropriate estimation of CCF probabilities including an adequate uncertainty analysis is of great importance. Since in most cases CCFs are very rare events statistical uncertainties have to be considered. Uncertainties arising from other sources like uncertainties of expert judgments on the impairments of components in CCF events or the possible inhomogeneity of populations have to be considered as well. To accomplish this, GRS has developed the coupling model and associated estimation procedure [1]. In the coupling model, uncertainties are treated in a consistent way by applying Bayesian statistical methods. The coupling model and the procedures for event assessment and parameter estimation have been continuously advanced in recent years [2,3] including a new procedure to consistently represent the remaining uncertainties related e.g. to a possible inhomogeneity of populations. One main feature of the coupling model is that it automatically allows for the extrapolation of CCF events to groups of different sizes. Model assumptions associated with this feature also cause undesirable convergence properties which may become more important since an increasing part of German operating experience has been evaluated recently with regard to CCF [4,5] and hence the number of CCF events available has increased. Therefore GRS has started a project to research possible improvements of CCF modeling with respect to this aspect. In the present paper, the first results of these efforts are discussed.

The paper is organized as follows: In chapter 2 the present coupling model and estimation procedure are described, including a recent development for the modeling of sources of additional uncertainties not included before (section 2.4). The convergence properties are also discussed (section 2.5). In chapter 3 two alternative models are developed which avoid the restrictive modelling assumptions leading to the undesirable convergence properties of the coupling model. In chapter 4 the estimation results of the different models are compared and discussed. In chapter 5 the use of operating experience from component groups of different size (so-called mapping) is briefly discussed. A simple mapping procedure is introduced and compared to estimation results of the coupling model. In chapter 6 conclusions are made.

For the sake of simplicity and compactness, no complete mathematical treatments are presented in this paper. These will be given in [6].

2. PRESENT COUPLING MODEL AND ESTIMATION PROCEDURE

2.1. Basic Equations of the Coupling Model

Like in the binomial failure rate (BFR) model [7], it is assumed in the coupling model that if a CCF phenomenon occurs in a component group, the individual components fail independently of each other with a probability η or remain unaffected with a probability $1-\eta$. The parameter η is denoted "coupling parameter". Unlike in the BFR model, it is not assumed that the coupling parameter is identical for all CCF phenomena. Therefore CCF failure probabilities are estimated separately for all observed CCF phenomena. The total common cause probability of a (k out of r) failure is calculated as the sum over all phenomena.

The probability $q_{k\backslash r;j}$ of a common cause (k out of r)-failure due to the CCF phenomenon j is given by

$$q_{k\backslash r;j} = \varphi_j \binom{r}{k} \eta_j^k \left(1-\eta_j\right)^{r-k} \tag{1}$$

with r denoting the size of the target component group, η_j denoting the coupling parameter of CCF phenomenon η and φ_j denoting the probability that a CCF due to phenomenon j occurs in the target component group.

Equation (1) has the form of a product of the probability that a CCF due to phenomenon j occurs in the target component group and the conditional probability that k out of r components fail, given that a CCF due to phenomenon j has occurred. Under the assumptions mentioned above, the number of failed components follows a binomial distribution with parameter η_j, when CCF phenomenon j occurred in the target component group.

The probability φ_j that a CCF due to phenomenon j occurs in the target component group is calculated as

$$\varphi_j = f_j \, t_j \, \lambda_j \tag{2}$$

with f_j denoting the applicability factor, t_j denoting the expected failure detection time for the CCF phenomenon j and λ_j denoting the rate of CCF phenomenon j in the observed population. The applicability factor is defined as the relative rate of an occurrence of the CCF phenomenon in the target component group with respect to the component group in which the CCF event occurred. The estimation of f_j is based on possible technical and operational differences between the observed and the target component group. If no substantial technical and operational differences exist, the observed CCF event j is fully applicable to the target group and therefore $f_j = 1$ holds, which applies in most cases.

Equation (2) is only valid if λ_j is small, i.e. $f_j \, t_j \, \lambda_j \ll 1$ holds. This generally is true in normal applications.

As noted before, the total common cause probability of a (k out of r) failure $q_{k\backslash r}$ is calculated as the sum of the probabilities $q_{k\backslash r;j}$ over all observed CCF phenomena:

$$q_{k\backslash r} = \sum_{j=1}^{N} q_{k\backslash r;j} \tag{3}$$

with N denoting the number of CCF events that occurred in the observed population of component groups.

