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A Reflection on Time and Parameters in Common Mode/Cause Failures

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Common cause, or common mode, failures (CCF) are often major contributors in large scale risk analyses of complex systems, such as nuclear probabilistic safety assessment (PSA). In this paper we discuss two challenges and limitations of the most widely used approaches regarding CCF quantification based on parametric CCF models. The first one deals with the time dependent behavior of a system under a staggered testing scheme. We illuminate differences in modeling and quantification which result from the application of different methods for staggered testing of components that share common cause failures. We aim at a simple and flexible way of specifying staggered tests that provides a possibility of a realistic quantification for real-life PSA models. Secondly, we illustrate conditions for using parametric CCF models and their limitations. From this perspective, we investigate alternative approaches for characterizing common cause failures. The goal is to increase flexibility for situations where classical parametric models are unsuitable.

Keywords: Common Cause Failures, Time-dependent Analysis, Staggered Testing, Generalized CCF Probabilities

1. Introduction

Textbook fault tree analysis methods assume that basic events are independent. This is not true in many real-life cases. Basic events representing the same failure mode of symmetrical components, typically the same component type in redundant subsystems or trains, belong to the most prominent examples. Probability of a combination of these basic events occurring at the same time might be greater than the product of their respective probabilities. They might fail together because of a common cause (IAEA (1992); Mosleh et al. (1988)). Common cause, or common mode, failures (CCF) are often major contributors in large scale risk analyses of complex systems, such as nuclear probabilistic safety assessment (PSA).

A simultaneous failure of several components by a common cause is typically modeled by a single event – a Common Cause Failure Event (CCF Event). Parametric CCF models define failure probabilities of CCF Events based on their multiplicity, i.e., how many components fail simultaneously. For example, the Multiple Greek Letters (MGL) or Alpha Factor models Mosleh and Siu (1987) define the failure probability of each CCF multiplicity as a fraction of the original event and these fractions can be calculated from model parameters. The time dependent behavior is the ability of the model to consider that the information about the component status may vary in time (and thereby affecting the likelihood of a CCF failure to occur).

The prevailing approach to CCF quantification uses parametric models. The time dependent behavior is either not considered or limited to sequential or staggered testing for the Alpha parametric model. This paper explores possibilities to generalize the time dependent behavior and what benefits this would bring. We will also discuss if using a more generalized definition of the CCF probability, rather than a parametric model, could bring flexibility and resolve some issues with CCF in current real-life probabilistic safety assessment models, like the possibility to define several CCF groups covering the same events.

2. Background

This section introduces the concept of common cause failures, time-dependent behavior and different approaches for CCF Event quantification in presence of staggered testing.

2.1. *Common Cause Failures*

A standard approach applied across various domains Stott et al. (2010) for representing these dependencies in fault trees takes four steps. First, an analyst identifies groups of components and their failure modes that share common cause failures. We call a group of basic events that represent failures of components that possibly share a common cause a Common Cause Failure Group (CCF Group). Second, new type of events – Common Cause Failure Events (CCF Events) – are created to model combinations of basic event occurrences, including an independent failure of each basic event, for components that share common cause failures. Each CCF Event contains failures of one or more components that happen of a common cause. Multiplicity of a CCF Event is the cardinality of the set of included basic events.

In the third step, we replace each of these basic events in the fault tree by an OR-gate. Inputs of an OR-gate replacing a basic event will comprise CCF Events that contain this basic event. A professional software tool would offer an automatic function for these two steps. Let us assume a CCF Group including basic events $B1$, $B2$ and $B3$. Figure 1 shows an OR-gate that replaces the basic event $B1$. Inputs to the OR-gate are four CCF Events representing the individual failure of $B1$, common cause failures of $(B1, B2)$, $(B1, B3)$ and a common cause failure of all three components.

Finally, we need to quantify CCF Events. Parametric CCF models Mosleh (1998) provide a standard way of quantification. A number of parameters, typically corresponding to the size of the CCF Group, is estimated from the operational experience. CCF Event parameters obtain their probabilities from a formula defined in the used parametric model. This formula takes the model parameters and the probability of basic events from the CCF Group as inputs.

