Interest of a global optimization tool for reliability models adjustment and systems optimization

A. CABARBAYE & J. FAURE & R. LAULHERET
CNES, 18 av. Edouard Belin, 31401 Toulouse - France

A. CABARBAYE
Cab Innovation, 3 rue de la Coquille, 31500 Toulouse - France

ABSTRACT: This paper shows why a global optimization tool is essential for the adjustment of complex probabilistic model from feedback operational data. It is illustrated with several examples of reliability models (Bertholon, 3 phases) maintenance models (Generalized Renewal Process, Jack) and accelerated aging models (Arrhenius with Weibull, Basquin), with adjustment problem in the past and are performed here by a tool based on a hybrid technique combining genetic algorithms and non-linear simplex. It also shows the coupling possibilities of such optimization tool with assessment system model to optimize different parameters (period of preventive actions, depreciation duration, etc.).

1 INTRODUCTION

Different theoretical models are proposed to assess the system reliability, taking into account the maintenance, the specific conditions of use and the environment. Tools are available to adjust these models from feedback operational data but they may give wrong results, especially when the number of parameters in the model is greater than 2. The reason is simple. These tools implement local optimization methods (pseudo gradient, non linear simplex…) to make adjustments by the maximum likelihood method, while the model functions have multiple optima. Using a Global Optimizer can overcome these difficulties. Thus the GENCAB tool (Cabarbaye, 2003), based on a hybrid technique combining genetic algorithms and non-linear simplex, makes correct adjustments. So, this paper presents reliability models, maintenance models and accelerated aging models, with adjustment problem in the past. It also shows the coupling possibilities of such optimization tool with assessment system model to optimise different parameters (period of preventive actions, depreciation duration, etc.).

2 THE GENCAB TOOL

Based on a hybrid method associating Genetic Algorithms, Differential Evolution and nonlinear Simplex (Nelder Mead algorithm), this generic tool under Excel® is illustrated by figures 1 and 2. Composed of various parameters (genes) of type real, integer or binary, the chromosomes are subjected to random mutation, crossings and differential evolutions (summation of a gene of chromosome with the difference between same genes of two other chromosomes). After selection, the best elements of the population can be improved at the local level by several steps of Simplex.

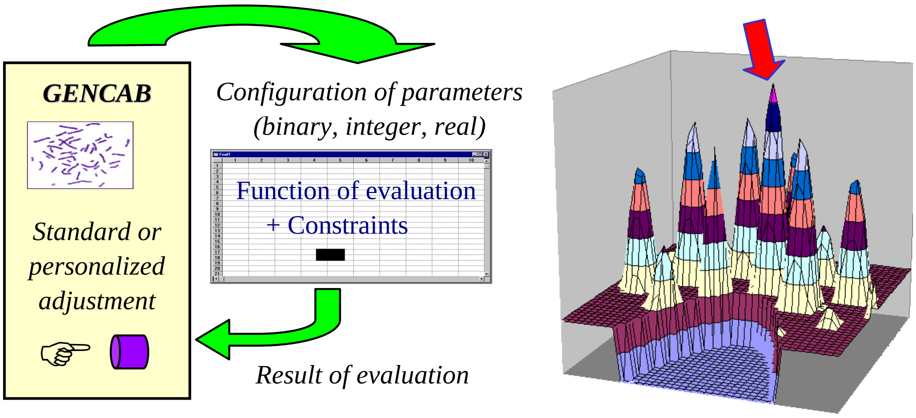


Figure 1. Principle of the tool

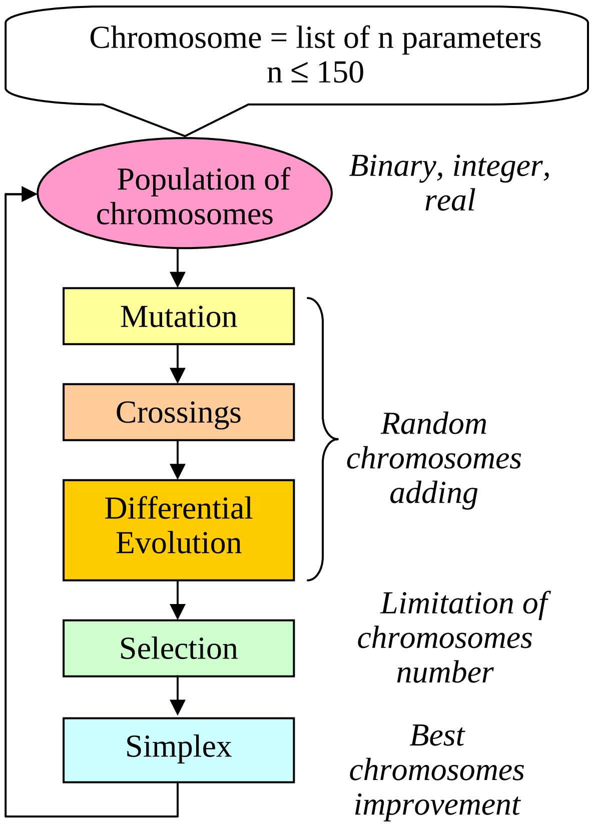


Figure 2. Algorithms

This hybridization of total (Genetic Algorithms) and local (Simplex) techniques, which can be possibly parameterized by the user, allows making the tool very efficient to find the global optimum and robust to the diversity of the problems addressed.

