Risk and Reliability Engineering for Crisis Management: Using Experience from Asset Management.

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Abstract.

History shows that scientific research in Risk and Reliability Engineering has not been very successful in improving Asset Management whilst a comparable disciple as control engineering is now fully integrated into the (process) engineering curriculum and widespread applied.
The author has 20 years' experience of teaching some 300 Master students, trying to close the intellectual gap between (stochastic) Operations Researchers and practical (especially, mechanical) engineers.
Discussing a number of common decision problems, it is shown that simple models that visualise the results of the AM decision process in time are powerful tools to store the insights produced by reliability engineering tools in memory. Such understanding is required in deciding on maintenance strategies to be applied, as well as on achieving agreement and endorsement between/from the various parties involved, in order to guarantee a long-lasting success of an implementation and to evaluate the results with field data.

Even these simple models yield results that hitherto are surprising to practicing engineers, as demonstrated by their use in the long series of Master Course RAM blocks. It is our experience that, after graduation, most course members successfully apply these techniques in practice.

Keywords: Asset Management, Decision Support Techniques, Dealing With Uncertainty, Stochastic Analysis

List of abbreviations.

AM	Asset Manager
CFO	Chief Financial Officer
CI	Critical Infrastructure
ETA	Event Tree Analysis
FMECA	Failure Mode Effect and Criticality Analysis
FTA	Fault Tree Analysis
HAZOP	HAZard and OPerability Study
MM	Maintenance Manager
NASA	National Aeronautics and Space Administration
RAS	Risk Assessment and Safety
RBD	Reliability Block Diagram
RCM	Reliability Centred Maintenance
SMART	Specific, Measurable, Achievable, Realistic, Time-bound
TPM	Total Productive Maintenance

1. Introduction.

Vital services continuity is a major societal security issue in modern society. The supply of the vital services is guaranteed thanks to a large variety of Critical Infrastructures (CIs). Some CIs' disruptions may endanger the security of the citizen, the safety of the strategic assets and even governance stability. The ESReDA project group (CI-PR/MS&A-Data) focusses on Modelling, Simulation and Analysis of these complex, interconnected systems aiming at providing decision support to a wide range of stakeholders including (multi)national emergency management, critical infrastructure asset managers, policymakers, and the society.
The dependencies between such critical infrastructures are complex and frequently non-obvious. Examples as the electric power disruptions in California in 2001 demonstrate cross-sectoral cascading consequences with time-dependent failure characteristics and (positive) feedback of natural gas production, pipeline fuel supply, refinery and power production. Such consequences may in reliability engineering terms be typified as low probability events in complex systems with extensive consequences developing in time. Within that context the experience built up in reliability and risk assessment/asset management in simpler systems (like industrial production processes, water management and the built environment, where the probability of occurrence is one to two orders larger and consequences the same order lower), may provide lessons learned.

2. The History and Progress of Reliability Engineering.

2.1 Where do we come from?

The 2nd World War created the need for new systems to be developed, manufactured and put into operation in a short time; the learning curve had to become steeper. The English radar installations in the Second World War necessarily employed while still in the development phase showed a mean time between failures in tropical conditions

of a few hours. The Germans were quite unlucky with launching their first V-1 missiles to destroy London; research after the war estimated a 40% failure rate of air-launched V-1s.

> *On the German side, the failures met with launching the first V-1 missiles led Robert Lusser, a mathematically oriented aviation engineer to presage systems theory thinking by bringing in new concepts of system representation and random failure. He went beyond the deterministic way of thinking of skilled engineers and introduced rules for the reliability of systems as a function of those of the components. The "weakest link" paradigm was born; the reliability of a series system with statistically independent failure mechanisms equals the product of the reliabilities of the components.*
>
> *In hindsight, this observation appears rather obvious for anyone with even a limited insight in probability theory. However, it gives an intriguing insight into the deterministic engineering mindset at that time, being focussed on component design and apparently missing the system insight. Lusser himself was so convinced of his theories to get in a furious dispute with Wernher von Braun, who led a team to "put a man on the moon", declaring in 1947 openly [1]that "man can never go to the moon, let alone to Mars." To his insight, because of the complexity of the spacecraft required, there was simply too much chance to fail; "the probability odds with which he had wrestled a lifetime were simply too great for the risk". Lusser felt morally obliged to leave the design team, went back to Messerschmitt-Bölkow in Germany where he investigated the reliability aspects of the adaptations that the company was making to the F-104 Starfighter, the results of which soon turned out to be tragically correct. During a skiing holiday he ruptured his Achilles tendon and spent his last days and a lot of his personal fortune trying to market a ski binding he had designed to release stress just at the right time. He was 69 when he died in January of 1969, seven months before engineers succeeded in what he thought to be in reliability terms almost impossible; Neil Armstrong as the first human set foot on the moon and came safely back.*

This story, in a nutshell, exemplifies the problems we meet in the use of reliability engineering principles in Asset Management. The majority of asset managers have a mechanical, electrical or nautical engineering background. Engineers rely on the use of *"safety factors[1]":* the ratio of a structure's absolute strength (structural capability) to actual applied load; considered to be a measure of the reliability of a particular design. Typical values for building structural members are 2, for pressure vessels 3.5 to 4, aircraft and spacecraft use 1.2 to 3.0 depending on the application and materials. This approach, however, results in engineers mentally exclude the potential lack of reliability in operation; failures thus consequentially becoming regarded as "acts of God" or realisations of Murphy's Law.

> *These thoughts are in line with the attitude of NASA on using risk calculations in the Apollo project. The calculated expected mission success probability was that low that it discouraged [2] NASA from further quantitative risk studies until after the Challenger accident in 1986. Instead, NASA relied on FMECA*

[1] A constant required value, imposed by law, standard, specification, contract or custom, to which a structure must conform or exceed. This can be referred to as a design factor, design factor of safety or required factor of safety. Typical values for building structural members are 2, for pressure vessels 3.5 to 4, aircraft and spacecraft use 1.2 to 3.0 depending on the application and materials.

studies and extensive testing; the risk study results were not widely circulated in NASA and sparingly if ever, released to the public at large.

Literature shows many examples of situations where engineers met unexpected reliability/safety problems and searched for external support. Reliability Centred Maintenance was born after United Airlines suffered from severe reliability problems which could not be solved by making the overhaul periods shorter. They took the lead to define a generally applicable approach for the design of maintenance programmes, now known as the MSG-1 (maintenance steering group) documents. MSG-1 is the primitive forerunner of RCM (Reliability Centred Maintenance). MSG-1 was rooted in engineering insight and lacked most of the quantitative aspects. MSG-1 was followed up by later versions up to MSG-4. The ministry of Defence[[3] issued in 1975 a contract to United Airlines to describe this process. In 1978 Stanley Nowlan and Howard Heap [3] fulfilled this contract and published the landmark report "Reliability-Centred Maintenance". In line with the DoD requirements, they brought in quantitative aspects under the heading "actuarial analysis", using hired-in statisticians. Its rather misleading interpretation of (overall /sub-system, not a component or single failure mode!) failure mechanisms (**Fig. 2-1**) still remains in RCM textbooks and publications.

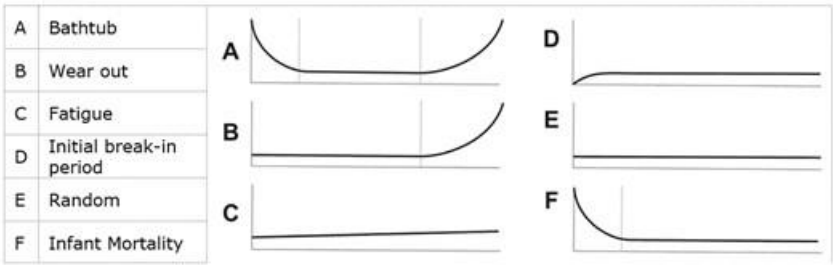


Fig. 2-1

Throughout history [4], the pendulum has been swinging back and forth from qualitative, experience (RCM, FMECA, HAZOP, TPM, ..) towards quantitative (ETA, FTA, RBD, ..) based decision support techniques. In cases where government bodies like the American Department of Defence or Industry experienced severe reliability problems, funding for academic research was widely available; technical problems were cast in stochastic OR research studies. However, most of the investigators had no direct link with real operations and considered the problems as interesting mathematical problems.

To quote Richard Barlow, one of the founders of reliability engineering [5]: "A mathematician is not going to read a typical engineering textbook because it is just too empirical."

It is, therefore, no surprise that the mathematical models receive little interest in the engineering community [6] whereas properly used they proved to be capable to solve real industrial problems [7]. In 2009 the author published[8] the results of a survey under Dutch maintenance engineers showing that in spite of the significant economic consequences and problems with outsourcing contracts, the level of underpinning and monitoring failure data and maintenance strategies leaves to be desired. The EFNMS (European Federation of National Maintenance Societies) survey of 2011, [9] arrives at similar conclusions; safety and costs score higher than system output. In both surveys, engineers mainly use qualitative techniques where the chance aspects and time-dependent characteristics are easily neglected. Ultimo [10], a provider of

Maintenance Management software, published in 2018 a report based on inputs from 150 MM's showing that MM's are rather focussed on technical aspects; only half of them having information on their contribution to the business. The repeated benchmarking studies from Solomon Associates [11] continue to observe apparent anomalies. From an engineering point of view differences in performance should logically be caused by such physical issues like size, age, location or organisational aspects like unionisation. However, in the long series of benchmarks [12] they continue to observe large variations in performance; the return on investment (ROI) varies from 16 per cent for the pacesetters to 4% in the bottom quartile plants. Unexpectedly, these differences show up for plants of the same ownership. The correlation with physical factors is quite weak; Solomon observes old plants both at the top as well as at the bottom of their ranking results and complexity plays a minor role. Such observations are in line with the results of the Merit team study in Shell [13].

In conclusion, over a period of some seven decades, we observe no large progress from experience towards evidence-based industrial asset (maintenance) management. The lack of systems theory, time-dependent behaviour and dealing with uncertainty in the education of engineers may be regarded as an impediment.

2.2 A comparison with control engineering.

Management problems can well be compared to process control problems. It is the task of a process control engineer to keep the output of a process (or any other process variable) at the desired value (the set point) in spite of external disturbances and changes in process characteristics. To that end, the actual process output value is compared with the desired (set) value. Any deviation (Fig. 2-2*) between the two is translated by a controller into steering one or more control variables.*

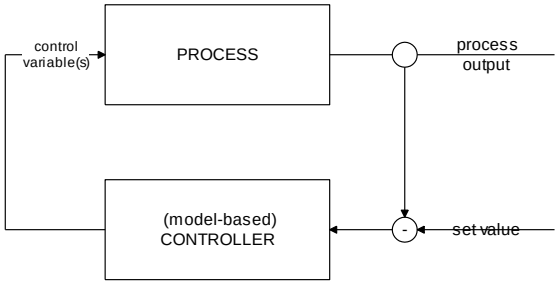


Fig. 2-2

Let us try to follow the reasoning of a control engineer. Before he/ she will start to work on a control problem the person will first check whether two conditions are met:

> *Observability: without mathematical rigour, this means that one can determine the full dynamic behaviour of the entire system from the system's outputs; you can write down the transfer function P from input to output.*
> *Controllability: again loosely speaking, this describes the ability of steering (control) inputs to move the internal state of a system from any initial state to any other final state in a finite time interval.*

If one of these conditions is not fulfilled he/she knows that the control approach will fail.

