What is aging?

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1. Introduction: what is aging?

The 1996 edition of the French *Robert* dictionary gives three definitions for the word "aging".

1 The fact of becoming old or weakened with age – a normal physiological process experienced by all living organisms during the last phase of life.

2 The fact of getting old or out-dated (the word "obsolescence" is given as being closely related to this second definition).

3 A natural or artificially-induced process during which wines change and acquire their bouquet.

According to the first definition, aging is essentially connected to everything living: nature, man, the heart, the spirit, animals, plants, a population… We could also extend this definition, however, to that which is "inert", such as industrial components or installations whether they are in service or simply available for operation.

It is a somewhat negative concept which inevitably leads to the notion of suspension of life and vital functions in the entity in question (death, for a living organism). It is for this reason that, particularly in the industrial world, we focus on the concept of the lifetime of a piece of equipment, its "durability".

Aging is a progressive and ongoing process. Very often, it depends on a great number of influencing co-variables: period of operation, loads, physical properties of materials and operating conditions, to mention only those that generally play a preponderant role. It translates into reduced efficiency due to a physical or chemical degradation mechanism characteristic of the component and of the materials it is made of, as well as to environmental, operating and maintenance conditions: wearout, fatigue, corrosion, erosion, irradiation, etc.

According to the second definition, however, aging may also be triggered by other technological, or even social or economic factors: performance inferior to that of new and more modern equipment; concept, design or materials surpassed by new technologies; incompatibility or obsolescence of the control and command system and software; lack of spare parts; profitability limit reached; more stringent regulations; stricter safety margins and finally, evolution in the operating profile of installations and in environmental regulations.

The effective period of operation of a piece of equipment or an installation will therefore depend on these various technical, economic and regulatory considerations.

The 3rd definition given in the Robert suggests a more positive view of aging, indicating that there can be improvement with age: this is the image of the good wine that matures, and perhaps of the component that adapts to its type of stress, the maintenance program that can enable improving the performance of a component and thereby postpone degradation. This type of improvement exists but, in any event, it is only temporary and, sooner or later, aging will inescapably be observed. History shows us, in fact, that there are very few mechanical structures which “survive” over a century, with the possible exception of the Jens Olsen’s astronomical clock in Copenhagen, whose still “intact” civil engineering structures have required major repair and refurbishment over the centuries.

We will recommend adopting the definition proposed by the OECD Nuclear Energy Agency, and retained by the Electric Power Research Institute (EPRI, 1992): the process by which the characteristics of a system, structure or component (SSC) are gradually changed with time or use.

We shall also recommend using the other terminology taken from Table 1 of the same reference.

Table 1- Terminology (reference: NEA-OECD and EPRI-NEI-US NRC, (EPRI, 1992))

(SSC = System, Structure or Component)

- ***Acceptance criterion:*** specified limit of a function or condition indicator used to assess the ability of an SSC to perform its design function.
- ***Aging:*** general process in which characteristics of an SSC gradually change with time or use.
- ***Aging effects:*** net changes in characteristics of an SSC that occur with time or use and are due to aging mechanisms.
- ***Aging management:*** engineering, operations and maintenance actions to control within acceptable limits aging degradation and wearout of SSCs.
- ***Aging mechanism (or degradation mechanism***): specific process that gradually changes characteristics of an SSC with time or use.
- ***Degradation***: immediate or gradual deterioration of characteristics of an SSC that could impair its ability to function within acceptance criteria; if the process is gradual, there is aging; the process is caused by operating conditions.
- ***Failure***: inability or interruption of ability of an SSC to function within acceptance criteria.
- ***Failure analysis***: systematic process of determining and documenting the mechanisms, superficial causes and root cause of the failure of an SSC.
- ***In-service inspection***: inspection or test of the integrity of an SSC during operation or shutdown.

- ***Maintenance:*** aggregate of direct and supporting actions that detect, preclude or mitigate degradation of a functioning SSC, or restore to an acceptable level the design functions of a failed SSC.

- ***Service conditions:*** actual physical states which have an impact on an SSC (normal operating conditions, operating transients, errors, accidental states).

There are therefore a number of possible definitions for aging.

In terms of reliability, certain experts consider that if the failure rate or failure intensity is on the rise (called IFR, Increasing Failure Rate), then aging is occurring. This appears to us to be an unjustified shortcut.

Indeed, if two components are considered in parallel, and each has a constant failure rate but the two rates are different, it can be shown that the life distribution of the parallel system is not IFR; however the failure rate is increasing on the average (IFRA = Increasing Failure Rate in Average, (Barlow, Proschan, 1975)).

Let us suppose that we want to calculate the mean life of an exponential component (the prior law of the exponential parameter will be taken as known). It can be shown that the unconditional or predictive life distribution has a decreasing failure rate function (Barlow, 2002). As a result, we cannot characterize aging in terms of IFR only.

To resolve this problem in studies to detect aging in a piece of equipment, Clarotti (Clarotti and al, 2002) considered that aging appears when there is a clustering of failures around the mean life. This definition corresponds to that of demographers.

Basing his estimates on the work of Spizzichino (1992), Barlow (Barlow, 2002) said that, if two similar items (exchangeable items) taken among a total of n similar items have survived a life test, the "younger" item is the "best" if and only if their joint survival function is concave as described by Schur (Schur concave). These very theoretical considerations have little practical value and work is currently under way in several American and Italian universities to represent Schur concavity.

