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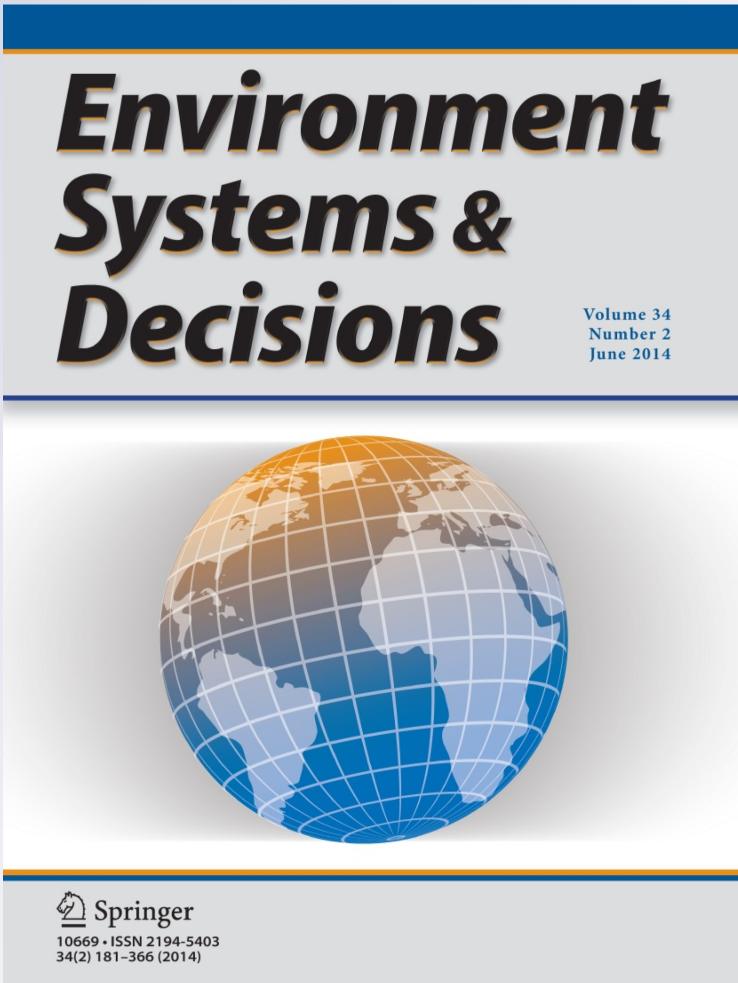

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Expertise, safety, reliability, and decision making: practical industrial experience

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Abstract This paper presents our practical experience of expert opinion deduced from concrete field applications, concerning mainly safety and reliability modeling. First, expertise is defined and the approach used for eliciting expertise is shortly described. Quality and value of information from experts are important challenges for decision making from risk analysis. Expertise is very useful for supplying data when not enough field observations are available for estimating parameter uncertainties and quantifying risk analysis models, which are inputs to a decision-making process. Applications presented herein concern mainly the role of expert judgment in reliability.

Keywords Expertise · Operation feedback · Reliability of components · Help for decision making · Risk analysis · Industrial applications

1 Introduction

Expertise is an important support for risk analysis and decision making, in the field of risk management, safety, and dependability. Expertise is mainly used for understanding the context and the physical phenomena, for supporting or improving input data, their variability being frequently one of the main sources of uncertainty, for proposing actions to suppress, to reduce or to postpone risk, and finally, to take optimal decisions.

From a general point of view, expert judgments are useful for quantifying risk models, because it has been impossible to make enough observations from operation feedback or physical tests, to quantify the model with objective experimental data. Expert judgment data are therefore used to estimate model parameter uncertainties and to construct a probability density function of these parameters.

Choosing experts, eliciting them with adequate questioning, scoring experts, combining expert assessments, joining them with field data are some of the main difficulties of the analyst who has to cope with expert opinion.

The present paper describes our practical experience of expert opinion deduced from real-field industrial examples. In a first step (Sect. 2), expertise is defined and the approach used for eliciting expertise is shortly described. Quality and value of information elicited from experts (Sect. 3) are important challenges for decision making deduced from risk analysis and are analyzed in Sect. 4. Then, some illustrative case studies concerning mainly safety, reliability modeling and maintenance management, risk analysis and proactive assessment are presented in Sect. 5.

Note that it does not exist any magical method for incorporating expert judgment in risk analysis. Every risk analysis problem, in any case, needs a specific methodology. Until now, there is no standard norm to elicit and to model expertise, but only specific guides have been proposed for particular areas.

First of all, before tackling the subject, it is necessary to define the actors at stake:

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1. the experts: persons with specific knowledge, wide experience, or training,
2. the analyst (or moderator) that uses expert opinions, quantifies the models, interprets the results obtained, and transfers them to the manager; note that often the analyst is not an expert of the problem analyzed, he is a support to express the expert's knowledge in the most appropriate way,
3. the manager (or decision maker) who will decide, taking into account risk analysis results but also economical and social stakes, knowing that very often he has preferred shares depending on his concern.

2 What is expertise?

2.1 Definition

Expertise is a skill in a particular field, a know-how.

It is a knowledge source of prior subjective information of a representative authorized and recognized person, based on the knowledge, training, practice, and experience in a particular area, at a given time.

It is a contribution to a technical problem facilitating a decision taken by a manager. It permits to complete, to improve existing data, when they are poor, incomplete, or questionable; or to supplement them when they are lacking (for instance in the case of bad field data or in case of an innovation …). Very often, it is the only source of information available, which can be used in a decision-making process. It is demonstrated to be a valuable information.

It is a source of data that can be qualitative or quantitative. It is essential when the future is not like the past: new risk, new design, innovation, refurbishment, new service conditions, new environmental conditions, modification of preventive maintenance programs.

2.2 History

Use of expert opinion-based methodologies is relatively recent. Since 40 years, expert opinion is mainly employed in the form of subjective probabilities as a dominant source of information for determining reliability parameters, like failure rates, and associated uncertainties [in the IEEE standards (1984), and in the famous reliability data handbooks like, in the nuclear field, the Swedish T-Book (2000) or the French EIReDA (Arsenis et al. 1999)]. It has been successfully employed in probabilistic risk assessment reports [like the Wash 1400 (1975) or the Canvey Island report (Health and Safety Executive 1978)]. In the 1990s, expert elicitation has been used to determine probability distributions of physical input variables for two probabilistic accident consequence codes (Goossens 2005). More recently (in the 2000s), expertise-based methodologies have been largely used in the framework of life cycle management and life extension studies, reliability studies, human factor analysis, and prognosis studies (see for instance Lannoy and Procaccia 2001, 2012; Bouzaïene-Marle 2005; Peres et al. 2007; US NRC 2011).

2.3 The elicitation process

The European guide Knowledge Engineering Expert Judgement Acquisition and Modeling (KEEJAM), which is a process in 15 steps based on knowledge management engineering, can be recommended (Cojazzi et al. 1998). Note that, this document is a guide and not a standard (norm). It recommends the following steps.

- *Choosing the experts* This step is one of the major issues of the analysis. It can be often considered that it is better to use a number of experts enough to represent a variety of opinions; "exotic" or "extreme" or "singular" opinions (sometimes they are innovative opinions) have to be analyzed and taken into account if explained by the concerned experts. According to (Cooke and Goossens 2000), criteria for selecting experts are as follows: 1 reputation in the field of interest, 2 experimental experience in the field of interest, 3 number and quality of publications, 4 familiarity with uncertainty concepts, 5 diversity in background, 7 awards, 8 interest in the project, and 9 availability for the project.
- Then, different methods of interrogation can be distinguished: interactive group of experts or Delphi method when the moderator wants to stimulate the creativity or wants to obtain a global consensus; individual interviews, more suitable for obtaining more personal opinions or for estimating uncertainties and quantified estimates.
- Another major issue is elicitation, which is the process to collect and collate the opinions of experts. Biases can occur at many levels (Meyer and Booker 1993; Lannoy and Procaccia 2001; Simola et al. 2005): cognitive biases (overconfidence, anchoring, availability) and motivational biases (social pressure, interpretation error). These difficulties cannot be avoided. They have to be reduced. Prior expertise experimentation is very useful to reveal biases problems.
- Then, Bayesian methods, often subjective or normalized probability distributions, can be used for combining expert opinions, mainly empirically.

Bayesian models for combining expert opinions are proposed in the technical documentation, for instance (Singpurwalla 2006; Procaccia 2009) for the more recent references. Indeed, Bayes' theorem is directly linked to expert judgment; prior information is generally given by expert opinions and is joint to experience by the likelihood function. An example proposed in the Sect. 5.3.2 presents how expertise can be combined with operation feedback.

If X is the quantity of interest and $x_1, x_2, \ldots, x_n$ are the n estimates of X from n experts, then analyst starts with a prior probability density over X, $p(x)$ (it could be his own opinion or the belief of the manager or a past experience), this prior density is updated with the information $x_1, x_2, \ldots, x_n$ provided by the n experts.