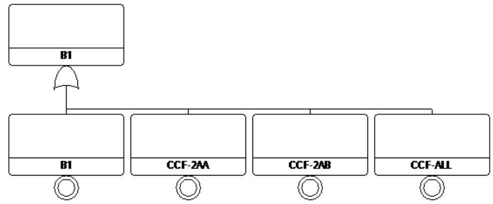

Fig. 1. An OR-gate representing the basic event $B1$ included in a CCF Group with two other basic events.

There are two assumptions behind most commonly used parametric CCF models implemented in software tools:

(i) All basic events within one CCF Group have the same definition. This means that the failure modes and failure logic/physics is the same for all related components. As a consequence, all basic events in one CCF Group have the same failure probability.
(ii) All CCF Events of the same multiplicity have the same probability. This means that it is only the *number* of events failing that determines the failure probability and not *which* events are failing together.

2.2. *Time-dependent Behavior*

Certain basic events representing on-demand failures, for instance those modeling a failure to start of a diesel generator, obtain their probability from the reliability model for periodically tested components. These components are characterized by a fixed failure rate. The longer the component waits in the stand-by mode, the higher the probability that it will not start successfully. The correct functioning of this component is tested periodically with a fixed time interval between test occasions. If the component fails at the test, it is immediately repaired. The failure probability of this component is therefore considered to be zero just after the test, but it grows with the time and is highest just before the next test occasion. Typically, an analysis considers the mean value of this failure probability in an analysis.

There are different strategies how to test symmetrical components in redundant trains or subsystems. One can test all components at a single occasion and then wait for the whole test interval for the next test occasion. This is so called *synchronous testing*. One can also spread testing effort in time and test only one component at a time. If it fails, the remaining components are also tested and those that fail are immediately repaired. The time until the next component is tested will be then the test interval divided by the number of the symmetrical components. By this, each component is tested with the same test interval, but each test occasion focuses on a different single component. This type of testing is called *staggered testing*.

There are other possibilities between these two strategies. For instance, one can test one half of the components at the beginning of the test interval and the other half in the middle of the test interval.

Staggered testing lowers the effort for each test occasion. At the same time, each occasion tests not only the individual component, but also all common cause failures including this component. If the component A works then it is not possible that components A and B fail together because of a common cause. This means that components are possibly tested more often with respect to common cause failures under a staggered testing scheme. CCF Event probabilities should be lower under a staggered testing scheme than under the non-staggered one.

All parametric CCF models provide a formula for CCF Event quantification under the assumption of non-staggered (synchronous) testing. The Alpha parametric model offers additionally a formula for groups of components tested according to the staggered testing scheme (Mosleh (1998)). For a CCF Event with multiplicity k from a CCF Group containing m basic events with probability Q_{tot}, α_k being the k-th model parameter, the probability is calculated by:

$$Q^S_{k|m} = \frac{1}{\binom{m-1}{k-1}} \alpha_k Q_{tot} \qquad (1)$$

In both cases, the exact timing of tests does not enter the formula. CCF Event probability is estimated only from the mean failure probability of basic events included in the same CCF Group and parameters of the selected CCF parametric model. It is up to the analyst to calculate the overall failure probability of a basic event included in a CCF group. Either it is entered directly as a probability value calculated externally or it is estimated from the parametric reliability model for periodically tested events. Here, a failure rate and a test interval determine the failure probability. Hence, this probability characterizes the modeled component in isolation, independently of other symmetrical components.

CCF parametric models are shortcuts transforming the total failure probability to failure probabilities of CCF events. A way to look at the CCF mechanism is that the failure rate of a component aggregates rates with which individual or common cause failures of different multiplicities occur. For small failure rate values, the current CCF parametric models can be directly applied to failure rates. Defining CCF events with the new CCF rates and the original test intervals gives us the same result as the current application of the CCF parametric model for the non-staggered case.

Software tools such as RiskSpectrum RiskSpectrum AB (2023) offer time-dependent analysis which can quantify CCF Events based on the exact test times defined in a staggered test scheme. Soga (2020) developed a general model for quantifying CCF Events under a staggered testing scheme. This model also takes exact test times into account and quantifies CCF Events depending on the included basic events. Vaurio (2003) presents exact formulas for the Alpha parametric model under the staggered testing scheme. Exact test times evenly spread over the test interval are implicitly considered in these formulas.

