Strål
säkerhets
myndigheten
Swedish Radiation Safety Authority

Authors: Günter Becker
Gunnar Johanson
Sandra Lindberg
Jussi Vaurio

Research

2009:07

Dependency Analysis Guidance Nordic/German Working Group on Common Cause Failure analysis

Phase 2, Development of Harmonized Approach and Applications for Common Cause Failure Quantification

Report number: 2009:07 **ISSN:** 2000-0456
Available at www.stralsakerhetsmyndigheten.se

Title: Dependency Analysis Guidance Nordic/German Working Group on Common cause Failure analysis. Phase 2, Development of Harmonized Approach and Applications for Common Cause Failure Quantification
Report number: 2009:07
Author/Authors: Günter Becker[1)], Gunnar Johanson[2)], Sandra Lindberg[2)] and Jussi Vaurio[3)]
[1)]RISA Sicherheitsanalysen GmbH, [2)]ES Konsult, [3)]Prometh Solutions
Date: Mars 2009

SSM Perspective

Background

The Regulatory Code SSMFS 2008:1 of Swedish Radiation Safety Authority (SSM) includes requirements regarding the performance of probabilistic safety assessments (PSA), as well as PSA activities in general. Therefore, the follow-up of these activities is part of the inspection tasks of SSM. According to the SSMFS 2008:1, the safety analyses shall be based on a systematic identification and evaluation of such events, event sequences and other conditions which may lead to a radiological accident. The research report Nordic/German Working Group on Common cause Failure analysis. Phase 2 project report: Development of Harmonized Approach and Applications for Common Cause Failure Quantification" has been developed under a contract with the Nordic PSA Group (NPSAG) and its German counterpart VGB, with the aim to create a common experience base for defence and analysis of dependent failures i.e. Common Cause Failures CCF. Phase 2 in this project if a deepen data analyses of CCF events and a demonstration on how the so called impact vectors can be constructed and on how CCF parameters are estimated.

Scope

The word Guidance in the report title is used in order to indicate a common methodological guidance accepted by the NPSAG, based on current state of the art concerning the analysis of dependent failures and adapted to conditions relevant for Nordic sites. This will make it possible for the utilities to perform cost effective improvements and analyses.

Results

The report presents a common attempt by the authorities and the utilities to create a methodology and experience base for defence and analysis of dependent failures. The performed benchmark application has shown how important the interpretation of base data is to obtain robust CCF data and data analyses results. Good features were found in all benchmark approaches. The obtained experiences and approaches should now be used in harmonised procedures. A next step could be to develop and agree on event & formula driven impact vector creation based on component impairments, time differences and shared cause assessment. Following the conclusions of phase 2 a decision is made to continue the data analyses work on additional components. The objectives of phase 2 have been to establish a common procedure and model of quantification for CCF events.

Effect on the SSM work

The SSM report is judged to be useful in supporting the authority's review of procedural and organizational processes at the licensees, and analyses methodologies associated for the analysis of dependent failures.

Possible Continued Activities within the Area

Experiences from the application of the Guidance shall be awaited for, i.e., major changes or extensions to the document shall be decided at a later stage. However, the development of methods is an on-going process which is guided by changes in the regulations, analysis assumptions or in increased level of detailed in the analysis of dependent failures. SSM encourages licensees, organisations and other, who need best available and harmonized CCF-data, to continue with the difficulties to get robust dependency data, with other countries.

Project information

SSM administrator for this project has been: Ralph Nyman – System Assessment
SSM reference: SSM 2008/197
SSM project number: 1094
References to other similar research work och reports
SKI Rapport 2007:41 (phase 1 report in this project)
SKI Rapport 2004:04

SSM-perspektiv

Background

Strålsäkerhetsmyndigheten (SSM) ställer krav på PSA-studier och PSA-verksamhet i föreskriften SSMFS 2008:1. Uppföljning av denna verksamhet ingår därför i SSM:s tillsynsverksamhet. Enligt krav i SSMFS 2008:1 skall säkerhetsanalyserna vara grundade på en systematisk inventering av sådana händelser, händelseförlopp och förhållanden vilka kan leda till en radiologisk olycka.

Forskningsrapporten "Nordic/German Working Group on Common cause Failure analysis. Phase 2 project report: Development of Harmonized Approach and Applications for Common Cause Failure Quantification" har utvecklats på uppdrag av Nordiska PSA-gruppen (NPSAG) tillsammans med sin tyska motsvarighet, VGB, med syftet att skapa en gemensam erfarenhetsbas för försvar och analys av beroendefel, s.k. Common Cause Failures (CCF). Fas 2 i detta projekt har inneburit en fördjupad dataanalys av CCF händelser och en demonstration i hur s.k. impact vector konstrueras och hur CCF parametrar beräknas.

Syfte

Ordet vägledning (Guidance) i rapporttiteln används för att tydliggöra en gemensam metodologisk och av NPSAG accepterad vägledning som baserar sig på den allra senaste kunskapen om analys av beroendefel och anpassade till förhållanden som anses gälla för nordiska kärnkraftverk. Detta kommer att göra det möjligt för tillståndshavarna att genomföra kostnadseffektiva förbättringar och analyser.

Resultat

Rapporten ""Nordic/German Working Group on Common cause Failure analysis. Phase 2. Development of Harmonized Approach and Applications for Common Cause Failure Quantification" presenterar ett gemensamt försök, mellan myndighet och tillståndshavare, att skapa en metodologi och erfarenhetsbas för försvar och analys av beroendefel och för tillämpning i PSA studier.

Den benchmark som har genomförts visar hur viktig tolkningen av data är för att erhålla robusta CCF-data och dataanalys resultat. Bra egenskaper har identifieras i samtliga tillvägagångssätt. Dessa erfarenheter bör användas till att utveckla ett harmoniserat tillvägagångssätt i CCF analyser. Nästa steg kan vara att utveckla händelse och formelstyrd generering av "impact vectors" baserat på komponentpåverkan, tidsskillnader och värdering av gemensamma orsaker. Efter slutförandet av fas 2 har beslut fattats att arbetet ska fortsätta med analys av ännu flera komponenter. Målsättningen med fas 2 har varit att utveckla en gemensam procedur och modell för kvantifiering av CCF händelser.

Effekt på SSM:s verksamhet

Denna SSM rapport bedöms även ge ett bra stöd för myndigheterna i sin granskning av olika tillståndshavares verksamhetsprocesser för att skapa robusta tillförlitlighetsdata, och analysmetoder förknippade med analyser av beroende fel.

Fortsatt verksamhet inom området

Erfarenheter från tillämpningen av rapportens vägledningar skall inväntas, eventuella större ändringar i vägledningsdokumentet beslutas om vid senare tillfälle. Utveckling av metoder och förfining av sådana pågår dock, vartefter det ställs högre krav på nya analysförutsättningar och -djup. SSM uppmanar tillståndshavarna, organisationer och andra, som behöver ha tillgång till harmoniserad CCF-data, att fortsätta att kämpa vidare med svårigheterna att skapa robusta beroendefelsdata, med andra internationella organisationer.

Projektinformation

SSM administratör för det här projektet har varit: Ralph Nyman – Systemteknik
SSM referens: SSM 2008/197
SSM projektnummer:1094
Referenser till tidigare forskningsarbeten och rapporter:
SKI Rapport 2007:41 (fas 1 rapporten i detta projekt)
SKI Rapport 2004:04

Content

1. STRUCTURE OF THE REPORT

MAIN REPORT

ATTACHMENTS

ATTACHMENT 1 – IMPACT VECTOR CONSTRUCTION

1-1 Phase 2, Task 1 report: Impact vector determination methodology
1-2 Impact vector calculator

ATTACHMENT 2 – PARAMETER ESTIMATION

2-1 PREB calculator

ATTACHMENT 3 – IMPACT VECTOR CONSTRUCTION VALIDATION

Review of phase 2, task 1 report:

3-1 Mankamo, Tuomas. *Review Notes on Phase 2/Task 1 Report Impact Vector Determination Methodology*, NAFCS-WN-TM21, Issue 2.
3-2 Klügel, Jens-Uwe. *Scientific Review of Phase 2, Task 1 Report: Impact Vector Determination Methodology*. Vaurio, Jussi. *Review of status on Phase 2 Task 1 methodology*, PROSOL-8002, rev. 1.
3-4 Table with gathered review comments and answers.
3-5 Vaurio, Jussi. *Time factor considerations in common cause failure quantification*, PROSOL-8005.

Application of impact vector construction approach on check valves and motor operated valves:

3-6 Event data set - MOV and CV
3-7 CV and MOV impact vector calculation

Expert assessment of check valves and motor operated valves:

3-8 Expert assessment exercise, minutes
3-9 Expert assessment exercise, results

Sensitivity analysis:

3-10 Sensitivity analysis

ATTACHMENT 4 – PARAMETER ESTIMATION VALIDATION

4-1 Becker, Günter. Technical note on PREB theory.
4-2 Vaurio, Jussi. *PREB estimation method and validations*, PROSOL-8004.
4-3 PEAK calculator
4-4 Input data for parameter estimation (diesels and pumps)
4-5 PREB results, diesels
4-6 PREB results, pumps
4-7 PEAK results, diesels and pumps

ATTACHMENT 5 – RAW DATA

Confidential data – Confidential under the ICDE proprietary agreement - not included – The attachment can be requested from SSM by ICDE member organizations.

2. SUMMARY

This report is the main report from the European Working Group on CCF analysis (EWG), including members from Finland, Germany and Sweden. The report provides an overview and summary on performed work on the development of a methodology for impact vector construction and CCF event quantification. An impact vector expresses the conditional failure probability, given an observed CCF, that different numbers of components would fail if an actual demand should occur during the presence of the CCF impact.

Denna rapport utgör huvudrapporteringen från the "European Working Group on CCF analysis (EWG)". Gruppen inkluderar projektmedlemmar från Finland, Tyskland och Sverige. Rapporten presenterar en överblick och sammanfattning av det arbete som utförts vad gäller utveckling av metod för "impact vector"-framtagning och kvantifiering av CCF-händelser. En "impact vector" (inverkans vektor) uttrycker den betingade felsannolikheten, givet en observerad CCF, att olika antal komponenter skall fela om ett verkligt behov skulle uppkomma vid närvaro av CCF inverkan.

A comprehensive procedure including all steps from CCF event input data, via event impact vectors, to final CCF parameters has been developed and validated.

One focus has been the development of a formula and coding driven procedure for impact vector construction. An analysis of data available from the NAFCS experiment clearly showed, that experts tend to use rather high values for CCF (i.e. in line with the high bound of NAFCS), if they see much damage in terms of impairment. In other cases, they usually select a value between NAFCS high bound and NAFCS low bound. There is some arbitrariness in how this value is selected, which has been demonstrated by the fact, that there exist at least two formulae, which both can reproduce the NAFCS best estimate results in sufficient quality, which have been used as input.

The formula selected is thus not based on a statistical analysis of the data alone, but on a probabilistic argument, which is related to the scenario based method of estimation developed in the NAFCS project. The formula and coding driven approach is a systematic approach to interpret the component impairment vector into an event impact vector.

The developed formula and coding procedure for Impact Vector construction offers a systematic and transparent approach to be applied in quantitative analysis of CCF events. The developed approach for impact vector construction fulfils the basic requirements that it shall be defendable and that it shall result in realistic modelling i.e. not too conservative.

A necessary assumption is that the expert assessments involved as a basis are representative for expert assessments in the area concerned. The authors have no reason to doubt, that this holds. This of course has not been verified empirically, and would take time to demonstrate or negate. If such quality assessment is desired, it could best be done in form of an international benchmark and CCF expert assessment.

The result of a CCF evaluation strongly depends on the impairments and on the mathematical procedure used, but less on the approach selected for impact vector construction, see table 9 in section 6.5.4.

Application of the approach demonstrates that it is possible to apply the approach for different component types. The results have also been used for comparison in an expert judgements exercise, where the experts have been aware of the limits imposed by High Bound and Low Bound results. These experts agreed that given that the impairments are dependable, impact vectors can be found using a simple automatic approach. They approve that in such cases a quasi automatic procedure is applicable to produce impact vectors from impairments and comparable information.

Guidelines are provided to assess the quality and homogeneity of the input data in view of quantification. The guidelines largely improve both efficiency and consistency in the event assessment and the event impact vector construction. It cannot be stressed too strongly, that the quality of input data is a critical issue for any automatic treatment of input data. It must be assured, that the input data is of high quality. For this reason, it would be premature to claim that a sufficient quantification of CCF could be performed simply by taking the degradation codes (as assessed in ICDE or a comparable data base) and a simple formula, possibly multiplied by single time- and shared cause factors. Additional expert re-assessments of a CCF data base ought to be made based on event descriptions and possibly plant-specific sources. The guidelines are provided in the check list given in this report and in the impact vector construction procedure described in attachment 1.

Concerning databases, such as the ICDE database, this should best be done when the ICDE data is generated, because in this case, most profit can be taken from this data from all users. If this cannot be guaranteed it is suggested to perform quality control of the input data for each event according to a checking procedure developed based on priority issues identified in the applications performed.

An algorithm for Empirical Bayesian parameter estimation has been applied. The Algorithm has been shown to be an applicable method for CCF parameter estimation application. Application to test cases is presented together with CCF parameters including their qualitative and quantitative uncertainties.

The algorithm has been applied to derive the uncertainty bounds. Table 1 presents the estimated parameters for Diesels for all failure multiplicities and present the mean values plus the 5% and 95% confidence bounds. The parameters represent the quantitative uncertainties.

Formula and coding driven	0 out of 4-failure	1oo4-failure (T book values)	2oo4-failure	3oo4-failure	4oo4-failure
FCD-M95	**1,0E+00**	5,86E-05	1,73E-05	1,74E-06	8,48E-07
FCD-Mc	**1,0E+00**	1,92E-05	3,02E-06	4,22E-07	2,03E-07
FCD-M5	**1,0E+00**	5,50E-07	3,93E-10	3,93E-10	1,66E-10

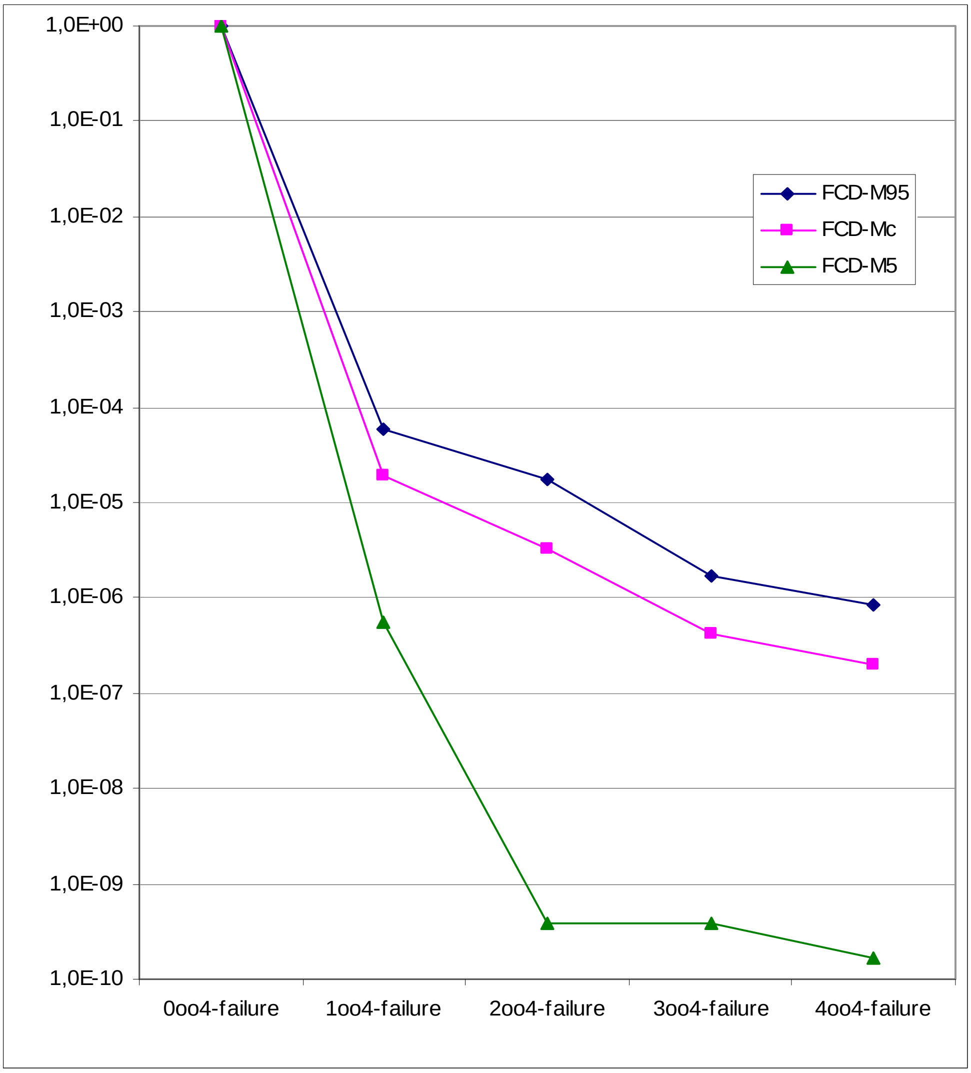


Table 1. Estimated CCF parameters, 95%, mean and 5% for Diesels (accumulated, e.g 3oo4 includes 4oo4 etc)

The approach for the impact vector construction is described in the report (chapter 3). The algorithm of the PREB estimation method for CCF rate estimation is presented (chapter 5). The overall procedure to enable the presentation of the estimated parameters as in table 1 are presented in Figure 1.

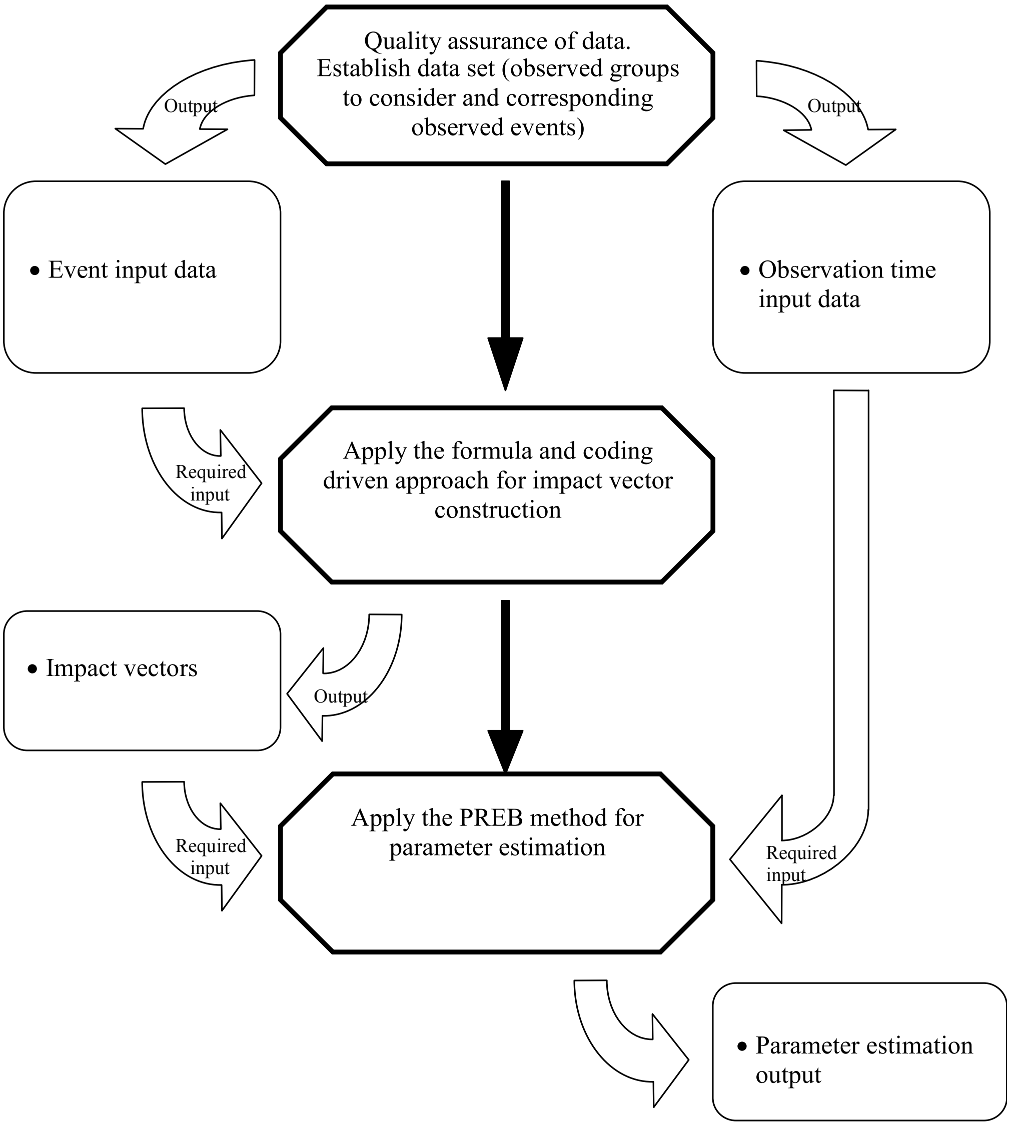


Figure 1. Procedure for parameter estimation

3. INTRODUCTION

This report is part of the reporting from the Nordic/German Working Group on CCF analysis, including members from Finland, Germany and Sweden. The report provides an overview and summary on performed work on the development of a methodology for impact vector construction and CCF event quantification.

The project is planned in two phases with a reporting and progress evaluation before initiation of the second phase.
Phase 1: Comparisons and application to test cases (2006-2007), SKI Report 2007:41.

Phase 2: Development of harmonized approach and applications (2007-2008), this report.

3.1 Comparisons and application to test cases

SKI Report 2007:41: The report summarizes the work during the 1st phase of the project, which included the following main tasks:

Task 1: Survey of databases.

Task 2: Survey of methods for classification and quantification of CCF-events and description of these methods.

Task 3: Classify events for application, using different approaches as recommended above.

Task 4: Draw conclusions for harmonization
Phase 1 was performed during 2006 and 2007, and Phase 2 was initiated following a project evaluation as a direct continuation of phase 1.

3.2 Development of harmonized approach and applications

Phase 2 is to consider development of harmonized approach and applications. The objectives for phase 2 are based on the results from phase 1 and on the meeting between NPSAG and VGB on September 5 2007.

3.2.1 Phase 2 objectives:

The main objective of the second phase is to establish a common procedure and model of quantification of CCF events. This is to be done by:

- Providing a common basis for methods and guidelines for data classification and assessment.
- Establishing format to allow data to be shared for quantifications and provide interpretation of raw data for exchange and use in quantification models.

3.2.2 Phase 2 activities:

The main activity in phase 2 is the development of harmonized applications. This is to be achieved firstly by agreement on common methods and guidelines for data classification and assessment, since a common procedure may be more justifiable and more defendable, and secondly by establishing a common format that allows data to be shared for quantifications and that provides interpretation of raw data for exchange and use in quantification models. This will also contribute to improving the consistency in international in-depth assessment of CCF events for parameter estimation.

Task 1: Work on impact vector construction, develop and agree formula driven approach.

- Development of formula driven impact vector construction using various approaches.
- Selecting a suitable approach taking into account existing cases for diesels and pumps.
- Overview of applied formula driven approach

Task 2: Validation of formula driven approach.

- Independent review of task 1 results and resolution of comments
- Generate impact vectors on events of a new CCF group.
- Development of impact vectors manually/expert judgement (unaware of formula driven results) and compare results, specific events only.
- “Expert judgment” check list
- Sensitivity analysis

Task 3: Work on parameter estimation, test and develop unified method.

- Application of separate methods using identical impact vectors to check convergence of results.
- Decision on unified approach based on criteria like being defensible, realistic results avoiding conservativeness, etc.
- Describe procedure including a unified approach and format in a common guideline
- Calculator

Task 4: Summary report issuing, review and dissemination.

4. IMPACT VECTOR CONSTRUCTION

This section provides a description of the development of a harmonised approach and procedure for impact vector construction (Attachment 1).

The first task comprises impact vector construction, as well as development and agreement on a formula driven approach. The formula and coding driven impact vector construction method has been developed using various approaches to select a suitable approach taking into account existing cases for diesels and pumps. For the agreed approach there have been two basic requirements; that it shall be defendable and that it shall result in realistic modelling.

As there is no specific German procedure for constructing impact vectors, two methods have been investigated; the Fortum (Finland) and the NAFCS (best estimate) (Sweden) approaches.

4.1 Procedure for Impact Vector construction

The developed procedure for Impact Vector construction is presented in Attachment 1.

The developed procedure for Impact Vector construction offers a systematic and transparent way to be applied in quantitative analysis of CCF events.

The approach is considered to be realistic and well defendable.

This is concluded since it is well formulated and can be properly described with the following arguments:

- It takes the most conservative approach possible given the data, when stronger impairment is seen

- It takes a less conservative approach when weak impairment as dominant observation is seen, because this is, what experts have been observed to do.

- On an average, the approach is still conservative in comparison with expert assessments.

- The advantages of the scenario / hypothesis based NAFCS best estimate approach are nearly obtained, but at much less effort

The produced results are rather close to the NAFCS best estimate results.

4.2 Selecting a suitable approach / Validation

As demonstrated in Attachment 1 the acceptance criteria for selecting the approach are met. Thus, this approach is considered to be acceptable as a realistic approach, since it is quite well in the lines of what experts estimate. In the NAFCS best estimate method a quality check is made on the judgments on impairment values as well as on the other identified factors. Even if the developed approach is a formula driven method an additional quality check on the data to be assessed is recommended. This is essential to render the possibility of improving the quality of produced results, since the formula and coding driven approach in itself does not include any expert judgment.

The Impact Vectors (or Sum Impact Vectors) constitute an input to the estimation of parameters for the CCF models. Direct estimation method or any other method can be used.

For further developments of the formula and coding driven approach one possibility is to investigate the option of applying different shared cause factor and time factor for different subsets of a considered common cause component group. However, such development will remove conservatism in the approach and sensitivity analysis shows that this conservatism is small. Therefore has this issue not been included in the formula driven approach, instead this issue is raised as a part of the expert judgment check list and review of the events.

4.3 Overview of applied approach and Probabilistic reasoning

The "probabilistic reasoning" of the applied approach can be defined as follows:

- The High Bound approach is adopted for cases with indication of stronger impairment or no clear pattern
  - For cases with more than one C (Complete impairment [1]) <u>or</u> at most one D, I, S. (Degraded, Incipient, Slight- impairment) [2]

[1] Possible attributes of impairment are*:*

- *complete failure of the component to perform its function*
- *degraded ability of the component to perform its function*
- *incipient/slight failure of the component*
- *default: component is working according to specification*

- This approach assumes the maximum dependence between the conditional failure probabilities of the components.

- Otherwise, the following, less conservative, approach is used to represent scenario based expert judgments for cases with indication of weak impairment as dominant observation
  - For cases with at most one C and more than one D, I, S.
  - The weight of the scenario with maximum multiplicity is assigned the smallest impairment. The weight of next smaller multiplicity is assigned the next impairment, if it is larger than the first one, etc, this procedure is according to the scenario based approach defined for expert judgment applications. If the next impairment is equal to the first one, an expert aware of the fact that the high bound is really an upper bound will distribute the available probability given by the impairment among the two positions. Given no additional information, equal probabilities are assigned to both assuming an unbiased assessor.

The model is either conservative or consistent with the formalism of expert judgments. This requires, however, that the event coding is consistent and quality assured.

	More than one C	At most one C
More than one D, I, S	High Bound applied	Less conservative approach (‘ignorance prior’)
At most one D, I, S	High Bound applied	High Bound applied

Table 2. Overview of applied approach.

4.4 Selected approach, quality and resources needed

In the formula and coding driven method the scenario method is applied for selected events, i.e. based on the event coding events are identified for which it is most likely that an expert would formulate hypothesis instead of applying a high bound approach.

The scenario method – developed in NAFCS pilot studies and used in several practical CCF data analysis – provides guidance on how to formulate hypotheses and to assign weights to assess the event and generate impact vectors. The method also has as inherent feature to ensure the quality of the impairment assessment. The heavy role of required engineering judgement is a problem in the scenario method.

The scenario method requires skill, experience, often communication with plant experts and time resources. The resource needs are increased by the requirement to do the Impact Vector construction by more than one expert in a well organized manner, which is a must in order to assure good quality. All people involved think this is affordable because of the high importance of CCFs.

The formula and coding driven method for Impact Vector construction offers means to make the expert judgment process more efficient and consistent, i.e. requires less resources. Improvements in this respect have also been recommended in the proposals made in NAFCS pilot study reports.

Another advantage of the formula and coding driven method is that it removes subjectivity from impact vector construction which could be the subject of long lasting discussions.

A generic approach to find component impairments without experts looking at the documentation of the event, and possibly even visiting plants is not possible. So, if quality of impairment assessment is not quality assured, additional expert assessment is unavoidable.

A warning is needed. A formula driven method for Impact Vector construction is likely to reduce the analysis to a mechanical calculation, maybe just to the use of a computerized algorithm, i.e. full automation, directly inputting CCF data – which still can suffer from incompleteness and other quality problems – without any experienced control connected to a deeper quantitative analysis, and also skipping the highly useful learning process of the deeper analysis.

Hence, the formula driven approach can only be applied under the following conditions:

- The impairments and the other ICDE [2] parameters have been determined with high requirements of quality.

- The application is focused on PSA and not on a learning process.

In addition, to quality assurance of the event records, tailoring of the data will always be needed to assure homogeneity, to adopt to plant design and plant specific CCF defences as well as to plant specific PSA model features, e.g. specific causal modelling. As for these latter reasons, the events will have to be inspected anyway, a check list has been developed to identify some possibly critical cases and to improve quality (see 5.2.3).

5. IMPACT VECTOR VALIDATION AND TEST APPLICATION

In this chapter validation of the developed method for Impact Vector construction is presented. This task has been performed with the following activities:

- Independent review of task 1 results and resolution of comments

- Generate impact vectors on events of a new CCF group.

- Development of impact vectors manually/expert judgement (unaware of formula driven results) and compare results, specific events only.

- "Expert judgment" check list

- Sensitivity analysis

5.1 Independent review

Independent reviews of the impact vector construction procedure have been performed by independent experts. The review reports are presented in attachment 3. In attachment 3 a comment response report is presented covering all issues during the review process and their treatment in the final reporting.

5.1.1 Criticisms and Answers

Some critical questions have been raised by various members of the working group and they are addressed in attachment 1.

Several important questions have been raised in the independent review. Selected issues are summarized below, a complete presentation on issues and responses are presented in attachment 3

- Probabilistic reasoning model: The issue of arbitrariness or lack of probabilistic reasoning model has been raised in the review. To better understand the applied approach, the description of the approach has been improved to include a "probabilistic reasoning" for the model

- Event specific accuracy: While the proposed formula produces in the average reasonable Sum Impact Vector for the test set of diesel generator (DG) and pump CCF events, it does not certainly provide event specific accuracy in sufficient degree. The validation cases performed confirm that the event specific estimates is in almost all cases (>90%) on the conservative side of available expert judgements.

- Fit to other component types or improved defences: The proposal is made in such a way that in the average it envelopes conservatively the dependency among the considered DG and pump CCF events but can fit poorly to other component types, e.g. to special component types with either strong or weak conditional dependence being typical in CCFs, or even to another set of DG or pump CCFs, for example, in the future after positive gain from improved defences against CCFs. Validation cases have been performed for motor operated valves (MOV) and check valves (CV). Check valves were chosen because they are very different compared to the pumps and diesels applied before, simple and almost passive. The exercises confirm that the formula is valid also for these component types. Improved defences against CCFs can not be covered by the formula driven method. This matter must be treated as part of the homogeneity assessment in the impact vector construction.

- Higher multiplicities: The proposal is much built to CCF group size of 4. It can be expected to work similarly in CCF group size of 3, and of course in the trivial size of 2, but may be less suitable in larger groups. Validation cases for higher multiplicities are not covered at this stage but it can be expected to work similarly or to be more conservative since as the multiplicity increases the inherent conservatism in the probabilistic reasoning model more likely will apply the high bound approach. FCD could do for 5 to 6 components, but it has been verified just for 4 components.

5.2 Validation of Impact Vector method

5.2.1 Motor operated valves and Check Valve application

Some of the criticisms against the formula and coding driven approach have focused on the small number of events and on the fact, that just two component types (DG and pumps) had been used to develop the model.

Therefore in response to this issue impact vectors on events for MOV and CV has been generated using the formula and coding driven approach. An event data set was concluded for CVs and MOVs. The event data applied in this exercise is based on this data set, limited to CCCG size 4. The resulting impact vectors are provided in table 2 and 3 below (where conservative assumption is made in case of lack of information

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode	FCD Impact Vector Multiplicity 1	2	3	4
1	CCWW	H	H	MA	0	1	0	0
2	CCCD	H	H	MC	0	0	0	0
12	CWWW	H	H	TA	1	0	0	0
13	CIII	H	H	MA	0,9	0,03333333	0,03333333	0,03333333
14	CDIW	H	H	MA	0,4	0,5	0,1	0
16	CIIW	H	H	MA	0,9	0,05	0,05	0
22	CCWW	0	0	0	0	1	0	0
				Sum:	3,2	2,58333333	0,18333333	0,03333333

Table 3. Results, CVs, exactly k-out-of-4.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode	FCD Impact Vector Multiplicity 1	2	3	4
17	CCWW	H	L	TI	0,1	0,1	0	0
22	CIII	H	H	MA	0,9	0,03333333	0,03333333	0,03333333
23	CCII	H	H	MA	0	0,8	0,1	0,1
24	CWWW	0	0	0	1	0	0	0
26	CCII	0	0	0	0	0,8	0,1	0,1
27	CCWW	0	0	0	0	1	0	0
28	CCWW	0	0	0	0	1	0	0
29	CCWW	0	0	0	0	1	0	0
32	CCCW	0	0	0	0	0	1	0
33	CSSS	0	0	0	0,99	0,00333333	0,00333333	0,00333333
40	CWWW	0	0	0	1	0	0	0
46	CIII	0	0	0	0,9	0,03333333	0,03333333	0,03333333
49	CWWW	0	0	0	1	0	0	0
50	CIII	0	0	0	0,9	0,03333333	0,03333333	0,03333333
51	CDWW	0	0	0	0,5	0,5	0	0
52	CWWW	0	0	0	1	0	0	0
53	CSSS	0	0	0	0,99	0,00333333	0,00333333	0,00333333
				Sum:	9,28	5,30666667	1,30666667	0,30666667

Table 4. Results, MOVs, exactly k-out-of-4.

The produced results for application of the formula and coding driven approach together with the low and high bounding, as described in the attachment 1, are presented further in attachment 3-9 together with the expert-judgement-result.

The results confirm that it is possible to apply the approach. The results are further used for comparison in the expert judgments exercise described in the following section.

5.2.2 Development of impact vectors manually / expert judgement

As events had been collected for MOV and CV in the context of the validation task of the project, impact vectors for these events have been estimated by a group of five experts from German operators.

As a guidance, the experts have been provided with the High Bound values and the Low Bound values (see attachment 1 for details on these approaches). Also, the theory behind these values was explained briefly, and two examples have been given, one, where dependency is rather high, and one, where the event could be assessed as conditionally independent.

Generally, these arguments have been understood, and only in very few cases, the High Bound has been exceeded by one or two of the experts.

The results have been compared and the following statements have been obtained

- Formula driven approach slightly conservative compared to expert assessment.

- Compared to experts for MOV and CV: + 10-20% conservatism using formula

- Compared to experts for MOV and CV: + 50% conservatism if using high bound

- Compared to formula for MOV and CV: + 30% conservatism if using high bound)

- Compared to experts for MOV and CV: Experts confirm formula driven approach as for Pumps and Diesels. I.e. formula driven approach in general slightly conservative compared to expert assessment

- Experts assessments allow to reduce conservatism in formula results for specific events

The experts agreed that given the impairments, there is not much degree of freedom any more to find consistent impacts. This explains why a rather simple model lead to good estimates.

Those among the experts, who had been involved in the assessment of impairments and CCF events before, shared the opinion, that – given the limits of Low Bound and High Bound, there is much less room for subjectivity in impact vector estimation, than there is in impairment assessment. Finding impairments is a much more difficult job. If impairments are dependable, impact vectors can be found using a simple automatic approach. They approve a quasi automatic procedure to produce impact vectors from impairments and comparable information. In the original NAFCS project, both assessment of impairments and assessment of impact have been performed simultaneously. For this reason, it was considered as even more complex than just assessment of impairments, as has been done for the VGB project.

The experts considered the validation exercise a good opportunity to obtain information and practical training in dealing with CCF events.

5.2.3 Homogenity and QA issues. "Expert judgment" check list and guidance

During the review process, it turned out, that there exist some doubts concerning quality of ICDE input data. If expert judgement is performed as in the original NAFCS project, where experts had access to the original plant documents or even visited the plant and had interviews with maintenance personal, inconsistencies between the results of expert assessment and the information stored in the ICDE will be resolved improving quality of results. Thus, expert assessment provides additional insight, even if the experts do not assess impacts, but just impairment and the other input data.

It cannot be stressed too strongly, that the quality of input data is a critical issue for any automatic treatment of this input data. It must be assured, that the input data is of high quality. This should best be done when the ICDE data is generated, because in this case, most profit can be taken from this data from all users.

It also must be mentioned, that the numerical values for impairment in the ICDE (C=1.0, D=0.5, I=0.1, W=0.0), and possibly also those for the shared cause factor and for the time factor are given as examples only. In some cases, the texts in ICDE indicate, that other values for D and I may be more appropriate. It must be assumed, that ICDE data is conservative in such cases. I.e. if there is good reason to assess an impairment of 0.2, it must be specified as D, not as I.

Latency time of CCF events is also an important issue, though not in the context of impact vector generation. If the CCF event has been noticed by some special test (i.e. not during routine periodic tests), it will require special treatment. The same holds, if the event has been detected, because procedures for routine periodic tests have been changed.

If it cannot be guaranteed, that the above issues are covered by the normal quality procedures of CCF data generation, it is suggested to use the following check list for each event. This check list can be applied, when the events are grouped to find a homogenous CCF population.

Review and assessment of the events needs to be quite open-minded because different CCF models may be called for (e.g. by time-related and demand caused failures or exceptional environments) and correct quantification may depend on some aspect not formally considered in the data collection scheme. Attention should be paid especially on attributes that may not be directly coded or asked in data collection. A check list representing present knowledge on relevant attributes is given below.

- Can it be concluded that failure entry times are close in time even if detections may be more spread in time?

- Can it be concluded that a subset of components may have a higher shared cause or time-factor (i.e. are closer in time) than the whole CCCG?

- Even if detections were close in time, were the degradations (like wear or vibration) slowly developing so that actual failed states would not occur so close in time?

- When an event was observed in a regular periodic test, would the situation be different in case of a true demand, e.g. there would be time for recovery before it is too late?

- If recovery was done, would it be impossible or unlikely in case of real demand?

- Are the degradations due to the same phenomenon (like wear, or lack of lubrication)? If so, is it likely that if a smaller degradation means failure in true demand, higher degradations would also?

- Are there hints that numerical values for impairments differ from the letters? If there are such differences, they should be documented.

- Is there any hint that the time factor is not correct? If there is, the true time factor has to be determined.

- Are latency times larger than normal PSA test interval? Reasons may be tests, which are less frequent than the standard test interval, or if a change in standard test procedure has occurred, which sometimes revealed a defect entered already at plant commissioning. The true latency time has to be documented.

This list must be subject to regular review based on experience gained by those using it.

5.3 Sensitivity analysis

5.3.1 Influence of detection mode

The impact of the detection mode is large when looking at pumps and diesels together. For the sum of the accumulated impact vectors, for the case of failure of 4 out of 4, there is an increase of the size of hundreds of percents when also monitored events are included (compared to the case when they are not included). When considering only pumps there is no influence at all. The reason for this is that there is no event in the considered data set that was monitored.

Conclusion: The treatment of detection modes has a large influence on the resulting event impact vector if it appears in the data and must be done as realistic as possible.

5.3.2 Influence of impairment code

The influence of variations in the treatment of impairment codes varies.

The sensitivity analysis includes presentation of evaluation of the influence of treating impairment code S (slightly degraded) as I (incipient degraded) and vice versa.

- S as I (numerical value of S=I=0.1) and

- I as S (numerical value of I=S=0.01).

The “normal” numerical value for I is 0.1 and for S 0.01.

For the case where S is treated as I it is concluded, for the sum of the accumulated impact vectors, that the influence is not that large, +15% for DG. Considering the case when I is treated as S compared to the “normal case” it is shown that the influence is large, especially for high multiplicity, -88% for DG.

The sensitivity analysis also includes presentation of evaluation of the influence of treating impairment code W (working) as S and vice versa.

- S as W (numerical value of S=W=0) and

- W as S (numerical value of W=S=0.01).

The "normal" numerical value for W is 0 and for S 0.01.
It is seen that if W would be treated as S there is a rather large influence for multiplicity 3 and 4, +43% for DG. When is considered the other way around, i.e. that S is treated as W, the influence is nearly neglect able, -5% for DG.

For both cases, the impact is less when considering pumps.
Conclusion: Impairment code I (incipient) has large influence on the final results and the interpretations of the component impairments are important for the resulting impact vector. A variation done between S and W is less important having smaller influence on the event impact vector but cannot be neglected.

5.3.3 Calculation of another approach

A study was made to compare the formula and coding driven approach with a method for the average between the low and high bounds, (see PROSOL-8002 in attachment 3). The average applied for the comparison is described by the following coding based formula:

$$V_{Average}(m|n) = (1-0,5*q*c)V_{Low\ bound}(m|n) + 0,5*q*c*V_{High\ bound}(m|n)$$

Both formulas are close enough to each other to justify taking them as two equally acceptable formulations. However the FCD "Scenario" will be the preferred option due to its sensitivity to existing results from expert judgments.

5.4 Conclusions on Validation and test application

Validation has been focused on the following items

- Further answers to comments of independent reviewers in addition to those already performed in task 1

- Perform sensitivity studies by varying impairments, formula, etc.

- Discussion of the issue of quality and homogeneity of the input information

- Performed an additional expert assessment for two component types (MOV and CV) and comparison with the formula and coding driven approach

The main issue is whether the developed approach is sufficiently robust. The process to validate and test the procedure has been presented here. Identified review and sensitivity issues are incorporated into the final impact vector construction procedure, attachment 1.

Some restrictions of applicability have been identified. These refer to

- the quality of the input data (see 5.2.3),

- homogeneity issues (see 5.2.4

- gaining additional insight (see 4.4).

If any of these restrictions exist, they have to be resolved before the formula and coding driven approach is used.

The work has shown that also when using expert assessments there are differences in the results. This points out that there are uncertainties also with expert assessments.

One suggestion is to use a checklist to assist the experts to review the events to use as input in the quantification (to make sure the data is if not correct at least conservative).

6. CCF PARAMETER ESTIMATION

This chapter covers the subject of parameter estimation. The performed activities, which are presented in the following, are:

- Application of separate methods using identical impact vectors to check convergence of results.
- Decision on unified approach based on criteria like being defensible, realistic results avoiding conservativeness, etc.
- Describe procedure including a unified approach and format in a common guideline
- Calculator

6.1 Introduction

This section includes both a theoretical presentation, including justification, as well as user presentation. This section provides a description of a procedure including a unified approach and format for CCF parameter estimation (common guideline part II).

6.2 Basic estimation procedures

Based on the final outcome of the impact vector construction the CCF parameter can be estimated. The estimation procedure used here is “direct estimation” of either the failure rate or the failure probability.

The following notation is used for the sum impact vector representing the observed failure statistics:

V(k|n) =‘k+1’th element of sum impact vector in a CCCG of size n.

The total number of tests/demands in the observation period, i.e. the number of so called Test/Demand Cycles (TDCs) is

ND = Number of demands on the whole CCCG

$$= \sum_{k=0}^{n} V(k \mid n)$$

It should be emphasized that the number of component demands is ’n*ND’.

For the failure rate based estimation the observation period is denoted by

E = Exposure time of the CCCG

Generally the exposure time need not be a single continuous period of calendar time but it can be constituted of a sum of observed exposure periods, e.g. standby or operation periods. The total component exposure time is 'n*E'.

The point (maximum likelihood) estimates for the multiple failure probabilities are obtained most straightforwardly in the following way:

$$\langle Q(k \mid n) \rangle = \frac{V(k \mid n)}{ND},$$

The point (maximum likelihood) estimates for the multiple failure rates are:

$$\langle L(k \mid n) \rangle = \frac{V(k \mid n)}{E}$$

Note, that for a detailed fault tree model, these values have to be divided by the number of combinations which exist for the multiplicity given, which is

$$\binom{n}{k}.$$

The implementation of Bayesian estimation method to derive the population distribution parameters for the common cause failure rate or common cause failure probability is described in the following procedure.

The determination of unavailabilities taking the test interval into account is described in Attachment 3-5.

6.3 Justification of Bayesian estimation method

In the following justification and decision on unified approach for Bayesian parameter estimation is provided.

6.4 Theoretical base

Empirical Bayesian parameter estimation is a method which can be used to estimate failure rates and failure probabilities per demand. Moment estimation is the basic of this approach [10], [8], [6], [7], [3] and the principles and the basic version of the PREB method was presented already in [4] and [5].

This means, the evidence of the component groups which have been assessed as similar is used to estimate the first two moments of the population distribution. These estimates then are used to find parameters of the population distribution. This distribution is used as à priori distribution to assess the à posteriori distribution for the components within a given plant.

The variant of Vaurio [3] has been used in the context of PSA of nuclear power plants. The variant of Spjøtvoll [6] has been used for the OREDA data base (off-shore). The variant of Arsenis [7] has been used in the context of the EuReData project, i.e. for components of NPP. These variants are described in attachment 4 (4-1).

Empirical Bayesian parameter estimation is a method used in several major data applications and the technique is well recognised and accepted. The technique is applicable and if properly adapted well suited for CCF parameter estimation application.

6.3.2 PREB: Characteristics and validation of the method

PREB (Parametric Robust Empirical Bayes) estimation method is designed for estimating failure rates (frequencies), initiating event rates and failure probabilities per demand (opportunity), when failure or degradation event data is available from one or more units (components, systems or plants).

The method estimates a sampling/prior distribution by a moment matching method, described in Ref. [3], [4], [5]. And in [9] the method is compared to other approaches.

The method has a "free" parameter δ that a user can adjust, between 0 and 1. In special cases (identical or pooled data) the "optimistic" value $\delta = 0$ is basically consistent with the classical lower bound confidence (or prior inversely proportional to the failure rate), the "conservative" value $\delta = 1$ is consistent with the upper bound (or uniform prior), and the "compromise" $\delta = ½$ (recommended) is consistent with the Jeffreys non-informative prior (inversely proportional to the square root of failure rate). Some other characteristics of the method are:

- A solution exists for all practical (non-negative) observations.

- Asymptotically for increasing sample size or observation times the relative value of bias terms diminishes. (Bias terms prevent underestimation of variances for special cases of clustered data.)

- With identical individual maximum likelihood estimates (which are a rare event) the method yields the parameters of pooled data for the unit with the longest observation time. For other units the uncertainties are larger.

- The sample mean is an unbiased estimate of the mean value of the prior.

- The recommended weights minimize the variance of the sample mean, and yield posterior mean values consistent with Stein's shrinkage-estimators, and tend to minimize the sum of squared errors of the posterior mean values, [11].

- Optimal weights are the same for all values of δ.

- A version adopted to the case of mixed gamma distributions, which are specific for CCF parameter estimation, exists.

In Attachment 4 *(*4-2*)* a full description and validation of the PREB estimation method is presented.

The validation demonstrates:

- That the method works logically for small samples of sizes 2 with few failures and with many failures, and for δ = 0, ½ and 1.

- That PREB is less optimistic (i.e. more conservative) than Dirichlet for a unit with zero failures. For a unit with the largest number of failures the mean values of the methods agree within 15%, the fractiles (5%, 50% and 95%) within 10%.

- Comparisons were made to a two-stage method that used four different hyper-priors called "uniform", "Pörn", "Jeffreys" and "ZEDB". Since there is no basis to claim one method as the "right one" or better than the others, one can only compare the results to see if PREB yields results reasonably within the variations of the other methods.

- When comparing posterior quantiles derived by PREB to several methods in five simulation examples where actually the true values of the rates were known. The number of units in these examples was 20. With PREB the median values were within 3% of the known true values in four cases, and the 95th percentiles were equally close in all five cases, and these were about as good as any of the methods used. The accuracy of PREB got worse when the error factor (ratio of the 95th percentile and the median) of the prior became 4 or higher, but all methods had great difficulties in estimating the 5th percentile in such diffuse cases.

6.3.3 Test Application of methods

In the first phase of this project parameter estimation was made for DG and centrifugal pumps, using three different approaches. In this phase the same has been done, but with the difference that the impact vectors used as input for parameter estimation for the three methods are the same, i.e. the impact vectors obtained from application of the formula and coding driven impact vector construction method.

The resulting parameter estimations for diesel generators are the following.

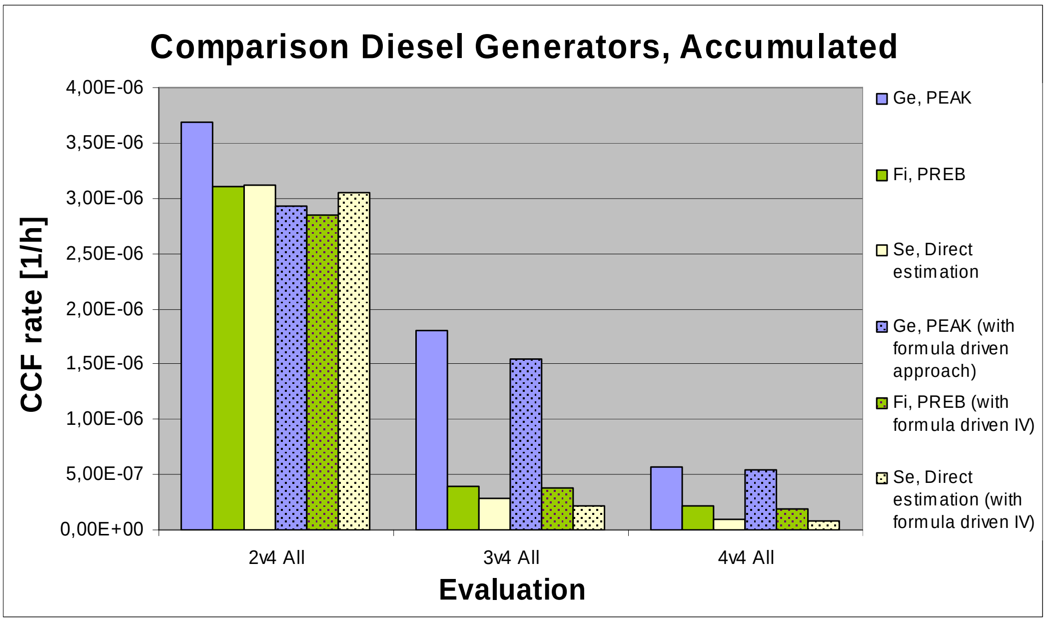


Figure 2. Estimated CCF rates for diesel generators

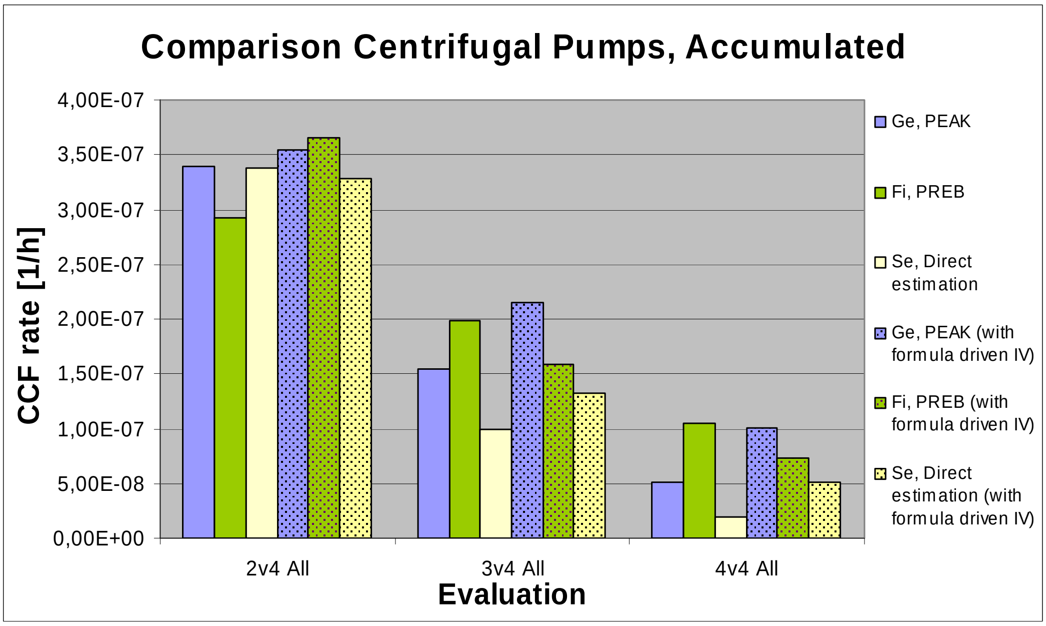


Figure 3. Estimated CCF rates for centrifugal pumps

It is seen that, for both diesels and pumps, there is an apparent convergence of the results for the direct estimation method and PREB, when the same impact vectors are used in all methods. Considering the PEAK results it is seen that for pumps the results are higher when using FCD impact vectors. Further it has been noticed that the PEAK results for 4oo4 failure of DG is dominated by the contribution of 2oo4 failure. So, there are the following arguments to select PREB in favour of direct estimation or PEAK:

- PREB yields parameter estimates, even if there is little information available.
- PREB will yield uncertainty information based on variability across the plants.
- PREB is well established in the mathematical context of moment based methods, and it has been applied in nuclear context before.
- For large multiplicities, PREB still is conservative, but this conservatism is tolerable, as due to using the same impact vectors, it has become much smaller compared with the task 1 results.

For these reasons, it appears as a convenient and justified decision to select PREB for the developed formula and coding driven approach.

6.3.4 Conclusion on justification of estimation method

Empirical Bayesian parameter estimation is an applicable method for CCF parameter estimation application. The validation confirms that PREB has no significant bias and behaves as well as or better than other known methods. This is valid especially for the case of CCF parameter estimation, because there is a specifically adopted PREB version for this. It preserves the population variability and yields credible prior and posterior estimates. See further Attachment 4.

6.4 Procedure and algorithm for parameter estimation

- Describe procedure including a unified approach and format in a common guideline

- Description of assessment procedure (guideline), presentation of excel calculator covering all steps from raw data to CCF parameters.

The approach for the impact vector construction is described in chapter 3, and in further detail in Attachment 1. The algorithm of the PREB estimation method for CCF rate estimation is presented in this section

An example application of the impact vector calculation method is provided in Attachment 2. This is a direct implementation of the calculations in Excel. The required input data is as described in Figure 4.

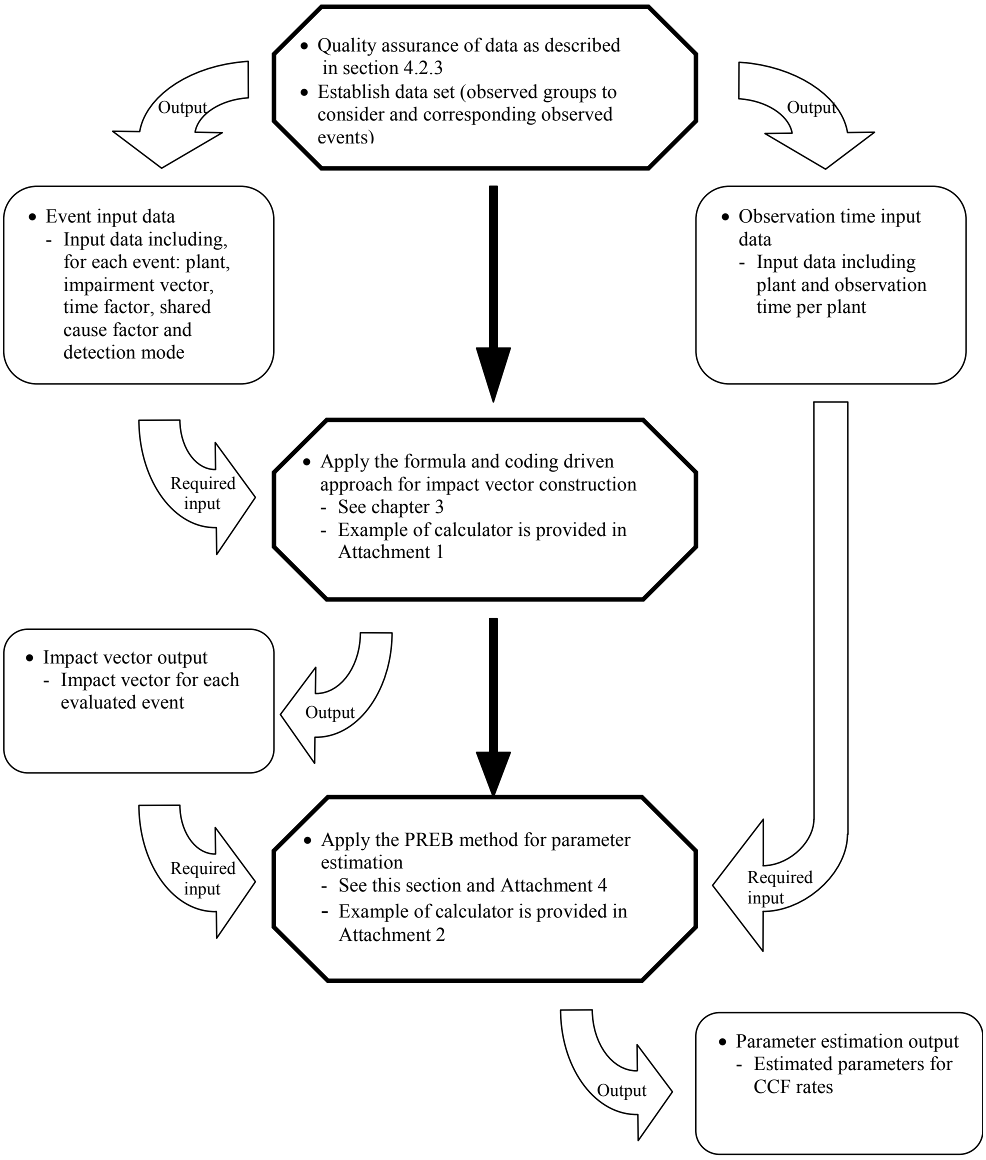


Figure 4. Procedure for parameter estimation.

The algorithm of the PREB estimation method for CCF rate estimation is presented below.

0. Determine $\hat{K}$ and $\hat{T}$:

$$\hat{K}(i) = \frac{\left(\sum_{j=1}^{N_i} V_i(k|n)_j\right)^2 + \delta \sum_{j=1}^{N_j} V_i(k|n)_j^2}{\delta + \sum_{j=1}^{N_i} V_i(k|n)_j \left(2 - V_i(k|n)_j\right)},$$

$$\hat{T}(i) = \frac{\delta + \sum_{j=1}^{N_i} V_i(k|n)_j}{\delta + \sum_{j=1}^{N_i} V_i(k|n)_j \left(2 - V_i(k|n)_j\right)} T(i), \text{ where}$$

$\hat{K}(i)$ is the effective number of events, of multiplicity *k*, at plant *i*,

N_i is the raw number of observed events at plant *i*, i.e. number of calculated impact vectors

$\hat{T}(i)$ is the effective observation time for plant *i*,

T(i) is the raw observation time for plant *i*,

$V_i(k|n)_j$ is the probability that in event *j*, at plant *i*, exactly k components failed out of n identical parallel components (i.e. an impact vector element for event *j*),

n is the group size,

k is the failure multiplicity, and

$0 \le \delta \le 1$; recommended value is δ=1/2[2].

1. If data is only available from one plant, select:

[2] δ = 0 'optimistic', δ = ½ 'compromise' or δ = 1 'conservative'. With failure truncation select δ=0.

yc = 0, and

xc = δ, and go to step 12.

If data is available from more than one plant, determine:

$\hat{T} = \sum_{i=1}^{I} \hat{T}(i)$, where I is the total number of observed plants,

and

select initial weights as $w_i = 1 / \hat{T}$, or $w_i = \hat{T}(i) / \hat{T}$, i = 1, 2,…, I.

2. $$\hat{T}^* = \hat{T} - \max\left(\hat{T}(i)\right)$$

3. $$m = \sum_{i=1}^{I} \left(w_i \frac{\hat{K}(i)}{\hat{T}(i)} \right)$$; (if m = 0 set $v = 0$, $y_0 = \hat{T}_m^*$, $x_0 = 0$ and go to step 9.)

4. $$v = \frac{1}{1 - \sum_{i=1}^{I} w_i^2} \sum_{i=1}^{I} w_i \left(\frac{\hat{K}(i)}{\hat{T}(i)} - m \right)^2 + \frac{m}{\hat{T}^*}$$

5. $$u_i = \hat{T}(i) \Big/ \left(\hat{T}(i) + \frac{m}{v} \right)$$, for i = *1, 2,…, I.*

6. $$w_i = u_i \Big/ \sum_{j=1}^{I} u_j$$ for j = *1, 2,…, I*, and i = *1, 2,…, I.*

7. Iterate step 3-6, unless all $\hat{T}(i)$ are equal, until m and v converge.

8. $y_0 = m/v$, $x_0 = m^2/v = my_0$

9. $x_c = x_0 + \delta\left(y_0 \Big/ \hat{T}^*\right)$, $y_c = y_0$

10. Prior moments: $M_c = m + \left(\delta \Big/ \hat{T}^*\right)$,

$V_c = v + \left(\delta \Big/ \left(y_0\,\hat{T}^*\right)\right)$

11. The posterior densities are $g\left(\lambda; \hat{K}(i) + x_c, \hat{T} + y_c\right)$, where g is a gamma distribution probability density function.

6.5 Application of Algorithm

6.5.1 Example, Diesel Generator, data

The event input data for DG and pumps are presented in Table 5 the events are coded with component degradations defining, for each component, the impairment of the components in the observed population, i.e. a component group of 4 DG at a specific plant. For each plant the total observation time is given, in the case there is more than one component group at a plant the observation time will increase accordingly to represent the total group observation time.

Event data					
Event ID (not neces-sary)	**Plant**	**Degradation vector**	**Shared cause factor**	**Time factor**	**Detection mode**
1	X-1	CCCC	H	H	MC
2	X-26	CCII	H	H	
3	X-3	CCWW	H	H	
4	X-14	CCWW	H	H	
5	X-13	CCWW	H	H	
6	X-12	CCWW	H	H	
7	X-3	CCWW	H	L	
8	X-3	CCWW	H	M	
9	X-6	CCWW	H	M	
10	X-1	CDII	H	M	
11	X-22	CDIW	H	H	
12	X-4	CDWW	H	H	MC
13	X-11	CIII	H	H	
14	X-15	CIIS	H	H	
15	X-10	CIWW	H	H	
16	X-15	CIWW	H	H	
17	X-4	CIWW	M	H	
18	X-4	CIWW	M	H	
19	X-8	CSSS	H	M	
20	X-27	CWWW	L	L	
21	X-7	CWWW			
22	X-14	CWWW			
23	X-3	DDII	H	H	
24	X-4	DDWW	H	H	
25	X-23	DIWW	H	L	
26	X-4	IIII	H	H	
27	X-3	IIIW	H	M	
28	X-4	IIWW	H	H	
29	X-11	IIWW	H	H	
30	X-21	IIWW	H	L	
31	X-27	IIWW	H	L	
32	X-3	IIWW	H	M	

Observation data	
Plant	**Obs.time**
X-1	225000
X-2	192816
X-3	203592
X-4	179712
X-5	163176
X-6	138864
X-7	94344
X-8	123408
X-9	103248
X-10	99192
X-11	121944
X-12	28512
X-13	43800
X-14	74832
X-15	49968
X-16	51792
X-17	43800
X-18	43800
X-19	43800
X-20	43800
X-21	113928
X-22	113928
X-23	113928
X-24	78864
X-25	78864
X-26	113928
X-27	113928
X-28	113928

Table 5. Event input data, diesel generators

6.5.2 Impact vector construction

The FCD approach as defined in section 4 is applied to DG event data and application of the FCD approach provides the following impact vectors Table 6, here presented together with the high bound and low bond results:

	FCD approach			High bound			Low bound		
Event ID	2oo4-failure	3oo4-failure	4oo4-failure	2oo4-failure	3oo4-failure	4oo4-failure	2oo4-failure	3oo4-failure	4oo4-failure
1	0	0	0	0	0	0	0	0	0
2	0,8	0,1	0,1	0,9	0	0,1	0,81	0,18	0,01
3	1	0	0	1	0	0	1	0	0
4	1	0	0	1	0	0	1	0	0
5	1	0	0	1	0	0	1	0	0
6	1	0	0	1	0	0	1	0	0
7	0,1	0	0	0,1	0	0	0,1	0	0
8	0,5	0	0	0,5	0	0	0,5	0	0
9	0,5	0	0	0,5	0	0	0,5	0	0
10	0,25	0,025	0,025	0,2	0	0,05	0,2475	0,0475	0,0025
11	0,5	0,1	0	0,4	0,1	0	0,5	0,05	0
12	0	0	0	0	0	0	0	0	0
13	0,033333	0,033333	0,033333	0	0	0,1	0,243	0,027	0,001
14	0,05	0,05	0,01	0	0,09	0,01	0,1863	0,0117	0,0001
15	0,1	0	0	0,1	0	0	0,1	0	0
16	0,1	0	0	0,1	0	0	0,1	0	0
17	0,05	0	0	0,05	0	0	0,05	0	0
18	0,05	0	0	0,05	0	0	0,05	0	0
19	0,001667	0,001667	0,001667	0	0	0,005	0,014702	0,000149	0,000001
20	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0
23	0,25	0,05	0,05	0,4	0	0,1	0,295	0,05	0,0025
24	0,25	0	0	0,5	0	0	0,25	0	0
25	0,01	0	0	0,01	0	0	0,005	0	0
26	0,025	0,025	0,025	0	0	0,1	0,0486	0,0036	0,0001
27	0,016667	0,0166667	0	0	0,05	0	0,0135	0,0005	0
28	0,05	0	0	0,1	0	0	0,01	0	0
29	0,05	0	0	0,1	0	0	0,01	0	0
30	0,005	0	0	0,01	0	0	0,001	0	0
31	0,005	0	0	0,01	0	0	0,001	0	0
32	0,025	0	0	0,05	0	0	0,005	0	0
33	0	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0	0

Table 6. Impact vectors for DG.

6.5.3 The *effective* observables Ki and Ti

As a fist step in the calculation algorithm the effective observables are calculated, Table 7. The procedure relies on non negative integer numbers of events, K(i), in time, T(i), at plant i. In the assessment to be performed we do not have any exact numbers of events, but rather impact vector weights for each event at each plant. These impact vector weights therefore need to be treated properly to obtain population distribution and plant specific posterior distribution for the rate of CCF events failing an exact number of trains per event. The effective observables take into account, that the components of the impact vector have no Poisson distribution (as the number of failures in the original model does). So, the mixed distribution, which really holds, is used to determine mean and standard deviation. In order to be able to use the existing framework, which is based on Poisson distribution, these two moments are used to calculate that K and T, which results in a Poisson distribution with just these same moments.