Applying the Bayes' theorem leads to

$$p(x/x_1, x_2, \ldots, x_n) \approx L(x_1, x_2, \ldots, x_n/x) \cdot p(x),$$

where L is the likelihood function.

If experts are independent, the likelihood function L is:

$$L = \prod p(x_i/x), \quad \text{for } i = 1, n.$$

In this condition, note that operational feedback data are more than precious and can also be combined as an expert opinion. Being an experimental objective information in the real service conditions, the general trend assigns to it the most important weight.

Bayesian treatment permits mixing of expertise and operation data. It is all the more since expert opinions are heterogeneous and independent. Nevertheless, a sensitivity analysis must always be performed for understanding the robustness of the global information.

3 Uncertainty and risk analysis

3.1 Value of information

Expertise is obviously uncertain. And sensitivity analysis is a way for quantifying uncertainty. Value of expertise information, accuracy, relevance, and informativeness are fundamental factors for the manager. Frequently, main estimate input given by experts is the median value (50 %), the mean value or an interval of dispersion generally assigned to the 5 and 95 % quantiles for the query variable.

Performance of experts has to be assessed.

A first qualitative method to assess expert's quality, always available, is to assign scores to experts according to their educative knowledge, their field experience, their training, their skills… (Forrester and Mosleh 2005). Do we have to renown experts? Relevance of the expert can be estimated by studying his reasoning process and his arguments, permitting to define and to calculate experts' scores (Lannoy and Procaccia 2001). Note that scoring expert is very difficult and can be unreliable: it is rarely used in case studies.

The first possibility, which is relatively classical, is that weights used to combine expert distributions are chosen according to the performance of experts on calibration questions, questions for which answers are known to the analyst (Cooke 1991). This is called the calibration method. It has been asked for the experts' uncertainties over a number of calibration variables. The quality of expertise can be measured by the difference between the empirical distribution given by the calibration variables from that deduced by the expert (Bedford and Cooke 2001; Goossens and Cooke 2005).

Level of experts' knowledge can be measured by Kullback entropy. Any information enrichment expresses as a reduction in entropy. A way of measuring is to calculate the Shannon entropy or relative information index of the empirical distribution with respect to the witness variables. It permits to define a relative index of more or less good or bad experts (Lannoy and Procaccia 2001).

Another simple method consists in comparing expertise data with observed operation feedback data. If these two types of data are of the same order, it can be concluded that confidence can be given to expertise. But if they are very different, the difference has to be explained.

Nevertheless, expertise data may have been employed for predicting future behavior of equipment consecutive, for instance, to a design modification or to a new preventive maintenance program. In the framework of operation, if expertise is used for completing insufficient operational data, it is likely that quality of the field data or of the expertise has to be verified. In conclusion, field observations are mainly interesting for an operational use, experts' judgment is mainly interesting when prediction or prognosis is required, or when field data are rare.

3.2 Uncertainty and risk

Uncertainty is linked to risk. Definition of risk by the ISO 31000 standard (2009) (which is a risk management standard) is the effect of uncertainty on objectives, thus causing the word risk to refer to positive possibilities as well as negative ones.

Uncertainty analysis has been introduced by the Wash 1400 report (1975) mainly because most of the probabilities were subjective, due to the extensive use of experts' opinions. Consequently, decision makers would not accept probability values without knowing estimates of the uncertainty of input variables. Uncertainty can be represented by a probability function (in this case, Bayesian methods are very well appropriate), or more simply by an error factor. At the present time, variability of input variables (the random uncertainty) and lack of knowledge in modeling (the epistemic uncertainty) are very often taken into account in a risk analysis study. Ambiguity and indetermination are more rarely considered. Note also that uncertainty analysis concerns also consequence modeling and structural reliability studies.

3.3 Main steps of risk analysis

A risk analysis tries to answer the following questions (Bedford and Cooke 2001):

1. What can happen?
2. How likely is it to happen?
3. Given that it occurs, what are the consequences?

Expertise can bring some answers to the decision maker:

1. An analysis of the context, underlining the different sources of danger, which may impact people or environment,
2. Uncertainty is quantified by probability; expertise can reduce the level of uncertainty, if the expert has been well calibrated (if he is an efficient expert and if he has been trained to assess probabilities) and consequently expertise can provide a better appraisal of probability,
3. Expertise can supply information about whether or not a danger can lead to potential negative consequences.

The process of risk management consists of several steps as follows:

- establishing the context,
- identification of sources of danger,
- risk assessment including deterministic and probabilistic quantitative analysis,
- risk options (or risk mitigation actions) and treatment,
- creating a risk management plan, including implementation, control, and practical experience.

4 Decision phase

4.1 The utility function

The decision maker's objective is often to maximize the expected utility function of a project (design of installation, equipment…), or of an intervention (system modification, new maintenance policy …), or correlatively to minimize the total cost, where

$$\text{Utility} = \Sigma\,(\text{Benefits}) - \Sigma\,(\text{Costs}).$$

Benefits are all the possible outcomes (in particular the gains in money) for a given decision. One cannot directly measure benefits or satisfaction from a service or a good. Generally, an estimation of expected gains or losses is carried out when comparing different technologies and their risks.

Total costs include

- investment–design–construction costs; they depend on predicted failure probability; weaker will be this failure probability, more important will be the investment cost,
- operation and maintenance costs during the service period also depend on the failure probability,
- failure costs, safety–security costs, unavailability costs depend strongly on the failure probability; these costs must include the value of statistical life, which is very difficult to estimate and generally badly known (Andersson and Treich 2010).

A simplified equation can be proposed, to calculate the total cost to be minimized, C_{T}:

$$C_{\mathrm{T}} = C_{\mathrm{i}} + P_{\mathrm{f}} \cdot C,$$

where C_{i} is the investment amount, P_{f} the failure probability, and C the failure cost (including inspection–maintenance costs, unavailability cost, and safety cost).

Expected total cost is generally a *U*-shaped curve, the minimum of which can be determined, so permitting to fix a target value of the failure probability. It is the classical maintenance optimization calculation when the operator has to select corrective or preventive maintenance.

This method is interesting when potential losses are only economical. In case of extreme events, when failure implies human losses and environmental damage, this method cannot be applied, because of the value, generally indeterminate, of statistical life and safety costs.

But the method is used for new products when no prior historical data are available. In this case, the failure probability is predicted or calculated from the observation time to the "end of life" target. It has been observed, mainly when using asset management models for optimizing life extension of equipment, that failure probability is very often the most influent parameter, before investment costs or capital additions, which is likely due to a more important uncertainty on failure probability than on costs.

4.2 Preferences

Risk analysis is frequently used to demonstrate the conformity of an industrial site to the requirements of regulation rules. Nevertheless, quantitative risk analysis can be considered as an important input of decision making. The task of the decision maker is very difficult in the sense that his decision can lead to negative consequences. Generally, he has to choose one action (or option) among many, every one leading to uncertain consequences, more or less serious.

First of all, he will listen to the analyst, looking at the results and their uncertainties, their robustness, the sensitivity analysis, the models used, the uncertainties

Table 1 Main decision analysis methods used in risk management, safety, and dependability

Methods	Use of the method	Use of expertise	Some characteristics
Cost–benefit analysis	Risk analysis	Probabilities, seriousness of potential accidents Costs of safety	Basis for a consensus decision
Decision tree	Reliability and corrective/preventive maintenance Design phase	Assessment of reliability parameters	Finite number of actions Economical utility
Making decision using Bayesian inference	Reliability, PSA, maintenance, durability Treatment of modifications	Updating of data Effects of modifications	After definition of a mitigation action (or option)
Influence diagrams	Organizational and management factors Maintenance Human factor probabilities	Influent factors Qualitative influence Conditional probabilities	Conditional independence
Multiattribute utility theory (MAUT) (Beaudoin and Munier 2009)	Risk analysis when rare events (small probabilities, major consequences) Safety, maintenance optimization, help for new design	Elicitation of preferences, of a utility function	Decision under uncertainty Action studied a priori defined Attributes measurable
Life cycle management (LCM)	Risk informed asset management Optimization of maintenance Life extension	Screening Definition of actions (options) Assessment of reliability parameters	Optimization of the net present value (NPV) Asset management models
Belief networks	Risk analysis Diagnosis, prognosis, optimization of maintenance Proactive behavior	Construction of the belief net Probabilities of the nodes, conditional probabilities Verification—validation of the model	Qualitative and quantitative variables Takes into account uncertainties Permits to think of new actions

concerning input data including quality and reliability of expertise, social, economic, and environmental stakes.

Since most actions may have uncertain negative consequences, considering the industry stakes, the decision maker must specify his preferences that can concern for instance:

- in the reliability centered maintenance (RCM) frame: safety, availability, maintenance costs (Beaudouin et al. 1999),
- or in the frame of design phase: availability, investment, and delay…

These parameters are called attributes, and the decision maker has to give a hierarchy of these attributes determining his degree of preferences (Beaudouin and Munier 2009). It is important that these attributes can be measured, even subjectively, or in using indicators that are representative and measurable. A utility function can be elicited taking into account the risk attitude of the decision maker.