Take the simple example of controlling your room temperature with a gas fired boiler. There is a temperature sensor in the room thermostat (observability) and the radiators receive hot water (controllability) from a boiler. First, think about the situation

without feedback control; your thermostat is decoupled and the gas flow to the boiler is set at a certain value. The (room) temperature will then reach an equilibrium where the incoming heat supply Q_{in} just balances the heat loss Q_{out} =(area A * heat transfer coefficient U* temperature difference) = A *U* (T-T_o). We thus have, in simple lumped form, for the heat mass MC_p :

$$MC_p \frac{dT}{dt} = Q_{in} - UA(T - T_o)$$

$$\tau \frac{dT}{dt} = -T + ku$$

$$where$$

$$\tau = \frac{MC_p}{UA}$$

$$ku = \frac{Q_{in}}{UA} + T_o$$

If the gas flow rate is changed stepwise, the room temperature will reach exponentially a new equilibrium value:

$$T(t) = \left(1 - e^{-t/\tau}\right) ku$$

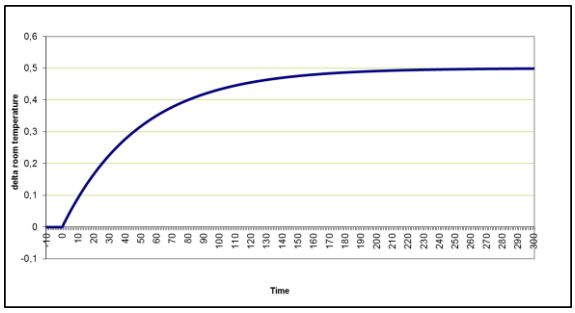


Fig. 2-3

An example is given in Fig. 2-3. This is the open loop response of the system; with no control present, the room temperature will decrease if the outside temperature drops. If we close the loop as in Fig. 2-3 the response with proportional control only will be (Fig. 2-4):

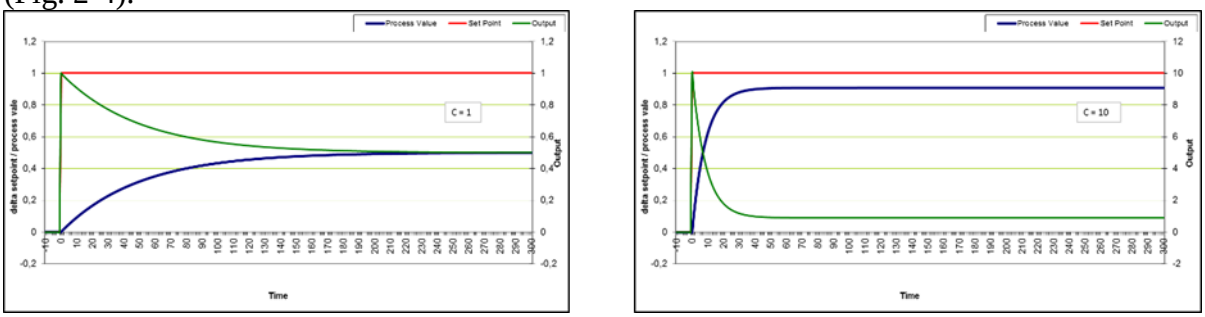


Fig. 2-4 Examples of closed loop control with various controller gains; P = 1

The deviation between set and measured value depends on the loop gain; the steady state error ε (measured value –set value) equals 1/ (1+PC) where P and C are the gains of the process (here 1) and controller, respectively. Time constants and external disturbances are reduced in the same proportion. Obviously, the control engineer aims

at a minimum value of ε but now the dynamics of the system (amplitude and phase shift between set and measured value) play a role. First, we will make the model a bit more realistic:

- The gas flow to the burner will not increase immediately; again a first-order process (FOP).
- The temperature of the water spiral due to the increase in burning gas flow leads to another FOP.
- So, will the local temperature of the water.
- The now hotter water needs to flow from the boiler to the cv radiator; control engineers denote this as a “distance velocity lag” or “dead time”.
- The air in the room has to be heated up with the now hotter radiator.
- The temperature measurement will inevitably show (small) delay.

It can easily be shown that a series of exponential lags can be approximated by a dead time τ_d with a resulting phase shift $\omega\tau_d$. In the figure below we have extended the first order model with a time constant 100 of Fig. 2-4 with a dead time term with value 10.

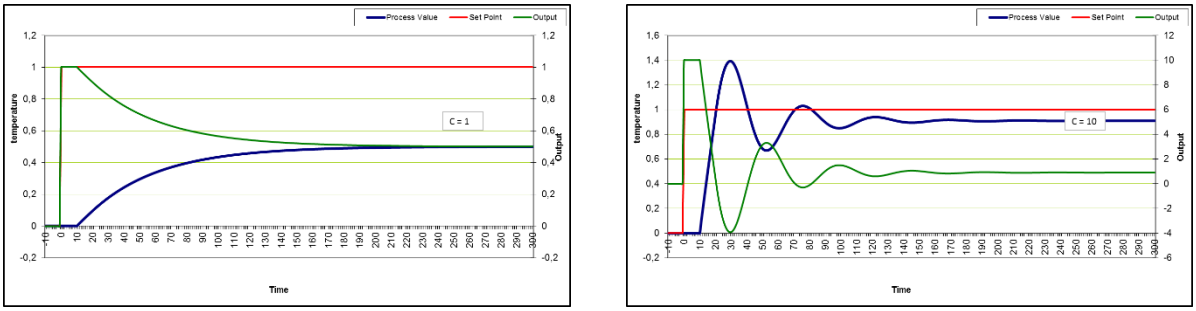


Fig. 2-5 The effect of a dead time on process stability

For the same controller gain setting of 10, we now observe significant oscillatory behaviour (Fig. 2-5). To understand this phenomenon we have to realise that both P and C are complex variables characterised by magnitude and phase shift. The transfer function reads H(s) = C(s) / (1 + P(s)C(s)) in the Laplace domain.

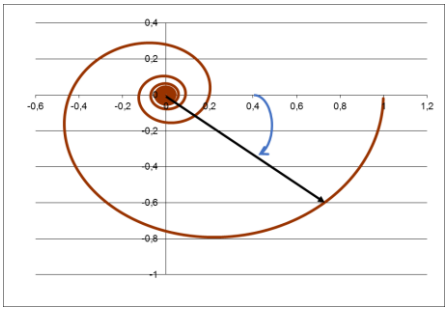


Fig. 2-6

Such a function may be sketched in the Nyquist diagram of Fig. 2-6 showing the magnitude (length of the vector) and phase angle of PC for increasing frequencies. Note that PC may approach the value -1 for a specific frequency where the gain tends to infinity. You may have experienced this phenomenon at a festival where the singer approaches with his microphone too close to the speakers!

With the transition from pneumatic to electronic controllers and later to full computer control the way towards more intelligent control was opened. In a number of cases, control variables may be strongly correlated, e.g. if you increase the temperature in a polypropylene solvent type reactor, the reaction rate increases consuming more propylene whereupon the reactor pressure will automatically drop. Rosenbrock [14] developed an engineering, *decoupling* approach to deal with this type of *multivariable* problems, using models based on transfer functions in the complex domain thus enabling the transition from single input – single output (SISO) to multiple input – multiple output (MIMO) control loops. Later, mathematicians like Kalman [15] and Athans [16] developed the concept of linear, time-invariant multivariate optimal control with models in state-space notation. From there on, model-based, nonlinear, multivariable, adaptive and robust control theories were developed both in the frequency, as well as in state space domain. Pseudo-random binary sequence (PRBS) signals U(i,k) excite the system in such a way (Fig. 2-7) that the response Y(I,k) can be used to fit a model in state space or in the time domain without seriously affecting process throughput or product quality. The resulting black box model is valid in a small region around the nominal process values only and the cause-consequence relationship is lacking. A more robust model is obtained if apriori information about the model structure and related physical processes is used in combination with the identification (a grey-box model).

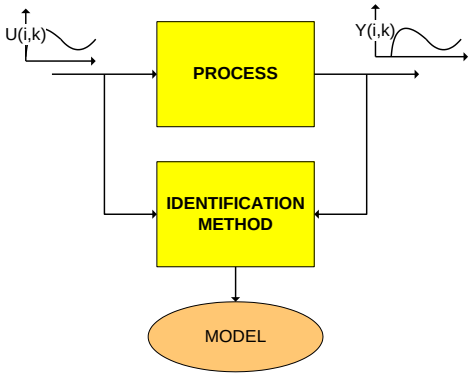


Fig. 2-7 Model identification in process control

The model-predictive approach was quickly taken up by Industry to stabilise and optimise more complex systems, respectively optimisation objectives. Shell introduced Dynamic Matrix Control ([17]) already in the seventies These techniques now find their way, via vendors as AspenTech, Honeywell, Emerson, Rockwell Automation and others who offer complete model and software libraries. In all cases, optimal (production rate/envelope, energy, ..) operation is found either by white box models, correlations obtained by (on-line) system identification (black box) or a mix (grey box). If the model predictions start to deviate from actual behaviour, plant and laboratory measurements are used to re-tune the model parameters. A distinct change from the analogue PID controllers is that digital model predictive control uses a control trajectory taking into account process constraints[2] such as maximum flow (pump capacity), maximum cooling (duty of heat exchangers), vapour transport (compressor).

[2] In most cases optimality is found at operation at one or more constraints!

Modern process control is fully accepted in Industry at large. Whereas control engineering started as a specific, separate discipline with specialists groups active only in major plants of large companies, nowadays it is integrated into the curriculum of chemical/process engineers. Supported by instrumentation vendors, these chemical engineers are qualified to install both simple and complex control and optimisation loops.

3. Decision making in Asset Management.

3.1 Introduction.

To start with, in contrast with control engineers, measured information in maintenance management is scarce and of a stochastic, rather than deterministic, nature. Since designers aim, within the scope of the budget, at high reliability, the frequency of observed failures is low (MTTF for critical items ranging from 5 -15 years in Industry, 20 - 50 and more in civil). Reliability databases at best give a range of MTTF's mainly at equipment level, seldom at a specific failure mode level. The trending of condition data leaves to be desired; in statutory inspections, we observe that only the last results are stored by both parties as a "permit to operate" for the next period.