2.2. Estimation of Model Parameters

To estimate the CCF failure probabilities with the coupling model, first the coupling parameters η_j have to be estimated (see equation (1)). Since the number of components m in the component group where a CCF took place is usually quite small, there is a large uncertainty associated with this estimation. This uncertainty is treated by using a Bayesian approach to estimate the coupling parameters. Using a non-informative prior [8] $\pi(\eta_j) \propto 1/\sqrt{\eta_j(1-\eta_j)}$ for the coupling parameter the a posteriori probability distribution is given by the Beta distribution

$$p(\eta_j) = \frac{\Gamma(r+1)}{\Gamma(k+1/2)\,\Gamma(r-k+1/2)}\,\eta_j^{k-1/2}\left(1-\eta_j\right)^{r-k-1/2} \tag{4}$$

if k out of r components failed during the CCF event j.

Operating experience shows that in many CCF events components are found which are more or less severely degraded but have not failed yet. In the coupling model, however, it is assumed that if a CCF phenomenon occurs in a component group, the components either fail or remain unaffected. Hence, degraded components are not directly modeled. This is done for two reasons: Firstly, in a PSA component states are also only modeled as failed or unaffected. Secondly, a CCF model would require additional parameters to model degraded states. Since the number of CCF events found in operating experience is very limited, estimation of such parameters would be difficult and would lead to large estimation uncertainties. In the coupling model this is resolved by interpreting degradations as probabilities of failure. Therefore, the number of failed components on which the estimation of the coupling parameter η_j (equation (1)) is based has to be treated as an uncertain quantity. This uncertainty has been termed “interpretation uncertainty” in [2]. It is treated in the following way: The probability $w_{k\backslash r}$ that k out of r components would fail during an additional demand is estimated for all $k = 0 \dots m$ using engineering judgment. These probabilities are represented by a so-called interpretation vector $W = \{w_{0\backslash r}, w_{1\backslash r}, \dots, w_{r\backslash r}\}$ where the condition $\sum_{k=0}^{r} w_{k\backslash r} = 1$ must hold.

Generally, it is not feasible for technical experts to directly assess such kinds of subjective probabilities. Therefore, a method was developed which automatically generates an interpretation vector W. This method consists of assessing degradation levels for each component of the component group where the CCF event took place. The degradation level is interpreted as the probability that the component would fail during the next demand due to the CCF phenomenon observed (e.g. 1 for failed components and 0 for completely unaffected components). Given the component impairments the interpretation vector W is determined using probability calculus [2]. This approach is well proven and is also used for other CCF models [9].

After determination of the interpretation vector W, the coupling parameter η_j for each CCF event j can be estimated. For each single interpretation alternative, the a posteriori distribution is determined according to equation (4). This results in an a posteriori distribution of the coupling parameter η_j which has the form of a weighted mixture of Beta distributions:

$$p(\eta_j) = \sum_{i=0}^{r} w_{i\backslash r} \frac{\Gamma(r+1)}{\Gamma(i+1/2)\,\Gamma(r-i+1/2)} \eta_j^{i-1/2} \left(1-\eta_j\right)^{r-i-1/2} \qquad (5)$$

This distribution expresses the uncertainty about the coupling parameter η_j taking into account both the statistical and the interpretation uncertainty.

To include the statistical uncertainty of the rates of the CCF events, the Bayes a posteriori distribution $p(\lambda_j)$ is calculated using the non-informative prior [8] $\pi(\lambda_j) \propto 1/\sqrt{\lambda_j}$. This results in a Gamma distribution as a posteriori distribution of λ_j:

$$p(\lambda_j) = \frac{T^{3/2}}{\Gamma(3/2)} \lambda_j^{1/2} e^{-\lambda_j T} = \frac{2}{\sqrt{\pi}} \sqrt{T^3 \lambda_j}\, e^{-\lambda_j T} \qquad (6)$$

Using equation (2), the probability distribution of $q_{k\backslash r;j}$ can be calculated. This is done with Monte Carlo methods.

2.3. Uncertainty Related to Expert Judgments

Since expert judgments are afflicted with uncertainties, a considerable number (usually 4 or more) of expert judgments on the impairment of the components and on the applicability factor is collected for each event observed. The procedure for clarifying the technical facts and performing the expert judgments is described in detail in [10]. Below, the entirety of expert assessments is denoted by $\mathfrak{E}$.