An approximate method is to use the expected numbers as K_i in the Bayesian procedures, but this method underestimates the uncertainties.

Because the true values K_i are not exactly known, a more accurate method is to determine the *effective* observables K_i and T_i so that both statistical and assessment uncertainties are correctly accounted for.

$T_{i,eff}$ is generally smaller than T_i , and $K_{i,eff}$ smaller than $E(K_i)$.

As intermediate results the observables can be presented as in Table 7.

	Delta = 0,5			
		2oo4	**3oo4**	**4oo4**
HI Bound	K_exp	8,080	0,240	0,465
	T_exp	2910696	2910696	2910696
	K_eff	6,458	0,046	0,115
	T_eff	2723810	2862466	2842845
	Xc	0,313	0,310	0,263
	Yc	116625	1518796	1131493
Expected	L_exp = K_exp/ T_exp	2,78E-06	8,25E-08	1,60E-07
Efficient	L_eff (Mg) = (delta+ K_eff)/ T_eff	2,55E-06	1,91E-07	2,16E-07
PREB Mc(Priori)	L_c (Mc) = xc/yc	2,68E-06	2,04E-07	2,32E-07
FCD	K_exp	7,722	0,402	0,245
	T_exp	2910696	2910696	2910696
	K_eff	6,104	0,081	0,040
	T_eff	2711042	2843610	2865075
	xc	0,287	0,241	0,386
	yc	110196	1101059	1898052
Expected	L_exp	2,65E-06	1,38E-07	8,42E-08
Efficient	L_eff	2,44E-06	2,04E-07	1,89E-07
PREB Mc(Priori)	L_c (Mc)	2,60E-06	2,19E-07	2,03E-07
Low Bound	K_exp	8,041	0,370	0,0162
	T_exp	2910696	2910696	2910696
	K_eff	6,302	0,091	0,0003
	T_eff	2703227	2860349	2907034
	xc	0,287	0,244	0,498
	yc	106388	1100217	2667323
Expected	L_exp	2,76E-06	1,27E-07	5,57E-09
Efficient	L_eff	2,52E-06	2,06E-07	1,72E-07
PREB Mc(Priori)	L_c (Mc)	2,70E-06	2,22E-07	1,87E-07

Table 7. The effective observables K_i and T_i.

In Table 8 the results for the same FCD case are presented with delta variations to demonstrate how the algorithm behaves.

	FCD			
		2oo4	3oo4	4oo4
delta=1	K_exp	7,722	0,402	0,245
Conservative	T_exp	2910696	2910696	2910696
	K_eff	5,977	0,060	0,0292
	T_eff	2772856	2872230	2885042
	xc	0,298	0,541	0,800
	yc	110859	1360834	2073430
Expected	L_exp = K_exp/ T_exp	2,65E-06	1,38E-07	8,42E-08
Efficient	L_eff (Mg) = (delta+ K_eff)/ T_eff	2,52E-06	3,69E-07	3,57E-07
PREB Mc(Priori)	L_c (Mc) = xc/yc	2,69E-06	3,98E-07	3,86E-07
delta=0,5	K_exp	7,722	0,402	0,245
Compromise	T_exp	2910696	2910696	2910696
	K_eff	6,104	0,081	0,040
	T_eff	2711042	2843610	2865075
	xc	0,287	0,241	0,386
	yc	110196	1101059	1898052
	L_exp	2,65E-06	1,38E-07	8,42E-08
	L_eff	2,44E-06	2,04E-07	1,89E-07
	L_c (Mc)	2,60E-06	2,19E-07	2,03E-07
delta=0,01	K_exp	7,722	0,402	0,245
Optimistic	T_exp	2910696	2910696	2910696
	K_eff	6,422	0,199	0,118
	T_eff	2437845	2623553	2650273
	xc	0,301	0,043	0,047
	yc	109056	503496	940692
	L_exp	2,65E-06	1,38E-07	8,42E-08
	L_eff	2,64E-06	7,95E-08	4,81E-08
	L_c (Mc)	2,76E-06	8,63E-08	5,04E-08

Table 8. Delta variations.

6.5.4 Application on Example Diesel data

As a first step the PREB algorithm is applied to the example data and compared to the direct estimates, Table 9. One can notice that the results converge for the different types of impact vectors, i.e. FCD, High bound and Low bound. This can be explained by the zero event estimator, $\delta=1/2$, that is dominating the result removing the differences that can be seen in the expected values (1/4 failure rate taken from T-book).

Delta 0.5 is a compromise that gives a small impact on high bound but in this case very high impact on the low bound results. However, both statistical and assessment uncertainties are correctly accounted for in both cases. Without any additional prior information and time-truncated observations, d = ½ is equivalent to so-called non-informative prior. And it is also heuristically justified based on the argument that there is on the average N+½ failures within an observation time T (i.e. T is in the middle of Nth and (N+1)th failure), when the end point of observation time T does not coincide systematically with the Nth failure event.

		0/4-failures	1/4-failures	2/4-failures	3/4-failures	4/4-failures
Hi	Direct est	1	2,6318E-05	3,0182E-06	2,4221E-07	1,5976E-07
FCD	Direct est	1	2,6175E-05	2,875E-06	2,2217E-07	8,4172E-08
Low	Direct est	1	2,6195E-05	2,8953E-06	1,3284E-07	5,566E-09
FCD	PREB Mc	1	2,6323E-05	3,0231E-06	4,2223E-07	2,0318E-07
Hi	PREB Mc	1	2,642E-05	3,1196E-06	4,3623E-07	2,32E-07
Low	PREB Mc	1	2,6404E-05	3,104E-06	4,0853E-07	1,8654E-07

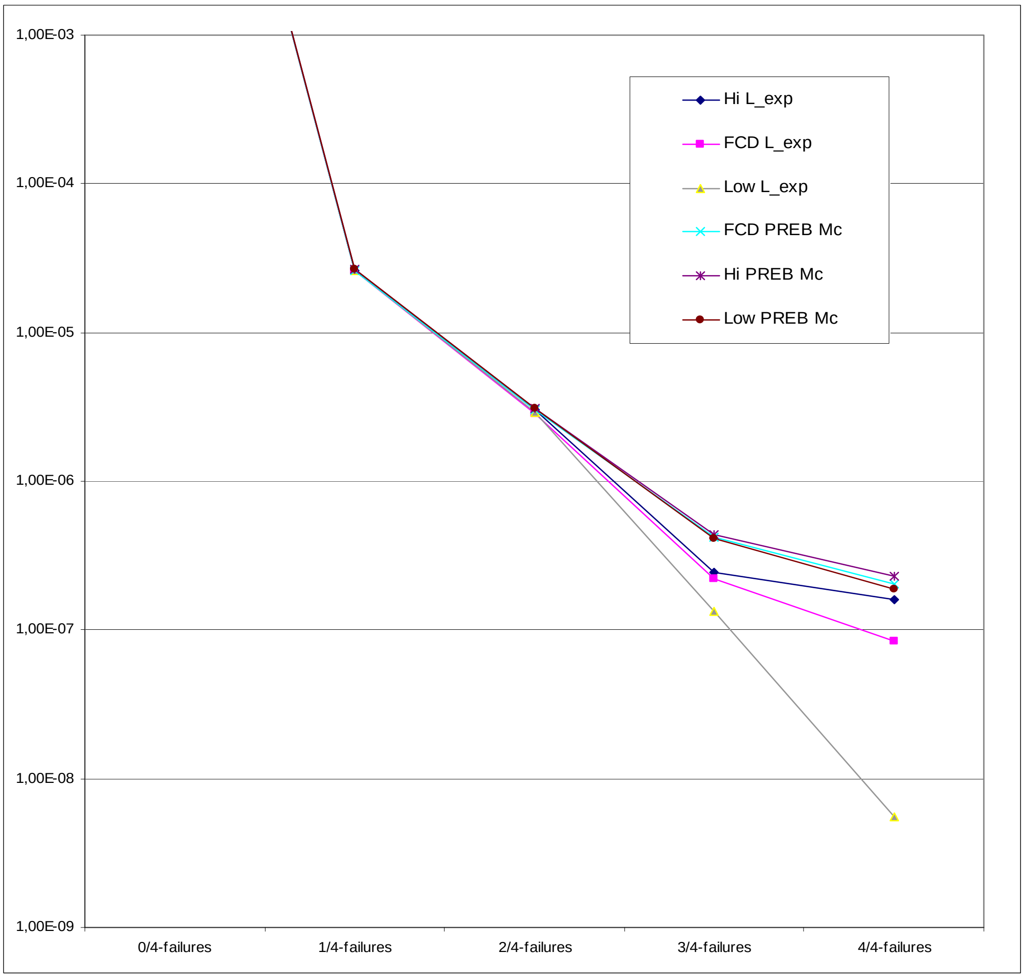


Table 9. PREB algorithm applied to the example data and compared to the direct estimates.(accumulated)

As a second step the PREB algoritm is applied to derive the uncertainty bounds FCD, High bound and Low bound impact vectors respectively. The application yields the following results. Table 10 provides the estimated parameters for Diesels for all failure multiplicities. As already pointed out it is also here seen that the differences for FCD, High Bound and Low bound are evened out in the parameter estimation procedure (compared to when considering only impact vectors). As expected for a gamma distribution there is an asymmetry in the uncertainty bounds.

		0oo4-failure	1oo4-failure	2oo4-failure	3oo4-failure	4oo4-failure
High bound	**HB-M95**	**1,0E+00**	5,90E-05	1,77E-05	1,83E-06	9,10E-07
	HB-Mc	**1,0E+00**	1,93E-05	3,12E-06	4,36E-07	2,32E-07
	HB-M5	**1,0E+00**	5,50E-07	4,30E-10	4,28E-10	3,92E-10
Nordic/German	**FCD-M95**	**1,0E+00**	5,86E-05	1,73E-05	1,74E-06	8,48E-07
	FCD-Mc	**1,0E+00**	1,92E-05	3,02E-06	4,22E-07	2,03E-07
	FCD-M5	**1,0E+00**	5,50E-07	3,93E-10	3,93E-10	1,66E-10
Low bound	**LB-M95**	**1,0E+00**	5,88E-05	1,75E-05	1,77E-06	7,18E-07
	LB-Mc	**1,0E+00**	1,93E-05	3,10E-06	4,09E-07	1,87E-07
	LB-M5	**1,0E+00**	5,51E-07	7,19E-10	7,17E-10	7,13E-10

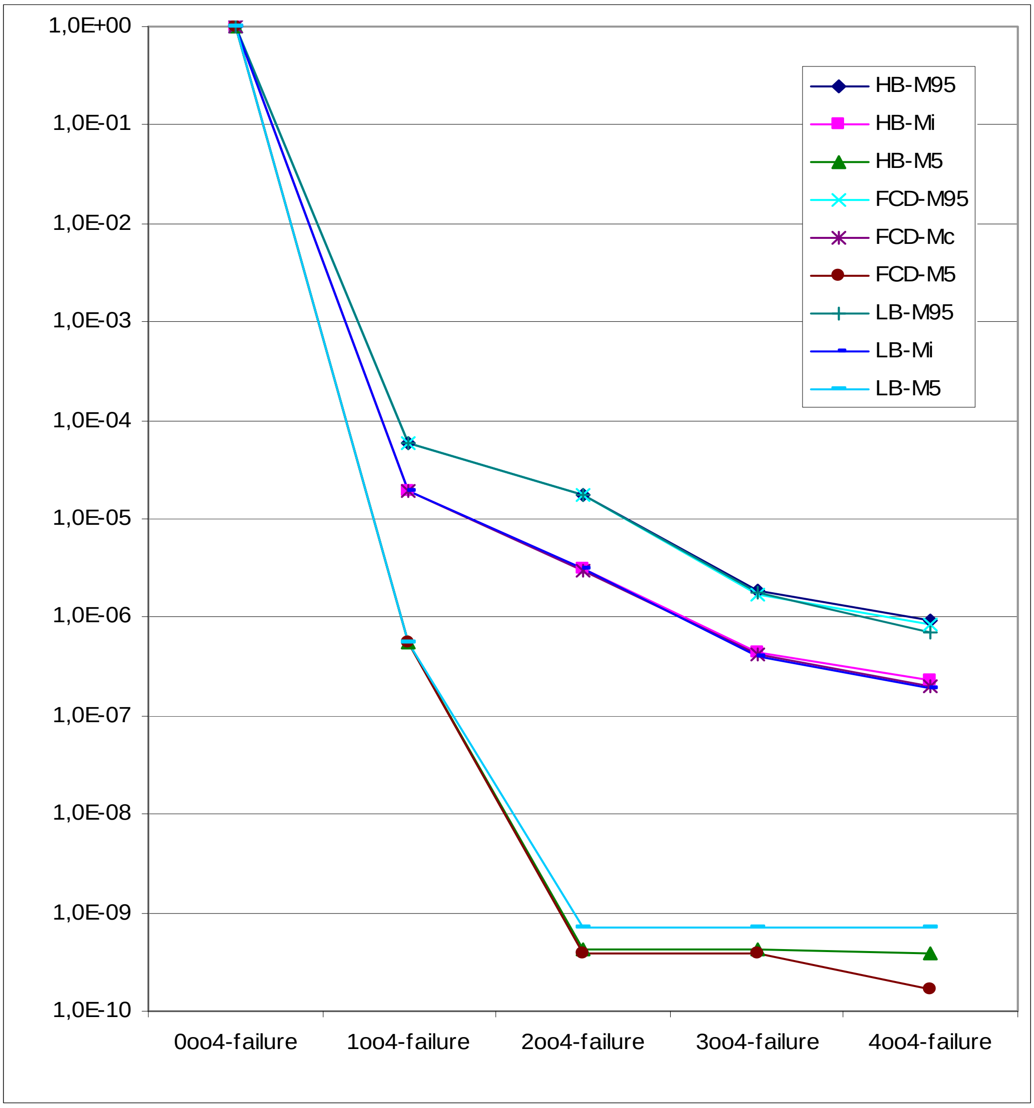


Table 10. Estimated CCF parameters for Diesels (accumulated)

6.5.5 Example of Plant specific results

Application of PREB for parameter estimation yields the following results for the failure rate for 2 out of 4 pumps to fail. In this case the observations contain a mixture of actual events and partial events coming from the impact vector analysis. In this case plant variation can be observed and plant specific parameters are presented. For most other cases, certainly for failure of higher multiplicity, the observations are weaker and the plant variations are not as apparent as in this case. Table 11 provides the estimated parameters for diesel generators and failure multiplicity 2.

2/4 failures

Prior parameters	x_c	y_c	M_c	$StDev_c$	M_5	M_{50}	M_{95}
	0,17738368	60619	2,93E-06	6,95E-06	4,90E-13	2,15E-07	1,55E-05
Group parameters	**ΣK**	**ΣT**	M_g				
	6,03070647	2672662,305	2,44E-06				

Posterior parameters	K_i	T_i	M_i	$StDev_i$	M_5	M_{50}	M_{95}
X-1	0,1	180000	1,15E-06	2,19E-06	5,83E-11	2,46E-07	5,41E-06
X-2	0	192816	7,00E-07	1,66E-06	1,17E-13	5,15E-08	3,72E-06
X-3	1,43250123	164505,2784	7,15E-06	5,64E-06	9,39E-07	5,74E-06	1,82E-05
X-4	0,16878359	129933,4441	1,82E-06	3,09E-06	6,57E-10	5,49E-07	7,93E-06
X-5	0	163176	7,93E-07	1,88E-06	1,33E-13	5,83E-08	4,21E-06
X-6	0,3	111091,2	2,78E-06	4,02E-06	8,51E-09	1,21E-06	1,09E-05
X-7	0	94344	1,14E-06	2,72E-06	1,92E-13	8,42E-08	6,08E-06
X-8	8,2782E-06	123000,043	9,66E-07	2,29E-06	1,62E-13	7,11E-08	5,13E-06
X-9	0	103248	1,08E-06	2,57E-06	1,81E-13	7,96E-08	5,75E-06
X-10	0,02173913	86253,91304	1,36E-06	3,04E-06	1,30E-12	1,39E-07	6,99E-06
X-11	0,01319648	107282,1114	1,14E-06	2,60E-06	5,76E-13	1,03E-07	5,92E-06
X-12	1	28512	1,32E-05	1,22E-05	9,85E-07	9,71E-06	3,74E-05
X-13	1	43800	1,13E-05	1,04E-05	8,41E-07	8,29E-06	3,19E-05
X-14	1	74832	8,69E-06	8,01E-06	6,48E-07	6,39E-06	2,46E-05
X-15	0,03650794	41243,42857	2,10E-06	4,54E-06	5,35E-12	2,59E-07	1,06E-05
X-16	0	51792	1,58E-06	3,75E-06	2,64E-13	1,16E-07	8,38E-06
X-17	0	43800	1,70E-06	4,03E-06	2,85E-13	1,25E-07	9,02E-06
X-18	0	43800	1,70E-06	4,03E-06	2,85E-13	1,25E-07	9,02E-06
X-19	0	43800	1,70E-06	4,03E-06	2,85E-13	1,25E-07	9,02E-06
X-20	0	43800	1,70E-06	4,03E-06	2,85E-13	1,25E-07	9,02E-06
X-21	7,3533E-05	112816,589	1,02E-06	2,43E-06	1,73E-13	7,54E-08	5,43E-06
X-22	0,3	91142,4	3,15E-06	4,55E-06	9,63E-09	1,37E-06	1,23E-05
X-23	0,00028852	111758,569	1,03E-06	2,45E-06	1,77E-13	7,62E-08	5,47E-06
X-24	0	78864	1,27E-06	3,02E-06	2,13E-13	9,35E-08	6,75E-06
X-25	0	78864	1,27E-06	3,02E-06	2,13E-13	9,35E-08	6,75E-06
X-26	0,65753425	101442,7397	5,15E-06	5,64E-06	1,61E-07	3,30E-06	1,65E-05
X-27	7,3533E-05	112816,589	1,02E-06	2,43E-06	1,73E-13	7,54E-08	5,43E-06
X-28	0	113928	1,02E-06	2,41E-06	1,70E-13	7,48E-08	5,39E-06

Table 11. Estimated plant specific parameters for failure of 2 out of 4 components.

7. GENERAL CONCLUSION

A comprehensive procedure including all steps from event input data, via impact vectors, to final CCF parameters has been developed and validated.

The formula driven impact vector construction has been developed using various approaches to select a suitable approach taking into account existing cases for diesels and pumps. This has been achieved by ensuring the following properties to be built in to the approach and formulas:

- It takes the most conservative approach possible given the data, when stronger impairment is seen

- It takes a less conservative approach when weak impairment as dominant observation is seen, because this is, what experts have been observed to do.

The developed procedure for Impact Vector construction offers a systematic and transparent way to be applied in quantitative analysis of CCF events. The approach for impact vector construction fulfils the basic requirements that it shall be defendable and that it shall result in realistic modelling i.e. not too conservative.

Several important questions have been raised in the independent review which has been addressed, such as probabilistic reasoning, expert judgement and quality assurance.

The formula and coding driven method for impact vector construction offers means to make the expert judgment process more efficient and consistent, i.e. requires less resources. A generic approach to find component impairments without experts looking at the documentation of the event, and possibly even visiting plants is not possible. So, if quality of impairment assessment is not assured, additional expert assessment is unavoidable. In addition, to quality assurance of the event records, tailoring of the data will always be needed to assure homogeneity, this to adopt to plant design and plant specific CCF defences as well as plant specific PSA model features, e.g. specific causal modelling.

Application of the approach for MOVs and CV demonstrate that it is possible to apply the approach for other components. The results are further used for comparison in the expert judgments exercise. These experts agreed that given that the impairments are dependable, impact vectors can be found using a simple automatic approach in this case. They approve a quasi automatic procedure to produce impact vectors from impairments and comparable information.

It cannot be stressed too strongly, that the quality of input data is a critical issue for any automatic treatment of this input data. It must be assured, that the input data is of high quality. Concerning databases, such as the ICDE database, this should best be done when the ICDE data is generated, because in this case, most profit can be taken from this data from all users. If it cannot be guaranteed it is suggested to perform quality control of the input data for each event according to a checking procedure developed based on priority issues identified in the applications performed.

An algorithm for Empirical Bayesian parameter estimation has been applied. The Algorithm has been shown to be an applicable method for CCF parameter estimation application. The validation confirms that PREB has no significant bias and behaves as well as or better than other known methods. It preserves the population variability and yields credible prior and posterior estimates.

Application to test cases is presented together with a comprehensive procedure including all steps from input data, via impact vectors, to final CCF parameters including their qualitative and quantitative uncertainties.

8. REFERENCES

[1] SKI 2007:41, Dependency Analysis Guidance, Nordic/German Working group on Common Cause Failure analysis - Phase 1 project report: Comparisons and application to test cases, Volume 1-2.

[2] OECD/NEA, (2004). International Common-cause Failure Data Exchange, ICDE General Coding Guidelines. Technical Note NEA/CSNI/R(2004)4

[3] Vaurio, J. K. On Analytic Empirical Bayes Estimation of Failure Rates, Risk Analysis, Vol. 7, 1987, No. 3, 329-338.

[4] Vaurio, J. K. and Linden, G.: Robust Methods for Failure Rate Estimation, Transactions of Am. Nucl. Soc., pp. 363-364, November 1985, San Francisco, California.

[5] Vaurio, J. K. and Linden, G.: On Robust Methods for Failure rate Estimation. Reliability Engineering 14 (1986) 123-132.).

[6] Spjøtvol, E., Estimation of Failure Rate from Reliability Data bases. Paper presented at the SRE Symposium, Trøndheim, Norwegen, 1985.

[7] Arsenis, S. P., Procaccia, H., Aufort, P., European Industry Reliability Data Bank, 3rd Edition, Crete University Press, 1998, ISBN 2 95 09092 0 5.

[8] Robbins, H., An Empirical Bayes Approach to Statistics. Proc. 3rd Berkeley Symp. Math Statist. Prob., I:157, 1956.

[9] Jussi K. Vaurio, Kalle E. Jänkälä: Evaluation and comparison of estimation methods for failure rates and probabilities. Reliability Engineering and System Safety 91 (2006) 209-221. Two typographical corrections published in a corrigendum, Reliability Engineering and System Safety 92 (2007) 131.

[10] Hill, J.R., Heger, A.S. and Koen, B.V. The application of Stein and related parametric empirical Bayes estimation to nuclear plant reliability data system, report NUREG/CR-3637, 1984.

[11] J.K.Vaurio & K.E.Jänkälä: James-Stein estimators for failure rates and probabilities, Reliability Engineering and System Safety 36 (1992) 35-39.

Attachment 1
Impact vector construction

January 2009

Attachment 1-1

Phase 2, Task 1 report: Impact vector determination methodology

Nordic/German Working Group on common cause failure analysis

NORDIC/GERMAN WORKING GROUP ON COMMON CAUSE FAILURE ANALYSIS

Authors:

Becker, Günter (RISA Sicherheitsanalysen GmbH)

Johanson, Gunnar (ES Konsult)

Lindberg, Sandra (ES Konsult)

Reviewers:

Jänkälä, Kalle (Fortum Nuclear Services Oy)

Knochenhauer, Michael (Relcon Scandpower AB)

Mankamo, Tuomas (Avaplan Oy)

Schubert, Bernd (Vattenfall Europe)

Vaurio, Jussi (Prometh Solutions)

Wohlstein, Ralf (E.ON Kernkraft, Maschinentechnik)

Summary:

This report is part of the reporting from the European Working Group on CCF analysis (EWG), including members from Finland, Germany and Sweden. The report provides a summary on performed work on impact vector construction.

TABLE OF CONTENTS

1 ACRONYMS, ABBREVIATIONS AND DEFINITION

NPSAG	Nordisk PSA Gruppen
VGB	"VGB PowerTech e.V:" (European technical association for power and heat generation).
CCF	Common Cause Failure
NAFCS	Nordisk Arbetsgrupp För CCF Studier
CCCG	Common Cause Component Group
ICDE	International Common cause Data Exchange
GRS	Gesellschaft für Anlagen- und Reaktorsicherheit mbH
PRA	Probabilistic Risk Analysis
PSA	Probabilistic Safety Analysis
FCD	Formula and Coding Driven
BFR	Binominal Failure Rate
CLM	Common Load Model

2 INTRODUCTION

This report is part of the reporting from the European Working Group on CCF analysis (EWG), including members from Finland, Germany and Sweden.

Phase 2 of the project is performed as a follow-up to the 1st phase as initially outlined in the phase 1 program. Phase 1 was performed during 2006 and 2007, and involved comparisons and application to test cases. Phase two is to consider development of harmonized approach and applications.

The objectives for phase 2 are based on the results from phase 1 and on the meeting between NPSAG and VGB on September 5 2007. Thus, the main objective of the second phase is to establish a common procedure and model of quantification of CCF events. This is to be achieved firstly by agreement on common methods and guidelines for data classification and assessment, since a common procedure may be more justifiable and more defendable, and secondly by establishing a common format that allows data to be shared for quantifications and that provides interpretation of raw data for exchange and use in quantification models. This will also contribute to improving the consistency in international in-depth assessment of CCF events for parameter estimation.

3 AIM AND SCOPE

The main activity in phase 2 is the development of harmonized applications. The first task has been finalised, and comprises impact vector construction, as well as development and agreement on a formula driven approach. The formula driven impact vector construction has been developed using various approaches to select a suitable approach taking into account existing cases for diesels and pumps. For the agreed approach there have been two basic requirements; that it shall be defendable and that it shall result in realistic modelling.

As there is no specific German procedure for constructing impact vectors, two methods have been investigated and utilized for validation; the Finish (Vaurio) and the NAFCS (best estimate) approaches which are described and compared in reference 0. The pump and diesel CCF events used as test samples are described and evaluated in the first phase 0.

4 THE IMPACT VECTOR METHOD

The impact vector is a generalized presentation of the outcome from a demand situation - in terms of number of failed components in a CCF Component Group (CCCG). It is especially useful in situations where the outcome is not perfectly known to be one certain failure state, but chances of several states exist. The impact vector provides the analyst with a way to express the spectrum of chances (or equivalently the uncertainty) by a distribution of the possible outcome of an actual demand over different failure states.

The impact vector constitutes an interface between the CCF event analysis and the statistical treatment and quantitative assessment of CCF probability. The parameters of different CCF models for a certain component type can be estimated from the impact vectors of occurred CCF events in an observed component population.

Thus, an impact vector expresses the conditional (on symptoms) failure probability, given an observed CCF, that different numbers of components would fail if an actual demand should occur during the presence of the CCF impact.

In a group of ‘n’ components, which is exposed to CCF, the impact vector contains ‘n+1’ elements, one for each order of failure ‘m’, including the outcome ‘no failure’ (m = 0) and ‘all failed’ (m = n). The elements describe the probability distribution for the outcome states of a postulated demand in the presence of the CCF mechanism.

The impact vector methodology was originally introduced in USA, 0, and was further developed in the NAFCS project, 0.

4.1 CONNECTION TO COMPONENT IMPAIRMENT VALUES

The impact vectors are needed to describe the more general outcome conditions from such cases where the functioning of every component is not perfectly known, i.e. the component state index – named the component impairment or degradation value d, which can fall in the range (0,1) – is evaluated not to be 0 (functioning) or 1 (failed), but a value in between.

The component degradation value is based on the evaluated status of the component, in terms of its capability to perform its function. In this way the parameter can be defined in the following way:

> d_k = The conditional probability that a specific component, indexed by ’k’, fails given that an actual demand should occur in the observed condition.

Correspondingly, the elements of the impact vector will then attain values in the range (0,1) with the following interpretation:

> v_m = The conditional probability that some ’m’ components in a CCCG consisting of n components fail and the other ‘n-m’ components in the CCF group survive given that an actual demand should occur in the observed condition.

There is no universal one-to-one correspondence between the impact vector and component degradation values. The assessment of component degradation values is easier, and they can be useful in the impact vector construction. An obvious connection is that the highest order of non-zero elements in the impact vector equals the number of components having non-zero degradation value.

It has to be pointed out that the definition of the Impact Vector means that following equality has to be met:

$$\sum_{m=0}^{n} v_m = 1$$

It can thus be said that the impact vector elements describe how the demand outcome probability is distributed over different failure multiplicities.

4.2 CONSTRUCTION OF IMPACT VECTORS

The general flow in the impact vector construction is presented in Figure 1. Steps 1-4 are concerned with the basic evaluation of CCF parameters for a defined component group, failure mode and observation period. In practice the data of identical or closely similar CCF groups of the same size are often pooled together. In a general case the analysis may include CCCGs of varying size from different systems and/or plants. Steps 5-6 concern the actual impact vector construction and the integration of the impact vectors for the estimation of reliability and dependence parameters.

The impact vector presentation is related to failure modes in a way similar to component and CCF models. Different functional failure modes each require a specific way of treatment. Especially, latent and monitored failure modes should be kept strictly separated because they differ significantly both regarding qualitative analysis and quantitative treatment.

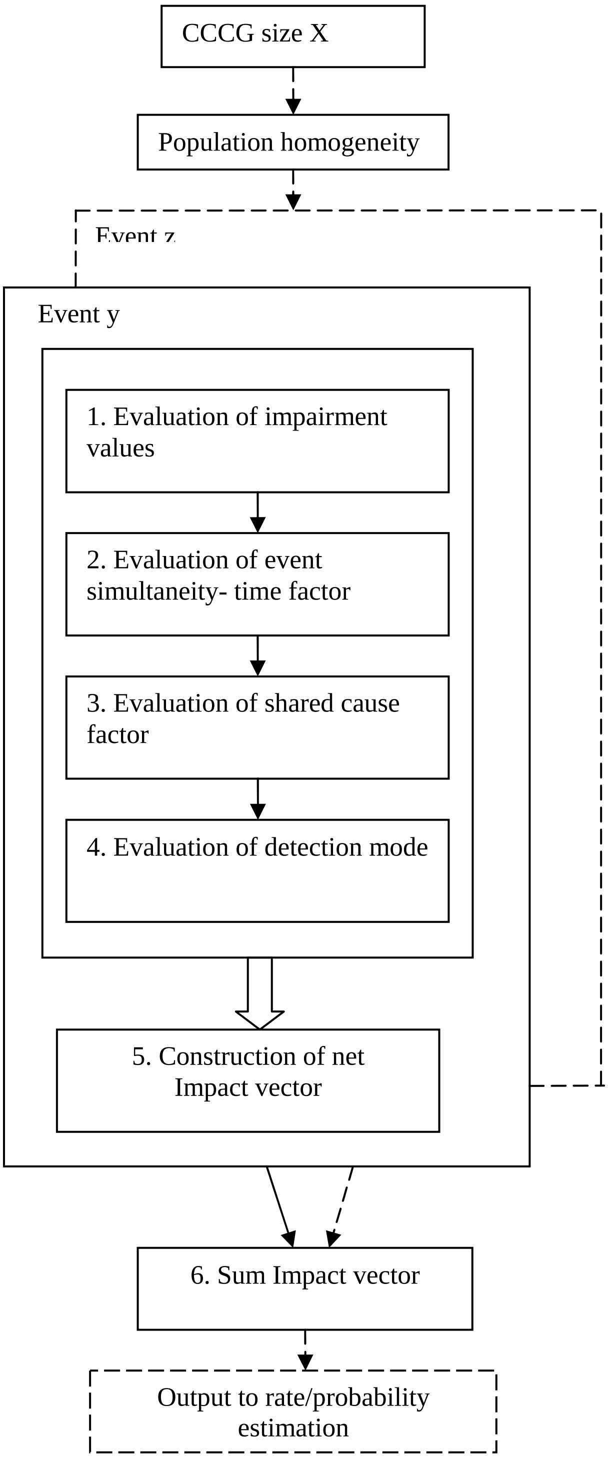


Figure 1. Steps and flow of the Impact Vector construction.

4.2.1 MATHEMATICAL IMPLEMENTATION

4.2.1.1 BASIC DEFINITION

In a CCCG of size ‘n’ the impact vector has ‘n+1’ elements:

$v = [v_0, v_1, v_2, \dots , v_n]$

In the basic case, where the functioning of each component at a demand is perfectly known to be either successful or failed, the number of failures is exactly determined: all impact vector elements are then zero, except $v_m = 1$ given that ‘m’ components failed, e.g.

$v = [1, 0, 0, \dots , 0]$, when all components functioned

$v = [0, 1, 0, \dots , 0]$, when one component failed

$v = [0, 0, 1, 0, \dots , 0]$, when two components failed

$v = [0, 0, \dots , 0, 1]$, when all n components failed

If it is important to show the total number of components, the elements can be denoted by $v_m = v(m|n)$.

4.2.1.2 SINGLE FAILURE OBSERVATIONS

The occurrence of a single failure, corresponding to the impact vector [0, 1 , 0, … , 0], is traditionally called the “independent” failure, and the number of such observations is denoted the ‘independent count’. The attribute “independent” is, however, partly misleading because it may be a coincidence for some cases that only one component failed and that all other components remained intact.

4.2.1.3 MULTIPLE FAILURE OBSERVATIONS

An observation representing the occurrence of an actual failure of multiplicity ‘m’, and with the remaining ‘n-m’ components known to be unaffected, is represented by the impact vector:

$v_m = 1$

$v_k = 0$, when $k \neq m$

In case of a multiple event with ‘m’ failed components and additional ‘j’ degraded components, the general form of the impact vector is:

$0 < v_k < 1$, when $m \leq k \leq m + j$

$v_k = 0$, when $k < m$ or $k > m + j$

Assume for example a multiple event within a CCCG of size four, with one component failed and two degraded. Then the corresponding impact vector could be:

$v = [0, 0.7, 0.2, 0.1, 0]$.

4.2.1.4 SUM IMPACT VECTOR

The net impact vectors (representing specific failures, observations, within a CCCG) can be added together to derive a sum impact vector of the considered CCCG. The sum impact vectors of different CCCGs are directly additive only if the group size is the same and the groups are mutually homogeneous. In such a case the event data can be simply pooled.

Summing up the impact vectors over the observations, *i*, of the observed population produces a sum impact vector (or an observation vector).

$$\mathbf{V(m)} = \sum_{i=1} \mathbf{v(m)}_i$$

A capital letter is used for the sum impact vector in order to distinguish it from the net impact vector.

It has to be emphasized that the sum impact vector is not anymore a conditional probability entity. Instead, it represents the number of events for different multiplicities.

The interpretation of the elements in the sum impact vector is very straightforward:

V_0 = Expected number of failure free observations

V_1 = Expected number of single failure observations

…

V_m = Expected number of observations with failure of multiplicity m

…

V_n = Expected number of observations with failure of all components

5 ASSUMPTIONS AND LIMITATIONS

5.1 ACCEPTANCE CRITERIA

For an approach towards impact vector construction to be accepted, as an agreed method, it is required to have a certain quality. To define this level of required quality some acceptance criteria have been formulated. These criteria have been prepared on basis of experience of existing impact vector methods and conclusions from the first phase of the project.

The conclusion is that for a formula driven approach towards impact vector construction to be suitable and acceptable it is required to comply with the following criteria:

- The approach should be defendable (has to be qualitatively acceptable).
- The events that are monitored need to be marked and excluded from the assessment.
- The approach should be conservative in comparison with expert judgments. It should be at least as conservative as the NAFCS best estimate method in 90 % of cases considered. Deviations from such conservatism can be acceptable if this can be justified for the specific case/event where the deviation is present.
- The approach should be close to the NAFCS best estimate, which is considered being something close to a best estimate.

Further, when doing a conservatism check it is considered that evaluation of approaches is to be made on accumulative impact vectors, not exact ones.[1] (This means that the

[1] Assume for example that the following impact vectors are to be compared; A - (0.4, 0, 0, 0.1, 0.5) and B - (0.8, 0, 0, 0.2, 0). If then the 3 out of 4 case is considered alone the conclusion would be that impact vector B is the most conservative one (since 0.2>0.1). This conclusion would be incorrect, since the case that 3 out of 4 component fails is also considered in the impact vector element for failure of 4 out of 4. This is to be treated by

impact vector elements to be evaluated are those considering “failure of at least k out of n”-cases instead of “failure of exact k out of n”-cases.) The cases to be considered are only 4 out of 4 cases, or when 4 out of 4 is zero 3 out of 4 cases is to be considered instead, etc.

6 DEFINITION OF INPUT INFORMATION REQUIRED

The required event information is collected, coded and documented according to the ICDE framework 0, or to another comparable format. The information, including event descriptions such as contained in the ICDE data, is in most cases sufficient for the impact vector construction.

Some parameters required to be able to perform impact vector construction are presented below.

6.1 GROUP SIZE

A component group is a set of identical components in a plant performing the same function, for example parallel diesel generators used for emergency cases. The number of components included in such a group adds up to the group size, i.e. the group size is the degree of redundancy in a component group.

Mapping up/down is an approach to transfer impact vectors between groups of different sizes, from a source group to a target group, in cases where there is not enough data for a certain group size. Mapping down is used if the target group is smaller and mapping up is used if the target group is larger. The method of mapping up is suffering from some controversial features and due to the major uncertainties in the extrapolation that is a necessary part of upwards mapping this approach is not used within this project.

6.2 DEFINITION OF A HOMOGENOUS POPULATION

It is assumed that the CCF events are identified as input information to the impact vector construction, i.e., the CCF identification, but before the process of impact vector construction can be initiated the data needs to be evaluated. If it has not been performed in an earlier stage the data needs to be evaluated concerning failure mode, internal symmetry and homogeneity.

In general, CCF events of a component group belonging to a certain population are supposed to be fully applicable to other component groups of this population. This implies that the incidence rate of the observed CCF phenomenon should be the same for all component groups in the population. However, for some CCF phenomena, an unrestricted application of the observed CCF event to the component group to be analysed would be inadequate, depending on the conditions, e. g. pumps working with clean or with raw water. For this reason the data needs to be screened concerning homogeneity. Once it is defined what groups at different plants that are to be included in the assessment, the evaluation of events to be included is also done. This though, is an iterative process. From this obtained amount of events it is actually not “allowed” to remove individual events, but rather to divide populations of which some fractions are to be included and some excluded.

Still, it must be understood that the homogeneity evaluation results are in the practical cases at the best only a good approximation when transferring data from one plant to another or when combining data. Pooling approximations must, however, often be accepted due to sparse data about CCFs.

---

using accumulative impact vector for comparisons. Accumulative impact vectors in the example would be A - (1.0, 0.6, 0.6, 0.6, 0.5), B - (1.0, 0.2, 0.2, 0.2, 0). Now, if the same comparison is done, for the 3 out of 4 cases the conclusion would be that impact vector A is more conservative, a conclusion that is correct.

The evaluation of events, which has been performed, must also be applied to the corresponding observation time. Consider for example the case with pumps, where some types of pumps are working with clean water while others work with raw water. If such components are removed from the population, the corresponding observation time should be excluded from the quantification as well. If this is not carried out it can possibly have a massive impact on the quantification results, making them misleading.

Another way of dealing with the issue of homogeneity is to use applicability factors. This is used in the German PEAK method, but in this task this option is not applied. It is described in the following: In some cases, a CCF is only applicable, if – in addition to the actual CCF – something else happens in an up-to-date modern European plant. E.g., a CCF could happen, but to become harmful, a testing procedure must be violated, such that the CCF is not detected. This can be modelled by an applicability factor in the order of magnitude, that such violation should occur. In other situations, there may be CCFs which occurred in the phase of commissioning. This can be modelled also by an applicability factor. In this case, the share of observation time, which was commissioning, must be decreased by the applicability factor, as well. If there is a CCF with reduced applicability because of differences in plant construction or operation, than the complete observation time must be reduced by the applicability factor.

6.3 IMPAIRMENT VALUES, OR DEGRADATION VALUES

This parameter, d_k, is used to describe the status of the concerned component in a particular failure event. Each individual component is assigned a degradation, or impairment, value, representing its status in the occurred event. This is in reality a matter of a continuous parameter but for analysis purpose it is used applied as a constant.

The following coding and related numerical values are suggested:

	Description	Code	Numerical value
Complete failure	The component has completely failed and will not perform its function	C	1.0
Degraded	The component is capable of performing the major portion of the safety function, but parts of it are degraded.	D	0.5
Incipient degraded	The component is capable of performing the safety function, but parts of it are in a state that- if not corrected – would lead to a degraded state.	I	0.1
Slightly degraded	Only traces of degradation are seen on the component, which in 1 out of 100 cases would lead to failure	S	0.01
Working	The component is working according to specifications.	W	0

Table 1. Impairment coding.

The codes C, D, I and W are applied within the ICDE project and the description of them originates from the ICDE coding guideline. The code S originates from VGB/GRS (although, the codes C, D, I and W are also applied within VGB/GRS).

As an optional treatment of this coding, conservatism can be built in. This can be done by treating components codes as W as if they were slightly degraded, i.e. code S, with the numerical value of 0.01 instead, i.e. merging the set of components coded as W with the ones coded as S. The reasoning for this is that by the fact that an event is observed there is a suspicion about a phenomenon affecting the component group and that such a suspicion should be reflected in the assessment. The numerical value of 0.01 should be applied, which is considered not so large that it should have a too big impact on the results while it would still add conservatism.

6.4 TIME FACTOR

The time factor parameter, q, is a measure of the simultaneity of multiple impairments and is determined by the time between detection of individual impairments. The applied coding/values depends on PRA mission time, failure mode, operating conditions, etc. The following coding and numerical weighting are used (from which exceptions exists):

	Description	Code	Numerical value
High	For failure to run/operate: Multiple component impairment occurring within PRA mission time. For other failures (to start, stop, etc): Multiple component impairment discovered during testing or by observation within one test cycle of length T (test cycle T is the time between two consecutive tests of one component).	H	1.0
Medium	For failure to run/operate: Multiple component impairment occurring outside PRA mission time, but within a one month's period (for operating components) or within double test cycle (for stand-by components). For other failure: Multiple component impairment discovered during testing or by observation within two subsequent test cycles (2T), the events being separated by at least T.	M	0.5
Low	For failure to run/operate: Multiple component impairment occurring more than one month apart (for operating components) or more than double mission time (for stand-by components) For other failure: Multiple component impairment discovered during testing or by observation two test cycles apart (at time 2T).	L	0.1

Table 2. Time factor coding.

The description of these categories originates form the definitions within ICDE.

6.5 SHARED CAUSE FACTOR

The shared cause factor, *c*, is a parameter representing the degree of confidence about the multiple impairments resulting from the same cause. The following coding and numerical weights are used:

	Description	Code	Numerical value
High	This code is applied when the analyst believes that the cause of the multiple impairment is the same, regardless of the cause. This code implies multiple impairments from the same root cause of impairment, often resulting in the same failure/degradation mechanism and affecting the same piece-parts of each of the multiple components.	H	1.0
Medium	This code is used when the event description does not directly indicate that multiple impairments resulted from the same cause, involving the same failure mechanism, or affected the same piece-parts, but there is strong evidence that the underlying root cause of the multiple impairments is the same.	M	0.5
Low	This code is used when the event description indicates that multiple impairments resulted from different causes, involved different failure mechanisms, or affected different piece-parts, but there is still some evidence that the underlying root cause of the multiple impairments is the same.	L	0.1

Table 3. Shared cause factor coding.

The description of these categories originates form the definitions within ICDE.

6.6 DETECTION MODE

This parameter, dmode, represents the mode in which an event is detected.

Latent and monitored failure modes should be kept strictly separated in assessments because they differ significantly both regarding qualitative analysis and quantitative treatment. The suggested coding is presented below. The numerical values assigned to each code is to represent whether events with the particular detection mode are to be included in the assessment or not (events to be included are given the value 1.0 while event to be excluded are given the value 0).

	Code	Numerical value
Monitoring on walkdown	MW	1.0
Monitoring in control room	MC	0.0
Maintenance/test	MA	1.0
Demand event (failure when the response of the component(s) is required)	DE	1.0
Test during operation/annual overhaul/laboratory	TI/TA/TL	1.0
Unscheduled test	TU	1.0
Unknown	U	1.0

Table 4. Detection mode coding.

This is actually a question of screening of the events, but because events that in the process of impact vector construction are screened out based on detection mode might be of interest later in the process of quantification it is suggested that such events are to be included in the data set (but ignored by assigning the value of 0).

The description of these categories originates form the definitions within ICDE.

6.7 QUALITY ISSUES

During the review process, it turned out, that there exist some doubts concerning quality of ICDE input data. If expert judgement is performed as in the original NAFCS project, where experts had access to the original plant documents or even visited the plant and had interviews with maintenance personal, inconsistencies between the results of expert assessment and the information stored in the ICDE will be resolved improving quality of results. Thus, expert assessment provides additional insight, even if the experts do not assess impacts, but just impairment and the other input data.

It cannot be stressed too strongly, that the quality of input data is a critical issue for any automatic treatment of this input data. It must be assured, that the input data is of highest quality. This should best be done when the ICDE data is generated, because in this case, most profit can be taken from this data from all users.

It also must be mentioned, that the numerical values for impairment in the ICDE (C=1.0, D=0.5, I=0.1, W=0.0), and possibly also those for the shared cause factor and for the time factor are given as examples only. In some cases, the texts in ICDE indicate, that other values for D and I may be more appropriate. It must be assumed, that ICDE data is conservative in such cases. I.e. if there is good reason to assess an impairment of 0.2, it must be specified as D, not as I. If in a CCF event of a group of four events, three components have failed between two consecutive tests, and the other one later, the time factor has to be set to high, etc.

Latency time of CCF events is also an important issue, though not in the context of impact vector generation. If the CCF event has been noticed by some special test (i.e. not during routine periodic tests), it will require special treatment. The same holds, if the event has been detected, because procedures for routine periodic tests have been changed.

If it cannot be guaranteed, that the above issues are covered by the normal quality procedures of CCF data generation, it is suggested to use the following check list for each event. This check list can be applied, when the events are grouped to find a homogenous CCF population.

Review and assessment of the events needs to be quite open-minded because different CCF models may be called for (e.g. by time-related and demand caused failures or exceptional environments) and correct quantification may depend on some aspect not formally considered in the data collection scheme. Attention should be paid especially on attributes that may not be directly coded or asked in data collection. A check list representing present knowledge on relevant attributes is given below.

- Can it be concluded that failure entry times are close in time even if detections may be more spread in time?
- Can it be concluded that a subset of components may have a higher shared cause or time-factor (i.e. are closer in time) than the whole CCCG?
- Even if detections were close in time, were the degradations (like wear or vibration) slowly developing so that actual failed states would not occur so close in time?
- When an event was observed in a regular periodic test, would the situation be different in case of a true demand, e.g. there would be time for recovery before it is too late?
- If recovery was done, would it be impossible or unlikely in case of real demand?
- Are the degradations due to the same phenomenon (like wear, or lack of lubrication)? If so, is it likely that if a smaller degradation means failure in true demand, higher degradations would also?
- Are there hints that numerical values for impairments differ from the letters? If there are such differences, they should be documented.
- Is there any hint that the time factor is not correct? If there is, the true time factor has to be determined.
- Are latency times larger than normal PSA test interval? Reasons may be tests, which are less frequent than the standard test interval, or if a change in standard test procedure has occurred, which sometimes revealed a defect entered already at plant commissioning. The true latency time has to be documented.
- This list must be subject to regular review based on experience gained by those using it.

7 PROPOSED APPROACH FOR NET IMPACT VECTOR CONSTRUCTION

7.1 ASSUMPTIONS AND LIMITATIONS

The first task of the Nordic/VGB CCF project is to find a common way among the partners to construct impact vectors. Based directly on the first and the fourth acceptance criteria there are two basic requirements for this method:

- Defendability
- Realistic modelling.

Although the approaches of Vaurio and NAFCS best estimate clearly allow for expert assessment of parameters, this possibility has been used in a very conservative way in most assessments according to Vaurio approach. The subjective assessment by NAFCS best estimate yielded smaller values in many cases. The NAFCS high bound (HB) method is identical to the Vaurio method if no expert assessments are applied in the Vaurio method (as in this project phase). The Vaurio method will therefore further on be referred to as the high bound (HB) method, se further section 7.7.1.

So, first, it must be investigated, how much expert assessment is required to yield realistic modelling.

As outlined in the third acceptance criteria the approach should be conservative in comparison with expert judgements, but less conservative than the High bound not to be unrealistic. Subsequently, this criterion will only be applied to data where NAFCS best estimate is available. Even though the Vaurio method has the potential to include expert judgement, this has not been made use of in the assessments. There is one exception in this criterion application, namely, if the value of Vaurio turns out to be lower than the one of NAFCS best estimate. Reasoning for this is provided in section 7.1.1.4 below. Any deviation from such conservatism must be discussed to find out if it can be justified.

7.1.1 SOME PROPERTIES OF IMPACT VECTOR CONSTRUCTION METHODS

7.1.1.1 ON THE NAFCS LOW BOUND

The NAFCS low bound treats impairments as independent. This is, however, not a contradiction to the idea of CCF because this independence is conditional on the event that a CCF occurred. Other models also have this conditional independency property. For example, in case of the BFR model 0, failure of the component is treated as independent under the condition of the shock. Also, the 'common load' model (CLM) 0 treats dependence via the common load distribution, whereas the distributions of individual strengths are identical, and they are multiplied, i.e. they are treated as conditionally independent (the model has also a common strength distribution but assumes failures conditionally independent, given a load). See further PROSOL-2007 in 0.

It is clear though, that this assumption of conditional independence cannot be verified, and it leads to rather small values.

7.1.1.2 ON THE HIGH BOUND

Also the assumption of maximum dependence in the high bound approach cannot be proven. The conditions, which cause one component to fail, may not necessarily fail the other ones. Even, if the strength of the cause is maximum, i.e., we are sure, that is a CCF, the components are not necessarily identical. Such differences between the components may lead to the observation that only some, or even only one, fails. Consider again the CLM, where there is one load distribution, but the distributions of resistivity are identical, but independent.

From the ICDE definition quoted in section 6.5, it has rather to be concluded, that it can best be interpreted as the probability that the event observed is in fact a CCF, but no indication on the strength of this shared cause is given, i.e. the shared cause factor is a subjective probability that a common root cause exists.

So, it becomes clear, that the assumption of maximum dependence is also not obvious. However, it appears to be conservative.

7.1.1.3 ARE THE RESULTS OF THE HIGH BOUND APPROACH CONSIDERED REALISTIC?

If there is a strong shared cause, NAFCS high bound can be considered believable. If the cause mechanism is so strong, that it will act independently from differences between the individual components, the high bound will be the correct result. Consider the following fictive example 1:

EXAMPLE 1

> In a can for a certain lubricant, there is some strong acid, which will not lubricate a component, but dissolve the lubricant, and corrode the surfaces, which were supposed to be lubricated.
>
> In this case, the strength of the shared cause may be the capability of the acid to destroy the components. If the acid is very strong, it will destroy all components, if it is very weak, it will destroy no component.

However, it is also possible, that the components have some individually different capability to cope with an attack. Then, even if the probability, that there has been a CCF is assessed to be one, the conditional probabilities of component failures may be smaller than one. E.g.: the time since the last maintenance, the amount of oil replaced or the operation time is different.

Consider the following fictive example 2:

EXAMPLE 2

> In a can for a certain lubricant, there is some strong acid mixed under the lubricant. So, lubrication will work, but there will be an attack of the acid, which is exactly similar for all components. However, the components have a coating against acidic attacks, which is sometimes weaker, sometimes stronger.
>
> In this case, even the shared cause factor may be assessed as one again, because there is no doubt, that there is a CCF. However, the conditional probability would be assessed to be smaller than one, because of the individual differences among the components, whereas in the first example, it has been assumed, that there are no such individual differences. It may be even considered conditionally independent.

From the previous reasoning it can be concluded that there is room for expert judgement. As a high bound and a low bound method exist it can be expected that a realistic value exists between these two cases.

7.1.1.4 ASSUMPTION OF VALID INPUT FOR EXPERT ASSESSMENT

Expert assessment takes into account the complete documentation of the CCF and in addition the assessment of impairment, shared cause factor, time factor, which are also a part of the data. Given the additional information, it is possible, that the expert decides that the impairments or the two factors are not correct. If this is allowed, it is nearly impossible to obtain a formula driven approach, as in this case, the formula driven approach will be based on erroneous data. So, it must be assumed, that the raw data given is correct. In a real application of this approach, this must be assured by a suitable quality control procedure. The data contains evidence, that this has not been followed completely. E.g. the data sets nr. 21 and 22 have been evaluated according to High bound with a value of 0.05. This is the maximum possible value according to the given input. NAFCS best estimate obtains an assessment of 0.2. This contradicts the evidence given; it is only possible if the impairments, the time factor or the shared cause factor is changed, based on insight gained by additional information.[2] For this reason, the High bound value will be considered as a lower limit if it is smaller than the NAFCS best estimate value, in order to filter out these cases.

7.1.1.5 THE UNKNOWN AMOUNT OF EXPERT JUDGEMENT

So, given the impairments, and the shared cause factor, and the time factor, there is still room for expert judgement based on the descriptions of the event. The interesting question is: How do experts judge? This can be observed only based on the existing data.

7.1.2 EVALUATION OF GIVEN DATA

In the following 41 analysed event of the previous phase shall be considered for validation. All of these are of group size 4.

The NAFCS best estimate results are influenced by expert judgement, whereas the High bound results are not. The High bound results are rather pessimistic. For this reason, realistic approaches should yield assessments which are close to NAFCS best estimate and not larger than High bound (unless High bound should be smaller than NAFCS best estimate). As the values for the maximum failure multiplicity are the most important in the context of PSA analysis, the range of impact vector element for failure multiplicity 4 for High bound and NAFCS best estimate has been considered as the most relevant criterion, which subsequently shall be called “coincidence”.

Given this criterion, it can be seen, that NAFCS best estimate coincides in 16 out of 41 given cases with High bound; in the other cases, it does not. It can be seen easily, that in the cases, where there are several failed components (impairment C), NAFCS best estimate nearly always coincides with High bound. Only, if there is at most one failed component NAFCS best estimate will sometimes assess differently. That is why, in the following table, two criteria have been used to divide the data set:

a) Is there more than one impairment C (complete failure)
b) Is there more than one impairment D (or I or S; partial failures)

	More than one C	At most one C
More than one D, I, S	0 differences out of 1	19 differences out of 21
At most one D, I, S	1 difference out of 9	5 differences out of 10

Table 5. Differences between NAFCS best estimate and Vaurio results.

An interpretation that can be made of this is that experts judge less, i.e. more optimistically, when less damage is seen. Given the information above, one can see that cases where there are at least two failed components, should be assessed using conditional probability one (for impact vector element of for failure multiplicity 4), because in just 1 out of 9 cases, the expert judgement differs. Assessment of the remaining cases depends on the question, how many degraded (coded as D, I or S) components there are. If there is more than one partially failed component, the expert

[2] This kind of deviation between the NAFCS best estimate and Vaurio is also found in data no. 2, 10-13, 15-18, 21-23, 26 and 30 when considering “at least k out of 4”-cases.

judgement differs in 90 % of the cases. If there is at most one partially failed component, the expert judgement differs in just 50 % of the cases. Thus, it appears reasonable, to develop an approach, which is influenced by the number of partially failed components. Of course, reasoning on the reason of the expected behaviour is speculative. However, there are two aspects, which explain the observations, and which are plausible:

- An expert will assess larger values, if he sees an undeniable CCF, i.e. an event, where at least two components have failed without doubt (complete failure C).
- An expert will assess a stronger CCF (with a large probability of occurrence), if he sees more damage. As an assessment of the strength of the shared cause is rather difficult given the information available, this appears reasonable.

These principles shall be implemented in a generic model of assessment.

7.2 FORMULA AND CODING DRIVEN (FCD) METHOD ON CCF ANALYSIS - IMPACT VECTOR CONSTRUCTION

The component degradation value is based on the evaluated status of the component, in terms of its capability to perform its function. In this way the parameter, d_k, can be defined as being a conditional probability that a specific component, k, fails given an actual demand in the observed condition.

For the NAFCS best estimate method, scenarios are considered. For each scenario an impact vector is established, where one impact vector element is one and all others are zero. The element that is to have the value one depends on how many components are assumed to fail in the particular scenario. For these scenarios, weights are then assessed originally subjectively, where the sum of all weights has to be one. The impact vector for the event is then obtained from the combination of the scenario specific impact vectors and their assigned weights. It can be seen, that if the smallest impairment multiplied by time factor and shared cause factor is assigned to the scenario with the largest multiplicity, this will result in the same value as the High bound approach.

Now, in the above analysis, it was shown, that High bound and NAFCS best estimate are nearly always identical for the highest failure multiplicity, for the cases where there is more than one component with impairment C. So, in this case, the weight of the scenario with highest multiplicity is assigned the smallest impairment value. The weight of second highest multiplicity is assigned the second (equal or larger) smallest impairment value where the weight of the higher multiplicity is withdrawn etc, according to the High bound approach, described also in 0 and section 7.7.1.

If there are less than two completely failed components, a less conservative approach is taken. The reason is, that based on the conservative approach, the assessment of the 4 out of 4-scenario of impairments like CCCI would be the same as CIII or even IIII. This appears to be unrealistic, because in the first case, really failed components have been seen, but in the last case only a little partial degradation. So, smaller values are assessed by the expert in the NAFCS best estimate method application. Concerning failure of multiplicity 4 this holds for 19 of the considered events, i.e. NAFCS best estimate results are smaller than High bound results[3]. If e.g. the value I occurs twice, like in CDII (case nr. 12 in table 8), then the expert might express his uncertainty between 3-out-of-4 and 4-out-of-4 CCFs by giving equal chances to both. So rather than assessing an impact vector (0, 0.4, 0.5, 0, 0.1), which is the conservative case, he would distribute the 0.1 between the two possible positions, and he would obtain (0, 0.4, 0.5, 0.05, 0.05).

[3] Please see events no. 11, 13, 15 – 19, 27-39 in table 8-9.

Generally, the value used will be the impairment divided by the number of times it occurs. This is, of course, by no means the only way, or defined as the way the experts obtained smaller values. It is, however, one approach which can be justified by reasoning. Measured against the expectation to have monotonously decreasing values in the impact vector (this would be expected from the approach of conditional independence, even if not proven by empirical evidence), this is still conservative, though less conservative than the case of maximum dependency.

	More than one C	At most one C
More than one D, I, S	High Bound applied	Less conservative approach ('ignorance prior')
At most one D, I, S	High Bound applied	High Bound applied

Table 6. Overview of applied approach in the FCD method.

7.3 MATHEMATICAL IMPLEMENTATION

Before starting this calculation it is, if needed, necessary to rearrange the impairment vector elements, d_k, to make sure it is in descending order of degradation value, i.e. $d_1 \geq d_2 \geq \ldots \geq d_k \geq \ldots \geq d_n$.

Construction of basic impact vector, v_{Basic} (m|n), where n represents the group size and k represents a position in the vector, is done with the following procedure:

n_C = nr of elements in the impairment vector with degradation value "C"

n_D = nr of elements in the impairment vector with degradation value "D"

n_I = nr of elements in the impairment vector with degradation value "I"

n_S = nr of elements in the impairment vector with degradation value "S"

if($n_C \geq 2$ or (n_D, n_I and n_S) <=1) :

$v_{Basic}(k|n) = d_k$

else, if ($d_k = 1$) :

$v_{Basic}(k|n) = 1$,

else, if ($d_k = 0{,}5$) :

$v_{Basic}(k|n) = d_k / n_D$,

else, if ($d_k = 0{,}1$) :

$v_{Basic}(k|n) = d_k / n_I$,

else, if ($d_k = 0{,}01$) :

$v_{Basic}(k|n) = d_k / n_S$,

else, if ($d_k=0$) :

$v_{Basic}(k|n) = d_k = 0$

This can be interpreted in the following way:

If $d_1 = d_2 = 1.0$ (“C”) or if n_D, n_I and n_S <=1:

The High bound is applied.

Else, for each impact vector element:

The basic impact vector equals the degradation vector with the following adjustments

If the degradation value for the element to be evaluated is C it remains the same, i.e. the impact vector element = the degradation vector element for the particular position in the vector.

Else, the impact vector element is assigned the value of the degradation value divided by the number of times this particular degradation value occurs in the degradation vector.

The FCD impact vector, $V_{FCD}(k|n)$, is obtained for the High bound cases by:

For k = n:

$V_{FCD}(k|n) = v_{Basic}(k|n) * c * q * dmode$

For k< n:

$$V_{FCD}(k|n) = (v_{Basic}(k|n) * c * q * dmode) - \sum_{i=k+1}^{n} V_{FCD}(i|n)$$

The impact vector, $V_{FCD}(k|n)$, is obtained for the ‘ignorance prior’ cases by:

For k = n:

$V_{FCD}(k|n) = v_{Basic}(k|n) * c * q * dmode$

For k< n:

if $(v_{Basic}(k|n) * c * q * dmode + \sum_{i=k+1}^{n} V_{FCD}(i|n) <= 1)$:

$V_{FCD}(k|n) = v_{Basic}(k|n) * c * q * dmode$

Else

$V_{FCD}(k|n) = (v_{Basic}(k|n)* c*q*dmode) – V_{FCD}(k+1|n) - V_{FCD}(k+2|n) - … - V_{FCD}(n|n)$

where,

c = numerical value of shared cause factor

q = numerical value of time factor

dmode = numerical value of detection mode

This can be interpreted in the following way:

If the sum of the impact vector elements becomes larger than one, this will be adjusted by decreasing the elements of the impact vector representing failure of lower multiplicity as follows: The elements of the impact vector are summed starting with the highest multiplicity. If in this process, some element of the impact vector obtains a sum larger then 1, exactly this element will be decreased such that the sum becomes exactly 1. This method can lead to an underestimation of the element with lower multiplicity, but also an overestimation of the elements with a larger multiplicity. This appears tolerable, see also section 9.4.

7.4 EXAMPLE APPLICATION

Assume there is an event with the following parameters:

- Impairment vector CIDW, i.e. numerical impairment vector (1.0, 0.1, 0.5, 0)
- Shared cause factor high, i.e. numerical value 1.0
- Time factor high, i.e. numerical value 1.0
- Detection mode TI, i.e. numerical value 1.0

The impairment values are arranged in descending order of degradation:

$d_1 = 1.0$, $d_2 = 0.5$, $d_3 = 0.1$, $d_4 = 0$.

The FCD impact vector is then calculated as below (High bound is applied):

$V_{FCD}(4|4) = v_{Basic}(4|4) \cdot c \cdot q = d_4 \cdot c \cdot q \cdot dmode = 0 \cdot 1 \cdot 1 \cdot 1 = 0$

$V_{FCD}(3|4) = v_{Basic}(3|4) \cdot c \cdot q - V_{FCD}(4|4) = d_3 \cdot c \cdot q \cdot dmode - V_{FCD}(4|4) = 0.1 \cdot 1 \cdot 1 \cdot 1 - 0 = 0.1$

$V_{FCD}(2|4) = v_{Basic}(2|4) \cdot c \cdot q - V_{FCD}(3|4) - V_{FCD}(4|4) = d_2 \cdot c \cdot q \cdot dmode - V_{FCD}(3|4) - V_{FCD}(4|4) = 0.5 \cdot 1 \cdot 1 \cdot 1 - 0.1 - 0 = 0.4$

Should the impairment vector be CDII, with the same values for shared cause factor and time factor as in the example above, then;

$d_1 = 1.0$, $d_2 = 0.5$, $d_3 = 0.1$, $d_4 = 0.1$

The FCD impact vector is then calculated as below:

$V_{FCD}(4|4) = v_{Basic}(4|4) \cdot c \cdot q = d_4/n_I \cdot c \cdot q \cdot dmode = (0.1/2) \cdot 1 \cdot 1 \cdot 1 = 0.05$

$V_{FCD}(3|4) = v_{Basic}(3|4) \cdot c \cdot q = d_3/n_I \cdot c \cdot q \cdot dmode = (0.1/2) \cdot 1 \cdot 1 \cdot 1 = 0.05$

$V_{FCD}(2|4) = v_{Basic}(2|4) \cdot c \cdot q = d_2/n_D \cdot c \cdot q \cdot dmode = 0.5/1 \cdot 1 \cdot 1 \cdot 1 = 0.5$

Further examples are presented in table 6 below (where c, q and dmode is set to 1.0):

Impairment vector	FCD impact vectors
CCCC	(0, 0, 0, 0, 1)
CCCI	(0, 0, 0, 0.9, 0.1)
CCII	(0, 0, 0.9, 0, 0.1)
DDDD	(0.5, 0.125, 0.125, 0.125, 0.125)
CDDI	(0, 0.4, 0.25, 0.25, 0.1)
DDII	(0.4, 0.25, 0.25, 0.05, 0.05)
CIII	(0, 0.9, 0.033, 0.033, 0.033)
DIII	(0.4, 0.5, 0.033, 0.033, 0.033)

Table 7. Further examples for the FCD impact vector generation.

It must be noted, that in total impact vector construction, the column for 0 and 1 failures will be augmented by the number of success observations and independent failures.

