Modelling and Quantification of Correlated Failures of Multiple Components due to Asymmetries of the Electrical Power Supply System of Nuclear Power Plants in PSA

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Abstract: Failures of multiple redundant trains of the electrical power supply systems at nuclear power plants (NPPs) have recently gained increasing attention by the nuclear community. This was triggered by events at different NPPs where single component failures affected multiple redundant trains, e.g., at the Byron and Forsmark NPPs. In both events, the electrical consumers remained connected to the fault and were exposed to an asymmetric voltage supply, leading to the unavailability and the destruction of safety related electrical equipment. To consider such events in probabilistic safety analyses (PSAs), the failures of electrical components due to an asymmetry in the electrical power supply system have to be adequately modelled and quantified. A comprehensive analysis of national and international operating experience has shown that component failures resulting from an asymmetry cannot be modelled as independent events but are strongly correlated. Identical components with comparable loads tend to fail simultaneously. This is highly important to safety since redundant components are likely to be affected by such correlated failures. To grasp this effect, different modelling approaches have been devised. Estimation algorithms for the respective model parameters have been developed and applied utilizing the available international operating experience.

1. INTRODUCTION

Faults simultaneously impairing multiple trains of the electrical power supply systems at nuclear power plants (NPPs) have recently gained increasing attention by the nuclear community [1]. This was triggered by events occurred at different NPPs that involved so-called asymmetrical faults. An asymmetrical fault results from the degradation (e.g. an interruption) of one or two of the three phases in a three-phase alternating current system. For example, at the Byron NPP in the U.S., an asymmetry in the power supply system resulted from a single failure of an insulator in the switchyard of the plant. The asymmetry failed to cause the reactor protection system (RPS) to initiate the isolation of the emergency bus bars and the operation of the emergency diesel generators. As another example, at the Forsmark NPP in Sweden, the failure of one pole of a breaker to open led to an open phase condition that was also not detected by the RPS. In both cases, the electrical consumers remained connected with the fault and were exposed to an asymmetric electric energy supply, leading to the unavailability and even the destruction of electrical equipment. The electrical power supply system is particularly susceptible to faults affecting multiple trains since there is no separation between the redundant trains during (normal) power operation.

Such events have generally not been included in PSAs of NPPs yet, which may be attributed to the apparent past general underappreciation of the possible importance of such phenomena. Therefore, GRS has initiated research projects aiming at a comprehensive in-depth analysis of events characterized by fault states of multiple trains of the electrical power supply system, including, but not limited to, open phase conditions, and at the development of modeling and quantification methods to include them in PSAs [1].

Initially, the failure of components due to an asymmetric electrical energy supply was modelled by an asymmetry-dependent failure probability, i.e., it was assumed that components fail independent from each other with a probability that is dependent on the asymmetry of the energy supply for the specific component. The relation between asymmetry and failure probability was derived from theoretical considerations in connection with selected operating experience. The asymmetries for the different components were calculated using a detailed model of the energy supply system at ra modern pressurized water reactor reference plant [2]. Generally, the asymmetry at different bus bars is different due to the effects of transformers and loads. Redundant bus bars usually have similar asymmetry values since they have similar loads and similar connections to other parts of the electrical energy supply system. This causes a correlation of failures of components on redundant bus bars, which generally includes the groups of identical and redundant components. The analysis of the international operating experience, however, showed that the observed correlation of failures of identical components with similar loads is much stronger than predicted by this model [1], i.e., in many cases, identical components with similar loads fail while other components at the same bus bars are unaffected. This is of high importance to PSA results since redundant components are likely to be affected by such correlated failures. Therefore, approaches to improve the modelling by more adequately including the correlations of failures of identical components with similar loads have been devised. Algorithms to estimate the model parameters and their uncertainties have been developed and applied utilizing international operating experience.

In the following, different modelling approaches are presented. The model parameters are estimated based on an analysis of national and international operating experience. Finally, the results are presented and discussed and an outlook on the planned further activities is given.

2. ANALYSIS OF OPERATING EXPERIENCE

As a basis for the modelling and quantification of the correlated failures of components due to an asymmetric electrical energy supply, in a first step the relevant national and international operating experience was analyzed. Since the rates of relevant initiating events had been assessed and quantified before [1-2] the present analysis focused on the (correlated) component failures. For the following ten events, quantitative information on component failures during asymmetries of the electrical energy supply system could be determined from sources available to the analysts including licensee event reports (LERs), e.g. [3], event reports of the IAEA International Reporting System for Operating Experience (IRS), e.g. [4], internal reports, e.g., [5], and documents and reports published by regulators, e.g., [6], or other organizations such as the IAEA, e.g. [7]):

- Kalinin, Unit 1, 1994,
- Balakowo, Units 1 und 3, 1997,
- South Texas, Unit 2, 2001,
- Vandellòs, Unit 2, 2006,
- Dungeness-B, 2007,
- Bruce A-1, 2012,
- Byron, Unit 2, 2012,
- Forsmark, Unit 3, 2013,
- Dungeness-B-2, 2014, and
- Biblis, Unit A, 2014.