2 Two concepts of aging

Consequently, if there is a clustering of failures, as described by Clarotti (Clarotti and al, 2002), there may be aging. Clarotti further considers that this is not a sufficient condition, as the clustering of failures may be due to a design fault. Clarotti considers also that field data are generally not sufficient for stating whether the aging phenomenon becomes relevant during the time the component is expected to function (mission period). One solution to this dilemma is postulating a priori that the aging becomes relevant at an aging "initiation time" which is before the end of the mission period. The purpose of the observed data will be to confirm or deny the reasonableness of this hypothesis. After this initiation time, clustering of failure times becomes more noticeable than it was before.

Failure results in a loss of function. Moreover, while in operation, a piece of equipment is progressively and continuously degraded though it may not fail. If its limits are not reached, function is not even altered, and the component continues to operate even though degraded; there is no loss of function.

We can clearly see that there are two perceptions of aging, a "reliability-based" concept which is an "all-or-nothing" view: either there is loss of function (therefore failure) or the component can operate (but is perhaps degraded); and a "physical aging" concept which corresponds to the slow, continuous process of degradation of component properties and equipment functions.

Table 2 compares these two concepts.

We can immediately see that analyzing the two concepts will require different types of feedback and different approaches. Once again, feedback can clearly be seen as a strategic and indispensable element.

Table 2. – The two concepts of aging

Concept	Reliability-oriented	Physically-oriented
Components concerned	Essentially active components	Essentially passive components
Degradation mechanisms	Many	Often only one
Failure modes	Many	Often only one (that can be prevented thanks to monitoring)
Speed of appearance of aging	Relatively rapid, sometimes sudden	Slow, a continuous degradation process
Modeling	Probabilistic (attempt to find a lifetime law using a sample of observed failures)	- Physical, if knowledge is sufficient, as the single degradation mechanism is known - or statistical, based on degradation data observed at more or less regular time intervals
Principal data (input data)	Failures (loss of function)	Degradations (for example, test data, wearout data, inspection data)
Other data used	Survival data (right-censored data) Expert assessments	When possible, physical data Expert assessments Analogous feedback
Indicators sought	Failure rate Failure intensity Probability of failure Mean lifetime	Failure rate Failure intensity Remaining life Influencing co-variables
Domain	Reliability and maintenance, RCM methodology	Physical probabilistic methodologies, condition-based maintenance

3 Why should we be interested in aging in an installation?

If the degradation mechanisms are well under control, the economic benefit of extending the life of an installation and its equipment is obvious, particularly for complex installations that require considerable investments. However, in addition to the technico-economic benefits of extending the life, it is indispensable to identify the main vectors of aging, to detect them, evaluate them, rank them and take all necessary measures to mitigate or postpone them, and even to eliminate them.

"Equipment lifetime" is unfortunately a "post mortem" concept. We only truly know the life after the occurrence of a major and irremediable failure. This case is rarely found in practice because we attempt to avoid such situations and generally, it is technico-economic optimization which determines lifetime in the industrial context.

We should note that the engineer seeks to determine durability, which is the capacity of a piece of equipment to fulfill the expected function under given conditions of wear and maintenance, until a boundary condition is reached (the definition of European norm EN 13306, June 2001). This boundary condition may be characterized by the end of its service life, or by its unsuitability for technical and/or economic reasons or for other relevant reasons.

In addition to real "post mortem" lifetime, the period that extends from fabrication to retirement, we can distinguish several kinds of life:

- design life or intrinsic life or life predicted on design, which is the period during which it is expected that an SSC will function within its limits of acceptance;
- residual life or remaining life: the period from a stated time to retirement of an SSC;
- regulatory life, which corresponds to the moment at which an administrative authority forbids operation to continue; this life is dependent on a component's technical condition, on operating and maintenance conditions, and on security constraints;
- technico-economic life: beyond a certain point, the additional investments needed may not be amortizable in the future, or the industrial risk may be considered too high; it is generally this criterion which determines the shutdown or retirement of an installation and its equipment;
- and finally, political life: a political decision may shut down the installation.

4 Reliability-oriented concept of aging

In this section, we shall particularly focus on the reliability-based perception of aging.

The service life of any equipment, from commissioning to retirement, generally comprises three main phases, characterized by a chance function and specific failure rates (Figure 1):

- A period of "infant mortality" or, to be more positive, a period of running-in, which takes the form of a failure rate that drops with increased operating time or number of demands: during the period; the most fragile equipment or equipment with faults will be eliminated during this period. This is the burn-in period for electronic equipment, and the running-in period for mechanical components. During this phase, it is important to conduct tests or trials on an equipment sample so as to be able, with a good assurance of success (optimization), to set aside what does not meet specifications or dependability targets.
- A period of technical maturity, called the service life, characterized by a constant failure rate and during which mortality is random, accidental and sudden. This is the normal period of operation for equipment; its design must be such that this period lasts longer than or at least as long as the mission assigned to the equipment. We should note that because failures are, by definition, random, it is not possible during this period to optimize tests, in-service inspections or preventive maintenance.
- And finally, a third period of so-called aging, during which the failure rate of equipment will increase with time or demand (IFR). One aging indicator for this equipment will thus be any observed rise in the failure rate (or in the failure

intensity). Two parameters are therefore important to characterize aging: the instant at which aging appears and its kinetics, once it has been detected.

