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Methods for Dependency Estimation and System Unavailability Evaluation Based on Failure Data Statistics

Summary Report

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ABSTRACT

This report introduces a new perspective on the basic concept of dependent failures where the definition of dependency is based on clustering in failure times of similar components. This perspective has two significant implications: firstly, it relaxes the conventional assumption that dependent failures must be simultaneous and result from a severe shock; secondly, it allows the analyst to use all the failures in a time continuum to estimate the potential for multiple failures in a window of time (e.g., a test interval), therefore arriving at a more accurate value for system unavailability. In addition, the models developed here provide a method for plant-specific analysis of dependency, reflecting the plant-specific maintenance practices that reduce or increase the contribution of dependent failures to system unavailability.

The proposed methodology can be used for screening analysis of failure data to estimate the fraction of dependent failures among the failures. In addition, the proposed method can evaluate the impact of the observed dependency on the system unavailability and plant risk. The formulations derived in this report have undergone various levels of validations through computer simulation studies and pilot applications. The pilot applications of these methodologies showed that the contribution of dependent failures of diesel generators in one plant was negligible, while in another plant, it was quite significant. It also showed that in the plant with significant contribution of dependency to Emergency Power System (EPS) unavailability, the contribution changed with time. Similar findings were reported for the Containment Fan Cooler breakers. Drawing such conclusions about system performance would not have been possible with any other reported dependency methodologies.

This report is written in two volumes; Volume 1 describes a summary of the study and Volume 2 contains detailed discussions of the methods, formulations, analyses, and applications. We believe these methods and the associated software can be useful to analyze the failure data to estimate the fraction of dependent failures, and to evaluate its impact on system unavailability. At the same time, further work is needed before these methods can be used in conventional PRAs to evaluate a plant-specific risk profile. We also showed that the methods can evaluate the safety significance of dependent failures, their plant-specific nature, and their dynamic variations with time. These methods appear useful to enhance early detection of risk significant dependencies and to take prompt corrective actions.

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1. INTRODUCTION

This report describes a method for surveying failure data to estimate the fraction of dependent failures and its contribution to system unavailability that is composed of several redundant components. The method compares the distribution of actual time-between-failures with the distribution expected if the failures were independent. The differences between these two distributions reflect dependent failures. Based on this method, software is being developed to estimate the fraction of component failures that are dependent, and system unavailability with this degree of dependency.

Dependent failures have been widely recognized as important contributors to risk. This report builds on earlier pioneering methods for analyzing dependent failures.¹⁻³ More recently, NUREG/CR-4780⁴, Section 5, proposed exploring common-cause failures (CCFs) using the concept of root cause, coupling mechanisms, and defensive mechanisms. NUREG/CR-5460⁵ further expanded on a comprehensive picture of CCFs that explicitly identifies the role of coupling and defenses through postulated generic classes of CCF mechanisms and cause-defense matrices. These studies resulted in general guidelines for assessing the potential for the occurrence of, and defenses against, common-cause events. Although these studies increased our understanding of the way CCFs occur and can be defended in a qualitative manner, they do not address quantitative aspects of the problem.

Also, NUREG/CR-4780 and NUREG/CR-5460 emphasize the lack of sufficient plant-specific data to develop meaningful estimates of CCF rates. This study attempts to provide a bridge between qualitative and quantitative assessments of CCFs, and also outlines an approach that can be used to analyze dependent failures from plant-specific data. The report describes basic models that can be used to estimate the potential for CCFs using plant operational data which are not necessarily limited to simultaneous failures of multiple components. Further, we describe specific methods consistent with the content of the data for estimating the CCF rate. Finally, specific indicators of CCFs are described and their capabilities are evaluated. Risk formulation of dependent failures, in general, are also detailed.

1.1 Overview

This section gives an overview of the methodology developed; to introduce the subject, we first define dependent and independent failures.

The failure of components in PSAs can be classified as independent and dependent. Independent failures are completely autonomous events. The failure of one component does not affect the performance of any other component, and, when a failure is repaired and the component is returned to service, the same component could fail again, without influence from the previous failure. It is very important to emphasize that there are *hard-wired dependencies* between the components in a system. These dependencies will always exist in a system as long as its design is unchanged. Examples of the *hard-wired dependencies* are those between support systems and front-line systems, i.e., a starting-air system (support system) providing the air to start a diesel generator (front-line system). If the starting-air system fails, the diesel generator invariably will fail to start. However, this direct dependency is completely defined, and can be modeled at the level of fault trees. Even if the support system is only degraded, the performance of the front-line system also will be degraded.

In more formal terms, independence between failures means that if several failures are observed, then all these failures obey the product law of probability (here called *Totality of Product Law*).

For example, if we have two independent failures A and B, then, the probability of the two failures happening is exactly:

$$P = Q_A \cdot Q_B \quad (1)$$

and Q_X represents the probability of X happening, i.e., instantaneous unavailability which is usually a function of time.

However, PSA studies generally use the average probability of failure (average unavailability) over a long period, which we will denote by $\overline{Q}_X$. Then, the probability of the two failures happening is:

$$P = \overline{Q}_A \cdot \overline{Q}_B \quad (2)$$

Expression (2) may lead to errors in the calculations. For example, when the instantaneous unavailabilities of A and B are correlated in time, independence between failures may happen only at *instantaneous* moments.

$$P = Q_A^i \cdot Q_B^i \quad (3)$$

only if Q_X^i is the instantaneous unavailability probability of X happening.

Dependent failures are failures of several components due to a common cause or "shock". Hence, dependent failures are known as "Common-Cause Failures". Since, in principle, a common cause or "shock" will affect several similar components, dependent failures also are known as "Common-Mode Failures". In this report, we use the term *dependent failures (DF)*.

Dependent failures are very important for a PSA study because they can affect several critical components (thus, making redundancy in a train or system useless) and, therefore, their impact on risk can be high. On the other hand, it is important not to overestimate them by assuming that all components in a system, or even similar components in several systems, are subjected to dependent failures.

The term *shock* is used to cover all circumstances that can affect several components, for example, harsh environments (temperature, humidity, vibration) that might affect all the components in a room.

Timing between failures is a very important issue in dependent failure analysis. In general, even if a shock affects several components, this does not necessarily mean that all the components will fail *at the same time (simultaneously)*. This could be the case, but more generally the shock will significantly increase the failure rates of the affected components, and the components affected by the same shock will eventually fail at some short interval from each other. The more severe the shock, the shorter is the interval.