7.5 RESULTS

The produced results are presented below (these values of the different multiplicities are those for 'exactly k-out-of-4', not accumulated to 'at least k-out-of-4'). Concerning the NAFCS best estimate results a part of the evaluated events were analyzed in the NAFCS pilot studies which values are retained, see 0 and 0.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode (if MC)	High bound Multiplicity			NAFCS best estimate Multiplicity			FCD impact vector Multiplicity		
					2	3	4	2	3	4	2	3	4
1	CCCC	H	H	MC	0	0	0	0	0	0	0	0	0
2	CCII	H	H		0,9	0	0,1	0,8	0,1	0,1	0,9	0	0,1
3	CCWW	H	H		1	0	0	1	0	0	1	0	0
4	CCWW	H	H		1	0	0	1	0	0	1	0	0
5	CCWW	H	H		1	0	0	1	0	0	1	0	0
6	CCWW	H	H		1	0	0	1	0	0	1	0	0
8	CCWW	H	L		0,1	0	0	0,1	0	0	0,1	0	0
9	CCWW	H	M		0,5	0	0	0,5	0	0	0,5	0	0
10	CCWW	H	M		0,5	0	0	0,98	0,01	0,01	0,5	0	0
12	CDII	H	M		0,2	0	0,05	0,2	0,05	0,05	0,25	0,025	0,025
13	CDIW	H	H		0,4	0,1	0	0,5	0,05	0	0,4	0,1	0
14	CDWW	H	H	MC	0	0	0	0	0	0	0	0	0
15	CIII	H	H		0	0	0,1	0,15	0,08	0,02	0,03333	0,0333	0,0333
18	CIIS	H	H		0	0,09	0,01	0,05	0,05	0,01	0,05	0,05	0,01
19	CIWW	H	H		0,1	0	0	0	0	0	0,1	0	0
20	CIWW	H	H		0,1	0	0	0,1	0	0	0,1	0	0
21	CIWW	M	H		0,05	0	0	0,2	0	0	0,05	0	0
22	CIWW	M	H		0,05	0	0	0,2	0	0	0,05	0	0
23	CSSS	H	M		0	0	0,005	0,01	0,01	0,01	0,0017	0,0017	0,0017

24	CWWW	L	L		0	0	0	0	0	0	0	0	0
25	CWWW				0	0	0	0	0	0	0	0	0
26	CWWW				0	0	0	0,005	0,005	0,005	0	0	0
30	DDII	H	H		0,4	0	0,1	0,198	0,111	0,045	0,25	0,05	0,05
31	DDWW	H	H		0,5	0	0	0,01	0	0	0,25	0	0
32	DIWW	H	L		0,01	0	0	0	0	0	0,01	0	0
33	IIII	H	H		0	0	0,1	0,045	0,013	0,003	0,025	0,025	0,025
34	IIIW	H	M		0	0,05	0	0,04	0,01	0	0,01667	0,0167	0
35	IIWW	H	H		0,1	0	0	0,02	0	0	0,05	0	0
36	IIWW	H	H		0,1	0	0	0,02	0	0	0,05	0	0
37	IIWW	H	L		0,01	0	0	0	0	0	0,005	0	0
38	IIWW	H	L		0,01	0	0	0	0	0	0,005	0	0
39	IIWW	H	M		0,05	0	0	0,02	0	0	0,025	0	0
40	IWWW	L			0	0	0	0	0	0	0	0	0
41	IWWW	L			0	0	0	0	0	0	0	0	0
				Sum:	8,08	0,24	0,465	8,148	0,489	0,253	7,72167	0,3017	0,245

Table 8. Results emergency diesel generators, exactly k-out-of-4.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode (if MC)	High bound Multiplicity			NAFCS best estimate Multiplicity			FCD impact vector Multiplicity		
					2	3	4	2	3	4	2	3	4
7	CCWW	H	H		1	0	0	1	0	0	1	0	0
11	CDDW	H	H		0	0,5	0	0,5	0,4	0	0,25	0,25	0
16	CIII	H	H		0	0	0,1	0,1	0,05	0,01	0,0333	0,0333	0,03333
17	CIII	H	H		0	0	0,1	0,1	0,04	0,01	0,0333	0,0333	0,0333
27	DDDD	H	H		0	0	0,5	0,1	0,05	0,05	0,125	0,125	0,125
28	DDDD	H	H		0	0	0,5	0,1	0,05	0,05	0,125	0,125	0,125
29	DDDD	H	H		0	0	0,5	0,15	0,1	0,05	0,125	0,125	0,125
				Sum:	1	0,5	1,7	2,05	0,69	0,17	1,6917	0,6917	0,4417

Table 9. Results, centrifugal pumps, exactly k-out-of-4.

Total sum impact vectors, for diesels and pumps together are presented in the following:

Event No.	High bound Multiplicity			NAFCS best estimate Multiplicity			FCD impact vector Multiplicity		
	2	3	4	2	3	4	2	3	4
1-41, sum impact vectors:	9,08	0,74	2,165	10,198	1,179	0,423	9,41333	0,9933	0,68667

Table 10. Results, emergency diesel generators and centrifugal pumps, exactly k-out-of-4.

The effect of the models feature of decreasing the value of the elements in the impact vector depending on the configuration of the impairment vector is seen in events 11, 12, 15-18, 23, 27-31, 33-39.

In the results it can be seen that the FCD approach favour monotonic property (failure of multiplicity 2 ≥ failure of multiplicity 3 ≥ failure of multiplicity 4, etc), this is a tendency that is also present in the NAFCS best estimate results. Based on a limited amount of empirical evidence, a formal proof is not considered possible. Thus, whether this property is realistic or not, has not been proven.

7.6 CONSERVATISM CHECK

The produced results are presented below (accumulated values). The conservatism check is made for (1) multiplicity 4, or (2) if results for multiplicity 4 are zero multiplicity 3 is considered instead. For reasoning, see section 7.1. Further, conservatism check is made in relation to NAFCS best estimate results, or when these results are more conservative than High bound results the comparison is made with High bound results instead. The reasoning for this is provided in 7.1.1.4. The impact vector elements of the FCD approach that are evaluated not to be conservative are indicated by being red-marked. The values, by either NAFCS best estimate or High bound, used for comparison is blue marked in the table below. Conservatism check for lower multiplicity is discussed in attachment 1.

Event No.	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded						Is FCD conservative compared with NAFCS best estimate (or compared to HB if NAFCS best estimate is larger than HB)?
						NAFCS best estimate Multiplicity		FCD approach Multiplicity		High bound Multiplicity		
						3	4	3	4	3	4	
1	diesel	CCCC	H	H	MC	0	0	0	0	0	0	Yes
2	diesel	CCII	H	H		0,2	0,1	0,1	0,1	0,1	0,1	Yes
3	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
4	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
5	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
6	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
7	pump	CCWW	H	H		0	0	0	0	0	0	Yes
8	diesel	CCWW	H	L		0	0	0	0	0	0	Yes
9	diesel	CCWW	H	M		0	0	0	0	0	0	Yes
10	diesel	CCWW	H	M		0,02	0,01	0	0	0	0	Yes
11	pump	CDDW	H	H		0,4	0	0,25	0	0,5	0	No
12	diesel	CDII	H	M		0,1	0,05	0,05	0,025	0,05	0,05	No
13	diesel	CDIW	H	H		0,05	0	0,1	0	0,1	0	Yes
14	diesel	CDWW	H	H	MC	0	0	0	0	0	0	Yes
15	diesel	CIII	H	H		0,1	0,02	0,0667	0,0333	0,1	0,1	Yes
16	pump	CIII	H	H		0,06	0,01	0,0667	0,0333	0,1	0,1	Yes
17	pump	CIII	H	H		0,05	0,01	0,0667	0,0333	0,1	0,1	Yes
18	diesel	CIIS	H	H		0,06	0,01	0,06	0,01	0,1	0,01	Yes
19	diesel	CIWW	H	H		0	0	0	0	0	0	Yes
20	diesel	CIWW	H	H		0	0	0	0	0	0	Yes

Event No.	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded						Is FCD conservative compared with NAFCS best estimate (or compared to HB if NAFCS best estimate is larger than HB)?
						NAFCS best estimate Multiplicity		FCD approach Multiplicity		High bound Multiplicity		
						3	4	3	4	3	4	
21	diesel	CIWW	M	H		0	0	0	0	0	0	Yes
22	diesel	CIWW	M	H		0	0	0	0	0	0	Yes
23	diesel	CSSS	H	M		0,02	0,01	0,0033	0,0017	0,005	0,005	No
24	diesel	CWWW	L	L		0	0	0	0	0	0	Yes
25	diesel	CWWW				0	0	0	0	0	0	Yes
26	diesel	CWWW				0,01	0,005	0	0	0	0	Yes
27	pump	DDDD	H	H		0,1	0,05	0,25	0,125	0,5	0,5	Yes
28	pump	DDDD	H	H		0,1	0,05	0,25	0,125	0,5	0,5	Yes
29	pump	DDDD	H	H		0,15	0,05	0,25	0,125	0,5	0,5	Yes
30	diesel	DDII	H	H		0,156	0,045	0,1	0,05	0,1	0,1	Yes
31	diesel	DDWW	H	H		0	0	0	0	0	0	Yes
32	diesel	DIWW	H	L		0	0	0	0	0	0	Yes
33	diesel	IIII	H	H		0,016	0,003	0,05	0,025	0,1	0,1	Yes
34	diesel	IIIW	H	M		0,01	0	0,0167	0	0,05	0	Yes
35	diesel	IIWW	H	H		0	0	0	0	0	0	Yes
36	diesel	IIWW	H	H		0	0	0	0	0	0	Yes
37	diesel	IIWW	H	L		0	0	0	0	0	0	Yes
38	diesel	IIWW	H	L		0	0	0	0	0	0	Yes
39	diesel	IIWW	H	M		0	0	0	0	0	0	Yes
40	diesel	IWWW	L			0	0	0	0	0	0	Yes
41	diesel	IWWW	L			0	0	0	0	0	0	Yes

	3oo4	4oo4	3oo4	4oo4	3oo4	4oo4
Sum accumulated impact vectors, diesels:	0,742	0,253	0,5467	0,245	0,705	0,465
Sum accumulated impact vectors, pumps:	0,86	0,17	1,1333	0,4417	2,2	1,7
Sum accumulated impact vectors, diesels and pumps:	1,602	0,423	1,68	0,6867	2,905	2,165

Table 11. Results, diesels and pumps, accumulated (at least k-out-of-4).

7.6.1 DIESELS

Concerning evaluation of diesel data the FCD approach is conservative in 32 of 34 cases, i.e. in about 94 % of the cases. The non conservative results are obtained for events 12 and 23.

Event 12:

The deviation is exactly a factor 2. The expert obtained a different assessment for the time factor, in this case the time factor can be judged to be high for multiplicity 3 or less. It should also be noted that the performed redundant assessment with application of the NAFCS best estimate method the impact vector is assessed to be (0, 0.8, 0.2, 0, 0), see 0. In comparison with this result the FCD approach is indeed conservative.

Event 23:

The absolute contribution of this value is negligible, since the impairments are CSSS. As the impairment S is a possibility, which just exists since the first phase of the project, it is possible to assume, that the expert had no experience yet with this task.

Considering the above, on top of the provided 90 % conservatism, it can be concluded that the FCD approach does provide required conservatism in the case of application on diesel data.

7.6.2 PUMPS

Concerning evaluation of pump data the FCD approach is conservative in 6 of 7 cases, i.e. in almost 86 % of the cases. The non conservative result is obtained for event 11.

Event 11:

In this case the impact vector element for failure multiplicity 4 is zero for both the NAFCS best estimate method and the FCD approach. The concerned deviation is related to failure multiplicity 3. The NAFCS best estimate evaluation of this event indicates a risk that the impairment vector, CDDW, might be underestimated 0. This points to the possibility that this judgment included some reassessment of the input information, whereas the event otherwise would have been judged less conservative. Further, the deviation is rather small (0.25 is obtained by the FCD approach rather than 0.4 in the NAFCS best estimate).

Considering the above, it is concluded that this deviation from the required 90 % of conservatism is justified.

7.6.3 IS THE FCD APPROACH CONSERVATIVE?

In the above it has been concluded that the FCD approach is conservative for both diesel and pump data evaluation. When both these groups of components are considered the approach is considered as realistic, as it obtains a sum close to the NAFCS best estimate when considering the 4 out of 4 case. The NAFCS best estimate method obtains a sum value of 0.423, while the FCD approach yields 0.687. This is still conservative, but much less conservative than the High bound, which corresponding value for the 4 out of 4 case is 2.165.

The observed deviations are relatively small and they influence overall results to a rather small extent. Further, it is also concluded that these deviations can be acceptable, since they are justified in the specific cases.

Therefore, it can be seen that the approach works well.

7.7 QUALITATIVE TREATMENT OF UNCERTAINTIES

The assumption that component impairment values represent mutually independent conditional failure probabilities of the components leads to a lower bound of the impact vector. The assumption of maximum dependence between conditional failure probability of the components - as described by the component impairment values - leads to a higher bound of the impact vector. The high and low bounds of the impact vector are very useful for the analyst to know as a background to the specific assessment. The “truth” is expected to be somewhere between maximum dependence and complete independence and such a compromise is what is attempted to be achieved in the FCD approach presented in the above. The high bound method described below is based on the Vaurio method described earlier 0.

7.7.1 HIGH BOUND

As argued section 7.2 the component degradation value, d_k, can be defined as being a conditional probability that a specific component, k, fails given an actual demand in the observed condition.

When considering a subgroup of components S, the following holds:

$P\left\{\prod_{k\in S} X_k \middle| E\right\} \leq P\left\{X_k \middle| E\right\} = d_k, \quad \text{for every } k \in S$. Thus $P\left\{\prod_{k\in S} X_k \middle| E\right\} \leq \underset{k\in S}{Min}\{d_k\}$

This approach assumes the maximum dependence between the conditional failure probabilities of the components. This is done by setting the chances of the failure of the whole subgroup equal to the failure probability of the least degraded component. For the derivation procedure it is convenient to arrange the degraded components into descending order of degradation value, $d_1 \geq d_2 \geq \ldots \geq d_k \geq \ldots \geq d_n$, which gives a straightforward expression:

$$P\left\{X_1 X_2 \ldots X_m \middle| E\right\} = d_m, \quad for \quad 1 \leq m \leq n$$

Before starting the calculation it is, if needed, necessary to rearrange the impairment vector to make sure it is in descending order of degradation value, i.e. $d_1 \geq d_2 \geq \ldots \geq d_k \geq \ldots \geq d_n$. The High bound impact vector is then obtained as the following:

$$V_{\text{High Bound}}(k|n) = \begin{cases} d_n \cdot c \cdot q \cdot \text{dmode, for k = n} \\ \text{d}_\text{k} \cdot c \cdot q \cdot \text{dmode - } \sum_{i=k+1}^{n} \text{V}_{\text{High Bound}}(i|n), \text{for k} = 0, 1, 2, \ldots, \text{n - 1} \end{cases}$$

7.7.2 LOW BOUND

For construction of a low bound the impairment values are treated as independent conditional failure probabilities, i.e. for a subgroup of components 1, 2, …, m the following holds, and similar for the other subgroups:

$$P\left\{X_1 X_2 \ldots X_m \middle| E\right\} \geq P\left\{X_1 \middle| E\right\} \cdot P\left\{X_2 \middle| E\right\} \ldots P\left\{X_m \middle| E\right\} = d_1 \cdot d_2 \cdot \ldots \cdot d_m$$

This inequality gives a low bound if the existing dependence is positive as it normally is in practical cases.

A vector, $v_{Min}(m|n)$ is then obtained through the following:

Group size	Low bound Impact Vector Element, $v_{Min}(m\|n)$		
	m = 2	m = 3	m = 4
n = 2	$d_1 \cdot d_2$		
n = 3	$d_1 \cdot d_2 \cdot (1-d_3) + d_1 \cdot d_3 \cdot (1-d_2) + d_2 \cdot d_3 \cdot (1-d_1)$	$d_1 \cdot d_2 \cdot d_3$	
n = 4	$d_1 \cdot d_2 \cdot (1-d_3) \cdot (1-d_4) + d_1 \cdot d_3 \cdot (1-d_2) \cdot (1-d_4) +$ $+ d_1 \cdot d_4 \cdot (1-d_2) \cdot (1-d_3) + d_2 \cdot d_3 \cdot (1-d_1) \cdot (1-d_4) +$ $+ d_2 \cdot d_4 \cdot (1-d_1) \cdot (1-d_3) + d_3 \cdot d_4 \cdot (1-d_1) \cdot (1-d_2)$	$d_1 \cdot d_2 \cdot d_3 \cdot (1-d_4) + d_1 \cdot d_2 \cdot d_4 \cdot (1-d_3) +$ $+ d_1 \cdot d_3 \cdot d_4 \cdot (1-d_2) + d_2 \cdot d_3 \cdot d_4 \cdot (1-d_1)$	$d_1 \cdot d_2 \cdot d_3 \cdot d_4$

Table 12. Expressions for low bound Impact Vector, $v_{Min}(m|n)$.

where d_k = degradation value of component ‘k’.

Analogous calculation principle is to be used for n > 4.

The low bound impact vector is obtained by weighting $v_{Min}(m|n)$ with the time factor and the shared cause factor (here it is also weighted with the detection mode parameter to exclude certain events as described in section 6.6):

$v_{Low\ bound}(k|n) = v_{Min}(k|n) * c * q * dmode$

8 APPLICATION ON DIESEL AND PUMP DATA

In the first phase of the project a harmonized data set was concluded. The data applied in this task is based on this harmonized data set.

Application of the approach described in chapter 7 and the low and high bounding, as described in chapter 7.8 yield the results presented below for diesels and pumps and both component types pooled together, see also attachment 1. In these graphs also the NAFCS best estimate is included to indicate how the agreed approach comes out in comparison with the expert judgments.

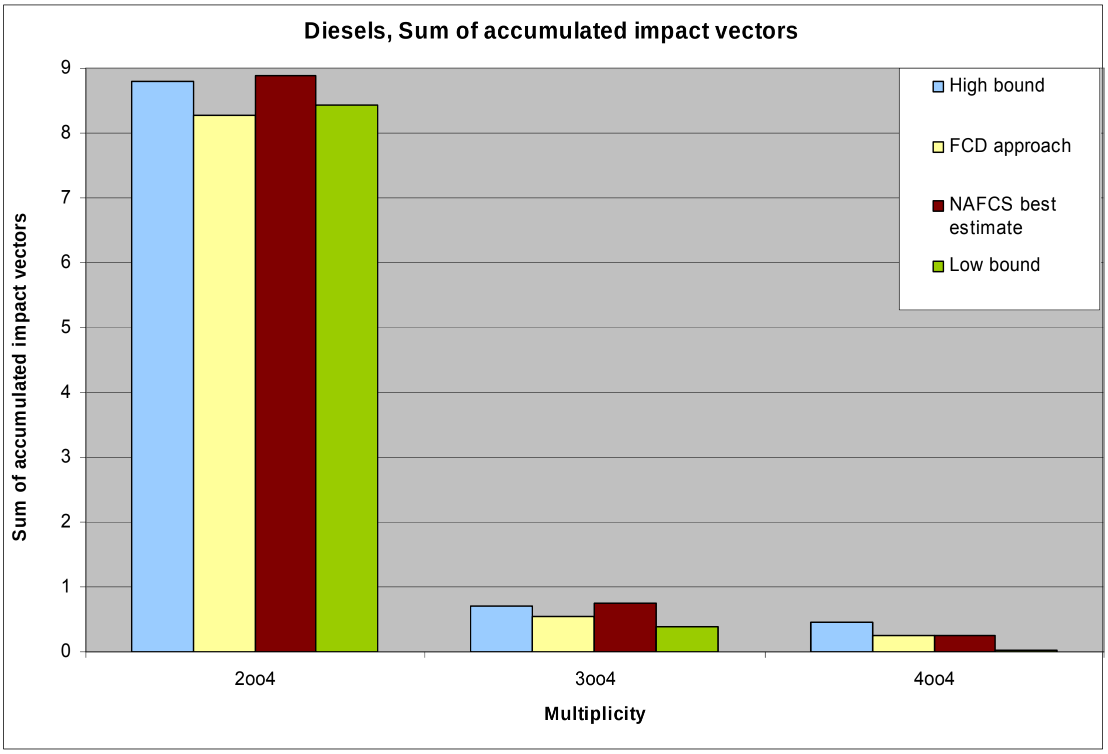


Figure 2. Accumulated, “at least k out of 4”, sum impact vectors for the FCD approach, NAFCS best estimate together with low and high bounds for data on diesels.

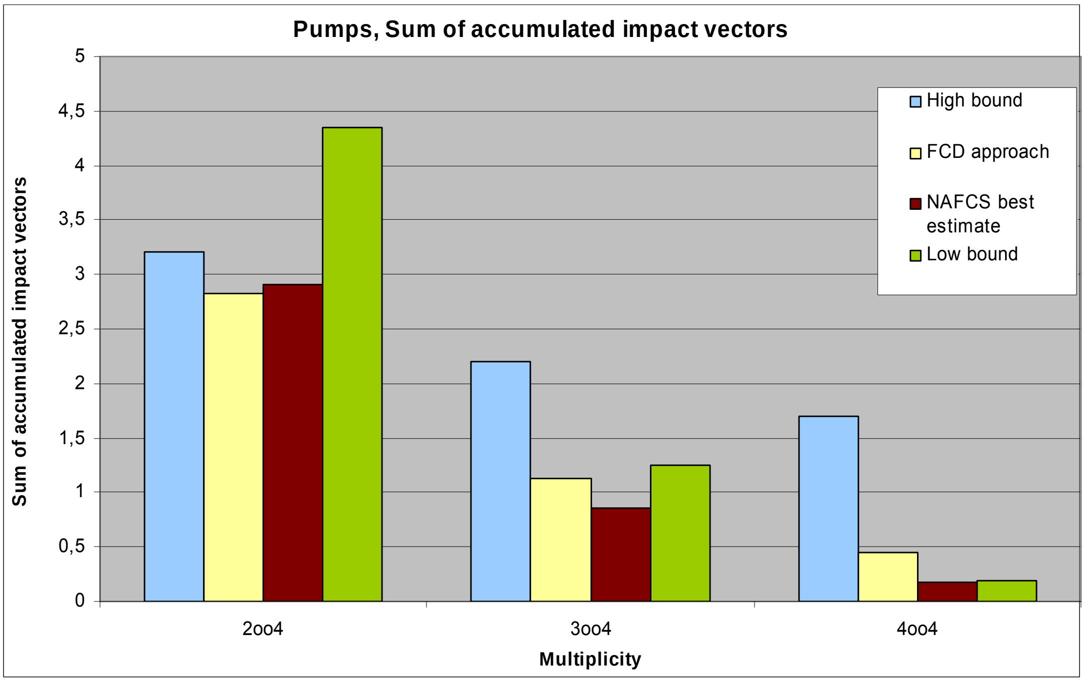


Figure 3. Accumulated, "at least k out of 4", sum impact vectors for the FCD approach, NAFCS best estimate together with low and high bounds for data on pumps.

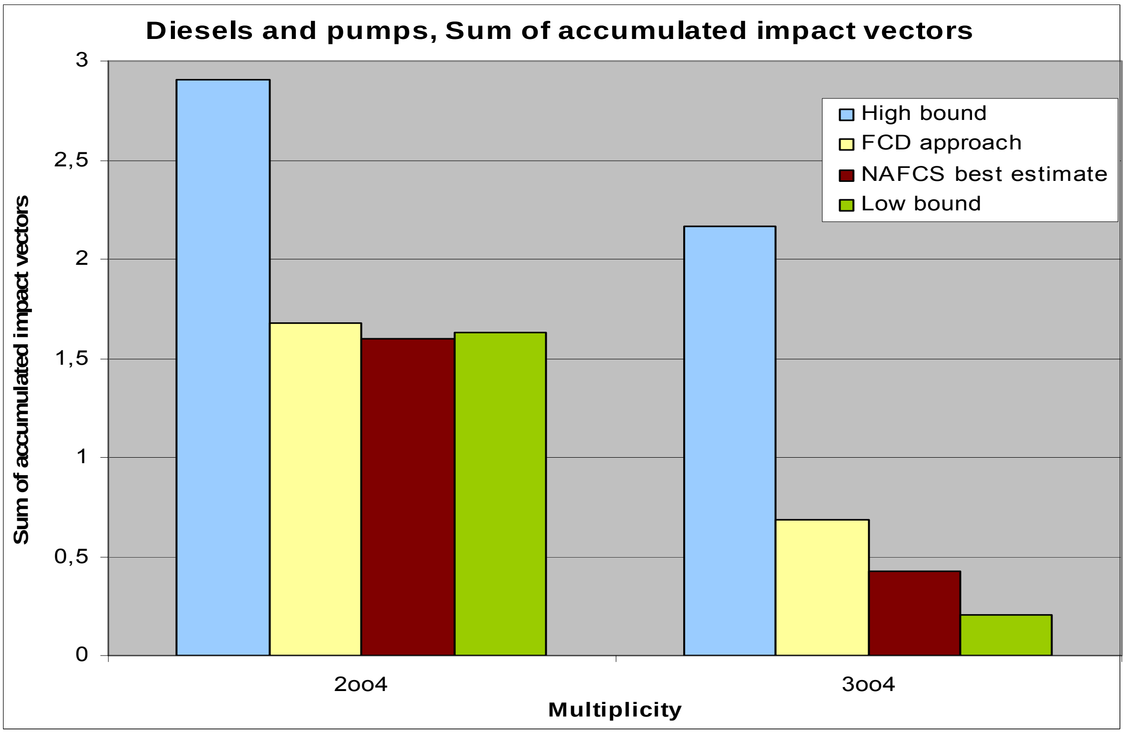


Figure 4. Accumulated, "at least k out of 4", sum impact vectors for the FCD approach, NAFCS best estimate together with low and high bounds.

9 CRITICISMS AND ANSWERS

Some critical questions have been raised by various members of the working group. These are summarized below, and they are addressed in this chapter.

- The FCD approach may be too close to the NAFCS best estimate.
- It should focus on similar impairments, rather than on level of damage.
- Performance should be measured differently (e.g. separately for pumps and Diesels)
- In some cases, cumulative values for 'at least 1 out of 4' do not correspond to the cumulative (total) level of impairments

9.1 THE FCD APPROACH IS TOO CLOSE TO NAFCS BEST ESTIMATE

Although the goal of this project has been to find a realistic approach, it has been questioned, whether the resulting values are too small. This is a subjective assessment, which is difficult to be answered. Put in an objective way, one might ask, whether the acceptance criteria are inadequate. Based on the intended use in PSA, the criteria mean, that on an average, the FCD model will result in higher values for the important CCF of a complete safety function, than the original NAFCS best estimate.

Due to the empirical nature of the approach, singular cases of optimism cannot be avoided. In case of very critical data, it is possible to use NAFCS high bound as a conservative alternative. However, the tendency towards realistic assessments, which can be seen in many parts of nuclear industry, should also be followed for CCF modelling.

9.2 THE APPROACH SHOULD FOCUS ON SIMILAR IMPAIRMENTS RATHER THEN ON LEVEL OF DAMAGE

An argument has been presented, that if similar impairment is seen on components, this should be seen as hint to assess large CCF values, because this indicates a rather strong root cause.

It has been the task in this phase of the project, to find out, how experts do behave, not how we believe they should. Though several among the authors expected to find this, it turned out, that the available data is not adequately described by an approach, which tries to bias similar impairments. Also, the argument, that much impairment is an indication for a strong CCF has been considered as logical by practitioners.

9.3 PERFORMANCE SHOULD BE MEASURED DIFFERENTLY

An argument has been presented, that performance should be measured in a different way. As in reality, CCF analysis is performed on a single component type at a time, performance should be measured e.g. based on pumps and Diesels.

As already mentioned, the method of assessment and model derivation has been statistical. This means, the larger the collective, the more accurate will the result be. Of course, the collective must be homogenous. As the target is to find out, how experts behave, the question must really be: Do experts behave differently, if they assess pump events and Diesel events? This question has been answered with a clear 'no' by the working group. Hence, it is correct to pool the events together for the task at hand.

9.4 IN SOME CASES, CUMULATIVE VALUES OF IMPACT VECTORS ARE LARGER FOR LESS IMPAIRMENT

It has been shown, that the cumulative values of impact vectors are sometimes larger, even if total impairment is less. An example for this case is the following:

Impairment	Impact vector	Cumulative impact vector
CDDD	(0, 0.5, 0.167, 0.167, 0.167)	(1, 1, 0.5, 0.333, 0.167)
CDDI	(0, 0.4, 0.25, 0.25, 0.1)	(1, 1, 0.6, 0.35, 0.1)

As can be seen, the fourth element of the cumulative impact vector (giving the impact for ”at least 3 out of 4”) is 0.333 for the first case, but 0.35 for the second case, although in the first case, the last component has impairment 0.5, whereas in the second case, which is otherwise identical, the last component has impairment 0.1. Also the third element is 0.6 in the second case, as opposed to 0.5 in the first case.

Although this difference is rather small (and so are similar differences), this lets the model appear inconsistent. So, an explanation has to be found.

At first, the following property of the High bound model used here shall be noted: The impairment at some position i in the ordered impairment vector is the maximum possible value of the corresponding position i+1 in the impact vector. This follows directly from the High bound model, if it is assumed, that shared cause factors are the same for each multiplicity (and also shared time factors). As the High bound model is conservative, it follows, that the 0.6 in the second cumulative impact vector is actually too large.

The 0.35 at position 4 is not too large per se. However, if the model would be modified, such that not a 0.5 is distributed across positions 3 and 4, but rather a 0.4 (0.4 = 0.5 – 0.1), then a value of 0.3 would result in this position of the cumulative impact vector.

One might argue, that the model could be changed in the way outlined above. However it would not fit well to the scenario driven approach any more. A likely explanation is, that not all experts have been aware about the above mentioned limit.

So, it is concluded, that the model should remain as it is, because

- it better fits to the scenario driven approach of the NAFCS best estimate,
- it can be shown, that this inconsistency is in the conservative direction
- the amount of inconsistency is small (a few percent).

10 CONCLUSIONS

The developed procedure for Impact Vector construction offers a systematic and transparent way to be applied in quantitative analysis of CCF events.

The approach is considered to be realistic and well defendable.

This is concluded since it is well formulated and can be properly described with the following arguments:

- It takes the most conservative approach possible given the data, when much degradation is seen
- It takes a less conservative approach when less damage is seen, because this is, what experts have been shown to do.
- On an average, the approach is still conservative in comparison with the original expert assessments.
- The advantages of the scenario / hypothesis based NAFCS best estimate approach are nearly obtained, but at much less cost.
- The produced results are rather close to the NAFCS best estimate results.

The acceptance criteria, as defined in section 5.1, are met.

Thus, this approach is considered to be acceptable as a realistic approach, which is quite well in the lines of what experts estimate.

In the NAFCS best estimate method a quality check is made on the judgments on impairment values as well as the other identified factors. Even if the FCD approach is a formula driven method additional, that in itself does not include any expert judgment, quality check on the data to be assessed is recommended when using the FCD approach to render the possibility of improving the quality of produced results.

Output to quantification assessment: The Sum Impact Vector (or integrated Sum Impact Vector) constitutes an input to the estimation of parameters for the CCF models. Direct estimation method or any other method can be used.

For further developments of the FCD approach one possibility is to use investigate the option of applying different shared cause factor and time factor for different subsets of a considered common cause component group is considered.

11 REFERENCES

[1] SKI 2007:41, Dependency Analysis Guidance, Nordic/German Working group on Common Cause Failure analysis - Phase 1 project report: Comparisons and application to test cases, Volume 1-2.

[2] U.S. Nuclear Regulatory Commission, Procedures for Treating Common Cause Failure in Safety and Reliability Studies, Volume 1 and 2, NUREG/CR-4780, 1988-1999.

[3] Dependency Defence and Dependency Analysis Guidance Volyme 2 - Impact Vector Method, Tuomas Mankamo, SKI report 2004:04, NAFCS-PR03.

[4] OECD/NEA, (2004). International Common-cause Failure Data Exchange, ICDE General Coding Guidelines. Technical Note NEA/CSNI/R(2004)4.

[5] Atwood, C.L., Estimators for the Binomial Failure Rate Common Cause Model, NUREG/CR-1401, U.S. Nuclear Regulatory Commission, Apr. 1980.

[6] Mankamo, T., Kosonen, M., Dependent failure modeling in highly redundant structures – Application to BWR safety valves, Reliability Engineering and System Safety, vol. 35, 1992, pp 235-244.

[7] Dependency Defence and Dependency Analysis Guidance Volyme 2 - Impact Vector Application to Diesel Generators, Tuomas Mankamo, SKI report 2004:04, NAFCS-PR10.

[8] Dependency Defence and Dependency Analysis Guidance Volyme 2 - Impact Vector Application to Pumps, Tuomas Mankamo, SKI report 2004:04, NAFCS-PR18.

1 APPENDIX 1 RESULTS AND CONSERVATISM

Results produced with the discussed approaches are presented in the following. For the purpose of conservatism check the accumulated results are to be investigated, as argued in section 5.1 in the main task 1 report.

1.1 ACCUMULATED RESULTS (AT LEAST K-OUT-OF-4)

In table 1-2 below the impact vector elements that are evaluated not to be conservative indicated by being red-marked. Conservatism check is done by comparison with either NAFCS best estimate results, or when they are more conservative than High bound the comparison has been made with High bound instead, as argued in section 7.1.1.4 in the main task 1 report. The value, either by NAFCS best estimate or by High bound, used for comparison is blue-marked in the tables 1-2. The check is made for multiplicity 2, 3 and 4.

In table 1, diesel data evaluation, in can be seen that besides event no. 12 and no. 23 that have already been discussed, see section 7.6.1, the approach produces non conservative results for event no. 15, 30 and 34. For event no. 15 the deviation is approximately 0,03 (multiplicity 3), for event no. 30 it is 0,004 (multiplicity 2) and for event no. 34 it is 0,017 (multiplicity 2). These three deviations are all so small that they are considered not having a significant impact on the overall evaluation.

In table 2, pump data evaluation, it can be seen that beside event no. 11 which has already been discussed, see section 7.6.2, there are no other non conservative results.

Considering the results for both diesels and pumps it is found that there are 6 out of 41 cases where the FCD approach is not conservative, i.e the approach is conservative in about 85 % of the cases when taking all multiplicities (2, 3 and 4) into account.

It is concluded that the observed deviations are relatively small and they influence the overall results to a rather small extent. Also, considering that the lower multiplicities will appear only in rare cases in the PSA results (possibly together with a scheduled maintenance event) this appears tolerable. Based on this, the approach is considered to work well also when taking failure of lower multiplicity into account.

Event No.	Component impairment vector	Shared cause factor c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	Low bound Multiplicity 3	Low bound Multiplicity 4	High bound Multiplicity 2	High bound Multiplicity 3	High bound Multiplicity 4	NAFCS best estimate Multiplicity 2	NAFCS best estimate Multiplicity 3	NAFCS best estimate Multiplicity 4	FCD impact vector Multiplicity 2	FCD impact vector Multiplicity 3	FCD impact vector Multiplicity 4
1	CCCC	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
2	CCII	H	H		1	0,19	0,01	1	0,1	0,1	1	0,2	0,1	1	0,1	0,1
3	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
4	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
5	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
6	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
8	CCWW	H	L		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
9	CCWW	H	M		0,5	0	0	0,5	0	0	0,5	0	0	0,5	0	0
10	CCWW	H	M		0,5	0	0	0,5	0	0	1	0,02	0,01	0,5	0	0
12	CDII	H	M		0,2975	0,05	0,0025	0,25	0,05	0,05	0,3	0,1	0,05	0,3	0,05	0,025
13	CDIW	H	H		0,55	0,05	0	0,5	0,1	0	0,55	0,05	0	0,5	0,1	0
14	CDWW	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
15	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,25	0,1	0,02	0,1	0,066666 667	0,033333 333
18	CIIS	H	H		0,1981	0,0118	0,0001	0,1	0,1	0,01	0,11	0,06	0,01	0,11	0,06	0,01
19	CIWW	H	H		0,1	0	0	0,1	0	0	0	0	0	0,1	0	0
20	CIWW	H	H		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
21	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
22	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
23	CSSS	H	M		0,0149	0,0001	5E-07	0,005	0,005	0,005	0,03	0,02	0,01	0,005	0,003333 333	0,001666 667
24	CWWW	L	L		0	0	0	0	0	0	0	0	0	0	0	0
25	CWWW				0	0	0	0	0	0	0	0	0	0	0	0
26	CWWW				0	0	0	0	0	0	0,015	0,01	0,005	0	0	0
30	DDII	H	H		0,3475	0,0525	0,0025	0,5	0,1	0,1	0,354	0,156	0,045	0,35	0,1	0,05
31	DDWW	H	H		0,25	0	0	0,5	0	0	0,01	0	0	0,25	0	0
32	DIWW	H	L		0,005	0	0	0,01	0	0	0	0	0	0,01	0	0
33	IIII	H	H		0,0523	0,0037	0,0001	0,1	0,1	0,1	0,061	0,016	0,003	0,075	0,05	0,025
34	IIIW	H	M		0,014	0,0005	0	0,05	0,05	0	0,05	0,01	0	0,033333 333	0,016666 667	0
35	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,05	0	0

Event No.	Component impairment vector	Shared cause factor c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	3	4	High bound Multiplicity 2	3	4	NAFCS best estimate Multiplicity 2	3	4	FCD impact vector Multiplicity 2	3	4
36	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,05	0	0
37	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,005	0	0
38	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,005	0	0
39	IIWW	H	M		0,005	0	0	0,05	0	0	0,02	0	0	0,025	0	0
40	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
41	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
				Sum:	8,4273	0,3866	0,0162	8,785	0,705	0,465	8,89	0,742	0,253	8,268333	0,546667	0,245

Table 13. Results diesels (accumulated), at least k-out-of-4.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	3	4	High bound Multiplicity 2	3	4	NAFCS best estimate Multiplicity 2	3	4	FCD impact vector Multiplicity 2	3	4
7	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
11	CDDW	H	H		0,75	0,25	0	0,5	0,5	0	0,9	0,4	0	0,5	0,25	0
16	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,16	0,06	0,01	0,1	0,066667	0,033333
17	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,15	0,05	0,01	0,1	0,066667	0,033333
27	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,2	0,1	0,05	0,375	0,25	0,125
28	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,2	0,1	0,05	0,375	0,25	0,125
29	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,3	0,15	0,05	0,375	0,25	0,125
				Sum:	4,3545	1,2435	0,1895	3,2	2,2	1,7	2,91	0,86	0,17	2,825	1,133333	0,441667

Table 14. Results pumps (accumulated), at least k-out-of-4.

1.2 RESULTS, EXACT (EXACT K-OUT-OF-4)

Event No.	Component impairment vector	Shared cause factor c	Time factorq	Detect-ion mode (if MC)	Low bound Multiplicity			High bound Multiplicity			NAFCS best estimate Multiplicity			FCD impact vector Multiplicity		
					2	3	4	2	3	4	2	3	4	2	3	4
1	CCCC	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
2	CCII	H	H		0,81	0,18	0,01	0,9	0	0,1	0,8	0,1	0,1	0,9	0	0,1
3	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
4	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
5	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
6	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
8	CCWW	H	L		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
9	CCWW	H	M		0,5	0	0	0,5	0	0	0,5	0	0	0,5	0	0
10	CCWW	H	M		0,5	0	0	0,5	0	0	0,98	0,01	0,01	0,5	0	0
12	CDII	H	M		0,2475	0,0475	0,0025	0,2	0	0,05	0,2	0,05	0,05	0,25	0,025	0,025
13	CDIW	H	H		0,5	0,05	0	0,4	0,1	0	0,5	0,05	0	0,4	0,1	0
14	CDWW	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
15	CIII	H	H		0,243	0,027	0,001	0	0	0,1	0,15	0,08	0,02	0,03333	0,03333	0,03333
18	CIIS	H	H		0,1863	0,0117	0,0001	0	0,09	0,01	0,05	0,05	0,01	0,05	0,05	0,01
19	CIWW	H	H		0,1	0	0	0,1	0	0	0	0	0	0,1	0	0
20	CIWW	H	H		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
21	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
22	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
23	CSSS	H	M		0,0147	0,0001	5E-07	0	0	0,005	0,01	0,01	0,01	0,00167	0,00167	0,00167
24	CWWW	L	L		0	0	0	0	0	0	0	0	0	0	0	0
25	CWWW				0	0	0	0	0	0	0	0	0	0	0	0
26	CWWW				0	0	0	0	0	0	0,005	0,005	0,005	0	0	0
30	DDII	H	H		0,295	0,05	0,0025	0,4	0	0,1	0,198	0,111	0,045	0,25	0,05	0,05
31	DDWW	H	H		0,25	0	0	0,5	0	0	0,01	0	0	0,25	0	0
32	DIWW	H	L		0,005	0	0	0,01	0	0	0	0	0	0,01	0	0
33	IIII	H	H		0,0486	0,0036	0,0001	0	0	0,1	0,045	0,013	0,003	0,025	0,025	0,025
34	IIIW	H	M		0,0135	0,0005	0	0	0,05	0	0,04	0,01	0	0,01667	0,01667	0

Event No.	Component impairment vector	Shared cause factor c	Time factorq	Detect-ion mode (if MC)	Low bound Multiplicity 2	3	4	High bound Multiplicity 2	3	4	NAFCS best estimate Multiplicity 2	3	4	FCD impact vector Multiplicity 2	3	4
35	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,05	0	0
36	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,05	0	0
37	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,005	0	0
38	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,005	0	0
39	IIWW	H	M		0,005	0	0	0,05	0	0	0,02	0	0	0,025	0	0
40	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
41	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
				Sum:	8,0406	0,3704	0,0162	8,08	0,24	0,465	8,148	0,489	0,253	7,72167	0,30167	0,245

Table 15. Results diesels (exact), exactly k-out-of-4.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	3	4	High bound Multiplicity 2	3	4	NAFCS best estimate Multiplicity 2	3	4	FCD impact vector Multiplicity 2	3	4
7	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
11	CDDW	H	H		0,5	0,25	0	0	0,5	0	0,5	0,4	0	0,25	0,25	0
16	CIII	H	H		0,243	0,027	0,001	0	0	0,1	0,1	0,05	0,01	0,0333	0,0333	0,0333
17	CIII	H	H		0,243	0,027	0,001	0	0	0,1	0,1	0,04	0,01	0,0333	0,0333	0,0333
27	DDDD	H	H		0,375	0,25	0,0625	0	0	0,5	0,1	0,05	0,05	0,125	0,125	0,125
28	DDDD	H	H		0,375	0,25	0,0625	0	0	0,5	0,1	0,05	0,05	0,125	0,125	0,125
29	DDDD	H	H		0,375	0,25	0,0625	0	0	0,5	0,15	0,1	0,05	0,125	0,125	0,125
				Sum:	3,111	1,054	0,1895	1	0,5	1,7	2,05	0,69	0,17	1,6917	0,6917	0,4417

Table 16. Results pumps (exact), exactly k-out-of-4.

2 APPENDIX 2 ILLUSTRATION OF RESULTS

In the following an illustration of results obtained for different impairment vectors for four components is provided. Numerical values for time factor, shared cause factor and detection mode is set to 1.0. The presented figures are the accumulated impact vectors.

Component impairment vector	FCD approach Multiplicity					Low bound Multiplicity					High bound Multiplicity				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
CCCC	1	1	1	1	1			1	1	1	1	1	1	1	1
CCCD	1	1	1	1	0,5			1	1	0,5	1	1	1	1	0,5
CCCI	1	1	1	1	0,1			1	1	0,1	1	1	1	1	0,1
CCCS	1	1	1	1	0,01			1	1	0,01	1	1	1	1	0,01
CCCW	1	1	1	1	0			1	1	0	1	1	1	1	0
CCDD	1	1	1	0,5	0,5			1	0,75	0,25	1	1	1	0,5	0,5
CCDI	1	1	1	0,5	0,1			1	0,55	0,05	1	1	1	0,5	0,1
CCDS	1	1	1	0,5	0,01			1	0,505	0,005	1	1	1	0,5	0,01
CCDW	1	1	1	0,5	0			1	0,5	0	1	1	1	0,5	0
CCII	1	1	1	0,1	0,1			1	0,19	0,01	1	1	1	0,1	0,1
CCIS	1	1	1	0,1	0,01			1	0,109	0,001	1	1	1	0,1	0,01
CCIW	1	1	1	0,1	0			1	0,1	0	1	1	1	0,1	0
CCSS	1	1	1	0,01	0,01			1	0,0199	0,0001	1	1	1	0,01	0,01
CCSW	1	1	1	0,01	0			1	0,01	0	1	1	1	0,01	0
CCWW	1	1	1	0	0			1	0	0	1	1	1	0	0
CDDD	1	1	0,5	0,3333	0,1667			0,875	0,5	0,125	1	1	0,5	0,5	0,5
CDDI	1	1	0,6	0,35	0,1			0,775	0,3	0,025	1	1	0,5	0,5	0,1
CDDS	1	1	0,51	0,26	0,01			0,7525	0,255	0,0025	1	1	0,5	0,5	0,01
CDDW	1	1	0,5	0,25	0			0,75	0,25	0	1	1	0,5	0,5	0
CDII	1	1	0,6	0,1	0,05			0,595	0,1	0,005	1	1	0,5	0,1	0,1
CDIS	1	1	0,5	0,1	0,01			0,5545	0,055	0,0005	1	1	0,5	0,1	0,01
CDIW	1	1	0,5	0,1	0			0,55	0,05	0	1	1	0,5	0,1	0
CDSS	1	1	0,51	0,01	0,005			0,51	0,01	0,0001	1	1	0,5	0,01	0,01
CDSW	1	1	0,5	0,01	0			0,505	0,005	0	1	1	0,5	0,01	0
CDWW	1	1	0,5	0	0			0,5	0	0	1	1	0,5	0	0
CIII	1	1	0,1	0,0667	0,0333			0,271	0,028	0,001	1	1	0,1	0,1	0,1
CIIS	1	1	0,11	0,06	0,01			0,1981	0,0118	0,0001	1	1	0,1	0,1	0,01
CIIW	1	1	0,1	0,05	0			0,19	0,01	0	1	1	0,1	0,1	0
CISS	1	1	0,11	0,01	0,005			0,118	0,0021	0,00001	1	1	0,1	0,01	0,01
CISW	1	1	0,1	0,01	0			0,109	0,001	0	1	1	0,1	0,01	0
CIWW	1	1	0,1	0	0			0,1	0	0	1	1	0,1	0	0
CSSS	1	1	0,01	0,0067	0,0033			0,0297	0,0003	0,000001	1	1	0,01	0,01	0,01
CSSW	1	1	0,01	0,005	0			0,0199	0,0001	0	1	1	0,01	0,01	0
CSWW	1	1	0,01	0	0			0,01	0	0	1	1	0,01	0	0
CWWW	1	1	0	0	0			0	0	0	1	1	0	0	0
DDDD	1	0,5	0,375	0,25	0,125			0,6875	0,3125	0,0625	1	0,5	0,5	0,5	0,5
DDDI	1	0,6	0,4333	0,2667	0,1			0,5375	0,1625	0,0125	1	0,5	0,5	0,5	0,1
DDDS	1	0,51	0,3433	0,1767	0,01			0,5038	0,1288	0,00125	1	0,5	0,5	0,5	0,01
DDDW	1	0,5	0,3333	0,1667	0			0,5	0,125	0	1	0,5	0,5	0,5	0

Component impairment vector	FCD approach Multiplicity					Low bound Multiplicity					High bound Multiplicity				
	0	1	2	3	4	0	1	2	3	4	0	1	2	3	4
DDII	1	0,6	0,35	0,1	0,05			0,3475	0,0525	0,0025	1	0,5	0,5	0,1	0,1
DDIS	1	0,61	0,36	0,11	0,01			0,3048	0,0278	0,00025	1	0,5	0,5	0,1	0,01
DDIW	1	0,6	0,35	0,1	0			0,3	0,025	0	1	0,5	0,5	0,1	0
DDSS	1	0,51	0,26	0,01	0,005			0,27	0,0053	0,00003	1	0,5	0,5	0,01	0,01
DDSW	1	0,51	0,26	0,01	0			0,255	0,0025	0	1	0,5	0,5	0,01	0
DDWW	1	0,5	0,25	0	0			0,25	0	0	1	0,5	0,5	0	0
DIII	1	0,6	0,1	0,0667	0,0333			0,1495	0,0145	0,0005	1	0,5	0,1	0,1	0,1
DIIS	1	0,61	0,11	0,06	0,01			0,105	0,006	0,00005	1	0,5	0,1	0,1	0,01
DIIW	1	0,6	0,1	0,05	0			0,1	0,005	0	1	0,5	0,1	0,1	0
DISS	1	0,61	0,11	0,01	0,005			0,06	0,0011	0,000005	1	0,5	0,1	0,01	0,01
DISW	1	0,5	0,1	0,01	0			0,055	0,0005	0	1	0,5	0,1	0,01	0
DIWW	1	0,5	0,1	0	0			0,05	0	0	1	0,5	0,1	0	0
DSSS	1	0,51	0,01	0,0067	0,0033			0,015	0,0001	0,000001	1	0,5	0,01	0,01	0,01
DSSW	1	0,51	0,01	0,005	0			0,01	0,0001	0	1	0,5	0,01	0,01	0
DSWW	1	0,5	0,01	0	0			0,005	0	0	1	0,5	0,01	0	0
DWWW	1	0,5	0	0	0			0	0	0	1	0,5	0	0	0
IIII	1	0,1	0,075	0,05	0,025			0,0523	0,0037	0,0001	1	0,1	0,1	0,1	0,1
IIIS	1	0,11	0,0767	0,0433	0,01			0,0304	0,0013	0,00001	1	0,1	0,1	0,1	0,01
IIIW	1	0,1	0,0667	0,0333	0			0,028	0,001	0	1	0,1	0,1	0,1	0
IISS	1	0,11	0,06	0,01	0,005			0,013663	0,000217	0,000001	1	0,1	0,1	0,01	0,01
IISW	1	0,11	0,06	0,01	0			0,0118	0,0001	0	1	0,1	0,1	0,01	0
IIWW	1	0,1	0,05	0	0			0,01	0	0	1	0,1	0,1	0	0
ISSS	1	0,11	0,01	0,0067	0,0033			0,0032	0,00003	0,000001	1	0,1	0,01	0,01	0,01
ISSW	1	0,11	0,01	0,005	0			0,0021	0,00001	0	1	0,1	0,01	0,01	0
ISWW	1	0,1	0,01	0	0			0,001	0	0	1	0,1	0,01	0	0
IWWW	1	0,1	0	0	0			0	0	0	1	0,1	0	0	0
SSSS	1	0,01	0,0075	0,005	0,0025			0,0006	0,00001	0,000001	1	0,01	0,01	0,01	0,01
SSSW	1	0,01	0,0067	0,0033	0			0,0003	0,00001	0	1	0,01	0,01	0,01	0
SSWW	1	0,01	0,005	0	0			0,0001	0	0	1	0,01	0,01	0	0
SWWW	1	0,01	0	0	0			0	0	0	1	0,01	0	0	0
WWWW	1	0	0	0	0			0	0	0	1	0	0	0	0

Table 17. Example impact vectors, accumulated values, for different impairment vectors.

3 APPENDIX 3 COMPARISON WITH AN AVERAGE APPROACH

Another approach for impact vector construction, also formula driven and based on coding, is a method based on the average of Low Bound and High Bound, biased with the shared cause factor and time factor is defined as the following:

$V_{Average}(m|n) = (1\text{-}0{,}5{*}q{*}c)V_{Low\ bound}(m|n) + 0{,}5{*}q{*}c{*}V_{High\ bound}(m|n)$

, where V(m|n) represent an impact vector element.

Below this is referred to as the FCD average method, while the developed FCD approach is referred to as the FCD Scenario method.

3.1 CONSERVATISM CHECK

A conservatism check of the FCD average method provides the following results when considering diesels and pumps:

Event No.	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded: NAFCS best estimate Multiplicity 3	NAFCS best estimate Multiplicity 4	FCD Average approach Multiplicity 3	FCD Average approach Multiplicity 4	High bound Multiplicity 3	High bound Multiplicity 4	Is FCD Average method conservative compared with NAFCS best estimate (or compared to HB if NAFCS best estimate is larger than HB)?
1	diesel	CCCC	H	H	MC	0	0	0	0	0	0	Yes
2	diesel	CCII	H	H		0,2	0,1	0,145	0,055	0,1	0,1	No
3	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
4	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
5	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
6	diesel	CCWW	H	H		0	0	0	0	0	0	Yes
7	pump	CCWW	H	H		0	0	0	0	0	0	Yes
8	diesel	CCWW	H	L		0	0	0	0	0	0	Yes
9	diesel	CCWW	H	M		0	0	0	0	0	0	Yes
10	diesel	CCWW	H	M		0,02	0,01	0	0	0	0	Yes
11	pump	CDDW	H	H		0,4	0	0,375	0	0,5	0	No
12	diesel	CDII	H	M		0,1	0,05	0,05	0,01438	0,05	0,05	No
13	diesel	CDIW	H	H		0,05	0	0,075	0	0,1	0	Yes
14	diesel	CDWW	H	H	MC	0	0	0	0	0	0	Yes
15	diesel	CIII	H	H		0,1	0,02	0,064	0,0505	0,1	0,1	Yes
16	pump	CIII	H	H		0,06	0,01	0,064	0,0505	0,1	0,1	Yes
17	pump	CIII	H	H		0,05	0,01	0,064	0,0505	0,1	0,1	Yes
18	diesel	CIIS	H	H		0,06	0,01	0,0559	0,00505	0,1	0,01	No
19	diesel	CIWW	H	H		0	0	0	0	0	0	Yes
20	diesel	CIWW	H	H		0	0	0	0	0	0	Yes
21	diesel	CIWW	M	H		0	0	0	0	0	0	Yes
22	diesel	CIWW	M	H		0	0	0	0	0	0	Yes
23	diesel	CSSS	H	M		0,02	0,01	0,00136	0,00125	0,005	0,005	No
24	diesel	CWWW	L	L		0	0	0	0	0	0	Yes
25	diesel	CWWW				0	0	0	0	0	0	Yes
26	diesel	CWWW				0,01	0,005	0	0	0	0	Yes
27	pump	DDDD	H	H		0,1	0,05	0,40625	0,28125	0,5	0,5	Yes
28	pump	DDDD	H	H		0,1	0,05	0,40625	0,28125	0,5	0,5	Yes

Event No.	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded: NAFCS best estimate Multiplicity 3	NAFCS best estimate Multiplicity 4	FCD Average approach Multiplicity 3	FCD Average approach Multiplicity 4	High bound Multiplicity 3	High bound Multiplicity 4	Is FCD Average method conservative compared with NAFCS best estimate (or compared to HB if NAFCS best estimate is larger than HB)?
29	pump	DDDD	H	H		0,15	0,05	0,40625	0,28125	0,5	0,5	Yes
30	diesel	DDII	H	H		0,156	0,045	0,07625	0,05125	0,1	0,1	Yes
31	diesel	DDWW	H	H		0	0	0	0	0	0	Yes
32	diesel	DIWW	H	L		0	0	0	0	0	0	Yes
33	diesel	IIII	H	H		0,016	0,003	0,05185	0,05005	0,1	0,1	Yes
34	diesel	IIIW	H	M		0,01	0	0,01288	0	0,05	0	Yes
35	diesel	IIWW	H	H		0	0	0	0	0	0	Yes
36	diesel	IIWW	H	H		0	0	0	0	0	0	Yes
37	diesel	IIWW	H	L		0	0	0	0	0	0	Yes
38	diesel	IIWW	H	L		0	0	0	0	0	0	Yes
39	diesel	IIWW	H	M		0	0	0	0	0	0	Yes
40	diesel	IWWW	L			0	0	0	0	0	0	Yes
41	diesel	IWWW	L			0	0	0	0	0	0	Yes
						3oo4	4oo4	3oo4	4oo4	3oo4	4oo4	
Sum accumulated impact vectors, diesels:						0,742	0,253	0,53224	0,22748	0,705	0,465	
Sum accumulated impact vectors, pumps:						0,86	0,17	1,72175	0,94475	2,2	1,7	
Sum accumulated impact vectors, diesels and pumps:						1,602	0,423	2,25399	1,17223	2,905	2,165	

Table 18. Results, diesels and pumps, accumulated (at least k-out-of-4).

In Table 2-3 below the impact vector elements that are evaluated not to be conservative indicated by being red-marked. Conservatism check is done by comparison with either NAFCS best estimate results, or when they are more conservative than High bound the comparison has been made with High bound instead, as argued in section 7.1.1.4 in the main task 1 report. The value, either by NAFCS best estimate or by High bound, used for comparison is blue-marked in the tables 1-2. The check is made for multiplicity 2, 3 and 4.

Event No.	Component impairment vector	Shared cause factor c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity			High bound Multiplicity			NAFCS best estimate Multiplicity			FCD Average method impact vector Multiplicity		
					2	3	4	2	3	4	2	3	4	2	3	4
1	CCCC	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
2	CCII	H	H		1	0,19	0,01	1	0,1	0,1	1	0,2	0,1	1	0,145	0,055
3	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
4	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
5	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
6	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
8	CCWW	H	L		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
9	CCWW	H	M		0,5	0	0	0,5	0	0	0,5	0	0	0,5	0	0
10	CCWW	H	M		0,5	0	0	0,5	0	0	1	0,02	0,01	0,5	0	0
12	CDII	H	M		0,2975	0,05	0,0025	0,25	0,05	0,05	0,3	0,1	0,05	0,285625	0,05	0,014375
13	CDIW	H	H		0,55	0,05	0	0,5	0,1	0	0,55	0,05	0	0,525	0,075	0
14	CDWW	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
15	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,25	0,1	0,02	0,1855	0,064	0,0505
18	CIIS	H	H		0,1981	0,0118	0,0001	0,1	0,1	0,01	0,11	0,06	0,01	0,14905	0,0559	0,00505
19	CIWW	H	H		0,1	0	0	0,1	0	0	0	0	0	0,1	0	0
20	CIWW	H	H		0,1	0	0	0,1	0	0	0,1	0	0	0,1	0	0
21	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
22	CIWW	M	H		0,05	0	0	0,05	0	0	0,2	0	0	0,05	0	0
23	CSSS	H	M		0,0149	0,0001	5E-07	0,005	0,005	0,005	0,03	0,02	0,01	0,012387875	0,00136175	0,001250375
24	CWWW	L	L		0	0	0	0	0	0	0	0	0	0	0	0
25	CWWW				0	0	0	0	0	0	0	0	0	0	0	0
26	CWWW				0	0	0	0	0	0	0,015	0,01	0,005	0	0	0
30	DDII	H	H		0,3475	0,0525	0,0025	0,5	0,1	0,1	0,354	0,156	0,045	0,42375	0,07625	0,05125
31	DDWW	H	H		0,25	0	0	0,5	0	0	0,01	0	0	0,375	0	0
32	DIWW	H	L		0,005	0	0	0,01	0	0	0	0	0	0,00525	0	0
33	IIII	H	H		0,0523	0,0037	0,0001	0,1	0,1	0,1	0,061	0,016	0,003	0,07615	0,05185	0,05005
34	IIIW	H	M		0,014	0,0005	0	0,05	0,05	0	0,05	0,01	0	0,023	0,012875	0
35	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,055	0	0
36	IIWW	H	H		0,01	0	0	0,1	0	0	0,02	0	0	0,055	0	0
37	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,00145	0	0

Event No.	Component impairment vector	Shared cause factor c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	Low bound 3	Low bound 4	High bound Multiplicity 2	High bound 3	High bound 4	NAFCS best estimate Multiplicity 2	NAFCS 3	NAFCS 4	FCD Average method impact vector Multiplicity 2	FCD 3	FCD 4
38	IIWW	H	L		0,001	0	0	0,01	0	0	0	0	0	0,00145	0	0
39	IIWW	H	M		0,005	0	0	0,05	0	0	0,02	0	0	0,01625	0	0
40	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
41	IWWW	L			0	0	0	0	0	0	0	0	0	0	0	0
				Sum:	8,4273	0,3866	0,0162	8,785	0,705	0,465	8,89	0,742	0,253	8,589862875	0,53223675	0,227475375

Table 19. Results diesels (accumulated), at least k-out-of-4.

Event No.	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode (if MC)	Low bound Multiplicity 2	Low bound 3	Low bound 4	High bound Multiplicity 2	High bound 3	High bound 4	NAFCS best estimate Multiplicity 2	NAFCS 3	NAFCS 4	FCD Average method impact vector Multiplicity 2	FCD 3	FCD 4
7	CCWW	H	H		1	0	0	1	0	0	1	0	0	1	0	0
11	CDDW	H	H		0,75	0,25	0	0,5	0,5	0	0,9	0,4	0	0,625	0,375	0
16	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,16	0,06	0,01	0,1855	0,064	0,0505
17	CIII	H	H		0,271	0,028	0,001	0,1	0,1	0,1	0,15	0,05	0,01	0,1855	0,064	0,0505
27	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,2	0,1	0,05	0,59375	0,40625	0,28125
28	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,2	0,1	0,05	0,59375	0,40625	0,28125
29	DDDD	H	H		0,6875	0,3125	0,0625	0,5	0,5	0,5	0,3	0,15	0,05	0,59375	0,40625	0,28125
				Sum:	4,3545	1,2435	0,1895	3,2	2,2	1,7	2,91	0,86	0,17	3,77725	1,72175	0,94475

Table 20. Results pumps (accumulated), at least k-out-of-4.

3.2 COMPARISON BETWEEN FCD AVERAGE AND FCD SCENARIO

	Sum of accumulated impact vectors			
	FCD Scenario approach			
	1oo4	2oo4	3oo4	4oo4
diesels	17,01	8,27	0,55	0,25
pumps	5,50	2,83	1,13	0,44
all	22,51	11,09	1,68	0,69
	FCD Average method			
	1oo4	2oo4	3oo4	4oo4
diesels	17,21	8,59	0,53	0,23
pumps	6,16	3,78	1,72	0,94
all	23,36	12,37	2,25	1,17
	Difference between FCD Scenario and FCD Average method for sum of accumulated impact vectors			
	1oo4	2oo4	3oo4	4oo4
diesels	0,20	0,32	-0,01	-0,02
pumps	0,66	0,95	0,59	0,50
all	0,86	1,27	0,57	0,49

Table 21. Sum of accumulated values.

Here it is seen that almost all difference is found for the pump events, which requires some special attention. Below are the resulting accumulated impact vectors for the evaluated events, for diesels and pumps, presented for failure of 3 out of 4 and 4 out of 4 components. Events where the FCD Scenario approach is not conservative compared to the FCD Average method are red-marked.

Event no.	Comp. Type	Comp. Impairment vector	Shared cause factor	Time factor	Det. Mode	FCD Scenario approach		FCD Average method		Difference between methods	
						3oo4	4oo4	3oo4	4oo4	3oo4	4oo4
1	diesel	CCCC	H	H	MC	0	0	0	0	0	0
2	diesel	CCII	H	H		0,1	0,1	0,145	0,055	-0,045	0,045
3	diesel	CCWW	H	H		0	0	0	0	0	0
4	diesel	CCWW	H	H		0	0	0	0	0	0
5	diesel	CCWW	H	H		0	0	0	0	0	0
6	diesel	CCWW	H	H		0	0	0	0	0	0
7	pump	CCWW	H	H		0	0	0	0	0	0
8	diesel	CCWW	H	L		0	0	0	0	0	0
9	diesel	CCWW	H	M		0	0	0	0	0	0
10	diesel	CCWW	H	M		0	0	0	0	0	0
11	pump	CDDW	H	H		0,25	0	0,375	0	-0,125	0
12	diesel	CDII	H	M		0,05	0,025	0,05	0,014375	0	0,010625
13	diesel	CDIW	H	H		0,1	0	0,075	0	0,025	0
14	diesel	CDWW	H	H	MC	0	0	0	0	0	0
15	diesel	CIII	H	H		0,06667	0,03333	0,064	0,0505	0,002667	-0,01717
16	pump	CIII	H	H		0,06667	0,03333	0,064	0,0505	0,002667	-0,01717
17	pump	CIII	H	H		0,06667	0,03333	0,064	0,0505	0,002667	-0,01717

Event no.	Comp. Type	Comp. Impairment vector	Shared cause factor	Time factor	Det. Mode	FCD Scenario approach		FCD Average method		Difference between methods	
						3oo4	4oo4	3oo4	4oo4	3oo4	4oo4
18	diesel	CIIS	H	H		0,06	0,01	0,0559	0,00505	0,0041	0,00495
19	diesel	CIWW	H	H		0	0	0	0	0	0
20	diesel	CIWW	H	H		0	0	0	0	0	0
21	diesel	CIWW	M	H		0	0	0	0	0	0
22	diesel	CIWW	M	H		0	0	0	0	0	0
23	diesel	CSSS	H	M		0,00333	0,00167	0,001362	0,001250	0,001972	0,000416
24	diesel	CWWW	L	L		0	0	0	0	0	0
25	diesel	CWWW				0	0	0	0	0	0
26	diesel	CWWW				0	0	0	0	0	0
27	pump	DDDD	H	H		0,25	0,125	0,40625	0,28125	-0,15625	-0,15625
28	pump	DDDD	H	H		0,25	0,125	0,40625	0,28125	-0,15625	-0,15625
29	pump	DDDD	H	H		0,25	0,125	0,40625	0,28125	-0,15625	-0,15625
30	diesel	DDII	H	H		0,1	0,05	0,07625	0,05125	0,02375	-0,00125
31	diesel	DDWW	H	H		0	0	0	0	0	0
32	diesel	DIWW	H	L		0	0	0	0	0	0
33	diesel	IIII	H	H		0,05	0,025	0,05185	0,05005	-0,00185	-0,02505
34	diesel	IIIW	H	M		0,01667	0	0,012875	0	0,003792	0
35	diesel	IIWW	H	H		0	0	0	0	0	0
36	diesel	IIWW	H	H		0	0	0	0	0	0
37	diesel	IIWW	H	L		0	0	0	0	0	0
38	diesel	IIWW	H	L		0	0	0	0	0	0
39	diesel	IIWW	H	M		0	0	0	0	0	0
40	diesel	IWWW	L			0	0	0	0	0	0
41	diesel	IWWW	L			0	0	0	0	0	0

Table 22. Impact vectors for diesel and pump events, accumulated values.

When seeing this it can be concluded that for the main part of these 10 “unconservative” cases the difference is neglectible. In one case the difference is only evident for 3 out of 4 failure. In 6 of the events the difference is less than 0,05. It is also noted that there is no difference larger than 0,157 (which is found in a 3 out of 4 failure case).

Based on this it is conclude that compared to the FCD Average method the FCD Scenario approach is satisfactory conservative.

Both method fulfils the criteria of acceptance and if it accepts the conservative approach which is evident from the data.

Advantages of the FCD “Average” method:

1) It is more sensitive to the shared cause and timing factors than FCD “Scenario”; these factors have been considered widely essential by international experts, e.g. in ICDE.

2) It is based on well-recognised and long widely used concepts as upper and lower bounds, without being extreme.

Advantages of the FCD "Scenario" method:

1) It is more sensitive to existing results from expert judgments than FCD "Average". The scenario method simulate how experts behave, i.e. based on the event coding events are identified for which it is most likely that an expert would formulate hypothesis instead of applying a high bound approach
2) It takes the most conservative approach possible given the data, when stronger impairment is seen. Based on well-recognised and long widely used concepts as upper bound
3) It takes a less conservative approach when weak impairment as dominant observation is seen, because this is, what experts have been observed to do. This is done based on well-recognised and long widely used concepts for formulation of hypothesis in expert judgments assuming equal weight.

Both formulas are close enough to each other to justify taking them as two equally acceptable formulations. However the FCD "Scenario" will be the preferred option due to its sensitivity to existing results from expert judgments.

Attachment 1-2
Impact vector calculator

IMPACT VECTOR CALCULATOR

The embedded file below provides an example of implementation of the formula and coding driven method for impact vector construction together with calculations of high and low bounding.

Impact vector calculator.xls

Attachment 2
Parameter Estimation

January 2009

Attachment 2-1

PREB calculator

PREB CALCULATOR

The embedded file below provides an example of implementation of the PREB method for CCF parameter estimation.

PREB calculator.xls

Attachment 3
Impact vector construction validation

January 2009

Attachment 3-1

Mankamo, Tuomas. *Review Notes on Phase 2/Task 1 Report Impact Vector Determination Methodology*, NAFCS-WN-TM21, Issue 2.

Review Notes on Phase 2/Task 1 Report
Impact Vector Determination Methodology

The review notes of this version are revised taking into account the response and discussions in the meeting of the working group (European Working Group (EWG) = Nordic/German Working Group on CCF Analysis), held on 17 June 2008 at Fortum, Espoo.
The alignments concern firstly certain misunderstandings due to incomplete or erroneous text, and secondly some comments are modified based on the additional clarifications about the proposed formula driven method. Principal review remarks and conclusions are, however, unchanged.
A separate working version will be submitted showing the changes from Issue 1 to Issue 2 in detail in order to support comments/response management.