Knowing the first parameter will enable optimization of preventive maintenance during the “selection of maintenance tasks” phase of the Reliability Centered Maintenance (RCM) method. Knowing the second will enable evaluating the speed at which the risk of failure will increase.

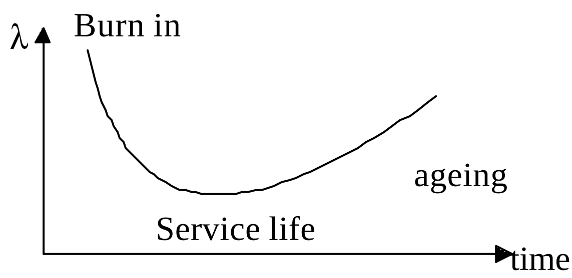

Figure 1 .Evolution of the failure rate of a component as a function of time operation (age).

This reliability-based vision essentially relates to active components. They are subject to periodical preventive maintenance or refurbishment. Aging generally first affects a sub-component whose failure results in a total or partial inability to fulfill the component’s mission, or in a serious drop in operating performance. The appearance of such failures appears to be random so that it is difficult to predict them and, therefore, to define an optimized preventive maintenance program.

It is the role of Reliability Centered Maintenance to optimize preventive maintenance programs, identify critical components and define the maintenance tasks best suited to avoiding failures. Equipment is monitored and feedback from this monitoring makes it possible to validate the preventive maintenance programs or, on the contrary, to adapt them periodically in light of observations.

Design modifications, preventive and condition-based maintenance, refurbishment, and replacement of faulty parts or of an entire piece of equipment are all possible remedies to offset or postpone aging.

Periodical tests or in-service inspections or, quite simply, monitoring of the equipment’s reliability parameters enable pointing up signs that aging has begun and providing assistance in determining the moment at which one of the remedies must be implemented.

On an industrial plane, then, we must distinguish:

- Equipment to undergo preventive maintenance so as to maintain a relatively stable failure rate; the end of its service life will generally be accidental and sudden. Such equipment is generally classified as “active”, and considered critical in terms of safety, availability and cost targets.
- Equipment not subject to maintenance will age naturally and deteriorate more or less rapidly, depending on the predominant physical phenomenon affecting it. In the absence of maintenance, it will still be inspected or monitored regularly. Such equipment is generally classified either as “passive” (and its behavior is monitored), or as active “non-critical” and failure is expected.

5 Physical aging

This generally concerns passive equipment (structures, pipes, pressurized containers, etc.). The aging process is associated with a mechanism of degradation of the material with which it is made.

The objective is to see that the degradation does not lead to a failure and a loss of function for the equipment: for example, corrosion will cause a through-wall crack (measurable effect) which can lead to more serious leakage or, more serious still, fast fracture (failure mode).

Optimization to prevent this type of occurrence will involve condition-based maintenance or in-service inspection, which must make it possible preventively to detect the start of a deterioration triggered by a degradation process, and its propagation, before an actual break. Once a degradation has been observed (through monitoring), it is sufficient to perform the preventive tasks that will prevent the failure.

For the materials used for electromechanical equipment, but also for concrete or the polymers used to sheathe electric cables, etc., the main degradation mechanisms are:

- thermal fatigue linked to the temperature cycles to which the equipment is subjected,
- crack-generating stress corrosion,
- erosion,
- mechanical wearout,
- embrittlement due to radiation,
- loss of prestressing in concrete, etc.

To understand the process from incipient fault to propagation, to detect faults and anticipate their evolution, it is necessary to identify the degradation mechanism at work (Bouzaïene-Marle et al, 2005) and have precise knowledge of the physical phenomena and the physical or statistical laws of degradation linked to the mechanism: this is one aspect of structure reliability (Figure 2).

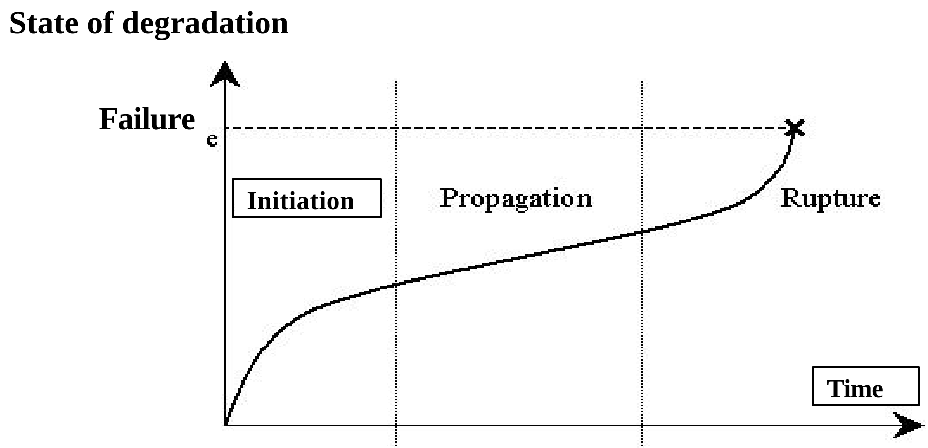

Figure 2 . Evolution in a degraded condition

In-service inspection and condition-based maintenance are the key elements in protection of passive components against degradation processes (Figure 3).