The calculation of the distributions of $q_{k\backslash r;j}$ as described in the last chapter is carried out individually for all experts, resulting in an expert-specific subjectivist probability distribution of $q_{k\backslash r;j}$. To combine the judgments of the different experts, the mixture distribution is calculated from these individual expert-specific subjectivist distributions. According to equation (3) the total probability of a CCF event with k failures is the sum of the individual phenomenon-specific probabilities $q_{k\backslash r;j}$. These calculations are carried out using Monte Carlo methods.

2.4. Consideration of Additional Uncertainties

Finally, the remaining uncertainties not considered before have to be included. Most prominent is the uncertainty related to a possible inhomogeneity of populations. This possible inhomogeneity implies that if $q_{k\backslash r}$ is the probability of a (k out of r)-CCF estimated from operating experience from a specific population, the probability of a (k out of r) CCF $\hat{q}_{k\backslash r}$ in a specific CCF group modelled in a PRA in general deviates from that value. This is quantified by a conditional distribution $p(\hat{q}_{k\backslash r}|q_{k\backslash r})$. The probability distribution of $\hat{q}_{k\backslash r}$ can be expressed as

$$p(\hat{q}_{k\backslash r}) = \int_0^1 p(\hat{q}_{k\backslash r}|q_{k\backslash r}) p(q_{k\backslash r}) dq_{k\backslash r} \qquad (7)$$

In general there is no information that the different sources of uncertainty take effect differently in different component groups or component types. Hence a universal distribution $p(\hat{q}_{k\backslash r}|q_{k\backslash r})$ is assumed for all component groups. Due to the limited number of CCF events it is not possible to estimate the functional form of $p(\hat{q}_{k\backslash r}|q_{k\backslash r})$ or its characteristics from operating experience. Therefore, the following assumptions are made:

1. **Preservation of expectation value:** It can neither be expected that $\hat{q}_{k\backslash r}$ is larger nor that it is smaller than $q_{k\backslash r}$ Therefore it is assumed that $p(\hat{q}_{k\backslash r}|q_{k\backslash r})$ preserves the expectation value, which implies $\int_0^1 \hat{q}_{k\backslash r} p(\hat{q}_{k\backslash r}|q_{k\backslash r}) d\hat{q}_{k\backslash r} = q_{k\backslash r}$.
2. **Scale-independence:** The shape and relative width of p shall be independent of $q_{k\backslash r}$. This implies that the standard deviation of $p(\hat{q}_{k\backslash r}|q_{k\backslash r})$ is proportional to $q_{k\backslash r}$ (with the proportionality factor denoted by ϱ).
3. **Minimal width:** The 95%-quantile should at least be 4 times as large as the mean. This criterion has been determined by expert judgments and is in agreement with the previous "broadening" described in German PRA guidelines [11].

These assumptions are applicable for $q_{k\backslash r} \ll 1$. This is generally valid in normal applications.

$p(\hat{q}_{k\backslash r}|q_{k\backslash r})$ is assumed to be a beta distribution, i.e.:

$$p(\hat{q}_{k\backslash r}|q_{k\backslash r}) = \frac{\left(1 - \hat{q}_{k\backslash r}\right)^{\beta-1} \hat{q}_{k\backslash r}{}^{\alpha-1}}{f_\beta(\alpha, \beta)} \tag{8}$$

with $f_\beta(\alpha, \beta)$ denoting the beta function.
The assumptions described above allow to determine the two ($q_{k\backslash r}$-dependent) parameters as

$$\begin{aligned} \alpha &= \frac{1 - q_{k\backslash r} - \varrho^2 q_{k\backslash r}}{\varrho^2} \\ \beta &= \frac{1 - 2\, q_{k\backslash r} - \varrho^2 q_{k\backslash r} + \left(q_{k\backslash r}\right)^2 + \varrho^2 \left(q_{k\backslash r}\right)^2}{\varrho^2} \end{aligned} \tag{9}$$

Assumption 3 implies $\varrho = 0.9463$. Equation (8) can seamlessly be implemented in the Monte Carlo simulation described above.