All of these time-dependent methods considering exact test times are based on the assumption that the parametric CCF model splits the failure rate of the basic event among the CCF Events. Once we equip CCF Events with their failure rate, we can derive their time-dependent behavior from the test scheme applied to the CCF Group. Note that this reverses the derivation of probabilities. First, the probabilities of individual CCF Events are calculated and then one can sum them up to obtain the total failure probability of the corresponding failure mode of the component in question. The Alpha parametric CCF model with staggered testing takes the total failure probability that has to be estimated beforehand and partitions it into failure probabilities of CCF Events containing a failure of this component.

Note also, that the total basic probability obtained by the time-dependent methods will be lower for staggered testing than for non-staggered testing. This is given by the fact that CCF Events are tested more often under a staggered testing scheme. Therefore, the on-demand failure probability decreases compared to the non-staggered testing. The failure rate of a component is independent of the testing scheme.

3. Staggered Testing in CCF Event Quantification

In this section, we reflect on the existing possibilities of modeling time-dependent behavior in CCF Event quantification from the perspective of a typical (nuclear) Probabilistic Safety Assessment (PSA) model. We also propose a simple method that brings greater flexibility for a very small cost.

Typically, a system with staggered testing in a nuclear PSA is modeled by basic events with the Periodically Tested reliability model. This means that users specify a failure rate and a test interval for each basic event. The test time offset can be also specified, but it is used only in the time-dependent analysis. The mean value of such basic events will be calculated from the failure rate and the test interval. This value corresponds to the non-staggered testing scheme of the components from the CCF Group.

We have the following possibilities to quantify CCF Events under the assumption of staggered testing.

- We can apply Equation 1 for the Alpha parametric CCF model with staggered testing.
- We can use Time-dependent Analysis in RiskSpectrum PSA.
- We can use an analytical approach, e.g., Equation 11 from Soga (2020).

As shown by Soga (2020), the results of the second and the third approach will coincide for reliable systems where the failure rate is small. The first approach might give different results for the following reasons.

- The common cause failure of all m components in the CCF Group, under the assumption of equal time intervals between component tests and a small failure rate, should be approximately m times lower than its failure probability calculated for non-staggered testing, $Q^S_{m|m}/Q^{NS}_{m|m} = 1/m$. Equation 1 will give this decrease if Q_{tot} corresponds to the value obtained from the time-dependent quantification with the staggered testing. This can be also approximated by $Q^S_{tot} = Q^{NS}_{tot}/\alpha_{tot}$, where $\alpha_{tot} = \sum_{k=1}^{m} k\alpha_k$, where Q^{NS}_{tot} is the total basic event probability for the non-staggered testing scheme. Using Q^{NS}_{tot} instead of Q^S_{tot} results in conservative estimates of CCF Event probabilities.
- Equation 1 implicitly assumes that the test intervals between components are equal for all multiplicities. For a CCF Group with three components A, B, and C, test interval 600 hours, and the staggered testing scheme, the CCF Event for A and B failing together assumes that there are 300 hours between the test of A and B. But the test interval 600 hours is split into three equal parts which means that there are 200 and 400 hours between tests of A and B. The probability evolution in time is depicted in Figure 2. This assumption leads to non-conservative estimates for multiplicities greater than one and smaller than m.

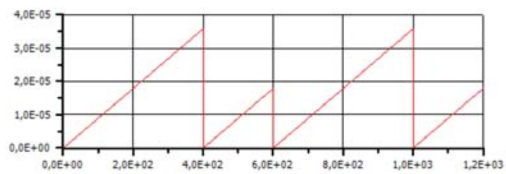

Fig. 2. Failure probability evolution over time for a CCF Event of multiplicity 2 out of 3 components with staggered testing.