Contents

Version control

Version	Date	Description
Outline	23 May 2008	Contents outline
Draft 1	02 June 2008	Preliminary draft including questions
Issue 1	09 June 2008	Discussed in working meeting on 17 June 2008
Issue 2	24 June 2008	

1 Background and Objectives

The review is based on the April 14, 2008 version of EWG Phase 2/Task 1 report [EWG-ImpVe-DMeth]. Certain aspects are looked as for clarification from Phase 1 report [SKI Report 2007:41].

The review is limited to commenting report text, focusing on so called “Nordic/German formula driven method”. Vaurio method for Impact Vector construction is not reviewed. Example case calculations are not checked. No Benchmarking nor further comparisons are done. Spot checks are done for a few cases where contradictory aspects have come up.

2 General Comments

C2.1 EWG has made a respectable attempt in order to invent a new formula driven method for Impact Vector construction. It will be seen how the trial succeeded.

C2.2 The draft report suffers from improper organization and missing explanations/details in several parts. Hopefully, these comments will help to finalize the report structure and text.

3 Topical Comments

The detailed comments are here divided into sections according to report chapters.

3.1 Aim and scope of the task

C3.1 An important implicit scope aspect turns out to be present: the developed formula for Impact Vector construction uses as only input arguments a specific set of codes/classifications in the current ICDE data, i.e. component degradation values, shared cause factor and time factor (and making the needed distinction between latent versus monitored failures). This is a problematic limitation which should be frankly made clear in the begin.

C3.2 The objective definition *“As there is no specific German procedure for constructing impact vectors, two methods have been investigated; the Finish (Vaurio) and the NAFCS (best estimate) approaches”* does not correspond what is actually aimed at and done. Rather, “NAFCS best estimate” and “Vaurio method” have been used as validation methods for the proposed simplified formula driven method.

C3.3 Regarding “NAFCS best estimate” and “Vaurio method”, it would be good to briefly characterize them, referring to Task 1 documentation and initial references for comprehensive definition and description.

C3.4 The sets of DG and pump CCF events used as test samples should be defined, referring for details to earlier documentation. It would be good to point out that a part of the considered CCF events were already analyzed in the NAFCS pilots [NAFCS-PR10, -PR18], and that the Impact Vectors assessed then are still retained for their part (?).

3.2 Description of Impact Vector method

C3.5 The presented brief methodological description in Chapter 4 builds much on the development done in the previous phase of NAFCS. It would be fair to explicitly indicate this aspect, generally referring to NAFCS-PR03 and –PR17, especially because I have not had possibility to continue on the subject.

C3.6 Following normal practice, it should also be noted that Impact Vectors were originally introduced in the USA […], and further developed in NAFCS, referring also to other essential recent developments.

3.3 Discussion of assumptions and limitations

C3.7 Assumptions and limitations are again discussed in Section 7.1, repeating mostly same as already said in Section 4. It is recommended to collect the clarification of key assumptions and limitations in one place of the report. Notice also the needed compatibility with Chapter 2, compare to Comment C3.1.

3.4 Definition of required input information

C3.8 Required input information seemingly equals to ICDE classifications/codes. It would be desired to indicate if ICDE guidelines are completely followed, or note any deviations. Compare to Comment C3.1

C3.9 One deviation from ICDE coding norm is clear: additional degradation class S with corresponding numeric value 0.01! For qualitative aims this addition might be reasonable. For quantitative analysis it is not sensible. Degradation values in the range of 0.01 bring very little statistical gain and are highly uncertain, and give in overall a wrong impression of accuracy. As emphasized in [NAFCS-PR03, -PR17], judgmental values less than 0.1 should not be generally used (for degradation values, scenario weights, etc). Exceptions are special cases with causal modeling and/or specific direct evidence.

It should be noticed that in the ICDE classifications degradation class I is often used in the situations where numeric value 0.1 is clearly very conservative, e.g. in cases where the component is practically intact but a preventive measure is taken after noticing a potential CCF. I.e., the numeric range of degradation class I extends from about 0.1 down to zero, or down to baseline failure probability, depending on the interpretation.

In my opinion, four qualitative degradation classes C, D, I and W are sufficient. But the numeric values should not be restricted to $d_k = 0.5$ for degradation class D and $d_k = 0.1$ for degradation class I in the quantitative analysis. The pilot cases [NAFCS-PR10, -PR18] used different values in certain cases, for example, $d_k = 0.2$ for degradation class D, or $d_k = 0.2$ or 0.05 for degradation class I, in order to make proper relative ranking between comparable cases. Besides, the component impairment classified initially in class I could be regarded as practically insignificant, i.e. component was considered as operable in quantitative analysis. (Qualitative degradation class was changed only if the initial classification was clearly wrong.)

3.5 Proposed formula-driven approach

C3.10 Section 7.1.1 deals with Impact Vector construction method – not with CCF methods, i.e. inadequate heading.

C3.11 Referring to the specific conditional independence property in CLM definition is somewhat misleading in this context. Here we deal with Impact Vector construction for a CCF event when the failure mechanism and its influences are not completely known. In the conceptual frame of CLM this corresponds to the situation that we cannot imagine to know the exact value of load variable. Instead we have to think that some conditional distribution applies, e.g. the existing knowledge can indicate that loading is likely in the extreme range. For a distributed load, the component failure probabilities are (conditionally) dependent per definition. Thus in particular, CLM definition cannot be used to justify conditional independence of component degradation values, except the idealized low bound case and some very special condition, but it rather points to conditional dependence in general.

C3.12 The problem of conditional independence in BFRM definition is partly analogous, but not commented further. In my opinion, BFRM should not be fitted at event level but only to pooled statistics. Here we must to recall the discussion in the 70-80'ies around the controversies of BFRM.

C3.13 High bound Impact Vector is based on the assumption of maximum dependence within the constraint imposed by component degradation values, when considered as conditional failure probabilities of each component. Compare to the original definition in [NAFCS-PR03]. The expression complete dependence is not good in that purpose, because "complete CCF" is a well-established term used for the extreme cases where all components fail (all component degradations equal to 1).

C3.14 The discussion of expert assessment in Section 7.1.1.4 mentions a discrepancy regarding Event No.s 21 and 22 (leaking fuel injection nozzles of DG, the impairment vector is CIWW in both events). The observed discrepancy can be explained by the fact that NAFCS best estimate corresponds to numeric value $d_2 = 0.2$ for degradation class I, see details in [NAFCS-PR10 – unfortunately, the Impact Vector construction sheets of these events contain the initial default $d_2 = 0.1$ and the high bound is thus not updated accordingly; a typical error of omission not caught in the quality control of pilots which was far from complete]. Compare to the previous discussion of assigning numeric values to component degradation classes, C3.9.
It is recommended to track for any other discrepancies of this type in the original NAFCS assessments. I noticed one more DG case of this type: Event No. 2 with impairment vector CCII. NAFCS best estimate Impact Vector is {0, 0, 0.8, 0.1, 0.1} and it corresponds to component degradation values $d_3 = d_4 = 0.2$. Another error of omission to update values for high bound generation.
Besides, when looking not at the calculated low bounds I noticed discrepancies also for low bounds, being above NAFCS best estimate. In several cases component degradation was regarded insignificant in contrast to initial qualitative classification. In some cases the operator recovery actions play important role to prevent actual CCF. It is impossible to fully take into account this kind of dependence aspect (relatively negative with respect to failure probability) in qualitative classification of component impairments. Coherent degradation values can be derived after having constructed a causal model for the CCF mechanism in consideration, i.e. both Impact Vector and component degradation values are derived from the same model. Compare to the treatment of snow blockage problems in DG air intake, Event No.s 32-33, to be discussed in C3.16.

C3.15 Similar discrepancy as discussed in the preceding comment is pointed out in [PROSOL-8002] concerning Event No.s 27 and 28 (vulnerability to pump trip due to bearing warm-up, the impairment vector is DDDD in both events, identical problem at twin units). The pump pilot used numeric value $d_k = 0.2$ for degradation class D in the Impact Vector construction for these events, see details in [NAFCS-PR18 – in these cases data on the Impact Vector construction sheets is in line]. In my opinion, according to the problem description and additional discussion with Kalle Jänkälä at the time of pump pilot, V assessment {?, ?, 0, 0, 0.5} for Impact Vector seems overly conservative, in comparison NAFCS best estimate was {0.65, 0.15, 0.10, 0.05, 0.05}. N/G formula output is {0.5, 0.125, 0.125, 0.125, 0.125}. The discussion in [PROSOL-

8002] sticks much on the ICDE codes. The event dates can mislead. They represent the time of periodic/additional tests when the tendency of bearing warm-up was observed and measured. Actually the problem had been latent from the begin of commercial operation (about 20 years), and revealed in 1993 owing to increased test run time. The noticed failure/dependency mechanism is a very complicated phenomenon because of correlation to special cyclic operation such as possible in Small LOCA demand. Also, realistic credit to recovery actions is important. Due to the special character, this CCF type should be treated specifically in quantitative analysis, preferably by explicit causal modeling, compare to the recommendations presented as conclusions from NAFCS pilots. It was a great pity that the resources at that phase were limited to orderly handle these kinds of special CCF types (there were observed several other similar cases).

C3.16 Event No.33 discussed in [PROSOL-8002] is the snow storm incident at Olkiluoto, blocking air intakes of the DGs tested during the storm, one at each unit OL1 and OL2. The Impact Vector construction is explained primarily for Event No.32, because of more severe impact to the DG tested at OL1. A trial was made to use CLM for modeling of conditional dependence under the observed conditions. The details are described in a separate small report prepared in the early times of ICDE [CR_ImpVe]. In the causal model, component degradation values, arranged in the order of functional positions, were {0.4, 0.1, 0.4, 0.1} and {0.2, 0.05, 0.2, 0.05} in comparison to (qualitative) impairment vectors DIDI and IIII of these events, respectively. These events with the risk snow blockage of DG air intake provides another example of special CCF types. The risk of snow blockage with implied dependency should rather be explicitly modeled as part of external hazards modeling.

C3.17 The introduced Impact Vector construction formula in Section 7.3 looks at first sensible, but a closer look raises questions. No probabilistic reasoning model is presented, instead, the proposal seems more or less arbitrary depending on the type of CCF event. Basing Impact Vector element of order m (beyond the degree of completely failed components) on degradation value of m^{th} component (when ordered in descending order of degradation) may be questionable. The Impact Vector elements are in general related to all component degradations as well illustrated by the low bound formulas. The relationship is simpler in high bound due to the assumption of maximum dependence. For possible consequences from the lack of well defined probabilistic basis, one implication is the situation with $n_C = 2$ where the proposal gives $v_{Basic}(m|n) = d_m$ for m > 2, which contradicts the high bound, e.g. impairment vector CCII leads to $v_{Basic} = \{0, 0, 0.8, 0.1, 0.1\}$ while $v_{Max} = \{0, 0, 0.9, 0, 0.1\}$ when using the nominal degradation values. Another observation of undesired features is the overflow problem in the element sum of Impact Vector discussed in the last paragraph of Section 7.3.

The proposed formula has an inbuilt tendency of producing monotonously decreasing or non-increasing Impact Vector elements for ascending order of $m \geq 2$. This seems to be actual always in groups $n \leq 6$. Although conservative, this kind of property is a serious limitation. Compare to the related discussion in C3.23.

Handling of time-spread events is greatly simplified in the proposed method. It is not possible to infer how the proposal behaves in details in these regards because the result tables omit presenting Impact Vector elements of 0^{th} and 1^{st} order.

It was agreed that the used notation d_m for detection mode is confusing in relation to the same notation used for component degradation values – to be changed.

Remarks of more general type will be presented in Concluding Remarks.

C3.18 Some equations on page 26 contain variable $v_{Part}(m|n)$. Presumably it should be $v_{Basic}(m|n)$?

C3.19 Heading of 2^{nd} column on Table 6 should be Nordic/German Impact Vector, not Basic Impact Vector? The values of Time Factor and Shared Cause Factor should be explicitly presented though evidently equal to 1 for all cases in the table.

C3.20 Why is field ‘Detection Mode’ left blank in Table 7, except if MC? Detection mode is relevant information.

C3.21 Pooling DG and pump data together is not sensible, compare to Table 9. People should not be encouraged to do that! Comparison is alright.

C3.22 Distinction is not made between different component failure modes. In particular, CCF mechanisms for principal failure modes of DGs and pumps, failure to start (FS) and failure to run (FR) are much different. They should be treated specifically in Impact Vector construction. Even testing of formula driven method should consider failure modes separately as they may differ with respect to goodness of fit. It is another matter, if the statistics of failure modes are combined or averaged at the end of quantitative analysis in a controlled manner.

C3.23 Impact Vector elements need not be monotonously decreasing for increasing multiplicity, compare to the last paragraph in Section 7.5. It just happens to be typical for DG and pump CCFs. For other component types, different patterns can be usual. The inbuilt property of the proposed formula in these regards was already discussed in C3.17.

3.6 Example application

C3.24 Example application has been mainly handled in Chapter 7. Alignment of heading is recommended for Chapter 8. It might be good to divide the massive Chapter 7.

3.7 Discussion of critical points

C3.25 Meaning of “measure of performance” is unclear, maybe formula’s goodness of fit ? In my opinion, different component types should be handled specifically with respect to Impact Vector construction, as well as in general for CCF data analysis, compare to the earlier comment C3.16. DGs and pumps are still reasonably close but DGs and control rods, for example, very apart from each other regarding important CCF mechanisms and defenses.

4 Concluding Remarks

In conclusion, I cannot support the proposed No/Ge formula for Impact Vector construction . Firstly due to its apparent arbitrariness (lack of probabilistic reasoning model) and overdriven simplicity, compare to preceding detailed comments, and secondly due to the following general arguments:

C4.1 While the proposed formula produces in the average reasonable Sum Impact Vector for the test set of DG and pump CCF events, it does not certainly provide event specific accuracy in sufficient degree.

C4.2 The proposal is made in such a way that in the average it envelopes conservatively the dependency among the considered DG and pump CCF events but can fit poorly to other component types, e.g. to special component types with either strong or weak conditional dependence being typical in CCFs, or even to another set of DG or pump CCFs, for example, in the future after positive gain from improved defenses against CCFs.

C4.3 The proposal is much built to CCF group size of 4. It can be expected to work similarly in CCF group size of 3, and of course in the trivial size of 2, but may be less suitable in larger groups.

In my opinion the scenario method – developed in NAFCS pilot studies and used in several practical CCF data analysis – is a preferred path to proceed among other developed viable approaches. The heavy role of required engineering judgment is a problem in scenario method but things can be improved in that respect as already recommended in the proposals made in NAFCS pilot study reports. Causal modeling should be used in any more complicated CCF phenomena. The human errors play an important part in many CCFs. For their part causal modeling can build on established HRA methods. Admittedly, the scenario method requires skill, experience, often communication with plant experts and time resources. The resource needs are increased by the requirement to do the Impact Vector construction by two experts in a well organized manner, which is a must in order to assure good quality as emphasized by NAFCS pilots. I think this is affordable because of the high importance of CCFs.

A formula driven method for Impact Vector construction requires less resources, but is likely to reduce to a mechanical calculation, maybe just to the use of a computerized algorithm, i.e. full automation, directly inputting ICDE data – which still suffers from incompleteness and other quality problems – without any experienced control connected to a deeper quantitative analysis, and also skipping the highly useful learning process of the deeper analysis.

5 References

EWG-ImpVe-DMeth
Impact Vector Determination Methodology, Phase 2/Task 1 Report of Nordic/German Working Group on CCF Analysis, Version 1.0, 2008-04-14.

SKI Report 2007:41
Dependency Analysis Guidance, Comparison and Application to Test Cases. Phase 1 Report of Nordic/German Working Group on CCF Analysis, October 2007.

NAFCS-PR03
Impact Vector Method. Topical Report NAFCS-PR03, prepared by Tuomas Mankamo, Issue 2, 31 August 2003.

NAFCS-PR10
Impact Vector Application to the Diesel Generators. Topical Report NAFCS-PR10, prepared by Tuomas Mankamo, Issue 1, 31 October 2002.

NAFCS-PR17
Impact Vector Construction. Topical Report NAFCS-PR17, prepared by Tuomas Mankamo, Issue 1, 10 October 2003.

NAFCS-PR18
Impact Vector Construction to the Pumps. Topical Report NAFCS-PR18, prepared by Tuomas Mankamo, Issue 1, 29 August 2003.

PROSOL-8002
Comments on Phase 2 Task 1 report. Jussi Vaurio, 27.04.2008.

CR_ImpVe Expressing the Impact of a CCF Mechanism. Work notes by T. Mankamo, Avaplan Oy, 17 September 1996.

Attachment 3-2

Klügel. Jens-Uwe. *Scientific Review of Phase 2, Task 1*
Report: Impact Vector Determination Methodology.

Prepared for Nordic/German Working Group on Common Cause Failure Analysis

23.05.2008

1 Introduction

As a part of a continuing effort of a common Nordic/German Working group on Common Cause Failure Analysis a procedure for the determination of impact vectors from observed operational events was developed. The procedure is reviewed from the following perspective:

- Technical adequacy of the approach
- Consistency of assumptions
- Treatment of uncertainty and dependency

2 Scope of the procedure

The procedure deals with the construction of net impact vectors for CCF-events avoiding giving preference to a specific quantification method. The authors put as an objective to develop a conservative procedure for the construction of impact vectors. Nevertheless they mainly focus on the NACFS and the Vaurio method. The objective to develop a procedure which is more conservative than expert judgement does not make sense to the reviewer. Expert judgement is subjective and therefore depends on the expert. The objective should consist in the development of a procedure which reproduces in a reasonable way empirical observations.

3 Technical adequacy of the approach

The general approach to the construction of net impact vectors is similar to approaches used in other countries (US) or for the ICDE-database. A key difference in the approach in comparison to “classical methods” consists in the attempt to capture dependency for the conditional probability of failure of multiple components given a demand to the components. The methodology shares the general problems of other CCCF quantification methods, by setting a degradation or impairment of a component equal to the observation of a “near-miss” damage, which later on statistically sums up to a “full failure” of more than one component. This effect occurs even under conditions, when none of the observed components has failed functionally. This is a misrepresentation of the task to be considered in PSA or PRA. The correct task is related to the question, to define the conditional probability of failure for different subsets i consisting of different numbers of failed components taken from a set of ***m*** components with the **same functional task** within the **mission time of a PRA** (usually 24 hours).
The aspect, that the components within a group should perform **the same functional task** is only partially covered by developing some criteria for population homogeneity. The aspect that the components should fail together within the mission time of a PRA is not considered for the **“fail to run”** failure modes, where it should have been considered.

Because of neglecting these aspects ageing events may appear to be considered as Common Cause Failures, which they are not. In general, all components of a NPP will fail as time passes without maintenance interference (repairs or preventive maintenance). But this has nothing to do with common cause failures, which are meant to deal with dependencies of failure of different components for the same failure mode. CCFs are just a mathematical,

statistical correction for the very strong assumption of independency of failures of different components used in usual PSA data analysis. A degradation of a component, observed during a test, not violating its functional capability is not considered a failure in usual data analysis and it shouldn't be considered as such without good reason. Even under conditions where an impairment of a second component is observed after a failure of another, first component, by the same mechanism does not mean that the failure of the second component will occur within the mission time of the PSA. The failure of the second component still occurs at a random failure time. Therefore, the failure times for the failure of multiple components are distributed independently, but may be distributed not identically due to the individuality of the components (different manufacturing times, different maintenance times, differences in material compositions and so on). Even the argument used in the report of the existence of a very strong shared cause (section 7.1.1.3 example acid) does not refute this argument, because the time, when the acid will destroy a second component maintains to be random.
It depends on the amount of acid and on the time, when the acid was introduced into the lubrication system (instead of oil), o the specific material combination (the resistance of one component to withstand the acid may be slightly different, than for the other, the amount of acid added to the lubrication system, may be different, the time of demand may be very short after the introduction of acid to the lubrication system before a malfunction could occur). Additionally, even under the condition of a strong shared cause, there is still the competition of different failure modes and a second component may fail for completely other reasons and may have been renewed (repaired), before a demand to the group of components occurred and the lubrication liquid may have been replaced. Because failure times for the occurrence of multiple failures for a group in general are random, **it is necessary** to include into the time factor analysis a criterion asking, whether the observed impairment/degradation will have failed the considered component within the mission time of a PSA (**recommendation 1 – for fail to run failure modes**). Additionally, it is necessary to restrict the selection of CCF-suspicious events to such observations, where at least one component has found to be failed. This is necessary to avoid a situation there a large amount of impairments or degradation observations, which may be the result of normal ageing before performing substantial maintenance will be treated as Common Cause Failures. The observation of partial degradations in tests or inspections before a malfunction occurs is a sign of a successful test or inspection procedure and not of a common cause failure as long as **no real malfunction event** was observed. Therefore, it is mandatory to include a criterion for the selection of potential CCF-events, that at least one component of a group of m components was found to be in a failed state (**recommendation 2**).
Because the failure times for the failure of different subsets of components (with i members) are independent, there is no reason to assume a very strong dependency for the conditional probability of failure between these groups. This is in general, the justification, why in other countries (US) these conditional failure probabilities are treated as independent. In combination with the use of non-informative priors for the distribution of these conditional failure probabilities, which only slowly improves due to lack of success data, this still results in conservative estimates.

From the report it is not clear, how the difference between staggered testing and simultaneous testing is treated.

4 Consistency of assumptions

In section 4.2.1.4 a very strong assumption is made with respect to the additivity of impact vectors requiring that the group size is the same and that the groups are mutually homogeneous. Under this condition and this is assumed in general throughout the report, the event data can be simply pooled. Unfortunately, this key assumption is never fulfilled in practice. The main reason is the already mentioned individuality of the stochastic process of occurrence of failures for different components and component groups at different plants. The criteria for the definition of homogeneity given in section 6.2 are not sufficient to ensure the selection of homogeneous populations. To improve the criteria **it is recommended** to prove the similarity of occurrence of "independent" failures by comparing the probability distributions of failure frequencies for the different groups to be compared or of the different components to be included as members into a larger CCF group (for example considering the case of constructing a CCF-group of pumps, operated in standby with borated water as medium, but differing in size, electrical power input, vendor, test and maintenance practices). In PSA practice (US NRC, A. Mosleh) it is assumed that the conditional failure probabilities can be scaled to the probability distribution for the frequency of independent failures to reduce this problem (scarcity of data). This **is a valid assumption** and if it shall be used it should be mentioned in the report (**recommendation 3**). Using the scaling approach, the requirement of mutual homogeneity can be relaxed.

5 Treatment of uncertainty and dependency

The procedure suggests to combine the assessment of uncertainty (which is epistemic of nature = lack of knowledge) by combining the assessment of uncertainty with the use of different assumptions on the dependency of the conditional probability of failure of i components in as subset of I failed components taken from a set of total **m** components This is a possible approach to consider one source of uncertainty – the lack of knowledge on the degree of dependency between the conditional failure probabilities for different components in case of occurrence of a CCF. The only justification is that this approach is conservative, the counter argument is – you can always construct a more conservative approach (see Beta-factor approach – all components have the same (and you may select a very conservative value for Beta)), so what? There are much more sources of "lack of knowledge" besides the lack of knowledge on the degree on dependency, which in any case should be low (see discussion in section 3 of the review)!
A more meaningful, but very conservative approach consists in using data from real observations combining them into a Bayesian approach, starting with a non-informative prior. Mapping may be required to develop distributions for higher redundant component groups. A better suggestion is to construct a constrained non-informative prior from existing data sources for the distribution parameters searched for, with a subsequent upgrading by Bayesian procedures on own plant experience. Mapping maybe required as well for this case. Both approaches can be considered as classical PSA-approaches to data analysis based on hierarchical Bayesian methods.
Another alternative consists in the direct use of expert judgement to assess uncertainty bounds. These approaches are only meaningful after the scaling assumption (see recommendation 3) is introduced.
A new alternative consists in an assessment of the upper limit of CCF-parameter distributions by direct modelling of dependencies using specific classes of copulas (Archimedean copulas, or special cases, like the Ali-Mikhail-Haq-copula (survival copula)), based on Sklar's

theorem. It is also possible to use extreme value copulas. By direct simulation it would be possible to estimate upper limits for the parameters for example for the Alfa-factor method. Hence, there are many other and simpler approaches available for the treatment of uncertainty. It is suggested to look for simpler approaches. The justification, that the assumption of full dependency is conservative, does not provide a good basis for the treatment of uncertainty. It is preferable to base on data models (**recommendation 4)**

6 Conclusions and recommendations

The general procedure for constructing net impact vectors does not differ very much from classical procedures except for the treatment of dependencies. The procedure shares some problems with other CCF-approaches. Some assumptions made are very strong or incompletely defined (homogeneity). The “scaling assumption” (to the probability distribution of frequency of independent failures) not used is necessary for a meaningful application. In some areas the procedure does not allow to distinguish between ageing effects and failure of a set of components by a shared cause. The treatment of uncertainty covers only one possible source of uncertainties (lack of knowledge on dependency). The model of complete dependency does not adequately describe the real situation of CCF occurrence, because the random character of failure times, which exists even, assuming a common demand (at the same time) to all components of a group, is not considered.

Recommendation 1: The time factor analysis suggested as a part of the methodology should be completed by adding factors to considering whether the observed incipient common cause failures (CCF, impairments degradations)) will indeed lead to a malfunction of the degraded component during the mission time of PSA. The suggested time factors for low probability of occurrence of CCFs (impairment or malfunction observed after more than 2 two test intervals or later than one month after the first observation) are considered to be too high (section 6.4).

Recommendation 2: Only events, where at least one component out of a group of m components (CCF-group) was observed to be failed (loss of function), shall be selected as potential common cause failures for further evaluation.

Recommendation 3: Conditional CCF probabilities shall be scaled (conditioned) to the probability distribution for the frequency of independent failures or the criteria for mutual homogeneity of CCF groups have to be extended to check the compatibility of probability distributions for the frequency of independent failures. This is **absolutely mandatory** to obtain a meaningful CCF-model, because the intent of introducing CCF models into PSA consists in the treatment of dependency between otherwise assumed as identical components. The similarity of the probability distributions of independent failures is a formal mathematical criterion for mutual homogeneity of CCF groups.

Recommendation 4: The assumption of complete dependency for the conditional probability of multiple failures within a CCF group of **m** components has no basis, because the failure times for failures subsequent to an observed “independent” failure remain to be random. The questions of treatment of uncertainty and dependency should be separated. Alternative, e.g. parametric methods for the treatment of uncertainty should be investigated (e.g. classical approach using beta-distributions for MGL-parameters or Alfa-factors combined with a Bayesian update procedure, hierarchical Bayesian methods)). Expert judgement methods to assess uncertainties as well as progressive alternatives (copulas, direct numerical simulation) should be investigated, too.

Attachment 3-3

Vaurio, Jussi. *Review of status on Phase 2 Task 1 methodology*, PROSOL-8002, rev. 1.

Nordic-German working group on common cause failure analysis
Phase 2 Task 1: Impact vector determination methodology

20.8.2008

Contents:

a) Review of expert judgments on selected cases: event descriptions and interpretations, degradation codes, shared cause factors and time factors, and formula for impact vector quantifications.

b) Relevant comments to Phase2 Task1 report (draft April 15, 2008).

c) Summary conclusions.

Part 1 of this review is based on Phase2 Task1 report and information available in May 2008. **Part 2** is an amendment based on reviews and comments made by Mr. T. Mankamo and Dr. G. Becker concerning certain Scandinavian and German event interpretations in June 2008.

Terms and notations:

c	shared cause factor
q	timing (simultaneity) factor
NBE	NAFCS-assessment, Nordic best estimate
N/G	Nordic/German estimate ("Becker-model" as of April 14, 2008)
NHB	Nordic high bound (high "coherence", high conditional probabilities)
NLB	Nordic low bound (low coherence, independent degradations)
V	Vaurio/Fortum original formal estimate based on codes
V_{new}	$(1 - ½cq)\cdot$ NLB + $½cq\cdot$V

Impact vector determination objective:

An evident objective of the N/G utility working group on CCF is to formulate the impact vector quantification based on a single formula that depends only on the impairment (degradation) codes C, D, I, and W (tentatively also S) so that specific values 1.0, 0.5, 0.1, and 0 (0.001) can be assigned to these letters. Coefficients c and q (also with values 1.0, 0.5, 0.1 or 0) are used as multipliers assumed valid for the whole group. The coding is basically the same as used in ICDE. A proper name for such an approach is "formula and coding driven method", e.g. FCD.

This approach would minimize any need to make expert assessments based on event descriptions available e.g. in ICDE data bank, or to go to more original data records or questionnaires. Possibly timing information (that is available in event coding or description) may be used to verify the consistency with assigned q, but this would be an exception to the objective to minimize judgment beyond the codes.

It should be noticed that in such an approach it is not possible, without additional event interpretation and expert assessment, to know e.g. the degree of recoveries that were carried out and which reduced the coincident existence of multiple failures. Also, it is not possible to conclude if impairments were present long before discovery, if the discovery was due to special tests/inspections rather than in routine periodic tests. (The time information in ICDE indicates mostly discovery times rather than failure occurrence times, which makes it difficult to derive coincident existence times without using event descriptions and interpretation.) These can have strong effects on CCF-model selection and on PSA results.

PART 1:

This is mainly a review of five events that cause most dramatic differences in certain candidate methods, especially V compared to NBE. The most important impact vector component is v(4/4), and the sum of these over the data set because it is roughly proportional to a CCF rate mean value estimate (separately for pumps and diesels). Numerical differences between NBE and V seem to be clearly larger for pumps than for diesels.

The set of five events were not selected based on any other criterion or expectation: the degree of alternatives of interpretations and inconsistencies between codes and numerical expert assessments is totally coincidental and could be expected to be similar in many other cases. In this sense this subset of five events is a random sample.

Pump events (Table 8, draft Task 1 Phase 2 report):

IMPACT VECTORS

	Vaurio (V)	NAFCS (NBE)	N/G
Multiplicity =>	2 3 4	2 3 4	2 3 4
Event, Codes d_i, c, q			
27, DDDD, H, H,	0, 0, 0.5	0.10, 0.05, 0.05	0.125, 0.125, 0.125
28, DDDD, H, H,	0, 0, 0.5	0.10, 0.05, 0.05	0.125, 0.125, 0.125
29, DDDD, H, H,	0, 0, 0.5	0.15, 0.10, 0.05	0.125, 0.125, 0.125

Events 27 and 28:

Events 27 and 28 are here considered once because they are identical, occurrences at different units (HPSI pumps).

Event descriptions and assessments are in SKI-2007-41 Volym 2.pdf , Appendix

Comments:

1) The original impact vector assessed (by Jänkälä & Korhonen) was: 0, 0, 0.1.

    The coding DDDD, H, H is not consistent with this by any method. Thus NAFCS must have changed both the coding and the impact vector.

    The original (J&K) impact vector implies coding IIII, H, H, in which case Vaurio V-vector would be 0, 0, 0.1. This change alone would reduce the sum of v(4/4) in V by 0.8, a remarkable change that would bring the sum v/4/4) of V closer to NBE. For V_{new} the reduction of the sum of v(4/4) would be 0.46. This alone would make V_{new} as close to NBE as N/G is now, as far as the sum v(4/4) is concerned.

    This indicates how important it is to have documented justifications for the degradation values by each analyst group, for others to be able to agree or disagree.

2) The dates for the observed events, 1993-06-22, 1993-07-27, 1993-07-27, 1993-07-27 indicate that a more correct time-factor q for the complete CCF (4/4-event) is M (not H), but for the triple- CCF the time factor is H (same date for 3 failures). This observation can be accounted for by the Vaurio/Fortum methods at least. If we assume that the impairment codes DDDD are correct, then the method V with new time-factors yields impact vector components 0, 0.25, 0.25. This change alone would reduce the sum of v(4/4) values by 0.5 for V and by 0.28 for V_{new}.

3) Assuming the current codes DDDD, there is a significant discrepancy between the vector components V and NBE: V assumes complete conditional dependency between degradations (like high bound NHB), while NBE corresponds to almost complete conditional independence: in this case v(4/4) would be $0.5^4 = 0.0625$, not far from the value 0.05 assigned by NAFCS. Which one is more realistic when considering the failure mechanism? The event description clearly states that the phenomenon is the TEMPERATURE RISE OF THE PUMP BEARING, and it obviously occurred in all four pumps. In the test this rise was not tolerated long enough to break the pumps, but in a real demand (initiating event) this could not be prevented. Temperatures would continue rising until the pumps fail, even if not exactly at the same moment. Thus, it is a physically justified vector V = 0, 0, 0.5 that results (when assuming the DDDD is correct).

The complete conditional independence (NLB) would yield the vector 0.375, 0.25, 0.0625. Even this is more conservative than NBE. From this information so far it is not possible to see the rationality in the quantitative values of NAFCS.

In this event, vector V seems most justified and NBE optimistic (whether the codes DDDD or IIII are correct).

If one assumes that pumps can be alternated in a real demand to prevent failures, then at least the probabilities are smaller (IIII) and the failures perhaps mutually less dependent. Event description should include information about such possibility.

Event 29:

1) The event description in SKI-2007-41 volym 2.pdf indicates that NAFCS assessment ended up with the coding DDDD, even if only 10 experts out of 17 agreed with it and the rest favored coding IIII. The vector NBE is almost identical to events 27 & 28. Weighting by the numbers of experts would yield somewhat smaller impairments 0.335, 0.335, 0.335, 0.335.

2) The actual quantification calculated a probability for a single failure as 3 cases out of 15 trials, i.e. 0.2. This implies that the assessors considered events as conditionally independent rather than a shock-type CCF, and degradations actually 0.2, 0.2, 0.2, and 0.2. This points to even stronger deviation from coding DDDD. This is critical to any formula-driven approach, because one should be able to trust that the impairment codes always mean the same value. (Based on the way of estimating individual probabilities, it is questionable to include this event as a CCF. The event may just increase the single failure probabilities, having 3 single failures in one test cycle.)

3) The failure mechanism in this case was a short over-current causing failures to start when manual switching was performed. The event description and interpretation do not indicate whether the same phenomena could occur in case of an automatic start-up when a real demand (initiating event) occurs. This could be crucial to quantification. Lacking more information, let us now assume everything could occur the same way in case of a true demand.

Another aspect not discussed is: would there be enough time in case of a real demand to reset switching devises and assure startup manually? Such recoveries are not explicitly coded in ICDE data; they could be inferred only from event descriptions. Any attempt to take them into account in degradation factors is somewhat arbitrary and not based on accepted principles.

4) Perhaps the most alarming observation is that the event description reports only three failures (or degradations), and there is not direct information about the condition of the fourth pump. If we make the assumption that the fourth was tested and found working, the degradation vector based strictly on observations can not be DDDD. It could be CCCW or DDDW. The interpretation text does not say why D's were considered more correct than C's. If one is not so sure about working of the fourth pump, perhaps DDDS or DDDI could be the appropriate coding. For these cases the impairment vectors V = 0, 0.49, 0.01 or V = 0, 0.4, 0.1 are clearly less conservative than the original vector based on DDDD.. This change would reduce the sum of v/4/4) for V-model by .49 or by .40. Consequently V_{new} would also be reduced.

5) In this case a long experience with similar individual events (according to the event description), and the way D = 0.2 was calculated, indicate randomness and conditional independence. This leads to assuming less identity in degradations and lack of conditional dependency in the spirit of NLB, less conservative than V and NHB. The quantification made based on hypothesis seems rather arbitrary or at least not clearly justified, ending up with values 0.15, 0.1, 0.05. After all, these are lower but not very far from NLB when D = 0.5 is assumed (about which the assessment group actually was not unanimous).

<u>Conclusions from events 27-29 together:</u>

- There are discrepancies or contradictions between the event **descriptions** and the degradation **codes**/vectors assigned, as well as varying opinions among experts about the impairment codes. Consequently, one can not blindly adopt and use the "official" coding of NAFCS (or any other expert group). –Discrepancies occur in both directions.

- There is no rule or formula-type method used in NAFCS to obtain the impact vector from the impairment codes alone. The hypothesis method is judgment-based. There is no rule stated e.g. to divide the degradation value I or D by the number of times it appears in a degradation vector (an assumption used in the proposed N/G-method).

- Hypothesis method allows accounting for the degree of coherence, but it seems not to be used. (It could help to determine the net impact vector closer to NHB or closer to NLB).

- A new assessment and interpretation of only 2-3 events easily reduced the sum of v(4/4) for the V-model by as much as 1.2 (and for V_{new} by 0.7) bringing the sums close to NBE and other compromise models.

There was also evidence that NBE is too optimistic in some cases considering complete CCF (4/4-events), i.e. v(4/4).

- Considering these events as a group, we have seen that some indicate clear coherence, high conditional failure probabilities if one fails, while others indicate conditional independence or randomness like in the NLB model. Without independent assessment it is not possible to know which is more realistic for each event. It seems appropriate, if event by event assessment is not carried out, to assume that the average of NLB and V can be a reasonable guess. Possible over- and under-estimations balance out reasonably when calculating the sums of impact vector components. –Instead of always using ½ as a weight for these models, one could take into account the product cq because when this product is low, it is less likely that the failures are coherent (strongly identical).

Diesel events 15 and 33 (Table 7, draft Phase 2 Task 1 report):

IMPACT VECTORS

	Vaurio (V)			NAFCS (NBE)			N/G		
Multiplicity =>	2	3	4	2	3	4	2	3	4
Event, Codes d_i, c, q									
15, CIII, H, H,	0,	0,	0.10	0.15,	0.08,	0.02	0.033,	0.033,	0.033
33, IIII, H, H,	0,	0,	0.10	0.045,	0.013,	0.003	0.025,	0.025,	0.025

Comments:

Event 15:

The impairment vector CIII had been given without justifications. However, the event description says: The manufacturer had "delivered faulty return-springs because of design changes of the exciter trip switches"; and "all 4 diesel generators had been fitted with the same kind of return springs".

Based on this, it is difficult to understand why not all 4 diesels were considered unavailable because of faulty springs. This was a problem of **faulty type/design,** not a random fault due to wear or other degradation. -The event description should say more clearly if only one was faulty, even when all 4 obviously were wrong type and design.

If CCCC is not a more correct degradation vector, then at least CIII should be interpreted in a most conservative way, according to V or V_{new} rather than NBE or N/G. NBE can be suspected to be an optimistic estimate. –Correcting for this event again would bring NBE and V_{new} closer to each other.

Event 33:

No description or interpretation seems to be available to justify the impairment vector IIII and the numerical values given by NAFCS.

Conclusions from diesel events:

There is no strong evidence to support changing the method V or especially V_{new} for diesel generators. Depending on the re-interpretation of event 15, NBE and N/G estimates should probably be adjusted upwards.

Summary conclusions (Part 1):

- The numerical impact vector estimates depend strongly on very few (2-3) event interpretations. Rejection of any of the concepts, V or V_{new} in particular, at this stage can not be justified by such limited data especially when event interpretations can be challenged.
- There is evidence that NBE can be too optimistic in some cases and V too pessimistic in some cases; NBE assessors evidently have not considered the presence of coherency effect.
- Correcting the errors/interpretations would have significant effect in Tables 7-10 of the Phase2-Task1 report, especially with V_{new} introduced as a candidate model.
- There are several "mapping" steps in CCF impact vector quantification, and errors possible in each step:
    - Mapping 1: event description => event interpretation
    - Mapping 2 : event interpretation => event coding (d_1,d_2,d_3,d_4, c_4,c_3,c_2, q_4,q_3,q_2)
        - simplified in N/G: (d_1,d_2,d_3,d_4, c, q), $c = c_4$, $q = q_4$.
    - Mapping 3: event codes => impact vector components
        - $cqF(d_1,d_2,d_3,d_4, cq)$ in V_{new}
        - $cqF(d_1,d_2,d_3,d_4)$ in V and in the suggested N/G
    - Function F(..) searched based on fitting to NBE expert judgment data set (41 events)

- Limited data set and few component types
- Practically no events with shared cause factor weaker than H
- Very few events with time factor weaker than H
- Several "mapping" steps potentially subject to errors
- Coding limited: no c or q assessment for subsets of a CCCG
- c and q ignored in F(..) for N/G approach
- Monotonic behavior of data set used (i.e. $v_{2/4} \geq v_{3/4} \geq v_{4/4}$)
- Monotonic N/G-formula (occasionally reversed order $v_{2/4} \leq v_{3/4} \leq v_{4/4}$)

One should notice that the cases analyzed in this report were not selected on the basis of questionable interpretations in advance: in this respect the cases were random sample. Nevertheless, so much room for re-interpretation was found that this makes very questionable the whole approach to base quantification calibration on the 41-event data sample.

One major conclusion is that one can not trust that ICDE- or NAFCS-codes for degradations correspond to expert assessment values 1, .5, .1 and 0, respectively. Already in this small sample of five cases D was marked when the assessor assessed 0.2 or even 0.1. In other examples .2 has been used for I instead of .1, and .8 has been used for C instead of 1.0. Thus, the suggested G/N approach (formula and ICDE-coding driven approach), does not seem reliable as it is.

OTHER CORRECTIONS to Phase 2 Task 1 report NEEDED

1) This first comment refers to the EXCEL table containing impact vectors obtained with several models/methods on April 10, 2008. The tables may have been corrected later.

There are some errors in the Excel-table, coloring errors in the attachment "Summary of formula driven approaches 0.4c.xls" (E-mail by Dr. G. Becker on April 10, 2008, “Present versions”).
The errors are in accumulated vector columns EZ (compared to DV) and FA (compared to DW). These errors give a wrong impression about the quality or optimism of V_{new} compared to NBE. The color-errors are in the following lines:

EZ: lines 30, 31, 32, 41, 42, 43, 44, 47
FA: lines 30, 31, 43, 47.

When these errors are corrected, V_{new} does not deviate much from NBE and other "compromise" candidates, certainly not in one direction.

2) Section 9.3 of the Phase 2 Task1 report (draft) has an incorrect justification for pooling data for pumps and diesels (and possibly other components). Even if the assessors were the same, different component types have different failure modes, vulnerabilities, causes and mechanisms, and therefore can have totally different ratios of different CCF-multiplicities, which is indicated by different impact vectors and potentially quite different formulas as well (if a formula-driven approach is adopted).

3) Section 9.4 indicates a logical inconsistency that is not acceptable to ignore, even if numerical differences were not so dramatic.

PART 2:

Part 2 is based on written comments made by Mr. Tuomas Mankamo on some of the cases discussed above. This reply is included (in red by JV) to show how the comments change or confirm the conclusions presented above in Part 1.
Reply comments are made also to the oral comments on German events made by Dr. Becker at the meeting on May 8, 2008, and later provided in writing.

Avaplan Oy/Mankamo comments in report NAFCS-WN-TM21, 09 June 2008; Review Notes on Phase 2/Task 1 Report, Impact Vector Determination Methodology:

TM: C3.15

“Similar discrepancy as discussed in the preceding comment is pointed out in [PROSOL-8002] concerning Event No.s 27 and 28 (vulnerability to pump trip due to bearing warm-up, the impairment vector is DDDD in both events, identical problem at twin units). The pump pilot used numeric value $d_k = 0.2$ for degradation class D in the Impact Vector construction for these events, see details in [NAFCS-PR18 – in these cases data on the Impact Vector construction sheets is in line]. In my opinion, according to the problem description and additional discussion with Kalle Jänkälä at the time of pump pilot, V assessment {?, ?, 0, 0, 0.5} for Impact Vector seems overly conservative, in comparison NAFCS best estimate was {0.65, 0.15, 0.10, 0.05, 0.05}.

N/G formula output is {0.5, 0.125, 0.125, 0.125, 0.125}.[1] The discussion in [PROSOL-8002] sticks much on the ICDE codes.[2] The event dates can mislead. They represent the time of periodic/additional tests when the tendency of bearing warm-up was observed and measured. Actually the problem had been latent from the begin of commercial operation (about 20 years), and revealed in 1993 owing to increased test run time.[3] The noticed failure/dependency mechanism is a very complicated phenomenon because of correlation to special cyclic operation such as possible in Small LOCA demand.[4] Due to the special character, this CCF type should be treated specifically in quantitative analysis, preferably by explicit causal modeling, compare to the recommendations presented as conclusions from NAFCS pilots.[5] It was a great pity that the resources at that phase were limited to orderly handle these kinds of special CCF types (there were observed several other similar cases)."

[1]JV: It should be realized that 0.5 in V comes automatically from the coding D, if the "formula and coding"-driven method is required! If d_k = 0.2 were known or given, the value 0.2 would be used.

[2]JV: This is because the EWG-group wanted to use strictly the coding (ICDE-coding) as it is, which is neither my recommendation nor Fortum approach.

[3]JV: The conclusion is that each event really needs to be assessed, and some need very different models and quantifications for PSA. In this case the model needs constant probabilities rather than rates of occurrence, if the analyst really considers the weaknesses present from the very beginning.

[4]JV: All this additional information does not change my earlier conclusions essentially, when a CCF analyst is supposed to use the ICDE-coding to determine numerical values, because he does not have access to possible other numerical values that an expert group has considered more realistic. The comment C3.15 confirms how uncertain and risky is a formula-driven approach, especially when it is also code-driven (relying on ICDE or other similar coding).

Additional errors can evidently be caused by misleading timing information. However, it is supposed to be better –in the average- to have and use timing information than not to have it or not to utilize it –unless it is predominantly in optimistic direction.

[5]JV: Explicit modeling seems to be needed/justified more often than originally anticipated.

TM: C3.16

"Event No.33 discussed in [PROSOL-8002] is the snow storm incident at Olkiluoto, blocking air intakes of the DGs tested during the storm, one at each unit OL1 and OL2. The Impact Vector construction is explained primarily for Event No.32, because of more severe impact to the DG tested at OL1. A trial was made to use CLM for modeling of conditional dependence under the observed conditions. The details are described in a separate small report prepared in the early times of ICDE [CR_ImpVe]."

"These events with the risk "snow blockage of DG air intake" provide another example of special CCF types. The risk of snow blockage with implied dependency should rather be explicitly modeled as part of external hazards modeling."

JV: The description does not tell what happened at those DGs that were not tested, or what would have happened if they were started at the same time. And how likely the intakes could be cleaned and kept open in case of a real demand. Impairment coding indicates that all were affected in the same way, but there was potential to clear the intakes in time, or the blockage was not quite complete.

The assessed impact vector components are monotonically decreasing (in the order of CCF multiplicity), which may indicate that clearing the intakes in sequence is possible in time, but less and less probable for more and more blockages (e.g. because on a single mechanic/crew). If this interpretation is correct, then evidently the conservative V-method is not applicable. But if clearing in sequence is not the explanation (for small impairment and monotonic impact vector), it is not easy to see why the same amount of snow (IIII) does not fail all four, with probability 0.1, as would be the case with the V-method.

Anyway, it seems that if recoveries are possible and taken into account, none of the available formal "formula and coding-driven" methods is automatically applicable. But the need for adjustment is not seen from the ICDE (or other) coding, it can be understood only based on sufficient event description.

Another issue is: should this event be included only in the external (weather) event PSA, or more generally.

Even if it certainly is needed in show/storm initiator models, it may be needed also for all other initiators (certainly LOOP) that are possible in winter. The probabilities then have to take into account the fraction of time that a snowstorm can be present.

For OL1 the event is evidently number 30: OL1-TR-R7-2/95, with impairments DDII.

For this event the description is given by Korhonen and Jänkälä (Phase 1 report, Vol.2, Jänkälä 2. Feb. 2007, p.16). The test was interrupted and the filter was replaced. How quickly, is not stated. It is still not clear whether the other DGs (that were not running) were blocked or not.

Event 29: Verbal discussion was made by Dr. Becker on May 8, 2008. The comment received later in writing:

"This event occurred, because motor protection devices turned of the pump motors prematurely in some cases. The pump motors partially behave like inductivity. It is well known, that, if voltage is attached to an inductivity, a large transient current may result, where the amount of this current depends on when (w.r.t. the periodic sine curve which the voltage follows) the voltage is attached. If under laboratory conditions, the pump would have been switched on always in the same 1/500th of a second within that sine curve, it would most likely have failed deterministically. So the only randomness in this event is the fact, that the point met in the sine curve is random, when the motor is switched on. At least, if mechanical switches are used, this randomness is quite likely to exist, because these switches usually are not built with a defined reaction within such short time.
So, the analyst faces the following situation:

- A common root cause exists, and it is known. So, this is definitely a CCF, and the shared cause factor is high.
- When it comes to impairments, the analyst has a problem. According to the damage seen, he should provide a subjective estimate on the probability, whether the component would have failed in a true demand, or not. He does not see any damage on any component, however. Even the failed component has no damage, and if it is switched on again, it will work (given the correct timing; see above).
- So, the analyst tries to provide the probability needed not by the things, he sees (or rather: does not see) on the components, but based on his background knowledge on the root cause. For this reason, he will necessarily find a value valid for all components, even for the one, which did not fail at all in the interval concerned. This is, what ICDE wants as input, or this is at least as close to their requirements as possible.

Note, that given manual switching, the events are conditionally independent. Note also, that the majority of the 17 assessors have been correct to conservatively provide the next higher impairment values D.
Now, what did the analysts do, who provided the NBE value?
Based on the impairments DDDD, they assessed a chance of 0.5 for no failed components. This is consistent with NHB (=Vaurio). In the case of conservative NHB value, the other 50 % would simply be put on the 4oo4 value. Now, there is evidence, that the events are not completely dependent. In fact, a more courageous expert might have assessed them as conditionally independent in the given situation, or given manual switching. Now, if a very precise switch is used, and switching is done simultaneously and automatically, a chance may exist, that switches open – if not simultaneously, then within some small time interval (smaller than ca. 1/100th of a second). So, the expert distributes the 50 % probability in such a way, that he ends up at a value smaller than NHB, but definitely larger than NLB.
By this reasoning, it can be concluded, that this assessment is reasonable. Perhaps, the expert did not fully get the mechanism; otherwise, an even smaller best estimate could have been possible. But it can be seen, that the expert compensates possibly unclear understanding by a more conservative assessment. This is perfectly normal behaviour for an expert (who cannot be an expert on everything).
So, this event shows that even best estimates still bear some conservatism. The data base is not challenged by this assessment."

JV: This discussion confirms my conclusion that failure rates of multiple components were increased, possibly temporarily, by some phenomenon. This could be taken into account by increased single-failure rates, or this behavior can be modeled as a CCF (causing increased rates for some period), but with completely different model than other shock-type (or constant-probability) events. Even if a similar cause is evident (a rate-increasing cause for all components but not identified in design phase), failures seem randomly independent for each component. Using the same formula-and coding-driven model gives impression that this event can simply be put in the same basket with other CCFs and modeled in the same way. This is not correct, and using one and the same formula for all events can be misleading.

Event 15: Verbal discussion was made by Dr. Becker on May 8, 2008. The comment received later in writing:

"This event occurred, because some switches in the boundary of the emergency power supply diesel generators had been erroneously issued with unsuitable mechanical springs. If this failure had occurred immediately after the springs had been built in, the assessment of CIII would in deed not make sense. But it would make sense, if the failure occurred only after several demands. After the failure occurred, the cause has been identified. As the same type of spring had been used on all switches, it has been clear, that the event is CCF. So, they checked the other switches, and they found some small damage, which caused them to assess an I to these. There is neither positive nor negative indication, that these damages would be conditionally dependent or independent. However, considering the fact, that a rather large difference (between the C and the Is) has been observed, one might assume rather little coupling between the components.
Now, what did the analysts do, who provided the NBE value?
Based on the assessment CIII, the analysts assessed a value of 0 for the first element of the impact vector. This is consistent with NHB, as at least one component is deterministically failed in this event. Then they assessed 25 % for the failure of more than one component. This is not consistent with the impairment of CIII, which according to NHB would allow 10 % as a maximum value for this case. It has been observed in the NAFCS report, that NBE estimations in some cases correct the

impairments given. As indicated in the final draft report, this can be seen as the effect of an additional quality control. Apparently, the analysts had something between CDII and CIII in their mind. However, it can be seen, that this adjustment again is in the conservative direction[1].
So, this event shows that even best estimates still bear some conservatism. The data base is not challenged by this assessment."[2]

[1]JV: How come CIII is more conservative than CDII?

[2]JV: If the event description had this much information it would be easier to agree with the degradations and impacts. But it does not confirm any optimistic formula, if even the smallest degradation would be able to cause a failure.
There was also discussion on possible human errors causing this CCF. It is possible that some want to model repeated errors in the human reliability part (HRA) of PSA rather than as CCF. Current formula and coding are unable to give enough information for correct modeling of repeated human errors.

SUMMARY CONCLUSIONS about the approach (Part 2)

Even this small sample of five events revealed several fundamental problems for any formula- and coding-driven approach:

Modeling and quantification of CCF: A formula and ICDE coding do not yield enough information for correct modeling of each event for PSA. CCF can originate a) at the time of commission, b) as a shock at random time, c) result in consecutive tests, or d) they can be due to coincidentally increased individual rates, observed in a regular test or in some special test (like a long operation of diesels). The same equation and codes alone do not tell how to model the event properly. Also, discovery in a test does not necessarily mean discovery in any periodic test. Only detailed assessment can provide enough information for correct modeling and relevant test intervals.

Some CCF may be relevant only for some *initiating events*, not for all. This is not indicated by coding alone but must be assessed based on event description.

Possible *recoveries* also complicate the assessment: they are *not taken into account* in ICDE coding, but may be revealed by the description text. (This could be one reason for why NAFCS numerical assessments sometimes seem to be inconsistent with the assigned coding. However, the relative fraction and impact of this feature is likely not the same for different types of components and failure modes.)

Also, different redundant trains can have very different latent failure times, which is not directly clear from the codes or even timing (because times of discovery are reported rather than times of occurrence).

List the concerns: Why I have difficulties approving the current version(s) of VGB-NPSAG CCF quantification approach. Some of these may be overcome with some adjustment, but others simply can not be satisfied by the limitations taken [like using only degradations in determining the ratios of impact vector components, not considering c and q for subsets of CCCG, and assuming component type-independence based on 2 types only). Simplifications are too serious for far-reaching conclusions.

1) When fitting a model to data it is common to require an order of magnitude more data points than there are unknown parameters. In our case we have about 50 different degradation vectors ("parameters") and only 41 data points to fit on.

This provides neither uniqueness nor a way to assess the accuracy, goodness of fit. The data base is simply too thin.

2) Because of limited descriptions (in NAFCS and ICDE), it is impossible to agree or disagree with the impact vectors assigned to many cases.

3) From 1 and 2 follows: too far-reaching conclusions are being made from too few events and component types.

4) Extrapolation to other component types and systems and failure modes.

5) Determining impact vector components (ratios, i.e. degree of coherence/dependency) only by degradation values is problematic. Degradations are defined and assessed for individual components and not intended in any way to assess the degree of coherence/conditional dependence between component failures.

6) Shared cause (c) and time-factors (q) are defined jointly to a group and at least partially measure the coherence, certainly more than degradations alone. This should be reflected in the approach.

7) Lack of considering c and q for subsets of CCCG. This would be particularly important for systems with success criterion other than 1-out-of-4, because a subset of 3 alone could fail the system. And two double failures could be as important as a single quadruple failure.

We should be aware and recognize these limitations and accept that all may not want to accept these assumptions but want to do more event-specific assessments and expand the data base significantly before going to a formula-driven approach.

Attachment 3-4

Table with gathered review comments and answers.

Table with gathered review comments and answers				
Comment by	**Chapter/ section**	**Comment no.**	**Comment**	**Answer / proposed update**
NAFCS-WN-TM21 (Issue 1)	Ch. 3	C3.1	An important implicit scope aspect turns out to be present: the developed formula for Impact Vector construction uses as only input arguments a specific set of codes/classifications in the current ICDE data, i.e. component degradation values, shared cause factor and time factor (and making the needed distinction between latent versus monitored failures). This is a problematic limitation which should be frankly made clear in the begin.	This is true. However, the intention of the project has been, that we automatically process ICDE information in such a way, that we get a method for impact vector construction, which ressembles NAFCS best estimate and is less conservative than NAFCS high bound. The approach has been to investigate a sample of assessments from NAFCS. According to a pattern identified in that sample, the approach has been constructed. Results of the approach have been compared with the original sample to assess validity.
NAFCS-WN-TM21 (Issue 1)	Ch.3	C3.2	The objective definition *"As there is no specific German procedure for constructing impact vectors, two methods have been investigated; the Finish (Vaurio) and the NAFCS (best estimate) approaches"* does not correspond what is actually aimed at and done. Rather, "NAFCS best estimate" and "Vaurio method" have been used as validation methods for the proposed simplified formula driven method.	It has been clarified that the two mentioned methods has been used for validation. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch.3	C3.3	Regarding "NAFCS best estimate" and "Vaurio method", it would be good to briefly characterize them, referring to Task 1 documentation and initial references for comprehensive definition and description.	Reference to phase 1 work has been added in chapter 3. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 3	C3.4	The sets of DG and pump CCF events used as test samples should be defined, referring for details to earlier documentation. It would be good to point out that a part of the considered CCF events were already analyzed in the NAFCS pilots [NAFCS-PR10, -PR18], and that the Impact Vectors assessed then are still retained for their part(?).	Clarification has been made in section chapter 3 and also in section 7.5. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 4	C3.5	The presented brief methodological description in Chapter 4 builds much on the development done in the previous phase of NAFCS. It would be fair to explicitly indicate this aspect, generally referring to NAFCS-PR03 and –PR17, especially because I have not had possibility to continue on the subject.	Reference has been included in chapter 4. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 4	C3.6	Following normal practice, it should also be noted that Impact Vectors were originally introduced in the USA […], and further developed in NAFCS, referring also to other essential recent developments.	References has been included in chapter 4. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 5	C3.7	Assumptions and limitations are again discussed in Section 7.1, repeating mostly same as already said in Section 4. It is recommended to collect the clarification of key assumptions and limitations in one place of the report. Notice also the needed compatibility with Chapter 2, compare to Comment C3.1.	Changes has been made in chapter 5 and section 7.1, so that the actual acceptance criteria are defined in chapter 5 and that description of how the method is tested against these acceptance criteria is presented in section 7.1 (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 6	C3.8	Required input information seemingly equals to ICDE classifications/codes. It would be desired to indicate if ICDE guidelines are completely followed, or note any deviations. Compare to Comment C3.1	In section 6.3, 6.4 and 6.5 it is pointed out that the definitions by ICDE are applied, and any exception from those is also pointed out (as with the degradation category "S").

Comment by	**Chapter/ section**	**Comment no.**	**Comment**	**Answer / proposed update**
NAFCS-WN-TM21 (Issue 1)	Ch. 6	C3.9	One deviation from ICDE coding norm is clear: additional degradation class S with corresponding numeric value 0.01! For qualitative aims this addition might be reasonable. For quantitative analysis it is not sensible. Degradation values in the range of 0.01 bring very little statistical gain and are highly uncertain, and give in overall a wrong impression of accuracy. As emphasized in [NAFCS-PR03, -PR17], judgmental values less than 0.1 should not be generally used (for degradation values, scenario weights, etc). Exceptions are special cases with causal modeling and/or specific direct evidence. It should be noticed that in the ICDE classifications degradation class I is often used in the situations where numeric value 0.1 is clearly very conservative, e.g. in cases where the component is practically intact but a preventive measure is taken after noticing a potential CCF. I.e., the numeric range of degradation class I extends from about 0.1 down to zero, or down to baseline failure probability, depending on the interpretation. In my opinion, four qualitative degradation classes C, D, I and W are sufficient.	It has been clarely written for each input parameter what coding and classification is adopted. For events obtained from German database the coding S was available. It is considered that the advantages of keeping this classification outweigh the disadvantages.
NAFCS-WN-TM21 (Issue 1)	7.1.1	C3.10	Section 7.1.1 deals with Impact Vector construction method – not with CCF methods, i.e. inadequate heading.	The heading has been revised. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	7.1.1	C3.11	Referring to the specific conditional independence property in CLM definition is somewhat misleading in this context. Here we deal with Impact Vector construction for a CCF event when the failure mechanism and its influences are not completely known. In the conceptual frame of CLM this corresponds to the situation that we cannot imagine to know the exact value of load variable. Instead we have to think that some conditional distribution applies, e.g. the existing knowledge can indicate that loading is likely in the extreme range. For a distributed load, the component failure probabilities are (conditionally) dependent per definition. Thus in particular, CLM definition cannot be used to justify conditional independence of component degradation values, except the idealized low bound case and some very special condition, but it rather points to conditional dependence in general.	Perhaps, the wording is misleading. However, the intention of this paragraph is to show, that even in case of maximum shared cause factor, there need not be maximum dependence. As one argument, I took conditional independence in some known models. My definition of conditional independence is pr(A∩B│C) = pr (A│C)pr (B│C) Consider CLM: $Psg(m) = \int_{-\infty}^{\infty} f_S(x)[F_R(x)]^m dx$ $Psg(m\|S) = \int_{-\infty}^{\infty} \delta(S-x)[F_R(x)]^m dx = [F_R(S)]^m$ So, Psg turns out to be a product of m independent factors, if the load is fixed and known. These independent factors are the probabilities of failure of the m components, given S. Similar argument holds for BFR model.
NAFCS-WN-TM21 (Issue 1)	7.1.1	C3.12	The problem of conditional independence in BFRM definition is partly analogous, but not commented further. In my opinion, BFRM should not be fitted at event level but only to pooled statistics. Here we must to recall the discussion in the 70-80'ies around the controversies of BFRM.	It is not suggested to use BFR model. It just serves as an example, that dependency need not necessarily be maximum (see above).
NAFCS-WN-TM21 (Issue 1)	7.1.1	C3.13	High bound Impact Vector is based on the assumption of maximum dependence within the constraint imposed by component degradation values, when considered as conditional failure probabilities of each component. Compare to the original definition in [NAFCS-PR03]. The expression complete dependence is not good in that purpose, because "complete CCF" is a well-established term used for the extreme cases where all components fail (all component degradations equal to 1).	The use of the term "complete dependence" has beenrevised – changed to "maximum dependence". (Update made in the task 1 report.)

Comment by	Chapter/ section	Comment no.	Comment	Answer / proposed update
NAFCS-WN-TM21 (Issue 1)	7.1.1.4	C3.14	The discussion of expert assessment in Section 7.1.1.4 mentions a discrepancy regarding Event No.s 21 and 22 (leaking fuel injection nozzles of DG, the impairment vector is CIWW in both events). The observed discrepancy can be explained by the fact that NAFCS best estimate corresponds to numeric value d2 = 0.2 for degradation class I, see details in [NAFCS-PR10 – unfortunately, the Impact Vector construction sheets of these events contain the initial default d2 = 0.1 and the high bound is thus not updated accordingly; a typical error of omission not caught in the quality control of pilots which was far from complete]. Compare to the previous discussion of assigning numeric values to component degradation classes, C3.9. It is recommended to track for any other discrepancies of this type in the original NAFCS assessments. I noticed one more DG case of this type: Event No. 2 with impairment vector CCII. NAFCS best estimate Impact Vector is {0, 0, 0.8, 0.1, 0.1} and it corresponds to component degradation values d3 = d4 = 0.2. Another error of omission to update values for high bound generation. Besides, when looking not at the calculated low bounds I noticed discrepancies also for low bounds, being above NAFCS best estimate. In several cases component degradation was regarded insignificant in contrast to initial	Discussion on data quality issues and the importance of input data quality control is added. (Update made in the summary report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 7	C3.15	Similar discrepancy as discussed in the preceding comment is pointed out in [PROSOL-8002] concerning Event No.s 27 and 28 (vulnerability to pump trip due to bearing warm-up, the impairment vector is DDDD in both events, identical problem at twin units). The pump pilot used numeric value dk = 0.2 for degradation class D in the Impact Vector construction for these events, see details in [NAFCS-PR18 – in these cases data on the Impact Vector construction sheets is in line]. In my opinion, according to the problem description and additional discussion with Kalle Jänkälä at the time of pump pilot, V assessment {?, ?, 0, 0, 0.5} for Impact Vector seems overly conservative, in comparison NAFCS best estimate was {0.65, 0.15, 0.10, 0.05, 0.05}. N/G formula output is {0.5, 0.125, 0.125, 0.125, 0.125}. The discussion in [PROSOL-8002] sticks much on the ICDE codes. The event dates can mislead. They represent the time of periodic/additional tests when the tendency of bearing warm-up was observed and measured. Actually the problem had been latent from the begin of commercial operation (about 20 years), and revealed in	Discussion on data quality issues and the importance of input data quality control is added. (Update made in the summary report.)

Comment by	Chapter/ section	Comment no.	Comment	Answer / proposed update
NAFCS-WN-TM21 (Issue 1)	Ch. 7	C3.16	Event No.33 discussed in [PROSOL-8002] is the snow storm incident at Olkiluoto, blocking air intakes of the DGs tested during the storm, one at each unit OL1 and OL2. The Impact Vector construction is explained primarily for Event No.32, because of more severe impact to the DG tested at OL1. A trial was made to use CLM for modeling of conditional dependence under the observed conditions. The details are described in a separate small report prepared in the early times of ICDE [CR_ImpVe]. In the causal model, component degradation values, arranged in the order of functional positions, were {0.4, 0.1, 0.4, 0.1} and {0.2, 0.05, 0.2, 0.05} in comparison to (qualitative) impairment vectors DIDI and IIII of these events, respectively. These events with the risk snow blockage of DG air intake provides another example of special CCF types. The risk of snow blockage with implied dependency should rather be explicitly modeled as part of external hazards modeling.	Discussion on data quality issues and the importance of input data quality control is added. (Update made in the summary report.)
NAFCS-WN-TM21 (Issue 1)	7.3	C3.17	The introduced Impact Vector construction formula in Section 7.3 looks at first sensible, but a closer look raises questions. No probabilistic reasoning model is presented, instead, the proposal seems more or less arbitrary depending on the type of CCF event. Basing Impact Vector element of order m (beyond the degree of completely failed components) on degradation value of mth component (when ordered in descending order of degradation) may be questionable. The Impact Vector elements are in general related to all component degradations as well illustrated by the low bound formulas. The relationship is simpler in high bound due to the assumption of maximum dependence. For possible consequences from the lack of well defined probabilistic basis, one implication is the situation with nC = 2 where the proposal gives vBasic(m|n) = dm for m > 2, which contradicts the high bound, e.g. impairment vector CCII leads to vBasic = {0, 0, 0.8, 0.1, 0.1} while vMax = {0, 0, 0.9, 0, 0.1} when using the nominal degradation values. Another observation of undesired features is the overflow problem in the element sum of Impact Vector discussed in the last paragraph of Section 7.3. The proposed formula has an inbuilt tendency of producing monotonously decreasing or non-increasing Impact Vector elements for ascending order of m ≥ 2. This seems to be actual always in groups n ≤ 6. Although conservative, this	It could rather be called an empirical model, because the general rule has been take from the sample observed, though in addition, a reasoning supporting it has been provided. The reasoning given is similar to an 'ignorance prior'. If it is known that there are six sides on a dice, and nothing else is known, a first guess is to give the same value to each side of the dice (1/6).
NAFCS-WN-TM21 (Issue 1)	7.4	C3.18	Some equations on page 26 contain variable $v_{Part}(m\|n)$. Presumably it should be $v_{Basic}(m\|n)$?	This has been revised. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	7.4	C3.19	Heading of 2nd column on Table 6 should be Nordic/German Impact Vector, not Basic Impact Vector? The values of Time Factor and Shared Cause Factor should be explicitly presented though evidently equal to 1 for all cases in the table.	Heading in table 6 has been revised and assumption on values for c, q and dmode is made. (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	7.5	C3.20	Why is field 'Detection Mode' left blank in Table 7, except if MC? Detection mode is relevant information.	MC has been the only detection mode distinguished from the others for the actual calculation of impact vectors in the current methods.