As a consequence maintenance engineers rely on "expert opinion" gathered in a series of team discussions where a basic system model and the few reliable data stored in the CMMS act as a framework for discussion. The well-known psychological traps as described by e.g. Kahneman and Tversky ([18]) like anchoring, scaling, bias due to availability, affect influenced, base rate fallacies, conjunction fallacies, .. require a well-skilled facilitator to steer the team and keep them motivated[3] through a number of meetings they are unfamiliar with and compete in time with their daily duties.

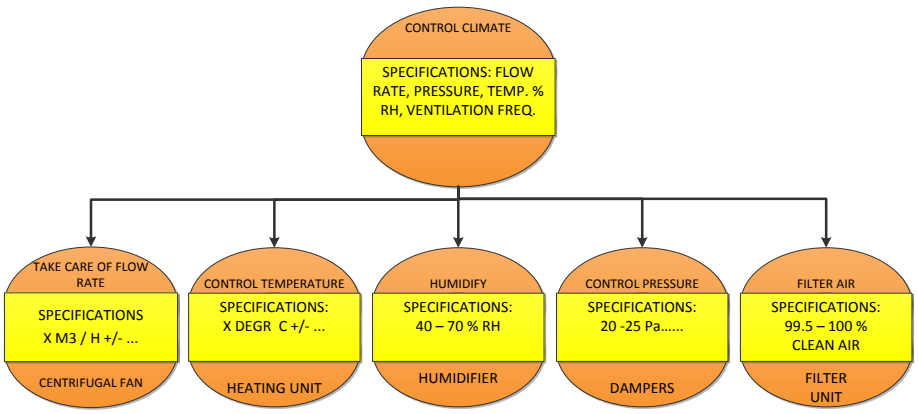


Fig. 3-1

3.2 The toolbox of MM's.

From various sources ([19-21] we know that the most frequently used decision support models in asset management are in descending order of frequency of use:

- Reliability Centred Maintenance (RCM)

[3] RCM is called mockingly Resource Consuming Monster!

- Failure Mode Effect (and Criticality) Analysis (FMECA) in combination with Risk Matrices.
- Reliability Block Diagrams (RBD)
- Fault / Event Tree Analysis (FTA, ETA)

All these techniques require a model of the process to be maintained (compare with the process control model discussed before). First of all, the asset register and the associated drawings have to be in place and updated. Functional block diagrams are recommended by IEC608012 and MIL_STD 1629A as a basis for FMECA and by Smith ([22]) as a basis for RCM. Zaal ([23]) uses the " hamburger model" (Fig. 3-1)

The question now arises how can these tools, in the light of the control engineering approach, support the asset manager in taking effective decisions:

- How do we make effective use of engineering knowledge and plant data to understand the system behaviour? (the control model)
- How can we substantiate the link between a maintenance procedure and the effect on the overall system requirements (the control action)
- How can a maintenance strategy be secured in the organisation (stability of control, observability of the desired trajectory in time)
- How do we make effective use of information to update the initially chosen strategy (the control feedback/ adaptation loop)

Aspect	RCM	FMECA /RM	FMECA/RP	RBD	FTA
Goal oriented' the line of sight"	☹	😐	😐☺	☺	☺
Mental model	☹	😐	😐☺	☺	☺
Lack of bias	☹	😐☺	☺	☺	☺
Completeness of model	☹	😐	😐	😐☺	☺
Need for field data	☺	😐☺	😐☺	☹	☹
Time dependent information	☹	☹	☹	☺	☹
Economic underpinning	☹	😐	😐☺	☺	n.a.
Acceptance in the organisation	☺	😐	😐☺	😐☺	😐☺

Table 3-1

The asset manager requires the "line of sight"; how do his / her decisions influence the goals of the organisation? RCM focusses, in principle, on one specific failure

mode and uses a broad description of the effects of failure: " trivial" versus " non-trivial" The FMECA approach conveys, for a list of functional failures, information on the ranges of likelihood and consequences. The RBD is the most complete system modelling tool; it provides insight on the process layout and, depending on the level of detail employed, it presents quantitative information on the cost-benefit of either " bought in reliability" in the design phase (the MTTF specification in the purchase order) and that of maintenance strategies. The FTA is rather similar but now the line of sight is mainly on the functional availability of safeguarding components to prevent a critical top event; economics then does not play a strong role.

Most of these techniques rely on input from a panel of experts. A requirement then is that each member of the team has an identical mental model of the problem. RCM does not have inherent characteristics to fulfil this goal; facilitators need to discuss the problem in the group to ascertain a common understanding. In FMECA the panel members are required to fill in significant detail on each fm but the overall system characteristics are part of the panel discussion

The sloppier the method, the more a person in the team may be influenced (biased) by others assuming their skill/experience is better. This applies foremost for RCM; again the quantity of prescribed input in the FMECA approaches calls for a more structured common opinion. In principle, RBD's and FT's suffer least from bias since, preferably, they use factual data where possible and may analyse subjective opinions via sensitivity analysis.

Building an RBD or FT is a major exercise carried out by well-trained engineers. It is quite common to note that these models start with coarse process blocks (mostly from the P&ID) and refined / more detailed in subsequent stages. In this way, the completeness of the model can well be managed. RCM, on the other hand, allows engineers to pick out fm's that have drawn attention because of system behaviour/insight " this component must be rather critical, because …." or in root cause analysis "we now have to get rid of this recurrent problem". The analysis thus easily can be stopped if the team decides that the most interesting fm's are covered. FMECA stands in between; the primary list of fm's for one system unit invites panel members to discuss others to be added.

Field data are essential in a learning organisation but, in practice, are difficult to get. RCM suffers least from this aspect; on the other end of the spectrum designers of RBD's / FT's should realise that their quantitative results critically depend on the accuracy of the input data and sensitivity analyses thus are a must. FMECA stands in the middle; the method uses ranges rather than specific values.

In order to be effective (SMART), the results of decisions have to be monitored over time. The decisionmaker thus needs to have information on the expected time-dependent character of the eventual observations. RCM and FMECA lack this support, relying fully on long term averages. The logic background of RBD's and FT's allow in theory such a description in the time domain and RBD packages invariably show the decision maker what to expect in the future given his decision. Since FT's are mainly used in safety/risk studies they commonly use point probabilities (long term averages) and thus produce point estimates of the probability of the undesired top event. Dynamic FT's have been introduced to specifically model sequence of events for scenario analysis.

The CFO will require a cost-benefit analysis of the use of such decision support techniques. RCM is notoriously poor at this point, FMECA provides better estimates of the ranges to be expected but not on the timing. RBD's are superior; not only do they

clearly demonstrate the underlying mechanisms of economically rewarding asset management decisions (the causal link) but also the pattern how and the time horizon it will take to become observable[4]. RBD's thus will give clear information to the final decision maker what and when to expect.
For a decision support tool to be effective, it should be fully accepted in the organisation. At that point, the simplicity of RCM is a plus. FMECA's are mainly used in well organised ISO 55001 compliant organisations. The more an organisation endorses this norm, the more FMECA will be an accepted tool. However, we also note that in public tenders the then required FMECA is regarded as an inevitable burden for which an outside consultant needs to be hired both for the process, as well as for the input data. It then is no surprise that the FMECA results will not easily become an effective improvement method. In most organisations, the construction of RBD's and FT's will be a dedicated task for in-house or external specialists. We then have the problem that the organisation is not well positioned to check the quality of this process and may take the results indiscriminately.

*We have seen before that the success of process control and optimisation relies on insight in the **possibilities** of control (controllability aspects, various types of control actions), in the **process** (the process model from black box to detailed process design or dynamic flowsheet type), **time-dependent behaviour** and **feedback** from **observed** data. From the list above we realise that in asset management the variety in maintenance strategies is limited, the underlying (deterioration) processes are poor understood, input (reliability) data are lacking to a great extent, decision support models frequently are aimed at long term averages only whereas on-line information on condition (and thus feedback) is scarce. A control engineer would classify such an approach as " open loop control" and warn for the consequences!*

4. Training Asset Managers; closing the gap between theory and practice.

4.1 Introduction.

We always start the Risk Assessment and Safety (RAS) Master course block by asking the participants what specific training will help them to build up their career. The majority responds along the lines of; "give us the tools to convince operational c.q. higher management that we take the best decisions possible"; that is more substantiated decision making.
From the control engineering, perspective the (future) MM's then should:

- Realise that they deal with the realisations of inherently stochastic processes, the outcomes of which are furthermore strongly influenced by operational conditions.
- Only the total system contributes to the profitability of the company, hence the effect of a single failure mode should be translated to the effect at system level.

[4] Later on we will discuss that the observability of these improvements may be difficult, given the inherent stochastic nature of the failure processes where strong overlaps in probability distributions may take place.

- The selection of a maintenance strategy (the control action) depends on the type of deterioration process (Weibull beta), the expected economic benefit and the maintainability aspects/quality of execution.
- In order for the decision to be accepted by the organisation and properly assured over the lifetime of the process, the outcomes of the decision support tool need to be transparent; they should properly explain the results to be expected in time as well as the inherent variations.
- After implementation, the observed results should be compared with the decision model outcomes (the feedback loop). However, this loop is very slow due to the low frequency of occurrences of critical failure modes. Furthermore, the stochastic character requires correct statistical analysis. For high MTTF values, periodic observation of conditions is the only practical way to learn the effect of decisions.
- Given the usually restricted employment period of the decision maker in relation to the lifetime of the installation, significant attention has to be given to the necessary storage of data and underlying information.

All this requires at first a proper understanding and mental image of the inherent underlying uncertainties. All engineers in the past had some training in basic probability theory that will be refreshed in the Master RAS course but experience shows that they regard this as "mathematical exercises" like standard arithmetic's that they solve along with the rules provided. A good starting point is the basic example of throwing a dice, students now that the chance of throwing a 3 is, as taught, on average 1/6 but do not realise that this holds only for a large number of repetitions. A simple Excel programme that shows how this probability develops over the series of throws (Fig. 4-1) effectively helps to memorise the stochastic behaviour; for most of the students, this is an aha experience!

