Common Cause Failure Parameters Quantification Using ICDE Database

Presenter: S. Yalaoui (CNSC) Co-Authors: S. Yu and M. Pandey (u Waterloo) Y. Akl (CNSC)





Outline

• Context

- New developments in CCF modeling
- ICDE project

Modeling of CCF

- Key ideas
- General Multiple Failure Rate Model

Statistical Estimation

- Empirical Bayes method
- Case Study
 - MOVs
- Summary

Common Cause Failures (CCF)

• CCF is a dependent failure

- in which two or more component fault states exist
- simultaneously, or within a short time interval, as a direct result of a shared cause
- CCF events can significantly impact the availability of safety systems of nuclear power plants

• ICDE project started in 1994

• systematically collecting and analysing CCF data

Objectives

- Review status of the CCF modeling techniques
 - Alpha factor, Multiple Greek letter and Binomial rate
- Investigate the technical aspects of Empirical Bayes method
- Implement the methods for data mapping and statistical estimation of CCF rates
- Present case studies to illustrate the analysis of CCF data
 - MOV data

Terminology

- $\Lambda_{k/n}$ = Failure rate (system level)
 - failure of ANY k out of n component

• λ_{12} = Failure rate (component level)

• Failure of specific components 1 and 2

Symmetry assumption

- $\lambda_{12} = \lambda_{13} = \lambda_{13} = \lambda_{2/3}$ same rate for dual failures
- Combinatorial relations between system and component rates

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$$\Lambda_{2/3} = 3\lambda_{2/3}$$

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$$\Lambda_{k/n} = \binom{n}{k} \lambda_{k/n}$$

Alpha Factors

 $\circ~\alpha_{\text{k/n}}$ It is the ratio of the failure rate $\Lambda_{\text{k/n}}$ to the total rate Λ_n

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$$\alpha_{k/n} = \frac{\Lambda_{k/n}}{\Lambda_n}$$
 and $\Lambda_n = \sum_{k=1}^n \Lambda_{k/n}$

Data Mapping

- CCF data are sparse
- Probabilistic concepts are developed to borrow the data from CCG of different sizes
- The CCF data are mapped to a target system of CCG n
- Mapping down
 - Data from CCG > n
- Mapping up
 - Data from CCG < n

0





Statistical Estimation

Data

• Population

Number of systems susceptible to CCF

• Exposure Time

• Duration during which CCF data are recorded

Number of failures

- Failures observed in the population
- It is an involved task

Impairment states

- C = complete failure (1), D = degraded (0.5)
- I = Incipient (0.1), W = working (0)

Impact Vector

 Probability of CCF failures under a demand and the observed impairment states

Estimation Methods

Two methods

- Maximum likelihood method (objective method)
- Bayesian Method (subjective method)

Maximum Likelihood Estimation (MLE)

- Simple and straightforward method
- Ample data are needed for robustness

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$$\hat{\lambda}_i = \frac{N_i}{T_i}$$

• Variance of the estimator
$$\sigma(\hat{\lambda}_i) = \sqrt{\frac{N_i}{T_i^2}}$$

Empirical Bayes (EB)

- $\circ~$ A prior distribution is assigned to λ
 - Gamma distribution (conjugate prior)
- The posterior distribution of the failure rate is also a gamma distribution
- Mean and variance of the CCF data are used to calculate two parameters (α , β) of gamma dist.
- Challenge
 - Pooling the data collected over different exposure time
 - Impact vector (uncertainty about CCF failures)

Examples

Illustrative Example - Data

i	N _i	T _i	MLE		Vaurio's EB			
			Mean	S.D.	W _i	Mean	S.D.	
1	31	236.9020	0.1309	0.0235	0.1539	0.1343	0.0238	
2	157	115.9440	1.3541	0.1081	0.1534	1.3532	0.1077	
3	30	36.8120	0.8150	0.1488	0.1513	0.8229	0.1480	
4	13	7.5970	1.7112	0.4746	0.1405	1.6664	0.4469	
5	7	5.4660	1.2806	0.4840	0.1358	1.2723	0.4525	
6	7	1.6890	4.1445	1.5665	0.1070	3.2439	1.1536	
7	0	1.1230	0.0000	0.0000	0.0926	0.4846	0.5089	
8	0	0.5520	0.0000	0.0000	0.0655	0.6974	0.7323	

Example-EB Prior

Prior distribution estimated by EB

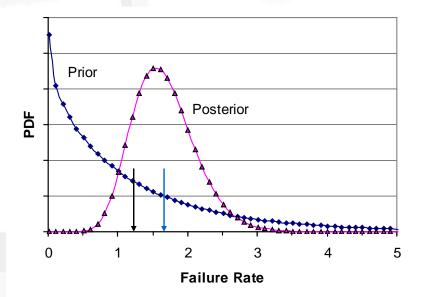
- $\alpha = 0.907, \beta = 0.7485$
- Mean failure rate = 1.2 failures/time
- Standard deviation = 1.27 failures/time



Example-Bayesian Updating

Posterior of failure rate of system 4

- Prior α = 0.907, β = 0.7485
- Data: $N_i = 13$, $T_i = 7.597$
- Posterior mean rate = 1.66 failures/time
- Posterior SD = 0.44 failures/time