Thus the Differential Evolution will be generally more effective to treat a convex function but will present the disadvantage, for others, simultaneously to exploit the whole of genes. This feature makes it a valuable tool for the adjustment of complex probabilistic models and for the overall system trade-off among multiple parameters.

3 RELIABILITY MODELS ADJUSTMENT

3.1 *Bertholon model*

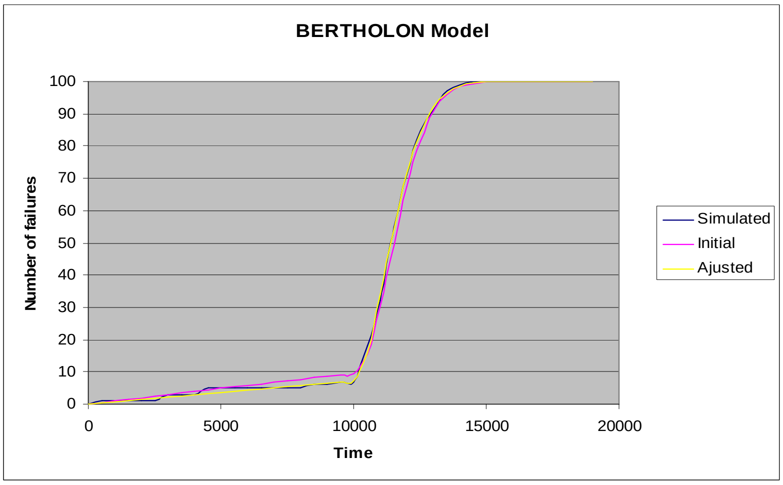
Bertholon (Ziani, 2008) model combines an exponential and a Weibull for the overall second and third parts of the bathtub curve (occasional failures and wear). This model seems likely to be used in the future to characterize the reliability of electronic components whose integration should lead to more and more severe life limitations. The model consists of two blocks in series, one corresponding to an exponential law and the second to a Weibull law. Its reliability is expressed by equation 1.

$$R(t) = \exp(-\lambda t)*\exp(-[\max(0,t-T)/\eta]^{\beta}) \quad (1)$$

The occurrence of a fault can be simulated by the formula 2, under Excel, considering the lowest value simulated from these two models (obtained by reversing the distribution function from random value given by the ALEA function):

$$\mathrm{MIN}(-\mathrm{LN}[\mathrm{ALEA}()]/\lambda \; ; \; T + \eta*(-\mathrm{LN}[\mathrm{ALEA}()])^{1/\beta}) \quad (2)$$

Simulated values	Lambda	R(t)	LN(f(t))
10503	0,000349677	0,838708505	-8,134392409
11717	0,000946266	0,378091446	-7,935605935
11290	0,000747039	0,542865757	-7,810286412
11810	0,000988673	0,345548304	-7,981769399
11865	0,001013198	0,327328131	-8,011435451
10720	0,000464344	0,767975416	-7,938882017
11123	0,000666228	0,611241014	-7,806142027
2900	7,30849E-06	0,979027915	-11,84766864
11570	0,000878485	0,43243491	-7,87563544
12111	0,00112384	0,251411265	-8,171669178
11472	0,000832679	0,4704039	-7,845025738
11442	0,000818708	0,482128741	-7,837326914
11397	0,00079772	0,49983564	-7,827228875
12203	0,001164337	0,226434094	-8,240905096
10309	0,000240401	0,888387469	-8,451547586
19	7,30849E-06	0,999862406	-11,82661112
10646	0,000425943	0,793551587	-7,992442716
10428	0,000308224	0,85975487	-8,235792266
11017	0,000614636	0,653906526	-7,819271397
11837	0,001000777	0,336498463	-7,996140429
13694	0,001796656	0,024739626	-10,02117701
11122	0,000665799	0,611600343	-7,806198765
12074	0,001107112	0,262183572	-8,144710414
10237	0,000198265	0,902388997	-8,628615461
11322	0,000762097	0,530059191	-7,81420289
10925	0,000568669	0,6907239	-7,842227188
11543	0,000865733	0,442921183	-7,866297055
11027	0,000619573	0,64987704	-7,8174521
10288	0,000228477	0,89264876	-8,497637317
11510	0,00085045	0,455578514	-7,85593192
10792	0,000501715	0,741493235	-7,89656845
10744	0,000476738	0,759357686	-7,923826057