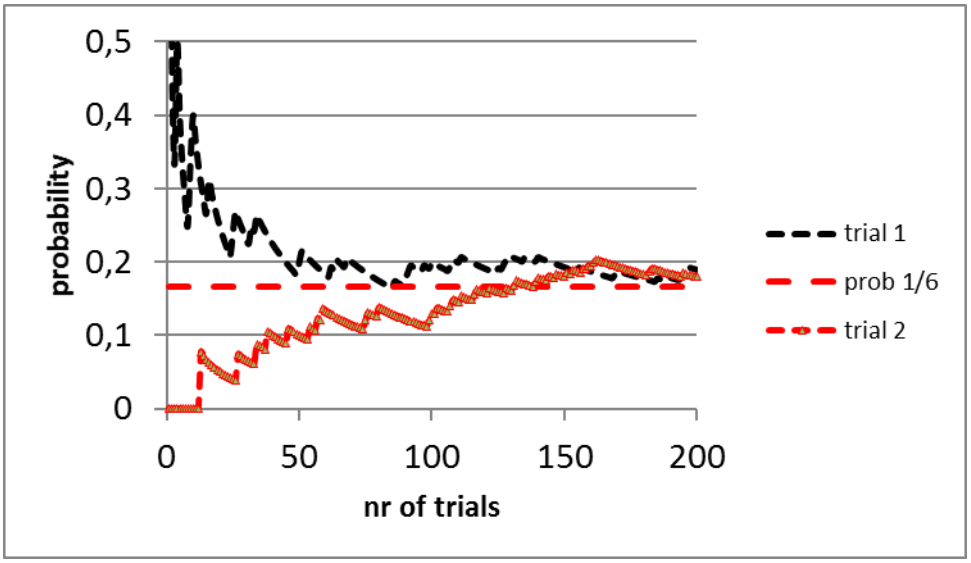


Fig. 4-1

4.2 Maintenance Management decision support tools.

MM's need to learn how to change from "gut-based" reasoning to the use of data and (Weibull) probability distributions. Regrettably, most organisations lack a proper failure database, especially over time periods that are sufficient to analyse. We strongly

advise against the use of the, since the nineties obsolete [24], MIL-HDBK-217 figures and inform that important partners have left the OREDA organisation. So, we challenge them, to use the "expert opinions" of in-house specialists in a structured team approach, paying specific attention to differences in individual opinions that unexpectedly may cast light on failure patterns. A general observation is that these engineers misinterpret the MTTF as a kind of useful life or guarantee period; to their surprise discovering that at that specific moment in time roughly 2/3 have failed! Combining individual 10, 50, 90 % estimates on the time to failure followed by visualisation of the expected failure pattern in time, the team arrives at (a range of) reasonable estimates of the Weibull scale and shape parameters, now trusting that, if used in computer models, the outcomes are in line with the best, substantiated opinion available, but sensitivity analyses are needed.

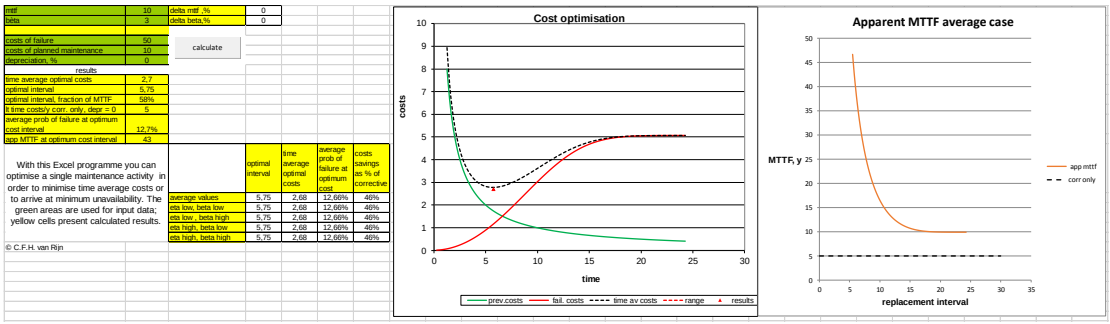


Fig. 4-2

Such data may be used in the selection and optimisation of time-based planned maintenance with the Barlow-Proschan model of Fig. 4-2. In this case, the failure mode has an MTTF of 10 years with a beta of 3 and the cost ratio between planned and corrective maintenance is 5. If the costs are booked on the operational budget without discounting, the model calculates an optimum replacement interval of 5.8 years where the time average PM costs are 46% of the corrective costs. It also shows that at this point one may expect about 13% of the failures under a corrective strategy leading to an apparent MTTF of 43 years.
Compared with an RCM study, the MM now gets a view on the economic consequences. The apparent MTTF plays a role in the criticality matrix of an FMECA; to what extent reduces PM the failure frequency compared with corrective only?

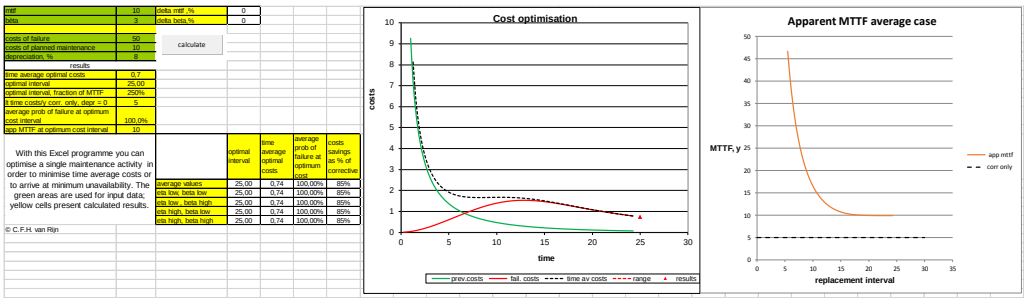


Fig. 4-3

However, if the costs of replacement are such that the CFO regards this as a capital investment, the discounting percentage[5] plays a strong role (Fig. 4-3). If the MM has to use a discounting percentage of 8% the optimum is lost; the model advises not to perform PM. This information may be used to change the opinion of the CFO to classify such replacements under the general investments.

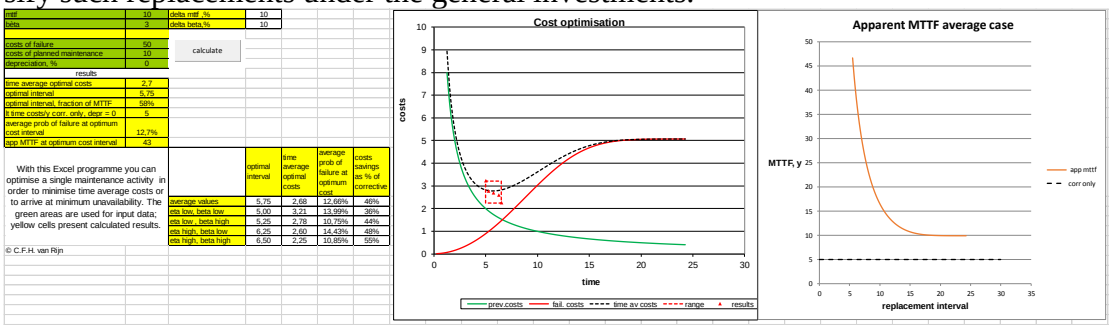


Fig. 4-4

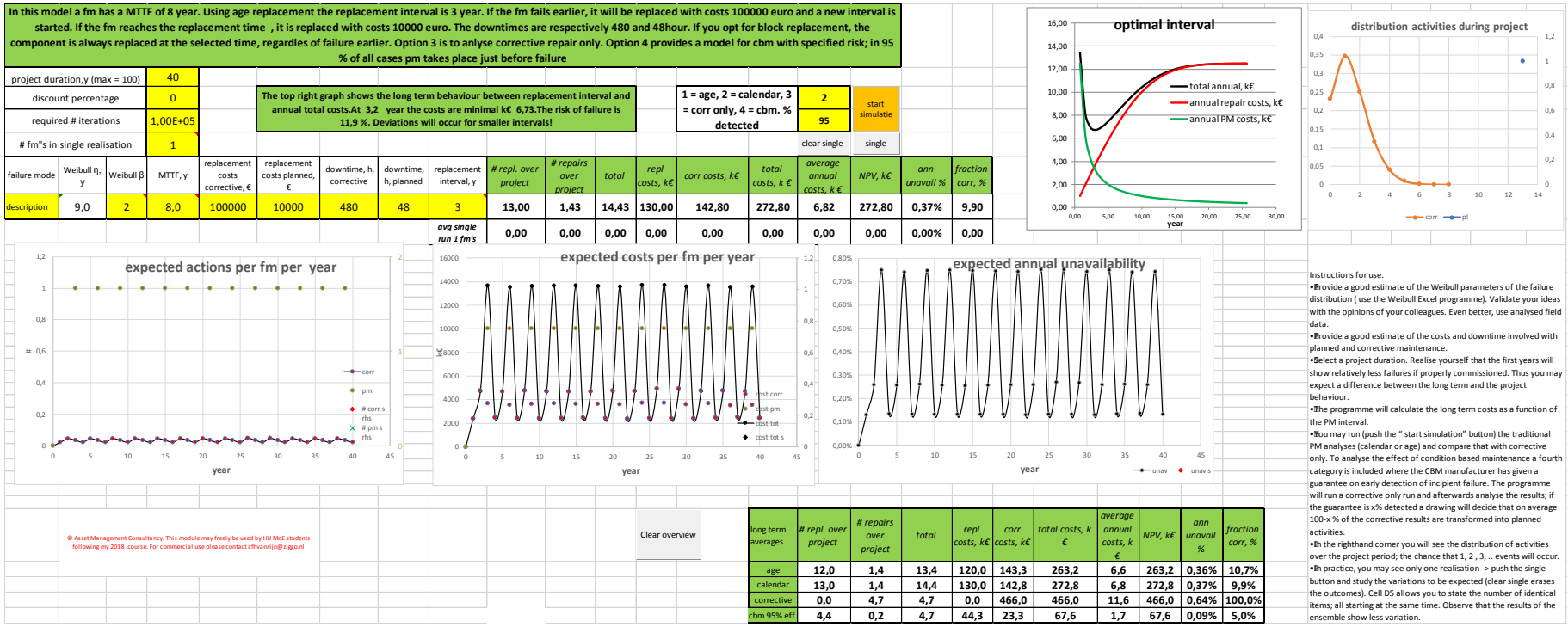
The CFO may also be critical on the expected economic benefit. A sensitivity analysis where a range of +/- 10% in the Weibull parameters is used shows that the expected savings range between 36 and 55%. The MM now also realises that the optimum replacement interval at best can be estimated to lie between 5 and 6.5 years. This range aspect is never used in the timing of work orders in the CMMS; exactly after, in this case, 5.8 years the CMMS will generate a work order. If the PM is not executed, the CMMS will increasingly remind the MM of the backlog in PM's executed. Since this is regarded as a key performance indicator, this message will eventually reach higher management and the MM will critically be questioned.

This is a nice example of Goodhart's Law[6]: "When a measure becomes a metric, it ceases to be a good measure"; in other words, when we set one specific goal, people will tend to optimize for that objective regardless of the consequences. The management objective, in this case, is to reduce the frequency of failures, which subsequentially should be monitored in time, but instead, the PM action required is followed. I have seen occasions where MM's hired in extra, even less skilled, mechanics to keep this KPI at level, disregarding costs and quality of execution!

