PRACTICAL CONDITION TRENDING AND ANALYSIS OF REPAIRABLE SYSTEMS

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INTRODUCTION.

Repairable systems are functional units consisting of many components that when one or more of the components fail the unit fails or breaks down (functional failure). When this happens the unit is almost immediately restored to its operating condition by either repairing or replacing the damaged component.
Most machines and equipment in Industrial Plants fall under this category. Typical examples are; pumps, compressors, presses, paper machines, cooling towers, robots, vehicles, etc.

When managing maintenance and reliability we often need to know what the general condition of a machine is at a particular point in time. The general condition of a machine is evaluated by determining which of 3 behaviors the machine is showing, over a span of past operating time to present time:

First behavior; has the machine's condition remained constant to present time?
Second behavior; is the machine's condition degrading or deteriorating over time?
Third behavior; is the machine's condition improving over time?

This in turn can answer questions such as; Are our maintenance Strategies being effective? Is the age of the machine affecting its performance? Has the change in level of technicians servicing the machine made an improvement?

A classical approach is using statistical distributions such as Weibull, normal or lognormal to model repairable system's behavior over time. These life analysis techniques are effective in modeling single components at the failure mode level However this distributions do not always model effectively a repairable system's life behavior because a repairable system consists of many different components with mixture of failures modes each with a different distribution.

We require statistical models or techniques that take into account the many different failures modes of the different components that can be used for monitoring machine condition by calendar time and for failure forecasting.

Popular Statistical models and techniques that can be used to monitor and analyze machine condition are:

1. TTF & TBF trend analysis.
2. Laplace statistic.
3. MTBF trend analysis
4. Crow-AMSAA

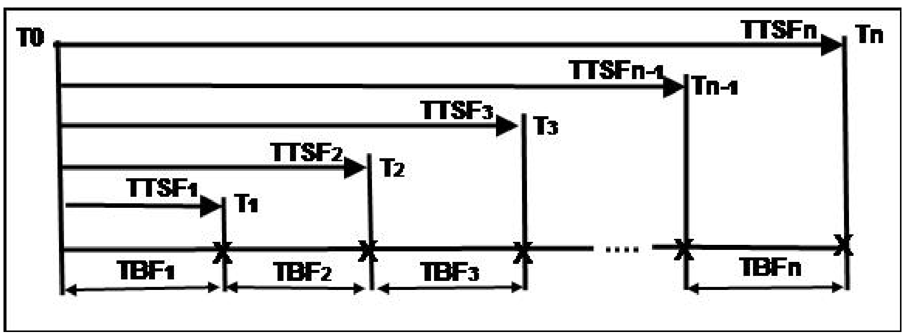
In order for a model to be effective and useful it has to meet the following criteria:

1. It should be able to consider all failure events that occurred within a time frame.
2. It should be able to handle; dirty data, missing portions of data and mixtures of failure modes.
3. In should be able to show present condition numerically or graphically.
4. It should be able to project into the future and forecast accurately future failure behavior.
5. It should be able to be trended in charts to make it easier for management to visualize the condition of the equipment.
6. It should be able to point negative trends, improvements and abrupt changes in condition.

TTSF AND TBF TREND ANALISIS..

When a repairable system operates in an industrial environment for a considerable amount of time, it falls into a operate-fail-repair-operate cycle that remains thought-out the life time of the system. This cycle consists of events which have a beginning point in time, a time duration and an ending point in time. These points in time depict events in the time continuum.
The occurrence of these events in time may be random or may follow a trend. It is our job to find this behavior.

If the duration (TTR) of the "repair" events is small compared to the duration of the "operate" events its duration can be considered 0 and the "repair" events ignored. The "fail" event (T) is in itself a point event with 0 time duration. Therefore the cycle becomes one of; operate-fail-operate-fail-operate. This cycle can now be determined in the time scale by the time to each "fail" event (TTSF) measured from a starting time equal to zero and by the times between failures (TBF).



T – Fail event (failure)
TTSF – Time to failure
TBF – Time between failures.
TTR =0 Ignored.

$$COT_n = \sum_{i=1}^{n} TBF_i$$

COT_n - cumulative operating time

Fig. 1 Operate-fail-operate cycle in the time scale.