LN Likelihood: -850,829668

	Adjusted	Initial
Lambda :	7,31E-06	1,00E-05
Bêta :	1,85315788	2
Eta :	1867,61618	2000
T :	9966,78908	10000

T	R(T) initial	N(t) intial	Frequency	N(t) simulated	R(T) ajusted	N(t) ajusted
0	1	0	0	0	1	0
500	0,99501248	0,49875208	1	1	0,99635242	0,36475777

Figure 3. Simulation and fitting a Bertholon model (from 100 values)

The density of the Bertholon law can be expressed by equation 3:

$$f(t) = \lambda(t) * R(t) \qquad (3)$$

$$\lambda(t) = \lambda + \mathrm{SI}(t > T \; ; \; \beta*(t-T)^{\beta-1}/\eta^{\beta} \; ; \; 0)$$

$$R(t) = \exp(-\lambda t)*\exp(-[\max(0,t-T)/\eta]^{\beta})$$

Figure 3 shows an adjustment of the Bertholon model made from a sample of 100 simulated values. The curves show the distribution functions of the theoretical model, the experimental model (simulated data) and the fitted model. We get approximately the values of model parameters used for simulation.

We remind that the method of maximum likelihood is to find the parameters of the theoretical law by maximizing the product of probability densities given by this law for the experimental data (or the sum of their logarithms). Performed by the optimization tool, the adjustment can be made from censored data by multiplying the product of densities by the product of the reliability values for censored data.

3.2 *Model with 3 phases*

Bertholon model can be generalized into a model to 7 parameters characterizing the three phases of the bathtub curve: a first Weibull law with $\beta < 1$ for the phase of youth failure, an exponential law for the phase of occasional failures and a second Weibull with $\beta > 1$ for the wear phase. It corresponds to three blocks in series, the first is a Weibull, initiated at $t = 0$ ($\gamma = 0$) and limited to duration T_1, and the other two corresponding to the Bertholon model. The occurrence of failure can be simulated by the formula 4 under Excel.

(4) $Ti = \eta_1*(-LN[ALEA()])^{1/\beta 1}$ $T = si(Ti<T_1 ; Ti ; MIN(-LN[ALEA()]/\lambda ; \gamma_2 + \eta_2*(-LN[ALEA()])^{1/\beta 2})$

The adjustment is the same way as above with the expression of the density given by the formula 5.

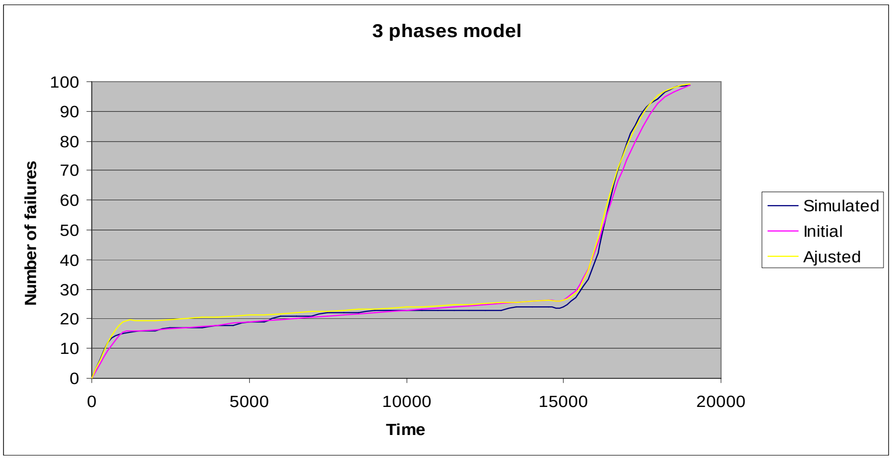
$$f(t) = \lambda(t) * R(t) \qquad (5)$$

$$\lambda(t) = si(t<T_1 ; \beta_1 * t^{\beta 1-1} / \eta_1^{\beta 1} ; 0) + \lambda + si (t>\gamma_2 ; \beta_2 * (t-\gamma_2)^{\beta 2-1} / \eta_2^{\beta 2} ; 0)$$

$$R(t) = \exp(-[\min(t ;T_1)/\eta_1]^{\beta 1}) * \exp(-\lambda t) * \exp(-[\max(0 ; t-\gamma_2)/\eta_2]^{\beta 2})$$

Again, we find approximately the values of model parameters used for simulation as shown in figure 4.