Unfortunately, long term averages have a specific meaning only at the design level where equipment selection and various configurations are investigated. Operations are faced with performance in specific time periods; with a Design, Build, Finance and Maintain contract (DBFM), the contractor is responsible for the design and construction of the project, as well as for financing and total maintenance over a specified time period. Furthermore, the employment period of most MM's is short in comparison with the slow dynamics of critical, thus with large MTTF values, failure modes. Hence, the MM needs a quick analysis / "what if tool" to get a perspective on the realisation in time. A simple Monte Carlo analysis then is of great help (Fig. 4-5).

[5] Note that this DCF is one of the major instruments of a CFO to rank investments and has virtually no relation with the sometimes stated comparison with receiving interest from a bank or the average yield in the stock market!

[6] More precisely: "any observed statistical regularity will tend to collapse once pressure is placed upon it for control purposes."



failure mode	Weibull η, y	Weibull β	MTTF, y	replacement costs corrective, €	replacement costs planned, €	downtime, h, corrective	downtime, h, planned	replacement interval, y	# repl. over project	# repairs over project	total	repl costs, k€	corr costs, k€	total costs, k €	average annual costs, k €	NPV, k€	ann unavail %	fraction corr, %
description	9,0	2	8,0	100000	10000	480	48	3	13,00	1,43	14,43	130,00	142,80	272,80	6,82	272,80	0,37%	9,90
								avg single run 1 fm's	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00%	0,00

long term averages	# repl. over project	# repairs over project	total	repl costs, k€	corr costs, k€	total costs, k €	average annual costs, k €	NPV, k€	ann unavail %	fraction corr, %
age	12,0	1,4	13,4	120,0	143,3	263,2	6,6	263,2	0,36%	10,7%
calendar	13,0	1,4	14,4	130,0	142,8	272,8	6,8	272,8	0,37%	9,9%
corrective	0,0	4,7	4,7	0,0	466,0	466,0	11,6	466,0	0,64%	100,0%
cbm 95% eff	4,4	0,2	4,7	44,3	23,3	67,6	1,7	67,6	0,09%	5,0%

Fig. 4-5

In the right hand upper corner, the MM finds the long-term optimisation[7] similar to that in Fig. 4-2. This optimal interval is used in a time-dependent analysis with data in the yellow cells. He/she may select five different maintenance strategies:

- Corrective repair, run to failure; repair takes place after failure.
- Calendar based optimisation; a strategy where we replace at fixed calendar intervals and in-between apply corrective maintenance (to an "as good as new" condition) whenever a failure occurs. We assume that this replacement will always take place at the planned moment, even if the element had to be correctively repaired just before.
- Age replacement; a maintainable element is replaced or restored to "as good as new" when it reaches a specific age t_p. If it fails before t_p we will apply corrective maintenance leading to the same situation as with PM. From that moment on, we start counting the t_p interval again. As such, it has a serious drawback on the scheduling of planned maintenance actions. Every time we encounter a failure within a predetermined PM interval we start a new cycle.

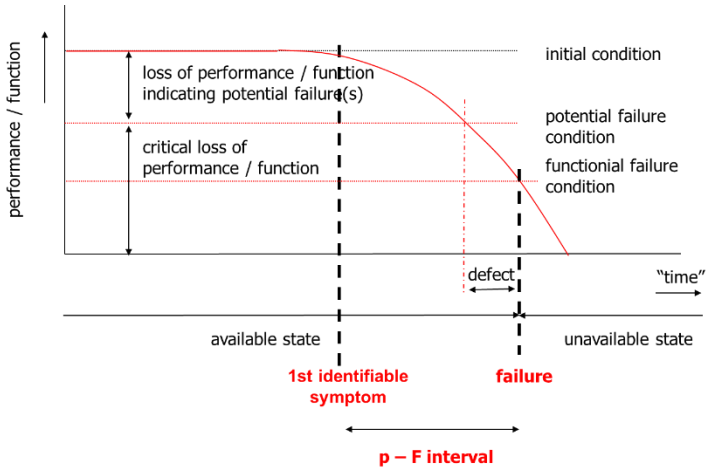
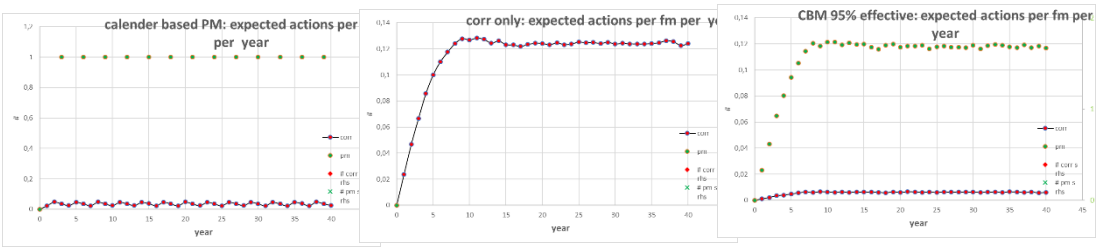


Fig. 4-6

- Using the PF interval (Fig. 4-6); a deceptively simple idea promoted by John Moubray [25] as a rather strange mix-up of a deterministic treatment of inherently stochastic processes since both the occurrence of the first identifiable symptom and the interval between this value and the loss of function (failure) will show acceptable spread in practice and thus should be treated as stochastic processes. Furthermore, we note a mix-up of concepts on a measurable condition (say, a wall thickness) and a probability of functional failure; the relationship of which is frequently difficult to determine. Professor Anthony Christer [26, 27] later on developed the concept of the delay time model which overcomes part of these restrictions but uses the stationary behaviour to find optimal solutions, for instance on the inspection interval given a probabilistic description of the occurrence of P and the P-F interval.

[7] For reasons of clarity, we have left out here the required sensitivity analysis on the input parameters!

- Using condition based maintenance; in this case, specifying only the degree of effectiveness, that is the percentage of imminent failures detected by the CBM system that early, that corrective repair could effectively take place. Note that the MM should primarily be interested in this result, rather than the techniques behind the CBM technique.



long term averages	# repl. over project	# repairs over project	total	repl costs, k€	corr costs, k€	total costs, k €	average annual costs, k €	NPV, k€	ann unavail %	fraction corr, %
age	12,0	1,4	13,4	120,0	143,3	263,2	6,6	263,2	0,36%	10,7%
calendar	13,0	1,4	14,4	130,0	143,2	273,2	6,8	273,2	0,37%	9,9%

Fig. 4-7

With this tool, the MM easily gets insight into the average time-dependent behaviour of the various measures of control (the maintenance strategies) and their cost-effectiveness (Fig. 4-7). In the top-right corner, he/she will notice the pdf of the corrective / PM activities to be expected. For instance, if the calendar based PM strategy is chosen, 13 replacements will need to be executed but, in spite of the PM action, on average 1.4 failures needing corrective action are expected with 23% probability of zero, up to a 5% probability of 4. It is the experience of the author, however, that this graph does not directly lead to a mental impression that is easily memorised.
For that purpose, the MM may opt for a series of single runs of the MC simulation of (Fig. 4-5) making the pdf clear to him/her (Fig. 4-8).

	# repl. over project	# repairs over project	total	repl costs, k€	corr costs, k€	total costs, k €	average annual costs, k €	NPV, k€	fraction corr, %
single run fm's	11,00	3,00	14,00	110,00	300,00	410,00	10,25	410,00	21,43
single run fm's	13,00	0,00	13,00	130,00	0,00	130,00	3,25	130,00	0,00

Fig. 4-8

All CMMS system will detect patterns of successive failures with unexpected small time intervals in between. This raises concern in the organisation, potentially leading to a more specific investigation like a root cause study. The MM should realise, however, that such series of events are inherent characteristics, albeit with small probability, of a stochastic process!

There is a strong trend nowadays towards the use of condition-based maintenance, predictive maintenance and exploiting the "Industrial Internet of Things, IIoT" where data cheaply and easily become available towards the revolution of "Industry 4.0".

Again, this forms a fruitful area for mathematical research, but a word of caution is on its place.

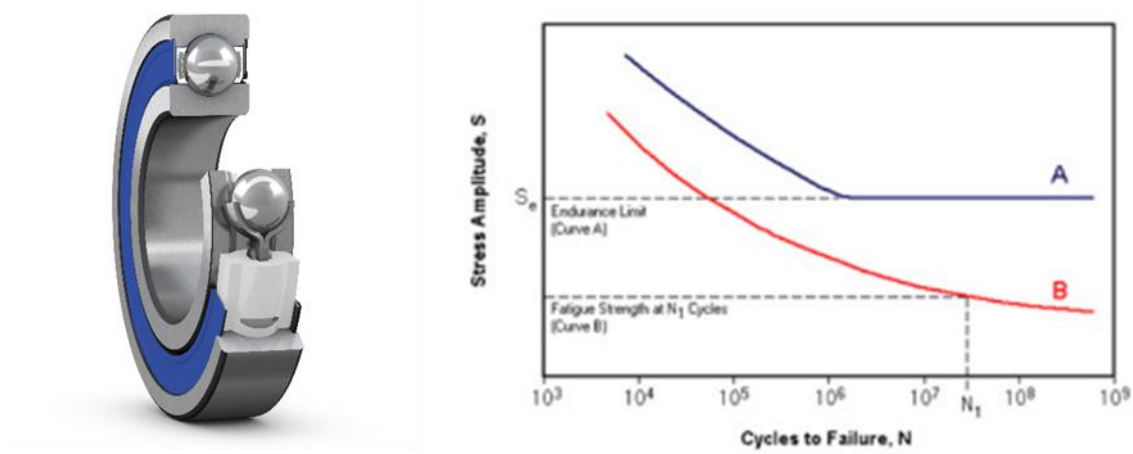


Fig. 4-9

Bearings (roller, ball, Fig. 4-9) are indispensable components of rotating equipment, failure of which causing appreciable downtime, costs and frequently loss of production. In theory (and in design) bearing life is determined by the number of hours/cycles it will take for the metal to "fatigue" which is a function (SN curve) of the load on the bearing, the number of rotations, and the amount of lubrication that the bearing receives. Hardened steel (curve A) shows a fatigue limit (or endurance limit); a value of the stress below which a material can presumably endure an infinite number of stress cycles which is the basis of the Lieblein- Zeelen [28] design equation. In practice, bearing life is limited and shows large variations (e.g.Van Rensselaer [29], Zaretsky [30]) with low Weibull beta values (around 1.5). There is a common understanding that the, in theory, infinite lifetime ends by external causes (misalignment, vibration, shock, dirt, corrosion pitting, excessive heat) causing operation outside the fatigue limit and subsequentially rapid deterioration.

Bearing health is monitored by vibration measurements. A simple vibration alarm may indicate the point of onset of deterioration (comparable with the “point” P in the PF interval). From that moment, the modelling of failure, the predictive approach, becomes cumbersome. Jardine [31], in his extensive survey article, describes a large number of techniques: short-time Fourier transform, wavelet transform, proportional hazards models, hidden Markov models, independent component analysis, cluster analysis, AI techniques, artificial neural networks, fuzzy logic, belief networks, ...The fact that that many techniques are investigated is strongly linked with the lack of a proper deterioration model; the first particle of bearing steel or debris causes an avalanche of further deterioration in a rather random fashion, strongly influenced by operational conditions. The validity of the approach than may be questioned; what is the decision problem of the AM? If he/she accepts the warning signal (damage initiation has been confirmed), the fundamental decision problem lies with the grace period until this vibration increases to the shutdown level; is that period long enough to take proper action? Now we have a model to steer on along the philosophy of the PF interval as described above.

