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Degradation trajectories for components in conventional power plants

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Abstract

For components in E-production units the optimum time for overhaul is ill known. With a quantitative model the planned unavailability in relation to unplanned unavailability can be optimized as a function of operating conditions. Such a quantitative model should answer the question how much more or less failures are to be expected when the overhaul interval is lengthened.

It can be expected that mechanical components show a degradation trajectory to failure. Therefore failure mechanisms and influence factors have been charted for such components. Use is made of FMECA results as well as KEMA failure investigations. The failure investigations have been used to obtain quantitative information for failure and degradation trajectories.

The failure investigations of power plants show that in practice there is a large amount of uncertainty in times to failure and degradation times. Even a failure database with 745 damages in some 30 types of components shows that there is still insufficient material to precisely estimate time to failure and degradation trajectories per failure mechanism. An uncertainty of a factor 2 in time to failure is not uncommon. Therefore expert judgment has been used to assess the probability of occurrence of a failure mechanism, the average time to failure and the degradation speed.

Degradation trajectories have been simulated with Monte Carlo analysis. The combination of expert judgment, FMECA, quantitative information from failure investigations and simulation is sufficient to calculate the optimum time between overhauls using Markov modeling of degradation trajectories. Such modeling is easy to understand and elegant.

Keywords – (Reliability, Availability, Maintainability, Failure, Degradation, Damage investigation)

Introduction

One of the ways to influence the forced unavailability of power plants is overhaul or otherwise planned maintenance. Usually overhaul of components in a plant is either prescribed by the government (boiler inspections) or is on the advice of the manufacturer (OEM). This overhaul interval will be on the safe side. However the owner, within constraints of safety, should be interested in the optimum maintenance strategy in terms of costs.

An investigation into the optimal timing of overhauls is therefore appropriate. In practice, little is known on the optimum situation and utilities apply expert judgment with regard to maintenance intervals. A quantitative model would allow optimizing planned unavailability and unplanned non-availability with the associated direct and indirect costs. To do this, the model should answer the question whether and how the number of expected failures will change as the revision interval is increased.

It can be expected that in particular mechanical components will show a degradation process to failure. If such degradation process allows measuring or estimating the condition of a component, this can serve as a basis for overhaul planning in order to avoid failures. To investigate this further, a combination of FMECA, failure and degradation modeling as well as Markov modeling and Monte Carlo simulation was applied.

Qualitative Degradation Model

Suppose that the initial condition in Figure 1 (as good as new) is set arbitrarily to 1 and that the condition "failure" is arbitrarily set to 0. For many components, especially the mechanical components, a per failure mechanism trajectory to failure will occur. Examples are pipes with cracks, with corrosion, with erosion, etc.