In total, 63 groups of identical components with similar loads that were exposed to the asymmetry and where components failed were identified. For 18 groups, the number of exposed and of failed components could be investigated, for three additional groups, incomplete information was found. Regarding these three groups, it could be established that multiple components had been exposed to the asymmetry and that all components failed while the exact number of exposed components could not be determined.

Generally, in this analysis only actually exposed components and actual component failures were considered. The results of technical analyses of further component failures that would have occurred if additional components were operated were not included.

In many cases, the exact number of exposed component groups could not be determined. In these cases, a rough estimate was used. An analysis of the operation of a German NPP similar to the reference plant showed that the number of groups of identical components with similar loads that would be exposed to an asymmetry of the electrical power supply system during normal operation and whose failure would likely be reported is approximately 90. This number of exposed component groups was also used for other plants if no specific information was available. The real number is expected to deviate significantly for different plants and different plant operational states (POS); however, a deviation by a factor larger than 3 (corresponding to less than 30 or more than 270 groups) appears to be unlikely. It should be noted that this number pertains to *groups* of identical components with similar loads, not individual components. Hence, the degree of redundancy implemented in the plant does not affect this number. If in an event two reactor units were affected by an asymmetry, the double number was used. In some instances, the exact number could be determined for a specific subset of components (e.g., in the Byron, Unit 2, 2012 event, the medium voltage loads). Then, only this subset was used.

3. MODELLING AND QUANTIFICATION OF CORRELATED FAILURES

Operating experience shows that, when exposed to an asymmetry of the electrical energy supply, identical components with similar loads are likely to fail together. Therefore, the model focusses on estimating the probability of specific failure combinations of components of such groups. First, the groups of identical components with similar loads are identified. In most cases, these are the sets of redundant components running at the onset of the asymmetry or started in the course of the event, e.g., the auxiliary feedwater pumps, or the diesel building air supply fans.

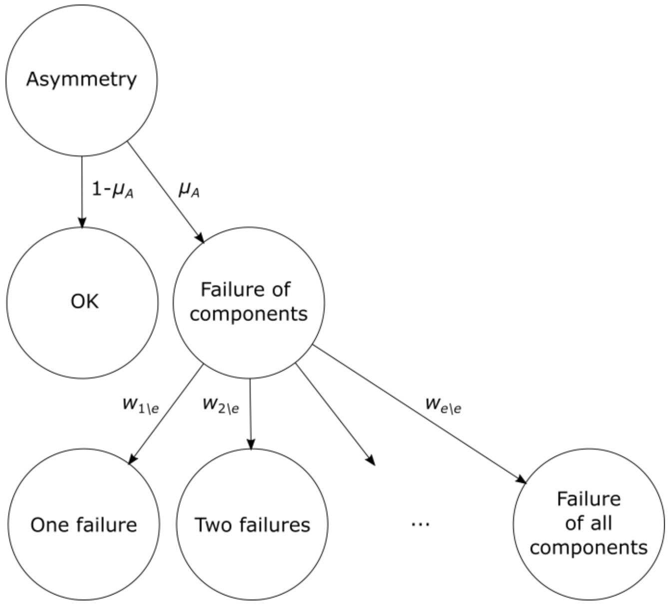
The general model consists of two stages (see Figure 1). If an asymmetry occurs with a certain probability μ_{A} failures occur in the group (stage I). If failures do occur k out of the e components exposed to the asymmetry fail with probability $w_{k\backslash e}$, $k = 1 \ldots e$ (stage II). For a specific event, μ_{A} and $w_{k\backslash e}$ are assumed to be identical for all component groups. They can, however, be different for different events, i.e., different asymmetries, as will be discussed later. According to the model, the probability $p_{k\backslash e}$ that k out of the e components fail is $q_{k\backslash e} = \mu_A \, w_{k\backslash e}$ while no components in the group fail with probability $q_{0\backslash e} = 1 - \mu_{\mathrm{A}}$.

In the following, for each of the two stages different specific modelling approaches are discussed.