Therefore, if the impact of dependent failures is to be assessed, and if, for this purpose, the observed dependent failures in a plant are compiled, the history of failures can be depicted as in Figure 1.

Figure 1. Example of failure clustering

In this diagram, we depicted hypothetical observations of the behavior (occurrence of failures) of several components as a function of time, starting from time t_0 . At this point, we do not know which failures are independent and which failures are dependent. If the reports from the plants were detailed enough, then tracing the cause of the failures would be sufficient to determine which ones share the same cause; and the rest would be independent failures. However, in most cases, the information given in the failure reports is not detailed enough to tell if a group of failures, out of the complete population, have occurred from the same cause. Hence, to assess the contribution of dependent failures to the unavailability of a system, it is necessary to assess the *degree of dependency* shown by field failure data from a nuclear power plant. The *degree of dependency* is best described by the degree to which observations deviate from what is expected under the independence assumption. The degree of deviation is estimated by the significance of the difference between an observed measure and its expectation under the independence assumption. Significance, here, is defined by the probability laws governing the likelihood of the observation (significance level). As described later, the measure is related to the expected time required for observing a failure of two or more individual redundant components. Other measures or risk-based indicators can be developed by estimating the system unavailability (minimal cut-set probability) based on observed failures and accounting for dependency, predicting the system unavailability under the independence assumption, and taking the difference between the two. Again, the significant deviation (difference) is inferred based on probability laws.

The methodology for these analyses will be discussed in Section 2, and the mathematical development in the appendices. However, the methodology is based on the identification of dependency between failures, given their closeness (in time) of occurrence.

The methodology looks at the overall behavior (in time) of the failure of the components, and then evaluates the indications for dependent failures. Therefore, even if *locally* there is indication of dependency or non-dependency between failures, the overall behavior will be examined to assess the dependent failure indicators.

Two important examples of the *local* effects are illustrated in Figure 1:

1. Even if several failures happen simultaneously, or very close in time, they may be independent failures which happen to occur at the same time (for example, Figure 1, failures F_5 , F_6 and F_7). For standby components and for practical purposes, such closeness refers to periods that are comparable with the component test intervals. Assuming the interval between occurrence of the failures to be the same as the intervals between the discovery of failures, plus and minus one half test interval will have minimal effect on the dependency analyses.

2. Even if several failures do not occur close in time, they may be related by the same cause (for example, failures F_1 , F_2 , and F_4 in Figure 1). In this case, the pattern of consecutive occurrence of failures in three different components may be indicative of dependency.

The development of dependent failure indicators presented here has the following features:

1. An unavailability expression (formula) is developed to take into account the contribution from dependent failures. This expression allows for a more accurate evaluation of unavailability than the traditional formula employed in today's PSAs.
2. The identification of dependent failures does not require them to be simultaneous.
3. Dependent failure indicators can be determined from a small amount of raw failure data.
4. The methodology can be applied to the failure observations of each particular plant, and therefore, can generate dependent failure indicators for each plant. Though this feature might not seem very important, it has a very important implication, namely, that generally, to evaluate the common-cause contribution in a PSA, generic data sources are consulted, and they present the *average* behavior of a large population of plants over a long period. However, the common-cause contribution for a particular plant may be quite different from the population average. This difference can underestimate or overestimate the common-cause contribution.
5. As shown before, the method can look at the overall behavior with time of the failures, thereby avoiding, as much as possible, local effects which can be misleading.

This report is organized in two volumes. The first volume presents a summary description of the methodology developed (Section 2), the results obtained (Section 3), and the conclusions (Section 4). Volume 2 is comprised of 7 appendices, with each appendix describing in detail a related subject.

2. APPROACH

In most cases, the contribution of *Common-Cause Failures* (CCF) to the risk of a plant in a PSA study is evaluated by consulting the values in a generic source. However, such values have been averaged over two domains: the average of several plants, and the average over a long time. However, because a particular nuclear power plant has its own environment, equipment, and operating procedures, these *averaged* values may be several orders of magnitude smaller or larger than the *real* contribution. Therefore, as a first step to evaluate the CCF contribution for a particular plant, field failure data must be collected, so that the information resembles, as much as possible, the actual failure behavior of the plant.

However, as we mentioned in the Introduction, if there was enough information to assess the cause of every failure then it would be possible to evaluate accurately the contribution of CCF to the risk of a plant. Since this is not the case, then we propose that the CCF contribution is evaluated by statistically testing for dependency in the raw failure data.

Accordingly, the methodology developed allows for dependency to be evaluated, which is not exactly what the term *Common-Cause Failures* means, i.e., several simultaneous failures due to the *same* cause.

However, we note that the term *Common-Cause Failure* (CCF) has been used rather loosely in the PSA field. It was used to explain previous occurrences of simultaneous failures, but in some cases, it was merely incorporated to improve the prediction of system unavailabilities.

The methodology presented here for dependency indicators has two direct contributions to the evaluation of dependent failures:

1. It provides a new formulation for the unavailability expression used in PSAs, which can take into account the contribution from dependent failures.
2. It provides a better estimation of the β factor or the parameters of other conventional CCF models.

In addition, the methodology can assess the degree of dependency in a particular set of field failure data. A measure of dependency also is proposed.

2.1 New Expression for Average Unavailability Accounting

When assessing the impact of dependent failures on the unavailability of a system, it is important to evaluate the unavailability of at least k components failing out of n . For example, if there are five electrical diesel generators in a nuclear power plant ($n=5$), then what is the probability that at least two ($k=2$) of them are unavailable?, and what is the probability that at least four ($k=4$), out of the five ($n=5$) diesel generators, are unavailable?

The methodology presented proposes an accurate expression for the average unavailability of at least k components failing out of n . Detailed derivation of the average system unavailability accounting for both failure and maintenance downtimes is discussed in Appendix B of Volume 2. Here, for the sake of simplicity, we concentrate on the contribution of the average system unavailability resulting from the component failures accounting for possible clustering of failure times. The more comprehensive

and expanded formulations given in Appendix B will not be discussed in this volume. The new expression for the average unavailability of at least k components failing out of n is the following:

$$\overline{Q}_k = \sum_{j=1}^k \left(\frac{A_j}{\xi_j} \right) \frac{1}{(\xi_j T)} \left[\xi_j T - (1 - e^{-\xi_j T}) \right] \quad (4)$$

where T is the test interval, A_j is a function of (depends on) only ξ_j , and the parameters ξ_j incorporate the dependency contribution, if any. The parameter ξ_j is typically defined as the reciprocal of the expected incremental cycle duration. This duration of "j" can be envisioned as the expected difference between the time required to observe the failure of "j" different redundant components and the time required to observe the failure of "j-1" different redundant components. If this time difference is short, then the "jth" failures were most probably due to the same degradation mechanism that disabled the previous "j-1" redundancies. The shorter this duration, the greater the value for ξ_j , which indicates the degree of dependency for the "jth" failure.