Simulated valus	λ(t)	R(t)	LN(f(t))
17879	0,001704401	0,059570533	-9,19513576
16602	0,000999617	0,337505248	-7,994312984
2087	6,9998E-06	0,804133105	-12,08762015
17318	0,001403475	0,142611235	-8,516436708
16125	0,000711457	0,508096721	-7,925279458
16607	0,001002714	0,335720031	-7,996522533
17864	0,00169631	0,061148021	-9,173757844
16905	0,001174247	0,242631291	-8,163340916
667	0,000165624	0,854848687	-8,862622444
41	0,000377753	0,978059026	-7,903453975
16136	0,000718686	0,503913251	-7,92343735
15801	0,000501821	0,618770747	-8,077286558
16981	0,001216923	0,221661673	-8,218032907
17049	0,00125511	0,203767923	-8,271305901
16258	0,000793898	0,459619173	-7,915912875
16931	0,00118841	0,235561762	-8,180921388
115	0,000277752	0,95533554	-8,234476162
32	0,000407678	0,981607206	-7,82359751
16382	0,000869291	0,41449236	-7,928533677
16935	0,001190697	0,234430178	-8,183813884
16634	0,001018478	0,326680225	-8,008219202
15707	0,000438571	0,646443389	-8,16825883
17217	0,00134828	0,16377001	-8,418218072
16422	0,000893024	0,400289051	-7,936465606
17027	0,001242582	0,209544912	-8,253380832
18528	0,002039838	0,017651354	-10,23182777
16136	0,000718632	0,50394438	-7,923450286
5713	6,9998E-06	0,783983496	-12,11299699
16701	0,00105736	0,304742795	-8,04026689
17687	0,001602829	0,081818034	-8,939242833
16459	0,000915301	0,387002665	-7,945581457
16619	0,001009727	0,331689185	-8,001632593
3671	6,9998E-06	0,795271263	-12,0987017
15560	0,000333888	0,684503194	-8,383766233



LN Likelihood: -866,32265

	Ajusted	Initial
Bêta 1 :	6,95E-01	0,8
Eta 1 :	9999,9996	10000
T 1 :	1012,454212	1000
Lambda :	6,9998E-06	1,00E-05
Bêta 2 :	1,835146599	2
Eta 2 :	1638,152353	2000
Gamma 2 :	15184,7033	15000

T	R(T) initial	N(t) intial	Frequency	N(t) simulated	R(T) ajusted	N(t) ajusted
0	1	0	0	0	1	0
500	0,90843839	9,156161148	12	12	0,87984013	12,0159869

Figure 3. Simulation and fitting a 4 phases model (from 100 values)

4 MAINTENANCE MODELS ADJUSTMENT

4.1 *Generalized Renewal Process*

After corrective maintenance action the equipment can be

- as good as new
- as bad as old (in the state for his age)
- better than old but worse than new (in an intermediate state, excluding statements better than new or worse than his age).

Also 3 models have been proposed to model respectively the 3 types of maintenance:

- The Renewal Process (RP)
- The Non-Homogeneous Poisson Process (NHPP)
- The Generalized Renewal Process (GRP) Type 1 or 2.

In the GRP model type 1, the corrective maintenance has a rejuvenating effect proportional to the time elapsed since the previous maintenance. The virtual age (Ar) of the equipment immediately after the r th maintenance action (at time tr) is given by the formula 6.

$$A_r = A_{r-1} + q^*(t_r - t_{r-1}) = A_{r-2} + q^*(t_{r-1} - t_{r-2}) + q^*(t_r - t_{r-1}) = q^* t_r \quad (6)$$

with q the rejuvenation factor .
q = 0: complete rejuvenation (equivalent to a PR)
q = 1: no rejuvenation (equivalent to a NHPP)

The probability that the equipment is down at t, knowing it was repaired at tr is given by the formula 7.

$$[F(t)-F(tr)]/R(tr) = (1-R(t)-1+R(tr)) / R(tr) = 1 - R(t)/ R(tr) \quad (7)$$

If the aging of equipment is modeled by a Weibull law, the corresponding distribution function is given by the formula 8.

$$F(t) = 1-\exp[(qtr/\sigma)\beta - ([qtr+(t-tr)]/\sigma)\beta] \quad (8)$$

And the probability density is given by the formula 9.

$$f(t) = \beta(qtr+(t-tr))\beta-1/\sigma\beta \exp[(qtr/\sigma)\beta - ([qtr+(t-tr)]/\sigma)\beta] \quad (9)$$

The GRP type 2 differs from type 1 by the fact that corrective maintenance led to a rejuvenation of the equipment proportional to its virtual age. The virtual age is given by the formula 10.

$$A_r = q^*(A_{r-1} + t_r - t_{r-1}) = q^*(q^*(A_{r-2} + t_{r-1} - t_{r-2}) + t_r - t_{r-1}) = q^r * t_1 + q^{r-1} * (t_2 - t_1) + \dots q *(t_r - t_{r-1})$$

$$A_r = \Sigma_1^r q^{r-i+1} *(t_i - t_{i-1}) \quad (10)$$

The corresponding distribution function is given by the formula 11.

$$F(t) = 1-\exp[(Ar/\sigma)\beta - ([Ar+t-tr]/\sigma)\beta] \quad (11)$$

And the probability density is given by the formula 12.