3.1. Stage I

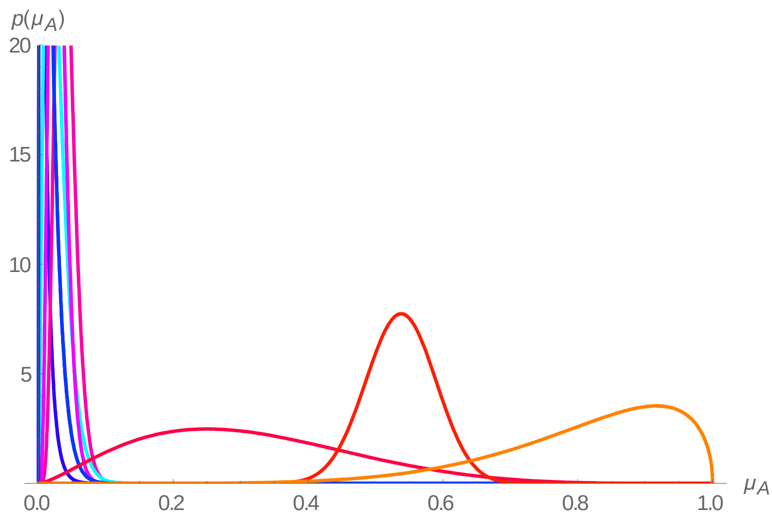
For stage I, two different approaches have been considered. Approach I.1 is based on the direct analysis of the national and international operating experience discussed above. Based on the numbers of groups of identical components with similar loads that were exposed to the asymmetry and on the numbers of these groups affected by component failures, an uncertainty distribution $p(\mu_{\mathrm{A}})$ was estimated.

Figure 1: Two Stages of the Model



If n groups have been exposed to the asymmetry and in n_{A} groups failures have been observed the statistical uncertainty of μ_{A} may be expressed as Bayesian posterior distribution. If a noninformative prior is chosen according to Jeffreys rule [8] as $1/\left(\sqrt{\mu_{\mathrm{A}}}\sqrt{1-\mu_{\mathrm{A}}}\right)$ the posterior is a Beta distribution with parameters $n_{\mathrm{A}}+1/2$ and $n-n_{\mathrm{A}}+1/2$, i.e., $p\left(\mu_{\mathrm{A}}|n_A,n_{ges}\right)=p_{\mathrm{Beta}}(\mu_{\mathrm{A}}|n_A+1/2,n-n_A+1/2)\propto {\mu_{\mathrm{A}}}^{n_A-1/2}(1-\mu_{\mathrm{A}})^{n-n_A-1/2}$. This distribution expresses the statistical uncertainty associated with the finite number of groups observed in one event. Observations from different events cannot be pooled since μ_{A} cannot be assumed to be identical in all events. This is illustrated in Figure 2: The different posterior distributions $p\left(\mu_{\mathrm{A}}|n_A,n_{ges}\right)$ estimated from the ten individual operating experience data sets identified do not overlap, i.e., a common value of μ_{A} pertaining to all events can be excluded.

Figure 2: Probability Density Functions of the Posterior Distributions of μ_A for Different Events*



* E.g., the orange curve shows the probability density function for the Byron, Unit 2 2012 event.

As demonstrated in Figure 2, in most cases the data indicate small values of μ_{A}, but some events also show large values $\mu_A \lesssim 1$. To model this, a mixture distribution of a uniform distribution on the unit interval and a Beta distribution can be used:

$$p_{\mathrm{Model}}(\mu_A) := \frac{1}{3} + \frac{2}{3}\, p_{\mathrm{Beta}}(\mu_A | 4.35, 178.67) \tag{1}$$

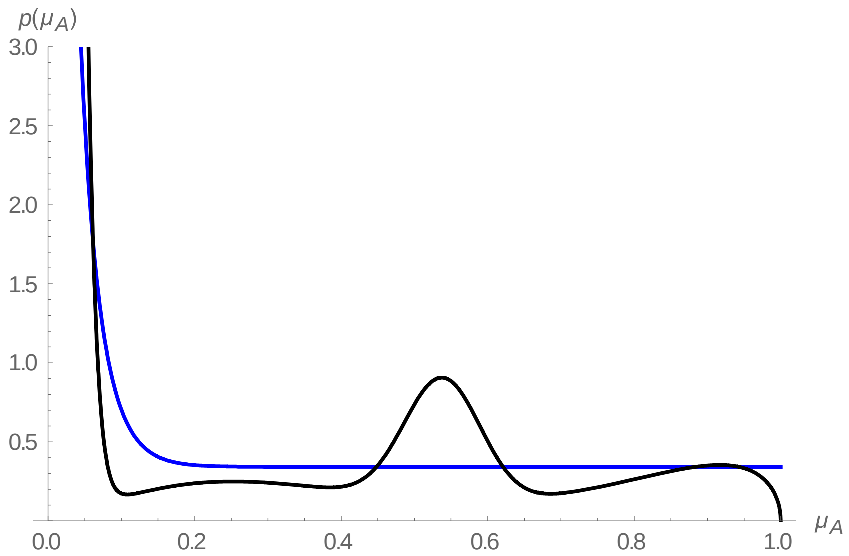
The distribution parameters of p_{Model} have been chosen such that they have similar characteristics as the mixture distribution (see Table 1). The choice of the weight 1/3 resulted from the following consideration: The probability function after the initial peak at $\mu_{\mathrm{A}} \approx 0$ is approximately 0.7. Since the tail of the Beta function beyond 0.1 may be neglected, this implies that the uniform distribution has a weight of approximately $0.3/0.9 = 1/3$.