Comment by	Chapter/ section	Comment no.	Comment	Answer / proposed update
NAFCS-WN-TM21 (Issue 1)	7.5	C3.21	Pooling DG and pump data together is not sensible, compare to Table 9. People should not be encouraged to do that! Comparison is alright.	It is expected that an expert to behave quite similarily, whether he sees a pump or a valve. This is why they are pooled. Of course, CCF probabilities are not to be derived based on this sample.
NAFCS-WN-TM21 (Issue 1)	Ch. 7	C3.22	Distinction is not made between different component failure modes. In particular, CCF mechanisms for principal failure modes of DGs and pumps, failure to start (FS) and failure to run (FR) are much different. They should be treated specifically in Impact Vector construction. Even testing of formula driven method should consider failure modes separately as they may differ with respect to goodness of fit. It is another matter, if the statistics of failure modes are combined or averaged at the end of quantitative analysis in a controlled manner.	See above.
NAFCS-WN-TM21 (Issue 1)	7.5	C3.23	Impact Vector elements need not be monotonously decreasing for increasing multiplicity, compare to the last paragraph in Section 7.5. It just happens to be typical for DG and pump CCFs. For other component types, different patterns can be usual. The inbuilt property of the proposed formula in these regards was already discussed in C3.17.	Is this not, what is said in that paragraph? It is something observed in the sample and also in the model.
NAFCS-WN-TM21 (Issue 1)	Ch. 8	C3.24	Example application has been mainly handled in Chapter 7. Alignment of heading is recommended for Chapter 8. It might be good to divide the massive Chapter 7.	The heading of chapter 8 has been improved (changed to “Application on diesel and pump data”). (Update made in the task 1 report.)
NAFCS-WN-TM21 (Issue 1)	Ch. 9	C3.25	Meaning of “measure of performance” is unclear, maybe formula’s goodness of fit ? In my opinion, different component types should be handled specifically with respect to Impact Vector construction, as well as in general for CCF data analysis, compare to the earlier comment C3.21. DGs and pumps are still reasonably close but DGs and control rods, for example, very apart from each other regarding important CCF mechanisms and defenses.	Given a model, how do you assess its quality? A performance measure is supposed to do this. Although we know, that the expert takes all kinds of back ground information on failure modes and mechanisms, all our model gets is the same independent from component type.
NAFCS-WN-TM21 (Issue 1)	-	-	In conclusion, I cannot support the proposed No/Ge formula for Impact Vector construction . Firstly due to its apparent arbitrariness (lack of probabilistic reasoning model) and overdriven simplicity, compare to preceding detailed comments, and secondly due to the following general arguments:	Probabilistic reasoning on the method has been added in improved description of the approach. See also Summary report, chapter 3.
NAFCS-WN-TM21 (Issue 1)	-	C4.1	While the proposed formula produces in the average reasonable Sum Impact Vector for the test set of DG and pump CCF events, it does not certainly provide event specific accuracy in sufficient degree.	Specific cases, with peculiar results, are discussed on event basis in section 7.6 in the task 1 report. The validation cases performed, with MOV and CV, confirms that the event specific estimates is in almost all cases (>90%) are on the conservative side of available expert judgments. Comment made in summary report chapter 4.1.
NAFCS-WN-TM21 (Issue 1)	-	C4.2	The proposal is made in such a way that in the average it envelopes conservatively the dependency among the considered DG and pump CCF events but can fit poorly to other component types, e.g. to special component types with either strong or weak conditional dependence being typical in CCFs, or even to another set of DG or pump CCFs, for example, in the future after positive gain from improved defenses against CCFs.	Validation cases have been performed for MOV and CV. The exercises confirm that the formula is valid also for these component types. Improved defenses against CCFs can not be covered by the formula driven method. This matter must be treated as part of the homogeneity assessment of the impact vector construction. Comment made in summary report chapter 4.
NAFCS-WN-TM21 (Issue 1)	-	C4.3	The proposal is much built to CCF group size of 4. It can be expected to work similarly in CCF group size of 3, and of course in the trivial size of 2, but may be less suitable in larger groups.	Validation cases for higher multiplicities is not covered at this stage but it can be expected to work similarly or to be more conservative. Comment made in summary report chapter 4.

Comment by	Chapter/ section	Comment no.	Comment	Answer / proposed update
NAFCS-WN-TM21 (Issue 1)	-	-	In my opinion the scenario method – developed in NAFCS pilot studies and used in several practical CCF data analysis – is a preferred path to proceed among other developed viable approaches. The heavy role of required engineering judgment is a problem in scenario method but things can be improved in that respect as already recommended in the proposals made in NAFCS pilot study reports. Causal modeling should be used in any more complicated CCF phenomena. The human errors play an important part in many CCFs. For their part causal modeling can build on established HRA methods. Admittedly, the scenario method requires skill, experience, often communication with plant experts and time resources. The resource needs are increased by the requirement to do the Impact Vector construction by two experts in a well organized manner, which is a must in order to assure good quality as emphasized by NAFCS pilots. I think this is affordable because of the high importance of CCFs. A formula driven method for Impact Vector construction requires less resources, but is likely to reduce to a mechanical calculation, maybe just to the use of a computerized algorithm, i.e. full automation, directly inputting ICDE	Discussion added in the summary report based on this comment. Summary report chapter 3.
Dr. Klügel		Rec.1	The time factor analysis suggested as a part of the methodology should be completed by adding factors to considering whether the observed incipient common cause failures (CCF, impairments degradations) will indeed lead to a malfunction of the degraded component during the mission time of PSA. The suggested time factors for low probability of occurrence of CCFs (impairment or malfunction observed after more than 2 two test intervals or later than one month after the first observation) are considered to be too high (section 6.4).	These are the definitions used within ICDE. Since this is an important source of data (at least within this project) the already established definitions is considered to remain (data is classified using these definitions). Further, the numerical value of the time factor is included in the impact vector construction by multiplying the basic impact vector elements with the time factor. The contribution of events with time factor “low” will only be 10 % relative the contribution by the same event with time factor “high”, i.e. in many cases such contributions could be neglected.
Dr. Klügel		Rec. 2	Only events, where at least one component out of a group of m components (CCF-group) was observed to be failed (loss of function), shall be selected as potential common cause failures for further evaluation.	Unfortunately the area of CCF event assessments often "suffers" from having a lack of data. It is therefore very important to consider any available information. It is further of great importance to also be aware of, and consider, situations where for example a component has has been capable of performning the major portion of a safety function but parts of it is degraded. A large amount of experience would be lost if such events are disregarded.
Dr. Klügel		Rec. 3	Conditional CCF probabilities shall be scaled (conditioned) to the probability distribution for the frequency of independent failures or the criteria for mutual homogeneity of CCF groups have to be extended to check the compatibility of probability distributions for the frequency of independent failures. This is **absolutely mandatory** to obtain a meaningful CCF-model, because the intent of introducing CCF models into PSA consists in the treatment of dependency between otherwise assumed as identical components. The similarity of the probability distributions of independent failures is a formal mathematical criterion for mutual homogeneity of CCF groups.	This discussion is interpreted as dealing with CCF quantification. The performed task, and related report, concerns impact vector construction only. Treatment of quantification will be further explored in the following tasks to be performed.

Comment by	Chapter/ section	Comment no.	Comment	Answer / proposed update
Dr. Klügel		Rec.4	The assumption of complete dependency for the conditional probability of multiple failures within a CCF group of **m** components has no basis, because the failure times for failures subsequent to an observed “independent” failure remain to be random. The questions of treatment of uncertainty and dependency should be separated. Alternative, e.g. parametric methods for the treatment of uncertainty should be investigated (e.g. classical approach using beta-distributions for MGL-parameters or Alfa-factors combined with a Bayesian update procedure, hierarchical Bayesian methods). Expert judgement methods to assess uncertainties as well as progressive alternatives (copulas, direct numerical simulation) should be investigated, too.	This discussion is interpreted as dealing with treatment of uncertainty for CCF quantification. The performed task, and related report, concerns impact vector construction only. Treatment of uncertainty will be further explored in the following tasks to be performed.

PROSOL-8002 Rev 1			**Summary conclusions (Part 1):**	
PROSOL-8002 Rev 1		1	The numerical impact vector estimates depend strongly on very few (2-3) event interpretations. Rejection of any of the concepts, V or V_{new} in particular, at this stage can not be justified by such limited data especially when event interpretations can be challenged.	Exercise with other component types and more events performed, see summary report section 4.2. JKV: This does not address the issue. The same problem with other component types.. Note that V and Vnew are not rejected. V: The Vaurio high bound are referred to and used as High bound both separately and as part of FCD. See 7.1 and 7.2 in phase 2 task 1 report. Vnew are discussed further as an option. Presently, we have the following: Experts tend to judge large CCF values (i.e., the high bound) for 4oo4, when they see much damage. For this result, it holds: - it appeals to common sense and engineering judgment - the 41 records are sufficient in size to support this - new assessments on MOV / CV also do not contradict this. If they see less damage, they take something between high bound and low bound. Here, there is in fact some arbitrariness, which we also observed in our experiment with the MOV / CV. 4oo4 for V_{new} results for CCII in 0.055, FCG results in 0.05. Subjective probabilities never have this accuracy. For 3oo4 and 2oo4, experts sometimes did not respect the high bound. In order to cover this, this has been tolerated in FCG JKV: The above mainly repeats the results “EWG” ended up with. It does not solve the problem “The numerical impact vector estimates depend strongly on very few event interpretations.”

PROSOL-8002 Rev 1		**2**	There is evidence that NBE can be too optimistic in some cases and V too pessimistic in some cases; NBE assessors evidently have not considered the presence of coherency effect.	Ignorance prior makes no assumption on the presence of coherency effect for certain patterns! See 7.2. For all other patterns high bound are assumed. The FCD approach has been shown to bee in between NBE and V (apart from what is said above). JKV: V_{new} also within uncertainties. They still have not considered coherency. If we doubt, whether FCG or V_{new} can be as good as experts, it appears somewhat ambitious to require it to be even better than experts. Expert assessments can at most be required to be correct (or conservative) on an average. If you add an additional expert, he will always some issues. It is not the question, whether NBE contains errors (this is true for almost all expert work), but whether they can be considered as typical expert estimates. JKV: I repeat my early criticism that experts have not documented enough their basis of assessment, so it is impossible to agree or disagree. There is no evidence that coherence was considered systematically or sporadically. Thus good "fit" to current experts does not solve the issue.
PROSOL-8002 Rev 1		**3**	Correcting the errors/interpretations would have significant effect in Tables 7-10 of the Phase2-Task1 report, especially with V_{new} introduced as a candidate model.	Quality issues on input data is discussed in the summary report. JKV: Discussion does not correct it. See above. Is the NBE sample (where the experts read additional documents, where they had discussions with plant personal etc) in such a way erroneous, that we believe, it is not representative for expert assessment? JKV: See above.

PROSOL-8002 Rev 1		**4**	There are several "mapping" steps in CCF impact vector quantification, and errors possible in each step: o Mapping 1: event description => event interpretation o Mapping 2: event interpretation => event coding (d_1,d_2,d_3,d_4, c_4,c_3,c_2, q_4,q_3,q_2) ▪ simplified in N/G: (d_1,d_2,d_3,d_4, c, q), c = c_4, q = q_4. o Mapping 3: event codes => impact vector components ▪ cqF(d_1,d_2,d_3,d_4, cq) in Vnew ▪ cqF(d_1,d_2,d_3,d_4) in V and in the suggested N/G o Function F(..) searched based on fitting to NBE expert judgment data set (41 events) - Limited data set and few component types - Practically no events with shared cause factor weaker than H - Very few events with time factor weaker than H - Several "mapping" steps potentially subject to errors - Coding limited: no c or q assessment for subsets of a CCCG - c and q ignored in F(..) for N/G approach - Monotonic behaviour of data set used (i.e. $v_{2/4} \geq v_{3/4} \geq v_{4/4}$) - Monotonic N/G-formula (occasionally reversed order $v_{2/4} \leq v_{3/4} \leq v_{4/4}$)	We try to do it and at the same time try to keep the influence of these factors within our uncertainty results/estimates. The influences of these factors are assessed in different parts of the validation. JKV: Sensitivity/validation addresses only some parts, but again under the assumption that a data set is sufficient, and NAFSC perfect! Requires a lot more "data", and spectrum of assessors with more plant experience. –At this early stage, why don't accept more than one candidate formula at least. I agree concerning the formulas. They could and should be presented as equivalent. I would not like, however, to loose, what is really backed by the data, i.e., if there is damage. For me, V_{new} would make much more sense, if it as applied in cases, where experts deviate from high bound. The data gives us clear indication, when this happens. The arbitrariness only comes, when we consider, how the experts will deviate. JKV: Many issues remain unsolved even if a good "fit" to current experts were possible. To me it indicates that CCF models and impacts need to be assessed event by event rather than by a formula, for a foreseeable future at least.

PROSOL-8002 Rev 1		**5**	One should notice that the cases analyzed in this report were not selected on the basis of questionable interpretations in advance: in this respect the cases were random sample. Nevertheless, so much room for re-interpretation was found that this makes very questionable the whole approach to base quantification calibration on the 41-event data sample.	Exercise for MOV and CV performed for further calibration and validation, see summary report chapter 4. JKV: Same interpretation problems prevail no matter how much components you include. Same argument as above. Experts are humans, and humans commit errors. I know at least one case in the pumps data section, and another among the MOV, where I'm rather sure, that experts have been unnecessarily pessimistic.
PROSOL-8002 Rev 1		**6**	One major conclusion is that one can not trust that ICDE- or NAFCS-codes for degradations correspond to expert assessment values 1, .5, .1 and 0, respectively. Already in this small sample of five cases D was marked when the assessor assessed 0.2 or even 0.1. In other examples .2 has been used for I instead of .1, and .8 has been used for C instead of 1.0. Thus, the suggested G/N approach (formula and ICDE-coding driven approach), does not seem reliable as it is.	Discussion on input data quality check added. Bounded by Expert check list. See summary report. JKV: Discussion does not correct the problem. Spending more resources on interpretation was what was tried to be avoided by FCD. There is no point limiting to FCD if you spend the expert judgment resources anyway. Both in Nordic and German assessments, no one just simply relied on ICDE data. In both cases, extensive expert judgment has been applied. In Germany, this has been done for impairments and a factor to multiply the impact vector with, but not for impact vectors. In our experiment on MOV and CV, experts have been familiarized with high bound and low bound (but not with the formula, of course). This caused them to see, that the assessment of impairments leaves much more freedom to the judgment, than the interval between high bound and low bound. Given correct impairments, experts have large uncertainty within the intervals given This is why there is necessarily some arbitrariness. JKV: If/when those experts deviated from the numerical ICDE code values for degradations, why should any other assessor believe in ICDE codes and just use a formula?

PROSOL-8002 Rev 1			SUMMARY CONCLUSIONS about the approach (Part 2): Even this small sample of five events revealed several fundamental problems for any formula- and coding-driven approach:	Actions defined in WG meeting. With the intention to be addressed in the validation part. JKV: Impossible to correct the problem by talking/writing. No, just difficult. Given the three arguments found above: - Arbitrariness is restricted to cases with little damage observed - experts are representative, even if they commit errors. - There is no reluctance to perform expert assessment; just the step from impairment and other factors to impact vectors should be assisted by a formula. I consider this problem solved. JKV: The many issues that remain show that real problems have not been solved, only fitting to this sample and this set of expert assessments.
PROSOL-8002 Rev 1		**7**	Modeling and quantification of CCF: A formula and ICDE coding do not yield enough information for correct modeling of each event for PSA. CCF can originate a) at the time of commission, b) as a shock at random time, c) result in consecutive tests, or d) they can be due to coincidentally increased individual rates, observed in a regular test or in some special test (like a long operation of diesels). The same equation and codes alone do not tell how to model the event properly. Also, discovery in a test does not necessarily mean discovery in any periodic test. Only detailed assessment can provide enough information for correct modeling and relevant test interval	Bounded by Expert check list, see summary report. JKV: Can not be reliably handled by bounding. The problem is already in ICDE, and can not be solved without improving ICDE system; except to some extent by spending necessary resources assessing the event descriptions and other info sources (Fortum approach). No one has objections to improve ICDE; it is a more political question, whether we should (more) clearly specify these findings in the report, or – as we did last time – leave it up to Gunnar to feed this into the ICDE gremium when he feels it is convenient.
PROSOL-8002 Rev 1		**8**	Some CCF may be relevant only for some *initiating events* , not for all. This is not indicated by coding alone but must be assessed based on event description.	Tailoring suggested, without tailoring bounded by conservatism, see summary report. JKV: Fault is already in ICDE, unless revealed by event description, which should be studied. = Spending resources that FCD tries to avoid.. See above. ICDE is not used without additional checks, and no objections to improve ICDE. We can suggest including this aspect in the ICDE analytical field to improve or assist tailoring and using of ICDE. JKV: OK, if possible.

PROSOL-8002 Rev 1		**9**	Possible *recoveries* also complicate the assessment: they are *not taken into account* in ICDE coding, but may be revealed by the description text. (This could be one reason for why NAFCS numerical assessments sometimes seem to be inconsistent with the assigned coding. However, the relative fraction and impact of this feature is likely not the same for different types of components and failure modes.)	Not credited and this way bounded by conservatism. JKV: Conservatism is not the answer. It should be avoided; was one motivation for the German partners to do this study. Recovery is an issue similar to the GRS transferability factor. Note, there are some thoughts on this in the report. Numerical assessments are covered in the check list JKV: OK to be in the check list. A PSA assessor has to consider: does he include a recovery in CCF quantification, or as a separate factor in PSA event model. This can not be a “formulae” for everybody.
PROSOL-8002 Rev 1		**10**	Also, different redundant trains can have very different latent failure times, which is not directly clear from the codes or even timing (because times of discovery are reported rather than times of occurrence).	Bounded by conservatism! JKV:This is not the answer!! (And not necessarily true.) ICDE Time factor is given based on latency time! There is a question on this in the check list, which tries to identify cases, where there may be a very high latency time. JKV: This issue is related to assessing time-factors for subsets of CCCG, which is not in the current FCD.

PROSOL-8002 Rev 1			List the concerns: Why I have difficulties approving the current version(s) of VGB-NPSAG CCF quantification approach. Some of these may be overcome with some adjustment, but others simply can not be satisfied by the limitations taken (like using only degradations in determining the ratios of impact vector components, not considering c and q for subsets of CCCG, and assuming component type-independence based on 2 types only). Simplifications are too serious for far-reaching conclusions.	No one said this is easy! But we try to do it anyway. JKV: But do not claim it is done, e.g. by selecting one FCD. (c and q are considered, but not for subsets of CCCG though.) So they can not influence ratios. Concerning FCD: see above. Concerning c, q: I think we put this in the quality section (must be conservative, if just one is used), and also in check list. JKV: OK for the report now, but not a permanent solution for CCF quantification.
PROSOL-8002 Rev 1		**11**	1) When fitting a model to data it is common to require an order of magnitude more data points than there are unknown parameters. In our case we have about 50 different degradation vectors ("parameters") and only 41 data points to fit on. This provides neither uniqueness nor a way to assess the accuracy, goodness of fit. The data base is simply too thin.	Generic problem of CCF quantification. JKV: Not in the same sense as in this approach. Bounded by Hi bound or PREB 95% or both?? JKV: Conservatism is not the answer. What we really took from our sample is just the distinction of amount of damage. For this 41 points are enough. The rest is arbitrary, but the data is used to check assessments. JKV: The issue not answered.

PROSOL-8002 Rev 1		**12**	2) Because of limited descriptions (in NAFCS and ICDE), it is impossible to agree or disagree with the impact vectors assigned to many cases.	Stressed in conclusions and summary (in the summary report). JKV: OK, but it does not solve the issue. Again: to what extent do we trust other experts? For all assessments, we had more information than in ICDE, but of course, not everything was documented. JKV: See 2, 4, 6.
PROSOL-8002 Rev 1		**13**	3) From 1 and 2 follows: too far-reaching conclusions are being made from too few events and component types.	But we can try! JKV: The issue is too serious to make a report that implies success, when it is only a try. OK: The success grade we can rephrase, Number of component types and events have been increased, and the model still holds, even though there may be other ones, for which this is also true. So, please rephrase, but do not sell this as a miss success.
PROSOL-8002 Rev 1		**14**	4) Extrapolation to other component types and systems and failure modes.	Exercise for MOV and CV performed for further calibration and validation, see summary report. JKV: This would be OK, if the other issues were solved. I don't think there is enough evidence to claim the same one model for all component types.
PROSOL-8002 Rev 1		**15**	5) Determining impact vector components (ratios, i.e. degree of coherence/dependency) only by degradation values is problematic. Degradations are defined and assessed for individual components and not intended in any way to assess the degree of coherence/conditional dependence between component failures.	Precondition given by ICDE format and this is an issue of this project to suggest resolution for. JKV: OK, but already the shared cause and time factors at least tell more about being CCF and likely more coherent, than degradations alone. The model is consistent in the sense, that it will assume higher dependency, when much damage is seen. JKV: It is possible that events with smaller degradations do not contribute much on the final contribution that CCFs make in PSA. But to demonstrate this takes more time and new benchmarks without bound to a formula in advance.

PROSOL-8002 Rev 1		16	6) Shared cause (c) and time-factors (q) are defined jointly to a group and at least partially measure the coherence, certainly more than degradations alone. This should be reflected in the approach.	Shared cause (c) and time-factors (q) given by ICDE for the whole group and these are considered in the FCD approach. Bounded by Expert check list, see summary report. JKV: FCD uses these only as multipliers and not to guide the coherence assessment, like in Vnew. In terms of ICDE, shared cause factor just yields the subjective probability, that this is a CCF. Nothing is said about dependency. Also time factor says something, whether there is some chance, that the CCF is noticed before it hit all components. We do not have other information in ICDE. Experts will consider it different to assess dependency. My criticism to this is: c*q are used also in FCD, by just multiplying. There are so few events with c*q <1, that we cannot resolve this arbitrariness. However, if we take the ICDE definition literally, there is not much choice apart from multiplying. JKV: I agree that ICDE does not address the coherence adequately.
PROSOL-8002 Rev 1		17	7) Lack of considering c and q for subsets of CCCG. This would be particularly important for systems with success criterion other than 1-out-of-4, because a subset of 3 alone could fail the system. And two double failures could be as important as a single quadruple failure.	Bounded by Expert check list, see summary report. JKV: This does not correct the issue. Only Vnew, or expert judgment (Fortum) Different time factors have been considered in the check list. Also, a requirement has been defined, that c and q must be conservative. Concerning the simultaneous independent occurrence of two CCFs of order 2 yielding a 4oo4 failure: This is not impossible, but very unlikely. JKV: This issue was discussed above (10). Guessing came until proved.
PROSOL-8002 Rev 1		18	We should be aware and recognize these limitations and accept that all may not want to accept these assumptions but want to do more event-specific assessments and expand the data base significantly before going to a formula-driven approach.	Stressed in conclusions and summary (summary report). JKV: Then recognize& allow at least some variant formulas. (Or leads back to Fortum approach.) Variant formula is ok, if it fulfils the criteria of acceptance and if it accepts the conservative approach which is evident from the data. OK: we can rephrase Perhaps, given this additional discussion , we do not need much rephrasing apart from what has been said in the comments. JKV: Clear statement is needed in the introduction that it would be premature to take the current formula(s) as a panacea to CCF quantification.

Attachment 3-5

Vaurio, Jussi. *Time factor considerations in common cause failure quantification,* PROSOL-8005.

12.9.2008

Time factors in impact vector assessment

The intended purpose of the *time factor* with grades H, M and L, numerically q = 1, 0.5, and 0.1, respectively, is discussed in this Section. Possible weaknesses in practical use and quantification are also discussed. Particular attention is on potential impacts of assessing and using separate time factors for subsets of a CCCG (a set of similar redundant components).

The general purpose of a time factor is to measure the simultaneity of failures or degradations. The more failures, degradations or impairments co-exist simultaneously, and the longer they exist in a safety system, the more serious is the event. The assessed time factor is supposed to correlate with such simultaneous residence.

In case of CCCG size 4, defects may exist along the timeline as follows:

```
          a _____________________________________ A
                     b __________________________________________ B
        c __________________________________ C
                d ____________________________________ D            Time =>
```

The most important interval in this case is b-C when all four components are down. During d-A at least three components are down, and during a-D at least a double failure is present. Multiple simultaneous failures are more likely due to common cause failures (CCF) than due to independent single failures, and that is why timing is considered in CCF modeling and quantification.

However, such details are rarely accurate in event descriptions, and can not be easily identified from a few codes or factors such as determined e.g. in ICDE data base.

To determine whether an event is due to a common cause is judged first by the *shared cause factor* that is assessed from the observations and symptoms associated with the event. However, because information is scarce and uncertain, a time factor as a measure of simultaneity has been defined for an *additional indicator how likely the event is due to a common cause.* For this purpose it would be best to observe or infer the *simultaneity of failure entry times* a, b, c, and d. For example, a strong external shock would make the entries practically simultaneous. Test-caused failures would take place within a test interval. A CCF-model appropriate for an event has to take into accounts both entry times and exit times of CCF (to determine whether to estimate and use rates per unit time, or probabilities per demand, for example).

However, that has not been considered possible in ICDE. Instead, the ICDE time factor is geared to measure the simultaneity of the discovery times A, B, C and D, because that may be easier to judge from event records. The drawback is that it does not measure directly the simultaneity of entry times and is therefore a surrogate for a more direct indicator. –With expert judgment it is possible to try to estimate the simultaneity of the entry times a, b, c and d as well.

Nevertheless, the way the time factor is determined for an event in ICDE is based on the difference of the first and the last defect *discovery* times, i.e. C and B in the picture. That is measured in units of a test interval for tests that are able to detect the type of failure. (Some failures are detected by monthly tests, others with somewhat different annual tests, for example.)

If one of the detection times (e.g. B) is very different from the others, it is logical to assume that the subset of three detections A, C and D indicate a triplet CCF more likely than a complete CCF of four components. Or nearly simultaneous C and A may indicate a double CCF more likely than failure of a larger group. A question arises: how often it happens that a time factor for a subset is larger than the factor for the whole group, and could this lead to significant differences in CCF quantification.

In the following a limited evaluation is made to assess mainly two aspects:

1) Has the time factor for the whole group been overestimated, perhaps because some failures were observed close in time or a subset of failures occurred close in time?

2) How often a subset time factor would be larger than the time factor for the whole group?

A set of 17 events on diesel generators and 13 events on pumps were used in this study to get some idea about the situation. These events are described and interpreted in document 2006018:003 in Appendix 1 to SKI Report 2007:41.

1) In several cases the expert judgment group (EWG or German) has raised the time factor for the whole group from that assigned by the plant staff. The reason in many cases was that failure discoveries were close in time. The plant staff had evidently taken into account that degradations were slowly developing (such as due to wear, or accumulation of deposits) and actual failure arrivals would be spread in time. Because of the importance of actual failure entry times the assessment of plant staff should be considered as more realistic.

   Sometimes half of the expert assessed lower degradation or time factor, but the official category of the experts was always assigned a higher factor.

   - Events of this sort were 00068, 00077, 00185, 00187, 00190, 00195, 00551, and possibly 00640.
   - Earlier judgments of two other events in this project, event 27 = LOTI-180181A-1, Lo1 and event 28 = LOTI-180181A-1, Lo2, also had the utility time factors raised by a later "expert" group based on the detection times rather than the defect entry times.

2) Shared cause and time factors were assigned for events with degradations CWWW or DWWW, which do not indicate any CCF at all. See events 00193, 00548, 00247, 00570, perhaps 00187.

3) In many cases the degradation vectors were of type XYWW, where only X and Y were degraded (other than W) and still the time factor H, M or L was assigned: It is not clear then whether the time factor is for four observations even when there were only two degradations. It seems obvious that the factor should be only for components that have degraded, i.e. *for a subset* of a CCCG. Events relevant to this issue are 00068, 00077, 00195, 00197, 00523, 00405, 00532, 00543, 00078, 00106, 00478, 00521 and 00523.

4) In several cases the "Scenario method" seemed to produce "net impact vectors" even higher (more pessimistic) than the "high bound", which is now considered to be the highest acceptable. This occurred for example in events 00185 and 00187.

Concerning the other question, the importance of time factors for subsets of components:

If complete CCFs of all components of a CCCG are an important contribution to system unavailability (as is the case in 1-out-of-4 systems), one can conclude that assessment of partial (subset) time factors is most important under two conditions:

- all components of a CCCG have degradation higher than W, and
- the time factor for the whole group is lower than H

Only in such cases the partial (subset) time factors, if higher than the time factor for the whole group, could contribute significantly to the system unavailability and risk. In the sample of 30 CCF-events (17 for diesel generators and 13 for pumps) two events, only events 00551 and 00640 originally satisfied these conditions, but even for these the group time factors were raised to H (based on simultaneity of observations, even when faults were slowly developing and the plant/utility staff had assigned the time factor lower than H). Thus, it was not possible to get a clear picture from this set of events on the question of how often and how much partial (subset) time factors could influence the results significantly. The importance of this issue depends on how large a fraction of events have a time factor for the whole group smaller than H, for cases that have degradations (higher than W) for the whole group or 4 components.
-Partial time factors can be particularly important for 2-out-of-4 systems because then triple failures (in addition to quadruple failures) can fail the system.

Note: In case of a degradation vector XYZW, where X, Y and Z are other than W, the time factor should be determined based on the timing of the 3 components that have degraded. There is no point using the observation time of a component that has not degraded.

Conclusions:

1) Expert assessments so far have led to conservative (i.e. pessimistic) time factors basically because most emphasis has been in the simultaneity of observations of degradations (rather than on the simultaneity of the failure state entry times, and this emphasis is also built in the ICDE coding rules. This aspect is particularly clear in slowly developing defects: then multiple degradations may be observed and repaired within a short time, but actual critical levels (failed states) could be reached with rather different rates and during an extended period.

2) The importance of assessing time factors for subsets of components of a CCCG has not been clearly demonstrated here for 1-out-of-4 systems. This is partly due to the conservative assessment of high time factors (H) for the whole group because in such cases subset time factors can not be higher than the factor for the whole group.
   If the conservatism of the whole group time factors is removed, then the subset time factors can become important. Furthermore, the subset time factors are more important for 2-out-of-4 systems because then a triple-failure also fails the system.

3) There is a lack of rules and coding how to take into account possible recoveries (repairs, resetting) if such would be possible in time in case of a real demand (initiating event), even if such was not needed or attempted in case of a regular test demand in which the failure was detected.
   This issue is not directly relevant to time factors but it could be taken into account in degradation coding.

Test intervals and staggering in basic event quantification

The time factors discussed above are relevant for determining the impact vectors, independent of whether the CCF events are caused by demand stresses (and modeled by probabilities per demand) or by time-related stresses (modeled by failure rates, probabilities per time unit). When the impact vectors are used for obtaining the probability parameters of a CCF model, the discussed time factors are not used anymore because their impact is included in the impact vector values.

However, different kinds of time-effects appear in CCF event probability quantification after impact vectors have been used in solving the CCF rates $\lambda_{k/n}$ or demand probabilities $q_{k/n}$. The simultaneous unavailability time of multiple components depends strongly on the length of a test interval as well as on the staggering scheme. This is illustrated in the following formulation of CCF event probabilities when CCFs are caused by time-related stresses.

Determination of unavailabilities

Finally, the rates are transformed to the probabilities $z_{ij..}$ of the basic CCF-events $Z_{ij..}$ (failing exactly specific k components i, j,.. out of n similar components) needed in the system fault tree. For standby safety components tested with test interval T these values are

$$\Pr(Z_{ij..}) = c_{k/n}\lambda_{k/n}T, \tag{4}$$

where $0 < c_{k/n} < 1$. The coefficients $c_{k/n}$ depend on k, n, test staggering, repair policy and the system success criterion (Vaurio 2000). They can be determined so that correct time-average risk is obtained by a single fault tree calculation. In case of sequential or simultaneous testing the average residence time of the failures would be approximately one half of the test interval, which gives us a general approximation similar to the single failure practice, $c_{k/n} = ½$, for $n = 1, 2, 3,\dots$ and $1 \le k \le n$.

With staggered testing there is a time-shift of T/n from one test to the test of next redundant train. The average residence time of a CCF is generally shorter than with sequential testing, especially if there is a group-repair policy (GRP): whenever a component is found failed, a CCF is identified (e.g. by testing other components as well) and all components failed by the same CCF are repaired. With this policy all terms are smaller than with sequential testing, especially for the complete (n-fold) CCF terms:

$$
\begin{array}{lllll}
n \ge 1: & z_i = \frac{1}{2}\lambda_{1/n}T, & i = 1, 2, \dots, n & & \\
n = 2: & z_{12} = \frac{1}{4}\lambda_{2/2}T, & & & \\
n = 3: & z_{ij} = \frac{5}{18}\lambda_{2/3}T, & 1 \le i < j \le 3, & z_{123} = \frac{1}{6}\lambda_{3/3}T, & \\
n = 4: & z_{12} = \frac{5}{16}\lambda_{2/4}T, & & z_{23} = \frac{5}{16}\lambda_{2/4}T, & \\
 & z_{34} = \frac{5}{16}\lambda_{2/4}T, & & z_{14} = \frac{5}{16}\lambda_{2/4}T, & (5) \\
 & z_{13} = \frac{1}{4}\lambda_{2/4}T, & & z_{24} = \frac{1}{4}\lambda_{2/4}T, & \\
 & z_{ijk} = \frac{3}{16}\lambda_{3/4}T, & 1 \le i < j < k \le 4, & & \\
 & z_{1234} = \frac{1}{8}\lambda_{4/4}T. & & &
\end{array}
$$

In case of staggered testing with individual repair policy (IRP), only scheduled tests are performed and a component found failed is individually repaired. In this case one has to consider different system success criteria for each n. The effective residence time of a CCF failure combination may depend on that. In a 1/3-system (1-out-of-3:G) a system failure due to λ_{123} is removed by the very first test (average residence time T/6), while in a 2/3-system it is removed only after two tests (average residence time T/6 + T/3 = T/2). After detailed derivations, the following conclusions can be drawn:

- For all 1/n-systems, all probabilities $z_{ij..}$ with IRP are the same as with GRP.
- For other systems the probabilities $z_{ij..}$ are the same as with GRP (Eqs.5), except the following exceptions for n = 3 and 4:

2/3 -system: $z_{123} = \frac{1}{2}\lambda_{3/3}T,$

2/4 -system: $z_{1234} = \frac{3}{8}\lambda_{4/4}T,$ (6)

3/4 -system: $z_{ijk} = \frac{1}{2}\lambda_{3/4}T, \quad 1 \le i < j < k \le 4; \quad z_{1234} = \frac{5}{8}\lambda_{4/4}T.$

The rates generally depend on n so that $\lambda_{2/n}$ for example, is not the same for n = 2, 3 and 4. One should also notice that with n = 4, $z_{12} \neq z_{13}$ and $z_{23} \neq z_{24}$ even in the symmetric case because of different mutual staggering of components 2 and 3 with respect to component 1, and components 3 and 4 with respect to component 2. The accuracy of the expressions $z_{ij..}$ of Eqs. 4 – 6 can be judged by comparisons with the analytical time-average unavailabilities $U_{m/n}$ of m-out-of-n: G systems ($1 \le m \le n \le 4$) obtained earlier by Vaurio (1994b), indicating the accuracy mostly within ±20 per cent.

All the values of $c_{k/n}$ to be used in the modelling have been presented by for the cases in which n is 2, 3 or 4. (Vaurio J. K.(1994b): The Theory and Quantification of Common Cause Shock Events for Redundant Standby Systems. Reliability Engineering and System Safety 43:3, 289-305, and Vaurio, J.K. (2005): Uncertainties and quantification of common cause failure rates and probabilities for system analyses. Reliability Engineering and System Safety 90(2005)186-195.)

Similar considerations about demand-related probabilities were presented in Report PROSOL7001, complementing the Fortum methodology description by K. Jänkälä (2007).

Attachment 3-6

Event data set – MOV and CV

1 CHECK VALVES, CV

There are totally 23 German, Finnish and Swedish events, which are presented in table 1.

CCF event ID	Plant	Failure mode	CCCG size	SCF	TF	Comp. Imp. V	Det. mode
1	X4	FC	4	H	H	CCWW	MA
2	X6	RC/IL	4	H	H	CCCD	MC
3	X11	FO	8	H	H	CIIWWWWW	TI
4	X17	FO	8	H	empty	CIIIWWWW	TI
5	X23	FC	2	H	H	CD	MA
6	X18	FO	8	H	H	CIWWWWWW	MA
7	X27	FC	3	H	H	CCC	
8	X27	FC	3	H	H	CCI	TA
9	X27	FC	11	H	H	DIIWWWWWWWW	MA
10	X27	RC/IL	2	H	H	DW	TI
11	X5	FO	6	H	H	CIWWWW	TI
12	X18	FC	4	H	H	CWWW	TA
13	X4	FC	4	H	H	CIII	MA
14	X4	FC	4	H	H	CDIW	MA
15	X12	FC	3	H	H	CCW	TI
16	X19	FC	4	H	H	CIIW	MA
17	X13	FC	8	M	L	CCWWWWWW	TI
18	X5		3			CDD	
19	X7		3			CDD	
20	X7		3			CDD	
21	X5		3			IIS	
22	X5		4			CCWW	
23	X6		8			ISSSWWWW	

Table 1. CV event data

2 MOTOR OPERATED VALVES, MOV

There are totally 53 German, Finnish and Swedish events, which are presented in table 2.

CCF event ID	Plant	Failure mode	CCCG size	SCF	TF	Comp. Imp. V	Det. mode
1	X7	FC	4	H	H	DDWW	TI
2	X5	FO	4	H	H	CIII	TI
3	X24	FO	4	H	H	D	MA
4	X24	FO	4	H	H	CCII	TA
5	X31	FO	2	H	H	CI	MC
6	X26	FO	4	H	H	CIWW	MA
7	X28	FO	6	H	H	CI	DE
8	X30	FO	8	H	H	DD	TI
9	X5	FO	3	H	H	CII	TI
10	X2	FO	24	H	H	CCWWWWWWWWWW WWWWWWWWWWWWW	TA
11	X6	FO	4	H	H	CIII	DE
12	X6	FO	4	H	H	CCCW	DE
13	X23	FO	14	H	H	CC	TI
14	X15	FO	4	H	H	CCII	TI
15	X1	FO	12	H	H	CCDDWWWWWWWW	TI
16	X2	FO	12	H	H	CDDDWWWWWWWW	TI
17	X1	FC	4	H	L	CCWW	TI
18	X27	FO	2	H	H	CI	MA
19	X27	FO	2	H	H	CC	
20	X27	FO	2	H	H	CI	MA
21	X27	FO	3	H	H	CII	MC
22	X27	FO	4	H	H	CIII	MA
23	X27	FO	4	H	H	CCII	MA
24	X6		4			CWWW	
25	X6		2			CC	
26	X10		4			CCII	
27	X10		4			CCWW	
28	X10		4			CCWW	
29	X10		4			CCWW	
30	X5		6			CCWWWW	
31	X5		6			CCWWWW	
32	X4		4			CCCW	
33	X18		4			CSSS	
34	X17		6			CCCIII	
35	X11		10			CCWWWWWWWW	
36	X6		6			CCDDWW	
37	X8		3			CDI	
38	x22		2			CW	
39	X4		3			CCW	
40	X15		4			CWWW	
41	x22		2			CD	
42	X5		2			CW	
43	X6		3			CCW	
44	X20		6			CCDDII	

CCF event ID	Plant	Failure mode	CCCG size	SCF	TF	Comp. Imp. V	Det. mode
45	X15		2			CI	
46	X15		4			CIII	
47	x22		2			CW	
48	X9		8			CSSSSSWW	
49	X6		4			CWWW	
50	X10		4			CIII	
51	X7		4			CDWW	
52	X4		4			CWWW	
53	X6		4			CSSS	

Table 2. MOV event data

Attachment 3-7
CV and MOV impact vector calculation

1 IMPACT VECTOR CONSTRUCTION

Within the work for Task 2 a data set was concluded for check valves, CVs, and motor operated valves, MOVs. The data applied in this task is based on this data set, limited to CCCG size 4.

The produced results for application of the FCD and the low and high bounding, as described in the Task 1 report are presented below (these values of the different multiplicities are those for 'exactly k-out-of-4', not accumulated to 'at least k-out-of-4'). In cases where information is not available, for example considering shared cause factor for event no. 22 in the data set for CVs, conservative assumption is made (i.e. in this case the shared cause factor is calculated with the numerical value 1.0).

Event No.	Plant code	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode	FCD impact vector Multiplicity				Low bound Multiplicity				High bound Multiplicity			
						1	2	3	4	1	2	3	4	1	2	3	4
1	X4	CCWW	H	H	MA	0	1	0	0	0	1	0	0	0	1	0	0
2	X6	CCCD	H	H	MC	0	0	0	0	0	0	0	0	0	0	0	0
12	X18	CWWW	H	H	TA	1	0	0	0	1	0	0	0	1	0	0	0
13	X4	CIII	H	H	MA	0,9	0,033333	0,033333	0,033333	0,729	0,243	0,027	0,001	0,9	0	0	0,1
14	X4	CDIW	H	H	MA	0,4	0,5	0,1	0	0,45	0,5	0,05	0	0,5	0,4	0,1	0
16	X19	CIIW	H	H	MA	0,9	0,05	0,05	0	0,81	0,18	0,01	0	0,9	0	0,1	0
22	X5	CCWW	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0
					Sum:	3,2	2,583333	0,183333	0,033333	2,989	2,923	0,087	0,001	3,3	2,4	0,2	0,1

Table 1. Results,CVs, exactly k-out-of-4.

Event No.	Plant code	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode	FCD impact vector Multiplicity				Low bound Multiplicity				High bound Multiplicity			
						1	2	3	4	1	2	3	4	1	2	3	4
17	X7	CCWW	H	L	TI	0	0,1	0	0	0	0,1	0	0	0	0,1	0	0
22	X5	CIII	H	H	MA	0,9	0,033333	0,033333	0,033333	0,729	0,243	0,027	0,001	0,9	0	0	0,1
23	X24	CCII	H	H	MA	0	0,9	0	0,1	0	0,81	0,18	0,01	0	0,9	0	0,1
24	X24	CWWW	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
26	X26	CCII	0	0	0	0	0,9	0	0,1	0	0,81	0,18	0,01	0	0,9	0	0,1
27	X6	CCWW	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0
28	X6	CCWW	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0
29	X15	CCWW	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0
32	X1	CCCW	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0
33	X27	CSSS	0	0	0	0,99	0,003333	0,003333	0,003333	0,970299	0,029403	0,000297	0,000001	0,99	0	0	0,01
40	X27	CWWW	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
46	X6	CIII	0	0	0	0,9	0,033333	0,033333	0,033333	0,729	0,243	0,027	0,001	0,9	0	0	0,1
49	X10	CWWW	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
50	X10	CIII	0	0	0	0,9	0,033333	0,033333	0,033333	0,729	0,243	0,027	0,001	0,9	0	0	0,1
51	X10	CDWW	0	0	0	0,5	0,5	0	0	0,5	0,5	0	0	0,5	0,5	0	0
52	X10	CWWW	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
53	X4	CSSS	0	0	0	0,99	0,003333	0,003333	0,003333	0,970299	0,029403	0,000297	0,000001	0,99	0	0	0,01
					Sum:	9,18	5,50667	1,106667	0,30667	8,627598	6,007806	1,441594	0,023002	9,18	5,4	1	0,52

Table 2. Results,MOVs, exactly k-out-of-4.

The accumulated impact vectors for CVs and MOVs lumped together are presented below.

Event No.	Plant code	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded						Is FCD conservative compared to Low bound for multiplicity 3 and 4?	Is FCD as high as High bound for multiplicity 3 and 4?
							FCD approach Multiplicity		Low bound Multiplicity		High bound Multiplicity			
							3	4	3	4	3	4		
1	X4	CV	CCWW	H	H	MA	0	0	0	0	0	0	Yes	Yes
2	X6	CV	CCCD	H	H	MC	0	0	0	0	0	0	Yes	Yes
12	X18	CV	CWWW	H	H	TA	0	0	0	0	0	0	Yes	Yes
13	X4	CV	CIII	H	H	MA	0,066667	0,0333	0,028	0,001	0,1	0,1	Yes	No
14	X4	CV	CDIW	H	H	MA	0,1	0	0,05	0	0,1	0	Yes	Yes
16	X19	CV	CIIW	H	H	MA	0,05	0	0,01	0	0,1	0	Yes	No
22	X5	CV	CCWW	0	0	0	0	0	0	0	0	0	Yes	Yes
17	X7	MOV	CCWW	H	L	TI	0	0	0	0	0	0	Yes	Yes
22	X5	MOV	CIII	H	H	MA	0,066667	0,0333	0,028	0,001	0,1	0,1	Yes	No
23	X24	MOV	CCII	H	H	MA	0,2	0,1	0,19	0,01	0,1	0,1	Yes	Yes
24	X24	MOV	CWWW	0	0	0	0	0	0	0	0	0	Yes	Yes
26	X26	MOV	CCII	0	0	0	0,2	0,1	0,19	0,01	0,1	0,1	Yes	Yes
27	X6	MOV	CCWW	0	0	0	0	0	0	0	0	0	Yes	Yes
28	X6	MOV	CCWW	0	0	0	0	0	0	0	0	0	Yes	Yes
29	X15	MOV	CCWW	0	0	0	0	0	0	0	0	0	Yes	Yes
32	X1	MOV	CCCW	0	0	0	1	0	1	0	1	0	Yes	Yes
33	X27	MOV	CSSS	0	0	0	0,006667	0,0033	0,0003	0,000001	0,01	0,01	Yes	No
40	X27	MOV	CWWW	0	0	0	0	0	0	0	0	0	Yes	Yes
46	X6	MOV	CIII	0	0	0	0,066667	0,0333	0,028	0,001	0,1	0,1	Yes	No
49	X10	MOV	CWWW	0	0	0	0	0	0	0	0	0	Yes	Yes
50	X10	MOV	CIII	0	0	0	0,066667	0,0333	0,028	0,001	0,1	0,1	Yes	No
51	X10	MOV	CDWW	0	0	0	0	0	0	0	0	0	Yes	Yes
52	X10	MOV	CWWW	0	0	0	0	0	0	0	0	0	Yes	Yes
53	X4	MOV	CSSS	0	0	0	0,006667	0,0033	0,0003	0,000001	0,01	0,01	Yes	No
Sum accumulated impact vectors, CVs:							0,216667	0,0333	0,088	0,001	0,3	0,1		

Event No.	Plant code	Comp-onent type	Component impairment vector	Shared cause factor, c	Time factor, q	Detect-ion mode, dm	Accumulated Impact vector - Events with detection mode MC excluded: FCD approach Multiplicity		Low bound Multiplicity		High bound Multiplicity		Is FCD conservative compared to Low bound for multiplicity 3 and 4?	Is FCD as high as High bound for multiplicity 3 and 4?
							3	4	3	4	3	4		
Sum accumulated impact vectors, MOVs:							1,613333	0,3067	1,4646	0,023002	1,52	0,52		
Sum accumulated impact vectors, CVs and MOVs:							1,83	0,34	1,5526	0,024002	1,82	0,62		

Table 3. Results, CVs and MOVs, accumulated (at least k-out-of-4).

Attachment 3-8

Expert assessment exercise, minutes

Participants	
Schubert	VENE
Böhm	VENE
Röß	RWE
Strohm	ENBW
Brahmstaedt	EON
Wohlstein	EON
Becker	RISA

Distribution	
Participants	
Johanson	ESKons.
Lindberg	ESKons.

Minutes of results

Project	Nordic VGB CCF project
Purpose	Perform subjective assessment of CCF events
Datum	23rd of September, 2008
Time	09:30 h till 16:30 h
Location	Vattenfall headquarter in Hamburg

▪

Topic	Description	Action
Introduction	Dr. Schubert as host of the meeting welcomed the participants, and he asked Dr. Becker to give an introduction into the purpose of the meeting.	
Methodology	Dr. Becker gave a presentation of the methodology, which is attached to these minutes. He defined the terms ‘impairment’ and ‘impact’, and he presented the upper limit (high bound) discovered by J. Vaurio, and the low bound used in USA, assuming conditional independence of failures.	
Materials	Materials had been distributed before the meeting. These are: Event descriptions of German CCF events, with impairments, which had been defined during the VGB GRS CCF study. A table, giving the events, impairments, shared cause factor, time factor, detection mode, and low bound values and high bound values for the impacts. A table with columns for the experts to fill in their assessments of impact.	

Topic	Description	Action
Assessment	For one event after the other, the expert read the event descriptions, then discussed details of the descriptions and their assessment. Dr. Becker helped to identify the boundary conditions for a consistent assessment given the impairments and the high bound. Finally, the expert filled in their table, if they had come to a decision on a subjective impact vector assessment.	
Final discussion	Those among the participants, who had been involved in the assessment of impairments during the VGB/GRS project, shared the opinion, that – given the limits of low bound and high bound, there is much less room for subjectivity in impact vector estimation, than there is in impairment assessment. They approve a quasi automatic procedure to produce impact vectors from impairments and comparable information. They considered the meeting as a good opportunity to obtain information and practical training in dealing with CCF events.	
Future actions	Dr. Schubert collected the forms filled in by the experts. He distributes them among the participants. Dr. Becker will produce minutes of the meeting, and a comparison of the results with the heuristic produced during the Nordic/VGB project, phase 2, task 1. This comparison will become part of phase 2, task 2 to provide validation for the approach developed.	

Written down on 26th of September, 2008

Günter Becker; RISA GmbH

Attachment 3-9

Expert assessment exercise, results

Input							Expert impact vectors				Formula and coding driven impact vectors			
		group		Shared	Time		Failure multiplicity				Failure multiplicity			
Nr.	Type	size	impairment	cause	factor	Detection	=1	=2	=3	=4	=1	=2	=3	=4
Expert 1														
1	CV	4	CCWW	H	H	MA	0	1	0	0	0	1	0	0
2	CV	4	CCCD	H	H	MC	0	0	0,5	0,5	0,5	0	0,5	0,5
3	CV	8	CIIWWWWW	H	H	TI								
4	CV	8	CIIIWWWW	H	H	TI								
6	CV	8	CIWWWWWW	H	H	MA								
11	CV	6	CIWWWW	H	H	TI								
12	CV	4	CWWW	H	H	TA	1	0	0	0	1	0	0	0
13	CV	4	CIII	H	H	MA	0,9	0,02	0,02	0,06	0,933333333	0,033333333	0,033333333	0,033333333
14	CV	4	CDIW	H	H	MA	0,5	0,4	0,1	0	0,4	0,5	0,1	0
15	CV	3	CCW	H	H	TI								
16	CV	4	CIIW	H	H	MA	0,85	0,05	0,1	0	0,9	0,05	0,05	0
17	CV	8	CCWWWWWW	M	L	UN								
18	CV	3	CDD	H	H	UN	0,5	0,25	0,25	0	0,5	0,25	0,25	0
19	CV	3	CDD	H	H	UN								
20	CV	3	CDD	H	H	UN								
21	CV	3	IIS	H	H	UN								
22	CV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
23	CV	8	ISSSWWWW	H	H	UN								
1	MOV	4	DDWW	H	H	UN								
2	MOV	4	CIII	H	H	UN								
9	MOV	3	CII	H	H	UN								
11	MOV	4	CIII	H	H	UN								
12	MOV	4	CCCW	H	H	UN								
14	MOV	4	CCII	H	H	UN								
24	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
25	MOV	2	CC	H	H	UN								
26	MOV	4	CCII	H	H	UN	0	0,9	0,06	0,04	0,1	0,8	0,1	0,1
27	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
28	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
29	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
30	MOV	6	CCWWWW	H	H	UN								
31	MOV	6	CCWWWW	H	H	UN								
32	MOV	4	CCCW	H	H	UN	0	0	1	0	0	0	1	0
33	MOV	4	CSSS	H	H	UN	0,99	0,003	0,003	0,004	0,993333333	0,003333333	0,003333333	0,003333333
34	MOV	6	CCCIII	H	H	UN								
35	MOV	10	CCWWWWWWWW	H	H	UN								

36	MOV	6	CCDDWW	H	H	UN								
37	MOV	3	CDI	H	H	UN								
38	MOV	2	CW	H	H	UN								
39	MOV	3	CCW	H	H	UN								
40	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
41	MOV	2	CD	H	H	UN								
42	MOV	2	CW	H	H	UN								
43	MOV	3	CCW	H	H	UN								
44	*MOV*	*6*	*CCDDII*	*H*	*H*	*UN*								
45	MOV	2	CI	H	H	UN								
46	MOV	4	CIII	H	H	UN	0,8	0,17	0,02	0,01	0,933333333	0,033333333	0,033333333	0,033333333
47	MOV	2	CW	H	H	UN								
48	*MOV*	*8*	*CSSSSSWW*	*H*	*H*	*UN*								
49	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
50	MOV	4	CIII	H	H	UN	*0,9*	*0,03*	*0,03*	*0,04*	0,933333333	0,033333333	0,033333333	0,033333333
51	MOV	4	CDWW	H	H	UN	0,5	0,5	0	0	0,5	0,5	0	0
52	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
53	MOV	4	CSSS	H	H	UN	0,99	0	0	0,01	0,993333333	0,003333333	0,003333333	0,003333333
Expert 2														
1	CV	4	CCWW	H	H	MA	0	1	0	0	0	1	0	0
2	CV	4	CCCD	H	H	MC	0	0	0,5	0,5	0,5	0	0,5	0,5
3	CV	8	CIIWWWWW	H	H	TI								
4	CV	8	CIIIWWWW	H	H	TI								
6	CV	8	CIWWWWWW	H	H	MA								
11	CV	6	CIWWWW	H	H	TI								
12	CV	4	CWWW	H	H	TA	1	0	0	0	1	0	0	0
13	CV	4	CIII	H	H	MA	0,9	0,05	0,04	0,01	0,933333333	0,033333333	0,033333333	0,033333333
14	CV	4	CDIW	H	H	MA	0,5	0,45	0,05	0	0,4	0,5	0,1	0
15	CV	3	CCW	H	H	TI								
16	CV	4	CIIW	H	H	MA	0,9	0,079	0,001	0	0,9	0,05	0,05	0
17	CV	8	CCWWWWWW	M	L	UN								
18	CV	3	CDD	H	H	UN	0,5	0,3	0,2	0	0,5	0,25	0,25	0
19	CV	3	CDD	H	H	UN								
20	CV	3	CDD	H	H	UN								
21	CV	3	IIS	H	H	UN								
22	CV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
23	CV	8	ISSSWWWW	H	H	UN								
1	MOV	4	DDWW	H	H	UN								
2	MOV	4	CIII	H	H	UN								
9	MOV	3	CII	H	H	UN								

11	MOV	4	CIII	H	H	UN								
12	MOV	4	CCCW	H	H	UN								
14	MOV	4	CCII	H	H	UN								
24	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
25	MOV	2	CC	H	H	UN								
26	MOV	4	CCII	H	H	UN	0	0,9	0,095	0,005	0,1	0,8	0,1	0,1
27	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
28	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
29	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
30	MOV	6	CCWWWW	H	H	UN								
31	MOV	6	CCWWWW	H	H	UN								
32	MOV	4	CCCW	H	H	UN	0	0	1	0	0	0	1	0
33	MOV	4	CSSS	H	H	UN	0,99	0,0034	0,0033	0,0033	0,993333333	0,003333333	0,003333333	0,003333333
34	MOV	6	CCCIII	H	H	UN								
35	MOV	10	CCWWWWWWWW	H	H	UN								
36	MOV	6	CCDDWW	H	H	UN								
37	MOV	3	CDI	H	H	UN								
38	MOV	2	CW	H	H	UN								
39	MOV	3	CCW	H	H	UN								
40	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
41	MOV	2	CD	H	H	UN								
42	MOV	2	CW	H	H	UN								
43	MOV	3	CCW	H	H	UN								
44	*MOV*	*6*	*CCDDII*	*H*	*H*	*UN*								
45	MOV	2	CI	H	H	UN								
46	MOV	4	CIII	H	H	UN	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
47	MOV	2	CW	H	H	UN								
48	*MOV*	*8*	*CSSSSSWW*	*H*	*H*	*UN*								
49	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
50	MOV	4	CIII	H	H	UN	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
51	MOV	4	CDWW	H	H	UN	0,5	0,5	0	0	0,5	0,5	0	0
52	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
53	MOV	4	CSSS	H	H	UN	0,99	0,005	0,003	0,002	0,993333333	0,003333333	0,003333333	0,003333333
Expert 3														
1	CV	4	CCWW	H	H	MA	1	1	0	0	0	1	0	0
2	CV	4	CCCD	H	H	MC	0	0	0,5	0,5	0,5	0	0,5	0,5
3	CV	8	CIIWWWWW	H	H	TI								
4	CV	8	CIIIWWWW	H	H	TI								
6	CV	8	CIWWWWWW	H	H	MA								
11	CV	6	CIWWWW	H	H	TI								

12	CV	4	CWWW	H	H	TA	1	0	0	0	1	0	0	0
13	CV	4	CIII	H	H	MA	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
14	CV	4	CDIW	H	H	MA	0,5	0,4	0,1	0	0,4	0,5	0,1	0
15	CV	3	CCW	H	H	TI								
16	CV	4	CIIW	H	H	MA	0,9	0,07	0,03	0	0,9	0,05	0,05	0
17	CV	8	CCWWWWWW	M	L	UN								
18	CV	3	CDD	H	H	UN	0,5	0,3	0,2	0	0,5	0,25	0,25	0
19	CV	3	CDD	H	H	UN								
20	CV	3	CDD	H	H	UN								
21	CV	3	IIS	H	H	UN								
22	CV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
23	CV	8	ISSSWWWW	H	H	UN								
1	MOV	4	DDWW	H	H	UN								
2	MOV	4	CIII	H	H	UN								
9	MOV	3	CII	H	H	UN								
11	MOV	4	CIII	H	H	UN								
12	MOV	4	CCCW	H	H	UN								
14	MOV	4	CCII	H	H	UN								
24	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
25	MOV	2	CC	H	H	UN								
26	MOV	4	CCII	H	H	UN	0	0,9	0,07	0,03	0,1	0,8	0,1	0,1
27	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
28	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
29	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
30	MOV	6	CCWWWW	H	H	UN								
31	MOV	6	CCWWWW	H	H	UN								
32	MOV	4	CCCW	H	H	UN	0	0	1	0	0	0	1	0
33	MOV	4	CSSS	H	H	UN	0,99	0,005	0,003	0,002	0,993333333	0,003333333	0,003333333	0,003333333
34	MOV	6	CCCIII	H	H	UN								
35	MOV	10	CCWWWWWWWW	H	H	UN								
36	MOV	6	CCDDWW	H	H	UN								
37	MOV	3	CDI	H	H	UN								
38	MOV	2	CW	H	H	UN								
39	MOV	3	CCW	H	H	UN								
40	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
41	MOV	2	CD	H	H	UN								
42	MOV	2	CW	H	H	UN								
43	MOV	3	CCW	H	H	UN								
44	*MOV*	*6*	*CCDDII*	*H*	*H*	*UN*								
45	MOV	2	CI	H	H	UN								
46	MOV	4	CIII	H	H	UN	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333

47	MOV	2	CW	H	H	UN								
48	*MOV*	*8*	*CSSSSSWW*	*H*	*H*	*UN*								
49	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
50	MOV	4	CIII	H	H	UN	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
51	MOV	4	CDWW	H	H	UN	0,5	0,5	0	0	0,5	0,5	0	0
52	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
53	MOV	4	CSSS	H	H	UN	0,99	0,005	0,003	0,002	0,993333333	0,003333333	0,003333333	0,003333333
Expert 4														
1	CV	4	CCWW	H	H	MA	0	1	0	0	0	1	0	0
2	CV	4	CCCD	H	H	MC	0	0	0,5	0,5	0,5	0	0,5	0,5
3	CV	8	CIIWWWWW	H	H	TI								
4	CV	8	CIIIWWWW	H	H	TI								
6	CV	8	CIWWWWWW	H	H	MA								
11	CV	6	CIWWWW	H	H	TI								
12	CV	4	CWWW	H	H	TA	1	0	0	0	1	0	0	0
13	CV	4	CIII	H	H	MA	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
14	CV	4	CDIW	H	H	MA	0,5	0,4	0,1	0	0,4	0,5	0,1	0
15	CV	3	CCW	H	H	TI								
16	CV	4	CIIW	H	H	MA	0,81	0,18	0,01	0	0,9	0,05	0,05	0
17	CV	8	CCWWWWWW	M	L	UN								
18	CV	3	CDD	H	H	UN	0,5	0,25	0,25	0	0,5	0,25	0,25	0
19	CV	3	CDD	H	H	UN								
20	CV	3	CDD	H	H	UN								
21	CV	3	IIS	H	H	UN								
22	CV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
23	CV	8	ISSSWWWW	H	H	UN								
1	MOV	4	DDWW	H	H	UN								
2	MOV	4	CIII	H	H	UN								
9	MOV	3	CII	H	H	UN								
11	MOV	4	CIII	H	H	UN								
12	MOV	4	CCCW	H	H	UN								
14	MOV	4	CCII	H	H	UN								
24	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
25	MOV	2	CC	H	H	UN								
26	MOV	4	CCII	H	H	UN	0	0,9	0,05	0,05	0,1	0,8	0,1	0,1
27	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
28	MOV	4	CCWW	H	H	UN								
29	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
30	MOV	6	CCWWWW	H	H	UN								
31	MOV	6	CCWWWW	H	H	UN								

32	MOV	4	CCCW	H	H	UN	0	0	1	0	0	0	1	0
33	MOV	4	CSSS	H	H	UN	0,985	0,005	0,005	0,005	0,993333333	0,003333333	0,003333333	0,003333333
34	MOV	6	CCCIII	H	H	UN								
35	MOV	10	CCWWWWWWWW	H	H	UN								
36	MOV	6	CCDDWW	H	H	UN								
37	MOV	3	CDI	H	H	UN								
38	MOV	2	CW	H	H	UN								
39	MOV	3	CCW	H	H	UN								
40	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
41	MOV	2	CD	H	H	UN								
42	MOV	2	CW	H	H	UN								
43	MOV	3	CCW	H	H	UN								
44	*MOV*	*6*	*CCDDII*	*H*	*H*	*UN*								
45	MOV	2	CI	H	H	UN								
46	MOV	4	CIII	H	H	UN	0,9	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
47	MOV	2	CW	H	H	UN								
48	*MOV*	*8*	*CSSSSSWW*	*H*	*H*	*UN*								
49	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
50	MOV	4	CIII	H	H	UN	0,99	0,05	0,03	0,02	0,933333333	0,033333333	0,033333333	0,033333333
51	MOV	4	CDWW	H	H	UN	0,5	0,5	0	0	0,5	0,5	0	0
52	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
53	MOV	4	CSSS	H	H	UN	0,99	0	0	0,01	0,993333333	0,003333333	0,003333333	0,003333333
Expert 5														
1	CV	4	CCWW	H	H	MA	0	1	0	0	0	1	0	0
2	CV	4	CCCD	H	H	MC	0	0	0,5	0,5	0,5	0	0,5	0,5
3	CV	8	CIIWWWWW	H	H	TI								
4	CV	8	CIIIWWWW	H	H	TI								
6	CV	8	CIWWWWWW	H	H	MA								
11	CV	6	CIWWWW	H	H	TI								
12	CV	4	CWWW	H	H	TA	1	0	0	0	1	0	0	0
13	CV	4	CIII	H	H	MA	0,9	0,03	0,03	0,04	0,933333333	0,033333333	0,033333333	0,033333333
14	CV	4	CDIW	H	H	MA	0,5	0,4	0,1	0	0,4	0,5	0,1	0
15	CV	3	CCW	H	H	TI								
16	CV	4	CIIW	H	H	MA	0,98	0,05	0,05	0	0,9	0,05	0,05	0
17	CV	8	CCWWWWWW	M	L	UN								
18	CV	3	CDD	H	H	UN	0,5	0,25	0,25	0	0,5	0,25	0,25	0
19	CV	3	CDD	H	H	UN								
20	CV	3	CDD	H	H	UN								
21	CV	3	IIS	H	H	UN								
22	CV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0

23	CV	8	ISSSWWWW	H	H	UN								
1	MOV	4	DDWW	H	H	UN								
2	MOV	4	CIII	H	H	UN								
9	MOV	3	CII	H	H	UN								
11	MOV	4	CIII	H	H	UN								
12	MOV	4	CCCW	H	H	UN								
14	MOV	4	CCII	H	H	UN								
24	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
25	MOV	2	CC	H	H	UN								
26	MOV	4	CCII	H	H	UN	0	0,9	0,05	0,05	0,1	0,8	0,1	0,1
27	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
28	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
29	MOV	4	CCWW	H	H	UN	0	1	0	0	0	1	0	0
30	MOV	6	CCWWWW	H	H	UN								
31	MOV	6	CCWWWW	H	H	UN								
32	MOV	4	CCCW	H	H	UN	0	0	1	0	0	0	1	0
33	MOV	4	CSSS	H	H	UN	0,99	0,007	0,002	0,001	0,993333333	0,003333333	0,003333333	0,003333333
34	MOV	6	CCCIII	H	H	UN								
35	MOV	10	CCWWWWWWWW	H	H	UN								
36	MOV	6	CCDDWW	H	H	UN								
37	MOV	3	CDI	H	H	UN								
38	MOV	2	CW	H	H	UN								
39	MOV	3	CCW	H	H	UN								
40	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
41	MOV	2	CD	H	H	UN								
42	MOV	2	CW	H	H	UN								
43	MOV	3	CCW	H	H	UN								
44	*MOV*	*6*	*CCDDII*	*H*	*H*	*UN*								
45	MOV	2	CI	H	H	UN								
46	MOV	4	CIII	H	H	UN	0,9	0,098	0,001	0,001	0,933333333	0,033333333	0,033333333	0,033333333
47	MOV	2	CW	H	H	UN								
48	*MOV*	*8*	*CSSSSSWW*	*H*	*H*	*UN*								
49	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
50	MOV	4	CIII	H	H	UN	0,99	0,03	0,03	0,04	0,933333333	0,033333333	0,033333333	0,033333333
51	MOV	4	CDWW	H	H	UN	0,5	0,5	0	0	0,5	0,5	0	0
52	MOV	4	CWWW	H	H	UN	1	0	0	0	1	0	0	0
53	MOV	4	CSSS	H	H	UN	0,99	0,007	0,002	0,001	0,993333333	0,003333333	0,003333333	0,003333333

Attachment 3-10
Sensitivity analysis

SENSITIVITY ANALYSIS – DIESEL AND PUMP CASE

1 IMPACT OF DETECTION MODE

Below are the results for the evaluation of the impact of the detection mode parameter on the diesel and pump case. The “normal” case is that monitored events are excluded as described in the Task 1 report.

