A survey of methods and tools used for reliability evaluation of SSCs

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Glossary

BRM	Bayesian Restoration Maximization (algorithm, [13])
FIABAYES	Bayesian reliability tool [15]
IBS	Bayesian Inference for the reliability law of a standby component (tool, [17])
IBW	Bayesian Inference for a Weibull law (tool, [16])
KM	Kaplan-Meier estimator
LCM	Life Cycle Management
ML	Maximum Likelihood [13]
PROBAN	PROBabilistic ANalysis (structural reliability tool, [19])
PSA	Probabilistic Safety Assessment
RCM	Reliabity Centered Maintenance [9]
SEM	Stochastic Expectation Maximization (algorithm, [13])
SSC	Systems, Structures and Components

Abstract

The first part of this paper will attempt to point out the principal difficulties inherent to the necessary collection and validation of the needed failure data. The second part will present a survey of the reliability methods and tools presently used at EDF (Électricité de France) to determine reliability parameters and their evolution with age. The conclusion will focus on some priority fields to be studied in the near future.

1 Context – RCM and LCM need reliability predictions

In today's context of an increasingly deregulated market, competitiveness and safety represent high stakes for all industrial sectors.

The desire to reduce global costs is a continuous concern. It drives optimization of preventive maintenance programmes and extension of equipment lifetime. In this framework, reliability performances and their evolution must be assessed but this is not possible if feedback data relative to failure and maintenance history, are not available.

The RCM method, developed in the early Nineties, optimizes preventive maintenance programmes. It includes three main phases:

- phase 1 enables ranking components in terms of their contribution to safety, availability and maintenance cost objectives; in particular, the criticality of a failure mode is evaluated by coupling the seriousness of its effects with its observed occurrence rate; PSAs will enable ranking the importance of these failure modes according to their contribution to accident situations,
- phase 2 is the phase in which one identifies the degradation mechanism at work; operating feedback analysis (component failures and maintenance history) is central, permitting calculation of reliability parameters and their evolution,
- for each critical failure, the most efficient reliability-based and cost-based maintenance task is determined in phase 3.

Failure and maintenance data must be reported [8, 9]. Reliability parameters (number of failures and degradations, failure rates) are important indicators [9]. It is important to detect any reliability trend. Reliability indicators are calculated and updated every five years, to monitor the behaviour of components and demonstrate that ageing effects are well controlled.

Similarly, LCM is the process of integrating plant engineering, operation, maintenance, regulatory, environmental and economic planning activities that:

- ensure control over ageing and assets,
- optimize operating life (including the options of licence renewal or early retirement),
- maximize return on investment,
- while maintaining, and even improving, safety.

In other words, the main objective of LCM is to improve the reliability of equipment; this implies the identification of critical components and the monitoring of their behaviour taking into account ageing and obsolescence factors.
Reliability parameters and their evolution are therefore essential. Failure rate (optimized maintenance requires that this rate remains constant) and cumulative failure probability (a key parameter contributing to decision analysis) are the two main reliability parameters to be determined. The reliability of important SSCs is indeed decisive for the technico-economic optimization of the life cycle.

2 Operating feedback

2.1 General remarks

Because safety targets are involved, the equipment found in most large-scale industries is generally well designed. It is reliable and failure data (also called complete data) is therefore rare.

Moreover, in order to limit the number and the consequences of failures, preventive maintenance operations are carried out whose objective is to reduce the probability of failure. At the time of the preventive maintenance task (but also on the date when observations are ended), the piece of equipment is not defective; it may, of course, be degraded or worn. Any failure (loss of function) will occur later, after the date of the preventive maintenance (or after observations are ended) if the equipment continues to function. Much of this kind of data is available, because preventive maintenance operations are widely carried out to avoid failures and eliminate degradations. These are called censored data, characterized by a large amount of missing data. The term "survival data" is also used. However, we must be cautious. Depending on the sector, this term may refer either to right censored data only, or to the sum of all complete data (failures) and incomplete data (censored data).

Lastly, it should be noted that other data may be available from feedback on equivalent components in the same environmental, operating and maintenance conditions; they may also be provided by expert assessments on the components, plant operators or maintenance engineers, and they must be exploited.

We must particularly stress the quality required of both complete and censored feedback data, without which it is extremely difficult to obtain reliable results and information that can be used [8]. The user must examine the accuracy, the relevance and the representativeness of the sample. It should remembered that validation requires logical analysis of the failure or degradation in light of an equipment tree (or maintenance model). Attribution and verification of the failure mode, the degree and the measurable effect (the physical degradation mechanism of the failure) are essential.

In this context, characterized by a limited number of complete observations, the failures, and a high proportion of censored data, one attempts to model the lifetime of a piece of equipment and its evolution in relation to the period of operation.