For example, for one out of two, components being unavailable, Eqn. (4) reduces to:

$$\overline{Q}_1 = \left(\frac{A_1}{\xi_1} \right) \frac{1}{(\xi_1 T)} \left[\xi_1 T - (1 - e^{-\xi_1 T}) \right] \quad (5)$$

where $A_1 = \xi_1$.

For the case of two out of two components being unavailable, Eqn. (2) reduces to:

$$\overline{Q}_2 = \left(\frac{A_1}{\xi_1} \right) \frac{1}{(\xi_1 T)} \left[\xi_1 T - (1 - e^{-\xi_1 T}) \right] + \left(\frac{A_2}{\xi_2} \right) \frac{1}{(\xi_2 T)} \left[\xi_2 T - (1 - e^{-\xi_2 T}) \right] \quad (6)$$

where, in this equation;

$$A_1 = \frac{\xi_1 \xi_2}{(\xi_2 - \xi_1)} \quad (7)$$

and,

$$A_2 = \frac{\xi_1 \xi_2}{(\xi_1 - \xi_2)} \quad (8)$$

Equation (6) can be simplified to illustrate the consistency of these equations with the current approach for estimating average system unavailability. To do so, the exponential term has to be expanded using a Taylor series up to the cubic term. That is:

$$e^{-\xi T} = 1 - (\xi T) + (1/2)(\xi T)^2 - (1/6)(\xi T)^3 \quad (9)$$

substituting Eqn. (9) into Eqn. (6), and with simple manipulation, Eqn. (10) can be obtained.

$$Q_2 = (1/6)\xi_1 \xi_2 T^2 \quad (10)$$

Under the independence assumption, the values of ξ_1 and ξ_2 are related to the individual component failure rate λ by the following relationship:

$$\xi_2 = \xi_1/2 = \lambda \quad (11)$$

Here, for the system unavailability under the independence assumption is:

$$Q_2 = (\xi_1 \xi_2) T^2/6 = (1/3)(\lambda T^2) \quad (12)$$

To illustrate the change in system unavailability when failures are clustered, a new value for ξ_2 greater than $\xi_1/2$ has to be assumed. If this value is denoted by ξ'_2 , then the dependent contribution to the system unavailability is:

$$Q_{\text{dep}} = \left((\xi'_2 - \xi_2) T/3 \right) \left((\xi_1 T)/2 \right) \quad (13)$$

The Equivalent Beta Factor (β) then can be expressed by:

$$\beta = \left((\xi'_2 - \xi_2) T / 3 \right) \quad (14)$$

Note, that if all failures are simultaneous failures detected in one test interval, then the value for ξ'_2 is $3/T$ (since, on average, the failures could have been only one third of the test interval apart). In this case, the Beta Factor will be maximum and approaches unity.

Equation (4) allows the determination of overall system unavailability from both independent and dependent contributions. However, it is important to note here that Eqn. (4) does not account for system unavailability due to maintenance downtimes. This contribution shall be handled separately. The detailed derivation of Eqn. (4) is shown in Appendix B, Volume 2.

2.2 Expression for the β Factor

In the previous section we discussed a derivation of the β factor based on the parameters of the new formulation of system unavailability composed of two redundancies. In this section, a general approach for the determination of β factors for any number of redundancy is discussed. To extract the conventional β factor, we can use the following procedure. We can say that the unavailability of a system due to failures is given by dependent and independent contributions. That is:

$$\overline{Q}_k = Q_{\text{dependent}} + Q_{\text{independent}} \quad (15)$$

The dependent contribution is the unavailability of a single component corrected by the β factor. Thus, Eqn. (15) becomes:

$$\overline{Q}_k = Q_{\text{single}} \beta + Q_{\text{independent}} \quad (16)$$

where Q_{single} is the average unavailability commonly used in PSAs:

$$Q_{\text{single}} = \frac{\lambda T}{2} \quad (17)$$

and $Q_{\text{independent}}$ is the estimated probability, using the conventional PRA formula, that several components have failed independently.

Therefore, once the unavailability is obtained from Eqn. (4), Eqn. (16) can be solved for the β factor:

$$\beta = \frac{\overline{Q}_k - Q_{\text{independent}}}{Q_{\text{single}}} \quad (18)$$

For example, for the case of two components, substituting Eqns. (17) and (19) into Eqn. (20), we get:

$$Q_{\text{independent}} = \frac{(\lambda T)^2}{4} \quad (19)$$

$$\beta = \frac{\overline{Q}_k - \frac{(\lambda T)^2}{4}}{\frac{\lambda T}{2}} \quad (20)$$

and the β factor can be directly obtained.

Therefore, Eqns. (4) and (20) are easily usable expressions to incorporate dependent failure contributions into PSA calculations. As shown in Appendix B of Volume 2, Eqns. (17) and (18) are an approximation to Eqn. (4) under the assumption of total independence. When a dependency is detected, the parameter ξ_j incorporates the dependency information from the field failure data into the PSA calculations. Thus, the parameters ξ_j are statistical estimations of dependency from observed failure data.

2.3 Dependency Indicators

Since the parameter ξ_j incorporates the dependency information from the field failure data into the PSA calculations, a methodology was developed to identify dependency between failures. In other words, statistical indicators of non-random failures have been developed. We started by noting that when there is dependency between failures, the failures become *clustered*. *Clustering* of failures are caused by a conditioning event which increases the failure rate among similar components. The increase in failure rate is terminated when a complete repair takes place. Therefore, three main processes are identified:

1. Occurrence of conditioning events or shocks which will trigger the process of dependency.
2. The failure rate of several similar components is increased.
3. There is an operational feedback to perform a complete repair on a single component when it fails, or on all similar components when a cluster of failures occur.