As can be seen the impact of the detection mode is large when looking at pumps and diesels together. For the sum of the accumulated impact vectors, for the case of failure of 4 out of 4, there is an increase of the size of hundreds of percents when also monitored events are included (compared to the case when they are not included). When considering only pumps there is no impact at all. The reason for this is that there is no event in the considered data set that was monitored.

	Difference between ("monitored" events included) and ("monitored" events excluded) for sum of accumulated impact vectors								
	FCD			**Low bound**			**High bound**		
	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4
diesels	1,50	1,00	1,00	1,50	1,00	1,00	1,50	1,00	1,00
pumps	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
all	1,50	1,00	1,00	1,50	1,00	1,00	1,50	1,00	1,00
	Difference in % (increase of the values if monitored events are included compared to excluding them)								
diesels	18,14	182,93	408,16	17,80	258,63	6172,65	17,07	141,84	215,05
pumps	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
all	13,52	59,52	145,63	11,74	61,34	486,14	12,52	34,42	46,19

Table 1. *Sum of accumulated impact vectors – monitored events included vs. excluded.*

2 IMPACT OF IMPAIRMENT CODE S

Below is a presentation of evaluation of the impact of treating impairment code S as I (numerical value of S=I=0.1) and treating I as S (numerical value of I=S=0.01). The “normal” numerical value for I is 0.1 and for S 0.01.

For the case where S is treated as I it is concluded, for the sum of the accumulated impact vectors, that the impact is not that large as can be seen below.

Considering the case when I is treated as S compared to the “normal case” it is shown that the impact is large, especially for high multiplicity.

	Difference between “normal case” (I=0.1, S=0.01) and when treating S as I (S=I=0.1) for sum of accumulated impact vectors								
	FCD approach			**Low bound**			**High bound**		
	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4
diesels	-0,0350	-0,0367	-0,0383	-0,1935	-0,0301	-0,0014	-0,0450	-0,0450	-0,1350
pumps	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
all	-0,0350	-0,0367	-0,0383	-0,1935	-0,0301	-0,0014	-0,0450	-0,0450	-0,1350
	Difference in %								
diesels	0,423	6,707	15,646	2,297	7,772	8,639	0,512	6,383	29,032
pumps	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
all	0,316	2,183	5,583	1,514	1,843	0,680	0,375	1,549	6,236
	Difference between “normal case” (I=0.1, S=0.01) and when treating I as S (I=S=0.01) for sum of accumulated impact vectors								
	FCD approach			**Low bound**			**High bound**		
	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4
diesels	0,8230	0,4883	0,2167	0,9515	0,3510	0,0160	0,8370	0,6300	0,4050
pumps	0,1800	0,1200	0,0600	0,4826	0,0554	0,0020	0,1800	0,1800	0,1800
all	1,0030	0,6083	0,2767	1,4341	0,4064	0,0180	1,0170	0,8100	0,5850
	Difference in %								
diesels	-9,954	-89,329	-88,435	-11,291	-90,773	-99,059	-9,528	-89,362	-87,097
pumps	-6,372	-10,588	-13,585	-11,083	-4,455	-1,054	-5,625	-8,182	-10,588
all	-9,041	-36,210	-40,291	-11,220	-24,929	-8,773	-8,486	-27,883	-27,021

Table 2. Sum of accumulated impact vectors – impact of impairment code I and S.

Below is presentation of a comparison between the “normal case” for impairment codes S and W and the cases where W is treated as S and where S is treated as W respectively.

It is seen that if W would be treated as S there is a rather large impact for multiplicity 3 and 4.

This is considered the other way around, i.e. that S is treated as W, the impact is nearly neglectable.

	Difference between “normal case” (S=0.01 W=0) and when treating W as S (W=S=0.01) for sum of accumulated impact vectors								
	FCD approach			**Low bound**			**High bound**		
	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4
diesels	-0,0951	-0,1387	-0,1074	-0,1407	-0,1192	-0,0011	-0,0221	-0,1411	-0,1561
pumps	-0,0100	-0,0200	-0,0200	-0,0025	-0,0249	-0,0026	0,0000	-0,0100	-0,0200
all	-0,1051	-0,1587	-0,1274	-0,1432	-0,1441	-0,0037	-0,0221	-0,1511	-0,1761
	Difference in %								
diesels	1,150	25,378	43,823	1,669	30,825	6,637	0,252	20,014	33,570
pumps	0,354	1,765	4,528	0,057	2,002	1,372	0,000	0,455	1,176
all	0,947	9,448	18,549	1,120	8,839	1,787	0,184	5,201	8,134
	Difference between “normal case” (S=0.01 W=0) and when treating S as W (S=W=0) for sum of accumulated impact vectors								
	FCD approach			**Low bound**			**High bound**		
	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4	2oo4	3oo4	4oo4
diesels	0,0150	0,0133	0,0117	0,0230	0,0019	0,0001	0,0050	0,0050	0,0150
pumps	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
all	0,0150	0,0133	0,0117	0,0230	0,0019	0,0001	0,0050	0,0050	0,0150
	Difference in %								
diesels	-0,181	-2,439	-4,762	-0,272	-0,504	-0,620	-0,057	-0,709	-3,226
pumps	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
all	-0,135	-0,794	-1,699	-0,180	-0,120	-0,049	-0,042	-0,172	-0,693

Table 3. Sum of accumulated impact vectors – impact of impairment code S and W.

Attachment 4
Parameter estimation validation

January 2009

Attachment 4-1

Becker, Günter. Technical note on PREB theory.

24.09.2008

Empirical Bayesian parameter estimation

Empirical Bayesian parameter estimation is a method which can be used to estimate failure rates and failure probabilities per demand. Moment estimation is the basic of this approach ROB56 [4], SPJ85 [2], ARS98 [3], VAU87 [1]. This means, the evidence of the component groups which have been assessed as similar is used to estimate the first two moments of the population distribution. These estimates then are used to find parameters of the population distribution. This distribution is used as à priori distribution to assess the à posteriori distribution for the components within a given plant. The variant of Vaurio [1] has been used in the context of PSA of nuclear power plants. The variant of Spjøtvoll [2] has been used for the OREDA data base (off-shore). The variant of Arsenis [3] has been used in the context of the EuReData project, i.e. for components of NPP. These variants are described subsequently.

Basic of moment estimation procedures

Consider n components or n groups of components of one or more plants with given observation periods T_i and number of failures observed N_i. Consider the task to estimate probability density functions of the plant specific failure rates λ_i.
Assuming that failure rates are constant w.r.t. time, the N_i observed are governed by a Poisson distribution and the corresponding likelihood function is:

$$L(N_i | \lambda_i, T_i) = \frac{(\lambda_i T_i)^{N_i}}{N_i!} e^{-\lambda_i T_i} \qquad (1)$$

As can be seen easily, the maximum likelihood estimator for λ_i is $\frac{N_i}{T_i}$.

It is assumed, that there exists a common distribution f ($\lambda | x, y$) with parameters x and y, such that each λ_i can be interpreted as an independent sample drawn from this distribution.

Let M= E{λ} be the expected value of the random failure rate Λ and V=E{(λ-M) ^{2}} its variance, then for prior distributions with two parameters (these are the only ones interesting for practical purposes), it holds:

M= g_1(x,y) (2)

and

V= g_2(x,y). (3)

Using the evidence N_i, T_i to obtain estimators $\hat{M}$ and $\hat{V}$ for M and V, (2) and (3) can be used to find estimators for the parameters x and y of the prior distribution. Let $\hat{x}$ and $\hat{y}$ be these estimates, the posterior distribution function for a plant according to the law of Bayes is

$$\mathrm{f}\ (\lambda_\mathrm{i}|E_i) = \frac{L(E_i|\lambda_i)\, f(\lambda_i|\hat{x},\hat{y})}{\int_{\lambda_i} L(E_i|\lambda_i)\, f(\lambda_i|\hat{x},\hat{y})d\lambda_i} \quad (4).$$

Using the Gamma distribution law, which is the conjugate prior of the Poisson likelihood function, one obtains

$$f(\lambda_I|x,y) = y\frac{(\lambda_i y)^x}{\Gamma(x+1)}e^{\lambda_I y} \quad (5)$$

The expected value M and the variance V of this distribution is:

$$\mathrm{M}=\frac{x+1}{y} = g_1(x,y) \quad (6)$$

$$\mathrm{V}=\frac{x+1}{y^2} = g_2(x,y) \quad (7)$$

Thus, parameters x and y result in

$$y = \frac{M}{V} \quad (8)$$

$$x = \frac{M^2}{V} - 1 \tag{9}$$

M and V are the moments of each single λ_i based on the distribution function $f(\lambda_i | x, y)$. Given the true values of x and y, the theorem of Bayes permits to determine the posterior distribution function of an individual λ_i by substituting (1) and (5) into (4) yields a gamma distribution $f(\lambda_i | K_i + x, T_i + y)$, with the expected value

$$E\{\hat{\lambda}_i\} = \frac{x + N_i + 1}{y + T_i} \tag{10}$$

and the variance

$$Var\{\hat{\lambda}_i\} = \frac{x + N_i + 1}{(y + T_i)^2} \tag{11}$$

All variants of empirical Bayesian estimation have these points in common. They differ in how they estimate M and V, which shall be given subsequently.

Estimation of M and V given variability within the population

As already mentioned, the expected value $M_i = E\{\Lambda\}$ of a subpopulation i is

$$\hat{\lambda}_i = \frac{N_i}{T_i} \tag{12}$$

Given the assumptions for a super population, it holds:

$E\{\tilde{\lambda}_i\} = E\{\Lambda_i\} = M$ and

$$Var\{\hat{\lambda}_i\} = Var\{\Lambda\} + \frac{E\{\Lambda\}}{T_i} = V + \frac{M}{T_i}$$

As it has been postulated, that the $\hat{\lambda}_i$ are independent given their distribution, it can be shown, that for a linear combination $\hat{\lambda}_a = a_1\hat{\lambda}_1 +,...,+ a_k\hat{\lambda}_k$, with $\sum_{i=1}^{k} a_i = 1$, it holds:

$$E\{\hat{\lambda}_a\} = M \tag{13}$$

$$Var\{\hat{\lambda}_a\} = \sum_{i=1}^{k} a_i^2 \left(\frac{M}{T_i} + Var\Lambda\right) \tag{14}$$

Note, that the linear estimator $\hat{\lambda}_a$ yields the correct expected value independent from the a_i. However, its variance (14) depends upon the selection ot the a_i.
Consider e.g. the following special cases

$$\hat{\lambda}_w = w_1\hat{\lambda}_1 + w_2\hat{\lambda}_2 + ... + w_n\hat{\lambda}_n \tag{15}$$

with $w_i = \dfrac{t_i}{t_1 + ... + t_n}$ (16)

and $\hat{\lambda} = \dfrac{\hat{\lambda}_1 + ... + \hat{\lambda}_n}{n}$ (17)

where $w_i = \dfrac{1}{n}$ (18)

Then, the variances are

$$Var\hat{\lambda}_w = \frac{E\Lambda}{n}\frac{1}{\overline{\overline{T}}} + \sum_{i+1}^{n} w_i^2 + Var\Lambda \tag{19}$$

resp.

$$Var\hat{\lambda} = \frac{E\Lambda}{n}\frac{1}{n}\sum_{i=1}^{n}\frac{1}{T_i} + \frac{Var\Lambda}{n} \tag{20}$$

where $\overline{T}$ is the arithmetic average of the observation periods for the sub populations.
Consider the difference of the variance estimators

$$Var\hat{\lambda}_w - Var\hat{\lambda} = \frac{1}{n}\left(\frac{1}{\overline{\overline{T}}} - \frac{1}{n}\sum_{i=1}^{n}\frac{1}{T_i}\right)E\Lambda + \left(\sum_{i=1}^{n} w_i^2 - \frac{1}{n}\right)Var\Lambda \tag{21}$$

The factor before EΛ is always negative, but the factor before VarΛ is always positive. Depending on the values of the t_i, either linear estimator can have advantages w.r.t. variance. Obviously, the weights in $\hat{\lambda}_a$ should be determined such, that the variance becomes minimal. The coefficients

$$a_i = \frac{\left(\frac{E\Lambda}{T_i} + Var\Lambda\right)^{-1}}{\sum_{i=1}^{n}\left(\frac{E\Lambda}{T_i} + Var\Lambda\right)^{-1}} \tag{22}$$

minimize the variance (14).

Note, that if there is no variability of Λ, i.e. VarΛ=0, $a_i = \frac{T_i}{\sum_{i=1}^{n} T_i} = w_i$ and $\hat{\lambda}_a = \hat{\lambda}_w$.

Also, if the variability of Λ is large, $a_i \rightarrow \frac{1}{n}$, i.e. the second case $\hat{\lambda}_a = \hat{\lambda}$ results.

According to (22), it is required to have E{Λ}=M and Var{Λ}=V to find the optimum coefficients a_i, which are just those to be estimated.

For E{Λ} estimators $\hat{\lambda}$ or $\hat{\lambda}_w$ can be used. This selection depends on whether one guesses, that the variability will be large or small.

To find a substitute for Var{Λ} consider the following.

The expected value of $\sum_{i=1}^{n} w_i (\hat{\lambda}_i - \hat{\lambda})^2$ can be found as

$$E\{\sum_{i=1}^{n} (\hat{\lambda}_i - \hat{\lambda}) = \frac{E\{\Lambda\}(n-1)}{n} \sum_{i=1}^{n} \frac{1}{t_i} + (n-1) Var\{\Lambda\} . \qquad (23)$$

Likewise, the expected value of $\sum_{i=1}^{n} w_i (\hat{\lambda}_i - \hat{\lambda}_w)^2$ is

$$E\{\sum_{i=1}^{n} (\hat{\lambda}_i - \hat{\lambda}_w) = \frac{E\{\Lambda\}(n-1)}{n\overline{T}} + (1 - \sum_{i=1}^{n} w_i) Var\{\Lambda\} . \qquad (24)$$

Using (24), for $\hat{\lambda}_a = \hat{\lambda}$, the estimator for the variance results in

$$\hat{\sigma}_1^2 = \begin{cases} \frac{\sum_{i=1}^{n} (\hat{\lambda}_i - \hat{\lambda})^2}{(n-1)} - \frac{\hat{\lambda}}{n} \sum \frac{1}{T_i} & \text{for} \quad \frac{\sum_{i=1}^{n} (\hat{\lambda}_i - \hat{\lambda})^2}{(n-1)} - \frac{\hat{\lambda}}{n} \sum \frac{1}{T_i} > 0 \\ 0 & \text{for} \quad \frac{\sum_{i=1}^{n} (\hat{\lambda}_i - \hat{\lambda})^2}{(n-1)} - \frac{\hat{\lambda}}{n} \sum \frac{1}{T_i} < 0 \end{cases} \qquad (25)$$

whereas for $\hat{\lambda}_a = \hat{\lambda}_w$:

$$\hat{\sigma}_2^2 = \begin{cases} \dfrac{1}{1-\sum_{i=1}^{n} w_1^2}\left[\sum_{i=1}^{n} w_1(\hat{\lambda}_i - \hat{\lambda}_w)^2 - \dfrac{\hat{\lambda}_w(n-1)}{n\overline{T}}\right] & \textit{for } \dfrac{1}{1-\sum_{i=1}^{n} w_1^2}\left[\sum_{i=1}^{n} w_1(\hat{\lambda}_i - \hat{\lambda}_w)^2 - \dfrac{\hat{\lambda}_w(n-1)}{n\overline{T}}\right] > 0 \\ 0 & \textit{for } \dfrac{1}{1-\sum_{i=1}^{n} w_1^2}\left[\sum_{i=1}^{n} w_1(\hat{\lambda}_i - \hat{\lambda}_w)^2 - \dfrac{\hat{\lambda}_w(n-1)}{n\overline{T}}\right] < 0 \end{cases} \tag{26}$$

Thus, two pairs of estimators result, which can be used as initial estimates for E{Λ} and Var{Λ} in (22):

$(\hat{\lambda}_w, \hat{\sigma}_1)$: if populations have small variability (27)

$(\hat{\lambda}\ , \hat{\sigma}_2)$: if populations have large variability (28)

Equation (27) corresponds to the model of Spjøtvol [2]. Equation (28) corresponds to the model of Arsenis [3].

Vaurio [1] found, that (22) converges, if iteratively, results obtained for the expected value and the variance are reused as starting values. His approach is as follows.

Vaurio's approach for M and V

Weighted estimators m and v for expected value and variance of a sample $(\hat{\lambda}_1, ..., \hat{\lambda}_n)$ can be given as

$$m = \sum_{i=1}^{n} a_i \hat{\lambda}_i \tag{29}$$

and $v = \dfrac{n}{n-1}\sum_{i=1}^{n} w_i(\hat{\lambda}_i - m)^2$ (30)

Vaurio [1] estimates M and V using M_c and V_c as defined below:

$$M_c = M_0 + \frac{\delta}{T^*} \tag{31}$$

$$V_c = \frac{M_c}{\frac{M_0}{V_0}} = \frac{M_c}{y_0} = V_0 + \frac{\delta}{(y_0 T^*)} \tag{32}$$

where:

$$M_0 = m \tag{33}$$

$V_0 = v + \frac{M_0}{T^*}$; with T^* =T-max (T_i) mit $T = \sum T_i$ (34)

$$\delta = \begin{cases} 0 & \text{for an optimistic estimate} \\ \frac{1}{2} & \text{for a realistic estimate} \\ 1 & \text{for a conservative estimate} \end{cases} \tag{35}$$

These estimators are biased, but they are consistent, as the bias will disappear for n→∞ resp. T→∞.

Vaurio [1] presents two reasons to introduce these biases:

- To avoid negative results for sample variance, which can e.g. appear using Spjøtvol's measure.
- To provide consistent treatment for the case of identical data, i.e. N_1= N_2=...= N_n und T_1 =T_2 =...=T_n.

He demonstrated, that this approach leads to known results from classical theory of statistical estimation in case of identical data

The iterative algorithm to determine the estimators defined above is given in the following section of pseudo code.

Note, that, as opposed to Arsenis [3] and Spjøtvol [2], Vaurio [1] uses no initial estimates for the expected value E{Λ} and the variance Var{Λ} to find optimal coefficients according to equation (22), but an iteration. As starting values for this iteration, $a_i = \frac{1}{n}$; i=1,...,k can be used.

Algorithm of Vaurio's [1] procedure of estimation:

1. $T = \sum T_i$

2. $T^* = T - \max(T_i)$

3. $m = \sum_{i=1}^{n} \frac{w_i K_i}{T_i}$

4. $S = R \sum_{i=1}^{n} w_i \left(\frac{N_i}{T_i} - m \right)^2$, where $R = \frac{1}{1 - \sum_{i=1}^{n} w_i^2}$

5. $M_0 = m$

6. $V_0 = S + \frac{M_0}{T^*}$

7. $u_i = \frac{T_i}{T_i + \frac{M_0}{V_0}}$

8. $w_i = \frac{u_i}{\sum_{j=1}^{n} u_j}$

9. Iterate steps 3-8 until V_0 and M_0 converge

10. $y_0 = \frac{M_0}{V_0}$

11. $x_0 = \frac{M_0^2}{V_0} - 1$

12. $y_c = y_0$

13. $x_c = x_0 + \frac{\delta y_0}{T^*}$

$$\delta = \begin{cases} 0 & \text{for optimistic estimate} \\ \frac{1}{2} & \text{for realistic estimate} \\ 1 & \text{for conservative estimate} \end{cases}$$

15. $M_c = M_0 + \frac{\delta}{T^*}$

16. $V_c = \frac{M_c}{y_0} = V_0 + \frac{\delta}{y_0 T^*}$

Using PREB for CCF calculations

In case of CCF, the moment based methods can be used. However, in CCF analysis, fractional numbers of failure occur, which express uncertainty of experts, what multiplicity of CCF is given by the events. For these fractional number of failures (which in fact are the components of the impact vectors of the events), the assumption of a Poisson distribution obviously makes no sense. Vaurio in [5] suggests an approach, which determines of an equivalent pair of number of events and observation time, which – used under the assumption of the Poisson distribution

– will lead to the same moments, as the original data, which is distributed by a linear mixture of gamma distributions.

These equivalent values are given as [5, also 6]

$$\hat{N}_{k/n}(i) = \frac{\left(\sum_{j=1}^{N_i} w_j\right)^2 + \delta \sum_{j=1}^{N_j} w_j^2}{\delta + \sum_{j=1}^{N_i} w_j \left(2 - w_j\right)} \tag{36}$$

$$\hat{T}_n(i) = \frac{\delta + \sum_{j=1}^{N_i} w_j}{\delta + \sum_{j=1}^{N_i} w_j \left(2 - w_j\right)} T_n(i) \tag{37}$$

Here, w_j is the component of the impact vector of an event. These weights are summed over all events in a sub population. Also, the sum of the squares of these weights is needed as input. Given these weights, the normal moment based method can be used.

Literature

[1] Vaurio, J. K. On Analytic Empirical Bayes Estimation of Failure Rates, Risk Analysis, Vol. 7, No. 3,1987.

[2] Spjøtvol, E., Estimation of Failure Rate from Reliability Data bases. Paper presented at the SRE Symposium, Trøndheim, Norwegen, 1985.

[3] Arsenis, S. P., Procaccia, H., Aufort, P., European Industry Reliability Data Bank, 3rd Edition, Crete University Press, 1998, ISBN 2 95 09092 0 5.

[4] Robbins, H., An Empirical Bayes Approach to Statistics. Proc. 3rd Berkeley Symp. Math Statist. Prob., I:157, 1956.

[5] Vaurio, J. K. From failure data to CCF – rates and basic event probabilities, NEA/CSNI/R(2001).

[6] Vaurio, J.K. Quantification of common cause failure rates and probabilities for standby-system fault trees using international event data sources. Proc. 6th Int. Conf. PSAM 6, 23-28 June 2002, San Juan, Puerto Rico. Vol.1, pp.31 – 37. (Editors E.J. Bonano et al), ELSEVIER Science Ltd, Amsterdam, 2002.

Günter Becker, RISA Sicherheitsanalysen GmbH, 24.9.8
With corrections by J.K. Vaurio 29.9.08.

Attachment 4-2

Vaurio, Jussi. *PREB estimation method and validations*, PROSOL-8004.

Nordic-German working group on common cause failure analysis
Contribution on Phase 2 Task 2

12.6.2008

PREB estimation method and validations

PREB (Parametric Robust Empirical Bayes) estimation method is designed for estimating failure rates (frequencies), initiating event rates and failure probabilities per demand (opportunity), when failure or degradation event data is available from one or more units (components, systems or plants). The method is fully described in **Appendix I** (specifically in Section 2 and Appendix A), which is a reproduction of the peer-reviewed article manuscript:

"Evaluation and comparison of estimation methods for failure rates and probabilities", Reliability Engineering and System Safety (RESS) 91 (2006) 209-221, with the corrigendum in RESS 92 (2007) 131.

The method in relation to CCF has been described in the Survey of Fortum methodology (Kalle Jänkälä, December 2006) and in PROSOL 7001 (rev 1) 2007, contributions in this project, Phase 1.

Validation

The following text is a summary of validations made for the parametric robust empirical Bayes estimation method and procedure PREB, most comprehensively described in Ref. [1].
The method estimates a sampling/prior distribution by a moment matching method. This version is only slightly different from the early version [2] to account better for special cases like identical zero failure data. Already the early version was shown to have many attractive theoretical, small sample and asymptotic properties (Chapter 3 in [2]). The method has a "free" parameter δ that a user can adjust, between 0 and 1. In special cases (identical or pooled data) the "optimistic" value $\delta = 0$ is basically consistent with the classical lower bound confidence (or prior inversely proportional to the failure rate), the "conservative" value $\delta = 1$ is consistent with the upper bound (or uniform prior), and the "compromise" $\delta = ½$ (recommended) is consistent with the Jeffreys non-informative prior (inversely proportional to the square root of failure rate). Some other characteristics of the method:

- A solution exists for all practical (non-negative) observations.
- Asymptotically for increasing sample size or observation times the relative value of bias terms diminishes. (Bias terms prevent underestimation of variances for special cases of clustered data.)
- With identical individual maximum likelihood estimates (which are a rare event) the method yields the parameters of pooled data for the unit with the longest observation time. For other units the uncertainties are larger.
- The sample mean is an unbiased estimate of the mean value of the prior.
- The recommended weights minimize the variance of the sample mean, and yield posterior mean values consistent with Stein's shrinkage-estimators, and tend to minimize the sum of squared errors of the posterior mean values.
- Optimal weights are the same for all values of δ.

Table 1 of [1] and Tables II and III of [2] illustrate that the method works logically for small samples of sizes 2 with few failures and with many failures, and for $\delta = 0$, ½ and 1.

Comparisons of PREB to so-called two-stage methods have been published in [1]. The first comparisons in Tables 2 and 3 of [1] are with a Dirichlet method [3]. The results show that PREB is less optimistic (i.e. more conservative) than Dirichlet for a unit with zero failures. For a unit with the largest number of failures the mean values of the methods agree within 15%, the fractiles (5%, 50% and 95%) within 10%.

The next set of comparisons in Tables 7,8 and 9 of [1] were made using three data sets used earlier in [4]. Comparisons were made to a two-stage method that used four different hyper-priors called "uniform", "Pörn", "Jeffreys" and "ZEDB". Since there is no basis to claim one method as the "right one" or better than the others, one can only compare the results to see if PREB yields results reasonably within the variations of the other methods:

Median values:

- For data set 1, PREB and ZEDB are about equal, 10-15% lower than the others.
- For data set 2, PREB is about 20% below and ZEDB 20% above "uniform", "Pörn" and "Jeffreys", which are about equal.
- For data set 3, PREB is in the middle of the variation of others.

95th percentile: PREB is well within the variation for data sets 1 and 2. For data set 3 PREB (δ=½) and ZEDB are about equal, slightly higher than the others.
The 5th percentile is generally highest for ZEDB and smallest for PREB. 5th percentile is not generally used for any decision making.

Ref. [4] used also log-normal prior distributions with the same hyper-priors mentioned above. The 50th and 95th percentiles were all different and non-conservative compared to PREB. Log-normal priors seem to reduce all quantiles compared to gamma priors, and the variation between different versions is large. This is unfortunate for a user who has to choose a method.

Table 10 of [1] compares posterior estimates obtained with three methods, HP2SB used in [5], PREB, and the third one using simply the non-informative prior. HP2SB is a variant of the original two-stage method introduced by Kaplan around 1983. HP2SB and PREB are mutually rather consistent, except in one small sample case (3 units) where the prior is sensitive to a single value. HP2SB draws the highest failure rate more down towards the average rate of the other units, as illustrated by Fig. 1 in [1] for data taken from Table B.2 of [6].

Finally, Table 11 of [1] compares PREB to several methods in five simulation examples used in [7] where actually **the true values of the rates were known**. The number of units in these examples was 20. With PREB the median values were within 3% of the known true values in four cases, and the 95th percentiles were equally close in all five cases, and these were about as good as any of the methods used in [7]. (There was no method in [7] universally better than the others.) The accuracy of PREB got worse when the error factor (ratio of the 95th percentile and the median) of the prior became 4 or higher, but all methods had great difficulties in estimating the 5th percentile in such diffuse cases.

The examples confirm that PREB has no significant bias and behaves as well as or better than other known methods. It preserves the population variability and yields credible prior and posterior estimates.

Ref. 1 also contains comparisons and validation examples about failure probabilities per demand.

[1] Jussi K. Vaurio, Kalle E. Jänkälä: Evaluation and comparison of estimation methods for failure rates and probabilities. Reliability Engineering and System Safety 91 (2006) 209-221. Two typographical corrections published in a corrigendum, Reliability Engineering and System Safety 92 (2007) 131.
[2] J.K. Vaurio: On Analytic Empirical Bayes Estimation of Failure Rates. Risk Analysis, Vol. 7, 1987, No. 3, 329-338.
[3] Bunea C, Cooke RM, Mazzuchi TA: A non-parametric two-stage Bayesian model using Dirichlet distribution. Proceedings of ESREL 2003, Bedford and van Gelder (Eds), vol. 1, 331 – 337. A.A.BALKEMA, Lisse, 2003.
[4] Bunea C, Charitos T, Cooke RM, Becker G: Two-stage Bayesian models – application to ZEDB project. Proceedings of ESREL 2003, Bedford and van Gelder (eds), vol. 1, 321 – 329. A.A. BALKEMA, Lisse, 2003.
[5] Hofer E & Peschke J: Bayesian modeling of failure rates and initiating event frequencies. Proceedings of ESREL'99 Conference held in Munich, Germany, Schueller and Kafka (eds), Balkema, Rotterdam, vol. 2, 881-886, 1999.
[6] Hofer E, Hora SC, Iman RL, Peschke J. On the solution approach for Bayesian modeling of initiating event frequencies and failure rates. Risk Analysis 17(2) 249-252, 1997.
[7] Meyer W Hennings W. Prior distributions in two-stage Bayesian estimation of failure rates. Proceedings of ESREL'99 Conference held in Munich, Germany, Schueller and Kafka (eds), Balkema, Rotterdam, vol. 2, 893-898, 1999.

Appendix I

Manuscript reproduction of article in Reliability Engineering and System Safety 91 (2006) 209-221:

Evaluation and Comparison of Estimation Methods for Failure Rates and Probabilities

Jussi K Vaurio[a,*] , Kalle E Jänkälä[b]

[a]*Fortum Power and Heat Oy, POB 23, 07901 Loviisa, Finland*
[b]*Fortum Nuclear Services, POB 10, 00048 Fortum, Finland*

Abstract

An updated parametric robust empirical Bayes (PREB) estimation methodology is presented as an alternative to several two-stage Bayesian methods used to assimilate failure data from multiple units or plants. PREB is based on prior-moment matching and avoids multi-dimensional numerical integrations. The PREB -method is presented for failure-truncated and time-truncated data. Erlangian and Poisson likelihoods with gamma prior are used for failure rate estimation, and Binomial data with beta prior are used for failure probability per demand estimation. Combined models and assessment uncertainties are accounted for. One objective is to compare several methods with numerical examples and show that PREB works as well if not better than the alternative more complex methods, especially in demanding problems of small samples, identical data and zero failures. False claims and misconceptions are straightened out, and practical applications in risk studies are presented.

Keywords: Bayes, beta, binomial, empirical, estimation, failure rate, gamma, parametric, Poisson, two-stage

---

1. Introduction

This paper compares important features of several Bayesian estimation techniques developed to assimilate data from multiple units to obtain effective estimators for failure rates of individual units. Typical observables are numbers of failures that obey Poisson distribution, depending on the failure rate and the observation time for each unit. The mainstream estimation method in recent years has been the hierarchical Bayes approach [1-4]. Associated methods are "two-stage" super-population methods [5,6] in which the choice of a hyper-prior and the order of integrations have been subject to comparative studies and controversy. Hofer et al.[7] noticed that the results obtained with the method are sensitive to the order and ranges of multidimensional integration, and in the limit the results behave as if the components (or plants) were completely identical. Such lack of variation was also noticed in a common-cause failure study [8]. Becker and Schubert obtained suspicious results with the 2-stage method [9]. Meyer and Hennings [10] studied the impacts of different forms of the improper hyper-priors and integration limits. Hofer and Peschke re-formulated the method so that the population variability is better accounted for [11]. Bunea et al [12] claim that this approach still has some mathematical problems, and the choice of super-population and integration ranges are not uniquely established. One disadvantage with all these 2-stage-methods is that numerical or Monte-Carlo simulation methods are needed to calculate multidimensional integrals. This can be a burden with hundreds of components in realistic risk assessment studies (PSA). Even if powerful computers can do such tasks [2], it is worth studying if simpler formalisms can produce equally accurate or at least satisfactory results for practical purposes.

*Corresponding author. Tel.: +358-10-4554700; fax: +358-10-4554435
E-mail address: jussi.vaurio@fortum.com

One 2-stage variant is an analytical formulation based on Dirichlet distributions [13]. It is mathematically simple and claimed to be non-parametric. Nevertheless, it requires a number of cells and boundary parameters to be subjectively selected. Thus, it seems that there are some ad-hoc features and subjective choices in all 2-stage methods, and therefore room for alternative simple, less opaque techniques.

Another line of development has been the parametric empirical Bayes (PEB) method in which the prior distribution parameters are estimated by the maximum likelihood or by matching moments [14,15]. Although these often work well enough, they can brake down or yield peculiar results in special cases e.g. when data is scarce or indicates little or no variation between units.

An alternative one-stage Parametric Robust Empirical Bayes method PREB is presented and tested in this paper. It is based on prior moment matching with additional bias terms. Optimal weights are used in moment equations, and the bias terms are selected so that the result is in a way a compromise between ordinary PEB and using a non-informative prior. It is robust in the sense that credible results are obtained even in most demanding cases of small samples and no variation. This method uses analytic closed-form equations, avoids complex numerical integration and has several theoretical and numerical advantages as demonstrated in applications and special cases like small samples, identical data on all plants, and failure-free cases. Even if the basic method was presented in the 1980's for estimating both failure rates [16,17,18] and failure probabilities per demand [19,20,18], it doesn't seem familiar to many practitioners. The methodology is presented in Section 2 with the latest refinements and recommendations. The main objective is to point out the important features and advantages, and to show with examples that PREB is equal or possibly better than most alternatives suggested so far. Comparisons with the 2-stage Dirichlet approach and various other numerical 2-stage methods are presented in Section 3. Applications of PREB in practical reliability and risk studies are described in Section 4. A summary and conclusions are presented in Section 5.

Notation and acronyms

$Y \sim \chi^2(K)$ Y obeys chi-squared (χ^2-) distribution with K degrees of freedom

g(z;x,y) gamma distribution probability density of random variable Z with values z

$$g(z;x,y) = y\frac{(zy)^{x-1}}{\Gamma(x)}e^{-zy},\ z,x \geq 0,\ y > 0.$$

G(z;x,y) $\int_0^z g(z';x,y)dz' = \int_0^{yz}\frac{u^{x-1}}{\Gamma(x)}e^{-u}du$

PSA Probabilistic safety assessment

Scale parameter y is a scale parameter when the cumulative distribution of an observable Z with values z depends only on the product yz or the ratio z/y.

2. Methodology

2.1 Single unit and failure truncation

Consider a single component with a constant failure rate λ. The time t_1 to the first failure is then exponentially distributed with the mean value $1/\lambda$. The sum t_K of K independent lifetimes obeys cumulative Erlangian (gamma) distribution $G(t;K,\lambda)$ with the mean value K/λ and the variance K/λ^2. This is also the distribution of the time to the K^{th} failure when the repairs or replacements are prompt (or the repair times are deducted from the total time count). When λ is the unknown to be estimated, the data collection setup is called *failure-truncated* when K is known or pre-set, and t_K is the observed continuous random variable.[1] Then the classical confidence bounds of λ are the quantiles of $G(t_K;K,\lambda)$, now considered the cumulative distribution of λ. Then one can say that classically λ has a confidence or fiducial density $g(\lambda;K,t_K)$, which is the absolute value of the derivative $\partial G(t_K;K,\lambda)/\partial\lambda$. Now this happens to be a gamma distribution with the mean value K/t_K and the variance K/t_K^2. The relationship between gamma and χ^2 –distributions is such that this is equivalent to saying that $2\lambda t_K \sim \chi^2(2K)$, independent of whether λ or t_K is considered the random variable.

[1] Note: In this setup it is of no additional value to know the individual failure times. The sum t_K contains all information about λ because the likelihood depends only on t_K, which is therefore called a *sufficient* statistic.

In a Bayesian formalism the posterior density of λ is proportional to a prior density and the likelihood $G'(t_K;K,\lambda) = \partial G(t_K;K,\lambda)/\partial t_K$. It can be shown that the above "classical" density $g(\lambda;K,t_K)$ for λ is obtained as a posterior when the prior density is selected inversely proportional to λ. This is a gamma density $g(\lambda;0,0+)$, even if improper (non-normalized). Actually, the "classical" density of a scale parameter can always be obtained as a posterior with the Bayes method by selecting the prior inversely proportional to the parameter. In case of Erlangian likelihood this happens to be the non-informative prior as defined by Jeffreys [21].

Thus both classical and Bayesian formalisms yield the estimator $\lambda \sim \chi^2(2K)/(2t_K)$ when data is available only from one unit.

2.2 Single unit data and time-truncation

Consider again a single component with a constant failure rate λ. An alternative to failure truncation is *time-truncation.* Then the observation time T is known or pre-determined and the number of failures during T is the discrete random variable K. In this case the exact time to the K^{th} failure is not known, and the confidence limits (or the prior) are not quite unique as in the failure-truncated case. A heuristic approach to define the bounds is as follows. The "optimistic" bound is obtained assuming that the K^{th} failure occurred just at T-. The "conservative" bound is obtained assuming that the $(K + 1)^{th}$ failure would occur at T+. In light of the previous Section these correspond to $\lambda \sim \chi^2(2K)/(2T)$ and $\lambda \sim \chi^2(2K+2)/(2T)$, respectively. In the Bayesian formalism these correspond to prior densities $\sim 1/\lambda$ and $\sim$ constant (uniform), respectively.

The same can be obtained more explicitly as follows. With prompt repairs the number K of failures in observation time T obeys the Poisson distribution probability

$$P(K;\lambda T) = P(K|\lambda T) = \frac{(\lambda T)^K}{K!}e^{-\lambda T}, K = 0,1,2,... \quad (1)$$

with the mean value and the variance of K both equal to λT. The maximum likelihood estimate (MLE) of λ is K/T. The conventional classical confidence limits are defined by the quantiles of the cumulative sum of the terms (1) up to the observed K, and from K upwards. The corresponding classical densities of λ are the derivatives of these sums with respect to λ. As a result λ has a gamma distribution, the density of which conditional on observed $K \geq 0$ in time $T > 0$ is

$$g(\lambda;K+\delta,T) = T\frac{(\lambda T)^{K-1+\delta}}{\Gamma(K+\delta)}e^{-\lambda T}, \qquad \lambda \geq 0, \quad (2)$$

the mean value $(K+\delta)/T$ and the variance $(K+\delta)/T^2$. The "conservative" value $\delta = 1$ is consistent with the classical upper confidence bounds while the "optimistic" value $\delta = 0$ is consistent with the lower bounds. The realistic "compromise" version has $\delta = ½$ (see note[2]).

In the Bayesian formalism the posterior (2) is proportional to a prior density and the likelihood (1). Thus, the consistent prior density is proportional to $\sim\lambda^{\delta-1}$, $0 \leq \delta \leq 1$. This is improper (not normalized to unity) but still used in the Bayesian formalism. The compromise case $\delta = ½$ happens to be the Jeffreys non-informative prior for a Poisson likelihood.

---

[2] Note: Rather than pick a single value for δ one may consider it uniformly distributed between 0 and 1 in a large number of estimation tasks. Then the posterior would be the integral of (2) over δ, approximately equal to $\frac{1}{4}g(\lambda;K,T) + \frac{1}{2}g(\lambda;K+½,T) + \frac{1}{4}g(\lambda;K+1,T) \cong g(\lambda;K+½,T)$. This is another reason to recommend $\delta = ½$, besides being consistent with Jeffreys non-informative prior.

2.3 Multiple units

A common task is to estimate the failure rate of a specific unit, or rates of all n similar components when data is available as pairs (K_i,T_i), K_i failure events observed in time T_i for component i, i = 1,2,…,n. A fundamental assumption here is that these n components are independent samples from the same population so that the failure rates λ_i are independent samples from the same density $g(\lambda;x,y)$ with some fixed parameters x,y. This is the case e.g. if the components are made by the same factory, perhaps even used in similar environments, like four redundant pumps in a power plant. Another example is n similar steam generators at several different power plants: there is enough similarity to assume a common population density $g(\lambda;x,y)$.

The theory of conditional probabilities says that when λ_i of component i is sampled from a common population density $g(\lambda;x,y)$ and the observed number K in time T_i obeys the likelihood or conditional probability $P(K;\lambda_i T_i)$, the conditional density of λ_i, given $K = K_i$ in T_i, is proportional to the product $P(K_i;\lambda_i T_i)\, g(\lambda_i;x,y)$, i.e.

$$p(\lambda_i \mid K_i, T_i) = P(K_i;\lambda_i T_i)g(\lambda_i;x,y) / \int_0^\infty P(K_i;\lambda T_i)g(\lambda;x,y)d\lambda \quad (3)$$

As a flexible density we assume a gamma density, conjugate to Poisson likelihoods:

$$g(\lambda; x, y) = y\frac{(\lambda y)^{x-1}}{\Gamma(x)}e^{-\lambda y}, x \geq 0, y > 0. \tag{4}$$

The moments exist when y > 0,

$$\text{mean value} \quad M = \frac{x}{y}, \quad \text{variance } V = \frac{x}{y^2}. \tag{5}$$

With Poisson likelihood (1) and gamma prior (4) Eq. 3 yields the posterior gamma equal to $g(\lambda_i; K_i + x, T_i + y)$, Eq. 4 with x replaced by $K_i + x$ and y replaced by $T_i + y$. The posterior mean value and variance are then

$$\mathrm{Mean}(\lambda_i) = (K_i + x)/(T_i+y), \qquad \mathrm{Var}(\lambda_i) = (K_i + x)/(T_i+y)^2 \tag{6}$$

The same results are obtained if K_i are known and T_i is the observed time to K_i^{th} failure. Only the Poisson likelihood in (3) is replaced with the Erlangian distribution.

When x and y are not known in advance, there are following possibilities:

A. If there is no other relevant information available about similar components (n = 1), one can justify the prior "density" $g \sim \lambda^{-½}$ (i.e. $x = \delta = ½$, $y = 0$) for time-truncation, and $g \sim \lambda^{-1}$ for failure-truncation. These are Jeffreys non-informative priors for Poisson and Erlangian likelihoods, respectively.

B. If there is data (K_i,T_i) available from altogether n >1 (i = 1,2,…,n) similar components (plants), one has at least two avenues available:

B1. Both hierarchical and 2-stage Bayes methods define distributions (hyperpriors) for x and y (hyperparameters). The 2-stage Bayes procedures single out one of the components as the only one of interest, and replace $g(\lambda;x,y)$ in (3) with another function that is not anymore a gamma density and depends on all other data except (K_i,T_i), the data of the unit of interest. This method essentially has a different sampling density of λ_i for each component or plant i (i = 1,2,…n). Some 2-stage methods use log-normal prior densities in the same way.

B2. An alternative is to stick with the assumption of a gamma sampling (prior) distribution in Eq. 3, common to all i, and estimate x and y the best way possible. Then one can estimate all n posterior distributions with the same prior. Ordinary PEB methods and also PREB belongs to this category. It solves parameters x and y of the prior distribution by matching two moments with the empirical moments of the individual maximum likelihood estimators K_i/T_i. The first versions of this method were published in 1986 for Poisson [16] and binomial observables [19,20] and refined in 1987 [17,18]. In the following the method is summarized for gamma-prior and Poisson and Erlang likelihood functions.
The key idea in PREB is to use a biased positive variance estimate to guarantee realistic solutions even in case the empirical variance happens to be small. Some of the following equations are results of inductive reasoning and may look peculiar at first, but at the end one can confirm excellent asymptotic and small-sample properties. Special cases are consistent with non-informative prior densities as well as with classical confidence limits.

2.4 PREB Procedure

The following PREB procedure yields estimates x_c, y_c, M_c, V_c for x, y, M, V, respectively.

1^o If data is available only from the plant of interest, n = 1, select $y_c = 0$ and $x_c = \delta$, $0 \le \delta \le 1$; recommended value is $\delta = ½$.[a] Go to 12^o.

If $n > 1$, determine $T = \sum_{i=1}^{n} T_i$ and select the initial weights all $w_i = 1/n$,

or $w_i = T_i/T$, i = 1, 2,...,n. [b]

2^o $T^* = T - \max(T_i)$.

3^o $m = \sum_{i=1}^{n} w_i \frac{K_i}{T_i}$; If m = 0 select a small positive ε and $m = \varepsilon/T^*$. [c]

4^o $$v = \frac{1}{1-\sum_{i=1}^{n} w_i^{\,2}} \sum_{i=1}^{n} w_i \left(\frac{K_i}{T_i} - m\right)^2 + \frac{m}{T^*}$$

5^o $u_i = \frac{T_i}{T_i + m/v}$ for i = 1, 2,. .. , n

6^o $w_i = u_i / \sum_{j=1}^{n} u_j$ for i = 1, 2,…, n

7^o Iterate 3^o through 6^o (unless all T_i are equal) until m and v converge

8^o $y_0 = \frac{m}{v}$, $x_0 = \frac{m^2}{v} = m y_0$

9^o Select $\delta = 0$ (“optimistic”), $\delta = ½$ (“compromise”) or $\delta = 1$ (“conservative”) [a]

10^o $x_c = x_0 + \delta \frac{y_0}{T^*}$, $y_c = y_0$

11^o Prior moments: $M_c = m + \frac{\delta}{T^*}$, $V_c = v + \frac{\delta}{y_0 T^*}$

12^o The posterior densities are $g(\lambda_i; K_i + x_c, T_i + y_c)$.

---

[a] With failure truncation select $\delta = 0$.
[b] Recommended normalized initial values are $w_i = (T + nT_i)/(2nT)$.
[c] Or set $v = 0$, $y_0 = T^*$, $x_0 = 0$ and go to 9^o.

The posterior gamma distribution moments are as in Eq. 5 with $x = x_c$ and $y = y_c$. Obviously this procedure can be used for any $n \geq 1$. Steps 5^o and 6^o produce near-optimal minimum variance weights, exactly so if m and v were exactly M and V, yielding minimum variance prior and posterior estimates [17,22]. The bias terms due to δ disappear asymptotically when n or T* increase.

Advantages of this procedure are:

(a) With increasing n or T the influence of the bias terms asymptotically diminishes and the moments are asymptotically unbiased. This is a desirable property of any acceptable method.

(b) The method yields reasonable solutions for all possible observations, i.e. special cases like small sample (n = 1 or 2), and equal values of K_i/T_i, even zero failures (m = 0). This is the main reason for calling the method "robust" PEB.

(c) With identical observations K_i/T_i (which are quite possible with small samples) the unit with the largest T_i has the same posterior distribution as the case of pooled data, i.e. observing $K = \Sigma_i K_i$ failures in total time T (assuming identical units) with the same prior (same δ);

- The conservative case $\delta = 1$ is consistent with the classical upper confidence bounds;

- The optimistic case $\delta = 0$ is consistent with the classical lower confidence bounds.

The components with shorter T_i have larger relative uncertainties, as expected.

(d) The weights minimize the variance of the sample (prior) mean value estimate m, and have other near-optimal properties, e.g.: the ideal weights proportional to $T_i/(T_i+M/V)$ and the shrinkage factors $B_i = M/(M + VT_i)$ together yield the minimum mean square error of the shrinkage estimators $l_i = (1 - B_i)K_i/T_i + B_i m$. [17,22]

(e) All quantiles of the prior and posterior distributions are in the order of δ:
optimistic $\leq$ compromise $\leq$ conservative

(f) The iteration steps 3^o to 6^o need not be repeated for other values of δ after the procedure has been performed once (e.g. for the optimistic $\delta = 0$).

(g) The posterior mean values (Eq.6) can be presented as Stein's shrinkage-estimators

$$\text{Mean}(\lambda_i) = (1 - B_i)K_i/T_i + B_i M, \qquad B_i = M/(M + VT_i). \qquad (7)$$

Thus, the sample MLE estimates with small T_i move more towards a common value M. This particular B_i minimizes the mean square error of the posterior mean. This property and (d) are merits even if M and V are known only approximately, as M_c and V_c.

In summary, the method in essence automatically agrees with Jeffreys prior to pooled data when the data show no between-unit variation, and it agrees with minimum variance moment matching PEB when the data show a lot of between-unit variability.

2.5 Estimating probabilities per demand

The formalism presented so far applies equally to normally operating components and to standby components as long as failures occur at random times, as modeled by failure rate parameters λ_i. This is not always the case with safety system components that are normally on standby and activated periodically to test if any failures entered since the previous test. These activations can consist of starting up pumps or diesel generators, and opening or closing valves or switches. These activations are "test-demands" for a unit, and there can also be "true demands" associated with actual initiating events that call a safety system into action. If the demands themselves can cause wear or other mechanisms to fail component i, it is appropriate to model this with some probability q_i per demand to fail the component. When this probability is constant from demand to demand, the number of failures observed in N_i demands obeys binomial distribution. Recording such data facilitates estimation of the probabilities q_i. A moment-matching PREB- formalism is presented in Appendix A for estimating these failure probabilities per demand from binomially distributed observations when the sampling (prior-) distribution is a beta distribution. This method is slightly improved from [20,18] and has similar favorable properties as the method for failure rates in Section 2.4.

2.6 Combined models

Periodically tested standby components have potentially two kinds of stresses and associated failure mechanisms:

* *Time-related stresses* can cause failure at random time: a random shock, or corrosion, thermal ageing, creep, embrittlement, continuous vibration, fatigue and wear, random external loads or chemical attacks, dust and dirt. These are properly modeled by a probability per unit time, i.e. by failure rate λ_i, even if the failures usually remain unrevealed until a test-demand.

* *Demand-related stresses* cause faults or degradation only during startup and test runs that are short compared to test intervals: wear due to cold startup or rotation or switching in tests, crack propagation or loosening due to startup shocks, chemical or other environmental changes during tests. These are properly modeled by a probability per demand, i.e. by probability q_i.

One should notice that both types of failures are typically observed only in periodic tests, as a failure to start or switch, or as a failure to run in a short time after a start. Repairs are then carried out immediately.

When both stresses are possible for the same component, the total probability of a failed state at time t after a test can be presented as $q_i + (1 - q_i)[1 - \exp(-\lambda_i t)] \cong q_i + \lambda_i t$, as a first approximation. (In reality, both λ_i and q_i may depend on the age of a unit.) This form assumes that both terms are small compared to unity, and the test and repair durations are short compared to the test interval. Both q_i and λ_i need to be estimated from failure events observed in N_i observations (e.g. tests) during observation time T_i. This means that one has to assess the symptoms and characteristics of every failure event to determine whether it occurred due to time-related stresses or demand-related stresses. Then one can count the corresponding numbers $K_{\lambda,i}$ and $K_{q,i,}$ of failures, respectively. The rates λ_i can then be estimated using $K_{\lambda,i}$ and T_i for each unit in the method of Section 2.4. The probabilities q_i can be estimated using $K_{q,i}$ and N_i in the method of Appendix A. Thus, the basic methodology exists if and when one can determine about every failure whether it occurred due to time- or demand- related stresses.

2.7 Uncertainties in data assessment

Event symptoms and documentation are not always clear enough to determine with certainty whether an event was a failure and was it due to time-related or demand-related failures. What the analyst can do is to assess his or her degrees of confidence about the alternatives. More specifically, the analyst should assess the following weights or probabilities for each observation k of each unit i ($k = 1, 2, ..., N_i$):

$u_{\lambda;i;k}$ [$u_{q;i;k}$] = the probability (conditional on the symptoms and characteristics observed) that observation k (at unit i) is a failure and the failure is caused by time-related [demand-related] stresses; $0 \le u_{\lambda;i;k}$ [$u_{q;i;k}$] ≤ 1.

Both stresses can be involved in a single observation, although this is rare. The causes need not be mutually exclusive even if only one failure can materialize in a single observation.
Assuming that not more than one event of each kind can occur within one observation, one can calculate the expected numbers $E(K_i)$ and the variances $\sigma^2(K_i)$ as sums

$$E(K_i) = \sum_{k=1}^{N_i} u_{\lambda,i,k}\ , \quad \sigma^2(K_i) = \sum_{k=1}^{N_i} u_{\lambda,i,k}(1-u_{\lambda,i,k}) \quad \text{for time-related failures,}$$

$$E(K_i) = \sum_{k=1}^{N_i} u_{q,i,k}\ , \quad \sigma^2(K_i) = \sum_{k=1}^{N_i} u_{q,i,k}(1-u_{q,i,k}) \quad \text{for demand-related failures.}$$

An approximate method is to use the expected numbers as K_i in the Bayesian procedures (Section 2.4 and the Appendix), but this method underestimates the uncertainties. Because the true values K_i are not exactly known, a more accurate method is to determine the *effective* observables K_i and T_i so that both statistical and assessment uncertainties are correctly accounted for. This method, analogous to the one derived earlier for common cause failures [23,24] justifies the following effective observables for each plant, individually and for the Bayesian procedure:

$$T_{i,eff} = \frac{\sum_{k=1}^{N_i} u_{\lambda,i,k}}{\sum_{k=1}^{N_i} u_{\lambda,i,k}(2-u_{\lambda,i,k})} T_i\ , \qquad K_{i,eff} = \frac{\sum_{k=1}^{N_i} u_{\lambda,i,k}}{\sum_{k=1}^{N_i} u_{\lambda,i,k}(2-u_{\lambda,i,k})} \sum_{k=1}^{N_i} u_{\lambda,i,k} \qquad (8)$$

$T_{i,eff}$ is generally smaller than T_i , and $K_{i,eff}$ smaller than $E(K_i)$. No assessment (epistemic) uncertainty exist if each weight $u_{\lambda,i,k}$ is either 0 or 1. With a fixed $E(K_i)$ the uncertainty is largest when all weights are equal $u_{\lambda,i,k} = ½$.

3. Numerical tests

The PREB procedure is now applied to several examples to demonstrate the efficiency and to counter some criticism presented earlier against this method. Results are compared to those obtained with other comparable methods to show that PREB yields results that are not systematically biased and are well within the variations of other methods.

First, consider the posterior distribution characteristics of two examples with n = 2. The data and posterior mean values and standard deviations (SD) are given in Table 1 for three different methods and prior distributions. The first Mean and SD are obtained for each component (i = 1, 2) with the individual data and x = ½, y = 0. The next Mean and SD are obtained with the “compromise” version of PREB (δ = ½). PREB-GROUP uses Bayesian updating which is equivalent to "coupling" i.e. assuming the units absolutely identical and pooling data to obtain the common distribution. In Example 1 the mean values move only slightly towards a common mean value. Obviously PREB works for n = 2 and even with identical data K_i/T_i , and yields realistic values with SD smaller than in the individual non-informative cases. In Example 2 the maximum likelihood estimates are equal for i = 1 and i = 2, and the posterior mean values of the units are close to each other. However, PREB yields larger SD for unit i = 1 consistent with intuition because of more abundant data for unit i = 2. The cases n = 1 and all $K_i = 0$ are explicitly accounted for in steps 1^o and 3^o of the procedure, respectively. These results show that PREB can be used for n smaller than 3 and even in case all $K_i = 0$, contrary to the claims of [12,13].

Comparisons to recent applications with other data sets are presented next. The other estimation methods in these are several variants of the so-called 2-stage methods.

One controversial issue has been whether one should use all units in estimating a common prior distribution, or should one leave out the particular unit for which the posterior is calculated. It has been claimed that one should not use the same component data twice, once for estimating the prior, and again in calculation of the posterior distribution. Based on this Bunea et al [12,13] claimed that PREB overemphasizes data of the unit of interest and leads to the posterior too close to the point estimate; it therefore optimistically underestimates if the unit of interest has a smaller point estimate than the other units. For one thing, the following examples prove that such claims are not generally true.

3.1 Comparisons with a Dirichlet prior 2-stage method

An example from Table 6 of Ref.13 is presented in Table 2 comparing the Dirichlet 2-stage model results with PREB results, "compromise" version. This case has n = 6 but the posterior mean value and percentiles are given only for the sixth unit (marked plant 0). PREB results are more conservative and further away from the point value of the plant of interest (0) than the 2-stage Dirichlet results taken from [13]. Dirichlet rather than PREB is non-conservative for units with zero failures or smallest point value. Even the "optimistic" version of PREB yields the mean value 1.89E-4 larger than the 2-stage Dirichlet mean value 1.30 E-4.

Another case of Table 6 of Ref. 13 is presented in Table 3.

In this case the point value K_i/T_i of the unit of interest is larger than the values of other units. Again the PREB mean value and median are slightly further away from the point value of unit 0 than the corresponding Dirichlet results. Results and conclusions with the same values K_i but shorter times $T_i = 1000$ are quite similar.
Refs [12,13] thought that PREB (and other methods that use all the data to construct a prior) would double count the unit of interest and therefore overly weight the posterior toward the data of that unit. This does not seem to be the case.

3.2 Comparisons with ZEDB and different priors

Three data sets are used to compare the the results obtained with PREB to those obtained earlier with other methods [12]. The data sets are in Tables 4, 5 and 6. The underlined field is the unit for which posterior distributions are calculated ("plant of interest").

The results are listed in Tables 7 through 9 when gamma prior densities are used with four different hyper priors in the 2-stage methods (denoted by headings “uniform”, “Pörn”, “Jeffreys” and “ZEDB”) as defined in [12], and the compromise and conservative versions of PREB (heading “PREB”). Jeffreys hyper prior density was taken as $x^{-½}y^{-1}$, Pörns proportional to $y^{-1}[x(x + y/T)]^{-½}$, where T is some defined observation time, and in ZEDB the hyper prior has the range of (x,y) truncated to a finite rectangle.

ZEDB seems to yield the smallest and PREB the largest ratios of 95% and 5% quantiles.
The results show that the simple 1-stage method PREB yields the median and 95th percentile well within the variation of the other methods. Mostly PREB -results are close to the ZEDB –results, or between ZEDB and the other methods. The 5th percentiles are somewhat smaller with PREB than obtained with the other methods, but not far from the next smallest alternative. One rarely if ever uses low quantiles for any decision making. The difference of the conservative and compromise PREB (δ=½ and δ=1) is generally small, except in Table 9, which is the case of scarce data shown in Table 6. The conservative version of PREB is not really justified or recommended.

Ref. [12] applied also lognormal prior distributions for λ and various alternative hyper-priors (Jeffrey’s rule applied to different parameterizations) to the same data sets 1, 2 and 3. The 50% and 95% quantiles of five lognormal versions (Tables 9, 10, 11 in [12]) were all different and all were non-conservative compared to the PREB –results obtained above. The same is true for the 5% quantiles of data sets 2 and 3. Only for data set 1 the 5% quantile is slightly smaller with PREB than with the other methods, yet within 10% of the value obtained with ZEDB. A general tendency in cases analyzed in [12] seems to be that log-normal priors reduced all posterior quantiles compared to gamma priors, leading to non-conservative direction. With a lognormal prior there was also a large variation between different versions (parameterizations). This is a problem for a practitioner as long as there is no way to know which version is best to use in applications.

3.3 Comparisons to earlier 2-stage methods

To further test the validity of the PREB method, the four examples of [11] were analysed. The results are summarised in Table 10 for the following three methods:

1. HP2SB, the modified 2-stage method suggested in [11],
2. PREB, the method being demonstrated here, and
3. non-informative prior density, proportional to $\lambda^{-½}$.

The first two methods are mutually consistent in Examples 1, 3 and 4, compared to the third (non-informative) method. The differences of HP2SB and PREB can be explained by the fact that the prior of HP2SB depends only on the other components (plants), not the one “under study”. In Examples 1 and 2, this feature draws the posterior of method HP2SB more towards the mean of the other two components (n = 3). This effect leads to particularly optimistic median values of HP2SB in Example 2.

Another example is based on data with n = 3 published by Hofer et al. [7], analyzed with several versions of 2-stage methods. Figure 1 shows the observations along the upper line and the posterior median values of the failure rates of component 3 along the lower line computed with 2-stage methods (old and new) and now with PREB also. OLD is the original 2-stage method [5,6] and NEW is the modified HP2SB used in Table 10, too. This shows that 2-stage methods tend to make unit 3 more equal to the other two components, while PREB does not underestimate as much. Data taken together does not intuitively suggest as much equality as claimed by the 2-stage methods, although this is still a matter of opinions to some extent.

.

Meyer & Hennings [10] carried out a simulation study with n = 20 and known x = α_o and y = β_o, and compared results with five different hyper-priors and integration limits. None of the 2-stage techniques was universally satisfactory or better than the others. The results now obtained with the PREB method are presented in Table 11 together with the results obtained with the known true values α_o, β_o and with the "best fit" in [10]. The 50% and 95% quantiles with PREB are about as good or better than the others obtained in [10]. The low end of the posterior ($\lambda_{0.05}$) seems to be most difficult to estimate correctly for observation 10 with any method. One should note that the "best" estimate in [10] was found only afterwards: no simple rule or criterion was yet found to select the hyper-prior and integration limits in advance to guarantee the optimum or suitability for all cases.

The examples confirm that PREB has no significant bias and generally behaves as well as or better than other defensible methods. It preserves the population variability and yields credible prior and posterior estimates.

3.4 Simulation studies with beta priors and binomial observations

The PREB -method for estimating prior and posterior distributions of the probabilities of failure per demand (q_i) based on the numbers of failures (K_i) in N_i demands at plants i (i = 1, 2,…,n) is presented in Appendix A. This method has been shown in [20] to have similar favorable features as listed in Section 2.4 for the gamma-Poisson method. The method has been compared with the Prior Moment Matching (PMM) method that was found by Shultis et al. in [5,27] to be the best among Weighted Marginal Matching Moments, Marginal Maximum Likelihood, Prior Maximum Likelihood and Unweighted Marginal Matching Moments methods. The comparisons in Ref. 27 were made as follows: (1) Prior parameters x and y were selected; (2) The number of trials N_i was sampled from a uniform distribution; (3) The number of failures K_i was sampled then from the beta-binomial distribution defined by x, y and N_i; (4) The values K_i, N_i were used to estimate the prior distribution parameters and posterior probabilities p_i. A large number of simulations proved that only PMM always yielded realistic estimators for x and y, and they were generally least biased. Simulations with the same cases using PREB indicated equal or smaller bias than PMM, especially for sample sizes n < 10. [20] Similarly with the variance, PMM had smallest variances in [27], and PREB even smaller for n < 10 in [20]. For prior parameters PMM had the smallest mean square errors in [27], and PREB seems to have also this property better than PMM [20]. The estimated failure probabilities obtained with PMM and PREB were compared in [20]. The results were close when data indicates clear between-unit variation. PMM yielded too small variances when observed point values were near each other. PMM yields no solution if the values K_i/N_i are equal, and one then usually assumes identical units and pools the data. PREB does not require pooling data even in such cases. PREB eliminates the need for statistical testing otherwise used to check whether pooling data is appropriate or not.

4. Applications

The following applications of PREB have been carried out as a part the PSA program for Loviisa power station:

1. *Component-specific* failure rates have been determined for most safety systems (emergency diesel generators, auxiliary feedwater pumps, safety injection system pumps, valves etc) using as a prior the population variability of similar redundant components (e.g. 8 diesel generators) on site. Altogether this has been done for more than 1500 components. The updating interval of these estimates ranges from one to few years. The same approach has been used since 1987 by utilising all currently available data, both the new and old observations. - Even nominally identical components can have rather different failure rates, sometimes even different trends. - Most if not all earlier PSA:s have assumed similar redundant components to have identical failure rates.

2. *Plant-specific* common-cause failure (CCF) rates for safety system components (pumps, valves diesel generators) have been determined using as a prior the plant-to-plant variability of corresponding CCF data on U.S. and Loviisa plants [25].

3. *Plant-specific* initiating event frequencies such as loss of coolant accidents, steam generator leakages, steam line breaks, safety/relief valve failures etc. have been determined using as a prior the population variability of similar events at relevant plants (PWR, VVER). Rates of reactor trips, loss of feedwater events, heat exchanger tube leakages, pump seal leakages and some pipe ruptures have been determined using as a prior the population variability of such events at the Loviisa units.

4. *Plant-specific and Operating State specific* initiating event frequencies have been estimated for the PSA of shutdown and low power states. These frequencies have been estimated separately for different plant operating states by taking into account only the observations of the relevant states. This approach showed considerable difference in the initiator frequencies per unit time e.g. for reactor trips in the steady state power operation and during stretch-out operation before shutdown.

5. *Plant-specific* fire probabilities for different buildings/room types have been determined using as a prior the population variability of such fires at U.S. nuclear power plants [26]. A partial example output of the computer code using PREB is presented in Table 12. Arbitrary code names are used for US plants to avoid identification. Available fire data did not always identify the plant where the fire occurred. Sensitivity studies were carried out by distributing the fires in different ways among the plants to verify that this had no significant impact on the estimated posterior rate for Loviisa plant.

5. Summary and conclusions

The PREB methodology for empirical Bayes estimation of failure rates and probabilities has been presented with the latest refinements, test examples and recommendations. Analytical and numerical simplicity and robustness for special cases are obvious advantages. In case of large between-unit variation the method approaches PEB, and in case of small between-unit variation PREB in a way approaches Jeffreys non-informative prior. This has been accomplished by using biased moment estimates and optimal weights. The prior moments could be used even with non-conjugate priors other than gamma or beta. The main objective here was to point out and demonstrate important features and to show with examples that PREB is equally effective and possibly more accurate than many alternative methods suggested so far. With many versions of the 2-stage methods and hyper-priors around, it is not quite possible to know yet which is the best method and in what sense. Even after several modifications there seem to be still open questions in the two-stage methods.

The PREB -method has some degree of freedom for a user: the time parameter T* (and N*) as defined is kind of maximal. It leads to a prior for the unit with the longest observation time T_i (N_i) as if all data can be pooled to that unit, if there is no between-unit variation in the observed point values. For other units with shorter observation times the method yields larger variances, but these could still be smaller than is actually warranted. On the other hand, other examples (e.g. Figure 1) show that PREB does not overemphasize equality. Further numerical studies could lead to improvements in the definitions of T* and N*. For the time being it is subject to judgment whether observed equal point values are equal accidentally or because the units really are identical. It is reasonable that equality of point values adds some degree of confidence to individual unit values, better than using non-informative priors to each unit individually. (This is illustrated by Example 2 in Table 1.)

One controversial issue has been whether one should use all units in estimating a common prior distribution, or should one leave out the particular unit for which the posterior distribution is calculated. Some statisticians favor the latter, even if it means a different sampling distribution for each unit. There is a somewhat dogmatic feeling that one should not use the same component data twice, once for estimating the prior, and again in calculation of the posterior distribution.[3] It has been claimed that PREB overemphasizes data of the unit of interest, leading the posterior too close to the point estimate, and therefore optimistically underestimates if the unit of interest has a smaller point estimate than the other units. Examples have now shown that this is not systematically true and that alternative 2-stage methods can be non-conservative, even for units with zero failures or smallest point value. PREB has also been shown feasible for small samples ($n < 3$) and in case of identical and failure-free data. Thus, many claims concerning possible drawbacks of PREB have been proven wrong. Current as well as earlier comparisons in [13] indicate that PREB quantiles are not systematically biased but are within the variations of other methods, and often close to those obtained with most recommended methods. Numerical studies have given no reason to reject the PREB -method that has been used extensively in a large scale PSA.

Finally, it is undeniable that all methods yield only estimates, approximations of true values of unknown parameters. No one can tell yet which method is most correct most often, or most accurate in some average sense, like the mean square error of the posterior mean value. The analogy with optimal shrinkage estimators seems to favor PREB in this sense. Probably no method is always better than the others. To find this out requires extensive simulation studies with known correct values of the parameters. Biasedness and mean square errors studied for the beta-binomial version [19,20] showed that PREB is very competitive. More simulations for gamma-Poisson version are suggested for future work. Two-stage methodology, comparisons with hierarchical Bayes methods and combining data with expert judgment are also potential subjects for the future.