Using Time-dependent Analysis or an analytical approach to quantify CCF Events will fully account for the timing information of test occasions for individual components. This can be useful especially in situations where the actual testing scheme does not split the test period evenly. For instance, consider a four-train system. One can test trains 1 and 3 in one test occasion at the beginning of the test period and trains 2 and 4 at the end of the test period. This corresponds neither to the staggered testing assumed in Equation 1 nor to the non-staggered testing. The common cause failure of all components can be approximated by one half of the failure probability under non-staggered testing. As another example, consider a system where either train 1 or 2 are in operation, alternating each week. Trains 3 and 4 are in stand-by, tested once in a month.

There are also disadvantages of these approaches. Apart from the complexity of the calculation, one also fully relies on the assumption that testing a component fully removes the possibility of a common cause failure including this component and this implies that failure probabilities of other components decrease by the corresponding amount. This is true only if the mathematical concept of testing in common cause failures captures all physical phenomena correctly. If this is not the case, then we might take undeserved credit for testing. Finally, the basic event probability depends on parameters of other basic events. Adjusting the testing offset for one basic event changes failure probability of other basic events from the same CCF Group.

Using the Periodically Tested reliability model and the Alpha Factor with staggered testing (Equation 1) does not present any relevant quantification issue for realistic values of alpha parameters (Krcal and Bäckström (2014)). Marshall et al. (1998) presents an estimate of Alpha Factor parameter α_2, with a mean value of 0.0425, and a 95% confidence interval of [0.0079, 0.0984]. One can also observe that α_1 is close to 1, and other α factors are generally in the same order of 10^{-2} or 10^{-3}. For example a 4-folded alpha factor model with value of $\alpha_k = 0.01, k > 1$, then $\alpha_1 = 0.97$ and $\alpha_{tot} = 1.06$; and a 8-folded alpha factor model with value of $\alpha_k = 0.01, k > 1$, then $\alpha_1 = 0.93$ and $\alpha_{tot} = 1.28$. This means that the non-staggered probability and the staggered probability are approximately equal and the uncertainties in the parameter estimates are more significant than this difference.

Finally, we propose a simple way to specify and quantitatively reflect the advantage one expects from staggered testing. For each multiplicity, an analyst specifies the minimal number of evenly spread tests of each CCF Event of this multiplicity. If this number is set to one then we assume only one test, i.e., non-staggered testing. If this number becomes k for a CCF Event of multiplicity k, then we assume k evenly spread tests, which is the assumption of Equation 1. For the CCF Group with four components tested in pairs and the CCF Event for a simultaneous failure of all of them, we can set this number to 2. The quantification procedure will use the non-staggered formula for the respective model and then divide the resulting probability by the specified number.

From the practical perspective, we believe that it is sufficient to specify the number of tests only for the highest multiplicity (simultaneous failure of all components). These CCF Events typically dominate the results. At the same time, we can use an arbitrary number that matches the actual testing strategy. It is easier to review this number than the fully specified time offsets of all components required by the time-dependent methods.

4. Asymetrical Dependencies

In this section, we analyze situations where the assumptions for parametric CCF models specified in Section 2.1 are not satisfied. One can use standard parametric models such as Alpha Factor or MGL only if the system satisfies both of these properties.

Let us consider the following multi-unit scenario. Unit 1 contains two symmetrical components with failures modeled by basic events A_1 and A_2. Unit 2 contains corresponding two components with failures modeled by basic events B_1 and B_2. Each pair of these basic events belonging to the same unit shares common cause failures. Let us assume that they are modeled by the Beta parametric model with the same parameter β for both units. Furthermore, we would like to consider a multi-unit CCF including all four basic events with the parameter β_m, where $\beta_m < \beta$. This corresponds to three CCF groups (two single-unit ones and one multi-unit) where each basic event belongs to two CCF groups (each basic event belongs to its single-unit CCF group and to the multi-unit CCF group at the same time).

One can attempt to merge these three CCF groups into one. Independent failures within a single unit also include failures across the units. For A_1, it means also failures (A_1, B_1), (A_1, B_2) and (A_1, B_1, B_2). Common cause failures in a single unit also include the multi-unit common cause failure. Under the assumption that two-folded CCFs have the same probability irrespective of whether they are within one unit or across units, this situation satisfies the assumptions above. Let us additionally assume that three-folded CCFs are not considered – they have zero probability. Then we can model this situation by a single CCF group with, e.g., the Alpha Factor parametric model.