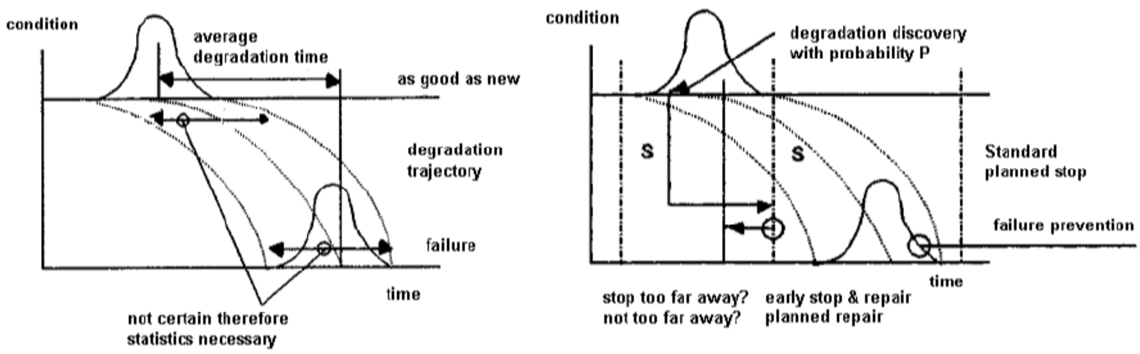

Figure 1: Qualitative model for degradation to failure

In figure 1 there is no preventive maintenance and the component will fail in due time once the degradation process has started. Failure in itself is certain but the time to failure is uncertain and can be described in a statistical way. The trajectory is characterized by the (uncertain) time the degradation starts, the (uncertain) rate of degradation and the (uncertain) time of failure. Aging is related to the time of failure. With random component failures, the cumulative number of failures is a straight line as a function of time (or another measure of "exposure" such as cycles, operating time, and idle time). With ageing, the slope of the number failures per unit time increases over time. When teething troubles are present, obviously the reverse is true.
The moment the start of the degradation process is noticed, failure can be avoided by corrective actions as depicted in the right hand of figure 1. Detection may be the result of measurements that can either be continuous (condition monitoring) or through an inspection with a (fixed) frequency in time (s = stop with inspection moment in Figure 1). Depending on the

degradation rate and the estimated condition by measurement or inspection, restoration can take place. This restoration can be performed immediately, in the next scheduled stop, or in the next stop that has been rescheduled to an earlier moment (or perhaps later) than previously planned. Figure 1 may help to eliminate the misconception that preventive maintenance would be pointless when random failures occur. This is only true for preventive replacements on a fixed time basis.

Failure Mode Effect Analysis FMEA

A FMEA allows to qualitatively chart failure mechanisms, causes, measures and risk in a well organized manner. Suppose the potential failure mode "cracking of LP blades" of a steam turbine is investigated. Table 1, based on a FMEA for a steam turbine in a CCGT plant, shows in the first four columns for just one failure mechanism & failure cause combination the standard information normally collected in a FMEA. In the remaining columns the information needed to estimate the degradation trajectory is given. The rate of degradation was estimated as a linear, an exponential or a double-exponential trajectory. Adding indices for probability of occurrence and the severity of consequence results in a risk priority number and a component criticality (as in a FMECA) which will further draw attention to the dominant risks and failure mechanisms.

Table 1: FMEA estimate of degradation trajectory

Failure mechanism	Failure cause	Failure root cause/ influence factor	Occurence probability	Time to onset of degradtion (yrs)			Time to failure from onset (yrs)			Trajectory
				low	mean	high	low	mean	high	
cracking at blade root	Stress corrosion cracking	condition machine when stopped	0.2	3	5	7	1	2	3	exponential

Numerical results from KEMA failure investigations

As part of KEMA services, on a regular basis damages and failures of power plant components are investigated to assess the (root) cause. The services cover the whole range of power plant equipment, from mechanical components such as steam and gas turbines, boilers and generator rotors to electrical equipment such as cables, transformers, etc.
Times to start of degradation as well as times to failure were analyzed in 745 failure investigations. Based on the investigation reports, the damage was classified either as degradation (f.i. crack initiation) or failure (tube leaking). For some 30 components and failure causes, the results could be summarized as in figure 2. The obtained failure and degradation rate (1/average time) can be compared with reliability data from power plants collected by NRG and KEMA since 1976. While the obtained mean failure rates compare reasonably well with these long term reliability data, figure 2 shows that (large) uncertainty exists in the data. Moreover, for some

components the average time to failure is positioned before the degradation average. This cannot be true. The main reason is that the damages brought to KEMA by its clients for analysis are not an a-select sample in which all failure mechanisms are equally present. This is one of the reasons why expert judgment is necessary.

The uncertainty has consequences for overhauls: if no experience with the component is present and the condition is not measured continuously in time, overhauls on a time basis can be disappointing: in some cases the components turn out to be as good as new during overhaul, in some cases the components fail between overhauls.