The effect of a shock is totally eliminated when all components affected are repaired. Another shock may occur again in the future, and the process of repair will take place once more.

To study the effect of shocks on the clustering of failures, several concepts are introduced. First, a failure sequence of any length is assigned a code. The code is a numerical value equal to the number of different components that are failed within the failure sequence. For example, if there are four components (A, B, C, D), the following are examples of sequences:

Code	Failure Sequence
1	A, AA, AAA
2	AB, AAB, ABA
3	ABC, ABABBC, ABABCB
4	ABBCADBA, ABCD, ABBCAD

These examples are not a complete list of all the possible failure sequences for four components. Strictly speaking, there are an infinite number of failure sequences of Code k for n components. For example, for Code 2, in addition to those shown in the table above, we may have BA, WP, AAAAB, and so on. We are interested in the *sequence of occurrence in time* of k components, not in their combinations or permutations.

Furthermore, the failure behavior of the components can be depicted in a diagram showing the approximate time of failure of the components. An arbitrary example of failure behavior is shown in Figure 2.

Figure 2. Example of failure clustering

By simply looking at the sequence of failures depicted in Figure 2, and in the absence of detailed information about the cause of each failure, it is not possible to assess if there is dependency between the failures. However, to develop the methodology of dependency indicators, several definitions are proposed. The new concepts defined are shown in Figure 3.

The first important concept is the "Minimal Sequence Cycle of Code K ", denoted as MSC- K , which is a sequence of failure such that the first k components were involved. For instance, a Minimal Sequence Cycle of Code 3 is a sequence of failures until three different components have failed; in

Figure 3, one MSC-3 is ABABC, and one MSC-4 is ABABCBCAD. A general definition of MSC-K is: A Minimal Sequence Cycle of Code "K" is a MSC-K if the code of the sequence, excluding the last failure, is "K-1".

Figure 3. Example of failure clustering

The next important concept is that of "Minimal Cycle Duration", which is the length of time that a particular MSC-K takes to fail. For example, the minimal cycle duration of the MSC-3 illustrated in Figure 3, is the length of time from t_0 to the first failure of C (fifth failure since the observation starting point, t_0). The third concept is that of "Incremental Cycle Duration," which is the length of time for a MSC-K to become a MSC-(K+1). Thus, there is an incremental cycle duration to go from an MSC-1 to an MSC-2, from an MSC-2 to an MSC-3, and so on. As an example, Figure 3 shows the incremental cycle duration from the MSC-3 ABABC to the MSC-4 ABABCBCAD.

According to these definitions, and the clustering (shock) model described above, then if a dependency exists, it is due to a shock that has increased the failure rate of the components, thereby causing clustering of the failures and decreasing both the minimal cycle duration and the incremental cycle duration. Since we are assuming that the failures are repaired after a shock, then the process has no memory of failures that have occurred in the past; therefore, as a first approximation, we propose that the distribution of the incremental cycle duration is characterized by the exponential distribution, that is:

$$g(w) = \xi e^{-\xi w} \quad (21)$$

where,

w is the incremental length period for MSC-K compared to MSC-(K-1), and

ξ is the parameter characterizing the exponential distribution.

Therefore, by fitting the field failure data to exponential distributions, such as that shown in expression (16), the parameters ξ_j of Eqn. (5) can be determined. If there is dependency between the failures, then its contribution to the average system unavailability will be taken into account by the parameters ξ_j of Eqn. (4).

The methodology developed is not restricted to an exponential distribution and, in fact, several statistical tests (statistical evaluation of cycle duration and incremental cycle duration) to detect clustering and dependency may be attempted:

1. Exponential
2. Mixture of Exponentials
3. Cusum
4. Cox Interspacing Model

An attempt may be made to fit the field failure data to any of these models, and then to use the best fit to estimate the parameters ξ_j . Appendix D describes these tests in detail.

In addition, it is useful to calculate the average system unavailability more accurately using Eqn. (4); the parameters ξ_j are dependency indicators themselves. However, they are not indicative by themselves of the presence of dependency in a particular set of field failure data. To obtain an indication of the dependency in such a set, the incremental cycle durations characterized by the parameters ξ_j may be used to obtain the distribution of the Minimal Cycle Durations. Appendix A describes in detail the derivation of these "Durations." Once these "Durations" are obtained, parameters can be obtained to decide whether or not there is dependency in a set of data or not.

First, under the assumption of independence, the Minimal Cycle Durations are obtained. Then, the actual Minimal Cycle Durations are obtained from the field failure data. If there is dependency, it is because a shock has happened, increasing the failure rate, and therefore, decreasing the Minimal Cycle Durations. Therefore, a parameter α_k can be the measure or indicator of dependency if we define it as the ratio of the actual Minimal Cycle Durations over the Minimal Cycle Durations under the assumption of independence, i.e.,

$$\alpha_k = f_k(\text{empirical}) / f_k(\text{theoretical}) \quad (22)$$

where,

f_k is a measure of the Minimal Cycle Duration for cycle k. Appendix A gives a formal definition of this parameter.

Formal methodologies have been introduced in this report to estimate the mean and standard deviation (σ) of α_k under the assumption of independence. Significant deviations from the independence assumption can then be expressed in terms of number of standard deviations away from the expectation (e.g., 3σ deviation). Thus, formal probabilistic confidence bounds can be assigned to the dependency inference.

3. RESULTS

The methodology proposed has been tested using simulation studies and pilot applications, details of which are given in Appendices F and G. Here, we briefly summarize the conclusions and some of the quantitative results obtained from this study.

There several definitions and formulations that need to be discussed before presenting our quantitative results. The PRA (PSA) approximate unavailability of multiple components as used in this report, is calculated using the following equation.

$$Q_{k,n} = \sum_{j=k}^n \binom{j}{n} q_s^j (1 - q_s)^{n-j} \quad (23)$$

where,

$Q_{k,n}$: is the PSA approximate unavailability of k or more redundancy out of n redundant components under independence assumption.

q_s : is the PSA unavailability of a single component defined by:

$$q_s = \frac{\lambda T}{2} \quad (24)$$

where λ is the failure rate for single diesel generator and T is the test interval.