2.5. Convergence Properties

As mentioned above, the coupling model has been developed to estimate CCF probabilities from operating experience data comprising usually only a small number of events for each component type. However, the model assumptions introduced to facilitate this also imply undesired convergence properties. Firstly, if the data is not compatible with the model assumption that the number of failed component obeys a Binomial distribution for each CCF phenomenon (eq. 1), a convergence to the true values $q_{k\backslash r}$ is generally not possible. More importantly, the assumption that different CCF phenomena may be characterized by different coupling parameters implies a separate estimation of the coupling factor for each event (eq. 4). This implies that distributions $p(q_{k\backslash r})$ are not getting narrower when the number of events grows. As an example, the resulting distributions are identical if one (2 out of 4)-event has been observed during an observation time T to a case where ten (2 out of 4)-events have been observed during observation time $10\,T$. This does not reflect the fact that the evidence on the probabilities of the various failure combinations has grown significantly, which should lead to a smaller estimation uncertainty and thus narrower width of the distributions.

As an increasing part of German operating experience has been evaluated with regard to CCF and hence the number of CCF events available has increased considerably [4,5] this issue is growing in importance. Therefore, GRS has started a research project to evaluate methods to improve CCF modelling with respect to this aspect, which will be described in the following chapter.

3. ALTERNATIVE MODELING OF CCF

3.1. Boundary Conditions of CCF Probability Estimation

Any further development of the model and the procedures for CCF probability estimation has to take into account the boundary conditions prevailing in Germany. According to German PRA guidelines, plant specific operating experience has to be used for quantification whenever possible. Therefore usually plant specific operating experience is used to quantify unavailabilities due to independent failures, while common cause failures are quantified using generic operating experience. As a consequence, only CCF-related information is available in the German CCF data pool. Events with non-systematic (single) failures are not included. Therefore, models which relate the CCF rate to single component failure rates – like the alpha-factor model – cannot directly be applied. The exact number of demands of stand-by components is not available. Instead, observation times have been determined. For the failures during demands operating times have also been calculated. Therefore CCF failure rates have to be estimated (see eq. 1). Not only true CCF, but also "potential CCF" events where multiple components were impaired due to a systematic cause while only one or even no component actually failed are included in the data pool. To improve the accuracy of estimations, this information should also be utilized for CCF quantification. For all events, component impairments and applicability factors have been quantitatively assessed by several experts to allow the consideration of the uncertainty of expert assessments. These uncertainties should be adequately represented in the improved model as well. Generally, the treatment of uncertainties should be as comprehensive and consistent as in the coupling model. Also, the results of CCF quantification (a posteriori distributions) should be representable in a form suitable for practically carrying out PRA calculations including data handling. Ideally they would be independent parametric distributions of the CCF probabilities or well approximable by such distributions.

Modelling approaches to fulfil these requirements are presented in the following section.

3.2. Alternative CCF models

To avoid the undesirable convergence properties associated with the model assumptions discussed above, they would need to be replaced with less restrictive assumptions. An obvious way to achieve this is to replace the phenomenon-dependent binomial distribution with a categorical distribution. Such distributions however do not have group-size independent parameters; hence the "auto-mapping" feature of the coupling model is lost. Therefore, separate mapping algorithms are needed. Alternatively, (k out of r)-CCF with different k could be considered independent elementary events. Here, separate mapping algorithms are needed as well. In the following, two model structures are discussed:

Model A

In model A, CCF events with k out of r failed components occur with a rate $\lambda_{k\backslash r}$. The probability of a (k out of r)-CCF is

$$q_{k\backslash r} = t\, \lambda_{k\backslash r} \tag{10}$$

Model B

In model B, CCF events occur with a rate λ. With conditional probability $\omega_{k\backslash r}$ k of r components fail if a CCF occurs (with $k = 2 \ldots r$). Hence $\sum_{k=2}^{r} \omega_{k\backslash r} = 1$ is valid. The probability of a (k out of r)-CCF is

$$q_{k\backslash r} = t\, \lambda\, \omega_{k\backslash r} \tag{11}$$

The model structures are shown in Figure 1. OK denotes a state where no CCF has occurred.

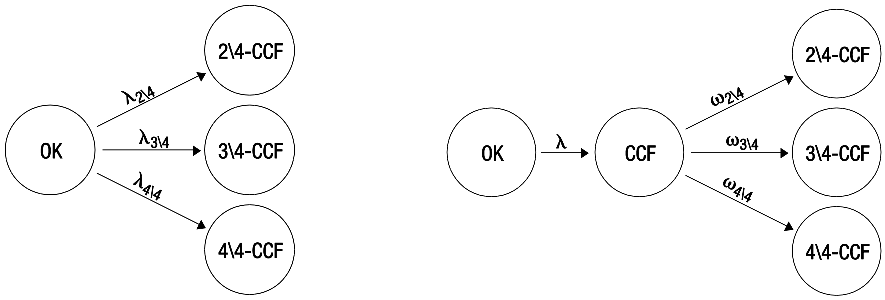

Figure 1: Model structures for model A (left) and B (right) for a CCF group of size 4.