4.3 Decision analysis methods

Main popular decision analysis methods are listed in the Table 1.

5 Applications in safety and reliability

5.1 Example 1: Probabilistic safety analysis (PSA) and reliability data handbooks

Most of the dependability methods need expertise. It is the cases of fault trees and event trees used in safety analysis. Many input data are necessary concerning initiating events, critical failures, human reliability probabilities, service profile.

Two hundred experts (IEEE) have been mobilized in the construction of the PSA Wash 1400 data and gave subjective probabilities using expert opinions.

Main comments concerning this safety analysis were related to the lack of field data and to the evaluation of uncertainties.

Likewise, expertise (from design engineers, operators, maintenance engineers, safety analysts) has been largely used for the T-Book (2000) and for the EIReDA '2000-European Industries Reliability DAta (Arsenis et al. 1999):

- selecting the most important safety components,
- grouping them into families of equipment,
- proposing a confidence interval for failure rate,

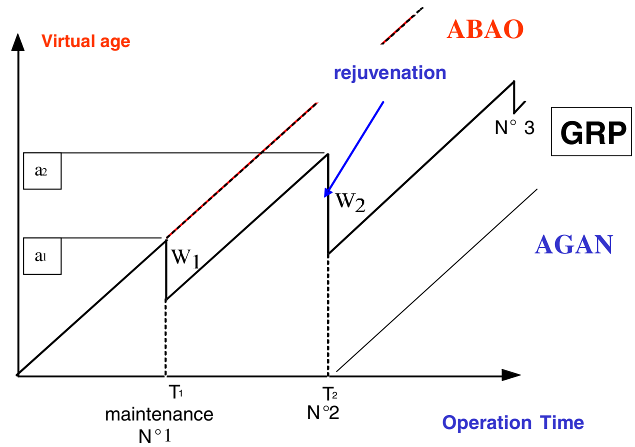


Fig. 1 Effect of maintenance (here positive) on the behavior of a repairable equipment. *ABAO* as bad as old, *AGAN* as good as new, *GRP* generalized renewal process or imperfect maintenance

- calculating a failure rate when zero failure has been observed after many years of operation.

5.2 Example 2: Effectiveness of maintenance action for repairable components

Figure 1 shows the impact of a preventive maintenance action on the age of equipment. Determination of the level of random rejuvenation impacted by each maintenance intervention, w_i, is the main problem.

When the maintenance impact is minimal, the equipment after maintenance is in the same state that it was before this maintenance. This state is named as bad as old (ABAO). The virtual age is identical to the operational time (here also calendar time). This situation generally corresponds to the occurrence of a failure of a component during operation of an industrial installation. The corrective repair is carried out rapidly allowing a quick restart of the installation. The corresponding maintenance rejuvenation factor, $w = 0$, is null.

When the maintenance is perfect, the component is equivalent to a new one component after the maintenance intervention. This state is named as good as new (AGAN). This situation generally corresponds to a preventive maintenance with replacement of the component by a new one: its virtual age is null after each maintenance task and the rejuvenation factor equals 100 %.

Finally, a real maintenance, unfortunately often named "imperfect maintenance" (words "effective maintenance" or generalized renewal process GRP are preferred by the authors), is intermediate between the two previous cases. The rejuvenation factor is comprised between 0 and 100 %.

Figure 2 shows an example of deterministic influence diagram allowing to quantify the maintenance effectiveness w_i. This influence diagram has been built by an expert and a reliability analyst. Expert judgment has been used to determine the a priori probabilities and the conditional probabilities of each state of a node given the state of the parent nodes. An expert specialized in the maintenance of valves has been selected and motivated to provide rigorous answers. The reliability analyst has shown the expert how to assess probabilities and confidence intervals.

Figure 3 shows an example for the determination of the maintenance rejuvenation factor from expertise made by manufacturer and maintenance teams, using a specific Bayesian software (Rexpert), after recording estimates from several teams of experts and modeling their answers.

5.3 Example 3: Maintenance optimization of a diesel generator engine

Two diesel generators assume the auxiliary electric power of nuclear plants safeguard systems in case of loss of the redundant 250 and 400 kV grids supplying the plant. Their role is important for the plant safety, and operators have to avoid any failure during the diesel operation in case of accident. To respect this objective, the initial basic preventive maintenance recommended a systematic replacement of all cylinder linings every 5 years.

5.3.1 *Probability of failure of a new cylinder lining*

After a yearly block lining endoscopic examination concluding to a good state diagnosis, or after its preventive replacement, the statistical analysis of recorded field data makes it possible to determine the future risk of failure of the diesel engine during the next operating year. Indeed, the field data collected during 20 years allow to determine the aging law of a new diesel cylinder lining, which is modeled with a Weibull distribution, if only the first failure data are taken into account (Fig. 4):

$$F(n) = 1 - e^{-\left(\frac{n}{\eta}\right)^{\beta}}$$

$F(n)$ is the failure probability after n start-up, β and η are, respectively, the shape and the scale parameters of this distribution.

These parameters calculated here by the maximum likelihood method are, respectively:

$\beta = 1.42;$

$\eta = 303$ start-up.

As seen previously, each year, the cylinder lining state is inspected by endoscopic control. If the cylinder's state is

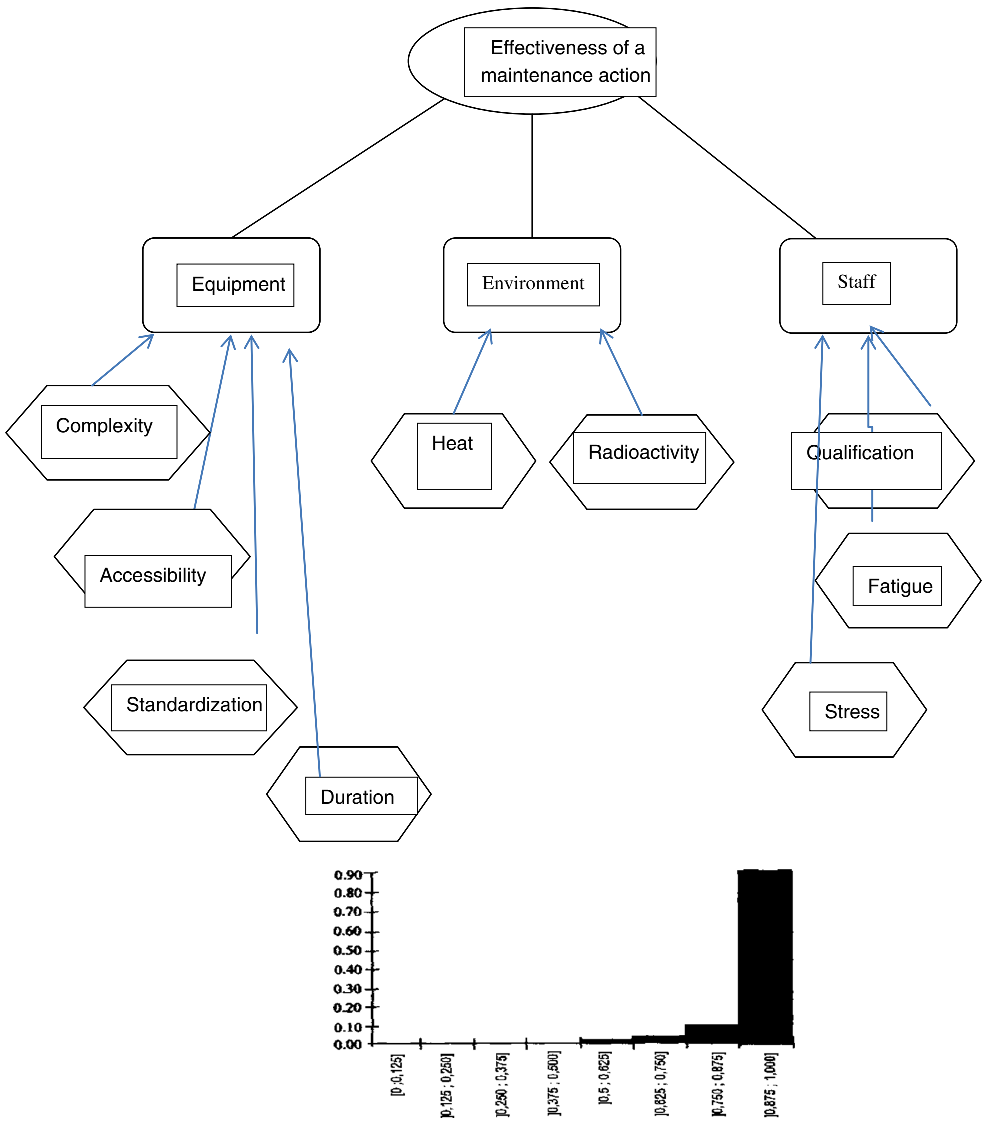


Fig. 2 Influence diagram and probability histogram for the evaluation of the effectiveness of a maintenance action (case of a pneumatic valve) (Clarotti et al. 1994). *Bottom* of the figure: histogram of probability answers for one specific maintenance task

still good, its failure probability during the next operation cycle can be estimated from this Weibull distribution.