The exact unavailability of k or more out of n redundancy, as was described in the previous section, and was given by Eqn. (4), is repeated here for clarity:

$$Q_k = \sum_{j=1}^k \left(\frac{A_j}{\xi_j} \right) \frac{1}{(\xi_j T)} \left[\xi_j T - (1 - e^{-\xi_j T}) \right] \quad (25)$$

where T is the test interval, and A_j is a function of only ξ_j . The above equation, Eqn. (25), can be quantified under two conditions which result in "Exact System Unavailability Under Independence Assumption", and "Exact System Unavailability Accounting For Dependence." The exact system unavailability under independence assumption is calculated when all values of ξ_j are calculated, based on their relation to ξ_1 as prescribed by independence assumption. The exact system unavailability accounting for dependence is calculated when all values of ξ_j s are estimated, based on field data not the independence relationship based on ξ_1 . This basically illustrates the versatility of Eqn. (25) for both cases of independence and dependence. In tabulated results that will be discussed next, Case 1 refers to the PSA approximate equation, Case 2 refers to the exact system unavailability under assumption of independence, and Case 3 refers to the exact system unavailability accounting for dependence.

Finally, the partial β factors of Type 1 are calculated based on the difference between the exact system unavailability accounting for dependence (Case 3), and the PSA approximate system unavailability (Case 1). The partial β factor of Type 2 are calculated based on the difference between the exact system unavailability accounting for dependency (Case 3) and the exact system unavailability under the independence assumption (Case 2).

3.1 Simulation Studies

Clustering of failures is usually caused by a conditioning/triggering event which increases the local failure rate among similar components that are affected by the condition. To study the effects of triggering events on the clustering of failures, and to evaluate the applicability of the methods developed in this study, we used a simulation approach. Our objective was to assess the appropriateness of the developed methods by computerized simulation of observations on component failure times, estimation of the system unavailability, and the clustering parameters, and compare these with the simulated values. The PSA approximate system unavailability based on simulated data was also calculated to show the improvement in the accuracy of estimation that can be obtained by using the methods developed here.

Appendix F has a detailed description of simulation case runs and these comparisons. The basic conclusions are summarized here:

1. For simulated failure times based on the assumption of independence, the methods developed provide accurate estimates of the system unavailability in agreement with the simulated quantities. The PRA approximate system unavailability for one out of two redundant system underestimate the simulated unavailability by about 30%. For higher levels of redundancy, the degree of underestimation in the PRA approximate unavailability significantly increases, e.g., a factor of about 2.5 for four redundant trains.
2. For simulated failure times accounting for dependency, i.e., simulated based on a periodic triggering event occurring with a frequency of about once a year and causing an increase in failure rate by a factor of 20 for a period of two months and then returning to its nominal failure rate, the following conclusions were reached (note, data was simulated for 10 years):
 - a. Clustering was detected and reflected in the estimates of the model parameters more than 80% of the time for systems composed of two or four redundant trains.
 - b. System unavailability calculated using the models developed in this study underestimated by about 30% for two redundant trains and about 50% for four redundant trains. These results were promising in comparison with the PSA approximate unavailabilities which underestimated system unavailability by a factor of 2.5 for a two-train system, and a factor of 10 for a four-train system. In 50% of simulation runs, no simultaneous failure of two or more components occurred within a test interval; therefore, it will be almost impossible to estimate an accurate β factor based on simultaneous failures of multiple components. The Type 2 partial β factors typically calculated in these simulation studies for a four train system based on our clustering model are:

$$\beta_{2/1}=0.05$$

$$\beta_{3/2}=0.1$$

$$\beta_{4/3}=0.26$$

- c. The degree of clustering and the estimated partial β factors increase almost proportional to the effect of conditioning or triggering events in terms of the magnitude of the increase in failure rate and the duration that this increase is sustained. The latter is a function of the maintenance strategies in the plant, that is, the effect of the conditioning event on the increase in failure rate will be eliminated if all the redundant components have been repaired. The repair of a redundant component may be initiated before its failure due to either an understanding of the cause of failure in other redundant components and determining if other redundant trains are susceptible, or due to detection of failure clustering in other redundant trains. Activities which control the duration of the failure increase are referred to as operational feedback mechanisms.

In conclusion, the simulation studies indicated the potential usefulness of these types of approach and set the stage for further validation through pilot applications.

3.2 Pilot Applications

Eight pilot applications of the methodology were made using the actual field data on failure times. Each pilot application was designated by a plant code:

Plant 1 - Diesel generator failure times were retrieved from the utility PSA (Individual Plant Examination-IPE Submittal). The data spans from 2/3/82 through 12/31/89. This two-unit plant initially had four diesel generators, with a fifth diesel added and operational on 2/17/87.

Plant 2 - Diesel Generator failure times were retrieved from Nuclear Power Reliability Data System (NPRDS) from January 1988 through March 1992. This two-unit plant had five diesel generators.

Plants 3, 4, 5, 6, and 8 - The breakers associated with containment cooling fans were studied. Each plant has four sets of breakers (except plant, 8 which had eight sets). The purpose of this study was to determine the plant-to-plant variability for single and multiple failure rates. Plant 8 analyses are discussed in Appendix G; they will not be summarized in this volume because of the difference in the number of breakers and the associated data.

Plant 7 - The four dampers associated with containment fans were studied. As expected, the failure rates were quite small and the data sparse. We obtained 11 failures during about 14 years. No significant dependencies were observed. This pilot study is discussed in Appendix G; it will not be discussed here.

The objective, main conclusions, and some of the quantitative results obtained for each of the case studies are discussed below; detailed quantitative results are given in Appendix G.

Plant 1

The main objective of Plant 1 study was to ascertain whether the conclusion of the utility's IPE, that is a lack of any common cause in failure of Diesel Generators, can be supported by the new methodology.

Two sets of quantitative results were generated. The first set of results, in Tables 1, 2, and 3 incorporate data for both valid and non-valid multiple diesel-generator failures; Tables 4, 5, and 6 exclude the non-valid multiple failures to be consistent with the utility assumptions. The definition of Cases 1, 2, and 3 is the same as that described earlier in this chapter. The definition of the partial β factors of Types 1 and 2, again, is the same as that discussed earlier in this chapter; however, the following points will provide a formulation for the way these quantities were derived.