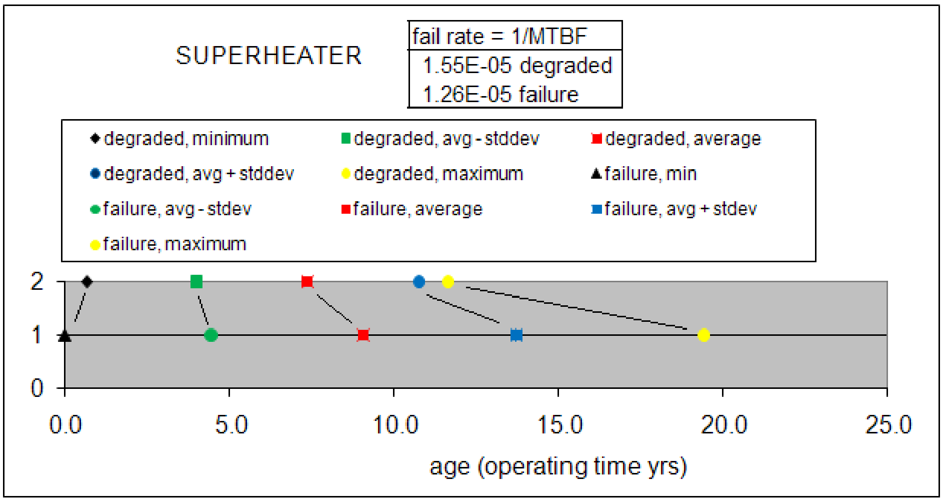

Figure 2 Degradation and times to failure for a superheater in a conventional boiler

Expert Judgment investigation

The KEMA failure analyses database shows that having information from a large number of damage investigations and FMECA's is in itself insufficient to accurately determine the probability of occurrence of the degradation mechanism, the time of initiation, the degradation trajectory and the time to failure. Expert Judgment, when systematically applied, offers an opportunity to determine these parameters in a specific case while taking into account the actual component geometry and load. The failure analyses provide the means to check the Expert Judgment.

KEMA regularly uses the Expert Choice software to perform Multi Criteria analysis. In such analyses, alternatives are compared on the basis of variable scores and weight factors. Determination of the weight factors is based on a verbal description of the factor (average, large, extremely large, etc. as compared with the alternative) in combination with graphical support. The verbal choice is converted into weights with a method according to Saaty (the Analytical Hierarchy Process AHP). Expert Choice proved to be convenient to estimate the relative fraction of failure mechanisms for a CCGT. Part of this work is shown in figure 3. A fraction of 0.769 of all CCGT failures is estimated to originate from the gasturbine, in which 0.080 is related to bearings, etc. The weight factors add up to 1, therefore to calculate for example the number of failures per year (which is certainly larger than 1), a multiplication factor (anchoring all results) must be applied.