5.3.2 *Failure probability of a degraded cylinder lining*

But what happens if the in-service inspection reveals a small lining degradation, which does not justify its replacement? Expert opinions are therefore needed to estimate three probabilities in this condition:

- the probability that one or more cylinder linings could operate during a specified time in a specific degraded condition, either during a diesel test—about 24 one-h tests/year), or either during one diesel mission time in case of plant accident (diesel failure rate);
- the on-demand failure probability of a degraded lining, when it is needed for its mission;
- the probability that a failure under one of these conditions would lead to a shutdown of the plant in application of operating procedures : a failure lasting longer than 72 h imposes indeed a plant shutdown, the field operation data feedback recorded during 20 years being inadequate (no shutdown was observed in this specific situation).

Only the first probability is considered hereunder. The same approach can be used to evaluate the two other probabilities.

Note that experts during an endoscopic inspection can distinguish six types of lining degradations (Table 2).

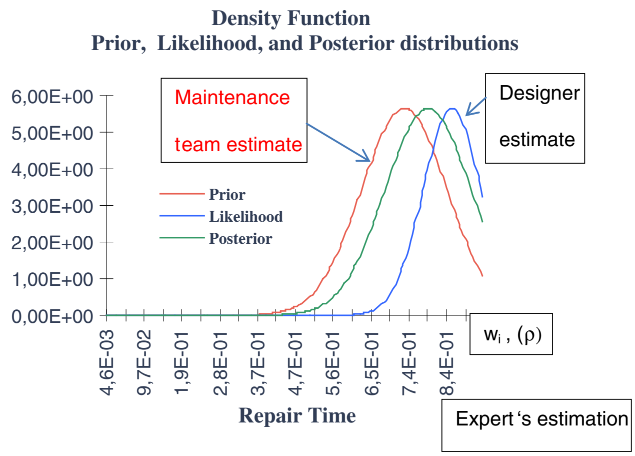


Fig. 3 Modeling prior preventive maintenance effectiveness estimates. *Left* preventive maintenance rejuvenation density deduced from expert's maintenance team (prior), *right* manufacturer team rejuvenation (likelihood function), *center* posterior density (joint expert's densities calculation and graph plotted by Rexpert software (Procaccia and Procaccia 2012), repair time in hours)

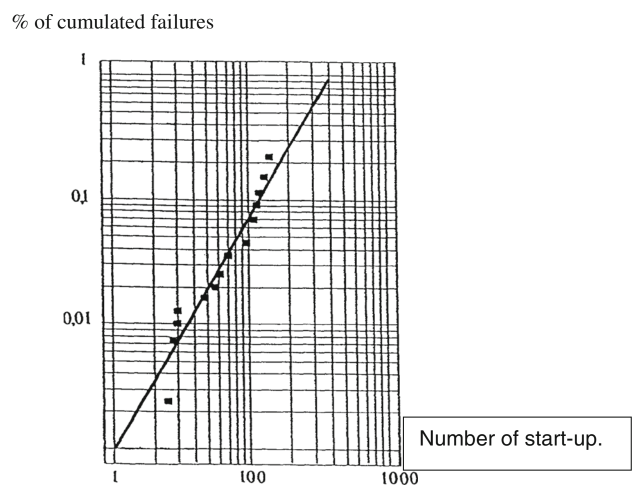


Fig. 4 Aging distribution of new engine cylinder linings

5.3.2.1 Expert's elicitation The questions asked to the maintenance experts concern the preventive replacement of diesel cylinder linings before any occurrence of degradation and the optimal periodicity of this replacement. Nine experts are questioned for determining the on-demand probability of cylinder failure (start-up of the generator), the failure rate during all the mission operation when cylinders are degraded, and the probability to get an unavailability >72 h after a failure, this time corresponding to the necessary time allowing the connection of one another generator existing in the plant.

The results of this expert elicitation questionings are given in Table 2.

Table 2 Maintenance optimization of a diesel generator—expertise elicitation

Questions	Answers		
Type of crack r_i	Can safely operate during t_j hours?	Number of answers: yes	Number of answers: no
Small crack	24	9	0
	48	9	0
	72	9	0
	200	9	0
Short crack	24	9	0
	48	9	0
	72	9	0
	200	5	4
Long crack	24	8	1
	48	8	1
	72	8	1
	200	4	5
Short deep crack[a]	24	7	1
	48	7	1
	72	5	3
	200	4	4
Long deep crack[a]	24	6	2
	48	6	2
	72	4	4
	200	2	6
Crack with oil leak or carter overpressure[a]	24	1	7
	48	1	7
	72	1	7
	200	0	8

[a] One expert (out of 9) did not answer

Answers are binary. Expertise data are so considered equivalent to binomial test results in the probabilistic analysis and are first jointed to a non-informative function (an uniform distribution), to obtain a prior probability density f(p/expertise) strongly weighted by the expertise. This last one is again combined, in a second time, with field data [called likelihood function, $L(\alpha, \beta/p)$] to obtain the posterior density, $f(p/\alpha, \beta)$.

5.3.2.2 Modeling expertise The general methodology to combine field data and expertise is summarized on Fig. 5 and in the example hereunder. Obviously, Bayesian technique allowing to associate prior expertise to feedback experience is employed.

Example During an endoscopic control, a long crack type is observed on a cylinder lining: 8 experts out of 9 consider that the diesel engine can safely operate 24 h with this type of crack (Table 2, line "long crack" at 24 h).

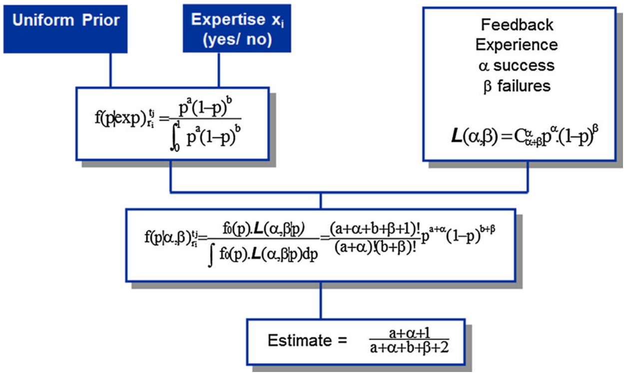


Fig. 5 Modeling of expertise for an observed type of crack r_i permitting safe operation during t_j hours, p being the survival probability

Following statistical distributions can be successively determined for the 24-h case:

- the prior density of expertise is a beta/binomial density:

  $90\,p^{(8+1)-1}(1-p)^{(1+1)-1} = 90 \cdot p^8 \cdot (1-p),$

- the field experience records five successes after five diesel tests: these test results can be modeled by a binomial law, and the corresponding likelihood function L (5/p) can be written as:

  $L(5/p) = p^5(1-p)^0,$

- finally, the Bayesian joint conjugate posterior density is:

  $210 \cdot p^{(14+1)-1} \cdot (1-p)^{(1+1)-1} = 210 \cdot p^{13} \cdot (1-p),$

- and the posterior expected success of the diesel operation during 24 h, with this type of crack (long crack), is the posterior expected mean:

  $p(r_i) = 0.875.$

5.3.3 Decision theory

A decision problem begins by listing all possible alternative actions (or options), considering only those that are the more relevant for the examined problem. This part of the analysis corresponding to the decision-making problem is very often regarded as the more valuable step of the decision analytic process. This process can be represented by a decision tree (Fig. 6).

The risk assessment associated with any envisaged option takes into account the consideration of all possible uncertain events related to the decision alternative actions (step called states of the world) and to their corresponding outcome consequences or utility function.

A "good" decision is the alternative action that at best takes into account the available information at the decision time and the preferences of the decision maker over all the possible consequences, weighted by their probability of occurrence.

These consequences are a means of appraising the decision-maker objectives, very frequently safety objectives, production availability, or expected economical benefits, but also other more or less tangible factors.

The theory of rational decision making says that the optimal decision rule is to select the action maximizing (or minimizing) the expected utility function (the loss function). It is the maximization of expected utility principle (MEU).

The theory can be simply divided into three steps: the alternative set of possible actions, the states of nature and the corresponding external uncertainties, and the set of induced consequences.