Table 1. Quantitative Results for EDG Failure Data From 2/3/82 to 2/17/87

Case	Multiple EDG Unavailability (Test Interval of One Month)				
	q_s	1/4	2/4	3/4	4/4
1	0.11	0.44	0.062	4.85×10^{-3}	1.5×10^{-4}
2	0.11	0.44	0.13	2.0×10^{-2}	1.4×10^{-3}
3	0.11	0.44	0.14	2.9×10^{-2}	2.5×10^{-3}

Table 2. Quantitative Results for EDG Failure Data From 2/17/87 to 12/31/89

Case	Multiple EDG Unavailability (Test Interval of One Month)					
	q_s	1/5	2/5	3/5	4/5	5/5
1	0.094	0.47	0.07	7.05×10^{-3}	3.57×10^{-4}	7.3×10^{-6}
2	0.094	0.47	0.15	3.0×10^{-2}	3.4×10^{-3}	1.7×10^{-4}
3	0.094	0.47	0.16	3.3×10^{-2}	3.9×10^{-3}	1.7×10^{-4}

Table 3. Partial Beta Factors Estimated for Plant 1 EDGs

	Before 2/17/87		Post 2/17/87	
	Type 1	Type 2	Type 1	Type 2
$\beta_{2/1}$	0.18	0.02	0.19	0.02
$\beta_{3/2}$	0.17	0.06	0.16	0.02
$\beta_{4/3}$	0.08	0.04	0.10	0.015
$\beta_{5/4}$	NA	NA	0.04	0

Table 4. Quantitative Results for EDG Failure Data From 2/3/82 to 2/17/87
(Excluding Invalid Multiple Failures)

Case	Multiple EDG Unavailability (Test Interval of One Month)				
	q_s	1/4	2/4	3/4	4/4
1	0.095	0.38	4.7×10^{-2}	3.1×10^{-3}	8.1×10^{-5}
2	0.095	0.38	0.087	0.01	5.9×10^{-4}
3	0.095	0.38	0.1	0.013	6.8×10^{-4}

Table 5. Quantitative Results for EDG Failure Data From 2/17/87 to 12/31/89

Case	Multiple EDG Unavailability (Test Interval of One Month)					
	q_s	1/5	2/5	3/5	4/5	5/5
1	0.072	0.36	4.5×10^{-2}	3.3×10^{-3}	1.26×10^{-4}	2.0×10^{-6}
2	0.072	0.36	8.3×10^{-2}	1.2×10^{-2}	9.3×10^{-4}	3.1×10^{-5}
3	0.072	0.36	8.3×10^{-2}	1.2×10^{-2}	9.3×10^{-4}	6.1×10^{-5}

Table 6. Partial Beta Factors Estimated for Plant 1 EDGs
(Excluding Invalid Failures)

	Before 2/17/87		Post 2/17/87	
	Type 1	Type 2	Type 1	Type 2
$\beta_{2/1}$	0.14	0.03	0.11	0
$\beta_{3/2}$	0.1	0.03	0.10	0
$\beta_{4/3}$	0.05	0.007	0.07	0
$\beta_{5/4}$	NA	NA	0.06	0

We can estimate partial β factors approximately (approximate MLG factors) using the following formula:

$$q_{k,n} = q_{k,n}^* + \beta_{k/k-1} q_{k-1} \quad (26)$$

where,

$q_{k,n}$: is the actual unavailability of k out of n diesel generators. These are the results generated from Case 3.

$q_{k,n}^*$: is the unavailability of k out of n diesel generators, calculated under assumption of independence. If $q_{k,n}^*$ is used from Case 2, gives an actual partial beta factor supported by data and is referred to by "Type 2." If $q_{k,n}^*$ is used from Case 1, it gives a correction factor that includes both the underestimation resulted from the use of PSA approximate formula for system unavailability as well as the dependency effect, and is referred to as "Type 1."

The following conclusions can be drawn from Tables 1 through 6.

1. Conventional PRA calculations significantly underestimate multiple diesel unavailabilities under assumption of independence (comparison of Case 1 with Case 2).
2. The actual clustering/dependency exhibited by the data has a minimal effect on estimates of multiple DG unavailability (at maximum, a factor of 2 based on comparison of Cases 2 and 3).
3. Tables 3 and 6 provide partial β factors calculated with methods described earlier. We note that the partial β factors from type 1 are those to be used with the IPE submittal to provide proper estimates of the unavailability of multiple diesel generators. As Tables 3 and 6 show, we find little dependency in diesel failures, consistent with the conclusions of the conclusions of the utility's PRA.
4. The IPE submittal calculated the diesel generator unavailability based on failure per demand. The demand-failure rates were indicative of an improving trend after 02/17/87. Furthermore, the fifth diesel generator appeared to have a different demand-failure rate compared to the others. Our methodology estimates and uses failure rate per unit time. We did not find any evidence of a significant improving trend after 02/17/87. Furthermore, the failure of the fifth diesel generator was consistent with that of the other diesel generators. The approach of failure rate per demand also underestimated single diesel unavailability. All these differences between the two approaches stems from the fact that the diesel demands were clustered. For example, the T.S. required many additional demands on the redundant diesel whenever one of the diesels was under repair. We concluded that an approach based on demand failure rate for stand-by components should be avoided unless there is a uniform distribution of demands throughout the observation period.

Plant 2

The main objective of studying the diesel generators at Plant 2 was to evaluate their susceptibility to dependent failures. This plant had a recent incident involving the unavailability of four out of five diesels. Therefore, finding a significant dependency among the failure of diesel generators, when this recent event is excluded, to some extent will validate the methodology developed here.

The raw data were retrieved from the NPRDS; about 4 years and 3 months of operational data during all modes of plant operation were collected from January 1988 to March 1992. The interpretation of this data required some judgment. A failure was decided to have happened if the following criterion (C) was satisfied: Failure would result in EDG not successfully responding to loss of offsite power for a mission time of 24 hours. To apply this criterion, the interpretation of the failure data followed these guidelines: All failures, resulting from all causes including automatic response, some operator action or auto start, were counted as failures as long as the above criterion (C) was satisfied. This interpretation of the data was performed independently by two staff members who identified 90 potential failures.

Following the methods described earlier, the unavailability of the diesel generators was estimated, taking into account the dependency between the failures, and not taking them into account. Table 7 compares these new values with the approximate PSA system unavailability described earlier. Cases 1, 2, and 3 in Table 7 are defined as before.