It should be noted that these models are equivalent since $\lambda_{k\backslash r} = \lambda\, \omega_{k\backslash r}$ is valid. Therefore, estimations from operating experience should lead to the very same results, if equivalent a priori distributions are used. However, the different model structures suggest using different a priori distributions, as will be discussed later.

For these models the total observation time T and the numbers $m_{k\backslash r}$ of CCF with k failed components ($k = 2 \dots r$) form a sufficient statistic. It can be written as $(r-1)$-tuple $M := \{m_{2\backslash r}, \dots, m_{r\backslash r}\}$. In general M is not precisely known as mentioned in chapter 2.2. A probability distribution $p(M|\mathfrak{E})$ has to be calculated from the expert assessments $\mathfrak{E}$ of component impairments and applicability factors. This can be done using probability calculus.

It is possible, however, to implement $p(M|\mathfrak{E})$ in a Monte Carlo procedure without calculating the $(r-2)$-dimensional distribution $p(M|\mathfrak{E})$ by noting that for each event the interpretation vector W (see section 2.2) is an expert-specific distribution of the number of failed components. The Monte Carlo procedure consists of first randomly choosing one of the available experts for each event. This reflects the assumption that all experts are equally competent in assessing the events. Then, a number of failed components is drawn from W as estimated by that expert. With probability f (applicability factor) this number is accepted, with $1-f$ the number of failed components is set to 0. This is repeated for every event observed. The total number of cases where $2, 3, \dots, r$ component failures occurred is summed up over all events to calculate the sample of M.

Given M, the model parameters can be calculated. For model A, the model parameter $\lambda_{k\backslash r}$ is only dependent on $m_{k\backslash r}$. This suggests choosing independent a priori distributions for all model parameters, i.e. $\pi(\lambda_{2\backslash r}, .., \lambda_{r\backslash r}) = \prod_{k=2}^{r} \pi_{k\backslash r}(\lambda_{k\backslash r})$. If a non-informative approach is followed, all $\pi_{k\backslash r}$ are chosen identically. Using Jeffreys' rule the a priori distribution becomes

$$\pi(\lambda_{2\backslash r}, .., \lambda_{r\backslash r}) \propto \prod_{k=2}^{r} (\lambda_{k\backslash r})^{-1/2} \tag{11}$$

The a posteriori distribution then also factorizes:

$$P(\lambda_{2\backslash r}, .., \lambda_{r\backslash r}|M) = \prod_{k=2}^{r} \frac{T^{m_{k\backslash r}+1/2}}{\Gamma(m_{k\backslash r}+1/2)} (\lambda_{k\backslash r})^{m_{k\backslash r}-1/2} e^{-\lambda_{k\backslash r}T} \tag{12}$$

with Γ denoting the Gamma function. Hence the model parameters are independent and distributed according to Gamma distributions with parameters $m_{k\backslash r} + 1/2$ and T.

For model B the model parameter λ is only dependent on the total number of CCF events $m_T := \sum_{k=2}^{r} m_{k\backslash r}$, not the individual $m_{j\backslash r}$. This suggests choosing the a priori distribution $\pi(\lambda, \Omega) = \pi(\lambda)\pi(\Omega)$ with $\Omega = \{\omega_{2\backslash r}, ..., \omega_{r\backslash r}\}$ denoting the parameter set of the categorical distribution. If a non-informative approach is followed and Jeffreys' rule is applied the a priori is

$$\pi\left(\lambda, \omega_{2\backslash r}, \ldots, \omega_{r\backslash r}\right) \propto \lambda^{-1/2} \prod_{k=2}^{r} \left(\omega_{k\backslash r}\right)^{-1/2} \tag{13}$$

This implies for the a posteriori distribution

$$P(\lambda, \Omega | M) = \frac{T^{m_T+1/2}}{\Gamma(m_T + 1/2)} \left(\lambda_{k\backslash r}\right)^{m_{k\backslash r}-1/2} e^{-\lambda T} \frac{\prod_{i=2}^{r} \left(\omega_{i\backslash r}\right)^{m_{k\backslash r}-1/2}}{B(m_{2\backslash r} + 1/2, \ldots, m_{r\backslash r} + 1/2)} \tag{14}$$

with $B\left(a_{2\backslash r}, \ldots a_r\right) = \prod_{i=2}^{r} \Gamma(a_{i\backslash r}) / \Gamma\left(\sum_{i=2}^{r} a_{i\backslash r}\right)$. λ is distributed according to Gamma distribution with parameter $m_T + 1/2$ and T. Ω is distributed according to a Dirichlet distribution with parameter set $\{m_{2\backslash r} + 1/2, \ldots, m_{r\backslash r} + 1/2\}$. This mathematically is similar to the alpha factor model; it should be noted though that the meaning of the model parameters is different (see above).