Feedback aims at improving understanding of the behaviour of an installation and of its constituent components, as well as of their degradation, dysfunction or damage modes. It is based on collection and processing of technical facts (failure and maintenance data), observed over the lifetime of an installation from its commissioning to its dismantling. Constitution of a satisfactory data sample for estimating a lifetime model for a piece of equipment therefore requires complete background information on the operation and maintenance of this component for a fixed period of observation [8].

2.2 The "disruptive" effect of preventive maintenance

It should be noted that one problem inherent to exploiting background information on a component is the degree to which the maintenance performed is efficient.

After maintenance, the component may be "*as good as new*", which means that it has been totally refurbished thanks to the maintenance operation. The date of this type of maintenance should be considered as the date of entry into service of a new component, and serves as the starting point for calculating the subsequent time to failure or to censored data.

After maintenance, the component may be "*as bad as old*", meaning that the maintenance has had no effect on the real age of the component, its lifetime has not been extended. In this case, the starting point for calculating failure data or censored data remains the date on which the equipment was entered into service or the date on which observations began.

In reality, the situation is generally somewhere between these two extremes which are used as a reference only because the real efficiency of maintenance is extremely difficult to model. Nevertheless some studies on this last point can be quoted [24, 25] and it is to be hoped that future research will focus on the question.

3 Methods and tools used

Two laws of probability are very widely used, when possible:

- the exponential law is appropriate for modelling the lifetime law for a component whose random failures occur with a virtually constant failure rate,
- the Weibull law with two parameters: the shape parameter and the scale parameter, is frequently used for modelling the lifetime law for a physical entity and is indeed very practical for physical interpretation.

The following table gives the main methods and tools, with their references, now used at EDF to estimate the reliability law of an important SSC, i.e. mainly:

- the evolution of the failure rate with age or operation time or the number of demands or fatigue cycles, etc. even in the long term,
- the evolution of the failure probability.

Reliability must be calculated for variety of SSCs which are designed for different lifetimes, ranging from a short lifetime for some components which are replaced at rather short intervals (less than 5 years) to a life expectancy of 30, 40 years or even more, mainly for structures and large components.

Predicted reliability is needed to maintain ageing degradation within acceptable limits.

Algorithms or tests to detect an ageing effect [10, 11, 12] must always to be used at the outset, before any calculation of evolution.

The uncertainties of the calculated parameters must always be determined, as they are used afterwards in the context of decision analysis.

The table below highlights the main progress to be hoped for in the near future:

- methodology in the absence of failure data, when equipment is very reliable,
- confidence region/range for the KM, [7]
- elicitation and modelling of expertise for Bayesian techniques,
- any improvement of data concerning structural reliability data: loads, non-destructive examination, kinetics of degradation which are often not very well known, even when the relevant degradation mechanisms are known,
- acceptance criteria.

Table – Evaluating the reliability law of an SSC: methods and tools

	Operating experience (failure data, maintenance history, operation times)		
Type of component	No data	A few failure data (≥ 1)	More than 20 failure data (≥ 20)
Active	Khi-2, ?	• non parametric: Johnson, KM [1, 2] • parametric, classic: SEM [13] • Bayesian: BRM [13], Fiabayes[1] [15], IBW [16]	• non parametric: “life table”, K-M • parametric, classic: ML, SEM [13], COX[3] [14] • Bayesian: BRM [13], IBW [16]
Standby, active	Khi-2, ?	• Bayesian: IBS [17], Fiabayes[1] [15]	• parametric, classic: ML • Bayesian: IBS [17]
Passive	Structural reliability: PROBAN [19 to 23] or specific tools²	Structural reliability: PROBAN [19 to 23] or specific tools²	Structural reliability or • parametric, classic: ML, SEM [13], COX[3] [14] • Bayesian: BRM [13], IBW [16]

1 when industrial reliability data are available.
2 tools adapted to the type of component, e.g. reactor vessel, steam generator, piping…
3 used for explanatory modelling of reliability; data mining techniques are also used.

4 Conclusions

It is clear that these methods are particularly well suited to the safety, maintenance and design issues encountered daily in industry. There are also potential uses for these methods and techniques in other sectors such as medicine.

Care must, however, be taken: any use of these methods with real feedback data requires prior validation of the data, in the absence of which the results obtained might be absurd. The main difficulty stems from this very validation, when it is necessary to pass judgement on the mode, the measurable effect and the degree in the context of a failure analysis.

The reliability of SSCs in design, operation and maintenance, remains largely a research field. Present research at EDF is focused on the following questions:

- the efficiency of a maintenance task, or the impact of maintenance on the reliability of a component [24, 25],
- long-term reliability prediction, including degradation modelling,
- the impact, including uncertainty ranges, of SSC reliability on performance and maintenance-replacement-redesign of SSCs,
- anticipation of failures by means of expert assessment,
- reliability / maintenance / costs-monitoring methods,
- sourcebooks identifying and containing all data necessary for a reliability assessment.

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