The parameters for the Alpha Factor model can be derived as follows. First, observe that failure probabilities of basic events within a single unit also include failures across the units. For A_1, it means also failures (A_1, B_1), (A_1, B_2) and (A_1, B_1, B_2). For (A_1, A_2), it means also (A_1, A_2, B_1), (A_1, A_2, B_2), and (A_1, A_2, B_1, B_2). Let us denote by Q_1^β, Q_2^β, Q_3^β, and Q_4^β probabilities of CCF Events within a single unit and by Q_1^α, Q_2^α, Q_3^α, and Q_4^α probabilities of CCF Events in the multi-unit scenario. We have that

$$\begin{aligned} Q_1^\beta &= Q_1^\alpha + 2Q_2^\alpha + Q_3^\alpha \\ Q_2^\beta &= Q_2^\alpha + 2Q_3^\alpha + Q_4^\alpha \end{aligned} \tag{2}$$

From the Beta Factor model within a single unit, we have:

$$\begin{aligned} Q_1^\beta &= (1-\beta)Q \\ Q_2^\beta &= \beta Q \end{aligned} \tag{3}$$

From the Alpha Factor model with parameters $\alpha_1, \ldots, \alpha_4$ and $\alpha_t = \alpha_1 + 2\alpha_2 + 3\alpha_3 + 4\alpha_4$ we have:

$$\begin{aligned} Q_1^\alpha &= \frac{\alpha_1}{\alpha_t}Q \\ Q_2^\alpha &= \frac{2\alpha_2}{3\alpha_t}Q \\ Q_3^\alpha &= 0 \\ Q_4^\alpha &= \frac{4\alpha_4}{\alpha_t}Q \end{aligned} \tag{4}$$

From the multi-unit CCF Event modeled by the Beta Factor with the parameter β_m, we have that:

$$Q_4^\alpha = \beta_m Q \tag{5}$$

Now we can derive all CCF Event probabilities:

$$\begin{aligned} Q_1^\alpha &= (1 - 3\beta + 2\beta_m)Q \\ Q_2^\alpha &= (\beta - \beta_m)Q \\ Q_3^\alpha &= 0 \\ Q_4^\alpha &= \beta_m Q \end{aligned} \tag{6}$$

And also Alpha Factor parameters:

$$\begin{aligned} \alpha_1 &= (1 - 3\beta + 2\beta_m)\alpha_t \\ \alpha_2 &= \frac{3}{2}(\beta - \beta_m)\alpha_t \\ \alpha_3 &= 0 \\ \alpha_4 &= \frac{1}{4}\beta_m \alpha_t \end{aligned} \tag{7}$$

If the operating experience of the units differs and the components have a different failure probability in each unit, i.e., $P(A_1) \neq P(B_1)$, then this scenario violates the first assumption of the parametric models above. Considering that two-folded CCF events across the units have zero probability (i.e., individual failures across the units are independent) violates the second assumption of parametric models. A two-folded CCF event (A_1, A_2) has non-zero probability, but the probability of (A_1, B_1) is zero. Also, considering that the beta factor of Unit 1, denoted β_1, is different from the beta factor of Unit 2, denoted β_2, violates the second assumption, because $P((A_1, A_2)) \neq P((B_1, B_2))$.

The second type of CCF parametric model extensions discussed in this paper is motivated by situations where at least one of the assumptions above is not valid. This implies asymmetrical dependencies between components. The four components in our model units are not fully symmetrical.

The case discussed above exemplifies asymmetric dependencies between units. This may seem abstract and not directly applicable to the standard PSA of a single unit, but it provides an illustrative way to explain an asymmetric situation. These types of situations can also occur within a plant; for example, if you have a 4-train system (A – D) where one train is always running. The train in operation is shifted on a weekly basis between trains A and B. All trains are also tested on a quarterly surveillance test interval. Practically this means that there is a start-up failure mode relevant between three trains (A, C, D or B, C, D), but one of the trains will have a test interval of one week (A or B), and the other two (C and D) will have a test interval of three months. There are modeling techniques developed to address such situations, but it would be desirable with a CCF model that can take such situations into account.