It is worth noting that $P\left(\lambda_{2\backslash r}, \ldots, \lambda_{r\backslash r} | M\right)$ factorizes into $r - 1$ one-dimensional Gamma distributions and $P\left(\lambda, \omega_{2\backslash r}, \ldots, \omega_{r\backslash r} | M\right)$ factorizes into a Gamma and a Dirichlet distribution, while $p(M|\mathfrak{E})$ does in general not factorize. Hence the resulting distributions of model parameters, given the expert assessments, also do not factorize. The same is true of the CCF probabilities $q_{k\backslash r}$. Therefore, in principle, joint probabilities should be used when carrying out uncertainty analyses. The effect of properly including the statistical dependencies in PRA uncertainty calculations is currently under investigation in a GRS research project.

Well-known properties of Gamma and Dirichlet distributions imply that the estimates (12) and (14) in the limit of an infinite number of events converge to their true values. If the number of relevant events is relatively small, however, the different a priori assumptions of model A and B may have a considerable effect on the estimation results.

If, for example, no failures occurred, in model A all $\lambda_{k\backslash r}$ are (independently) distributed with a Gamma distribution with parameters $1/2$ and T. Hence the expectation values are $\langle q_{k\backslash r} \rangle = t / (2T)$. In model B λ is distributed with a Gamma distribution with Parameters $1/2$ and T. $\{\omega_{2\backslash r}, \ldots, \omega_{r\backslash r}\}$ are distributed according to a Dirichlet distribution with parameters $\{1/2, \ldots, 1/2\}$. Hence, the expectation values are $\langle q_{k\backslash r} \rangle = t / (2T(r-1))$, which is smaller by a factor of $(r - 1)$. This may be significant for large CCF groups.

Generally, due to the different a priori assumptions for a finite number of events the expectation values $\langle q_{k\backslash r} \rangle$ are always larger for model A than for model B. Also the width of the uncertainty distributions is larger (see also figures 2-4).

4. COMPARISON OF ESTIMATION RESULTS

To compare the different models, they were used for CCF quantification in various different CCF data sets of German operating experience. The information contained in the German CCF database is partly proprietary. Therefore, representative modified data sets have been prepared which allow to compare the quantification results while protecting the proprietary information. Two of these datasets will be discussed below. Data set one represents populations with a large number of observed events, while data set two represents populations with a very small number of observed events. Data set one has been created by first dropping from an original dataset all events that occurred in a CCF group of a size different from 4 and then dropping a small number of random additional events and multiplying the observation time T by a random number. This data set comprises 15 events. In some events all components were impaired. No more than two components completely failed. Data set two has been created by picking a typical event from component datasets where very few events occurred. In this particular event, one component failed and the remaining three were considered impaired by three experts and unaffected by one expert. The observation time T was selected arbitrarily. The intermediate results before the additional uncertainties (see section 2.4) are included are shown in figure 2.

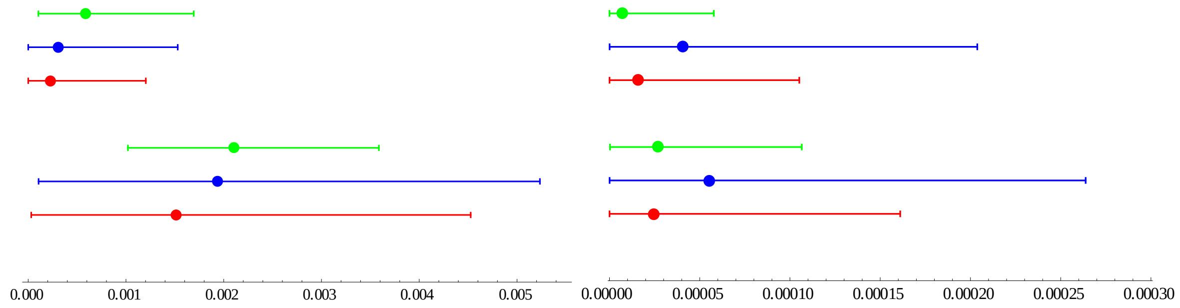

Figure 2: Intermediate estimation results for dataset 1 (left) and dataset 2 (right). Shown are the expectation values (circles) and 95%-confidence intervals (error bars) of estimates of $q_{4\backslash 4}$ (top) and $q_{2\backslash 4}$ (bottom). Estimates of model A are shown in blue, estimates of model B in red, estimates of the coupling model in green.