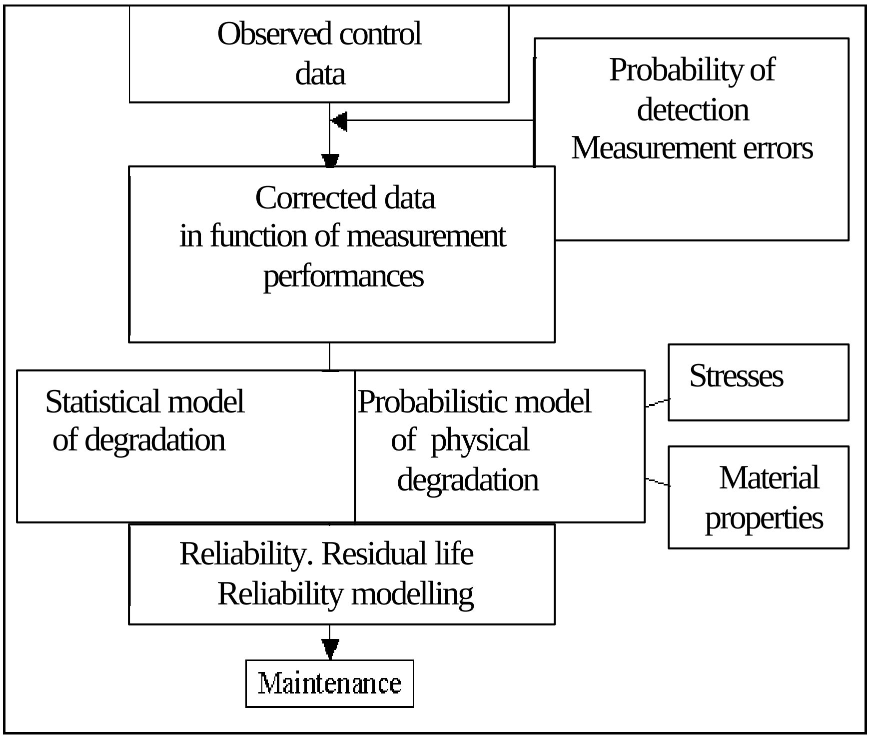

Figure 3 – Modeling degradations

6 The consequences in terms of extension of lifetime

Above and beyond the life initially projected at the time of design, the longevity of industrial equipment has major economic impacts: once equipment investment is amortized, operating costs are reduced, of course, but also capital is saved due to the elimination of the need to reinvest in new equipment.

Extending the life of an installation implies understanding the equipment aging process and carrying out the necessary servicing, maintenance and refurbishment tasks, respecting operating efficiency, safety and regulations and understanding that requirements are increasingly stringent in these domains. There are therefore socio-economic or industrial limits to the investments one is willing to make to extend the lifetime of installations or equipment.

Strategies for defense against aging involve first taking into account potential degradation mechanisms from the time of design, putting in place a monitoring program to verify the validity of the design options chosen, gathering feedback and, finally, carrying out preventive maintenance and, where necessary, repair, modification, refurbishment or replacement of components which have reached their age limit or are obsolete in technical, economic or regulatory terms.

We should note that for all active and passive equipment, maintenance and refurbishment operations have a cost, not only in financial terms but also in terms of outage, image, doses to humans, etc., implying deadlines and constraints which may impact the real lifetime of the equipment.

Problems of technico-economic optimization will play a role in the choice among possible strategies.

7 What do we now know about reliability-oriented assessment of aging?

The most advanced work on aging today is done from a reliability perspective.

How can we evaluate or measure equipment lifetime? Beginning in the 20th century, experts based their work on studies of human demography which we can trace back to John Graunt (1620-1674), attempting to develop a theory of industrial reliability based on observation and analysis of operating feedback data (Graunt, 1662).

These methods were transposed to many domains including the biomedical, pharmaceutical and economics sectors, with a view to modeling the lifetime of a company or a period of inactivity.

The probability distribution of failure times can be characterized by:

- a cumulative distribution function F(t), which gives the probability that a component will break down before time t,
- a probability density f(t), which is the derivative of the preceding function and which represents the relative instantaneous frequency of failures as a function of time,
- a function of survival or reliability R(t), which is the complement of the failure distribution function:

$$R(t) = 1 - F(t),$$

- a chance function or instant failure rate, which is the probability of having a failure within the next time interval, dt, knowing that the component functioned up to t. It represents the bathtub curve of Figure 1.1, associated with the failure rate.
- a quantile t_p which is the time for which a given proportion p of the component population is broken down.

All distributions are completely defined by their first two moments: mathematical expectancy, or mean value, and variance, representing the uncertainty with regard to the mean value.