5.3.4 Diesel engine application

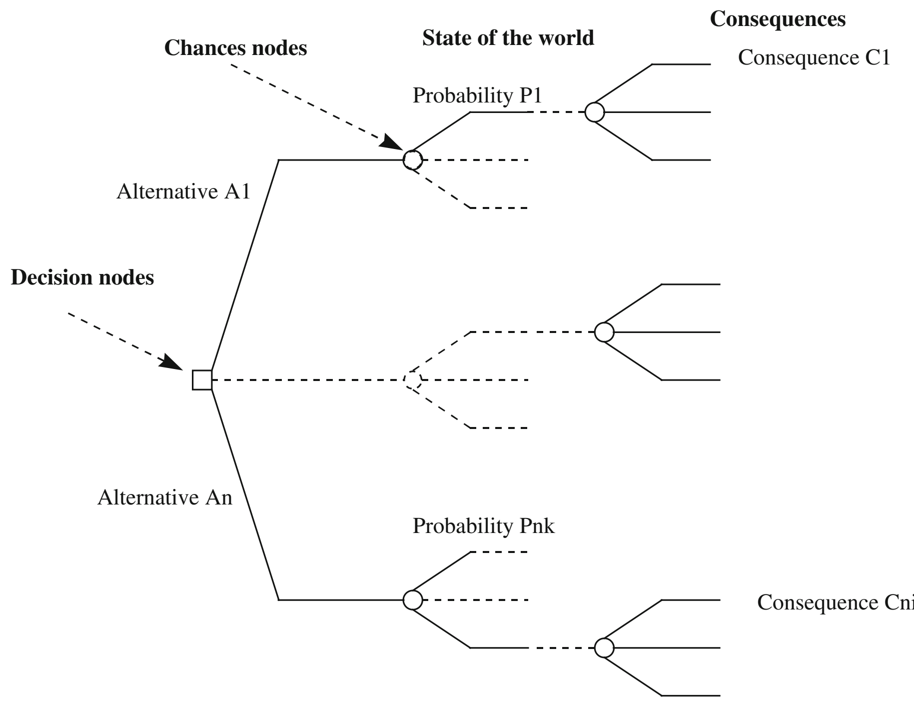
Two decision trees have been developed for the diesel application, the objective being to optimize the preventive maintenance of cylinder linings, and mainly the conditional maintenance given the endoscopic observations:

- when, during an endoscopic control, one or more scratched linings are found, the question is: do we have to replace or not the degraded linings, given the number of tests remaining to be performed before the next endoscopic control, and given the probability of being needed for a mission during the remaining service period of the linings?
- the second decision tree concerns the optimal frequency of lining replacement, given their age; the field of possible actions is large; the study has been restricted to the evaluation of risks associated with discrete replacement periods of 5 years (the reference solution), 7, 10, and 15 years, and estimating the corresponding loss functions, calculated in cost terms (of repair, down time, and replacement).

The optimal decision is the one that leads, here, to the lowest expected loss function. This function represents the probabilized economic consequences arising from a given action.

To illustrate the first decision tree, let us take the example of a lining degraded with a long crack. The computed failure risks and the associated loss functions for one more operating year of the diesel are, respectively:

Fig. 6 Decision tree



Probability of failure during mission/new cylinder = $8.71 \cdot 10^{-6}$
Probability of failure during mission/degraded cylinder = $3.49 \cdot 10^{-4}$
Probability of failure during test/new cylinder = $2.32 \cdot 10^{-3}$
Probability of failure during test/degraded cylinder = $7.44 \cdot 10^{-2}$
Loss relative function: lining replacement = 1.00
Loss function: no replacement = 0.28
The «best» decision is: «do not replace the degraded lining until the next scheduled endoscopic in-service inspection»

The costs taken into account are the followings:

- the reference elementary cost is the one lining replacement cost: C1 = C;
- the systematic preventive replacement cost of the 20 cylinders is: C2 = 20 C;
- the failure cost during a test is: C3 = 3 C;
- the failure cost during a mission is: C4 = 140 C;
- the mean cost of 24-h down time is: C5 = 40 C.

The decision tree as a whole is complex, because it must take into account all lining degradation and failure probabilities in each operating cycle, the results of the endoscopic examinations, and the actions proposed by experts on the basis of these results, between two systematic preventive lining replacements.

The corresponding decision tree is given on Fig. 7.

The relative loss function for linings preventive replacement periodicity every 5, 7, 10, and 15 years is plotted on Fig. 8.

The minimum of the loss expectation lies in the vicinity of 10 years and is relatively flat until 15 years. The decision to extend the periodicity of systematic linings replacement from 5 to 15 years has been finally taken by the utility, and the goodness of this decision has been, since, proved and the decision has been generalized.

5.4 Example 4: Weibull analysis with high rate of right-censored data

In case of high rate of censored data, the algorithm Bayesian restoration maximization (BRM) is preferably used (Bacha et al. 1998). The problem is to construct a prior distribution for the shape parameter (gamma law) and the scale parameter (beta law) of a two-parameter Weibull distribution. Four questions are asked to experts (generally designers or operators or maintenance engineers). Information obtained permits the assessment of these two parameters.

- Q1—Is it an aging equipment?
- Q2—Do you observe an important increase of maintenance actions?
- Q3—Are your previous answers based on technical facts (operation feedback, preventive maintenance programs …)?

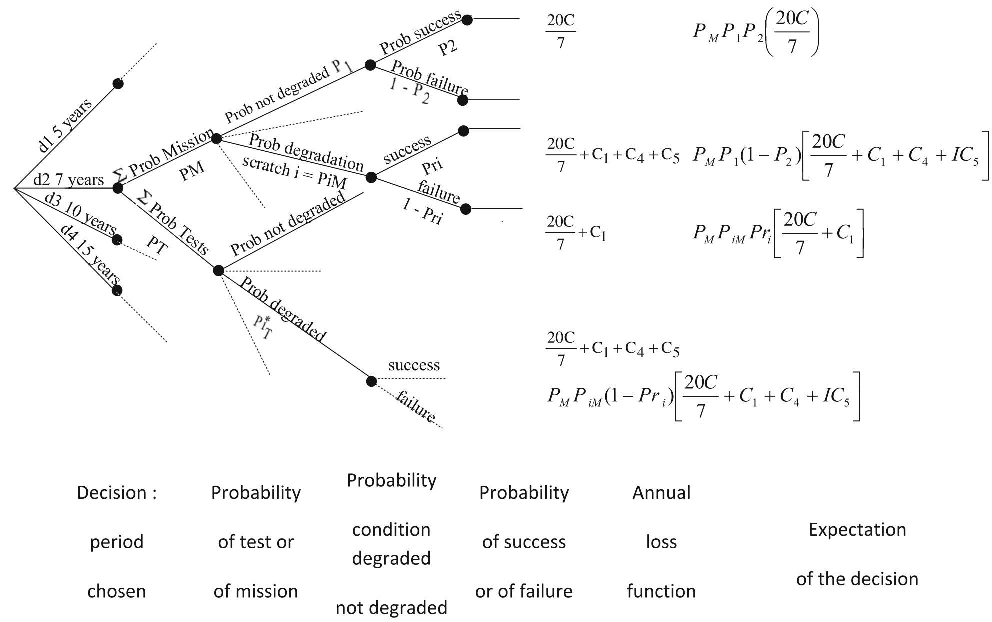


Fig. 7 Diesel engine decision tree

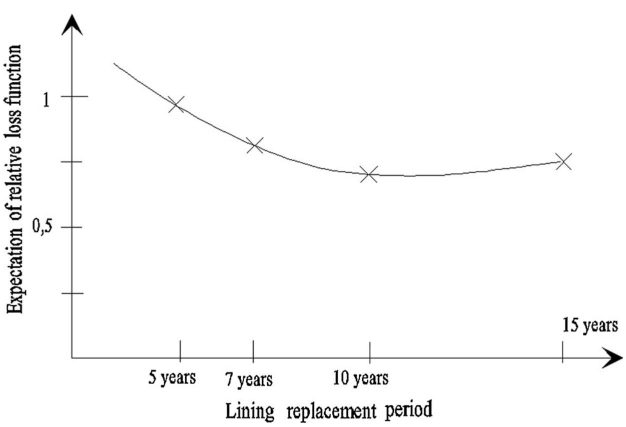


Fig. 8 Loss function versus periodicity of lining replacement

- Q4—Considering service—environment and maintenance conditions—could you give an interval for the lifetime of equipment, from commercial operation time to the end of life?

As in the previous example, expertise is then jointed to field data and has given good results in evaluating aging of non-repairable equipment (an example is given in Table 5—Sect. 5.6). Sensitivity analysis is recommended.

5.5 Example 5: Durability and maintenance costs

The purpose is to distinguish the trends of maintenance costs of an aging plant, in a proactive perspective. Belief network technique has been used. Here, it is an excerpt of a larger net containing more than 200 relevant variables. These last ones (Table 3), described in precise terms, have been selected by experts, permitting the construction of the net (Fig. 9), which is a directed acyclic graph. Most of the experts participated in the study (Chatelain and Lannoy 2001). The net has been verified and validated, and then quantified using expert judgment or field data. Then, it will be possible to think of new actions for the manager by looking at the critical influencing factors and determining ways limiting or breaking the influences. Maintenance costs (variable T10) will experience a sharp increase evolution if the absence of suppliers for spare parts (G1) or more stringent safety rules (R1).