Figure 3 compares the mixture distribution of the posterior distributions of the ten individual events with p_{Model}.

Table 1: Comparison of the Characteristics of the Model Distribution and the Mixture Distribution of the Posterior Distributions of the Individual Events

	Model distribution p_{Model}	Mixture distribution of the posterior distributions of the individual events
Mean	0.18	0.18
Standard deviation	0.28	0.28
Median	0.030	0.032
5%-quantile	0.28	0.28
95%-quantile	0.85	0.84
K95[†]	28.8	26.5

Figure 3: Comparison of p_{Model} (Blue) with the Mixture Distribution of the Posterior Distributions of μ_{A} of the Individual Events (Black)



In the further course of the project, additional approaches such as a two-stage Bayesian model also will be considered.

[†] K95 is the quotient of the 95% quantile and the median.

In the alternative approach I.2, the model for component failures developed in the previous stage of the project [1-2] is used. Assuming all components of the group are exposed to a similar asymmetry and hence have a similar individual failure probability f (which turned out to be the case in all simulations carried out so far), a relation between the individual failure probability of a component and the probability that at least one failure occurs in a group can be established using the average number of failures in a group with e exposed components, $e\,f = \mu_{\mathrm{A}} \sum_{k=1}^{e} k\, w_{k\backslash e}$. The result

$$\mu_{\mathrm{A}} = \frac{e\,f}{\sum_{k=1}^{e} k\, w_{k\backslash e}} \tag{2}$$

depends on both f and on the results of stage II of the model (i.e., the values of the $w_{k\backslash e}$, see Section 2.2). In well-known PSA codes (e.g., RiskSpectrum and SAPHIRE) this calculation can be done implicitly by applying the automated common cause failure (CCF) modelling with the Alpha factor model: For each component, a basic event is generated that represents the failures of the individual components due to an asymmetry. CCF groups are defined as groups of such basic events pertaining to identical components with similar loads.

In this approach, the different possible scenarios leading to an asymmetry are reflected by different values for f resulting from the simulation of the respective scenario in the model of the electric energy supply system.

3.2. Stage II

For stage II, also two different approaches have been considered. The first approach II.1 consists of directly estimating the $w_{k\backslash e},\ k = 1 \dots e$ from operating experience similar to the Alpha factor model. Here, obviously, only operating experience with a matching number of exposed components e may be used, unless additional "mapping" algorithms are applied, which are based on assumptions on how many failures would have occurred for a different number of exposed components. From the available operating experience, events have been observed for group sizes of 2 to 4. The uncertainty of the parameters can be expressed as Bayesian posterior distributions. If a noninformative prior is chosen according to Jeffreys [8] and $n_{k\backslash e}$ events with k failures out of the e exposed components, $k = 1 \dots e$, have been observed the resulting distribution is a Dirichlet distribution with parameters $a_{k\backslash e} = n_{k\backslash e} + 1/2$, i.e.,

$$p\left(w_{1\backslash e}, w_{2\backslash e}, \dots\ w_{e\backslash e}\right) = p_{\mathrm{Dirichlet}}\left(w_{1\backslash e}, w_{2\backslash e}, \dots\ w_{e\backslash e} | a_{1\backslash e}, a_{2\backslash e}, \dots\ a_{e\backslash e}\right) \\ \propto \prod_{k=1}^{e} \left(w_{k\backslash e}\right)^{n_{k\backslash e}-1/2} \tag{3}$$