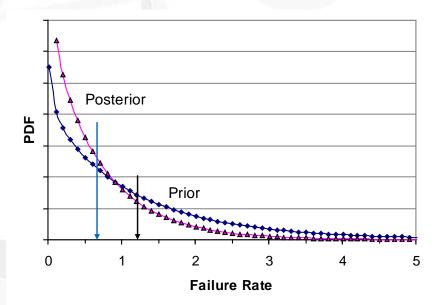
Posterior failure rate

Median	1.62
5 th percentile	1.0
95 th percentile	2.46

Example-Bayesian Updating

• Posterior of system 8

- Prior α = 0.907, β = 0.7485
- Data: $N_i = 0, T_i = 0.552$
- Posterior mean rate = 0.7 failures/time
- Posterior SD = 0.73 failures/time



Posterior failure rate

Median	0.464		
5 th percentile	0.027		
95 th percentile	2.162		

Illustrative Case Study

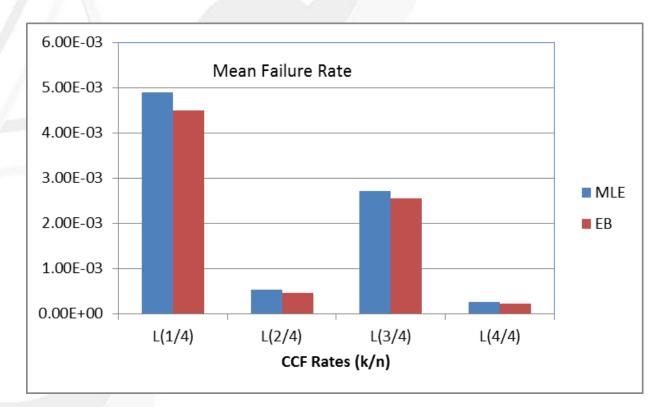
o Data

- Sample similar to that of motor operated valves (MOV) in nuclear safety systems
- A system of CCG of 4 is considered, data mapping was performed

System size		Number of failures $N_{k/n}$						
n		1/n	2/n	3/n	4/n	5/n	6/n	
2	original	36	1	0	0	0	0	
2	mapped	36	0.6400	0.3200	0.0400	0	0	
4	original	18	2	10	1	0	0	
4	mapped	18	2	10	1	0	0	
8	original	6	1	0	0	0	0	
0	mapped	3.5714	0.2143	0	0	0	0	
16	original	13	1	0	0	0	1	
16	mapped	4.0456	0.4209	0.1099	0.0082	0	0	
sum	mapped	61.6170	3.2752	10.4299	1.0482			

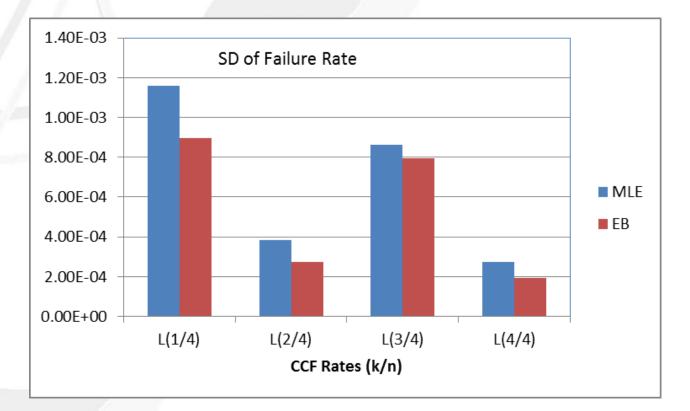


• Comparison of MLE and EB

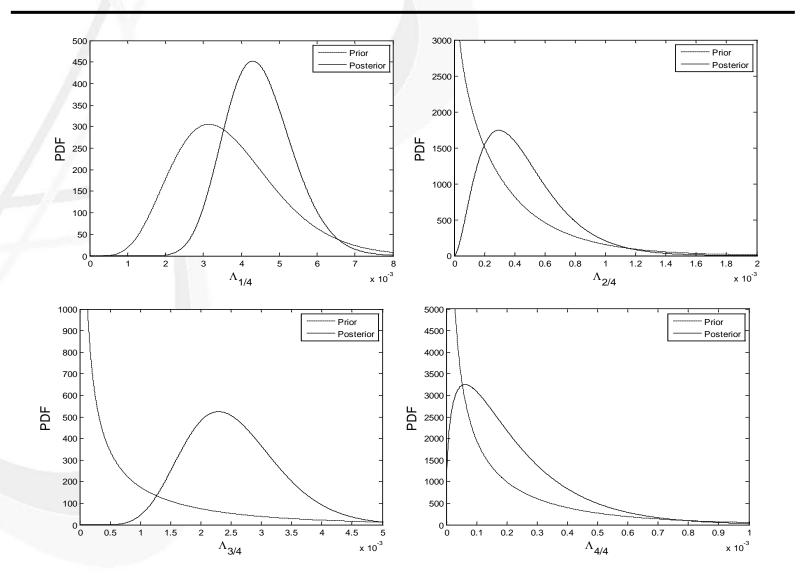


Results-2

• Comparison of standard deviations



Posterior Distributions (EB)



Summary

- Application of CCF models and data mapping method to ICDE data
- "General multiple failure rate model" for modeling CCF data
- Investigation of statistical estimation methods
 - Empirical Bayes (EB)
- A case study is presented

Concluding Remarks

- This project demonstrates the development of a capacity to analyze CCF rates using the Empirical Bayesian (EB) method
- Bayesian approach is a logical and consistent way to analyze problems confounded by "uncertainties"
- Empirical Bayes allows to pool the data from different CCGs and plants
- Implementation of EB method in practice is feasible (Excel-based programs)

Recommendations

- More case studies considering real data from plant safety systems should be undertaken
- The impact of testing scheme, such as staggered testing, should be considered

Thanks for your attention