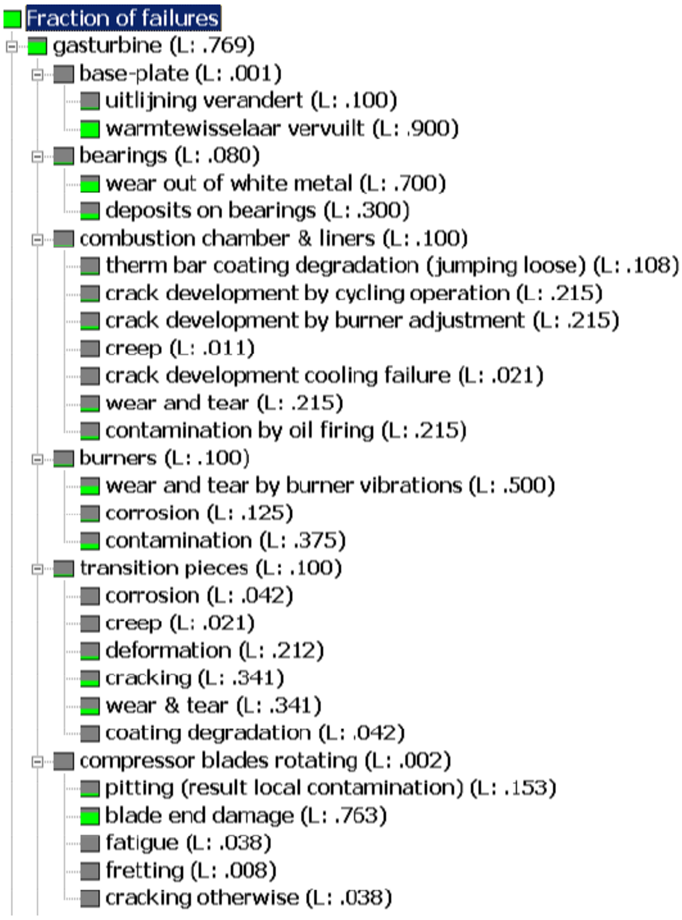

Figure 3 Expert opinion on failure probability

Simulation

To be able to optimize overhaul intervals by means of degradation modeling in combination with already existing Markov spreadsheets, the following steps were carried out:

- Development of a stochastic model for failure in combination with a degradation trajectory. The input is derived from the expert judgment and failure investigations;
- Combining stochastic models per failure cause and Monte Carlo simulation of degradation trajectories, resulting in a distribution of degradation states ending in failure (including competing failure modes). For convenience a Gamma distribution was used;
- Fitting the matrix coefficients for the Markov model using the simulation results.

The steps are graphically shown in figure 4. The maintenance optimization in itself is not part of the present paper. For this, reference is given to the optimization of maintenance for electric motors in the flue gas desulphurization system at the G13 coal fired plant in Nijmegen[1].

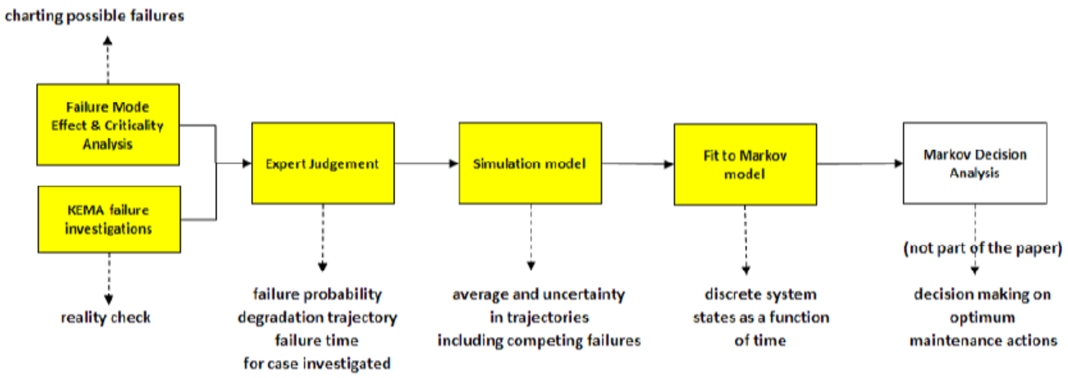

Figure 4 Steps in degradation modeling

When software is available to carry out direct optimization of overhauls together with the Monte Carlo simulation of the degradation trajectories, the step of fitting the simulation results to a Markov model is not needed. However, Markov modeling and Decision Analysis is elegant in applying decisions for specific system states and the possibility to analytically calculate these results.

Stochastic modeling in Excel in itself is simple. A Gamma distribution described by two parameters α and β is a convenient distribution describing either aging or teething troubles, depending on the choice of the parameters. Figure 5 shows the Monte Carlo distribution for the degradation trajectory starting at t 0 using @RISK to accommodate such modeling.

[1] H.C. Wels e.a., "Optimum times for maintenance", Energie Techniek May 2003 (in Dutch)

Figure 5 Monte Carlo distribution for degradation and life times

Markov model

A Markov model is – contrary to the above mentioned simulation model – a discrete model, with in this example four condition states (as-good-as-new, slightly degraded, severely degraded, failure) as is shown in Figure 6.