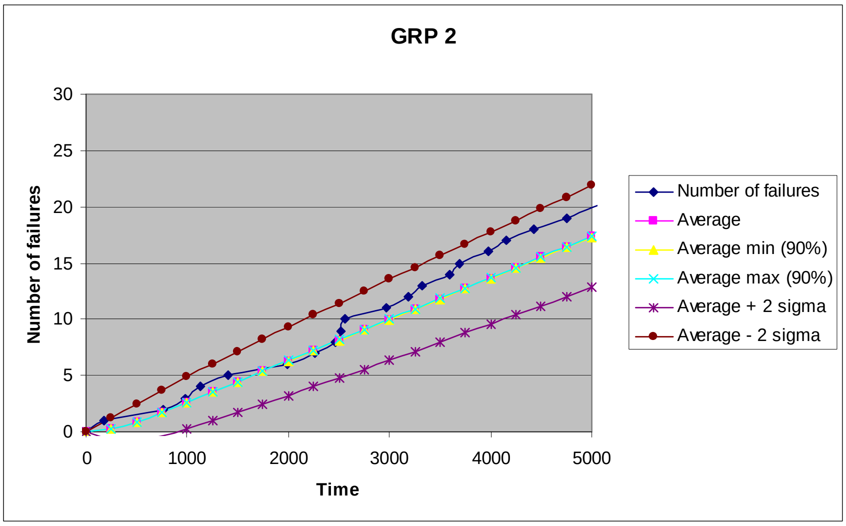
$$f(t) = \beta(Ar+t-tr)\beta-1/\sigma\beta \exp[(Ar/\sigma)\beta - ([Ar+t-tr]/\sigma)\beta] \quad (12)$$

Figure 5 shows an adjustment of the GRP model type 2 made from a sample of 200 simulated values. We get approximately the values of model parameters used for simulation. The curves show the results of simulation results (number of failures as a function of time for 1 and 2000 simulations).

Generalized Renewal Process (GRP) Type 2

Bêta :	2
Sigma :	500
q :	0,5

T	Age virtuel	Nb pannes
0	0	0
178	89	1
765	338	2
986	280	3
1127	210	4
1406	245	5
1984	412	6
2257	342	7
2463	274	8
2522	166	9
2560	103	10
2975	259	11
3194	239	12
3330	187	13
3603	230	14
3699	163	15
3980	222	16
4154	198	17
4425	234	18
4757	283	19
5010	268	20
5345	302	21
5712	334	22
6246	434	23
6355	272	24
6656	286	25
6720	175	26
6877	166	27
7102	196	28
7147	121	29
7613	293	30



Adjustment

	Weibull
Bêta :	2,13
Sigma :	523,64
q :	0,53

N° of failure	t(hr)	Operating time	Virtual Age	Probability density (logarithms)
1	561	561	280	-6,66400718
2	662	102	191	-6,060101916
3	778	115	153	-6,24090356
4	912	134	144	-6,311498698

Figure 5. Simulation and fitting a GRP2 model (from 200 values)

4.2 *Jack Models*

Jack (Jack, 1998) proposes two models of aging in which the preventive and corrective maintenance have an effect of rejuvenation. This effect is greater in the case of a preventive maintenance (changing of several wear parts) than in the case of corrective maintenance (change of the one part down).

Jack type 1 :

- At the end of a corrective maintenance action, the virtual age of the equipment is equal to the one he had at the previous maintenance action (corrective or preventive) plus a proportion ρ_c of the time elapsed since.
- At the end of a preventive maintenance action, the virtual age of the equipment is equal to the one he had in the previous action of preventive maintenance, plus a proportion ρ_p of the time elapsed since.

Jack type 2 :

- At the end of a corrective maintenance action, the virtual age of the equipment is equal to the one he had just before this action multiplied by a proportion ρ_C.
- At the end of a preventive maintenance action, the virtual age of the equipment is equal to the one he had just before this action multiplied by a proportion ρ_P.

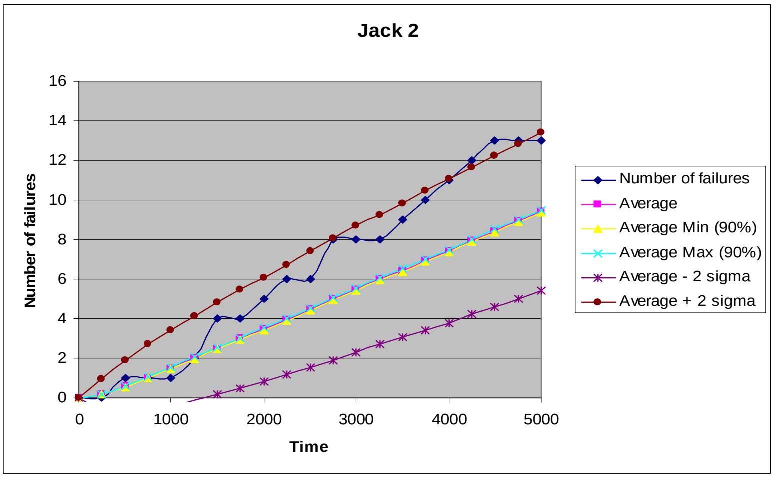
Similarly to the GRP model, the Jack type 2 model has been simulated by considering a periodic preventive maintenance, then it was adjusted from a sample of simulated values. Figure 6 shows the different results. Once again, we get approximately the values of parameters used for simulation.