The IIoT is heralded as cheaply bringing in large amounts of data. However, the crux lies with the translation of these data into information for decision support, the dynamic model of degradation. Many techniques rely on observed correlations, but the causality remains unaddressed; a critical perspective is required!

4.3 Using process control models for CBM.

As outlined above, process control engineers need to model the constraints of operation in order to optimise production. These constraints are usually found as maximum cooling rate, maximum gas flow, etcetera.

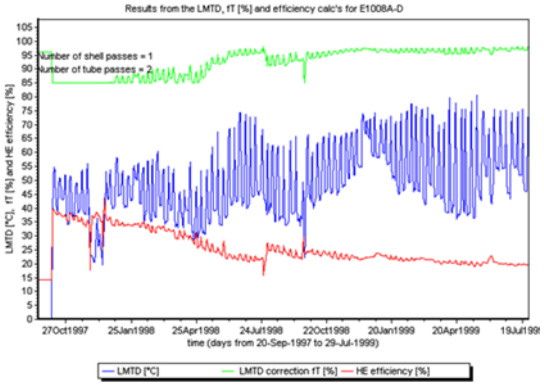


Fig. 4-10

Fig. 4-10 provides an example where the heat efficiency of a shell and tube heat exchanger is estimated from the flowrates and the logarithmic mean temperature difference (the red curve). This concept was introduced in Shell by my research group in the eighties and now receives great attention; Chevron[8], using wireless transmitters and Microsoft's Azure cloud computing, expects "Savings could be in the millions if you can monitor and predict the health across all of our exchangers".

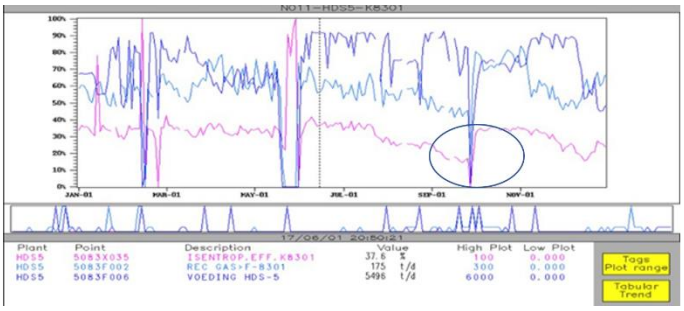


Fig. 4-11

A similar concept can be followed to optimise the clean out rotary vane compressors (Fig. 4-11), note the effect of the cleanout operation in September. For pumps, the condition is assessed by following the relationship between the pump head centrifugal and the volumetric flow rate (Q), that a pump can maintain.
Note that, in these cases, we use process measurements that frequently will already be available. Secondly, the model outcomes will readily be accepted by engineers, the

[8] https://blogs.wsj.com/cio/2018/09/05/chevron-launching-predictive-maintenance-to-oil-fields-refineries retrieved December 2018

more so, since they directly may be associated with production losses. Crossing the traditional cultural barrier between Operations and Maintenance thus has great value.

4.4 Maintenance Management decision support tools at system level.

The simple tools described above produce results only at failure mode level, whereas the economic benefit is produced at the system level.

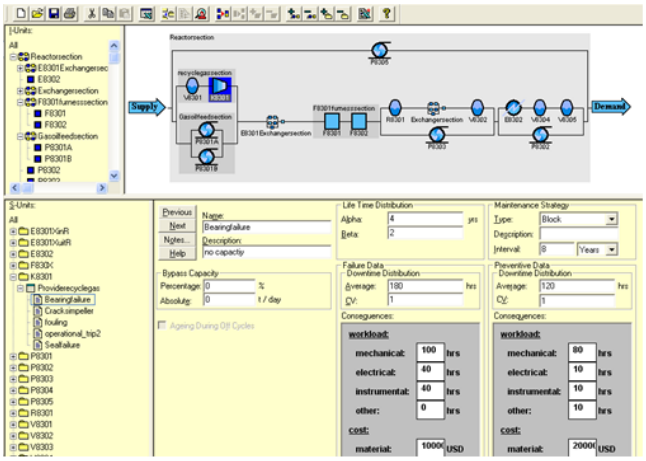


Fig. 4-12

Any master course will therefore treat the concepts of reliability block diagrams and fault trees. These calculations can either be calculated analytically (SPARC, Fig. 4-12) [32] or via Monte Carlo simulation (RAPTOR (free download), commercial software packages like BlockSim, AvSim, Maros, RiskTec, Miriam, ..). One of the authors of SPARC (now solely an in-house tool in Shell) has developed an interesting package called ARTIS (Availability and Reliability Tracking Information System) [9] for addressing the risks to production availability which includes event tracking from a CMMS.

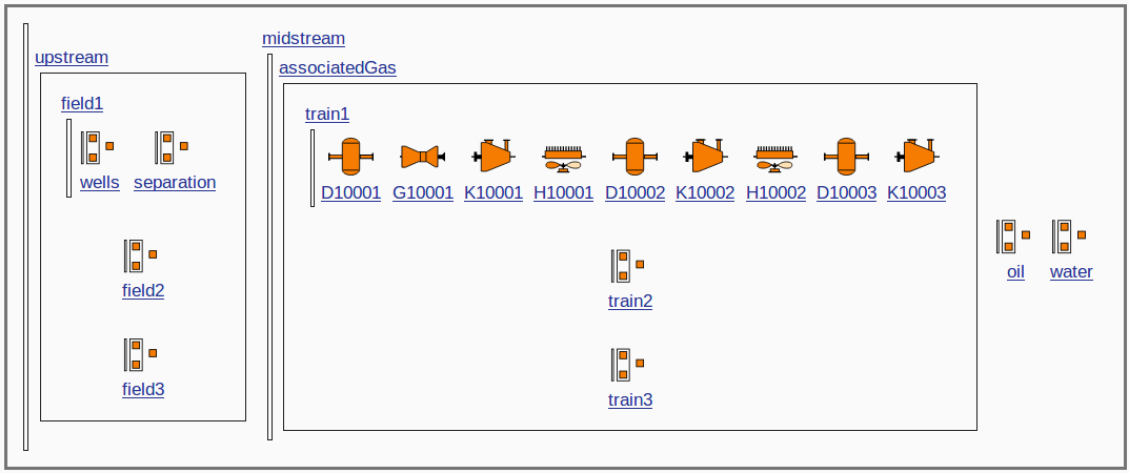


Fig. 4-13

[9] The user interface can be found at: www.artis.la/V24/models/artis.html, the user manual at wiki.artis.la

Artis is freely available for testing and demonstration purposes, small models can be run free of charge but, in this free mode, response times might be slow. Short- and long term service agreements are available for commercial use.

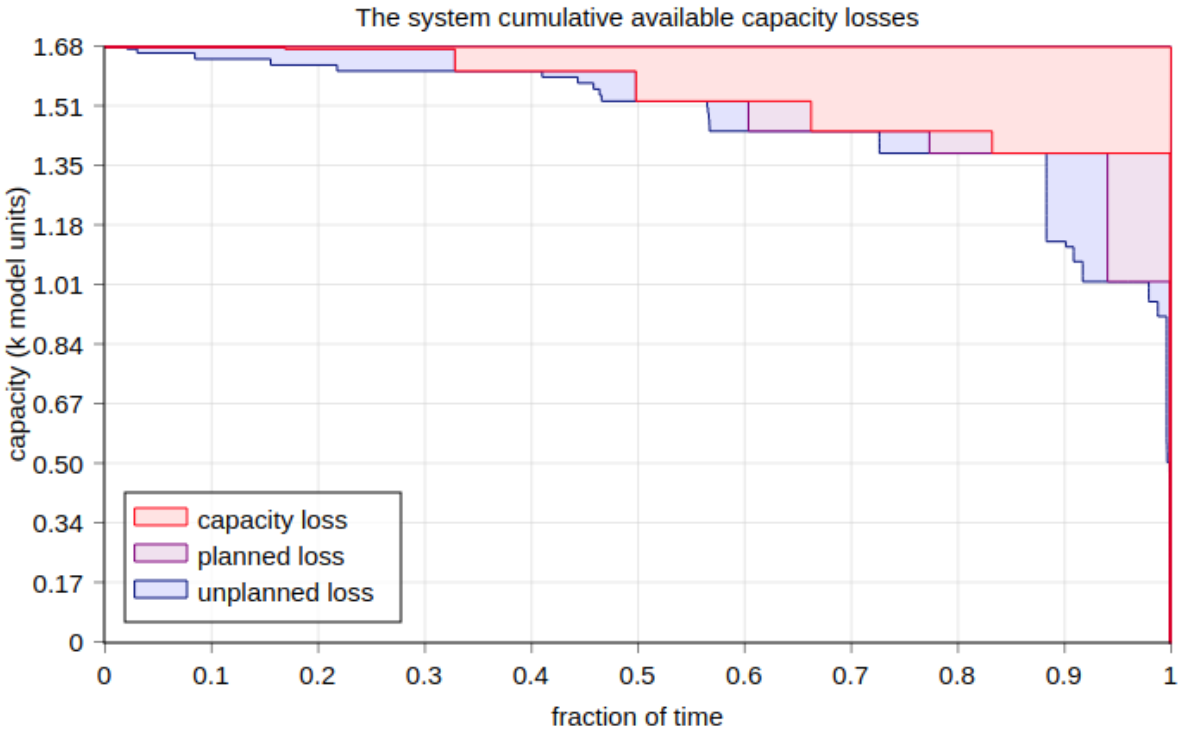


Fig. 4-14

This important system information can only be obtained if detailed information is available on the failure distribution and the maintenance data. In practice, the problem lies with the former; real data are available only after analysing data over a long period. For design purposes, where the problem frequently is to select alternatives of configurations, information from databases like OREDA [33] can be used with care. Fig. 4-14 gives an example of the capacity profile calculated with ARTIS of a gas production platform, where, using OREDA data, the initial configuration of 3 trains each with 35% capacity proved to yield insufficient system capacity, because of the train downtime. The design team proposed a fourth train but ARTIS showed that 3 trains each with 50% capacity were an economically better alternative.

For the optimisation of operational asset management, we are frequently forced to use engineering judgement, next to sparsely available data. Inevitably there thus will be appreciable uncertainty of the quantitative (system) results which need to be investigated by sensitivity[10] analyses. The benefit of applying RBD packages then depends strongly on fast, but structured, " what if" analyses steering the team in reaching a good decision, rather than on achieving precise quantitative output values.