In 1939, the Swedish mathematical engineer W. Weibull proposed a universal lifetime law in "A statistical theory of strengths of materials" (Ing. Vetenskaps Akad. Handl., N° 151). This law representing evolution in the failure rate $\lambda(t)$ with time,t, is known as the Weibull law.

$$\lambda(t)=\frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1}$$

It represents evolution in the failure rate during the three phases in the life of a component: youth, maturity, age (the bathtub curve of figure 1), and has generally two parameters:

- the scale parameter η, linked either to the end of the running-in period during the "youth" of the component or to the time at which aging sets in,
- the shape parameter β, linked to the intensity of the running in, when it is less than 1, or to the intensity of the aging kinetic, when it is more than 1; when it is equal to 1, the Weibull law becomes an exponential law representative of the occurrence of random failures, i.e. representing the service life or maturity of the component.

Very practical procedures for estimating these parameters are given in the documentation and use either a graphic method, (Moss, 2005) known as the Allan-Plait paper or the Weibull paper, either computer algorithms (Lannoy, Procaccia, 2005).

8. A software example : REXPERT (Procaccia, 2005; siadcom1@wanadoo.fr).

Mathematic estimation of Weibull law parameters is not really easy. A large number of complete data is indeed necessary to obtain a relatively precise estimation. When this number is too small or the rate of censored observations is high, it is suggested to simulate data or to use bayesian techniques, simulated data or expertise compensating the missing information in the computation algorithm.

The Maximum Likelihood (ML) estimates of the Weibull law parameters are obtained by solving the following equations with an iterative procedure generally using the Newton-Raphson or Simpson methods:

$$\hat{b} = \frac{1}{\dfrac{\sum_{i=1}^{k} t_i^b \ln t_i + (n-k) t_s^b \ln t_s}{\sum_{i=1}^{k} t_i^b + (n-k) t_s^b} - \dfrac{1}{k}\sum_{i=1}^{k} \ln t_i}$$

$$\hat{h} = [\frac{1}{k}\sum_{i=1}^{k} t_i^b + (n-k) t_s^b]^{\frac{1}{b}}$$

t_i being the observed failure times and t_j the censored times.
This methodology is used in many software tools, in particular in the REXPERT software, which collects and modelizes expertises and observed data, and estimates the Weibull law parameters, β and η.
When the number of collected data is limited, simulation-based methods provide more precise estimates of parameters. The most popular simulation methods are the bootstrap sampling and the Monte Carlo simulation, both used in REXPERT:

- the principle of bootstrap sampling is to simulate the repeated sampling process, to use the information from the distribution of appropriate statistics in the bootstrap samples, to compute the relevant parameters; it is necessary to generate a large number of simulated samples from the original data sample; in the fully parametric bootstrap sampling method, the ML estimates determined from the actual data are used to replace the unknown parameters;
- the Monte Carlo method consists in generating series of values of random variables with specified probability densities; the results of the simulation are treated as if they were experimental data.

Generally, due to the high quality of design and to a very demanding maintenance programme, failure data are limited, and most of the field data are right censored data. In this case, Maximum Likelihood estimation can be strongly biased, and Stochastic Expectation Maximisation (SEM) is preferred (Bacha et al, 1998).
A first approximation of the Weibull parameters β_i, η_i is performed from observed data or from expert assessments.
Then, the conditional expectation of censored data is simulated with a Weibull distribution having (β_i, η_i) parameters, and is maximised using observed data.
Each iteration has two steps:

.completing the sample of failure data with a simulation of each censored data, beyond the censored time;

.computation of the parameter estimates (β_{i+1}, η_{i+1}) with the ML method.

The process is stopped when each parameter becomes stable.
Finally bayesian probabilistic inference based on combining operating experience data - the likelihood function- with expert opinions relative to the representative mathematical model - the prior information -, is also implemented in REXPERT. This approach is well adapted to rare events.

The component reliability over time is modelled with a two-parameter Weibull distribution of the reliability of the component which is in a Bayesian context:

$$R_W(t) = \int_1^{+\infty} db \int_0^{+\infty} dh \exp\left(-\left(\frac{t}{h}\right)^b\right) p(b,h) \qquad \text{(a)}$$

β,η, being respectively the Weibull random shape and scale parameters, and π(β,η) the posterior distribution relative to these unknown parameters, deduced from expert judgement (prior information) and field data (likelihood function).

The input display screen of REXPERT is given figure 4.