[3] This reluctance follows from a different thought-process in the two-stage methods; it is not generally adopted in statistics: one regularly uses the same data to estimate the mean value and the variance, or several parameters of a hypothetical regression model.

Appendix A

PREB - estimation of failure probabilities: Binomial data and beta prior

Notation:

N_i Number of demand/start-up events observed at unit i, i = 1,2,…,n

q_i Probability of failure per demand/start-up event at unit i

K_i Number of failures at demand/start-up observed at unit i

The likelihood function in this case is the Binomial probability

$$P(K_i;q_i,N_i) = \frac{N_i!}{K_i!(N_i-K_i)!} q_i^{K_i}(1-q_i)^{N_i-K_i} \quad , 0 \le q_i \le 1,\ 0 \le K_i \le N_i \qquad \text{(A1)}$$

Consider now a beta distribution of q_i as a prior with density

$$b(q_i;x,y) = \frac{\Gamma(y)}{\Gamma(x)\Gamma(y-x)} q_i^{x-1}(1-q_i)^{y-x-1} \quad , \quad 0 \le q_i \le 1,\ 0 \le x \le y \qquad \text{(A2)}$$

with

$$\text{mean value} \quad M = \frac{x}{y}, \quad \text{variance } V = \frac{x(y-x)}{y^2(y+1)}.$$

Then the posterior density of q_i , proportional to the product of (A1) and (A2), is a beta density b(q;K+x,N+y) with moments

$$\text{Mean}(q_i) = \frac{K_i + x}{N_i + y}, \qquad \text{Var}(q_i) = \frac{(K_i + x)(N_i + y - K_i - x)}{(N_i + y)^2 (N_i + y + 1)} \qquad \text{(A3)}$$

When each unit is considered individually (or n = 1), the classical lower confidence limits are consistent with the "optimistic" combination x = 0, y = 1, the upper limit with "conservative" x = 1, y = 1 , and the "compromise" non-informative combination is x = ½, y = 1. [The uniform "ignorant" prior x = 1, y = 2 was used by reverend Bayes in his original work.]

In case of multiple units the values x and y are determined from data by the following moment matching procedure.

The following procedure yields estimates x_c, y_c, M_c, V_c for x, y, M, V, respectively.

1° If data is available only from the unit of interest, n = 1, select $y_c = 1$ and $x_c = \delta$, $0 \le \delta \le 1$; recommended $\delta = ½$. Go to 12°.

If n > 1, determine $N = \sum_{i=1}^{n} N_i$ and select the initial weights $w_i = 1/n$, or

$w_i = N_i/N$, or the recommended average $w_i = (N + nN_i)/(2nN)$.

2° $N^* = N - \max(N_i)$

3° $m = \sum_{i=1}^{n} w_i \frac{K_i}{N_i}$; $\qquad M_0 = \frac{N^*}{N^*+1} m$

If m = 0 set $y_0 = N^*$, $x_0 = 0$ and go to 9° , else

4° $$v = \frac{1}{1 - \sum_{i=1}^{n} w_i^2} \sum_{i=1}^{n} w_i \left(\frac{K_i}{N_i} - m \right)^2 + \frac{M_0 (1 - M_0)}{N^* + 2},$$

5° $y_0 = M_0(1 - M_0)/v - 1$; $\quad u_i = \frac{N_i}{N_i + y_0}$ for i = 1, 2,. .. , n

6° $w_i = u_i / \sum_{j=1}^{n} u_j$ for i = 1, 2,…, n

7° Iterate 3° through 6° (unless all N_i are equal) until m and v converge

8° $y_0 = M_0(1 - M_0)/v - 1$, $x_0 = M_0 y_0$

9° Select $\delta = 0$ ("optimistic"), $\delta = ½$ ("compromise") or $\delta = 1$ ("conservative")

10° $x_c = x_0 + \delta \frac{y_0}{N^* + 1}$, $\quad y_c = y_0$

11^o Prior moments: $M_c = M_0 + \dfrac{\delta}{N^* + 1}$, $V_c = M_c(1 - M_c)/(y_c + 1)$

12^o The posterior beta -densities are $b(q_i;K_i + x_c,N_i + y_c)$.

This procedure has advantages similar to those listed for the Poisson-gamma procedure in Section 2.4. The procedure has been tested and compared to the best among several PEB methods, as described in Section 3.4.

References

[1] Berger JO. *Statistical Decision Theory and Bayesian Analysis, Second Edition*, Springer, 1985.

[2] Spiegelhalter DJ, Thomas A, Best NG, and Gilks WR. *BUGS: Bayesian Inference Using Gibbs Sampling, Version 0.50*, MRC Biostatistics Unit, Cambridge, UK, 1995.

[3] Atwood CL, LaChance JL, Martz HF, Anderson DJ, Engelhardt M, Whitehead D, and Wheeler T. *Handbook of Parameter Estimation for Probabilistic Risk Assessment*. NUREG/CR-6823, SAND2003-3348P, 2003.

[4] Gelman A, Carlin JB, Stern HS, and Rubin DB. *Bayesian Data Analysis, Second Edition*, Chapman & Hall/CRC, 2004.

[5] Shultis J K et al. Use of Non-Conjugate Prior Distributions in Compound Failure Models. Report NUREG/CR-2374, U.S. Nuclear Regulatory Commission, 1981.

[6] Kaplan S. Two-stage Poisson-type problem in probabilistic risk analysis. *Risk Analysis*, vol. 5, no. 3, 227-230, 1985 (See also *IEEE Trans. Power App. Syst*. 102, 195-202, 1983.

[7] Hofer E, Hora SC, Iman RL, Peschke J. On the solution approach for Bayesian modeling of initiating event frequencies nd failure rates. *Risk Analysis* 17(2) 249-252, 1997.

[8] Bidwell D A & In Y H. Insights from the application of INEL's common cause database at Commonwealth Edison's Byron and Braidwood. Proceedings PSA'99, 305-309, 1999.

[9] Becker G & Schubert B. ZEDB – A Practical Application of a 2-Stage Bayesian Analysis Code. *Safety and Reliability,* Proceedings of ESREL'98 Conference held in Trondheim, Norway, Lydersen, Hansen and Sandtorf (eds), Balkema, Rotterdam, vol. 1, 487-494, 1998.

[10] Meyer W Hennings W. Prior distributions in two-stage Bayesian estimation of failure rates. Proceedings of ESREL'99 Conference held in Munich, Germany, Schueller and Kafka (eds), Balkema, Rotterdam, vol. 2, 893-898, 1999.

[11] Hofer E & Peschke J. Bayesian modeling of failure rates and initiating event frequencies. Proceedings of ESREL'99 Conference held in Munich, Germany, Schueller and Kafka (eds), Balkema, Rotterdam, vol. 2, 881-886, 1999.

[12] Bunea C, Charitos T, Cooke RM, Becker G: Two-stage Bayesian models – application to ZEDB project. Proceedings of ESREL 2003, Bedford and van Gelder (eds), vol. 1, 321 – 329. A.A. BALKEMA, Lisse, 2003.

[13] Bunea C, Cooke RM, Mazzuchi TA: A non-parametric two-stage Bayesian model using Dirichlet distribution.
Proceedings of ESREL 2003, Bedford and van Gelder (eds), vol. 1, 331 – 337. A.A. BALKEMA, Lisse, 2003.

[14] Morris C. Parametric empirical Bayes inference: Theory and applications, *J. Am. Statist. Assoc.*, vol. 78,
1983, pp. 47-65.

[15] Kass RE and Steffey D. Approximate Bayesian inference in conditionally independent hierarchical models
(parametric empirical Bayes models), *J. Am. Statist. Assoc*., vol 84, 1989, pp 717-726.

[16] Vaurio J K, Lindén G. On Robust Methods for Failure Rate Estimation. *Reliability Engineering* 14 (1986)123-132.

[17] Vaurio J K. On analytic empirical Bayes Estimation of failure rates. *Risk Analysis*, Vol. 7, No. 3, 329-338, 1987.

[18] Jänkälä K E & Vaurio J K. Empirical Bayes data analysis for plant specific safety assessment. Proceedings of PSA'87, Int. Topical Conf. on Probabilistic Safety Assessment and Risk Management, Zurich, August 30- September 4, 1987. Vol. I: 281-286, TUV Rheinland GmbH, Köln, 1987.

[19] Vaurio J K, Jänkälä K. Comparison of Methods for Estimating Failure Probabilities. The 7th SRE-Symposium, Oct. 14-16, 1986, Tech. Res. Centre, Espoo, Finland. Society of Reliability Engineers, Scandinavian Chapter.

[20] Vaurio J K, Jänkälä K. Robust Method For Estimating Failure-on-Demand Probabilities. Proceedings 5th Intl. Conf. Reliability and Maintainability, Biarritz, France, October 6-10, 1986. Le Commissariat a L'Energie Atomique (C.E.A.), 1986.

[21] Jeffreys HJ. *Theory of Probability*. Third Edition. Oxford; Clarendon Press, 1961.

[22] Vaurio J K & Jänkälä K E, James-Stein Estimators for Failure Rates and Probabilities. *Reliability Engineering and System Safety* 36, 35-39, 1992 (also in SRE Symposium, Nyköping, 8-10 October 1990).

[23] Vaurio J K. Estimation of Common Cause Failure Rates Based on Uncertain Event Data. *Risk Analysis* 14, No.4,
1994, 383-387.

[24] Vaurio J K. Extensions of the uncertainty quantification of common cause failure rates. *Reliability Engineering and System Safety*, Vol. 78, No. 1, October 2002, pp. 63 – 70. Elsevier Science Ltd.

[25] Jänkälä K E and Vaurio J K. Residual Common Cause Failure Analysis in a Probabilistic Safety Assessment. Proc. PSA'93, International Topical Meeting, 804-810, January 26-29, 1993, Clearwater Beach, Florida. Am. Nucl. Soc., 1993.

[26] Lehto M, Jänkälä K, Mohsen B, Vaurio J K. Fire risk analysis for Loviisa 1 during power operation. Proceedings PSA´96, Sept. 29-Oct. 3, 1996, Park City, Utah, USA, 507-514. Am. Nucl. Soc., 1996.

[27] Shultis J K, Buranapan W, Eckhoff ND. Properties of parameter estimation techniques for a beta-binomial failure model. NUREG/CR-2372, Washington DC, 1981.

[28] Vaurio J K & Jänkälä K E, Effective Empirical Parametric Estimation of Failure Rates and Event Frequencies. *PSAM 5-Probabilistic Safety Assessment and Management*, Kondo & Furuta (eds), vol. 4, 2143 – 2148. Universal Academy Press, Tokyo, 2000. (Proceedings of the 5th International Conference on Probabilistic Safety Assessment and Management, held on November 27 - December 1, 2000, in Osaka, Japan.).

Table 1. Posterior Distribution Characteristics of two Examples.

DATA			Individual Non-informative ($\delta = ½$)		PREB compromise		PREB-GROUP ($\delta = ½$)	
i	K_i	T_i	Mean	SD	Mean	SD	Mean	SD
Example 1:								
1	2	10	0.250	0.158	0.257	0.155	1.025	0.226
2	18	10	1.850	0.430	1.750	0.404	1.025	0.226
Example 2:								
1	1	1	1.500	1.225	1.250	0.793	1.010	0.141
2	50	50	1.010	0.142	1.010	0.141	1.010	0.141

Table 2. Comparison 1 between PREB and Dirichlet methods.

Plant	T_i	K_i	K_i / T_i	Posterior results for unit 0:				
1	10000	5	0.0005					
2	10000	5	0.0005		Mean	5%	50%	95%
3	10000	5	0.0005	Dirichlet:	1.30E-4	1.81E-5	1.02E-4	3.17E-4
4	10000	5	0.0005	PREB	1.94E-4	6.08E-5	1.76E-4	3.88E-4
5	10000	5	0.0005					
0	10000	0	0					

Table 3. Comparison 2 of PREB and Dirichlet methods.

Plant	T_i	K_i	K_i/T_i	Posterior results for unit 0:				
1	10000	0	0.0					
2	10000	0	0.0		Mean	5%	50%	95%
3	10000	0	0.0	Dirichlet	5.03E-4	2.03E-4	4.16E-4	9.37E-4
4	10000	0	0.0	PREB	4.34E-4	1.75E-4	4.07E-4	7.88E-4
5	10000	0	0.0					
0	10000	5	0.0005					

Table 4. Data Set 1 [12]

Unit	1	2	3	4	5	6	7	8	9	10	11	12
Nr. failures	7	1	3	2	1	2	0	0	0	2	0	0
Obs. time	24000	24000	24000	24000	24000	24000	24000	24000	24000	24000	24000	24000

Table 5. Data Set 2 [12]

Nr. failures	1	0	0	0	1	2
Obs. time	20000	2000	4000	6000	10000	12000

Table 6. Data Set 3 [12]

Nr. failures	0	0	1
Obs.time	12000	2000	3000

Table 7. The 5%, 50% and 95% quantiles of the posterior distribution of λ for data set 1.

	Uniform	Pörn	Jeffreys	ZEDB	PREB (δ=½)	PREB (δ=1)
5%	2.397 E-5	2.843 E-5	2.867 E-5	3.252 E-5	1.831 E-5	1.854 E-5
50%	8.051 E-5	8.499 E-5	8.568 E-5	6.993 E-5	6.839 E-5	6.889 E-5
95%	2.001 E-4	2.060 E-4	2.067 E-4	1.304 E-4	1.725 E-4	1.733 E-4

Table 8. The 5%, 50% and 95% quantiles of the posterior distribution of λ for data set 2.

	Uniform	Pörn	Jeffreys	ZEDB	PREB (δ=½)	PREB (δ=1)
5%	4.237 E-5	3.931 E-5	4.385 E-5	1.222 E-4	3.336 E-5	3.674 E-5
50%	1.460 E-4	1.428 E-4	1.491 E-4	1.725 E-4	1.139 E-4	1.206 E-4
95%	2.001 E-4*	3.322 E-4	2.067 E-4*	3.447 E-4	2.744 E-4	2.845 E-4

* These 95% values are the same for data sets 1 and 2 in [12]; probably a typographical error

Table 9. The 5%, 50% and 95% quantiles of the posterior distribution of λ for data set 3.

	Uniform	Pörn	Jeffreys	ZEDB	PREB (δ=½)	PREB (δ=1)
5%	3.398 E-5	3.650 E-5	3.639 E-5	1.214 E-4	2.840 E-5	3.972 E-5
50%	1.751 E-4	2.125 E-4	2.071 E-4	2.577 E-4	2.188 E-4	2.559 E-4
95%	5.891 E-4	6.652 E-4	6.564 E-4	7.408 E-4	7.643 E-4	8.300 E-4

Table 10. Posterior quantiles of specific observations of [11]

Method	$\lambda_{0.05}$	$\lambda_{0.5}$	$\lambda_{0.95}$
Example 1 (n = 3)			
HP2SB	1.9E-5	1.2E-4	3.8E-4
PREB	1.2E-5	.92E-4	3.3E-4
Non-informative	1.8E-5	1.2E-4	3.9E-4
Example 2 (n = 3)			
HP2SB	5.5E-5	1.8E-4	1.1E-3
PREB	6.2E-5	4.8E-4	1.7E-3
Non-informative	1.8E-4	1.2E-3	3.9E-3
Example 3 (n = 9)			
HP2SB	1.8E-4	1.8E-3	5.2E-3
PREB	2.1E-4	1.3E-3	4.1E-3
Non-informative	4.0E-6	4.6E-4	3.9E-3
Example 4 (n = 9)			
HP2SB	3.8E-3	6.9E-3	1.2E-2
PREB	3.9E-3	6.8E-3	1.1E-2
Non-informative	5.0E-3	9.0E-3	1.5E-2

Table 11. Posterior quantiles of specific observations used in Examples of [10]

Method	$\lambda_{0.05}$	$\lambda_{0.5}$	$\lambda_{0.95}$
Observation 1, $\alpha_o = \beta_o = 1/16$			
PREB	11.00	12.83	15.41
Known α_o, β_o	11.06	13.01	15.17
Best method in [610]	11.07	13.02	15.19
Observation 6, $\alpha_o = 1$, $\beta_o = 1$			
PREB	0.24	0.48	0.83
Known α_o, β_o	0.23	0.46	0.81
Best method in [610]	0.23	0.47	0.83
Observation 16, $\alpha_o = 1$, $\beta_o = 10$			
PREB	0.013	0.091	0.31
Known α_o, β_o	0.020	0.094	0.27
Best method in [610]	0.019	0.088	0.26
Observation 10, $\alpha_o = 1$, $\beta_o = 10$			
PREB	5E-5	0.011	0.12
Known α_o, β_o	0.003	0.035	0.15
Best method in [610]	1E-4	0.042	0.14

Table 12. Fire data and distribution characteristics for electrical rooms at Loviisa units 1 & 2 (FI-1 & FI-2) and US – plants (partial list).

FIRE FREQUENCIES (1/a)
METHOD = gamma, compromise

Prior parameters

x	y	Average	St. Dev.	Fract. 5%	Fract. 95%
1,92E-01	4,19E+00	4,58E-02	1,05E-01	2,54E-08	2,30E-01

Group parameters

Fires	Time	Average	St. Dev.	Fract. 5%	Fract. 95%
43	1189,93	3,66E-02	5,54E-03	2,79E-02	4,61E-02

	Data			Posterior parameters			
Nr	Unit	Fires	Time	Average	St. Dev.	Fract. 5%	Fract. 95%
1	FI-1	0	18,8	8,34E-03	1,91E-02	4,62E-09	4,19E-02
2	FI-2	0	15,2	9,89E-03	2,26E-02	5,48E-09	4,97E-02
3	US-29	1	27,6	3,75E-02	3,43E-02	2,87E-03	1,05E-01
4	US-155	1	25,9	3,96E-02	3,63E-02	3,03E-03	1,11E-01
5	US-213	0	21,1	7,58E-03	1,73E-02	4,20E-09	3,81E-02
6	US-SHI	0	19,7	8,03E-03	1,83E-02	4,45E-09	4,03E-02
7	US-219	1	19,2	5,10E-02	4,67E-02	3,90E-03	1,42E-01
8	US-237	0	18,7	8,38E-03	1,91E-02	4,64E-09	4,21E-02
9	US-244	0	18,6	8,42E-03	1,92E-02	4,66E-09	4,23E-02
10	US-10	0	18,2	8,57E-03	1,96E-02	4,74E-09	4,30E-02
11	US-220	1	18,2	5,32E-02	4,88E-02	4,07E-03	1,49E-01
12	US-206	1	18,1	5,35E-02	4,90E-02	4,09E-03	1,49E-01
13	US-266	0	18,1	8,60E-03	1,96E-02	4,76E-09	4,32E-02
14	US-245	0	17,9	8,68E-03	1,98E-02	4,81E-09	4,36E-02
15	US-261	1	17,9	5,40E-02	4,94E-02	4,13E-03	1,51E-01
16	US-263	0	17,6	8,80E-03	2,01E-02	4,87E-09	4,42E-02
17	US-409	0	17,5	8,84E-03	2,02E-02	4,90E-09	4,44E-02
18	US-249	0	17,2	8,97E-03	2,05E-02	4,96E-09	4,50E-02
19	US-255	1	17,1	5,60E-02	5,13E-02	4,28E-03	1,56E-01
20	US-301	0	16,3	9,36E-03	2,14E-02	5,18E-09	4,70E-02
21	US-271	0	16,2	9,41E-03	2,15E-02	5,21E-09	4,72E-02
22	US-250	2	16,1	1,08E-01	7,30E-02	2,14E-02	2,51E-01
23	US-280	1	16,1	5,87E-02	5,38E-02	4,49E-03	1,64E-01
24	US-309	1	16,1	5,87E-02	5,38E-02	4,49E-03	1,64E-01
25	US-254	0	16,0	9,50E-03	2,17E-02	5,26E-09	4,77E-02
26	US-265	1	15,9	5,93E-02	5,43E-02	4,54E-03	1,66E-01
27	US-281	1	15,8	5,96E-02	5,46E-02	4,56E-03	1,66E-01
28	US-269	1	15,6	6,02E-02	5,52E-02	4,61E-03	1,68E-01
29	US-251	0	15,4	9,79E-03	2,24E-02	5,42E-09	4,92E-02
30	US-282	0	15,1	9,94E-03	2,27E-02	5,51E-09	4,99E-02

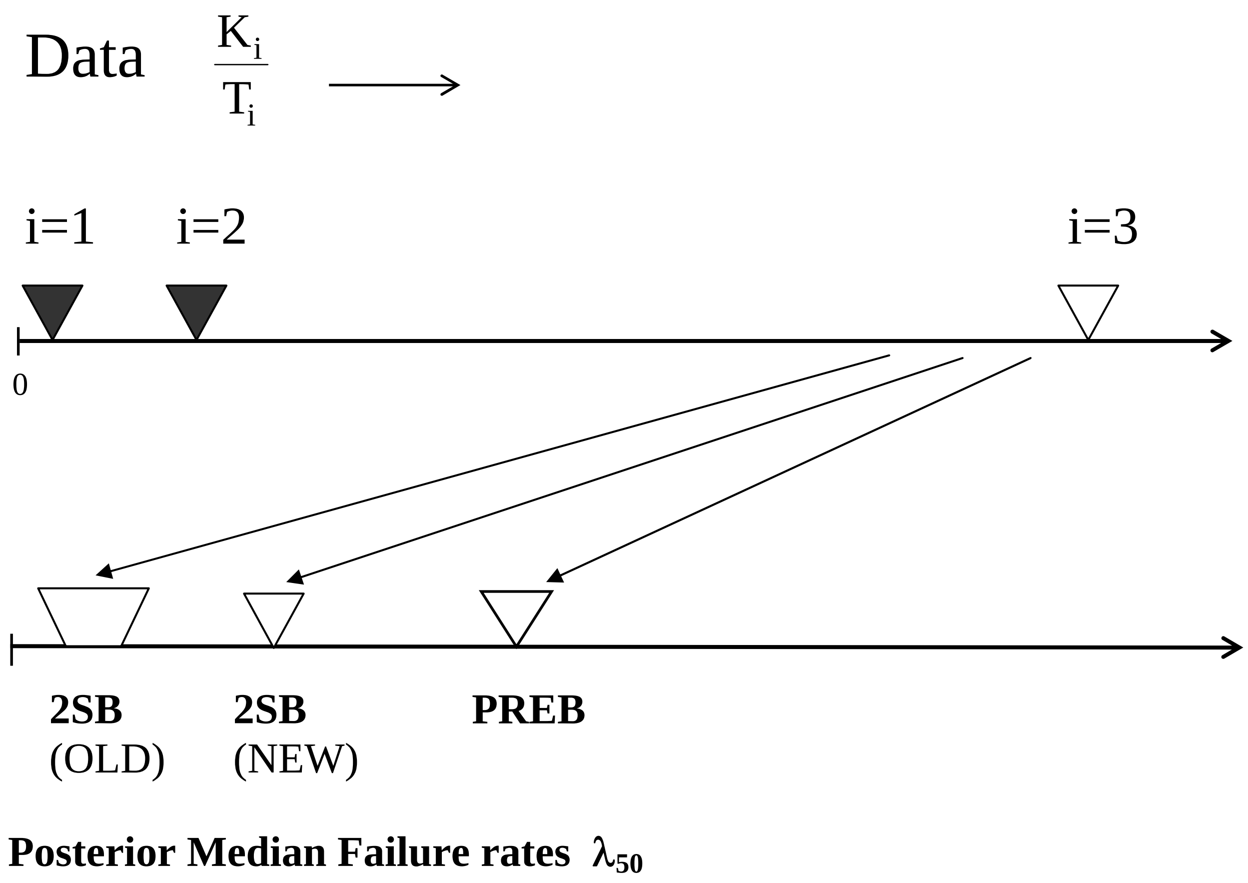


Figure1. The posterior median values obtained with different methods using data with n = 3 from Table B.2 of Ref. [7].

Attachment 4-3
PEAK calculator

PEAK CALCULATOR

The embedded file below provides an example of implementation of the PEAK method for CCF parameter estimation.

PEAK calculator.xls

Attachment 4-4

Input data for parameter estimation (diesels and pumps)

Pumps, Impact vectors

Event data input*						Impact vectors, FCD					High bound					Low bound				
EWG Event no.	Plant code	Imp.vec.	SCF	TF	Det.mod	0oo4	1oo4	2oo4	3oo4	4oo4	0oo4	1oo4	2oo4	3oo4	4oo4	0oo4	1oo4	2oo4	3oo4	4oo4
7	X-22	CCWW	H	H		0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
11	X-12	CDDW	H	H		0	0,5	0,25	0,25	0	0	0,5	0	0,5	0	0	0,25	0,5	0,25	0
16	X-17	CIII	H	H		0	0,9	0,0333	0,0333	0,0333	0	0,9	0	0	0,1	0	0,729	0,243	0,027	0,001
17	X-6	CIII	H	H		0	0,9	0,0333	0,0333	0,0333	0	0,9	0	0	0,1	0	0,729	0,243	0,027	0,001
27	X-1	DDDD	H	H		0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
28	X-2	DDDD	H	H		0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
29	X-13	DDDD	H	H		0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
					Sum:	1,5	2,675	1,6917	0,6917	0,4417	1,5	2,3	1	0,5	1,7	0,1875	2,458	3,111	1,054	0,1895

* In cases where information is missing, conservative assumption is made.

Observation data	
Plant code	Obs.time
X-1	899328
X-2	771264
X-3	455712
X-4	455712
X-5	396480
X-6	521784
X-7	313584
X-8	258816
X-9	316944
X-10	276624
X-11	402768
X-12	314016
X-13	188592
X-14	157728
X-15	219792
X-16	170064
X-17	173712
X-18	157728
X-19	157728
X-20	262896
X-21	271656
X-22	136320
X-23	133464
X-24	306720
X-25	266928
X-26	271656
X-27	113928
X-28	227856
Sum:	8599800

Pumps, Impact vectors summarized per plant

	Impact vectors, FCD					High bound					Low bound				
Plant code	0oo4	1oo4	2oo4	3oo4	4oo4	0oo4	1oo4	2oo4	3oo4	4oo4	0oo4	1oo4	2oo4	3oo4	4oo4
X-1	0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
X-2	0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
X-3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-6	0	0,9	0,033333	0,033333	0,033	0	0,9	0	0	0,1	0	0,729	0,243	0,027	0,001
X-7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-12	0	0,5	0,25	0,25	0	0	0,5	0	0,5	0	0	0,25	0,5	0,25	0
X-13	0,5	0,125	0,125	0,125	0,125	0,5	0	0	0	0,5	0,0625	0,25	0,375	0,25	0,0625
X-14	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-17	0	0,9	0,033333	0,033333	0,033	0	0,9	0	0	0,1	0	0,729	0,243	0,027	0,001
X-18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-22	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0
X-23	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X-28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sum:	1,5	2,675	1,691667	0,691667	0,442	1,5	2,3	1	0,5	1,7	0,1875	2,458	3,111	1,054	0,1895

Attachment 4-5
PREB results, diesels

Diesels, 2/4 failures, FCD approach

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,17742221	60359	2,94E-06	4,87E-11	6,98E-06	1,77E-01	1,66E-05	7,87E+00	4,94E-13	2,16E-07	1,56E-05
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	6,09913478	2677066,766	2,47E-06	9,21E-13	9,60E-07	6,60E+00	3,74E-07	6,60E+00	1,13E-06	2,34E-06	4,23E-06
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,1	180000	1,15E-06	4,80E-12	2,19E-06	2,77E-01	4,16E-06	2,08E-01	5,84E-11	2,46E-07	5,41E-06
X-2	0	192816	7,01E-07	2,77E-12	1,66E-06	1,77E-01	3,95E-06	1,35E-01	1,18E-13	5,16E-08	3,72E-06
X-3	1,43250123	164505,2784	7,16E-06	3,18E-11	5,64E-06	1,61E+00	4,45E-06	1,18E+00	9,40E-07	5,74E-06	1,82E-05
X-4	0,16878359	129933,4441	1,82E-06	9,56E-12	3,09E-06	3,46E-01	5,26E-06	2,36E-01	6,59E-10	5,50E-07	7,94E-06
X-5	0	163176	7,94E-07	3,55E-12	1,88E-06	1,77E-01	4,47E-06	1,30E-01	1,34E-13	5,84E-08	4,21E-06
X-6	0,3	111091,2	2,78E-06	1,62E-11	4,03E-06	4,77E-01	5,83E-06	3,09E-01	8,53E-09	1,21E-06	1,09E-05
X-7	0	94344	1,15E-06	7,41E-12	2,72E-06	1,77E-01	6,46E-06	1,08E-01	1,93E-13	8,44E-08	6,09E-06
X-8	8,2782E-06	123000,043	9,68E-07	5,28E-12	2,30E-06	1,77E-01	5,45E-06	1,19E-01	1,63E-13	7,12E-08	5,14E-06
X-9	0	103248	1,08E-06	6,63E-12	2,57E-06	1,77E-01	6,11E-06	1,12E-01	1,82E-13	7,98E-08	5,76E-06
X-10	0,02173913	86253,91304	1,36E-06	9,27E-12	3,04E-06	1,99E-01	6,82E-06	1,17E-01	1,31E-12	1,39E-07	7,01E-06
X-11	0,01319648	107282,1114	1,14E-06	6,78E-12	2,60E-06	1,91E-01	5,97E-06	1,22E-01	5,78E-13	1,03E-07	5,93E-06
X-12	1	28512	1,32E-05	1,49E-10	1,22E-05	1,18E+00	1,13E-05	3,78E-01	9,88E-07	9,74E-06	3,75E-05
X-13	1	43800	1,13E-05	1,09E-10	1,04E-05	1,18E+00	9,60E-06	4,95E-01	8,43E-07	8,31E-06	3,20E-05
X-14	1	74832	8,71E-06	6,44E-11	8,03E-06	1,18E+00	7,40E-06	6,52E-01	6,50E-07	6,40E-06	2,46E-05
X-15	0,03650794	41243,42857	2,11E-06	2,07E-11	4,55E-06	2,14E-01	9,84E-06	8,68E-02	5,37E-12	2,59E-07	1,07E-05
X-16	0	51792	1,58E-06	1,41E-11	3,76E-06	1,77E-01	8,92E-06	8,19E-02	2,66E-13	1,16E-07	8,40E-06
X-17	0	43800	1,70E-06	1,64E-11	4,04E-06	1,77E-01	9,60E-06	7,46E-02	2,87E-13	1,25E-07	9,04E-06
X-18	0	43800	1,70E-06	1,64E-11	4,04E-06	1,77E-01	9,60E-06	7,46E-02	2,87E-13	1,25E-07	9,04E-06
X-19	0	43800	1,70E-06	1,64E-11	4,04E-06	1,77E-01	9,60E-06	7,46E-02	2,87E-13	1,25E-07	9,04E-06
X-20	0	43800	1,70E-06	1,64E-11	4,04E-06	1,77E-01	9,60E-06	7,46E-02	2,87E-13	1,25E-07	9,04E-06
X-21	7,3533E-05	112816,589	1,02E-06	5,92E-12	2,43E-06	1,77E-01	5,77E-06	1,16E-01	1,74E-13	7,55E-08	5,44E-06
X-22	0,21052632	89943,15789	2,58E-06	1,72E-11	4,14E-06	3,88E-01	6,65E-06	2,32E-01	2,17E-09	9,03E-07	1,08E-05
X-23	0,00028852	111758,569	1,03E-06	6,00E-12	2,45E-06	1,78E-01	5,81E-06	1,15E-01	1,78E-13	7,64E-08	5,48E-06
X-24	0	78864	1,27E-06	9,15E-12	3,03E-06	1,77E-01	7,18E-06	1,01E-01	2,14E-13	9,38E-08	6,76E-06
X-25	0	78864	1,27E-06	9,15E-12	3,03E-06	1,77E-01	7,18E-06	1,01E-01	2,14E-13	9,38E-08	6,76E-06
X-26	0,81543624	107046,443	5,93E-06	3,54E-11	5,95E-06	9,93E-01	5,97E-06	6,35E-01	2,99E-07	4,10E-06	1,78E-05
X-27	7,3533E-05	112816,589	1,02E-06	5,92E-12	2,43E-06	1,77E-01	5,77E-06	1,16E-01	1,74E-13	7,55E-08	5,44E-06
X-28	0	113928	1,02E-06	5,84E-12	2,42E-06	1,77E-01	5,74E-06	1,16E-01	1,71E-13	7,49E-08	5,40E-06

Diesels 3/4 failures, FCD approach

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,3997788	1945958	2,05E-07	1,06E-13	3,25E-07	4,00E-01	5,14E-07	5,85E-01	2,12E-10	7,45E-08	8,54E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,0436346	2845923,1	1,91E-07	6,71E-14	2,59E-07	5,44E-01	3,51E-07	5,44E-01	1,15E-09	9,33E-08	7,12E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,0017065	215017,06	1,86E-07	8,60E-14	2,93E-07	4,01E-01	4,63E-07	3,99E-02	1,97E-10	6,77E-08	7,71E-07
X-2	0	192816	1,87E-07	8,74E-14	2,96E-07	4,00E-01	4,68E-07	3,60E-02	1,93E-10	6,78E-08	7,77E-07
X-3	0,0092511	182963,74	1,92E-07	9,02E-14	3,00E-07	4,09E-01	4,70E-07	3,52E-02	2,31E-10	7,15E-08	7,92E-07
X-4	0,0017065	171738,43	1,90E-07	8,95E-14	2,99E-07	4,01E-01	4,72E-07	3,26E-02	2,01E-10	6,91E-08	7,87E-07
X-5	0	163176	1,90E-07	8,99E-14	3,00E-07	4,00E-01	4,74E-07	3,09E-02	1,96E-10	6,87E-08	7,88E-07
X-6	0	138864	1,92E-07	9,20E-14	3,03E-07	4,00E-01	4,80E-07	2,66E-02	1,98E-10	6,95E-08	7,97E-07
X-7	0	94344	1,96E-07	9,60E-14	3,10E-07	4,00E-01	4,90E-07	1,85E-02	2,02E-10	7,10E-08	8,14E-07
X-8	8,278E-06	123000,04	1,93E-07	9,34E-14	3,06E-07	4,00E-01	4,83E-07	2,38E-02	2,00E-10	7,00E-08	8,03E-07
X-9	0	103248	1,95E-07	9,52E-14	3,09E-07	4,00E-01	4,88E-07	2,01E-02	2,01E-10	7,07E-08	8,11E-07
X-10	0	99192	1,95E-07	9,56E-14	3,09E-07	4,00E-01	4,89E-07	1,94E-02	2,02E-10	7,09E-08	8,12E-07
X-11	0,002947	114996,31	1,95E-07	9,48E-14	3,08E-07	4,03E-01	4,85E-07	2,25E-02	2,12E-10	7,14E-08	8,10E-07
X-12	0	28512	2,02E-07	1,03E-13	3,20E-07	4,00E-01	5,06E-07	5,77E-03	2,09E-10	7,34E-08	8,41E-07
X-13	0	43800	2,01E-07	1,01E-13	3,18E-07	4,00E-01	5,03E-07	8,80E-03	2,08E-10	7,28E-08	8,35E-07
X-14	0	74832	1,98E-07	9,79E-14	3,13E-07	4,00E-01	4,95E-07	1,48E-02	2,04E-10	7,17E-08	8,22E-07
X-15	0,0062762	45995,649	2,04E-07	1,02E-13	3,20E-07	4,06E-01	5,02E-07	9,38E-03	2,34E-10	7,52E-08	8,43E-07
X-16	0	51792	2,00E-07	1,00E-13	3,16E-07	4,00E-01	5,01E-07	1,04E-02	2,07E-10	7,25E-08	8,32E-07
X-17	0	43800	2,01E-07	1,01E-13	3,18E-07	4,00E-01	5,03E-07	8,80E-03	2,08E-10	7,28E-08	8,35E-07
X-18	0	43800	2,01E-07	1,01E-13	3,18E-07	4,00E-01	5,03E-07	8,80E-03	2,08E-10	7,28E-08	8,35E-07
X-19	0	43800	2,01E-07	1,01E-13	3,18E-07	4,00E-01	5,03E-07	8,80E-03	2,08E-10	7,28E-08	8,35E-07
X-20	0	43800	2,01E-07	1,01E-13	3,18E-07	4,00E-01	5,03E-07	8,80E-03	2,08E-10	7,28E-08	8,35E-07
X-21	0	113928	1,94E-07	9,42E-14	3,07E-07	4,00E-01	4,85E-07	2,21E-02	2,00E-10	7,03E-08	8,07E-07
X-22	0,0217391	99067,826	2,06E-07	1,01E-13	3,17E-07	4,22E-01	4,89E-07	2,04E-02	3,01E-10	7,93E-08	8,41E-07
X-23	0	113928	1,94E-07	9,42E-14	3,07E-07	4,00E-01	4,85E-07	2,21E-02	2,00E-10	7,03E-08	8,07E-07
X-24	0	78864	1,97E-07	9,75E-14	3,12E-07	4,00E-01	4,94E-07	1,56E-02	2,04E-10	7,16E-08	8,20E-07
X-25	0	78864	1,97E-07	9,75E-14	3,12E-07	4,00E-01	4,94E-07	1,56E-02	2,04E-10	7,16E-08	8,20E-07
X-26	0	113928	1,94E-07	9,42E-14	3,07E-07	4,00E-01	4,85E-07	2,21E-02	2,00E-10	7,03E-08	8,07E-07
X-27	0	113928	1,94E-07	9,42E-14	3,07E-07	4,00E-01	4,85E-07	2,21E-02	2,00E-10	7,03E-08	8,07E-07
X-28	0	113928	1,94E-07	9,42E-14	3,07E-07	4,00E-01	4,85E-07	2,21E-02	2,00E-10	7,03E-08	8,07E-07

Diesels 4/4 failures, FCD approach

Prior parameters	**x_c**	**y_c**	**M_c**	**V_c**	**$StDev_c$**	**α_c**	**β_c**	**M_c*T_c**	**M_5**	**M_{50}**	**M_{95}**
	0,386826147	1918164	2,02E-07	1,05E-13	3,24E-07	3,87E-01	5,21E-07	5,75E-01	1,66E-10	7,03E-08	8,48E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,034672	2853387	1,87E-07	6,57E-14	2,56E-07	5,35E-01	3,50E-07	5,35E-01	1,04E-09	9,03E-08	7,03E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,001706485	215017,06	1,82E-07	8,54E-14	2,92E-07	3,89E-01	4,69E-07	3,92E-02	1,55E-10	6,38E-08	7,64E-07
X-2	0	192816	1,83E-07	8,68E-14	2,95E-07	3,87E-01	4,74E-07	3,53E-02	1,51E-10	6,39E-08	7,70E-07
X-3	0,006276151	187406,86	1,87E-07	8,87E-14	2,98E-07	3,93E-01	4,75E-07	3,50E-02	1,72E-10	6,64E-08	7,80E-07
X-4	0,001706485	171738,43	1,86E-07	8,90E-14	2,98E-07	3,89E-01	4,78E-07	3,19E-02	1,58E-10	6,52E-08	7,80E-07
X-5	0	163176	1,86E-07	8,93E-14	2,99E-07	3,87E-01	4,80E-07	3,03E-02	1,53E-10	6,48E-08	7,81E-07
X-6	0	138864	1,88E-07	9,14E-14	3,02E-07	3,87E-01	4,86E-07	2,61E-02	1,55E-10	6,56E-08	7,90E-07
X-7	0	94344	1,92E-07	9,55E-14	3,09E-07	3,87E-01	4,97E-07	1,81E-02	1,58E-10	6,70E-08	8,08E-07
X-8	8,27819E-06	123000,04	1,90E-07	9,28E-14	3,05E-07	3,87E-01	4,90E-07	2,33E-02	1,56E-10	6,61E-08	7,97E-07
X-9	0	103248	1,91E-07	9,47E-14	3,08E-07	3,87E-01	4,95E-07	1,98E-02	1,58E-10	6,67E-08	8,04E-07
X-10	0	99192	1,92E-07	9,50E-14	3,08E-07	3,87E-01	4,96E-07	1,90E-02	1,58E-10	6,69E-08	8,06E-07
X-11	0,002946955	114996,31	1,92E-07	9,43E-14	3,07E-07	3,90E-01	4,92E-07	2,20E-02	1,67E-10	6,74E-08	8,04E-07
X-12	0	28512	1,99E-07	1,02E-13	3,19E-07	3,87E-01	5,14E-07	5,67E-03	1,64E-10	6,93E-08	8,35E-07
X-13	0	43800	1,97E-07	1,00E-13	3,17E-07	3,87E-01	5,10E-07	8,64E-03	1,62E-10	6,87E-08	8,29E-07
X-14	0	74832	1,94E-07	9,74E-14	3,12E-07	3,87E-01	5,02E-07	1,45E-02	1,60E-10	6,77E-08	8,16E-07
X-15	0,000288517	49016,503	1,97E-07	1,00E-13	3,16E-07	3,87E-01	5,08E-07	9,65E-03	1,63E-10	6,87E-08	8,27E-07
X-16	0	51792	1,96E-07	9,97E-14	3,16E-07	3,87E-01	5,08E-07	1,02E-02	1,62E-10	6,85E-08	8,25E-07
X-17	0	43800	1,97E-07	1,00E-13	3,17E-07	3,87E-01	5,10E-07	8,64E-03	1,62E-10	6,87E-08	8,29E-07
X-18	0	43800	1,97E-07	1,00E-13	3,17E-07	3,87E-01	5,10E-07	8,64E-03	1,62E-10	6,87E-08	8,29E-07
X-19	0	43800	1,97E-07	1,00E-13	3,17E-07	3,87E-01	5,10E-07	8,64E-03	1,62E-10	6,87E-08	8,29E-07
X-20	0	43800	1,97E-07	1,00E-13	3,17E-07	3,87E-01	5,10E-07	8,64E-03	1,62E-10	6,87E-08	8,29E-07
X-21	0	113928	1,90E-07	9,37E-14	3,06E-07	3,87E-01	4,92E-07	2,17E-02	1,57E-10	6,64E-08	8,00E-07
X-22	0	113928	1,90E-07	9,37E-14	3,06E-07	3,87E-01	4,92E-07	2,17E-02	1,57E-10	6,64E-08	8,00E-07
X-23	0	113928	1,90E-07	9,37E-14	3,06E-07	3,87E-01	4,92E-07	2,17E-02	1,57E-10	6,64E-08	8,00E-07
X-24	0	78864	1,94E-07	9,70E-14	3,11E-07	3,87E-01	5,01E-07	1,53E-02	1,60E-10	6,75E-08	8,14E-07
X-25	0	78864	1,94E-07	9,70E-14	3,11E-07	3,87E-01	5,01E-07	1,53E-02	1,60E-10	6,75E-08	8,14E-07
X-26	0,02173913	99067,826	2,03E-07	1,00E-13	3,17E-07	4,09E-01	4,96E-07	2,01E-02	2,42E-10	7,53E-08	8,35E-07
X-27	0	113928	1,90E-07	9,37E-14	3,06E-07	3,87E-01	4,92E-07	2,17E-02	1,57E-10	6,64E-08	8,00E-07
X-28	0	113928	1,90E-07	9,37E-14	3,06E-07	3,87E-01	4,92E-07	2,17E-02	1,57E-10	6,64E-08	8,00E-07

Diesels, 2/4 failures, High bound

Prior parameters	**x_c**	**y_c**	**M_c**	**V_c**	**$StDev_c$**	**α_c**	**β_c**	**M_c*T_c**	**M_5**	**M_{50}**	**M_{95}**
	0,186475	61789	3,02E-06	4,88E-11	6,99E-06	1,86E-01	1,62E-05	8,09E+00	1,10E-12	2,58E-07	1,58E-05
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	6,388967	2680307,6	2,57E-06	9,59E-13	9,79E-07	6,89E+00	3,73E-07	6,89E+00	1,20E-06	2,45E-06	4,36E-06
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,069767	183139,53	1,05E-06	4,27E-12	2,07E-06	2,56E-01	4,08E-06	1,92E-01	2,32E-11	1,92E-07	5,03E-06
X-2	0	192816	7,32E-07	2,88E-12	1,70E-06	1,86E-01	3,93E-06	1,41E-01	2,68E-13	6,25E-08	3,84E-06
X-3	1,54642	163386,18	7,70E-06	3,42E-11	5,85E-06	1,73E+00	4,44E-06	1,26E+00	1,13E-06	6,28E-06	1,91E-05
X-4	0,380734	131898,72	2,93E-06	1,51E-11	3,89E-06	5,67E-01	5,16E-06	3,86E-01	2,14E-08	1,48E-06	1,08E-05
X-5	0	163176	8,29E-07	3,68E-12	1,92E-06	1,86E-01	4,45E-06	1,35E-01	3,03E-13	7,08E-08	4,35E-06
X-6	0,3	111091,2	2,81E-06	1,63E-11	4,03E-06	4,86E-01	5,78E-06	3,13E-01	9,55E-09	1,25E-06	1,09E-05
X-7	0	94344	1,19E-06	7,65E-12	2,77E-06	1,86E-01	6,40E-06	1,13E-01	4,37E-13	1,02E-07	6,26E-06
X-8	0	123408	1,01E-06	5,44E-12	2,33E-06	1,86E-01	5,40E-06	1,24E-01	3,68E-13	8,60E-08	5,28E-06
X-9	0	103248	1,13E-06	6,85E-12	2,62E-06	1,86E-01	6,06E-06	1,17E-01	4,13E-13	9,65E-08	5,93E-06
X-10	0,021739	86253,913	1,41E-06	9,50E-12	3,08E-06	2,08E-01	6,75E-06	1,21E-01	2,50E-12	1,62E-07	7,17E-06
X-11	0,021739	106038,26	1,24E-06	7,39E-12	2,72E-06	2,08E-01	5,96E-06	1,32E-01	2,21E-12	1,43E-07	6,32E-06
X-12	1	28512	1,31E-05	1,46E-10	1,21E-05	1,19E+00	1,11E-05	3,75E-01	9,96E-07	9,69E-06	3,71E-05
X-13	1	43800	1,12E-05	1,06E-10	1,03E-05	1,19E+00	9,47E-06	4,92E-01	8,52E-07	8,28E-06	3,17E-05
X-14	1	74832	8,68E-06	6,36E-11	7,97E-06	1,19E+00	7,32E-06	6,50E-01	6,58E-07	6,40E-06	2,45E-05
X-15	0,021739	43450,435	1,98E-06	1,88E-11	4,34E-06	2,08E-01	9,50E-06	8,60E-02	3,52E-12	2,28E-07	1,01E-05
X-16	0	51792	1,64E-06	1,45E-11	3,80E-06	1,86E-01	8,80E-06	8,50E-02	6,00E-13	1,40E-07	8,61E-06
X-17	0	43800	1,77E-06	1,67E-11	4,09E-06	1,86E-01	9,47E-06	7,74E-02	6,46E-13	1,51E-07	9,26E-06
X-18	0	43800	1,77E-06	1,67E-11	4,09E-06	1,86E-01	9,47E-06	7,74E-02	6,46E-13	1,51E-07	9,26E-06
X-19	0	43800	1,77E-06	1,67E-11	4,09E-06	1,86E-01	9,47E-06	7,74E-02	6,46E-13	1,51E-07	9,26E-06
X-20	0	43800	1,77E-06	1,67E-11	4,09E-06	1,86E-01	9,47E-06	7,74E-02	6,46E-13	1,51E-07	9,26E-06
X-21	0,000289	111758,57	1,08E-06	6,20E-12	2,49E-06	1,87E-01	5,76E-06	1,20E-01	4,03E-13	9,23E-08	5,64E-06
X-22	0,210526	89943,158	2,62E-06	1,72E-11	4,15E-06	3,97E-01	6,59E-06	2,35E-01	2,58E-09	9,41E-07	1,09E-05
X-23	0,000289	111758,57	1,08E-06	6,20E-12	2,49E-06	1,87E-01	5,76E-06	1,20E-01	4,03E-13	9,23E-08	5,64E-06
X-24	0	78864	1,33E-06	9,43E-12	3,07E-06	1,86E-01	7,11E-06	1,05E-01	4,85E-13	1,13E-07	6,95E-06
X-25	0	78864	1,33E-06	9,43E-12	3,07E-06	1,86E-01	7,11E-06	1,05E-01	4,85E-13	1,13E-07	6,95E-06
X-26	0,815436	107046,44	5,93E-06	3,51E-11	5,93E-06	1,00E+00	5,92E-06	6,35E-01	3,06E-07	4,12E-06	1,78E-05
X-27	0,000289	111758,57	1,08E-06	6,20E-12	2,49E-06	1,87E-01	5,76E-06	1,20E-01	4,03E-13	9,23E-08	5,64E-06
X-28	0	113928	1,06E-06	6,04E-12	2,46E-06	1,86E-01	5,69E-06	1,21E-01	3,88E-13	9,06E-08	5,57E-06

Diesels, 3/4 failures, High bound

Prior parameters	**x_c**	**y_c**	**M_c**	**V_c**	**$StDev_c$**	**α_c**	**β_c**	**M_c*T_c**	**M_5**	**M_{50}**	**M_{95}**
	0,317602	1547760	2,05E-07	1,33E-13	3,64E-07	3,18E-01	6,46E-07	5,90E-01	3,65E-11	5,47E-08	9,22E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,046098	2873559,9	1,90E-07	6,61E-14	2,57E-07	5,46E-01	3,48E-07	5,46E-01	1,16E-09	9,31E-08	7,07E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0	225000	1,79E-07	1,01E-13	3,18E-07	3,18E-01	5,64E-07	4,03E-02	3,19E-11	4,78E-08	8,05E-07
X-2	0	192816	1,82E-07	1,05E-13	3,24E-07	3,18E-01	5,75E-07	3,52E-02	3,24E-11	4,87E-08	8,19E-07
X-3	0,006276	187406,86	1,87E-07	1,08E-13	3,28E-07	3,24E-01	5,76E-07	3,50E-02	3,92E-11	5,13E-08	8,33E-07
X-4	0	179712	1,84E-07	1,06E-13	3,26E-07	3,18E-01	5,79E-07	3,30E-02	3,27E-11	4,90E-08	8,26E-07
X-5	0	163176	1,86E-07	1,08E-13	3,29E-07	3,18E-01	5,84E-07	3,03E-02	3,30E-11	4,95E-08	8,34E-07
X-6	0	138864	1,88E-07	1,12E-13	3,34E-07	3,18E-01	5,93E-07	2,61E-02	3,35E-11	5,02E-08	8,46E-07
X-7	0	94344	1,93E-07	1,18E-13	3,43E-07	3,18E-01	6,09E-07	1,82E-02	3,44E-11	5,16E-08	8,69E-07
X-8	0	123408	1,90E-07	1,14E-13	3,37E-07	3,18E-01	5,98E-07	2,35E-02	3,38E-11	5,07E-08	8,53E-07
X-9	0	103248	1,92E-07	1,17E-13	3,41E-07	3,18E-01	6,06E-07	1,99E-02	3,42E-11	5,13E-08	8,64E-07
X-10	0	99192	1,93E-07	1,17E-13	3,42E-07	3,18E-01	6,07E-07	1,91E-02	3,43E-11	5,14E-08	8,66E-07
X-11	0	121944	1,90E-07	1,14E-13	3,38E-07	3,18E-01	5,99E-07	2,32E-02	3,38E-11	5,07E-08	8,54E-07
X-12	0	28512	2,01E-07	1,28E-13	3,58E-07	3,18E-01	6,34E-07	5,74E-03	3,58E-11	5,37E-08	9,05E-07
X-13	0	43800	2,00E-07	1,25E-13	3,54E-07	3,18E-01	6,28E-07	8,74E-03	3,55E-11	5,32E-08	8,96E-07
X-14	0	74832	1,96E-07	1,21E-13	3,47E-07	3,18E-01	6,16E-07	1,46E-02	3,48E-11	5,22E-08	8,79E-07
X-15	0,018083	43877,244	2,11E-07	1,33E-13	3,64E-07	3,36E-01	6,28E-07	9,25E-03	5,96E-11	6,10E-08	9,30E-07
X-16	0	51792	1,99E-07	1,24E-13	3,52E-07	3,18E-01	6,25E-07	1,03E-02	3,53E-11	5,30E-08	8,92E-07
X-17	0	43800	2,00E-07	1,25E-13	3,54E-07	3,18E-01	6,28E-07	8,74E-03	3,55E-11	5,32E-08	8,96E-07
X-18	0	43800	2,00E-07	1,25E-13	3,54E-07	3,18E-01	6,28E-07	8,74E-03	3,55E-11	5,32E-08	8,96E-07
X-19	0	43800	2,00E-07	1,25E-13	3,54E-07	3,18E-01	6,28E-07	8,74E-03	3,55E-11	5,32E-08	8,96E-07
X-20	0	43800	2,00E-07	1,25E-13	3,54E-07	3,18E-01	6,28E-07	8,74E-03	3,55E-11	5,32E-08	8,96E-07
X-21	0	113928	1,91E-07	1,15E-13	3,39E-07	3,18E-01	6,02E-07	2,18E-02	3,40E-11	5,10E-08	8,58E-07
X-22	0,021739	99067,826	2,06E-07	1,25E-13	3,54E-07	3,39E-01	6,07E-07	2,04E-02	6,36E-11	6,06E-08	9,05E-07
X-23	0	113928	1,91E-07	1,15E-13	3,39E-07	3,18E-01	6,02E-07	2,18E-02	3,40E-11	5,10E-08	8,58E-07
X-24	0	78864	1,95E-07	1,20E-13	3,46E-07	3,18E-01	6,15E-07	1,54E-02	3,47E-11	5,21E-08	8,77E-07
X-25	0	78864	1,95E-07	1,20E-13	3,46E-07	3,18E-01	6,15E-07	1,54E-02	3,47E-11	5,21E-08	8,77E-07
X-26	0	113928	1,91E-07	1,15E-13	3,39E-07	3,18E-01	6,02E-07	2,18E-02	3,40E-11	5,10E-08	8,58E-07
X-27	0	113928	1,91E-07	1,15E-13	3,39E-07	3,18E-01	6,02E-07	2,18E-02	3,40E-11	5,10E-08	8,58E-07
X-28	0	113928	1,91E-07	1,15E-13	3,39E-07	3,18E-01	6,02E-07	2,18E-02	3,40E-11	5,10E-08	8,58E-07

Diesels, 4/4 failures, High bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,433517821	1925525	2,25E-07	1,17E-13	3,42E-07	4,34E-01	5,19E-07	6,33E-01	3,92E-10	8,92E-08	9,10E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,093594722	2809891,5	2,11E-07	7,52E-14	2,74E-07	5,94E-01	3,56E-07	5,94E-01	1,90E-09	1,10E-07	7,63E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,006276151	207112,97	2,06E-07	9,67E-14	3,11E-07	4,40E-01	4,69E-07	4,27E-02	3,92E-10	8,30E-08	8,29E-07
X-2	0	192816	2,05E-07	9,66E-14	3,11E-07	4,34E-01	4,72E-07	3,95E-02	3,56E-10	8,11E-08	8,27E-07
X-3	0,02173913	177036,52	2,17E-07	1,03E-13	3,21E-07	4,55E-01	4,76E-07	3,83E-02	5,06E-10	9,02E-08	8,60E-07
X-4	0,02173913	156271,3	2,19E-07	1,05E-13	3,24E-07	4,55E-01	4,80E-07	3,42E-02	5,11E-10	9,11E-08	8,68E-07
X-5	0	163176	2,08E-07	9,94E-14	3,15E-07	4,34E-01	4,79E-07	3,39E-02	3,61E-10	8,23E-08	8,39E-07
X-6	0	138864	2,10E-07	1,02E-13	3,19E-07	4,34E-01	4,84E-07	2,92E-02	3,66E-10	8,32E-08	8,48E-07
X-7	0	94344	2,15E-07	1,06E-13	3,26E-07	4,34E-01	4,95E-07	2,02E-02	3,74E-10	8,51E-08	8,67E-07
X-8	7,3533E-05	122204,11	2,12E-07	1,03E-13	3,22E-07	4,34E-01	4,88E-07	2,59E-02	3,69E-10	8,39E-08	8,55E-07
X-9	0	103248	2,14E-07	1,05E-13	3,25E-07	4,34E-01	4,93E-07	2,21E-02	3,72E-10	8,47E-08	8,63E-07
X-10	0	99192	2,14E-07	1,06E-13	3,25E-07	4,34E-01	4,94E-07	2,12E-02	3,73E-10	8,49E-08	8,65E-07
X-11	0,02173913	106038,26	2,24E-07	1,10E-13	3,32E-07	4,55E-01	4,92E-07	2,38E-02	5,23E-10	9,34E-08	8,90E-07
X-12	0	28512	2,22E-07	1,14E-13	3,37E-07	4,34E-01	5,12E-07	6,33E-03	3,86E-10	8,79E-08	8,96E-07
X-13	0	43800	2,20E-07	1,12E-13	3,34E-07	4,34E-01	5,08E-07	9,64E-03	3,83E-10	8,73E-08	8,89E-07
X-14	0	74832	2,17E-07	1,08E-13	3,29E-07	4,34E-01	5,00E-07	1,62E-02	3,77E-10	8,59E-08	8,76E-07
X-15	0,000288517	49016,503	2,20E-07	1,11E-13	3,34E-07	4,34E-01	5,06E-07	1,08E-02	3,84E-10	8,71E-08	8,87E-07
X-16	0	51792	2,19E-07	1,11E-13	3,33E-07	4,34E-01	5,06E-07	1,14E-02	3,82E-10	8,69E-08	8,86E-07
X-17	0	43800	2,20E-07	1,12E-13	3,34E-07	4,34E-01	5,08E-07	9,64E-03	3,83E-10	8,73E-08	8,89E-07
X-18	0	43800	2,20E-07	1,12E-13	3,34E-07	4,34E-01	5,08E-07	9,64E-03	3,83E-10	8,73E-08	8,89E-07
X-19	0	43800	2,20E-07	1,12E-13	3,34E-07	4,34E-01	5,08E-07	9,64E-03	3,83E-10	8,73E-08	8,89E-07
X-20	0	43800	2,20E-07	1,12E-13	3,34E-07	4,34E-01	5,08E-07	9,64E-03	3,83E-10	8,73E-08	8,89E-07
X-21	0	113928	2,13E-07	1,04E-13	3,23E-07	4,34E-01	4,90E-07	2,42E-02	3,70E-10	8,43E-08	8,59E-07
X-22	0	113928	2,13E-07	1,04E-13	3,23E-07	4,34E-01	4,90E-07	2,42E-02	3,70E-10	8,43E-08	8,59E-07
X-23	0	113928	2,13E-07	1,04E-13	3,23E-07	4,34E-01	4,90E-07	2,42E-02	3,70E-10	8,43E-08	8,59E-07
X-24	0	78864	2,16E-07	1,08E-13	3,28E-07	4,34E-01	4,99E-07	1,71E-02	3,77E-10	8,57E-08	8,74E-07
X-25	0	78864	2,16E-07	1,08E-13	3,28E-07	4,34E-01	4,99E-07	1,71E-02	3,77E-10	8,57E-08	8,74E-07
X-26	0,02173913	99067,826	2,25E-07	1,11E-13	3,33E-07	4,55E-01	4,94E-07	2,23E-02	5,25E-10	9,37E-08	8,93E-07
X-27	0	113928	2,13E-07	1,04E-13	3,23E-07	4,34E-01	4,90E-07	2,42E-02	3,70E-10	8,43E-08	8,59E-07
X-28	0	113928	2,13E-07	1,04E-13	3,23E-07	4,34E-01	4,90E-07	2,42E-02	3,70E-10	8,43E-08	8,59E-07

Diesels, 2/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,188757312	62781	3,01E-06	4,79E-11	6,92E-06	1,89E-01	1,59E-05	8,00E+00	1,32E-12	2,66E-07	1,57E-05

Group parameters	ΣK	ΣT	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	6,210192446	2661207,1	2,52E-06	9,47E-13	9,73E-07	6,71E+00	3,76E-07	6,71E+00	1,16E-06	2,40E-06	4,31E-06

Posterior parameters	Ki	Ti	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0,098404273	180121,69	1,18E-06	4,87E-12	2,21E-06	2,87E-01	4,12E-06	2,13E-01	8,39E-11	2,68E-07	5,48E-06
X-2	0	192816	7,38E-07	2,89E-12	1,70E-06	1,89E-01	3,91E-06	1,42E-01	3,24E-13	6,53E-08	3,86E-06
X-3	1,454844383	164901,88	7,22E-06	3,17E-11	5,63E-06	1,64E+00	4,39E-06	1,19E+00	9,78E-07	5,82E-06	1,82E-05
X-4	0,161905694	130918,33	1,81E-06	9,35E-12	3,06E-06	3,51E-01	5,16E-06	2,37E-01	7,24E-10	5,57E-07	7,87E-06
X-5	0	163176	8,35E-07	3,70E-12	1,92E-06	1,89E-01	4,43E-06	1,36E-01	3,67E-13	7,39E-08	4,37E-06
X-6	0,3	111091,2	2,81E-06	1,62E-11	4,02E-06	4,89E-01	5,75E-06	3,12E-01	9,79E-09	1,25E-06	1,09E-05
X-7	0	94344	1,20E-06	7,65E-12	2,77E-06	1,89E-01	6,36E-06	1,13E-01	5,28E-13	1,06E-07	6,28E-06
X-8	0,00061264	120029,97	1,04E-06	5,67E-12	2,38E-06	1,89E-01	5,47E-06	1,24E-01	4,78E-13	9,25E-08	5,41E-06
X-9	0	103248	1,14E-06	6,85E-12	2,62E-06	1,89E-01	6,02E-06	1,17E-01	4,99E-13	1,01E-07	5,94E-06
X-10	0,02173913	86253,913	1,41E-06	9,48E-12	3,08E-06	2,10E-01	6,71E-06	1,22E-01	2,91E-12	1,67E-07	7,18E-06
X-11	0,098836565	96978,122	1,80E-06	1,13E-11	3,36E-06	2,88E-01	6,26E-06	1,75E-01	1,30E-10	4,09E-07	8,35E-06
X-12	1	28512	1,30E-05	1,43E-10	1,19E-05	1,19E+00	1,10E-05	3,71E-01	9,91E-07	9,61E-06	3,67E-05
X-13	1	43800	1,12E-05	1,05E-10	1,02E-05	1,19E+00	9,38E-06	4,89E-01	8,49E-07	8,23E-06	3,15E-05
X-14	1	74832	8,64E-06	6,28E-11	7,92E-06	1,19E+00	7,27E-06	6,46E-01	6,58E-07	6,37E-06	2,44E-05
X-15	0,101490724	38223,691	2,87E-06	2,85E-11	5,33E-06	2,90E-01	9,90E-06	1,10E-01	2,26E-10	6,63E-07	1,33E-05
X-16	0	51792	1,65E-06	1,44E-11	3,79E-06	1,89E-01	8,73E-06	8,53E-02	7,24E-13	1,46E-07	8,61E-06
X-17	0	43800	1,77E-06	1,66E-11	4,08E-06	1,89E-01	9,38E-06	7,76E-02	7,78E-13	1,57E-07	9,26E-06
X-18	0	43800	1,77E-06	1,66E-11	4,08E-06	1,89E-01	9,38E-06	7,76E-02	7,78E-13	1,57E-07	9,26E-06
X-19	0	43800	1,77E-06	1,66E-11	4,08E-06	1,89E-01	9,38E-06	7,76E-02	7,78E-13	1,57E-07	9,26E-06
X-20	0	43800	1,77E-06	1,66E-11	4,08E-06	1,89E-01	9,38E-06	7,76E-02	7,78E-13	1,57E-07	9,26E-06
X-21	2,98805E-06	113701,28	1,07E-06	6,06E-12	2,46E-06	1,89E-01	5,67E-06	1,22E-01	4,70E-13	9,46E-08	5,59E-06
X-22	0,3	91142,4	3,18E-06	2,06E-11	4,54E-06	4,89E-01	6,50E-06	2,89E-01	1,11E-08	1,42E-06	1,23E-05
X-23	7,3533E-05	112816,59	1,08E-06	6,12E-12	2,47E-06	1,89E-01	5,69E-06	1,21E-01	4,75E-13	9,52E-08	5,62E-06
X-24	0	78864	1,33E-06	9,41E-12	3,07E-06	1,89E-01	7,06E-06	1,05E-01	5,85E-13	1,18E-07	6,97E-06
X-25	0	78864	1,33E-06	9,41E-12	3,07E-06	1,89E-01	7,06E-06	1,05E-01	5,85E-13	1,18E-07	6,97E-06
X-26	0,672279527	101950,73	5,23E-06	3,17E-11	5,63E-06	8,61E-01	6,07E-06	5,33E-01	1,79E-07	3,40E-06	1,65E-05
X-27	2,98805E-06	113701,28	1,07E-06	6,06E-12	2,46E-06	1,89E-01	5,67E-06	1,22E-01	4,70E-13	9,46E-08	5,59E-06
X-28	0	113928	1,07E-06	6,04E-12	2,46E-06	1,89E-01	5,66E-06	1,22E-01	4,69E-13	9,45E-08	5,59E-06