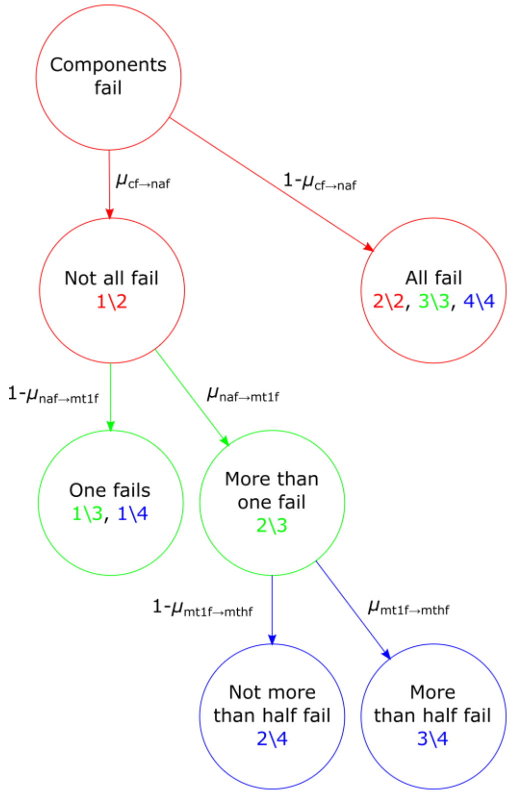
The parameter estimates resulting from using the operating experience described above are given in Table 2.

Table 2: Parameters of the Dirichlet Distributions of $w_{k\backslash e}$

Number e of exposed components	$a_{1\backslash e}$	$a_{2\backslash e}$	$a_{3\backslash e}$	$a_{4\backslash e}$
2	0.5	9.5	N.A.	N.A.
3	0.5	0.5	5.5	N.A.
4	1.5	1.5	0.5	2.5

The alternative approach II.2 is based on a hierarchical model. The model topology (cf. Figure 4) is based on the following considerations: The loads and the configuration of the protective devices of the components of a component group can be such that the failure of the components is certain if the asymmetry occurs. Therefore, the graph initially branches into "failure of all components" and "no failure of all components". If a failure of all components is not certain, the probability of failure of the components may be so low that it is unlikely that more than one component will fail. Therefore, the graph now branches into failures of only one component and failures of multiple (but not all) components. For groups of size 4, this node cannot be uniquely assigned to a failure combination, so there is a further branching into the nodes “failure of more than half of the components” and “failure of not more than half of the components”.

Figure 4: Hierarchical Model II.2



For groups of two exposed components, only the red part of the graph is relevant, for groups of three, the red and the green part and for groups of four the whole graph. In Figure 4, the end states for all possible failures for group size up to four are shown in the respective nodes. For groups larger than four, a specific failure still maps to a unique path in the model, i.e., such events can be used to calculate model parameters. To estimate failure probabilities, however, the model must be extended. E.g., to cover groups up to the size of six, two subsidiary notes of “failure of not more than half of the components” for two and three failures of six exposed components, respectively, are added. Similarly, two subsidiary notes of “failure of more than half of the components” are added for four and five failures, respectively. If no operating experience is available to quantify the transitions to these states, the a priori distribution of the transition probabilities as discussed above describes the uncertainty of the transition probabilities.

This model also allows for the utilization of incomplete information: If, e.g., for a group of identical components with similar loads it is known that all exposed components failed while the exact number of exposed components is unknown this information can still be utilized for the estimation of the model parameter $\mu_{cf\to naf}$.

The model has three independent parameters: The conditional probability that not all components failed, given that failures occurred in the group $\mu_{\mathrm{cf}\to\mathrm{naf}}$, the conditional probability that more than one component failed, given that not all components failed $\mu_{\mathrm{naf}\to\mathrm{mt1f}}$ and the conditional probability that more than half of the components failed, given that more than one component failed $\mu_{\mathrm{mt1f}\to\mathrm{mthf}}$.

It is important that, if any subsidiary nodes can be accessed from a node for a specific group size, all subsidiary nodes can in principle be accessed for that group sizes. Otherwise, the transition probabilities would have to be calculated group-size-dependent (which neglects the main advantage of the model) or a bias in estimations would occur depending on the statistics of observed group sizes.

For the estimation of the model parameters, it is important that any observation corresponds to a unique path through the model. This allows to exactly calculate the number of transitions from each node to its subsidiary nodes. With this information, the transition probabilities and their uncertainties can be calculated. The uncertainties are, again, expressed as Bayesian posterior distributions and a noninformative prior according to Jeffreys is chosen. If a node "h" is superior to nodes "$l1$" and "$l2$" and $n_{h\to l1}$ transitions from "h" to "$l1$" and $n_{h\to l2}$ transitions from "h" to "$l2$" occurred, the transition probability $\mu_{h\to l1}$ is distributed according to a Beta distribution with parameters $n_{h\to l1} + 1/2$ and $n_{h\to l2} + 1/2$. Correspondingly $\mu_{h\to l2} = 1 - \mu_{h\to l2}$ is distributed according to a Beta distribution with parameters $n_{h\to l2} + 1/2$ and $n_{h\to l1} + 1/2$.