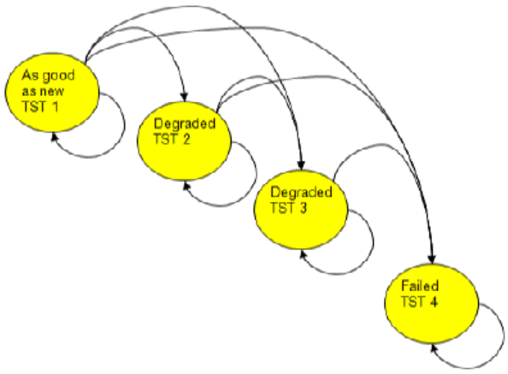

Figure 6 Markov model

Coming from the initial state (TST1), for each time step a probability of transition to other states (TST2, TST3 or TST4) is defined. It is also possible that with a certain probability (0.749) the component remains in state TST1.

Table 2: Markov system transition state matrix

System state	**1**	**2**	**3**	**4**
1	0,749	0,201	0,035	0,015
2	0	0,904	0,047	0,049
3	0	0	0,846	0,154
4	0	0	0	1

In the Markov model of Figure 6 an end-state TST 4 is shown: given time for any set of realizations components will end in this failure state (while no repair or betterment of condition is carried out). Using a Markov decision model, for each time step a decision can be implemented: apply maintenance (periodic or state dependent) to bring the component in TST 1 (or possible TST 2) again. Arbitrarily 10% and 60% were applied for the amount of degradation in the intermediate states TST2 and TST3. Figure 7 shows a realization. The transition coefficients of the transition matrix, as given in table 2, must be optimized in such a way that the average of the Monte Carlo simulation equals the average of the Markov realizations for all time steps. The result is shown in figure 8. These coefficients can be optimized further to have the uncertainty in figure 8 closer to that in figure 5.

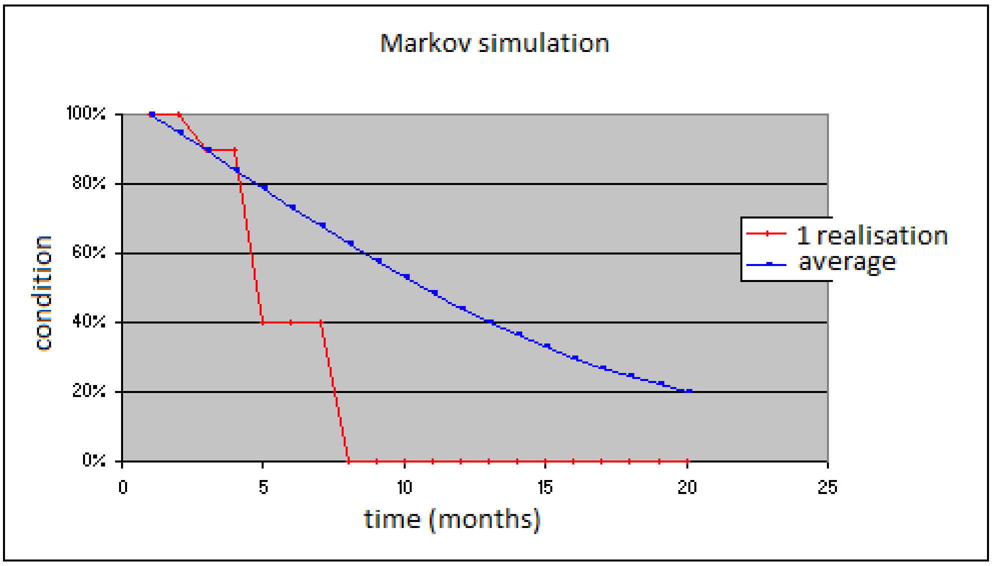

Figure 7 Single realization of Markov model and average from gamma distributions

At first instance this optimization was carried out using the Excel add-in @ RISKOPTIMIZER. This add-in works with a genetic algorithm based on continuous binary combination of the best solutions from a number of initial solutions. By converting bits by small amounts (comparable with mutation processes in nature) it is ensured that a local optimum is avoided and, in principle, a global optimum is reached. Disadvantages are that the optimization is lengthy and the optimum is not sharply defined. Furthermore it was found that the coefficients for states that are not present much of the time (TST2 and TST3) are difficult to optimize.