Further, some data sources do not provide data directly suitable for calculating CCF factors. Or the data may be given directly as the CCF probability or rate.

The last resort option is always to model the dependencies induced by common cause failures explicitly. This means that we have to add new basic events for all combinations of basic events that share common cause failures. These basic events then represent CCF Events. We assign probabilities of the simultaneous failure by a common cause to these new events manually.

Whilst the explicit modelling is very flexible, defining explicit probabilities can be tedious and error prone and the approach often means that one overestimates the failure probability of the individual failure (one simply does not lower the individual failure probability considering the CCF failure probabilities).

Two possible ways of achieving a greater flexibility in the above-mentioned cases, but that would simplify the modeling for the user could be to specify probabilities of common cause failures by conditional probabilities, or to introduce a CCF model where each multiplicity has its own definition.

The use of conditional probability to specify common cause failures is based on a setup where one instead of splitting the total probability of a single basic event into multiple CCF events, specifies the conditional probability of an event, given that one or more events from the same CCF group have occurred. The most significant difference of this approach compared to the explicit approach is that a single minimal cut set encodes both a combination of independent failures as well as common cause failures.

A positive aspect of using conditional probabilities is that the MCS list will contain only the original event combinations – which makes interpretation potentially easier and also importance analyses will be done based on the original event. This would also lift the first assumption from Section 2.1 – that the basic events included in a CCF Group have the same definition.

RiskSpectrum PSA allows users to specify conditional probabilities of basic events, given that a combination of other basic events has occurred. For higher-order quantification and success treatment, it is important to decide how complementary conditional probabilities are quantified. Krcal et al. (2020) argue that this quantification differs for Human Reliability Analysis (HRA) and for CCF applications. The current implementation in RiskSpectrum PSA keeps HRA as its primary target (Krcal et al. (2022)) which would be directly comparable to an approach with explicit modeling where the independent failure probability is not lowered. We are however looking for an extension that would cover also CCF quantification where the probability of the independent event is managed as in the prevailing CCF methods today.

Another way to provide greater flexibility, still very much alike the existing CCF approaches, would be to provide the ability to define each CCF multiplicity separately. Exactly how this would be set up remains to be defined, but the construct would intend to satisfy the flexibility. In a simple form, it would allow the user to specify the probability of each CCF multiplicity (considering the number of CCF events of that multiplicity). The user could select whether the total failure probability would remain the same (that is, the independent probability would be lowered) or that the CCF failures are additive. Note that, with this approach the independent events can have different failure probability (or a different setup with regard to for example test interval). It would also be possible to extend the model from just specifying the probability of each multiplicity, to provide a reliability model for each multiplicity. In this way the staggering could be considered. And lastly, such a model could also allow the same event to be a part of several CCF Groups – as it is not necessarily the original probability that is split into different multiplicities.

Both the conditional probability, and an explicit definition of the probability/reliability mode of each multiplicity have several positive characteristics that should be further investigated. At this point, the main negative aspect is "the power of habit" – most PSA practitioners are very familiar with the existing models and their limitations.

5. Conclusions

In this paper we have discussed some aspects and limitations of the existing prevailing methods for CCF modeling in PSA.

We have studies the time dependent behavior induced by staggered testing of components and have come to the general conclusion that the difference between the more precise time dependent methods and the Alpha Factor model with staggered testing differ only slightly. The conservative bias induced by using the Periodically Tested reliability model for basic events becomes negligible for typical values of Alpha parameters. Also, for the typically dominating CCF Event including failures of all components, the Alpha Factor model with staggered testing does not underapproximate the probability.

To extend the flexibility of the staggered approach, we propose a method where the user can specify the amount of tests that are performed at different occasions within the CCF Group. This would allow for a more flexible use of the staggered approach, but still have a definition of the CCF Group that is easy to review and understand.

We also discuss asymmetric CCF and the possibility to extend the methods for CCF definition. The two concept we propose are use of conditional quantification and definition of CCF Groups by specification of each multiplicity separately.

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