If groups of sizes two, three or four have been observed, the numbers of transitions can be calculated from the observed failure combinations $n_{k\backslash e}$ as

$$\begin{aligned}
&n_{\text{cf}\to\text{naf}} = n_{1\backslash 2} + n_{1\backslash 3} + n_{1\backslash 4} + n_{2\backslash 3} + n_{2\backslash 4} + n_{3\backslash 4},\\
&n_{\text{cf}\to\text{af}} = n_{2\backslash 2} + n_{3\backslash 3} + n_{4\backslash 4},\\
&n_{\text{naf}\to\text{mt1f}} = n_{2\backslash 3} + n_{2\backslash 4} + n_{3\backslash 4},\\
&n_{\text{naf}\to\text{1f}} = n_{1\backslash 3} + n_{1\backslash 4},\\
&n_{\text{mt1f}\to\text{mthf}} = n_{3\backslash 4},\\
&n_{\text{mt1f}\to\text{nmthf}} = n_{2\backslash 4}.
\end{aligned} \tag{4}$$

As mentioned before, for some events with incomplete information it may be possible to determine part of the path. Then, the respective numbers of transitions are added to the numbers in equation 4.

Considering the respective paths through the model, the conditional failure probabilities can easily be calculated as

$$\begin{aligned}
&w_{1\backslash 2} = \mu_{\text{cf}\to\text{naf}},\\
&w_{2\backslash 2} = 1 - \mu_{\text{cf}\to\text{naf}},\\
&w_{1\backslash 3} = \mu_{\text{cf}\to\text{naf}}(1 - \mu_{\text{naf}\to\text{mt1f}}),\\
&w_{2\backslash 3} = \mu_{\text{cf}\to\text{naf}}\,\mu_{\text{naf}\to\text{mt1f}},\\
&w_{3\backslash 3} = 1 - \mu_{\text{cf}\to\text{naf}},\\
&w_{1\backslash 4} = \mu_{\text{cf}\to\text{naf}}(1 - \mu_{\text{naf}\to\text{mt1f}}),\\
&w_{2\backslash 4} = \mu_{\text{cf}\to\text{naf}}\,\mu_{\text{naf}\to\text{mt1f}}(1 - \mu_{\text{mt1f}\to\text{mthf}}),\\
&w_{3\backslash 4} = \mu_{\text{cf}\to\text{naf}}\,\mu_{\text{naf}\to\text{mt1f}}\,\mu_{\text{mt1f}\to\text{mthf}},\\
&w_{4\backslash 4} = 1 - \mu_{\text{cf}\to\text{naf}}.
\end{aligned} \tag{5}$$

Due to the relations in equation 5, the $w_{k\backslash e}$ are dependent, i.e., their joint distribution does not factorize. Their distribution and also the marginal distributions of $w_{k\backslash e}$, $k = 1 \ldots e-1, e > 2$ cannot be expressed analytically. They are, however, easily assessable by a Monte Carlo simulation, as shown below.

Both models have advantages and disadvantages: Model II.1 does not rely on any specific assumptions. But for every group size, only operating experience pertaining to groups of that size can be utilized. In contrast, model II.2 allows the use of the entire operating experience and the extrapolation to larger groups. This is important, since groups of size 6 are present in the PSA model of the reference plant. The assumptions underlying the model are plausible but cannot be verified given the limited data available. In contrast to model II.1, model II.2 allows for the utilization of incomplete information.

3.3. Combination of the Two Stages

To estimate the probabilities $p_{k\backslash e}$ that k out of the e components fail, the results of both stages have to be combined. Since no simple analytic expression for the uncertainty distribution of $q_{k\backslash e} = \mu_A \, w_{k\backslash e}$, $k = 1 \ldots e$ is available, a Monte Carlo approach need to be applied.

If the $w_{k\backslash e}$ are modelled directly (model II.1), the Monte Carlo algorithm is as follows:

Repeat the following steps S times:

1. Draw a sample of values $w_{1\backslash e}, w_{2\backslash e}, \ldots\, w_{e\backslash e}$ from $p_{\mathrm{Dirichlet}}\left(w_{1\backslash e}, w_{2\backslash e}, \ldots\, w_{e\backslash e} \middle| n_{1\backslash e} + 1/2, n_{2\backslash e} + 1/2, \ldots\, n_{e\backslash e} + 1/2\right)$.
2. a. For model I.1: Draw a sample of μ_A from $p_{\mathrm{Model}}(\mu_A)$, see equation 1.
   b. For model I.2: Calculate μ_{A} according to equation 2.
3. Calculate values $q_{k\backslash e} = \mu_{\mathrm{A}} \, w_{k\backslash e}$ for $k = 1 \ldots e$.