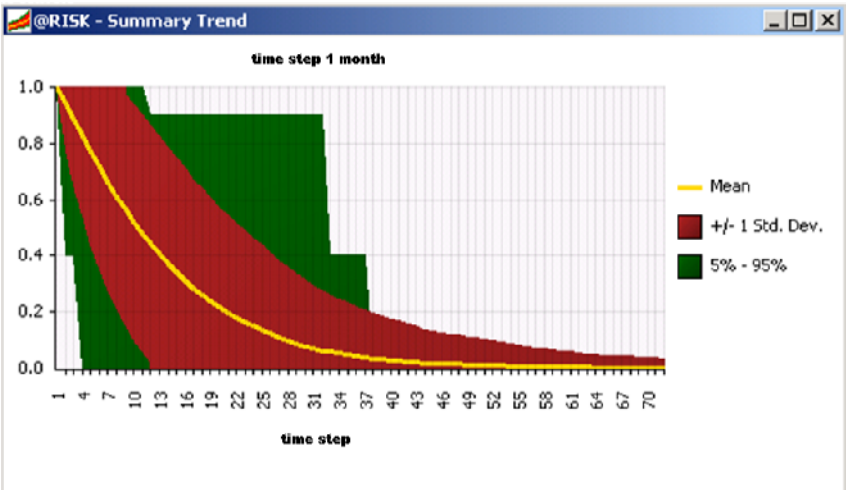

Figure 8 Uncertainty in degradation trajectories, Markov simulation

It is of course also possible to optimize the coefficients for the probability of a transition state directly by calculating the mean value by numerical integration and apply optimization with @RISK or Excel Solver . This was carried out to make sure no errors were present in Excel by using NRG's Markov computer program based on precise numerical integration with small time steps. The result for this program for states 2 (slight degradation) and state 4 (failure) is shown in figure 9.