[10] Both SPARC and Artis allow the user to change all or a selected group of Weibull parameters by a chosen percentage for such an analysis.

4.5 Decision support in change programmes.

Active asset managers regularly organise improvement procedures along the lines of "the number of unforeseen failures per month must be lower"; a valuable KPI. The change manager will formulate such a case in terms of:

- Setting a new performance goal.
- Investigating the expected reasons for a lower than desired performance.
- Ranking causes of failures, thus determining focus.
- Providing a clear distinction between and prioritization of controllable and non-controllable aspects.
- Clarity about the relationship between improvement measures and system performance.
- Controlled management of the implementation of improvement measures.
- Prognosis of effect improvement measures; how to validate the costs involved against the benefits expected?
- A managerial formulation of the way to monitor the progress of the improvement process in time.

Note the similarity with the process control approach! The last bullet item touches upon the observability of the maintenance process; remember that this is one of the pre-requirements of the control engineer but he/she is dealing with deterministic values (measurements) rather than the outcome of stochastic processes like in maintenance. The asset manager may choose to monitor:

1. The process of improvement as observed by the estimated increase of the MTTF, which requires statistical investigation of the TTF of field data
2. The process of improvement as observed by the decrease in number of failures per time interval, which is the standard form of reporting in CMMS's

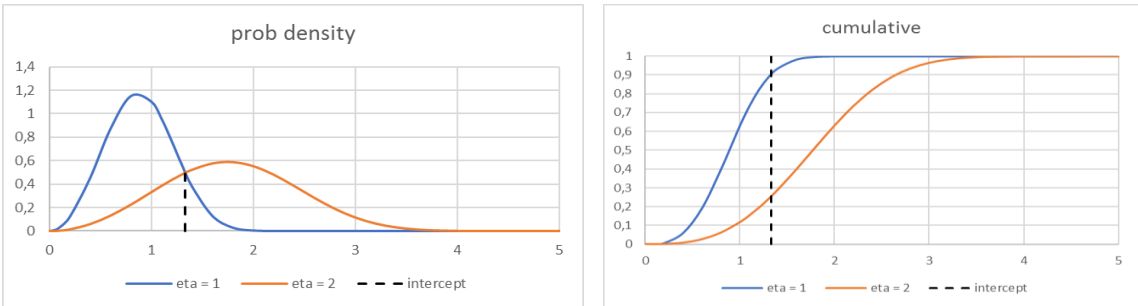


Fig. 4-15

Suppose, we have an improvement process in which the MTTF is doubled by choosing higher quality components (the scale factor eta of a Weibull distribution with shape factor beta 3 goes from 1 to 2). The left side of Fig. 4-15 shows the two probability density curves. The "measurement" (compare with process control) of our process now follows from drawing samples from the probability density distribution. However, we see that the two curves show an overlap that can be calculated from the cumulative distributions of process 1 and 2 (right side Fig. 4-15). We arrive at a value of 35%, which means that if we completely replace process 1 with process 2 we run a risk of 35% of drawing samples (observing failure) in the overlapping part. In those cases, we will not observe any improvement while it has indeed taken place! Hence,

the observability is restricted to 65%.

Fig. 4-16

Fig. 4-16 shows an overview in which the x-axis represents the ratio between the improved situation with respect to the original value and the y-axis the fraction of observability. Suppose that in practice we achieve an improvement of a factor of 2, we see that at a beta value of 3 (close to the normal distribution) we have a probability of approximately 65% to observe this improvement from the field data.) For completely random failure ($\beta = 1$) the probability drops to around 25%.

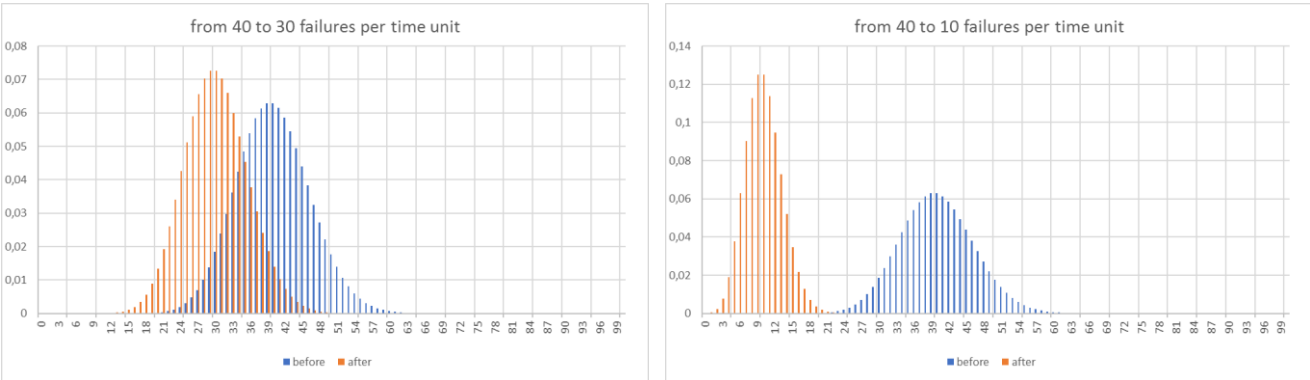


Fig. 4-17

Now, if the MM follows the number of failures in a given time period, we deal with a (for β > 1: pseudo) Poisson process. In such an improvement process as in Fig. 4-17 where the number of failures is reduced from 40 to 30 per period, we note again an overlap between the probability densities as can be seen in the left graph. This overlap becomes smaller as the achieved improvement increases; the right-hand graph shows that if the # of failures are reduced by 80%, the overlap almost disappears. If the observations lie in the common area of the two probability density functions we cannot make a distinction between the two situations; a change is unobservable.

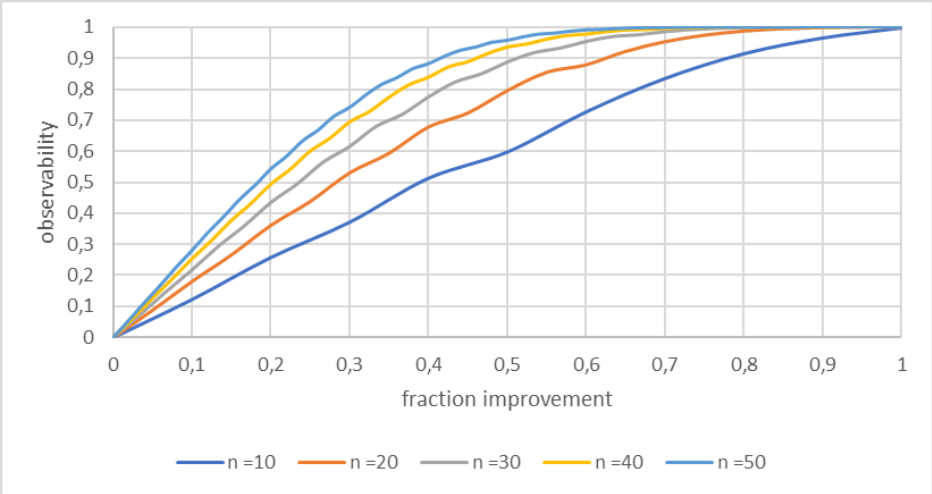


Fig. 4-18

Whereas the observability is 60% in the first case, it is 99,8% in the last one.
The observability depends in this case (Fig. 4-18) on the number of failures in a time period *and* the fraction improvement. In the case of a relatively small improvement, we have to average over a very long interval.

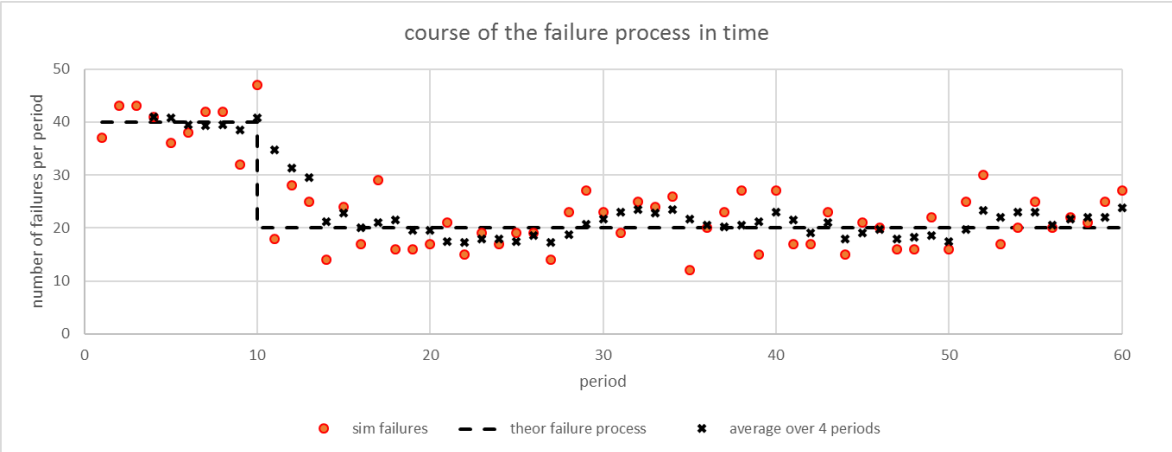


Fig. 4-19

Fig. 4-19 shows a simulation of a process with 40 components each having the same failure mode of the beta =1 type. At period 10 all 40 are replaced[11] by new components with twice higher MTTF; reducing the expected number of failures per period from 40 to 20. The orange dots indicate the observed number of failures resulting from the simulation process; note the difference in each period between the expected and observed value. The black crosses indicate the rolling 4-period average; clearly a lagging indicator. In this process the observability is 94%; the improvement is noticeable after period 15.

Realise that Fig. 4-19 is just one realisation of this chance process; we may also observe a result as sketched in Fig. 4-20; where the asset manager may unjustified worry about the sudden increase in the number of failures between period 30 and 40.