For the parameter describing failures where substantial empirical evidence is present ($q_{2\backslash 4}$ for data set 1) the results are quite similar (deviations of less than a factor 1.4 in the mean and 1.5 in the 97.5%-quantile). For parameters describing failures that are "extrapolated" from the events observed the deviations between all models are somewhat larger (deviations of up to a factor 5.67 in the mean and 5.52 in the 97.5%-quantile). This can be attributed to the different modelling and a priori assumptions.

The 95%-confidence intervals $[Q_{2.5\%}, Q_{97.5\%}]$ show a very large overlap. In all cases the expectation values of all models lie within the confidence intervals of all other models.

In figure 3 the final results after considering the additional uncertainties are shown.

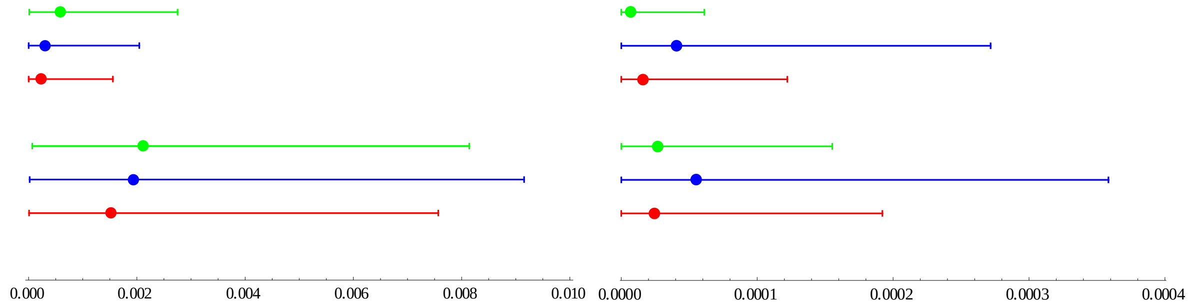

Figure 3: Final estimation results for dataset 1 (left) and dataset 2 (right) after "broadening". Shown are the expectation values (circles) and 95%-confidence interval (error bars) of estimates of $q_{4\backslash 4}$ (top) and $q_{2\backslash 4}$ (bottom). Estimates of model A are shown in blue, estimates of model B in red, estimates of the coupling model in green.

The final results after inclusion of the additional uncertainties are qualitatively the same. While the confidence intervals have grown the mean has not changed (see chapter 2.4).

5. MAPPING

As noted before, for models A and B – in contrast to the coupling model – only those operating experience events can be used directly that occurred in groups with size identical to the component groups CCF probabilities are estimated for. Therefore, if not enough such operating experience is available, separate mapping algorithms have to be used to determine how many components would have failed in groups of different size. This would be especially important in Germany where in many cases group sizes are different in different plants. For example, emergency diesel generators groups of size 2, 3, 4, 5 and 6 exist or existed. Several approaches have been discussed but since CCF genesis and detection are complex and multifarious processes it appears difficult to rate the different approaches or justify a specific approach (see e.g. [12,13] and references therein). Different aspects like the assessment of the modelling uncertainty or the compatibility with a priori beliefs need to be considered. E.g. the assumption that a CCF group is statistically equivalent to an arbitrary subgroup of a larger group is generally not consistent with choosing a non-informative a priori distribution by simply applying Jeffreys' rule like in eq. (11) and (13), an approach that is usually also used for the alpha factor model [12]. This can be easily seen by a simple example: If a group of size three is considered a subgroup of a group of size four $\omega_{2\backslash 3} = 1/2\, \omega_{2\backslash 4} + 3/4\, \omega_{3\backslash 4}$ holds which implies $\omega_{2\backslash 3} \leq 3/4$. This is not consistent with the non-informative prior chosen according to Jeffreys' rule $\pi\left(\lambda, \omega_{2\backslash 3}, \omega_{3\backslash 3}\right) \propto 1/\sqrt{\lambda \omega_{2\backslash 3} \omega_{3\backslash 3}}$ where no bounds on $\omega_{2\backslash 3}$ are present. This is due to the fact that the information mentioned above is not accounted for. Similarly, the assumption of a Binomial distribution often used for mapping is conflicting with the a priori belief of eq. (11) and (13). Estimation procedures utilizing such assumptions and conflicting non-informative priors would suffer from inconsistency.