Diesels, 3/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,25652506	1175227	2,18E-07	1,86E-13	4,31E-07	2,57E-01	8,51E-07	6,20E-01	4,89E-12	4,02E-08	1,05E-06
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,079466919	2839615,9	2,04E-07	7,19E-14	2,68E-07	5,79E-01	3,52E-07	5,79E-01	1,65E-09	1,05E-07	7,44E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,005709676	207825,89	1,90E-07	1,37E-13	3,70E-07	2,62E-01	7,23E-07	3,94E-02	5,38E-12	3,64E-08	9,05E-07
X-2	0	192816	1,88E-07	1,37E-13	3,70E-07	2,57E-01	7,31E-07	3,62E-02	4,20E-12	3,45E-08	9,01E-07
X-3	0,006349836	187263,9	1,93E-07	1,42E-13	3,76E-07	2,63E-01	7,34E-07	3,61E-02	5,62E-12	3,72E-08	9,20E-07
X-4	3,83291E-05	178441	1,90E-07	1,40E-13	3,74E-07	2,57E-01	7,39E-07	3,38E-02	4,25E-12	3,49E-08	9,10E-07
X-5	0	163176	1,92E-07	1,43E-13	3,78E-07	2,57E-01	7,47E-07	3,13E-02	4,29E-12	3,53E-08	9,21E-07
X-6	0	138864	1,95E-07	1,49E-13	3,85E-07	2,57E-01	7,61E-07	2,71E-02	4,37E-12	3,59E-08	9,38E-07
X-7	0	94344	2,02E-07	1,59E-13	3,99E-07	2,57E-01	7,88E-07	1,91E-02	4,53E-12	3,72E-08	9,71E-07
X-8	6,61175E-08	123371,38	1,98E-07	1,52E-13	3,90E-07	2,57E-01	7,70E-07	2,44E-02	4,43E-12	3,63E-08	9,49E-07
X-9	0	103248	2,01E-07	1,57E-13	3,96E-07	2,57E-01	7,82E-07	2,07E-02	4,49E-12	3,69E-08	9,64E-07
X-10	0	99192	2,01E-07	1,58E-13	3,97E-07	2,57E-01	7,85E-07	2,00E-02	4,51E-12	3,70E-08	9,67E-07
X-11	0,001976427	116153,73	2,00E-07	1,55E-13	3,94E-07	2,59E-01	7,74E-07	2,33E-02	4,87E-12	3,74E-08	9,59E-07
X-12	0	28512	2,13E-07	1,77E-13	4,21E-07	2,57E-01	8,31E-07	6,08E-03	4,77E-12	3,92E-08	1,02E-06
X-13	0	43800	2,10E-07	1,73E-13	4,15E-07	2,57E-01	8,20E-07	9,22E-03	4,71E-12	3,87E-08	1,01E-06
X-14	0	74832	2,05E-07	1,64E-13	4,05E-07	2,57E-01	8,00E-07	1,54E-02	4,60E-12	3,77E-08	9,86E-07
X-15	0,000392413	48863,803	2,10E-07	1,71E-13	4,14E-07	2,57E-01	8,17E-07	1,03E-02	4,78E-12	3,87E-08	1,01E-06
X-16	0	51792	2,09E-07	1,70E-13	4,13E-07	2,57E-01	8,15E-07	1,08E-02	4,68E-12	3,85E-08	1,00E-06
X-17	0	43800	2,10E-07	1,73E-13	4,15E-07	2,57E-01	8,20E-07	9,22E-03	4,71E-12	3,87E-08	1,01E-06
X-18	0	43800	2,10E-07	1,73E-13	4,15E-07	2,57E-01	8,20E-07	9,22E-03	4,71E-12	3,87E-08	1,01E-06
X-19	0	43800	2,10E-07	1,73E-13	4,15E-07	2,57E-01	8,20E-07	9,22E-03	4,71E-12	3,87E-08	1,01E-06
X-20	0	43800	2,10E-07	1,73E-13	4,15E-07	2,57E-01	8,20E-07	9,22E-03	4,71E-12	3,87E-08	1,01E-06
X-21	0	113928	1,99E-07	1,54E-13	3,93E-07	2,57E-01	7,76E-07	2,27E-02	4,46E-12	3,66E-08	9,56E-07
X-22	0,006276151	104870,96	2,05E-07	1,60E-13	4,00E-07	2,63E-01	7,81E-07	2,15E-02	5,96E-12	3,96E-08	9,79E-07
X-23	0	113928	1,99E-07	1,54E-13	3,93E-07	2,57E-01	7,76E-07	2,27E-02	4,46E-12	3,66E-08	9,56E-07
X-24	0	78864	2,05E-07	1,63E-13	4,04E-07	2,57E-01	7,97E-07	1,61E-02	4,58E-12	3,76E-08	9,83E-07
X-25	0	78864	2,05E-07	1,63E-13	4,04E-07	2,57E-01	7,97E-07	1,61E-02	4,58E-12	3,76E-08	9,83E-07
X-26	0,058724021	93609,28	2,48E-07	1,96E-13	4,43E-07	3,15E-01	7,88E-07	2,33E-02	4,14E-11	6,55E-08	1,12E-06
X-27	0	113928	1,99E-07	1,54E-13	3,93E-07	2,57E-01	7,76E-07	2,27E-02	4,46E-12	3,66E-08	9,56E-07
X-28	0	113928	1,99E-07	1,54E-13	3,93E-07	2,57E-01	7,76E-07	2,27E-02	4,46E-12	3,66E-08	9,56E-07

Diesels, 4/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,497274271	2665989	1,87E-07	7,00E-14	2,65E-07	4,97E-01	3,75E-07	5,42E-01	7,13E-10	8,44E-08	7,18E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,000328694	2906121,4	1,72E-07	5,92E-14	2,43E-07	5,00E-01	3,44E-07	5,00E-01	6,79E-10	7,84E-08	6,61E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	1,85646E-05	223888,91	1,72E-07	5,95E-14	2,44E-07	4,97E-01	3,46E-07	3,85E-02	6,57E-10	7,79E-08	6,62E-07
X-2	0	192816	1,74E-07	6,08E-14	2,47E-07	4,97E-01	3,50E-07	3,35E-02	6,64E-10	7,87E-08	6,70E-07
X-3	1,85646E-05	202586,63	1,73E-07	6,04E-14	2,46E-07	4,97E-01	3,49E-07	3,51E-02	6,62E-10	7,85E-08	6,67E-07
X-4	2,9988E-08	179676,08	1,75E-07	6,14E-14	2,48E-07	4,97E-01	3,51E-07	3,14E-02	6,68E-10	7,91E-08	6,73E-07
X-5	0	163176	1,76E-07	6,21E-14	2,49E-07	4,97E-01	3,53E-07	2,87E-02	6,71E-10	7,96E-08	6,77E-07
X-6	0	138864	1,77E-07	6,32E-14	2,51E-07	4,97E-01	3,57E-07	2,46E-02	6,77E-10	8,03E-08	6,82E-07
X-7	0	94344	1,80E-07	6,53E-14	2,55E-07	4,97E-01	3,62E-07	1,70E-02	6,88E-10	8,16E-08	6,93E-07
X-8	7,49999E-13	123407,88	1,78E-07	6,39E-14	2,53E-07	4,97E-01	3,59E-07	2,20E-02	6,81E-10	8,07E-08	6,86E-07
X-9	0	103248	1,80E-07	6,48E-14	2,55E-07	4,97E-01	3,61E-07	1,85E-02	6,86E-10	8,13E-08	6,91E-07
X-10	0	99192	1,80E-07	6,50E-14	2,55E-07	4,97E-01	3,62E-07	1,78E-02	6,87E-10	8,14E-08	6,92E-07
X-11	2,98805E-06	121701,33	1,78E-07	6,40E-14	2,53E-07	4,97E-01	3,59E-07	2,17E-02	6,81E-10	8,08E-08	6,87E-07
X-12	0	28512	1,85E-07	6,85E-14	2,62E-07	4,97E-01	3,71E-07	5,26E-03	7,05E-10	8,36E-08	7,10E-07
X-13	0	43800	1,84E-07	6,77E-14	2,60E-07	4,97E-01	3,69E-07	8,04E-03	7,01E-10	8,31E-08	7,06E-07
X-14	0	74832	1,81E-07	6,62E-14	2,57E-07	4,97E-01	3,65E-07	1,36E-02	6,93E-10	8,21E-08	6,98E-07
X-15	2,9988E-08	49958,011	1,83E-07	6,74E-14	2,60E-07	4,97E-01	3,68E-07	9,15E-03	6,99E-10	8,29E-08	7,05E-07
X-16	0	51792	1,83E-07	6,73E-14	2,59E-07	4,97E-01	3,68E-07	9,48E-03	6,99E-10	8,28E-08	7,04E-07
X-17	0	43800	1,84E-07	6,77E-14	2,60E-07	4,97E-01	3,69E-07	8,04E-03	7,01E-10	8,31E-08	7,06E-07
X-18	0	43800	1,84E-07	6,77E-14	2,60E-07	4,97E-01	3,69E-07	8,04E-03	7,01E-10	8,31E-08	7,06E-07
X-19	0	43800	1,84E-07	6,77E-14	2,60E-07	4,97E-01	3,69E-07	8,04E-03	7,01E-10	8,31E-08	7,06E-07
X-20	0	43800	1,84E-07	6,77E-14	2,60E-07	4,97E-01	3,69E-07	8,04E-03	7,01E-10	8,31E-08	7,06E-07
X-21	0	113928	1,79E-07	6,43E-14	2,54E-07	4,97E-01	3,60E-07	2,04E-02	6,83E-10	8,10E-08	6,89E-07
X-22	0	113928	1,79E-07	6,43E-14	2,54E-07	4,97E-01	3,60E-07	2,04E-02	6,83E-10	8,10E-08	6,89E-07
X-23	0	113928	1,79E-07	6,43E-14	2,54E-07	4,97E-01	3,60E-07	2,04E-02	6,83E-10	8,10E-08	6,89E-07
X-24	0	78864	1,81E-07	6,60E-14	2,57E-07	4,97E-01	3,64E-07	1,43E-02	6,92E-10	8,20E-08	6,97E-07
X-25	0	78864	1,81E-07	6,60E-14	2,57E-07	4,97E-01	3,64E-07	1,43E-02	6,92E-10	8,20E-08	6,97E-07
X-26	0,000288517	111758,57	1,79E-07	6,45E-14	2,54E-07	4,98E-01	3,60E-07	2,00E-02	6,86E-10	8,11E-08	6,89E-07
X-27	0	113928	1,79E-07	6,43E-14	2,54E-07	4,97E-01	3,60E-07	2,04E-02	6,83E-10	8,10E-08	6,89E-07
X-28	0	113928	1,79E-07	6,43E-14	2,54E-07	4,97E-01	3,60E-07	2,04E-02	6,83E-10	8,10E-08	6,89E-07

Attachment 4-6
PREB results, pumps

Pumps, 2/4 failures, FCD approach

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,04348318	149318	2,91E-07	1,95E-12	1,40E-06	4,35E-02	6,70E-06	2,39E+00	#OGILTIGT!	#OGILTIGT!	1,46E-06

Group parameters	ΣK	ΣT	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	1,20163859	8220471,546	2,07E-07	2,52E-14	1,59E-07	1,70E+00	1,22E-07	1,70E+00	2,95E-08	1,68E-07	5,17E-07

Posterior parameters	Ki	Ti	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0,03191489	765385,5319	8,24E-08	9,01E-14	3,00E-07	7,54E-02	1,09E-06	6,31E-02	3,62E-24	6,63E-11	4,78E-07
X-2	0,03191489	656394,8936	9,36E-08	1,16E-13	3,41E-07	7,54E-02	1,24E-06	6,14E-02	#OGILTIGT!	#OGILTIGT!	5,42E-07
X-3	0	455712	7,19E-08	1,19E-13	3,45E-07	4,35E-02	1,65E-06	3,28E-02	#OGILTIGT!	#OGILTIGT!	3,60E-07
X-4	0	455712	7,19E-08	1,19E-13	3,45E-07	4,35E-02	1,65E-06	3,28E-02	#OGILTIGT!	#OGILTIGT!	3,60E-07
X-5	0	396480	7,97E-08	1,46E-13	3,82E-07	4,35E-02	1,83E-06	3,16E-02	#OGILTIGT!	#OGILTIGT!	3,99E-07
X-6	0,00294695	492055,6385	7,24E-08	1,13E-13	3,36E-07	4,64E-02	1,56E-06	3,56E-02	#OGILTIGT!	#OGILTIGT!	3,74E-07
X-7	0	313584	9,39E-08	2,03E-13	4,50E-07	4,35E-02	2,16E-06	2,95E-02	#OGILTIGT!	#OGILTIGT!	4,71E-07
X-8	0	258816	1,07E-07	2,61E-13	5,11E-07	4,35E-02	2,45E-06	2,76E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-9	0	316944	9,33E-08	2,00E-13	4,47E-07	4,35E-02	2,14E-06	2,96E-02	#OGILTIGT!	#OGILTIGT!	4,68E-07
X-10	0	276624	1,02E-07	2,40E-13	4,90E-07	4,35E-02	2,35E-06	2,82E-02	#OGILTIGT!	#OGILTIGT!	5,12E-07
X-11	0	402768	7,88E-08	1,43E-13	3,78E-07	4,35E-02	1,81E-06	3,17E-02	#OGILTIGT!	#OGILTIGT!	3,95E-07
X-12	0,1	251212,8	3,58E-07	8,94E-13	9,46E-07	1,43E-01	2,50E-06	9,00E-02	1,34E-15	1,25E-08	1,99E-06
X-13	0,03191489	160503,8298	2,43E-07	7,85E-13	8,86E-07	7,54E-02	3,23E-06	3,91E-02	#OGILTIGT!	#OGILTIGT!	1,41E-06
X-14	0	157728	1,42E-07	4,61E-13	6,79E-07	4,35E-02	3,26E-06	2,23E-02	#OGILTIGT!	#OGILTIGT!	7,10E-07
X-15	0	219792	1,18E-07	3,19E-13	5,65E-07	4,35E-02	2,71E-06	2,59E-02	#OGILTIGT!	#OGILTIGT!	5,91E-07
X-16	0	170064	1,36E-07	4,26E-13	6,53E-07	4,35E-02	3,13E-06	2,32E-02	#OGILTIGT!	#OGILTIGT!	6,83E-07
X-17	0,00294695	163814,8527	1,48E-07	4,74E-13	6,88E-07	4,64E-02	3,19E-06	2,43E-02	#OGILTIGT!	#OGILTIGT!	7,66E-07
X-18	0	157728	1,42E-07	4,61E-13	6,79E-07	4,35E-02	3,26E-06	2,23E-02	#OGILTIGT!	#OGILTIGT!	7,10E-07
X-19	0	157728	1,42E-07	4,61E-13	6,79E-07	4,35E-02	3,26E-06	2,23E-02	#OGILTIGT!	#OGILTIGT!	7,10E-07
X-20	0	262896	1,05E-07	2,56E-13	5,06E-07	4,35E-02	2,43E-06	2,77E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-21	0	271656	1,03E-07	2,45E-13	4,95E-07	4,35E-02	2,38E-06	2,81E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-22	1	136320	3,65E-06	1,28E-11	3,58E-06	1,04E+00	3,50E-06	4,98E-01	2,08E-07	2,57E-06	1,08E-05
X-23	0	133464	1,54E-07	5,44E-13	7,37E-07	4,35E-02	3,54E-06	2,05E-02	#OGILTIGT!	#OGILTIGT!	7,71E-07
X-24	0	306720	9,53E-08	2,09E-13	4,57E-07	4,35E-02	2,19E-06	2,92E-02	#OGILTIGT!	#OGILTIGT!	4,78E-07
X-25	0	266928	1,04E-07	2,51E-13	5,01E-07	4,35E-02	2,40E-06	2,79E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-26	0	271656	1,03E-07	2,45E-13	4,95E-07	4,35E-02	2,38E-06	2,81E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-27	0	113928	1,65E-07	6,27E-13	7,92E-07	4,35E-02	3,80E-06	1,88E-02	#OGILTIGT!	#OGILTIGT!	8,28E-07
X-28	0	227856	1,15E-07	3,06E-13	5,53E-07	4,35E-02	2,65E-06	2,63E-02	#OGILTIGT!	#OGILTIGT!	5,78E-07

Pumps, 3/4 failures, FCD approach

Prior parameters	**x_c**	**y_c**	**M_c**	**V_c**	**$StDev_c$**	**α_c**	**β_c**	**M_c*T_c**	**M_5**	**M_{50}**	**M_{95}**
	0,24598706	2686431	9,16E-08	3,41E-14	1,85E-07	2,46E-01	3,72E-07	7,53E-01	1,29E-12	1,55E-08	4,45E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,20163859	8220471,546	8,54E-08	1,04E-14	1,02E-07	7,02E-01	1,22E-07	7,02E-01	1,50E-09	4,97E-08	2,90E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,03191489	765385,5319	8,05E-08	2,33E-14	1,53E-07	2,78E-01	2,90E-07	6,16E-02	4,15E-12	1,72E-08	3,77E-07
X-2	0,03191489	656394,8936	8,31E-08	2,49E-14	1,58E-07	2,78E-01	2,99E-07	5,46E-02	4,28E-12	1,78E-08	3,90E-07
X-3	0	455712	7,83E-08	2,49E-14	1,58E-07	2,46E-01	3,18E-07	3,57E-02	1,10E-12	1,32E-08	3,81E-07
X-4	0	455712	7,83E-08	2,49E-14	1,58E-07	2,46E-01	3,18E-07	3,57E-02	1,10E-12	1,32E-08	3,81E-07
X-5	0	396480	7,98E-08	2,59E-14	1,61E-07	2,46E-01	3,24E-07	3,16E-02	1,12E-12	1,35E-08	3,88E-07
X-6	0,00294695	492055,6385	7,83E-08	2,46E-14	1,57E-07	2,49E-01	3,15E-07	3,85E-02	1,26E-12	1,36E-08	3,80E-07
X-7	0	313584	8,20E-08	2,73E-14	1,65E-07	2,46E-01	3,33E-07	2,57E-02	1,15E-12	1,39E-08	3,99E-07
X-8	0	258816	8,35E-08	2,84E-14	1,68E-07	2,46E-01	3,40E-07	2,16E-02	1,17E-12	1,41E-08	4,06E-07
X-9	0	316944	8,19E-08	2,73E-14	1,65E-07	2,46E-01	3,33E-07	2,60E-02	1,15E-12	1,38E-08	3,98E-07
X-10	0	276624	8,30E-08	2,80E-14	1,67E-07	2,46E-01	3,37E-07	2,30E-02	1,17E-12	1,40E-08	4,04E-07
X-11	0	402768	7,96E-08	2,58E-14	1,61E-07	2,46E-01	3,24E-07	3,21E-02	1,12E-12	1,35E-08	3,87E-07
X-12	0,1	251212,8	1,18E-07	4,01E-14	2,00E-07	3,46E-01	3,40E-07	2,96E-02	4,24E-11	3,56E-08	5,14E-07
X-13	0,03191489	160503,8298	9,76E-08	3,43E-14	1,85E-07	2,78E-01	3,51E-07	1,57E-02	5,03E-12	2,09E-08	4,57E-07
X-14	0	157728	8,65E-08	3,04E-14	1,74E-07	2,46E-01	3,52E-07	1,36E-02	1,22E-12	1,46E-08	4,21E-07
X-15	0	219792	8,46E-08	2,91E-14	1,71E-07	2,46E-01	3,44E-07	1,86E-02	1,19E-12	1,43E-08	4,12E-07
X-16	0	170064	8,61E-08	3,01E-14	1,74E-07	2,46E-01	3,50E-07	1,46E-02	1,21E-12	1,46E-08	4,19E-07
X-17	0,00294695	163814,8527	8,73E-08	3,06E-14	1,75E-07	2,49E-01	3,51E-07	1,43E-02	1,41E-12	1,51E-08	4,23E-07
X-18	0	157728	8,65E-08	3,04E-14	1,74E-07	2,46E-01	3,52E-07	1,36E-02	1,22E-12	1,46E-08	4,21E-07
X-19	0	157728	8,65E-08	3,04E-14	1,74E-07	2,46E-01	3,52E-07	1,36E-02	1,22E-12	1,46E-08	4,21E-07
X-20	0	262896	8,34E-08	2,83E-14	1,68E-07	2,46E-01	3,39E-07	2,19E-02	1,17E-12	1,41E-08	4,06E-07
X-21	0	271656	8,32E-08	2,81E-14	1,68E-07	2,46E-01	3,38E-07	2,26E-02	1,17E-12	1,41E-08	4,04E-07
X-22	0	136320	8,71E-08	3,09E-14	1,76E-07	2,46E-01	3,54E-07	1,19E-02	1,23E-12	1,47E-08	4,24E-07
X-23	0	133464	8,72E-08	3,09E-14	1,76E-07	2,46E-01	3,55E-07	1,16E-02	1,23E-12	1,47E-08	4,24E-07
X-24	0	306720	8,22E-08	2,75E-14	1,66E-07	2,46E-01	3,34E-07	2,52E-02	1,16E-12	1,39E-08	4,00E-07
X-25	0	266928	8,33E-08	2,82E-14	1,68E-07	2,46E-01	3,39E-07	2,22E-02	1,17E-12	1,41E-08	4,05E-07
X-26	0	271656	8,32E-08	2,81E-14	1,68E-07	2,46E-01	3,38E-07	2,26E-02	1,17E-12	1,41E-08	4,04E-07
X-27	0	113928	8,78E-08	3,14E-14	1,77E-07	2,46E-01	3,57E-07	1,00E-02	1,24E-12	1,48E-08	4,27E-07
X-28	0	227856	8,44E-08	2,90E-14	1,70E-07	2,46E-01	3,43E-07	1,92E-02	1,19E-12	1,43E-08	4,11E-07

Pumps, 4/4 failures, FCD approach

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	$M_c{*}T_c$	M_5	M_{50}	M_{95}
	0,356896	4548853	7,85E-08	1,72E-14	1,31E-07	3,57E-01	2,20E-07	6,50E-01	3,59E-11	2,47E-08	3,39E-07
Group parameters	**ΣK**	**ΣT**	M_g	V_g	$StDev_g$	α_g	β_g	$M_g{*}T_g$	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	0,101639	8283274,7	7,26E-08	8,77E-15	9,36E-08	6,02E-01	1,21E-07	6,02E-01	6,91E-10	3,83E-08	2,61E-07
Posterior parameters	**Ki**	**Ti**	M_i	V_i	$StDev_i$	α_i	β_i	$M_i{*}T_i$	M_5	M_{50}	M_{95}
X-1	0,031915	765385,53	7,32E-08	1,38E-14	1,17E-07	3,89E-01	1,88E-07	5,60E-02	6,25E-11	2,57E-08	3,07E-07
X-2	0,031915	656394,89	7,47E-08	1,44E-14	1,20E-07	3,89E-01	1,92E-07	4,90E-02	6,38E-11	2,62E-08	3,13E-07
X-3	0	455712	7,13E-08	1,42E-14	1,19E-07	3,57E-01	2,00E-07	3,25E-02	3,27E-11	2,25E-08	3,08E-07
X-4	0	455712	7,13E-08	1,42E-14	1,19E-07	3,57E-01	2,00E-07	3,25E-02	3,27E-11	2,25E-08	3,08E-07
X-5	0	396480	7,22E-08	1,46E-14	1,21E-07	3,57E-01	2,02E-07	2,86E-02	3,31E-11	2,27E-08	3,12E-07
X-6	0,002947	492055,64	7,14E-08	1,42E-14	1,19E-07	3,60E-01	1,98E-07	3,51E-02	3,48E-11	2,27E-08	3,08E-07
X-7	0	313584	7,34E-08	1,51E-14	1,23E-07	3,57E-01	2,06E-07	2,30E-02	3,36E-11	2,31E-08	3,17E-07
X-8	0	258816	7,42E-08	1,54E-14	1,24E-07	3,57E-01	2,08E-07	1,92E-02	3,40E-11	2,34E-08	3,21E-07
X-9	0	316944	7,33E-08	1,51E-14	1,23E-07	3,57E-01	2,06E-07	2,32E-02	3,36E-11	2,31E-08	3,17E-07
X-10	0	276624	7,40E-08	1,53E-14	1,24E-07	3,57E-01	2,07E-07	2,05E-02	3,39E-11	2,33E-08	3,20E-07
X-11	0	402768	7,21E-08	1,46E-14	1,21E-07	3,57E-01	2,02E-07	2,90E-02	3,30E-11	2,27E-08	3,11E-07
X-12	0	314016	7,34E-08	1,51E-14	1,23E-07	3,57E-01	2,06E-07	2,30E-02	3,36E-11	2,31E-08	3,17E-07
X-13	0,031915	160503,83	8,26E-08	1,75E-14	1,32E-07	3,89E-01	2,12E-07	1,33E-02	7,05E-11	2,90E-08	3,46E-07
X-14	0	157728	7,58E-08	1,61E-14	1,27E-07	3,57E-01	2,12E-07	1,20E-02	3,47E-11	2,39E-08	3,28E-07
X-15	0	219792	7,48E-08	1,57E-14	1,25E-07	3,57E-01	2,10E-07	1,64E-02	3,43E-11	2,36E-08	3,23E-07
X-16	0	170064	7,56E-08	1,60E-14	1,27E-07	3,57E-01	2,12E-07	1,29E-02	3,46E-11	2,38E-08	3,27E-07
X-17	0,002947	163814,85	7,64E-08	1,62E-14	1,27E-07	3,60E-01	2,12E-07	1,25E-02	3,72E-11	2,43E-08	3,29E-07
X-18	0	157728	7,58E-08	1,61E-14	1,27E-07	3,57E-01	2,12E-07	1,20E-02	3,47E-11	2,39E-08	3,28E-07
X-19	0	157728	7,58E-08	1,61E-14	1,27E-07	3,57E-01	2,12E-07	1,20E-02	3,47E-11	2,39E-08	3,28E-07
X-20	0	262896	7,42E-08	1,54E-14	1,24E-07	3,57E-01	2,08E-07	1,95E-02	3,40E-11	2,34E-08	3,20E-07
X-21	0	271656	7,40E-08	1,54E-14	1,24E-07	3,57E-01	2,07E-07	2,01E-02	3,39E-11	2,33E-08	3,20E-07
X-22	0	136320	7,62E-08	1,63E-14	1,28E-07	3,57E-01	2,13E-07	1,04E-02	3,49E-11	2,40E-08	3,29E-07
X-23	0	133464	7,62E-08	1,63E-14	1,28E-07	3,57E-01	2,14E-07	1,02E-02	3,49E-11	2,40E-08	3,29E-07
X-24	0	306720	7,35E-08	1,51E-14	1,23E-07	3,57E-01	2,06E-07	2,25E-02	3,37E-11	2,31E-08	3,18E-07
X-25	0	266928	7,41E-08	1,54E-14	1,24E-07	3,57E-01	2,08E-07	1,98E-02	3,39E-11	2,33E-08	3,20E-07
X-26	0	271656	7,40E-08	1,54E-14	1,24E-07	3,57E-01	2,07E-07	2,01E-02	3,39E-11	2,33E-08	3,20E-07
X-27	0	113928	7,65E-08	1,64E-14	1,28E-07	3,57E-01	2,14E-07	8,72E-03	3,51E-11	2,41E-08	3,31E-07
X-28	0	227856	7,47E-08	1,56E-14	1,25E-07	3,57E-01	2,09E-07	1,70E-02	3,42E-11	2,35E-08	3,23E-07

Pumps, 2/4 failures, High bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,035333	132708	2,66E-07	2,01E-12	1,42E-06	3,53E-02	7,54E-06	2,29E+00	#OGILTIGT!	#OGILTIGT!	1,18E-06

Group parameters	ΣK	ΣT	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	1	8599800	1,74E-07	2,03E-14	1,42E-07	1,50E+00	1,16E-07	1,50E+00	2,05E-08	1,38E-07	4,54E-07

Posterior parameters	Ki	Ti	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0	899328	3,42E-08	3,32E-14	1,82E-07	3,53E-02	9,69E-07	3,08E-02	#OGILTIGT!	#OGILTIGT!	1,52E-07
X-2	0	771264	3,91E-08	4,32E-14	2,08E-07	3,53E-02	1,11E-06	3,01E-02	#OGILTIGT!	#OGILTIGT!	1,73E-07
X-3	0	455712	6,00E-08	1,02E-13	3,19E-07	3,53E-02	1,70E-06	2,74E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-4	0	455712	6,00E-08	1,02E-13	3,19E-07	3,53E-02	1,70E-06	2,74E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-5	0	396480	6,68E-08	1,26E-13	3,55E-07	3,53E-02	1,89E-06	2,65E-02	#OGILTIGT!	#OGILTIGT!	2,96E-07
X-6	0	521784	5,40E-08	8,25E-14	2,87E-07	3,53E-02	1,53E-06	2,82E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-7	0	313584	7,92E-08	1,77E-13	4,21E-07	3,53E-02	2,24E-06	2,48E-02	#OGILTIGT!	#OGILTIGT!	3,51E-07
X-8	0	258816	9,02E-08	2,30E-13	4,80E-07	3,53E-02	2,55E-06	2,34E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-9	0	316944	7,86E-08	1,75E-13	4,18E-07	3,53E-02	2,22E-06	2,49E-02	#OGILTIGT!	#OGILTIGT!	3,48E-07
X-10	0	276624	8,63E-08	2,11E-13	4,59E-07	3,53E-02	2,44E-06	2,39E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-11	0	402768	6,60E-08	1,23E-13	3,51E-07	3,53E-02	1,87E-06	2,66E-02	#OGILTIGT!	#OGILTIGT!	2,92E-07
X-12	0	314016	7,91E-08	1,77E-13	4,21E-07	3,53E-02	2,24E-06	2,48E-02	#OGILTIGT!	#OGILTIGT!	3,50E-07
X-13	0	188592	1,10E-07	3,42E-13	5,85E-07	3,53E-02	3,11E-06	2,07E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-14	0	157728	1,22E-07	4,19E-13	6,47E-07	3,53E-02	3,44E-06	1,92E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-15	0	219792	1,00E-07	2,84E-13	5,33E-07	3,53E-02	2,84E-06	2,20E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-16	0	170064	1,17E-07	3,85E-13	6,21E-07	3,53E-02	3,30E-06	1,98E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-17	0	173712	1,15E-07	3,76E-13	6,13E-07	3,53E-02	3,26E-06	2,00E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-18	0	157728	1,22E-07	4,19E-13	6,47E-07	3,53E-02	3,44E-06	1,92E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-19	0	157728	1,22E-07	4,19E-13	6,47E-07	3,53E-02	3,44E-06	1,92E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-20	0	262896	8,93E-08	2,26E-13	4,75E-07	3,53E-02	2,53E-06	2,35E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-21	0	271656	8,74E-08	2,16E-13	4,65E-07	3,53E-02	2,47E-06	2,37E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-22	1	136320	3,85E-06	1,43E-11	3,78E-06	1,04E+00	3,72E-06	5,25E-01	2,15E-07	2,70E-06	1,14E-05
X-23	0	133464	1,33E-07	4,99E-13	7,06E-07	3,53E-02	3,76E-06	1,77E-02	#OGILTIGT!	#OGILTIGT!	5,88E-07
X-24	0	306720	8,04E-08	1,83E-13	4,28E-07	3,53E-02	2,28E-06	2,47E-02	#OGILTIGT!	#OGILTIGT!	3,56E-07
X-25	0	266928	8,84E-08	2,21E-13	4,70E-07	3,53E-02	2,50E-06	2,36E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-26	0	271656	8,74E-08	2,16E-13	4,65E-07	3,53E-02	2,47E-06	2,37E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!
X-27	0	113928	1,43E-07	5,81E-13	7,62E-07	3,53E-02	4,05E-06	1,63E-02	#OGILTIGT!	#OGILTIGT!	6,35E-07
X-28	0	227856	9,80E-08	2,72E-13	5,21E-07	3,53E-02	2,77E-06	2,23E-02	#OGILTIGT!	#OGILTIGT!	#OGILTIGT!

Pumps, 3/4 failures, High bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,078518	749221	1,05E-07	1,40E-13	3,74E-07	7,85E-02	1,33E-06	8,95E-01	#OGILTIGT!	#OGILTIGT!	6,09E-07
Group parameters	**ΣK**	**ΣT**	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	0,3	8536996,8	9,37E-08	1,10E-14	1,05E-07	8,00E-01	1,17E-07	8,00E-01	2,57E-09	5,87E-08	3,04E-07
Posterior parameters	**Ki**	**Ti**	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0	899328	4,76E-08	2,89E-14	1,70E-07	7,85E-02	6,07E-07	4,28E-02	#OGILTIGT!	#OGILTIGT!	2,77E-07
X-2	0	771264	5,16E-08	3,40E-14	1,84E-07	7,85E-02	6,58E-07	3,98E-02	#OGILTIGT!	#OGILTIGT!	3,00E-07
X-3	0	455712	6,52E-08	5,41E-14	2,33E-07	7,85E-02	8,30E-07	2,97E-02	#OGILTIGT!	#OGILTIGT!	3,79E-07
X-4	0	455712	6,52E-08	5,41E-14	2,33E-07	7,85E-02	8,30E-07	2,97E-02	#OGILTIGT!	#OGILTIGT!	3,79E-07
X-5	0	396480	6,85E-08	5,98E-14	2,45E-07	7,85E-02	8,73E-07	2,72E-02	#OGILTIGT!	#OGILTIGT!	3,98E-07
X-6	0	521784	6,18E-08	4,86E-14	2,20E-07	7,85E-02	7,87E-07	3,22E-02	#OGILTIGT!	#OGILTIGT!	3,59E-07
X-7	0	313584	7,39E-08	6,95E-14	2,64E-07	7,85E-02	9,41E-07	2,32E-02	1,51E-23	8,24E-11	4,29E-07
X-8	0	258816	7,79E-08	7,73E-14	2,78E-07	7,85E-02	9,92E-07	2,02E-02	1,60E-23	8,69E-11	4,53E-07
X-9	0	316944	7,36E-08	6,91E-14	2,63E-07	7,85E-02	9,38E-07	2,33E-02	1,51E-23	8,22E-11	4,28E-07
X-10	0	276624	7,65E-08	7,46E-14	2,73E-07	7,85E-02	9,75E-07	2,12E-02	1,57E-23	8,54E-11	4,45E-07
X-11	0	402768	6,82E-08	5,92E-14	2,43E-07	7,85E-02	8,68E-07	2,75E-02	#OGILTIGT!	#OGILTIGT!	3,96E-07
X-12	0,3	251212,8	3,78E-07	3,78E-13	6,15E-07	3,79E-01	1,00E-06	9,50E-02	2,67E-10	1,28E-07	1,60E-06
X-13	0	188592	8,37E-08	8,93E-14	2,99E-07	7,85E-02	1,07E-06	1,58E-02	1,72E-23	9,34E-11	4,86E-07
X-14	0	157728	8,66E-08	9,55E-14	3,09E-07	7,85E-02	1,10E-06	1,37E-02	1,77E-23	9,66E-11	5,03E-07
X-15	0	219792	8,10E-08	8,36E-14	2,89E-07	7,85E-02	1,03E-06	1,78E-02	1,66E-23	9,04E-11	4,71E-07
X-16	0	170064	8,54E-08	9,29E-14	3,05E-07	7,85E-02	1,09E-06	1,45E-02	1,75E-23	9,53E-11	4,96E-07
X-17	0	173712	8,51E-08	9,22E-14	3,04E-07	7,85E-02	1,08E-06	1,48E-02	1,74E-23	9,49E-11	4,94E-07
X-18	0	157728	8,66E-08	9,55E-14	3,09E-07	7,85E-02	1,10E-06	1,37E-02	1,77E-23	9,66E-11	5,03E-07
X-19	0	157728	8,66E-08	9,55E-14	3,09E-07	7,85E-02	1,10E-06	1,37E-02	1,77E-23	9,66E-11	5,03E-07
X-20	0	262896	7,76E-08	7,66E-14	2,77E-07	7,85E-02	9,88E-07	2,04E-02	1,59E-23	8,65E-11	4,51E-07
X-21	0	271656	7,69E-08	7,53E-14	2,74E-07	7,85E-02	9,80E-07	2,09E-02	1,58E-23	8,58E-11	4,47E-07
X-22	0	136320	8,87E-08	1,00E-13	3,16E-07	7,85E-02	1,13E-06	1,21E-02	1,82E-23	9,89E-11	5,15E-07
X-23	0	133464	8,90E-08	1,01E-13	3,17E-07	7,85E-02	1,13E-06	1,19E-02	1,82E-23	9,92E-11	5,17E-07
X-24	0	306720	7,44E-08	7,04E-14	2,65E-07	7,85E-02	9,47E-07	2,28E-02	1,52E-23	8,30E-11	4,32E-07
X-25	0	266928	7,73E-08	7,60E-14	2,76E-07	7,85E-02	9,84E-07	2,06E-02	1,58E-23	8,62E-11	4,49E-07
X-26	0	271656	7,69E-08	7,53E-14	2,74E-07	7,85E-02	9,80E-07	2,09E-02	1,58E-23	8,58E-11	4,47E-07
X-27	0	113928	9,10E-08	1,05E-13	3,25E-07	7,85E-02	1,16E-06	1,04E-02	1,86E-23	1,01E-10	5,28E-07
X-28	0	227856	8,04E-08	8,22E-14	2,87E-07	7,85E-02	1,02E-06	1,83E-02	1,65E-23	8,97E-11	4,67E-07

Pumps, 4/4 failures, High bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,155714	889406	1,75E-07	1,97E-13	4,44E-07	1,56E-01	1,12E-06	1,42E+00	3,14E-15	8,35E-09	9,56E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,943478	8137246,3	1,77E-07	2,18E-14	1,48E-07	1,44E+00	1,23E-07	1,44E+00	1,95E-08	1,39E-07	4,68E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,3	719462,4	2,83E-07	1,76E-13	4,20E-07	4,56E-01	6,22E-07	2,04E-01	6,65E-10	1,18E-07	1,12E-06
X-2	0,3	617011,2	3,03E-07	2,01E-13	4,48E-07	4,56E-01	6,64E-07	1,87E-01	7,11E-10	1,26E-07	1,20E-06
X-3	0	455712	1,16E-07	8,61E-14	2,93E-07	1,56E-01	7,43E-07	5,28E-02	2,08E-15	5,52E-09	6,32E-07
X-4	0	455712	1,16E-07	8,61E-14	2,93E-07	1,56E-01	7,43E-07	5,28E-02	2,08E-15	5,52E-09	6,32E-07
X-5	0	396480	1,21E-07	9,42E-14	3,07E-07	1,56E-01	7,78E-07	4,80E-02	2,17E-15	5,77E-09	6,62E-07
X-6	0,021739	453725,22	1,32E-07	9,84E-14	3,14E-07	1,77E-01	7,45E-07	5,99E-02	2,23E-14	9,73E-09	7,01E-07
X-7	0	313584	1,29E-07	1,08E-13	3,28E-07	1,56E-01	8,31E-07	4,06E-02	2,32E-15	6,17E-09	7,07E-07
X-8	0	258816	1,36E-07	1,18E-13	3,44E-07	1,56E-01	8,71E-07	3,51E-02	2,43E-15	6,47E-09	7,41E-07
X-9	0	316944	1,29E-07	1,07E-13	3,27E-07	1,56E-01	8,29E-07	4,09E-02	2,31E-15	6,15E-09	7,05E-07
X-10	0	276624	1,34E-07	1,15E-13	3,38E-07	1,56E-01	8,58E-07	3,69E-02	2,39E-15	6,37E-09	7,30E-07
X-11	0	402768	1,21E-07	9,33E-14	3,05E-07	1,56E-01	7,74E-07	4,85E-02	2,16E-15	5,75E-09	6,58E-07
X-12	0	314016	1,29E-07	1,08E-13	3,28E-07	1,56E-01	8,31E-07	4,06E-02	2,32E-15	6,17E-09	7,07E-07
X-13	0,3	150873,6	4,38E-07	4,21E-13	6,49E-07	4,56E-01	9,61E-07	6,61E-02	1,03E-09	1,83E-07	1,74E-06
X-14	0	157728	1,49E-07	1,42E-13	3,77E-07	1,56E-01	9,55E-07	2,35E-02	2,67E-15	7,09E-09	8,12E-07
X-15	0	219792	1,40E-07	1,27E-13	3,56E-07	1,56E-01	9,02E-07	3,09E-02	2,52E-15	6,69E-09	7,67E-07
X-16	0	170064	1,47E-07	1,39E-13	3,72E-07	1,56E-01	9,44E-07	2,50E-02	2,64E-15	7,01E-09	8,03E-07
X-17	0,021739	151053,91	1,71E-07	1,64E-13	4,05E-07	1,77E-01	9,61E-07	2,58E-02	2,88E-14	1,26E-08	9,05E-07
X-18	0	157728	1,49E-07	1,42E-13	3,77E-07	1,56E-01	9,55E-07	2,35E-02	2,67E-15	7,09E-09	8,12E-07
X-19	0	157728	1,49E-07	1,42E-13	3,77E-07	7,85E-02	9,55E-07	2,35E-02	1,54E-23	8,37E-11	4,36E-07
X-20	0	262896	1,35E-07	1,17E-13	3,42E-07	1,56E-01	8,68E-07	3,55E-02	2,42E-15	6,44E-09	7,38E-07
X-21	0	271656	1,34E-07	1,16E-13	3,40E-07	1,56E-01	8,61E-07	3,64E-02	2,40E-15	6,39E-09	7,33E-07
X-22	0	136320	1,52E-07	1,48E-13	3,85E-07	1,56E-01	9,75E-07	2,07E-02	2,72E-15	7,24E-09	8,29E-07
X-23	0	133464	1,52E-07	1,49E-13	3,86E-07	1,56E-01	9,78E-07	2,03E-02	2,73E-15	7,26E-09	8,32E-07
X-24	0	306720	1,30E-07	1,09E-13	3,30E-07	1,56E-01	8,36E-07	3,99E-02	2,33E-15	6,21E-09	7,11E-07
X-25	0	266928	1,35E-07	1,16E-13	3,41E-07	1,56E-01	8,65E-07	3,59E-02	2,41E-15	6,42E-09	7,36E-07
X-26	0	271656	1,34E-07	1,16E-13	3,40E-07	1,56E-01	8,61E-07	3,64E-02	2,40E-15	6,39E-09	7,33E-07
X-27	0	113928	1,55E-07	1,55E-13	3,93E-07	1,56E-01	9,97E-07	1,77E-02	2,78E-15	7,40E-09	8,48E-07
X-28	0	227856	1,39E-07	1,25E-13	3,53E-07	1,56E-01	8,95E-07	3,18E-02	2,50E-15	6,65E-09	7,61E-07

Pumps, 2/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,084225	215712	3,90E-07	1,81E-12	1,35E-06	8,42E-02	4,64E-06	3,13E+00	9,94E-22	7,42E-10	2,27E-06

Group parameters	ΣK	ΣT	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	2,06153	8006192,1	3,20E-07	4,00E-14	2,00E-07	2,56E+00	1,25E-07	2,56E+00	7,51E-08	2,79E-07	7,03E-07

Posterior parameters	Ki	Ti	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0,190141	709329,13	2,97E-07	3,21E-13	5,66E-07	2,74E-01	1,08E-06	2,10E-01	1,34E-11	6,20E-08	1,40E-06
X-2	0,190141	608320,9	3,33E-07	4,04E-13	6,36E-07	2,74E-01	1,21E-06	2,03E-01	1,51E-11	6,96E-08	1,57E-06
X-3	0	455712	1,25E-07	1,87E-13	4,32E-07	8,42E-02	1,49E-06	5,72E-02	#OGILTIGT!	#OGILTIGT!	7,31E-07
X-4	0	455712	1,25E-07	1,87E-13	4,32E-07	8,42E-02	1,49E-06	5,72E-02	#OGILTIGT!	#OGILTIGT!	7,31E-07
X-5	0	396480	1,38E-07	2,25E-13	4,74E-07	8,42E-02	1,63E-06	5,45E-02	#OGILTIGT!	#OGILTIGT!	8,01E-07
X-6	0,095554	418237,33	2,84E-07	4,47E-13	6,69E-07	1,80E-01	1,58E-06	1,19E-01	5,88E-14	2,17E-08	1,50E-06
X-7	0	313584	1,59E-07	3,01E-13	5,48E-07	8,42E-02	1,89E-06	4,99E-02	4,05E-22	3,02E-10	9,27E-07
X-8	0	258816	1,77E-07	3,74E-13	6,12E-07	8,42E-02	2,11E-06	4,59E-02	4,52E-22	3,37E-10	1,03E-06
X-9	0	316944	1,58E-07	2,97E-13	5,45E-07	8,42E-02	1,88E-06	5,01E-02	4,02E-22	3,00E-10	9,21E-07
X-10	0	276624	1,71E-07	3,47E-13	5,89E-07	8,42E-02	2,03E-06	4,73E-02	4,35E-22	3,25E-10	9,96E-07
X-11	0	402768	1,36E-07	2,20E-13	4,69E-07	8,42E-02	1,62E-06	5,48E-02	#OGILTIGT!	#OGILTIGT!	7,93E-07
X-12	0,3	251212,8	8,23E-07	1,76E-12	1,33E-06	3,84E-01	2,14E-06	2,07E-01	6,47E-10	2,85E-07	3,47E-06
X-13	0,190141	148748,62	7,53E-07	2,07E-12	1,44E-06	2,74E-01	2,74E-06	1,12E-01	3,41E-11	1,57E-07	3,54E-06
X-14	0	157728	2,26E-07	6,04E-13	7,77E-07	8,42E-02	2,68E-06	3,56E-02	#OGILTIGT!	#OGILTIGT!	1,31E-06
X-15	0	219792	1,93E-07	4,44E-13	6,66E-07	8,42E-02	2,30E-06	4,25E-02	4,92E-22	3,67E-10	1,13E-06
X-16	0	170064	2,18E-07	5,66E-13	7,52E-07	8,42E-02	2,59E-06	3,71E-02	#OGILTIGT!	#OGILTIGT!	1,27E-06
X-17	0,095554	139239,31	5,06E-07	1,43E-12	1,19E-06	1,80E-01	2,82E-06	7,05E-02	1,05E-13	3,88E-08	2,68E-06
X-18	0	157728	2,26E-07	6,04E-13	7,77E-07	8,42E-02	2,68E-06	3,56E-02	#OGILTIGT!	#OGILTIGT!	1,31E-06
X-19	0	157728	2,26E-07	6,04E-13	7,77E-07	7,85E-02	2,68E-06	3,56E-02	#OGILTIGT!	#OGILTIGT!	1,22E-06
X-20	0	262896	1,76E-07	3,68E-13	6,06E-07	8,42E-02	2,09E-06	4,63E-02	4,48E-22	3,34E-10	1,03E-06
X-21	0	271656	1,73E-07	3,55E-13	5,95E-07	8,42E-02	2,05E-06	4,69E-02	4,40E-22	3,28E-10	1,01E-06
X-22	1	136320	3,08E-06	8,75E-12	2,96E-06	1,08E+00	2,84E-06	4,20E-01	1,92E-07	2,20E-06	8,97E-06
X-23	0	133464	2,41E-07	6,91E-13	8,31E-07	8,42E-02	2,86E-06	3,22E-02	#OGILTIGT!	#OGILTIGT!	1,40E-06
X-24	0	306720	1,61E-07	3,09E-13	5,56E-07	8,42E-02	1,91E-06	4,94E-02	4,10E-22	3,06E-10	9,39E-07
X-25	0	266928	1,75E-07	3,62E-13	6,01E-07	8,42E-02	2,07E-06	4,66E-02	4,44E-22	3,32E-10	1,02E-06
X-26	0	271656	1,73E-07	3,55E-13	5,95E-07	8,42E-02	2,05E-06	4,69E-02	4,40E-22	3,28E-10	1,01E-06
X-27	0	113928	2,56E-07	7,75E-13	8,80E-07	8,42E-02	3,03E-06	2,91E-02	#OGILTIGT!	#OGILTIGT!	1,49E-06
X-28	0	227856	1,90E-07	4,28E-13	6,54E-07	8,42E-02	2,25E-06	4,33E-02	4,83E-22	3,61E-10	1,11E-06

Pumps, 3/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,254817	2196172	1,16E-07	5,28E-14	2,30E-07	2,55E-01	4,55E-07	9,44E-01	2,42E-12	2,11E-08	5,58E-07
Group parameters	**ΣK**	**ΣT**	**M_g**	**V_g**	**$StDev_g$**	**α_g**	**β_g**	**M_g*T_g**	**M_5**	**M_{50}**	**M_{95}**
	Observation	Time/trials									
	0,403953	8132135,7	1,11E-07	1,37E-14	1,17E-07	9,04E-01	1,23E-07	9,04E-01	4,37E-09	7,38E-08	3,45E-07
Posterior parameters	**Ki**	**Ti**	**M_i**	**V_i**	**$StDev_i$**	**α_i**	**β_i**	**M_i*T_i**	**M_5**	**M_{50}**	**M_{95}**
X-1	0,1	719462,4	1,22E-07	4,17E-14	2,04E-07	3,55E-01	3,43E-07	8,76E-02	5,33E-11	3,80E-08	5,27E-07
X-2	0,1	617011,2	1,26E-07	4,48E-14	2,12E-07	3,55E-01	3,55E-07	7,78E-02	5,53E-11	3,94E-08	5,46E-07
X-3	0	455712	9,61E-08	3,62E-14	1,90E-07	2,55E-01	3,77E-07	4,38E-02	2,00E-12	1,74E-08	4,62E-07
X-4	0	455712	9,61E-08	3,62E-14	1,90E-07	2,55E-01	3,77E-07	4,38E-02	2,00E-12	1,74E-08	4,62E-07
X-5	0	396480	9,83E-08	3,79E-14	1,95E-07	2,55E-01	3,86E-07	3,90E-02	2,05E-12	1,78E-08	4,73E-07
X-6	0,001976	497008,1	9,53E-08	3,54E-14	1,88E-07	2,57E-01	3,71E-07	4,74E-02	2,16E-12	1,76E-08	4,58E-07
X-7	0	313584	1,02E-07	4,05E-14	2,01E-07	2,55E-01	3,98E-07	3,18E-02	2,11E-12	1,84E-08	4,89E-07
X-8	0	258816	1,04E-07	4,23E-14	2,06E-07	2,55E-01	4,07E-07	2,69E-02	2,16E-12	1,88E-08	5,00E-07
X-9	0	316944	1,01E-07	4,03E-14	2,01E-07	2,55E-01	3,98E-07	3,21E-02	2,11E-12	1,84E-08	4,88E-07
X-10	0	276624	1,03E-07	4,17E-14	2,04E-07	2,55E-01	4,04E-07	2,85E-02	2,15E-12	1,87E-08	4,96E-07
X-11	0	402768	9,80E-08	3,77E-14	1,94E-07	2,55E-01	3,85E-07	3,95E-02	2,04E-12	1,78E-08	4,72E-07
X-12	0,1	251212,8	1,45E-07	5,92E-14	2,43E-07	3,55E-01	4,09E-07	3,64E-02	6,35E-11	4,53E-08	6,28E-07
X-13	0,1	150873,6	1,51E-07	6,44E-14	2,54E-07	3,55E-01	4,26E-07	2,28E-02	6,62E-11	4,72E-08	6,54E-07
X-14	0	157728	1,08E-07	4,60E-14	2,14E-07	2,55E-01	4,25E-07	1,71E-02	2,25E-12	1,97E-08	5,21E-07
X-15	0	219792	1,05E-07	4,37E-14	2,09E-07	2,55E-01	4,14E-07	2,32E-02	2,20E-12	1,91E-08	5,08E-07
X-16	0	170064	1,08E-07	4,55E-14	2,13E-07	2,55E-01	4,23E-07	1,83E-02	2,24E-12	1,95E-08	5,18E-07
X-17	0,001976	165463,62	1,09E-07	4,60E-14	2,15E-07	2,57E-01	4,23E-07	1,80E-02	2,46E-12	2,00E-08	5,22E-07
X-18	0	157728	1,08E-07	4,60E-14	2,14E-07	2,55E-01	4,25E-07	1,71E-02	2,25E-12	1,97E-08	5,21E-07
X-19	0	157728	1,08E-07	4,60E-14	2,14E-07	7,85E-02	4,25E-07	1,71E-02	#OGILTIGT!	#OGILTIGT!	1,94E-07
X-20	0	262896	1,04E-07	4,21E-14	2,05E-07	2,55E-01	4,07E-07	2,72E-02	2,16E-12	1,88E-08	4,99E-07
X-21	0	271656	1,03E-07	4,18E-14	2,05E-07	2,55E-01	4,05E-07	2,81E-02	2,15E-12	1,87E-08	4,97E-07
X-22	0	136320	1,09E-07	4,68E-14	2,16E-07	2,55E-01	4,29E-07	1,49E-02	2,28E-12	1,98E-08	5,26E-07
X-23	0	133464	1,09E-07	4,70E-14	2,17E-07	2,55E-01	4,29E-07	1,46E-02	2,28E-12	1,99E-08	5,26E-07
X-24	0	306720	1,02E-07	4,07E-14	2,02E-07	2,55E-01	4,00E-07	3,12E-02	2,12E-12	1,85E-08	4,90E-07
X-25	0	266928	1,03E-07	4,20E-14	2,05E-07	2,55E-01	4,06E-07	2,76E-02	2,15E-12	1,88E-08	4,98E-07
X-26	0	271656	1,03E-07	4,18E-14	2,05E-07	2,55E-01	4,05E-07	2,81E-02	2,15E-12	1,87E-08	4,97E-07
X-27	0	113928	1,10E-07	4,77E-14	2,19E-07	2,55E-01	4,33E-07	1,26E-02	2,30E-12	2,00E-08	5,31E-07
X-28	0	227856	1,05E-07	4,34E-14	2,08E-07	2,55E-01	4,13E-07	2,40E-02	2,19E-12	1,91E-08	5,06E-07

Pumps, 4/4 failures, Low bound

Prior parameters	x_c	y_c	M_c	V_c	$StDev_c$	α_c	β_c	M_c*T_c	M_5	M_{50}	M_{95}
	0,439763007	6373698	6,90E-08	1,08E-14	1,04E-07	4,40E-01	1,57E-07	5,81E-01	1,31E-10	2,78E-08	2,77E-07

Group parameters	ΣK	ΣT	M_g	V_g	$StDev_g$	α_g	β_g	M_g*T_g	M_5	M_{50}	M_{95}
	Observation	Time/trials									
	0,028307863	8423021,2	6,27E-08	7,45E-15	8,63E-08	5,28E-01	1,19E-07	5,28E-01	3,27E-10	2,99E-08	2,36E-07

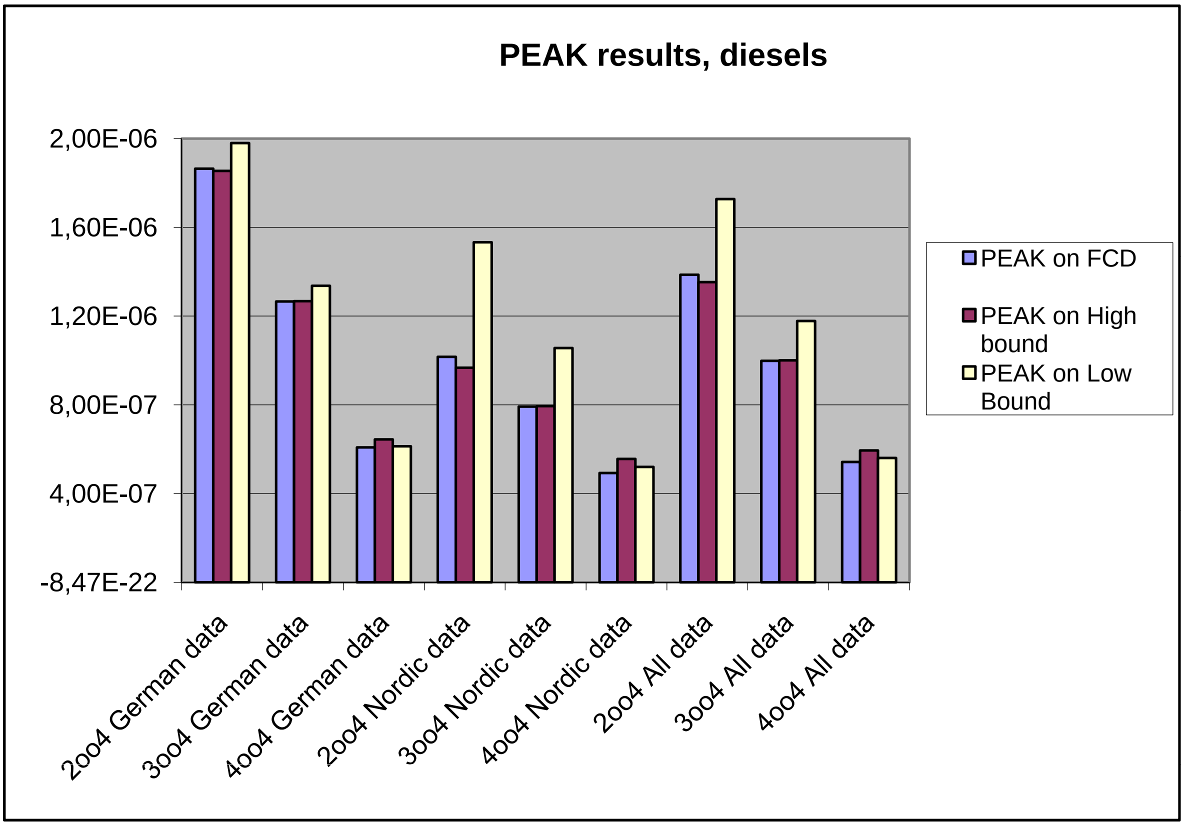
Posterior parameters	Ki	Ti	M_i	V_i	$StDev_i$	α_i	β_i	M_i*T_i	M_5	M_{50}	M_{95}
X-1	0,009433962	814485,74	6,25E-08	8,69E-15	9,32E-08	4,49E-01	1,39E-07	5,09E-02	1,35E-10	2,57E-08	2,49E-07
X-2	0,009433962	698503,25	6,35E-08	8,98E-15	9,48E-08	4,49E-01	1,41E-07	4,44E-02	1,37E-10	2,61E-08	2,53E-07
X-3	0	455712	6,44E-08	9,43E-15	9,71E-08	4,40E-01	1,46E-07	2,93E-02	1,22E-10	2,59E-08	2,59E-07
X-4	0	455712	6,44E-08	9,43E-15	9,71E-08	4,40E-01	1,46E-07	2,93E-02	1,22E-10	2,59E-08	2,59E-07
X-5	0	396480	6,50E-08	9,59E-15	9,80E-08	4,40E-01	1,48E-07	2,58E-02	1,23E-10	2,61E-08	2,61E-07
X-6	2,98805E-06	520745,63	6,38E-08	9,25E-15	9,62E-08	4,40E-01	1,45E-07	3,32E-02	1,21E-10	2,57E-08	2,56E-07
X-7	0	313584	6,58E-08	9,83E-15	9,92E-08	4,40E-01	1,50E-07	2,06E-02	1,25E-10	2,65E-08	2,64E-07
X-8	0	258816	6,63E-08	1,00E-14	1,00E-07	4,40E-01	1,51E-07	1,72E-02	1,26E-10	2,67E-08	2,67E-07
X-9	0	316944	6,57E-08	9,82E-15	9,91E-08	4,40E-01	1,49E-07	2,08E-02	1,25E-10	2,64E-08	2,64E-07
X-10	0	276624	6,61E-08	9,94E-15	9,97E-08	4,40E-01	1,50E-07	1,83E-02	1,26E-10	2,66E-08	2,66E-07
X-11	0	402768	6,49E-08	9,58E-15	9,79E-08	4,40E-01	1,48E-07	2,61E-02	1,23E-10	2,61E-08	2,61E-07
X-12	0	314016	6,58E-08	9,83E-15	9,92E-08	4,40E-01	1,50E-07	2,06E-02	1,25E-10	2,65E-08	2,64E-07
X-13	0,009433962	170800,3	6,86E-08	1,05E-14	1,02E-07	4,49E-01	1,53E-07	1,17E-02	1,48E-10	2,82E-08	2,74E-07
X-14	0	157728	6,73E-08	1,03E-14	1,02E-07	4,40E-01	1,53E-07	1,06E-02	1,28E-10	2,71E-08	2,71E-07
X-15	0	219792	6,67E-08	1,01E-14	1,01E-07	4,40E-01	1,52E-07	1,47E-02	1,27E-10	2,68E-08	2,68E-07
X-16	0	170064	6,72E-08	1,03E-14	1,01E-07	4,40E-01	1,53E-07	1,14E-02	1,28E-10	2,70E-08	2,70E-07
X-17	2,98805E-06	173366,31	6,72E-08	1,03E-14	1,01E-07	4,40E-01	1,53E-07	1,16E-02	1,28E-10	2,70E-08	2,70E-07
X-18	0	157728	6,73E-08	1,03E-14	1,02E-07	4,40E-01	1,53E-07	1,06E-02	1,28E-10	2,71E-08	2,71E-07
X-19	0	157728	6,73E-08	1,03E-14	1,02E-07	4,40E-01	1,53E-07	1,06E-02	1,28E-10	2,71E-08	2,71E-07
X-20	0	262896	6,63E-08	9,98E-15	9,99E-08	4,40E-01	1,51E-07	1,74E-02	1,26E-10	2,67E-08	2,66E-07
X-21	0	271656	6,62E-08	9,96E-15	9,98E-08	4,40E-01	1,50E-07	1,80E-02	1,26E-10	2,66E-08	2,66E-07
X-22	0	136320	6,76E-08	1,04E-14	1,02E-07	4,40E-01	1,54E-07	9,21E-03	1,28E-10	2,72E-08	2,72E-07
X-23	0	133464	6,76E-08	1,04E-14	1,02E-07	4,40E-01	1,54E-07	9,02E-03	1,28E-10	2,72E-08	2,72E-07
X-24	0	306720	6,58E-08	9,85E-15	9,93E-08	4,40E-01	1,50E-07	2,02E-02	1,25E-10	2,65E-08	2,65E-07
X-25	0	266928	6,62E-08	9,97E-15	9,99E-08	4,40E-01	1,51E-07	1,77E-02	1,26E-10	2,66E-08	2,66E-07
X-26	0	271656	6,62E-08	9,96E-15	9,98E-08	4,40E-01	1,50E-07	1,80E-02	1,26E-10	2,66E-08	2,66E-07
X-27	0	113928	6,78E-08	1,04E-14	1,02E-07	4,40E-01	1,54E-07	7,72E-03	1,29E-10	2,73E-08	2,72E-07
X-28	0	227856	6,66E-08	1,01E-14	1,00E-07	4,40E-01	1,51E-07	1,52E-02	1,27E-10	2,68E-08	2,68E-07

Attachment 4-7
PEAK results, diesels and pumps

PEAK results (with FCD impact vectors), diesels	
2oo4 German data	1,86E-06
3oo4 German data	1,27E-06
4oo4 German data	6,08E-07
2oo4 Nordic data	1,02E-06
3oo4 Nordic data	7,92E-07
4oo4 Nordic data	4,92E-07
2oo4 All data	1,39E-06
3oo4 All data	9,98E-07
4oo4 All data	5,43E-07

PEAK results (with High Bound impact vectors), diesels	
2oo4 German data	1,85E-06
3oo4 German data	1,27E-06
4oo4 German data	6,44E-07
2oo4 Nordic data	9,67E-07
3oo4 Nordic data	7,94E-07
4oo4 Nordic data	5,56E-07
2oo4 All data	1,35E-06
3oo4 All data	1,00E-06
4oo4 All data	5,95E-07

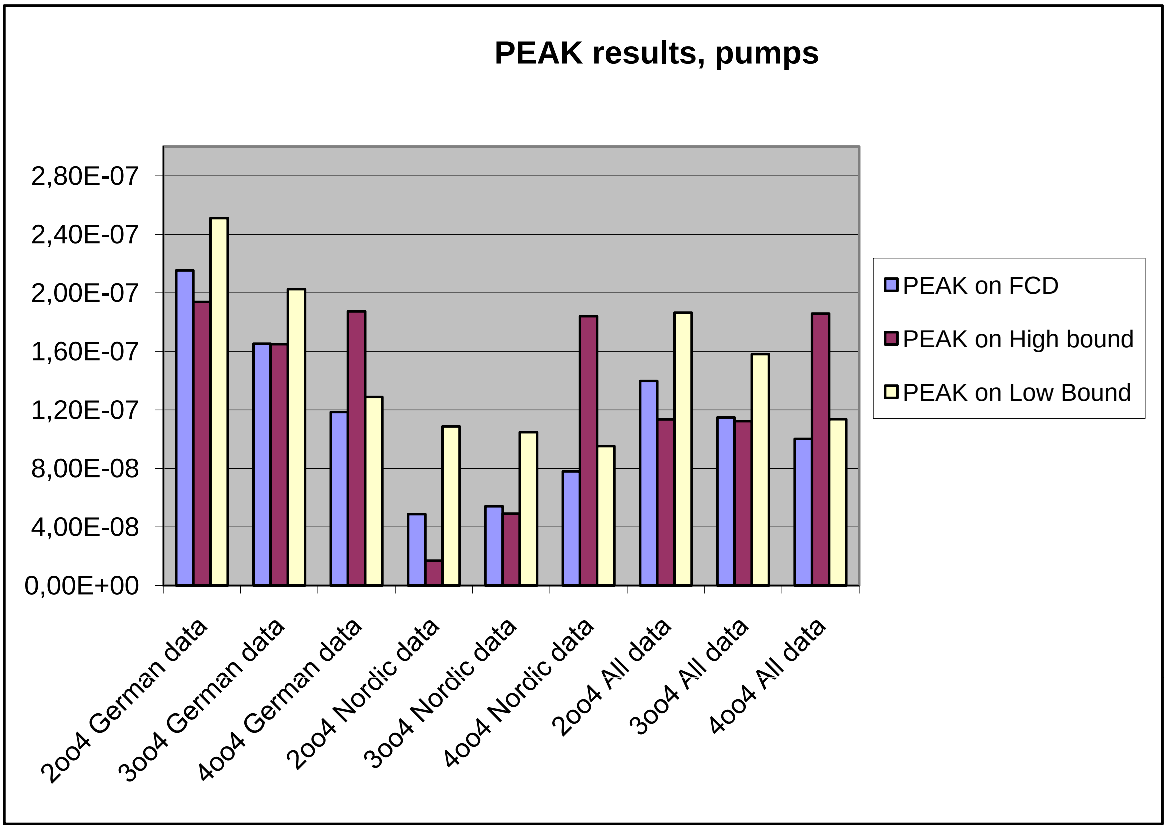
PEAK results (with Low Bound impact vectors), diesels	
2oo4 German data	1,98E-06
3oo4 German data	1,34E-06
4oo4 German data	6,13E-07
2oo4 Nordic data	1,53E-06
3oo4 Nordic data	1,06E-06
4oo4 Nordic data	5,20E-07
2oo4 All data	1,73E-06
3oo4 All data	1,18E-06
4oo4 All data	5,60E-07


PEAK results, diesels
2,00E-06
1,60E-06
1,20E-06
8,00E-07
4,00E-07
-8,47E-22
2oo4 German data
3oo4 German data
4oo4 German data
2oo4 Nordic data
3oo4 Nordic data
4oo4 Nordic data
2oo4 All data
3oo4 All data
4oo4 All data
PEAK on FCD
PEAK on High bound
PEAK on Low Bound

PEAK results (with FCD impact vectors), pumps	
2oo4 German data	2,15E-07
3oo4 German data	1,65E-07
4oo4 German data	1,19E-07
2oo4 Nordic data	4,88E-08
3oo4 Nordic data	5,41E-08
4oo4 Nordic data	7,80E-08
2oo4 All data	1,40E-07
3oo4 All data	1,15E-07
4oo4 All data	1,00E-07

PEAK results (with High Bound impact vectors), pumps	
2oo4 German data	1,94E-07
3oo4 German data	1,65E-07
4oo4 German data	1,87E-07
2oo4 Nordic data	1,70E-08
3oo4 Nordic data	4,91E-08
4oo4 Nordic data	1,84E-07
2oo4 All data	1,14E-07
3oo4 All data	1,12E-07
4oo4 All data	1,86E-07

PEAK results (with Low Bound impact vectors), pumps	
2oo4 German data	2,51E-07
3oo4 German data	2,03E-07
4oo4 German data	1,29E-07
2oo4 Nordic data	1,09E-07
3oo4 Nordic data	1,05E-07
4oo4 Nordic data	9,52E-08
2oo4 All data	1,87E-07
3oo4 All data	1,58E-07
4oo4 All data	1,14E-07


PEAK results, pumps
2,80E-07
2,40E-07
2,00E-07
1,60E-07
1,20E-07
8,00E-08
4,00E-08
0,00E+00
2oo4 German data
3oo4 German data
4oo4 German data
2oo4 Nordic data
3oo4 Nordic data
4oo4 Nordic data
2oo4 All data
3oo4 All data
4oo4 All data
PEAK on FCD
PEAK on High bound
PEAK on Low Bound

Strålsäkerhetsmyndigheten
Swedish Radiation Safety Authority

SE-171 16 Stockholm
Solna strandväg 96

Tel: +46 8 799 40 00
Fax: +46 8 799 40 10

E-mail: registrator@ssm.se
Web: stralsakerhetsmyndigheten.se