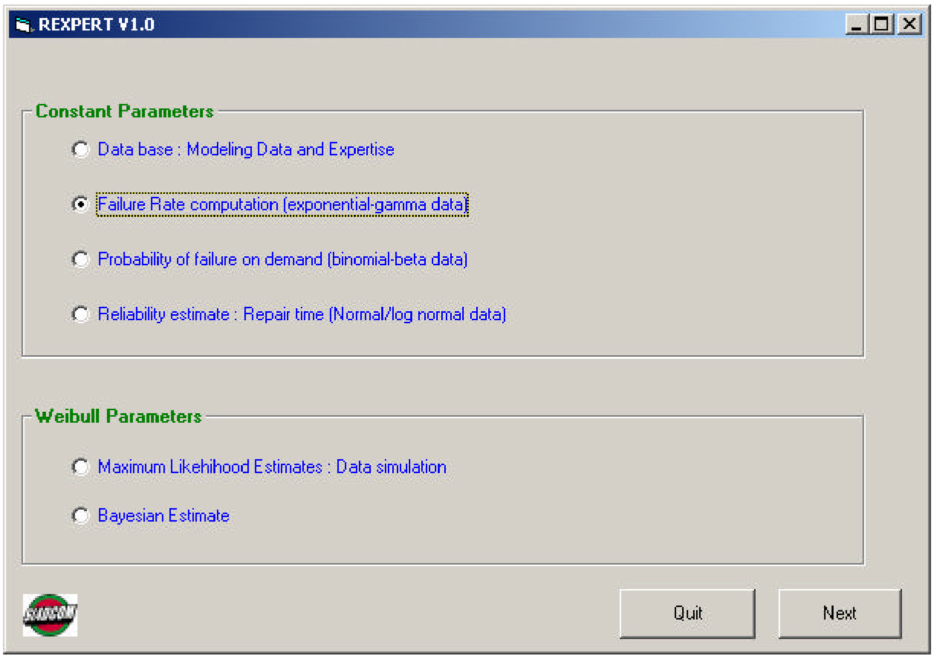

Figure 4- REXPERT input display screen

The first part of the software (top of the figure) concerns the collection and the modeling of expertise and data from the field (feedback experience): reliability parameters from similar data bank collection, and computation of failure rate, probability of failure on demand, mean repair time, calculation made from non informative or informative expertise and from field data. Figure 5 shows input of prior information relatively to expertise or feedback data for computation of exponential failure rate. Note that the analyst has the possibility to weight or to balance the available information in function of the relative attached confidence (use of the relative Fisher information).

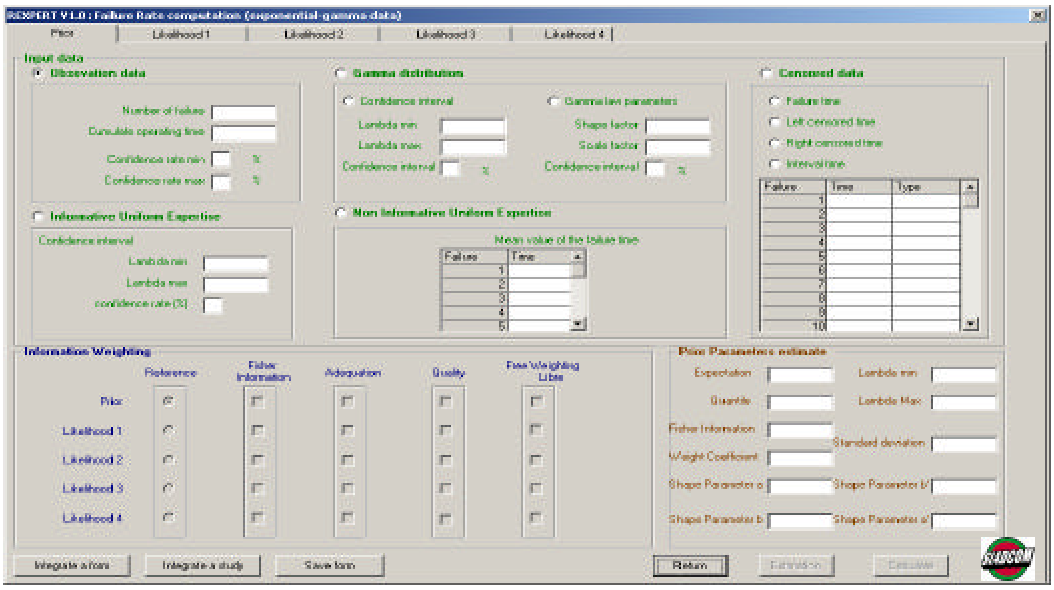

Figure 5- Input of prior information

The second part of the software concerns the determination of Weibull law parameters, either with a frequential calculation if the number of failure data is important, either with a bayesian algorithm when it is not the case and when expertise is available.

To illustrate the possibilities of the software with the bayesian computation of the Weibull parameters, data recorded from type I tests on four identical horizontal reciprocating compressors in a petrochemical installation (Moss, 2005) have been chosen. Observations cease after 8760 hours of operation. They are time-terminated right-censored sample of data. The observed data are given in table 3, failure times and censored data are in hours.

Table 3. Reciprocating compressors test results (Moss, 2005)

Compressor	Time of 1st failure	Time of 2nd failure	Time of 3rd failure	Censored Time
A	3600	7408	8058	8760
B	4200			8760
C	2408	5426	7076	8760
D	3003	8408		8760

Figure 6 represents input data display in a bayesian approach: the left part of the display screen collects expertises (Lannoy, Procaccia, 2003) on shape parameter (burn in or aging) in a gradual estimation (top), the estimated uncertainty of expertise (middle), and at the bottom, a min and a max value of the expected mid-life of the compressor (and not the scale parameter). On the right part are recorded the test observations (from table 3).