Therefore, for the present studies a simple procedure was applied. When mapping down, it consists of "deleting" the least affected components. When mapping up, it consists of "duplicating" the most affected components. This means an event with 2 failed and 2 impaired components would be mapped to an event with 2 failed and one impaired component for group size three or to an event with 3 failed and 2 impaired components for group size five. It is evident that this approach is conservative under any circumstances. While for large differences in group sizes this approach appears to be overly conservative, for small differences, e.g. group sizes differing by only one it may lead to reasonable results. One example is shown in figure 4. Here a data set comprising CCF groups of size 3 and 4 was considered. The observation time for CCF groups of size 3 was 5 % of the total observation time. There is one event in a component group of size 3 and 15 events in groups of size 4. Estimates using model A have been calculated both from data from groups of size 3 and from data from groups of sizes 3 and 4, applying the mapping algorithm described above. The coupling model has been applied to data from both groups of sizes 3 and 4, making use of the "auto mapping" feature.

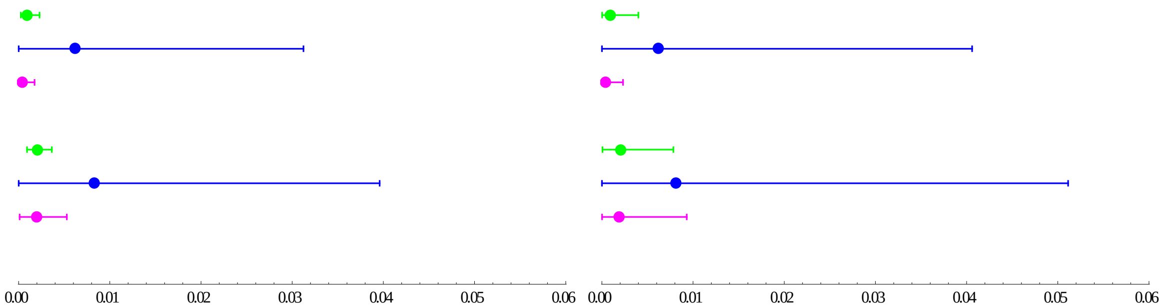

Figure 4: Intermediate (left) and final estimation results (right). Shown are the expectation values (circles) and 95%-confidence interval (error bars) of estimates of $q_{3\backslash 3}$ (top) and $q_{2\backslash 3}$ (bottom). Estimates of model A using the data set of events and observation time in component groups of size 3 are shown in blue, estimates of model A using the data set of events in component groups of size 3 and mapped events of group size 4 and appropriate observation time are shown in magenta. Estimates with the coupling model are shown in green.

The results for model B using the data set including mapped data and the coupling model result in similar estimates. In all four cases the expectation values lie within the confidence intervals of the other model. The estimates using operating experience only of groups of size 3 are significantly different. Both uncertainty and expectation values are larger. This can be attributed to the considerably smaller amount of operating experience both in terms of observation time and number of events.

6. CONCLUSION

The methods for quantification of CCF applied by GRS have been continuously improved. A new procedure for the consideration of additional uncertainties not treated before which is consistent with the Bayesian framework used in CCF quantification has been established. The convergence properties of the coupling model have been researched. Theoretical considerations show that for very large data sets the coupling model has undesirable properties preventing an adequate representation of the reduction of statistical uncertainty. Therefore comparative studies have been carried out to assess the relevance for the actual operating experience with regard to CCF in Germany. Two different models have been developed which are suitable for estimating CCF probabilities from the information available in the German CCF database. They do not use the restrictive modelling assumption on which the coupling model is based and therefore no undesirable convergence properties are present. Comparisons show that for present German operating experience no significant deviations are found. The deviations of the numerical results between all the three different methods are comparable. Therefore, modeling decisions need to be based on theoretical properties and practical considerations. While the coupling model has the convenient "auto-mapping" feature, Model A is free from any, possibly non-conservative, modeling assumptions. In the further course of the research project these properties will be evaluated in more detail. The development and evaluation of suitable mapping algorithms will be an additional focus of future research.

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