5.6 Example 6: Reliability growth, design modification of an equipment

Five failures and 9 right-censored data have been observed during 2,068 h on identical components. Considering these bad results, design modifications have been decided. After modification, new field data have been recorded during 1,183 operation hours: two degradations and six right-censored data have been then observed.

Two groups of experts (design engineers, operation and maintenance engineers) have been elicited about the design modification effectiveness. Expertise results are summarized in Table 4. Reliability calculations before and after the modification are given in the Table 5, using different reliability methods. The conclusion is that complementary field data are necessary for concluding a reliability growth (Clarotti et al. 2004).

Table 3 List of relevant variables

Abbreviation	Class of variables	Variables	Modality
T1	Technical variables	Maintenance policy	Optimized/not optimized
T2		Replaceability of components	Easy/difficult
T3		Aging of components difficult to replace	Acceptable/problematic
T4		Aging of other components	Acceptable/problematic
T5		Overall conditions of components	Acceptable/problematic
T6		Maintenance information system	Good/to be improved
T7		Existence of spare parts	Yes/no
T8		Appearance of new design faults	Yes/no
T9		Available technical margins	Yes/no
T10		Increase of maintenance costs (output variable)	No increase/sharp increase
R1	Regulatory variables	Safety rules	Statu quo/more stringent
R2		Dosimetry regulations	Statu quo/more stringent
R3		Standards	Statu quo/more stringent
E1	Miscellaneous variables	Control of the industrial context	Yes/no
H1		Production loss following an incident	Minor/great
G1		Presence of suppliers	Yes/no
G2		Staff motivation	Weak/strong
S1		Continuity in skills	Well managed/poorly handled

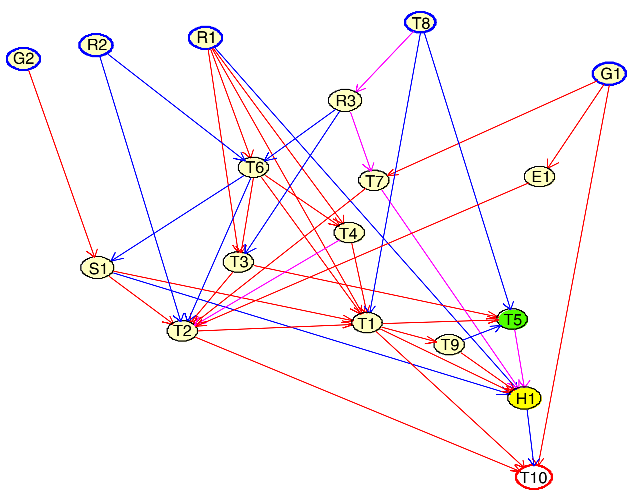


Fig. 9 The belief net for the trends of maintenance costs

Several statistic models have been used to evaluate the impact of the modification on the equipment aging. Results are compared in Table 5.

5.7 Example 7: Analysis of petrochemical compressors piston-liner and ring cracking degradation during test. New maintenance age reduction models [arithmetic reduction in age (ARA)] for repairable equipment

Statistic distributions like the Weibull distribution can only be used to model reliability for identic and independent equipment having same failure law, and for only modeling one failure mode. In fact, after any maintenance, one specific equipment becomes different of the other similar equipment, which are not yet maintained: the maintenance intervention has rejuvenated it, and statistic distributions cannot represent the failure distribution of a whole set of nonidentical and interchangeable equipment. A counting failure process, the non-homogeneous poisson process (NHPP), is then used to model the behavior of repairable equipment. Generally, the power law process (PLP) supports the Poisson process. The most popular process to represent the maintenance impact on the reliability of equipment and systems is the ARA model that has already been presented in Fig. 1 (Sect. 5.2). Other models are available as the arithmetic reduction in failure intensity (ARI) and the log-linear process support (Procaccia et al. 2011).

The ARA model has been used in this example. It needs to determine at least 3 or 4 parameters: the 2 parameters for the support process law: β and η, and one or two parameter(s) characterizing the maintenance age reduction.

Table 4 Reliability growth, results of elicitation

Groups	Deterioration rate with age	Median lifetime of the modified equipment
Designers	Continuous, weak	5,000 ± 1,500
Maintenance engineers	Mean	4,000 ± 1,500

Table 5 Reliability growth, results

Methods used	Old equipment		Modified equipment		Observations
	Shape parameter	Scale parameter	Shape parameter	Scale parameter	
Johnson method	1.3	1,400	1.4	1,400	No improvement
Wayne–Nelson method	1.2	1,450	1.0	1,750	Improvement
Maximum of likelihood[a]	1.7	1,450	1.6	1,700	Likely improvement
Stochastic expectation maximization (SEM)[a]	1.8 ± 0.1	1,450 ± 50	2.4 ± 0.1	1,350 ± 150	No improvement
BRM[a]					
4,000–6,000 h	1.4	3,850	1.6	4,360	Strong improvement
1,000–6,000 h	2.0	2,050	2.0	2,360	
1,000–4,000 h	2.1	1,800	2.2	1,900	
Method IBW					
4,000–5,000 h	Not calculated		1.1	2,060	Strong improvement
4,500–5,000 h	Not calculated		1.3	4,700	

BRM Bayesian restoration maximization (Sect. 5.4), *IBW* Bayesian inference for a Weibull law

[a] Bacha et al. (1998)

The age reduction factor estimation needs to collect a large sample of data in a statistic (or frequentist) evaluation. It is not the case in this example, and Bayesian approach is preferable.

This latter approach is used here, complementary to the frequentist approach. Concretely, maintenance experts are asked about either the mean estimate of the maintenance rejuvenation effectiveness, q, or either on the complementary equipment restoration factor, ρ. Their estimates are related to an average of all maintenance impacts on the maintained equipment, in a three-parameter model, or, better, in a four-parameter model if experts can appraise an averaged impact factor for corrective CM, and for preventive maintenance PM.

Due to the complexity of the latter ARA model, the rare existing market software generally determines three parameters for repairable equipment model.

Even in this case, the algorithm is rather complex and it requires a tool for the iterative maximization of the log-likelihood function for failures and maintenance operations. When 4 or more parameters have to be evaluated, in case for instance of many different types of preventive maintenance (current or overhaul), only Bayesian technique with elicitation of expert's judgements on the different maintenance effectiveness can solve the problem.

5.7.1 Field recorded data and process models for repairable equipment

The experts' application presented here concerns four reciprocating compressors (Fig. 10) monitored during a test of 8,760 h (censored test), performed to determine the structural reliability of the cylinder block set: piston liners and rings (piston segments) (Moss 2005).

Two types of failures occurred during the tests:

- (1) compressor performance losses (due to ring cracking or liner degradation and leakage),
- (2) compressor lubrication failures (seal cracking).

The observed data during the compressor tests are given in the Table 6.

The type of maintenance performed is either a corrective maintenance (CM) after a complete failure, either a preventive maintenance (PM, here a condition-based maintenance) in case of degradation observed during a mid-test in-service inspection. All failures are taken into account here (type 1 and type 2) to increase the data sample, which is very small.

Several age reduction maintenance models have been compared in this case study.

The first step of expertise consists in evaluating the "best" maintenance model fitting to the test field data (see Fig. 1):

- ABAO model, the maintenance carried out to restore the function has no impact on the compressor age: the state of the compressor is the same after repair than the state it had just before failure,
- AGAN, the maintenance totally renews the compressor,
- imperfect maintenance or GRP, modeled with either ARA_1 model, in which the maintenance restoration implies a reduction in age between two maintenance interventions, or either ARA_∞ model, where

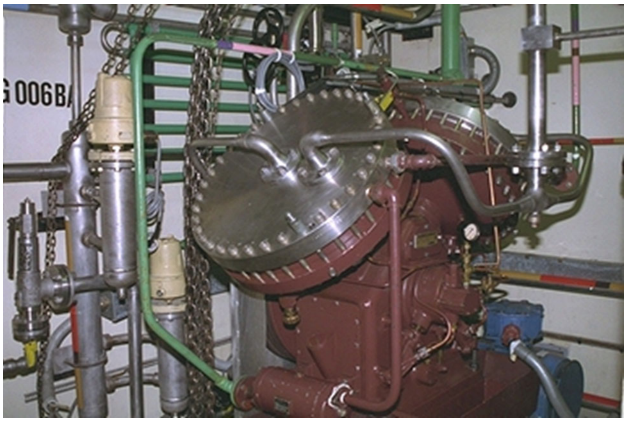


Fig. 10 Reciprocating compressor

Table 6 Observed field data table (hours) [failure modes: (1) performance losses, (2) lubrication failures]

Compressor	Failure no. 1	Failure no. 2	Failure no. 3	Censor
A	3,600 (1)	7,408 (1)	8,058 (1)	8,760
B	4,200 (1)			8,760
C	2,408 (1)	5,426 (2)	7,076 (1)	8,760
D	3,003 (2)	8,408 (1)		8,760

maintenance restoration implies age reduction in the cumulated compressor age at the time of maintenance.