If the $w_{k\backslash e}$ are modelled indirectly, i.e., are derived from the graph in Figure 4 (model II.2), the Monte Carlo algorithm is:

Repeat the following steps S times:

1. Draw a sample of $\mu_{\mathrm{cf \to naf}}$ from $p_{\mathrm{Delta}}(\mu_{\mathrm{cf \to naf}} | n_{\mathrm{cf \to naf}} + 1/2, n_{\mathrm{cf \to acf}} + 1/2)$ with $n_{\mathrm{cf \to acf}}$ denoting the number of events where all component failed and $n_{\mathrm{cf \to naf}}$ the number of events where not all component failed.
2. Draw a sample of $\mu_{\mathrm{naf \to mt1f}}$ from $p_{\mathrm{Delta}}(\mu_{\mathrm{naf \to mt1f}} | n_{\mathrm{naf \to mt1f}} + 1/2, n_{\mathrm{naf \to 1cf}} + 1/2)$ with $n_{\mathrm{naf \to mt1f}}$ denoting the number of events where more than one (but not all) component failed and $n_{\mathrm{naf \to 1cf}}$ the number of events where one component failed.
3. Draw a sample of $\mu_{\mathrm{mt1f \to mthf}}$ from $p_{\mathrm{Delta}}(\mu_{\mathrm{mt1f \to mthf}} | n_{\mathrm{mt1f \to mthf}} + 1/2, n_{\mathrm{mt1f \to nmthf}} + 1/2)$ with $n_{\mathrm{mt1f \to mthf}}$ denoting the number of events where more than half of the components (but neither all nor one) failed and $n_{\mathrm{mt1f \to nmthf}}$ the number of events where not more than half of the components (but neither all nor one) failed.
4. Calculate values $w_{1\backslash e}, w_{2\backslash e}, \ldots\, w_{e\backslash e}$ using equation 5.
5. a. For model I.1: Draw a sample of μ_A from $p_{\mathrm{Model}}(\mu_A)$, see equation 1.
   b. For model I.2: Calculate μ_{A} according to equation 2.
6. Calculate values $q_{k\backslash e} = \mu_{\mathrm{A}} \, w_{k\backslash e}$ for $k = 1 \ldots e$.

The set of S resulting e-tuples is distributed according to the desired distribution $p(q_{1\backslash e}, q_{2\backslash e}, \ldots\, q_{e\backslash e})$.

As an alternative, the calculation of $q_{k\backslash e}$ can in part be done by PSA programs using the automated CCF modelling. Then, for model II.1, step 3, and for model II.2, step 6 is implemented in the PSA software. When using model I.2, the failure probability of the individual components f required for the calculation is already available (see Section 2.1). Then, steps 2.b. and 5.b. are unnecessary. For Model I.1, after drawing a sample of μ_A (steps 2.a or 5.a) the failure probability of the individual components may be calculated as $f = \frac{1}{e} \mu_{\mathrm{A}} \sum_{k=1}^{e} k \, w_{k\backslash e}$ (inversion of equation 2).

A generalization to models with additional nodes is straightforward.

4. RESULTS

In the following, estimates of $q_{k\backslash e}$ are shown. Here, regarding stage I only results with an estimation of μ_A based on the operating experience presented in chapter 1 are considered (model I.1) since in the alternative approach I.2 the values of f are dependent on the specific scenario and on the specific group of exposed components in that scenario, and no statistics of these values is currently available. Comparisons of the different approaches for stage I will be carried out when the results of the current modelling efforts are integrated into the PSA model of the reference plant.

Table 3 presents the mean values and the standard deviations of the resulting marginal distributions of the probability $q_{k\backslash e}$ that k out of e exposed components fail.

Table 3: Comparison of the Mean Values and the Standard Deviations (SD) of the Marginal Distributions of the Probability $q_{k\backslash e}$ that k out of e Exposed Components Fail as Estimated with Models II.1 and II.2

Model		$q_{1\backslash 2}$	$q_{2\backslash 2}$	$q_{1\backslash 3}$	$q_{2\backslash 3}$	$q_{3\backslash 3}$	$q_{1\backslash 4}$	$q_{2\backslash 4}$	$q_{3\backslash 4}$	$q_{4\backslash 4}$
II.1	Mean	9.13 E-03	0.17	1.40 E-02	1.41 E-02	0.15	4.57 E-02	4.57 E-02	1.51 E-02	7.62 E-02
II.2	Mean	2.90 E-02	0.15	1.82 E-02	1.09 E-02	0.15	1.82 E-02	8.18 E-03	2.73 E-03	1.50 E-01
	Quot.	3.17	0.88	1.29	0.78	0.99	0.40	0.18	0.18	2.02
II.1	SD	2.64 E-02	0.27	3.97 E-02	3.97 E-02	0.25	9.04E-02	9.03 E-02	4.24 E-02	1.30 E-01
II.2	SD	5.22 E-02	0.24	3.51 E-02	2.35 E-02	0.24	3.51 E-02	1.87 E-02	8.77 E-03	2.40 E-01
	Quot.	1.98	0.89	0.88	0.59	0.98	0.39	0.21	0.21	1.79