Table 7. Unavailability Calculations for Plant 2 Diesel Generators

Combination	Unavailability (PRA approximation)	Unavailability (BNL exact calculation without dependency)	Unavailability (BNL exact calculation including dependency)
One Diesel Out	0.53	0.53	0.53
Two Diesels Out	9.04×10^{-2}	0.2	0.28
Three Diesels Out	1.01×10^{-2}	0.05	0.10
Four Diesels Out	5.78×10^{-4}	7.2×10^{-3}	2.9×10^{-2}
Five Diesels Out	1.34×10^{-5}	4.5×10^{-4}	2.9×10^{-3}

Table 7 shows that when five diesels are out, even when no dependency is taken into account, the BNL exact calculation is about one order of magnitude larger than traditional PRA calculations. When the approximate PRA calculations are compared with the BNL exact calculations including dependency, it is clear that the PRA calculations underestimate the unavailability by about two orders of magnitude. Due to this significant difference, it can be concluded that here there is dependency amongst the failures. This dependency, in turn, affects the unavailability of the diesel generators.

The approximate estimate for the Type 1 partial β factors (approximate MLG factors) are given in Table 8 as in the case of Plant 1 diesel generators using Eqn. (26), these are the partial β factors that shall be used with PRA calculations. As shown, the partial β factors in Plant 2 compared to Plant 1 indicates a very strong dependency and a potential for common-mode failure.

Table 8. Beta Factors for Plant 2 Diesel Generators

Partial Beta Factor	Value
$\beta_{2/1}$	0.36
$\beta_{3/2}$	0.32
$\beta_{4/3}$	0.28
$\beta_{5/4}$	0.10

From Section 2.3, we defined the parameter α_k as a dependency indicator, with Expression (23), which is the ratio of the empirical (observed) Minimal Cycle Durations over the theoretical ones. We introduced the general idea that, if a shock has occurred, the observed Minimal Cycle Durations will be shorter than the theoretical ones. However, for the case of the Plant 2 diesel generators, one very interesting phenomenon can be observed. The observed and theoretical Minimal Cycle Durations (MCD), given in Table 9, show that the observed MCD did not decrease in comparison with the theoretical MCD, but even increased. The reason for this phenomenon is that the (failure) behavior of the diesel generators is not constant in time, but shows *trends*. If the failure data is screened more closely, it can be seen that from the beginning of the observations to December 1989, the failures occurred independently. However, from December 1989 to the end of the observation period, there is a clear *trend* in the failures to be affected by dependencies.

Table 9. Observed and Theoretical Minimal Cycle Durations for the Whole Set of Failure Data of Plant 2 Diesel Generators

Number of the Cycle	Observed MCD	Theoretical MCD
1	17	17
2	40	38
3	76	66
4	130	108
5	260	193

This phenomenon was not a surprise. The CUSUM test had detected the trends, and we also found that a mixture of exponentials fitted the data better than a single exponential. The mixture fits better, in this case, because it can take into account separately the contributions from the independent trend and from the dependent trend.

We note that this discussion about the phenomenon caused by *trends* is of more academical than of practical interest. If an end user wants more accurate figures for the unavailability (or for β factors) taking into account dependencies, the methods described in this report can be used directly.

If the field failure data is divided into "before December 1989" and "after December 1989," the *trends* we have described can be clearly identified from the results obtained, using the methods described in this report. Table 10 shows the results for the "before December 1989" period.

Table 10. Results for Plant 2 Diesel Generators for the "Before December 1989" Period

Number of the Cycle	Observed MCD	Theoretical MCD	Unavailability (BNL exact calculation without dependency)	Unavailability (BNL exact calculation including dependency)
1	56	56	2.26×10^{-1}	2.26×10^{-1}
2	127	126	3.04×10^{-2}	3.28×10^{-2}
3	271	219	2.41×10^{-3}	2.43×10^{-3}
4	530	358	1.03×10^{-4}	8.83×10^{-5}
5	648	638	2.28×10^{-6}	5.26×10^{-6}

Table 10 shows that the observed and theoretical MCD are very close to each other for cycles of 2, 3, and 5 failures. For the cycle of 4 failures, the observed MCD is slightly larger than the theoretical MCD, indicating no dependencies were detected between any four diesels. The unavailabilities also are close to each other for all cycles. For the cycle of 4 failures, the exact calculation including dependency is slightly less than the exact calculation without dependency; as stated, this is the result of no dependencies detected between any four diesels. For the cycle of 5 failures, the exact calculation including dependency is about twice as large as the exact calculation without dependency.

Table 11 shows the results for the "after December 1989" period.

Table 11. Results for Plant 2 Diesel Generators for the "After December 1989" Period

Cycle Number	Observed MCD	Theoretical MCD	BNL exact calculation without dependency	BNL exact calculation including dependency
1	20	20	4.86×10^{-1}	4.86×10^{-1}
2	22	44	1.63×10^{-1}	2.45×10^{-1}
3	41	77	3.50×10^{-2}	8.53×10^{-2}
4	61	127	4.31×10^{-3}	2.73×10^{-2}
5	110	225	2.30×10^{-4}	3.20×10^{-3}

Table 11 clearly indicates the dependency effect for the "after December 1989" period. The observed MCD is shorter than the theoretical MCD for all cycles, and the exact calculation without dependency underestimates the unavailability for all cycles (2, 3, 4, and 5). For cycles 4 and 5 the underestimation is as much as one order of magnitude.

In conclusion, this pilot application supports the idea that the recent incident involving the unavailability of multiple diesel generators most probably was caused by the dependency. Furthermore, we can show that dependent failures have significantly increased after 1989. Summarizing the findings from the pilot applications for plants 1 and 2, we make the following conclusions.

Dependency varies significantly from plant to plant. Even within a plant and a system dependency varies with time. The effect of dependency on system unavailability is significant and increases with the number of redundancies. The variation among the plants and with time is strongly indicative of a dynamic behavior which best can be used in dynamic PSA.

Pilot Application for Plants 3,4,5, and 6

The objective of this pilot application was to analyze dependent failures in a standard system across several plants. The system selected was the breakers associated with the slow and fast operation of Containment Fans (CF) in Pressurized Water Reactors (PWRs).

Table 12 shows the unavailability results for the four plants (Plant 3, 4, 5, and 6) for Cases 1, 2, and 3, as defined earlier. The following conclusions can be made from this table.