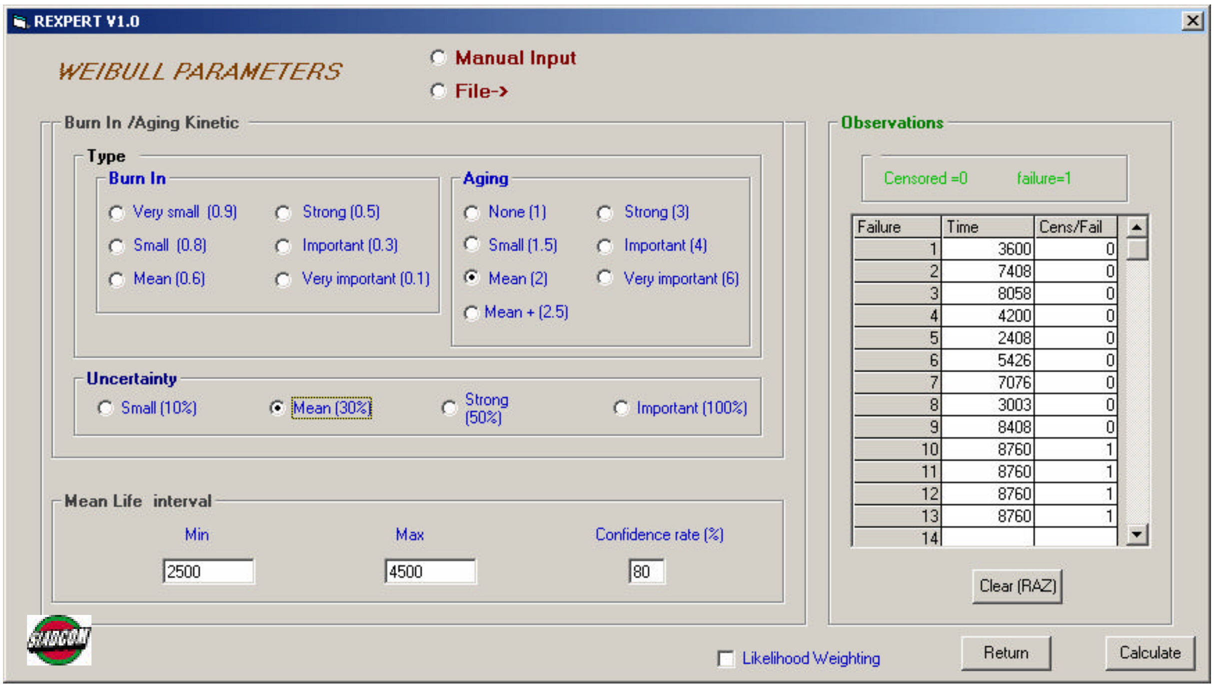

Figure 6 - REXPERT aging input data

The obtained results on scale and shape parameters are given on the figure 7, where the computation are realized without weighting between prior and likelihood information. Mean value of each Weibull parameter, standard deviation, shape and scale parameters of gamma distributions which represent uncertainty of Weibull parameters, are computed for prior distribution (the expertise), likelihood (the observed data), and posterior joint distribution (given on the figure 7).

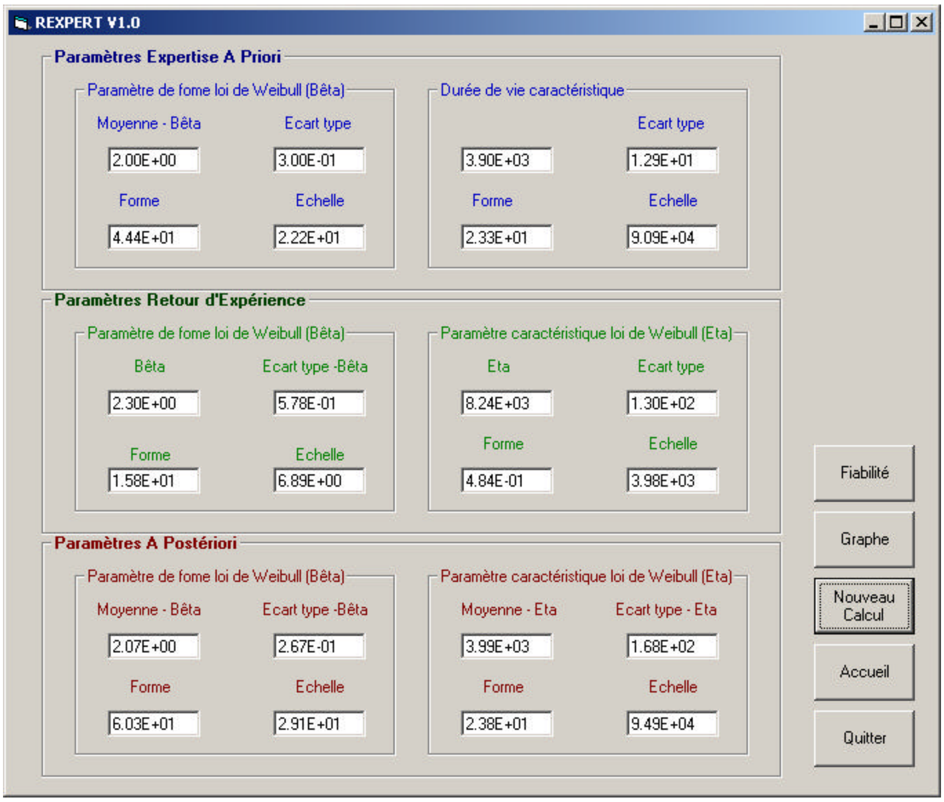

Figure 7 - Posterior computed Weibull parameters (without weigthing).

If a Fisher weighting is used with the goal to give the same importance to expertise and to observed data, the respective posterior results are:

- $\beta = 2{,}16$
- $\eta = 7440$ hours

Figure 8 represents the graphs of posterior distributions of shape and scale Weibull parameters.