The results of the two different approaches are quite similar. The most significant differences concern two and three failures, respectively, out of four exposed components. Here, the different bases of the estimations become apparent: While for small groups of size two to three, only failures of the whole group have been observed, for groups of size four also failures of a subset of components occurred. Therefore, in model II.2, where all observations enter, the estimates of $q_{2\backslash 4}$ and $q_{3\backslash 4}$ are much smaller than in model II.1. Conversely, $q_{4\backslash 4}$ is larger in model II.1. These differences, however, may be expected to be of minor importance since they are smaller than the widths of the uncertainty distributions (see also Table 4 in the Appendix). This will be further analyzed as soon as the corelated failures have been implemented in the PSA model. Then, also systematic comparisons of the approaches I.1 and I.2 will be carried out. When performing an uncertainty analysis, it is necessary to use coupled random variables, since the different $q_{k\backslash e}$ are strongly correlated due to their common factor μ_{A}.

5. CONCLUSION

Different approaches have been developed which allow to more realistically model the correlated failures of components exposed to an asymmetry of the electrical energy supply. The models have been quantified based on the analysis of ten relevant events observed from national and international operating experience in nuclear power plants using Bayesian statistical methods.

In the further course of the project, models and quantifications presented in this paper will be applied to the PSA model of the reference plant to quantitatively assess the importance of events with an asymmetry of the electrical power supply system in NPPs.

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APPENDIX

The following Table 4 provides characteristics of the marginal distributions of the conditional probabilities $q_{k\backslash e}$ that k out of a group of e exposed identical components with similar loads fail when exposed to an asymmetry. Both estimates using model II.1 and II.2 are presented.

Table 4: Characteristics of the Marginal Distributions of the $q_{k\backslash e}$

$k\backslash e$	Model	Mean	Standard Deviation	5% Quantile	Median	95% Quantile	K95†
1\2	II.1	9.13 E-03	2.64E-02	5.30 E-07	4.52 E-04	5.27 E-02	116.7
1\2	II.2	2.90 E-02	5.22E-02	2.03 E-05	3.32E-03	1.50 E-01	44.1
2\2	II.1	1.70 E-01	2.70 E-01	1.49 E-04	2.21E-02	8.10 E-01	36.7
2\2	II.2	1.50 E-01	2.40 E-01	1.31 E-04	1.94 E-02	7.20 E-01	36.8
1\3	II.1	1.40 E-02	3.97 E-02	8.49 E-07	7.15E-04	8.18 E-02	114.5
1\3	II.2	1.82 E-02	3.51 E-02	1.09 E-05	1.96 E-03	9.46 E-02	48.4
2\3	II.1	1.41 E-02	3.97 E-02	8.29 E-07	7.11 E-04	8.25 E-02	116.1
2\3	II.2	1.09 E-02	2.35 E-02	4.93 E-06	1.04E-03	5.89 E-02	56.5
3\3	II.1	1.50 E-01	2.50 E-01	1.30 E-04	1.95 E-02	7.30 E-01	37.5
3\3	II.2	1.50 E-01	2.40 E-01	1.30 E-04	1.95 E-02	7.20 E-01	36.7
1\4	II.1	4.57 E-02	9.04 E-02	2.39 E-05	4.70 E-03	2.50 E-01	52.6
1\4	II.2	1.82 E-02	3.51 E-02	1.12 E-05	1.96 E-03	9.45 E-02	48.2
2\4	II.1	4.57 E-02	9.03 E-02	2.37 E-05	4.69 E-03	0.24802	52.9
2\4	II.2	8.18 E-03	1.87 E-02	3.16 E-06	7.23 E-04	4.4 8E-02	62.0
3\4	II.1	1.51 E-02	4.24 E-02	9.15 E-07	7.75 E-04	8.89 E-02	114.7
3\4	II.2	2.73 E-03	8.77 E-03	1.25 E-07	1.16 E-04	1.51 E-02	130.1
4\4	II.1	7.62 E-02	1.30 E-01	5.29 E-05	8.8 1E-03	3.90 E-01	44.2
4\4	II.2	1.50 E-01	2.40 E-01	1.33 E-04	1.95 E-02	7.20 E-01	36.7