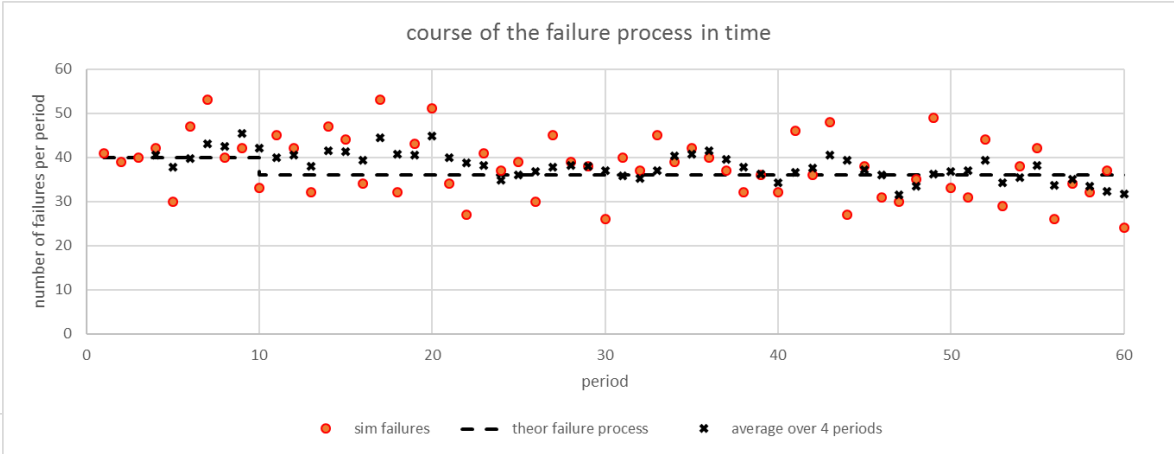
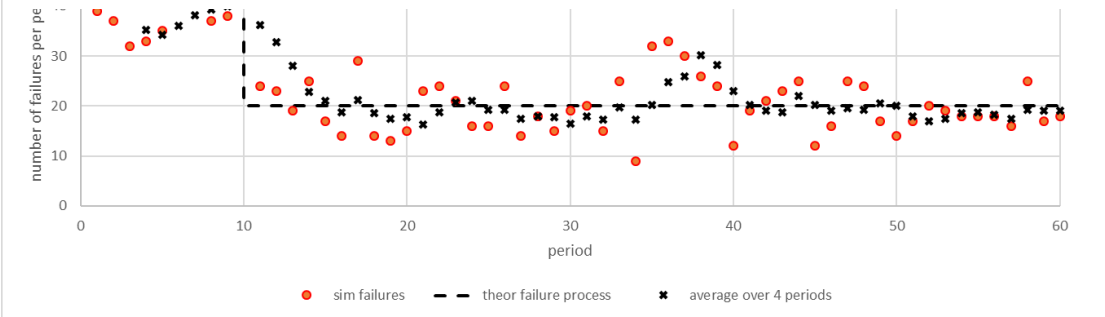


Fig. 4-21



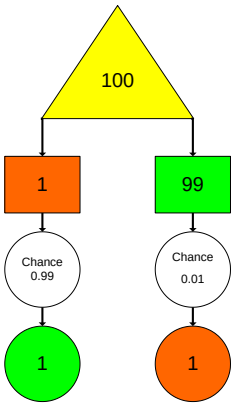
In Fig. 4-21 the same process is sketched but now with an improvement of 10 %. The observability is here some 25% and in this specific realisation, the improvement is difficult to observe in the first 15 periods after the change.

4.6 Inspection.

Statutory inspections with a regular return interval, both on the safeguarding aspects as well as on the physical condition, are a significant part of the Asset Management portfolio in complying with standards. One would, therefore, expect that results of these inspections over the lifetime of systems are readily available. However, in

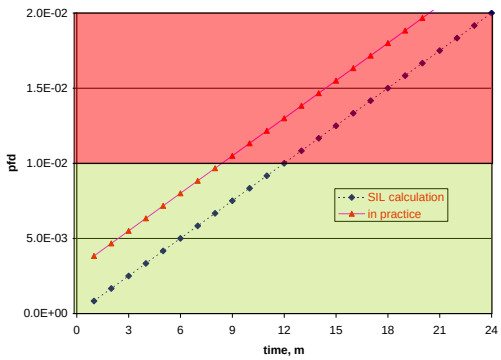
[11] Such a sudden change is unrealistic in practice; the simulation model has a facility to take the implementation period in consideration but this facility is not used here for clarity.

practice, frequently only the last results are stored / easily retrievable. In such cases, there is no trending and the information gathered thus does not contribute to a learning organisation.
In safeguarding inspections, in line with IEC 61508, 61511, Bayes rule plays an important role, the type I type II error. The influence of human errors is clearly mentioned in the norms and even more detailed in application papers like [34], but in qualitative terms only. Since most engineers shy away from mathematics, the psychological approach of Gigerenzer [35] is effective.



Take the case where the required probability of failure on demand (PFD) is 10^{-2}. Gigerenzer warns that even an explanation in terms of percentages is psychologically less transparent than using pure numbers. Hence, he proposes the following approach:
"Assume that you have to test this item 100 times. To the best of our knowledge, we know that only in 1 out of these 100 cases there will be a defect. So, the fact that you repeatedly observe a functioning system is normal.
I take it for granted, that you, as an experienced mechanic, say in 99 out of the 100 cases will correctly find this defect, repair it, such that it is working again.

The problem now lies with the 99 cases where the component is functioning correctly. If you are not careful enough, you may introduce a fault; for instance, forget to put back the override switch. Suppose that this happens in 1 out of 100 cases, you see that testing does not improve the situation!



$$PFD = \frac{1}{2} * \lambda * T_i + p_{mi}$$

Fig. 4-22

Fig. 4-22 shows the formal results with λ the overall constant failure rate, T_i the inspection interval and p_{mi} the probability of maintenance induced failure. For the latter no formal data are available but students invariably estimate a range between 1 – 5 %. Accepting the views of Gigerenzer, from thereon they will better take care to guard the quality of intervention, for instance by using the "four eyes "principle.

loc / time	wall thickness, mils							
	year 1	year 2	year 4	year 6	year 8	year 10	year 12	year 14
1	311	311	311	314	309	308	308	305
2	316	318	310	315	305	300	302	298
3	308	300	298	301	295	291	295	292
4	305	305	302	304	295	294	290	289
5	318	311	304	305	300	299	295	285
6	321	318	313	313	308	305	300	295
year	1	2	4	6	8	10	12	14
eta	316,1	312,5	309,1	311,7	304,7	302,6	301,1	297,3
beta	53,2	50,6	54,5	50,3	39	48,4	46,7	43,3
R^2	0,97	0,99	0,97	0,88	0,96	0,96	0,92	0,95
average	312,8	309,1	305,9	308,2	300,4	299,1	297,7	293,5

Table 4-1

Table 4-1 shows published data [36] on pipe wall thickness over a period of 14 years measured at 6 fixed locations with the fitted Weibull distributions. Note that the fit expressed by the R^2 value in year 6 and 12 is below 0.95; the 6 (!) data points showing appreciable scatter. The decrease in time of the beta values indicate the corrosion process to become more inhomogeneous

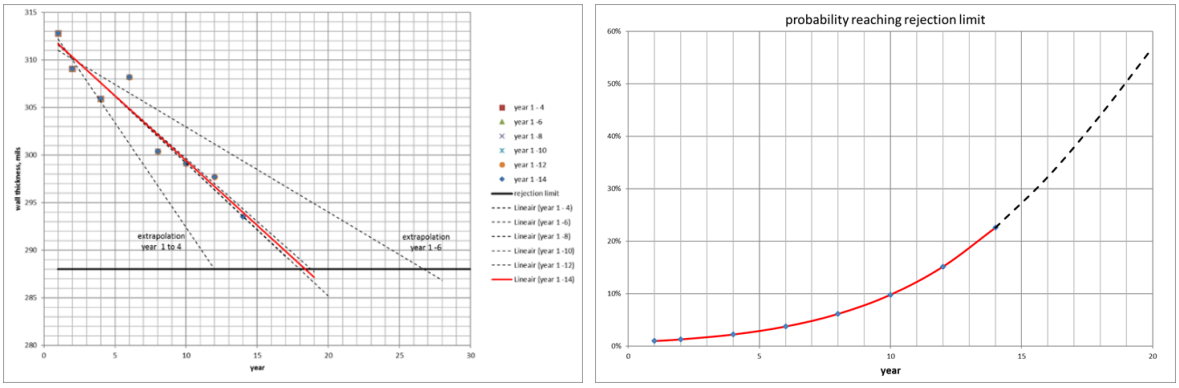


Fig. 4-23

The left side of Fig. 4-23) shows the trend of the decrease in wall thickness over time-based on the Weibull average value, which is comparable to that of the arithmetic averages of the measurements. Note the large uncertainty in extrapolated values over the first 6 years, gradually the expected time value of meeting the rejection limit stabilises around 18 – 19 years. The right side of Fig. 4-23) shows that the probability of crossing the rejection limit (the failure) steeply increases with time. Whilst the trending of the averages focusses the asset manager on the year of occurrence of passing the rejection limit (18 – 19 years), this figure shows that already in year 10 the risk is some 10%. Such information may be used in an economic evaluation of the optimal time of replacement, balancing the costs of early execution against that of operating below the rejection limit.

Field data are extremely valuable [37] [38] in a learning organisation. However, this requires the CMMS to be set up such that information at failure mode level becomes available whereas these systems usually focus at equipment level. The need to interpret textual information generated by technicians who are not trained on later use of the information at maintenance execution level is cumbersome.

5. Conclusions.

Over the past seven decades, several benchmarking studies show that the effectiveness of Asset Management has not significantly changed; it appears that extensive academic research has not found widespread application.

We have shown that this evolution is at strong variance with that in the (comparable) discipline of control engineering. Process control is at the end of the learning curve and taught in standard curricula. Process engineers thus are professionally capable to use all kinds of measured/inferred process variables to set up stable simple and advanced control and optimisation systems, that are fully accepted in operation and of which the economic benefit is readily demonstrated.

In Asset Management most (especially, mechanical) engineers are technically driven and reason mainly in deterministic terms. Compared with control engineers, their system insight, views on observability and controllability and interest for time-dependent processes are less developed. Reliability engineering still is mainly an add on in engineering education; companies may at best have a few in-house reliability engineering specialists. These persons struggle with the lack of input data for decision support models and lack proper information on the physics / chemistry of degradation models. In monitoring the effect of implemented decisions, they meet a paucity of data. Thus, where applied, their decision support models do not easily find widespread support from colleagues and management. These models, aiming at long term characteristics clash with the drive for business results to be achieved in specific (in comparison with the system dynamics, short) time slots and the needs of a learning organisation.

Many academia in stochastic OR focus, frequently underestimating the data problem, on black box (statistical time to failure) develop decision support models aiming at long term averages; physics of failure only recently being partly included. It appears that the academic focus more lies on mathematically elegant solutions with novel techniques than on AM decision making in practice.

Discussing a number of common decision problems, we have shown that simple models that *visualise* the AM decision process in time are powerful tools to store the insights produced by reliability engineering tools in memory. Such understanding is effective in deciding on achieving agreement and endorsement between/from the various parties involved. With this insight, the inherent variability in realisations (observability) and the restrictions in management effectiveness (controllability) becomes part of the mental image. Structured team consultation provides suitable starting data at least for ranking and evaluating decisions; sensitivity analyses are necessary to provide an understanding of the spread in model outcomes. The uncertainty in input data should then, where possible, later on, be verified by processing field data.

Even these simple models yield results that are hitherto surprising to practicing engineers, as demonstrated by their use in a long series of Master Course RAM blocks. It is our experience that, after graduation, most course members successfully apply these techniques in practice.

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