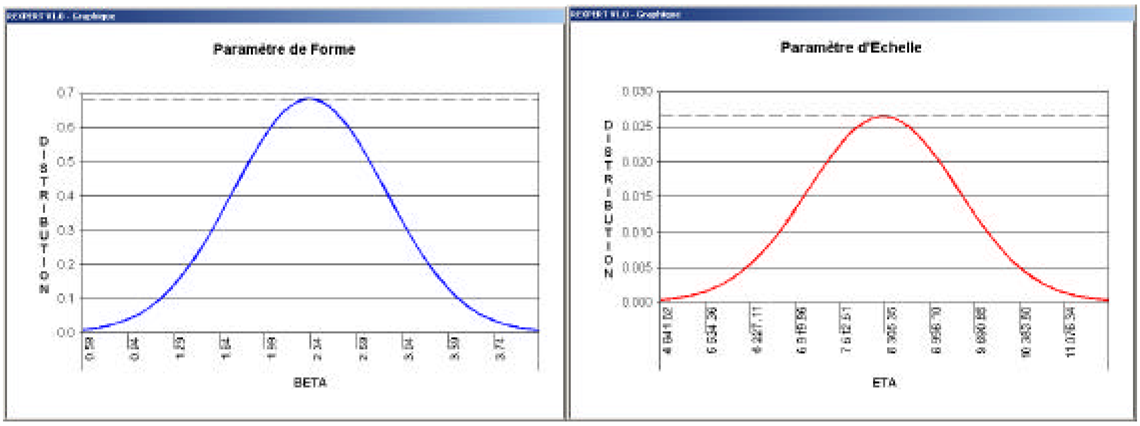

Figure 8 - Posterior Weibull shape and scale parameter distributions

Finally the computed reliability in this case is given figure 9.

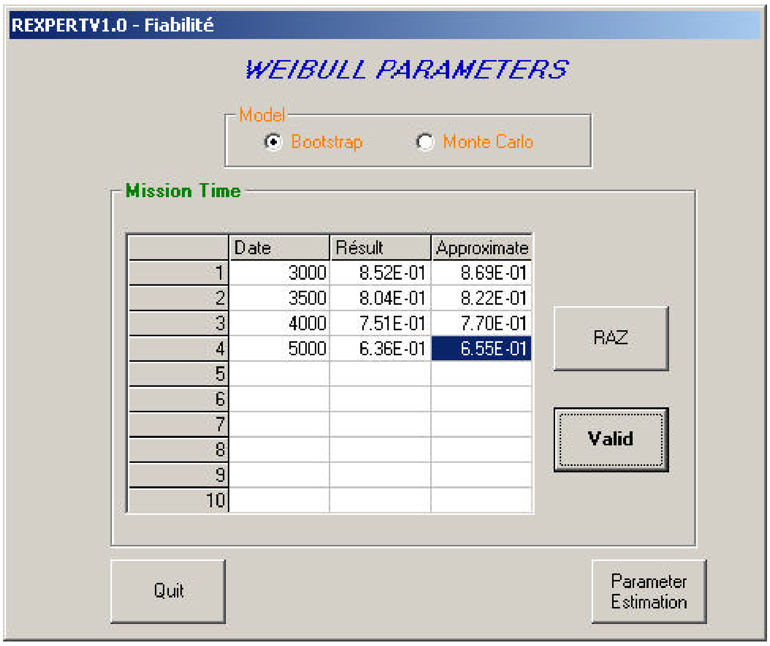

Figure 9 Computed reliability

(result exact computation relation (a); approximate with parameters estimates)

The Weibull law has been and is still widely used in parametric methodologies, but there are also others which are less used.

In particular, we might mention the Cox model (Cox, 1972), which uses a vector of explicative exogenic variables in the failure rate or in a degradation model; these variables can, in turn, depend on time.

Parametric methods provide a simple means of obtaining an estimation of the parameters of a law on the basis of a limited number of observed data, and their confidence interval. However, one is bound to the choice of the model retained, which may be different from the real model studied.

Non-parametric models like the Kaplan-Meier estimator (1958) of the reliability function, a complement of the distribution function for failure times F(t), presupposes no particular shape for the failure rate distribution. They may represent a preliminary step prior to the choice of a parametric model, but they require at least 5 observations.

The main characteristic of probabilistic lifetime models is that the variables are positive: the normal law one can use will not be the reference model. Another characteristic is the presence of incomplete data (survival data) which will complicate statistical procedures, since the information obtained from feedback is incomplete (Celeux, 2000). The data are considered to be truncated or type I or type II censored depending on whether observation has ended due to a limit on the observation time or to a predefinition of the number of failures.

As concerns modeling of degradations, work in this domain seems very recent. Nonetheless, in the Fifties, reliability experts focused on physical analysis of failures observed in feedback, with a view to determining the physical causes, the degradation mechanisms at work, the kinetics, etc., and on finding solutions essentially related to design or fabrication. This aspect of reliability seems to be undergoing a revival if we consider the current economic concerns of industrialists seeking to extend service life or control aging, and if we look at recent research publications (see, for example, Bagdonavicius, Nikulin, 2002).

To review current knowledge in the field of aging and aging management will therefore need to examine two aspects: reliability studies and modeling of degradations.

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