It should be noted that the adjustment has always given a higher likelihood to that obtained with original parameters configuration used to generate the data sample.

Jack Model type 2

Bêta :	2
Sigma :	600
ρc :	0,7
ρp :	0,3
Maintenance period:	300

Preventive Maintenance	Failure	Virtual age	T	Number of failures
		0	0	0
300		210	431	1
	431	102	1032	2
600		190	1272	3
900		343	1301	4
	1032	142	1927	5
1200		218	2248	6
	1272	87	2588	7
	1301	35	2674	8
1500		163	3260	9
1800		324	3722	10
	1927	135	3907	11
2100		216	4230	12
	2248	109	4448	13
2400		183	5540	14
	2588	111	6394	15
	2674	59	6768	16
2700		59	6826	17
3000		252	6959	18
	3260	154	7318	19
3300		135	7771	20
3600		305	8150	21
	3722	128	8811	22
3900		214	9230	23
	3907	66	10060	24
4200		251	10292	25
	4230	84	11045	26



	Adjusted	Initial
Bêta :	2,21	2
Sigma :	623,14	600
ρc :	0,70	0,7
ρp :	0,26	0,3

∑ LN V: -489,7435

N° of maintenance action	Preventive (hr)	Corrective (hr)	Virtual age	Operating time	Probability density (logarithms)	Reliability (logarithms)	LN likelihood
1		152	45	152	-7,391030081	-0,044427389	-7,39103
2	300		143	148	-7,13331614	-0,071782503	-0,071783
3		303	43	3	-7,397104081	-0,001766909	-7,397104
4	600		253	297	-6,633710368	-0,259924731	-0,259925
5	900		411	300	-6,417985991	-0,631766738	-0,631767
6		1198	210	298	-6,417998167	-0,933284022	-6,417998
7	1200		157	2	-6,95189905	-0,001630553	-0,001631

Figure 6. Simulation and fitting a Jack 2 model (from 200 values)

5 ACCELERATED AGING MODELS ADJUSTMENT

Accelerated aging models are useful to reduce the duration of reliability testing or assessing reliability under the conditions of use and the environment. But they can also be used to fit a model of reliability from operational data obtained under various conditions of use and the environment, as showed in the following examples.

5.1 *Arrhenius with Weibull model*

The Arrhenius acceleration factor (13) can make the correspondence between periods of operation under different temperatures.

$$FA = e^{\frac{Ea}{K}\left(\frac{1}{T_1}-\frac{1}{T_2}\right)} \qquad (13)$$

With: T: absolute temperature in degrees Kelvin (° K = ° C + 273,15)

Ea: activation energy in eV (depending on the material and its mechanisms of damage varies between 0,2 and 1,1 eV)

K: Boltzmann constant (8,617385 10-5 eV / ° K)

You may want to adjust a Weibull law from operational data obtained under various conditions of temperature, without knowing the value of the activation energy of the product. Then you have to fit a model with 4 parameters as shown in Figure 7.

Weibull law with Arrhenius acceleration factor (activation energy unknown)

Boltzmann constant:	8,62E-05
activation energy:	**0,26**
β :	**3,90904**
σ :	**489,186**
γ :	**7,5E-10**

T°C : 40		FA : 1,61	
Failure data		*Censored data*	
ti	ln(f(ti))	ti	ln(1-F(ti))
		1000	-6,6277923
		950	-6,659762

T°C : 50		FA : 2,16	
899	-6,48447102	1000	-6,8647056

T°C : 60		FA : 2,84	
410	-6,53821473		
720	-6,36331959		

T°C : 70		FA : 3,68	
178	-7,78959471	470	-0,8552137
261	-6,74277736	550	-1,5809741
267	-6,68463165	600	-2,2214771
272	-6,6377125		
279	-6,57432342		
286	-6,5135633		
334	-6,16453867		
362	-6,01356056		
419	-5,82583612		
426	-5,81416101		
440	-5,79856344		
470	-5,8010579		
483	-5,81794151		
531	-5,96882917		
534	-5,98312366		
543	-6,02960919		
581	-6,28797582		
589	-6,35576158		