The parameters of these different models have been estimated with Rexpert software, either from a classic statistic data analysis, or either based on a Bayesian approach, using experts' judgments.

5.7.2 *ARA maintenance models comparison*

The failure data analysis compares, on Table 7, several ARA model results:

- minimal repair (ABAO) and perfect maintenance (AGAN), two-parameter models, only characterized by the parameters of the power law supporting the counting process, β and η, and GRP "imperfect maintenance" process, with the two alternative age reduction models: ARA_1 and ARA_∞, which, at least, contain three parameters β, η, and the mean maintenance restoration factor ρ,
- then, the generalized Bayesian renewal maintenance model, characterized by several maintenance restoration factors, at least ρ_{PM} and ρ_{CM}, with possibly several distinct restoration factors for each preventive or corrective maintenance.

All models confirm a more or less rapid intrinsic aging leading to cracking or leakage of compressor cylinder block set. Except the minimal repair model, each other model has a shape parameter $\beta \geq 2.5$, meaning very likely friction rubbing or stress corrosion initiation (but not yet fatigue aging—generally characterized by a β factor around 2, the number of compressor start-up being small).

The mid-test PM impact has been supposed insignificant during the time of the test for all models.

5.7.3 *The Bayesian model for repairable equipment*

Table 7 also shows the Bayesian refined parameters obtained again with the software Rexpert in the case of the GRP with 4-parameter model, distinguishing here the two types of failure modes: loss of performance (1) and lubrication (2).

Here, the maintenance restoration factors have been estimated by elicitation of two groups of experts—designers and maintenance team—in the same way as it has been seen previously in the example of Fig. 3:

- for lining cracks or ring repairs, the mean expert's restoration factor estimate is $\rho = 80\ \%$: the degraded item is generally replaced by a new one part, but experts consider that the restoration is never totally AGAN because the new replaced part of the compressor is installed in an aged environment;
- in case of lubrication failure, the mean restoration factor assessed by experts is only 25 %, because the repair generally consists on the replacement of a seal, which is only a small part of the entire lubrication system.

5.7.4 *Overview of the results*

Figure 11 shows the results associated with each compressor (in spite of the lack of data), and the global estimates for all the compressors set, in cases of three-parameter models ARA_1, ARA_∞.

Figure 12 gives the comparison of the individual compressor reliability, and the global reliability of the compressors set.

And finally, Fig. 13 shows the results obtained with the GRP Bayesian model.

These three ARA frequentist and Bayesian models are considered as the best maintenance models for the compressors by experts.

5.7.5 *Choice of the "best" model*

The choice of the «best» model is based on the information entropy giving a relative measure of the information lost between the model and the reality. The most popular and currently used criterion is the log-likelihood value (LKV), which is an increasing function versus the number of collected data and the number of model parameters k to be estimated. The best model has the highest LKV.

Table 7 Comparison of estimated parameters between ARA models

Model	β	λ/η	ρ_1 (%) restoration factor 1 mean CM and PM	ρ_2 (%) restoration factor 2	LKV
Minimal repair[a] ABAO	1.81 ± 0.66	1.64E−7 5,496 h	0	0	−82.1
Perfect maintenance AGAN[a]	2.46 ± 0.62	1.60E−9 3,770 ± 1,450 h	100	100	−79.5
GRP ARA_1^a 3 parameters	2.96 ± 0.43	2.6 E−11 3,760 ± 1,230 h	88	–	−79.2
GRP ARA_∞^a 3 parameters	2.75 ± 0.17	8.1E−9 4,680 ± 1,420 h	70	–	−79.6
Bayesian GRP 4 parameters 2 failure modes, 1, 2	2.61 ± 0.27	2.5E−10 4,750 ± 1,730 h	80 type 1 performance	25 type 2 lubrication	−79.5

LKV log-likelihood value

[a] All data: modes (1) + (2)

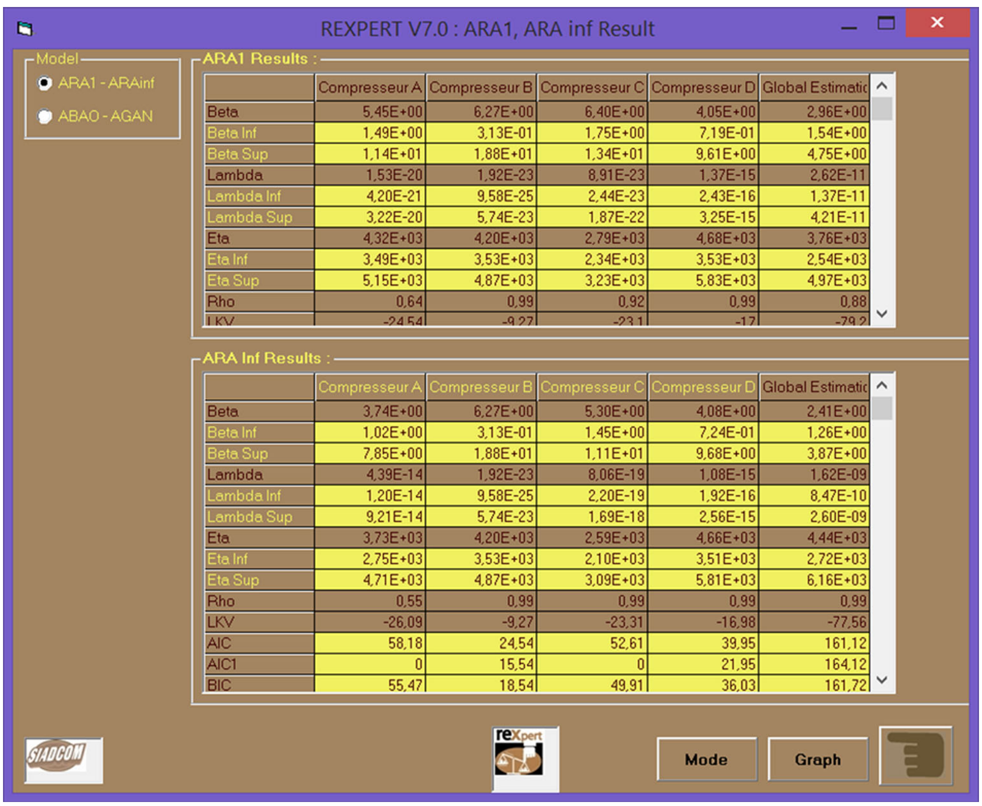


Fig. 11 Calculated individual parameters for ARA_1 and ARA_∞ models [calculated by Rexpert software (Procaccia and Procaccia 2012)]

Here, the highest LKV between ARA models is associated with the ARA_1 model, but LKV for ARA_∞ and Bayesian ARA are very close. The LKV of the Bayesian model is lower than the LKV of the frequentist ARA models. But, in fact, this model is penalized by the share of data between two failure modes aggravating the context of the limited data. Nevertheless, the shape (2.61) and the scale (4,750 h) parameters of this Bayesian model lead to a better calculated reliability for the compressor compared to the reliability deduced from ARA frequentist models (Fig. 13).

Meanwhile, the Bayesian four-parameter ARA model, characterized by different age impacts of the two failure modes (performance and lubrication), and with corresponding different restoration factors is preferred by experts. The mean log-likelihood function of this model indicates a close relationship with the simple AGAN