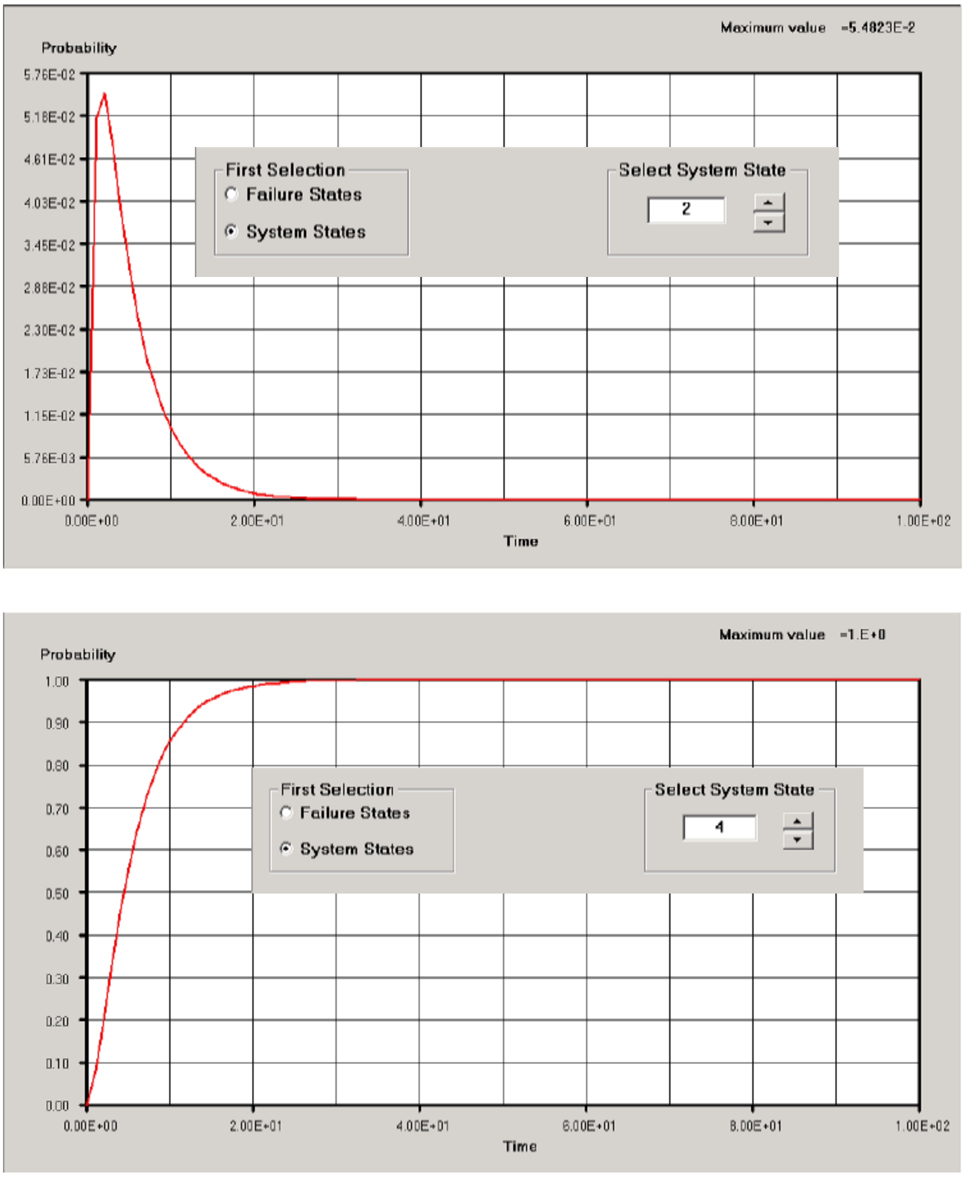

Figure 9 Results Markov model by numerical integration

Conclusions and recommendations

Given the average trajectories from degradation to failure and their uncertainties, the next step is to apply Markov Decision Analysis to optimize maintenance actions with respect to costs. Is it optimum to carry out preventive maintenance actions when the component is slightly degraded, heavily degraded or failed given the frequencies of these states and the costs of both maintenance and consequential material and customer damage? This step has already been investigated for electric motors.

Even the KEMA database with 745 failure investigations is not specific enough to accurately subdivide into failure mechanisms per component. This is due to the a-select type of damages brought to KEMA by its clients. The failure investigations show that in practice a high degree of scatter is likely for the times to failure and the times at which degradation occurs. An uncertainty of a factor 2 in failure time is not unusual. This is also evident from the failure times in well-defined conditions (for instance in the EEC database fatigue for pressure vessels[2]). Overhauls on a fixed time basis can therefore be disappointing.

A failure investigation or damage database can however be supplemented with systematic expert judgment (to estimate the failure mechanisms per component and to add to component level, to calibrate with other databases f.i. for availability data, to estimate whether failure mechanism A is considerably faster / slower than B, etc.). Expert Judgment is necessary to estimate the variables of interest as best as possible for the component and operating conditions under consideration.

Tools to quantify the occurrence of failure mechanisms and degradation trajectories using Monte Carlo simulation are easily made in Excel. Comparison with analytical models and extensively tested other software helps to prevent errors.

Finally, the "old" Dutch Stoomwezen rule for power plants (inspection at 50% of the design life) is probably not bad at all, given the ratio of the standard deviation to the mean value for life in the KEMA damage investigations. This is consistent with information about the strength of airplane frames investigated between 1935 and 1955[3] [2]. While these frames were designed at 120% of the "fully factored load", they were found to fail randomly between 50% and 150% of this load.

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[2] Maddox, Fatigue Design Review Task 5, Assembly of available fatigue data relevant to presure equipment design, September 2001

[3] J.E. Gordon, Structures or why things don't fall down, ISBN 0-306-81283-5, 1981