∑ln(f(Ti)) :	-132,18957
∑ln(1-F(Tj)):	-24,809925
LN likelihood:	-156,99949

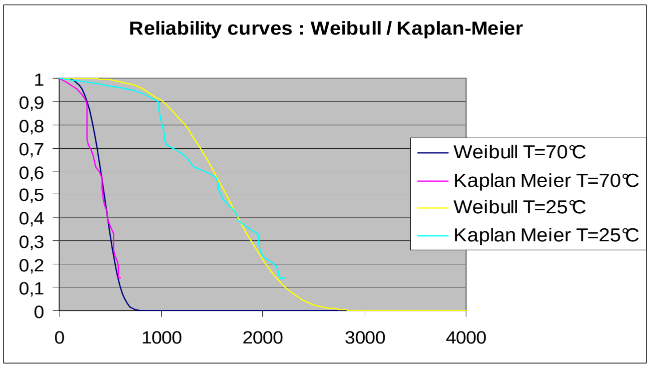


Figure 7. Fitting Weibull law with Arrhenius acceleration factor (activation energy unknown)

5.2 *Fatigue model*

Basquin's model (formula 14) is a model of fatigue acceleration making the correspondence between the numbers of cycles before failure for different values of constraint.

$$FA = N/N_0 = (\tau_0/\tau)^B \quad (14)$$

Moreover, experience shows that a significant dispersion exists between parts of the same batch. They are approximately following lognormal law based on the number of cycles.

From operational data obtained under various constraints, it is then possible to fit a lognormal law considering the coefficient B as additional parameter of optimization as shown in Figure 8.

Accelerated fatigue model (Basquin's model)

mu :	**10,34**
sigma :	**1,01**
B :	**17,27**

∑ln(f(Ni)) :	-18,95
∑ln(1-F(Ni)):	-2,36
LN Likelihood:	**-21,31**

τ/τ_e : 90%		FA :	1101
Failure	ln(f(Ni))	Censorship	ln(1-F(Ni))
3	-3,38		
11	-1,36		
35	-0,95		
52	-1,12		

τ/τ_e : 80%		FA :	144
155	-0,98		
292	-0,98		
621	-1,48		
825	-1,81		

τ/τ_e : 70%		FA :	14
950	-1,26	1503	-0,45
1568	-0,98	1822	-0,57
1963	-0,94	1965	-0,62
2536	-0,94	2000	-0,63

τ/τ_e : 60%		FA :	1
4450	-2,77	8000	-0,09

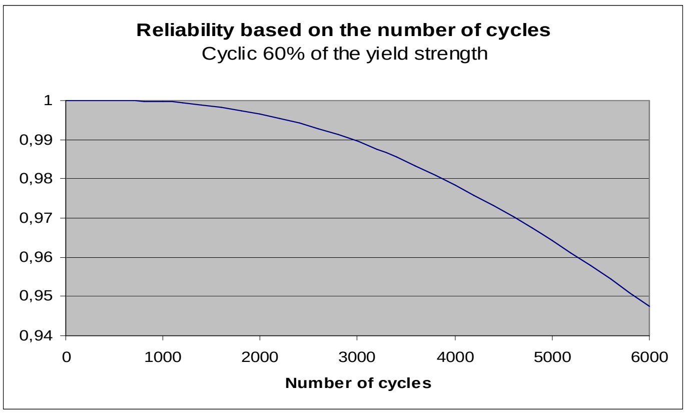


Figure 8. Fitting Lognormal law with Basquin' acceleration factor

6 OPTIMIZATION SYSTEM

6.1 *Coupling between optimization tool and assessment model*

The coupling between optimization tool and assessment model allows optimizing globally many parameters of architecture and operating system (level of redundancy, quality of components, maintenance actions duration, size of spare stock, period of preventive actions, depreciation duration, etc.) as shown in figure 9 (Faure, 2008).
The optimization can be based on a criterion and respecting various constraints such as availability greater than 0,98 at minimum cost or maximum availability and cost less than 5000 k€ for example.
The coupling between optimization and assessment model by Monte-Carlo simulation is particularly restrictive in computing time. That is why the tool GENCAB has a particular algorithm (Cabarbaye, 2006) limiting to only the necessary number of simulations used to evaluate each solution (the overall computation time is roughly divided by 30 by this technique). The optimization of the maintenance (period of preventive actions, depreciation duration, etc.) can be made directly from a simulation model without having to use an analytical formula often complex or impossible to define. For example, optimization of preventive maintenance actions is the subject of the next section.

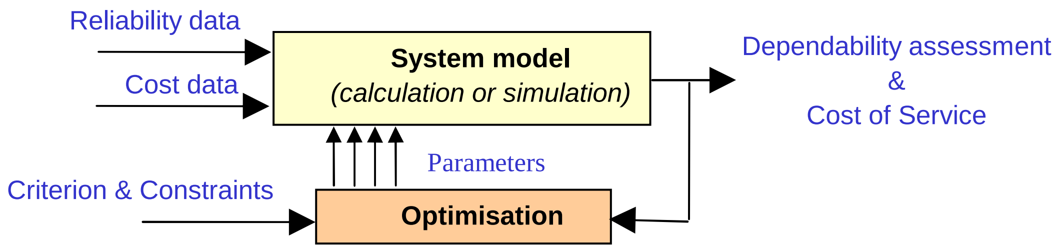


Figure 9. System optimisation

6.2 *Optimization of preventive maintenance*

In the case of equipment subject to wear, periodic maintenance may not be always optimal because preventive actions are too often at the beginning and not enough at the end of the process. Other strategies can be envisaged, such as those proposed below:
- Maintenance can be done to ensure the same level of risk of failure between two preventive maintenance actions..
- Preventive maintenance can be performed so as to make the average hourly cost of maintenance equal to a constant value during all the process.