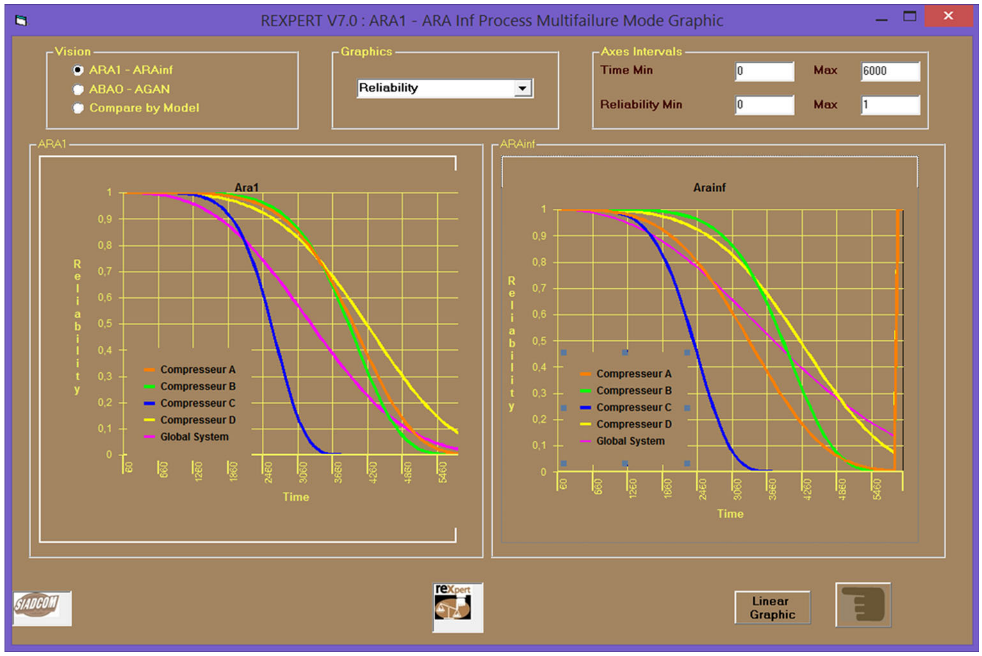


Fig. 12 Comparison of compressor reliabilities

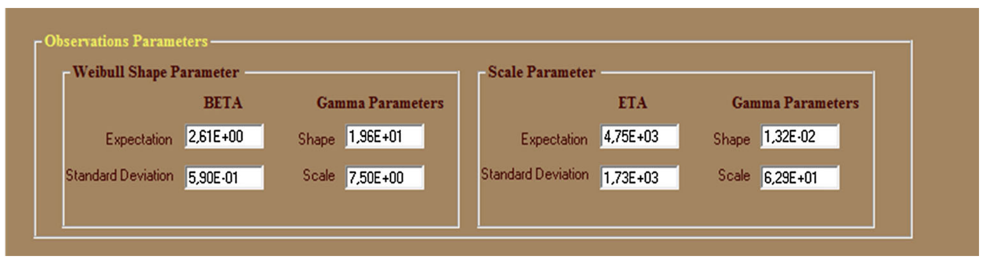


Fig. 13 Estimates obtained with the Bayesian model

model, meaning practically a renewal of the cylinder block after a repair.

This observation is accepted by experts because most of the repairs concern type 1 failures that are repaired by replacement of the failed item by a new one.

5.7.6 *Optimizing the "best" in-service inspection or maintenance time*

On the other hand, Fig. 14 clearly shows two different failure trends, before and after 3,000 h of test, with a strong increasing in the kinetic of failures after 3,000 h. This observation means that the technical optimal time to perform a preventive maintenance would be just before 3,000 operating hours.

The best goodness of fit between model and data obviously occurs when the failure data of type 1 and type 2 are mixed, because the sample data size is increased; the corresponding LKV is consequently higher.

Nevertheless, when the two failure modes are distinguished, it is possible to determine the parameters corresponding to each failure mode, using the Bayesian model

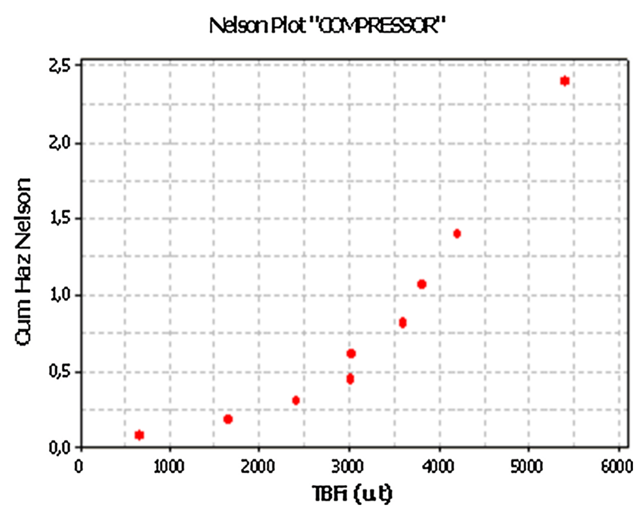


Fig. 14 Nelson–Aalen plot of cumulative failures type 1 and type 2 (x-axis: time intervals between failures; y-axis: estimator of the cumulated hazard rate; plotted by Relcode software)

(Table 8 for ARA models). Again, this table shows a large difference between the two failure modes, confirming the graph of Fig. 14.

Table 8 ARA_1 and ARA_∞ parameters for type 1 and type 2 failure modes

Failure mode	Type 1: performance loss		Type 2: lubrication	
Model	ARA_1	ARA_∞	ARA_1	ARA_∞
β	2.58	2.06	0.72	3.97
η	5,810 h	8,410 h	2,770 h	2,760 h
λ	2.84 E−10	8.22 E−9	1.06 E−14	2.19 E−14
ρ	77 %	68 %	0.99	0.99
LKV	−54.96	−56.01	−17.44	−17.48

5.7.7 Economical maintenance optimization

As said before, only a visual control at mid-test interval has been performed during the test period.

A mid-test (around time 4,000 h) consisting in a systematic total replacement of the piston cylinder block set has been simulated. The set is then considered as a new cylinder block set. Costs of preventive and corrective maintenance are fictive but are relatively correctly weighted, with a 70 k€ preventive maintenance cost, compared with a 180 k€ corrective maintenance including the loss of production cost.

Figure 15 shows the results obtained with two maintenance scenarios: scenario 1 corresponds to a "no maintenance" scenario, scenario 2 includes a preventive maintenance at mid-test.

Note that a systematic preventive maintenance reduces the number of compressor failures by a multiplicative factor 2 (dark zone of the graph), but the preventive maintenance cost is largely higher, and the total maintenance cost is multiplied by a factor >2. Considering these conditions, the "best" economical maintenance scenario seems to be scenario 1: wait for failure. The conclusion would be certainly inversed if the safety of the plant is concerned.

6 Conclusions

Although it is an uncertain information, expert opinion is very useful and valuable for many reasons:

- understanding the context and physical phenomena at stake,
- supplying data when not enough observations to quantify with field data are available,
- quantifying risk analysis models,
- refining, enriching, and updating estimates from field data,
- estimating model parameter uncertainties.

Safety and reliability require quantitative risk analysis studies. These last ones are performed first to show that an industrial site and its equipment conform to the regulation requirements. But quantitative risk analysis is mainly an input to a decision-making process. The decision maker will not only use risk analysis results but he also will examine input data and their uncertainties, influence of expert opinions on final results and will use sensitivity analysis and cost–benefit analysis before taking any decision. Expertise generally is an advantage for the acceptability of a project but it could be also an handicap.

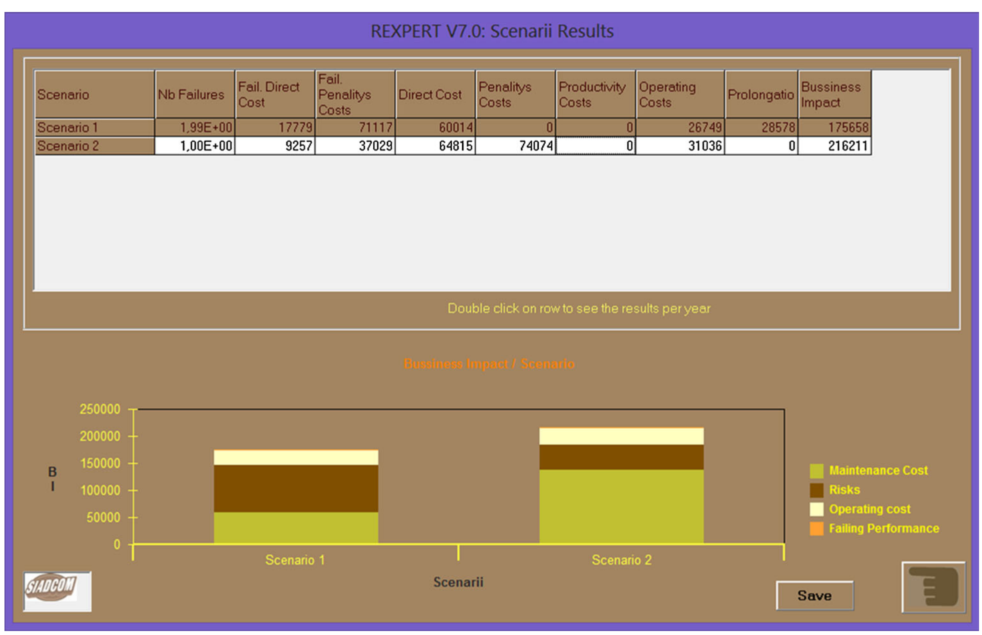


Fig. 15 Compressor maintenance optimization

Many help for decision-making methods are presently available. Maybe the most popular ones are the decision tree for its simplicity, the MAUT method because it takes into account of the manager's risk attitude, the LCM method, which answers correctly the stakes of safety and life extension, and the belief network, which takes into account uncertainties and which fits very well to a large number of risk management problems. Contribution of expertise is essential for all these methods.

The most important is to make sure that the whole decision process including expertise is completely documented and consequently transparent. The more it is, easier the decision will be accepted. Specially, when safety is concerned, transparency of input data and managing process is an obligation.

Main problems met when using expertise are certainly the value of information: is it worth? Is it robust? At which confidence level does it correspond? Another problem linked to this first one is the labeling of experts: do we have to score experts? Nevertheless, all information (coming from field data or from expertise or from physical testing) is precious and has to be included and considered.

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