1. The breaker failure rate is consistent among the four plants. A single breaker unavailability for a test interval of one month can be obtained from the values of "Unavailability of at least one component" from Table 12, divided by the number of redundant components (i.e., "4" for this pilot application). Single breaker unavailability derived from this data ranges between $2.5E-2$ to $3.1E-2$, that translates to failure rates from $6.0E-5$ to $9.0E-5$ per hour.
2. Even though the single breaker failure rate and unavailability is consistent among the four plants, the multiple breaker failures varies from a plant to plant, depending on the degree of the dependency among the times of failures. As an example, the unavailability of the four breakers varies from $1.6E-5$ to $4.76E-6$, about a factor of 4.
3. All the four plants show a clear dependency contribution to varying degrees. To better understand the degree of dependency, the partial β factors and the overall single β factor for all the four components for Types 1 and 2, as defined before, were calculated (Table 13). To better clarify the degree of dependency, we calculated the fraction of the unavailability of the four breakers that is attributed by the dependency. This is shown in Table 14. The calculated fractions are calculated based on the difference of unavailability of Case 3 minus Case 1, divided by the unavailability of Case 1 for Type 1 contribution. The Type 2 calculations are done similarly by substituting Case 2 for Case 1 unavailabilities. These fractions show that the Type 1 contributions range from 80% to 96% and for Type 2 from 22% to 86%. Plant 3 shows the largest contribution from dependent failure. Plants 4 and 5 show the same amount of dependency, whereas Plant 6 shows a minimal dependency contribution.

Table 12. System Unavailabilities for Containment Fan Breakers

Unavailability of at Least												
Plant	1 Component			2 Components			3 Components			4 Components		
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
	1.10E-1	1.10E-1	1.10E-1	3.68E-3	6.35E-3	6.92E-3	8.15E-5	1.88E-4	4.55E-4	5.72E-7	2.24E-6	1.6E-5
3	1.16E-1	1.16E-1	1.16E-1	4.04E-3	7.17E-3	1.04E-2	9.54E-5	2.26E-4	3.96E-4	7.07E-7	2.88E-6	7.72E-6
4	1.00E-1	1.00E-1	1.00E-1	3.10E-3	5.24E-3	5.18E-3	6.13E-5	1.40E-4	4.41E-4	3.91E-7	1.51E-6	5.71E-6
5	1.24E-1	1.24E-1	1.24E-1	4.54E-3	8.09E-3	7.88E-3	1.16E-4	2.72E-4	3.03E-4	9.24E-7	3.70E-6	4.76E-6
6												

Table 13. Partial β Factors for Containment Fan Breakers - Plants 3, 4, 5, and 6

Plants	$\beta_{2/1}$		$\beta_{3/2}$		$\beta_{4/3}$	
	Type 1	Type 2	Type 1	Type 2	Type 1	Type 2
3	0.03	0.005	0.10	0.042	0.19	0.07
4	0.055	0.028	0.075	0.024	0.074	0.02
5	0.021	NA	0.123	0.06	0.087	0.03
6	0.027	NA	0.41	0.004	0.033	0.004
NA means not applicable; basically no dependency was observed.						

Table 14. Fraction of Unavailability of Four Fan Cooler Breakers due to Dependency

Plants	Type 1	Type 2
3	96%	86%
4	91%	63%
5	93%	73%
6	80%	22%

4. CONCLUSIONS

This report introduces a new perspective on the basic concept of dependent failures where the definition of dependency is based on clustering in failure times of similar components. This perspective has two significant implications: firstly, it relaxes the conventional assumption that dependent failures must be simultaneous and result from a severe shock; secondly, it allows the analyst to use all the failures in a time continuum to estimate the potential for multiple failures in a window of time (e.g., a test interval), therefore arriving at a more accurate value for system unavailability. In addition, the models developed here (including the Appendices in Volume 2) provide a method for plant-specific analysis of dependency, reflecting the plant-specific maintenance practices that reduce or increase the contribution of dependent failures to system unavailability.

The proposed methodology, as discussed in Volume 2, can be used for screening analysis of failure data to estimate the fraction of dependent failures among the failures. In addition, the proposed method can evaluate the impact of the observed dependency on the system unavailability and plant risk.

The formulations derived in this report have undergone various levels of validations through computer simulation studies and pilot applications. For example, the pilot applications of these methodologies, as discussed in Chapter 3 and Appendix G of Volume 2, showed that the contribution of dependent failures of diesel generators in one plant was negligible, while in another plant, it was quite significant. It also showed that in the plant with significant contribution of dependency to Emergency Power System (EPS) unavailability, the contribution changed with time. Similar findings were reported for the Containment Fan Cooler breakers (Appendix G). Drawing such conclusions about system performance would not have been possible with any other reported dependency methodologies. The validation studies through computer simulation also showed that the formulation of system unavailability based on this new methodology is sound and more accurate than the conventional methods for estimating system unavailability presently used in PRAs.

From the results of these validation studies we draw the following conclusions:

1. The methodology is sound and provides accurate estimates when compared to underlying simulated results.
2. The new formulation of the system unavailability accounting for clustering parameters provides a more accurate and justifiable estimate of system unavailability than using standard PRA techniques. The difference in the two estimates in a system with a high level of redundancy can be quite significant; this is mainly due to the inherent approximation in PRA-type calculations.
3. The proposed model can be applied to plant-specific data and accounts for specific plant maintenance and surveillance activities. Conventional common-cause models, on the other hand, are usually based on industry-wide data and gives no credit to plant-specific maintenance practices. The pilot applications reported in this volume and detailed in Appendix G of Volume 2, demonstrates the power and the capability of the methodologies in addressing the plant-specific dependency by analyzing the clustering of failures.

4. The effect of the clustering of failures on system unavailability is significant, as verified both by simulation studies and by pilot applications, (typically, one order of magnitude). Such an effect could change the perceived risk profile of the plant and the prioritization of dominant accident sequences and accident sequence minimal cut sets.
5. Software is being developed to analyze times between failures to estimate dependency parameters and generate estimates of the conventional beta factors presently used in PRAs. Appendix C outlines a road map of how the approach can be extended beyond the system unavailability calculations for estimating the plant core damage probability and risk.

We believe these methods and software can be useful to analyze the failure data to estimate the fraction of dependent failures, and to evaluate its impact on system unavailability. At the same time, further work is needed before these methods can be used in conventional PRAs to evaluate a plant-specific risk profile. We also showed that the methods can evaluate the safety significance of dependent failures, their plant-specific nature, and their dynamic variations with time. These methods appear useful to enhance early detection of risk significant dependencies and to take prompt corrective actions.

5. REFERENCES

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