Illustrated by figure 10, the first of these strategies has been the subject of optimization shown in Figure 11.

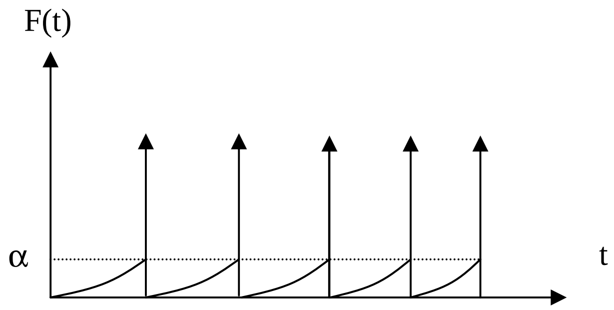


Figure 10. Preventive maintenance policy

Considering the average cost of preventive action ($Cost_{preventive}$), the average cost of corrective action ($Cost_{corrective}$), and the cost of equipment replacement ($Cost_{replacement}$), the maintenance optimization is to find the value α of risk of failure and the duration of equipment depreciation ($T_{depreciation}$) such that the average hourly cost, defined by formula 15, is minimized.

$$(N_p * Cost_{préventive} + N_c * Cost_{corrective} + Cost_{replacement}) / T_{depreciauion} \qquad (15)$$

Np and Nc are the respective average numbers of preventive and corrective maintenance actions performed during the period of depreciation of the equipment.

7 CONCLUSION

A global optimization tool is essential for the proper adjustment of probabilistic model a little complex from feedback operational data.
This kind of adjustment opens the door to many opportunities for optimization of architecture, maintenance or depreciation of the products.
Beyond the field of reliability, a global optimization tool is valuable to perform the overall trade-off of system engineering between multiple parameters.
The models presented in this paper were only chosen to illustrate the adjustment possibilities without analyse of their respective merits. Many others would have their place such as GEV (Generalized Extreme Value) or GPD (Generalized Pareto Distribution) laws used in the theory of extreme values, for example.

Maintenance optimisation (Jack 2 model)

Bêta :	2
Sigma :	600
ρc :	0,7
ρp :	0,3
Preventive action cost:	300
Corrective action cost:	1000
Replacement cost:	5000

T depreciation: 28202 hours

Risk level : 0,32

Σ Cost /hr: 2,97849153

T	Next scheduled action	Next failure	Virtual age	Cost
0	376	488	0	5000
376	656	628	113	300
628	827	1542	255	1000
827	1091	1086	136	300
1086	1277	1178	277	1000
1178	1376	1357	258	1000
1357	1536	1572	306	1000
1536	1794	2049	145	300
1794	2068	1875	121	300
1875	2135	2099	142	1000
2099	2298	2413	256	1000
2298	2562	3230	136	300

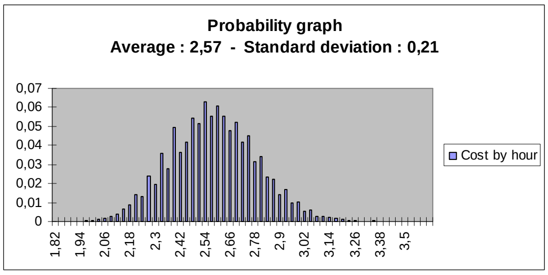


Figure 11. Optimization of preventive maintenance

REFERENCES

Jack, N.1998. Age-reduction models for imperfect maintenance. IMA Journal of Management Mathematics 9, pp. 347-354,

Cabarbaye, A. 2003. Outil générique d'optimisation dans le domaine discret et/ou continu éventuellement stochastique - ROADEF'03 – Avignon.

Cabarbaye, A. & Faure, J. & Laulheret, R. 2006. Couplage entre optimisation et simulation stochastique, ROADEF'06, Lille

Faure, J. & Laulheret, R. & Cabarbaye, A. 2008. Is Optimized Design of Satellites Possible? ESREL, 22 - 25 September 2008, Valencia, Spain.

Ziani, R. & Antoni, M. 2008. Modélisation du vieillissement des appareils de signalisation par le modèle de Bertholon et optimisation de la maintenance, lambda mu 16, 7-9 octobre 2008, Avignon, France.

GENCAB® is a tool of CAB INNOVATION Company (contact@cabinnovation.com)