If we plot the Cumulative Operating Time (COT) vs. the Cumulative Number of Failures of 3 different systems from table fig. 2 we get a plot that might look like the one shown in figure 2a

Failure Order Number (i)	System A Times to Failure (TTSFi)	System B Times to Failure (TTSFi)	System C Times to Failure (TTSFi)
1	58	177	15
2	118	242	42
3	176	293	74
4	233	336	117
5	292	368	168
6	352	395	233
7	410	410	410

Figure 2. System's failure data in days.

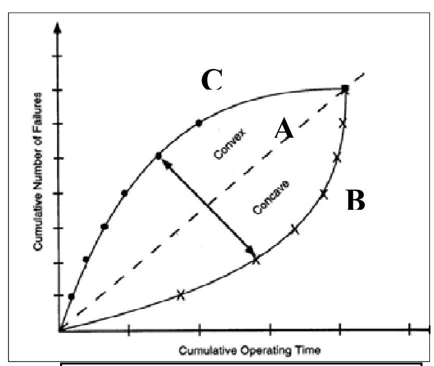


Fig 2a Cumulative Operating Time vs. the Cumulative Number of Failures

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The graph of figure 2a shows the 3 behavior patterns mentioned before, of the 3 different systems plotted:
The straight dotted line of system A shows the first behavior pattern; the machine’s condition remains constant to present time.
The concave curve of system C shows the second behavior pattern. The machine’s condition is degrading or deteriorating over time.
The convex curve of system B shows the third behavior pattern. The machine’s condition is improving over time.

The basic units of performance used to determine condition would be TTSF times to failure and TBF times between failures. And the interpretation is as shown in figure 3:

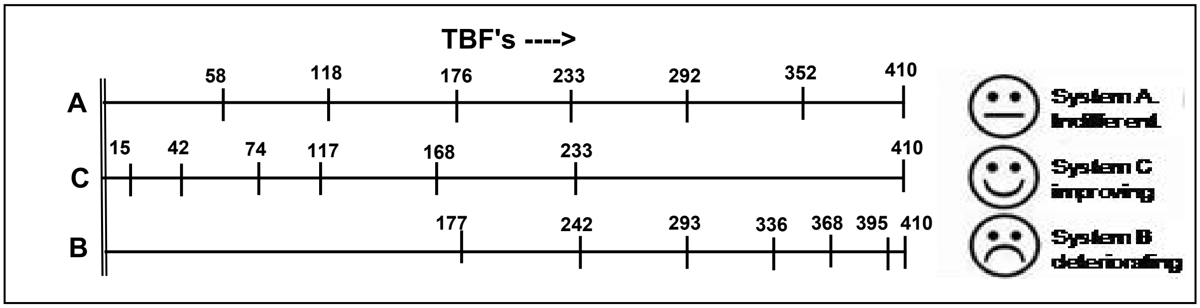

Fig. 3

In system A the TBF’s vary randomly and show no trend with time. Failures occur at random times.
In system C the TBF’s show a increasing trend with time. Failures are occurring less often.
In system B the TBF’s show a decreasing trend with time. Failures are occurring more often.

The shape of the graph gives an indication of the condition of the 3 different systems as shown in fig. 4 and the interpretation is self evident.

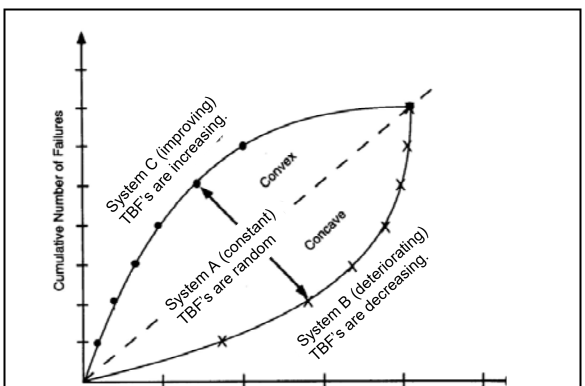

Figure 4

LAPLACE STATISTIC.

Now if we want to determine the condition of a system statistically and obtain a numerical value to corroborate it, we can use the LAPLACE STATISTIC method from Reference 2.

The Laplace test statistic for a process with "n" failures is:

$$u = \frac{\left[\left(\sum_{i=1}^{n-1} TTSF_i\right) / (n-1)\right] - \left(TTSF_n / 2\right)}{TTSF_n \sqrt{1 / (12 \times (n-1))}}$$

Trend analysis conclusions based on the Laplace statistic are:

(a) $u \cong 0$ (lack of trend)

(b) $u > 0$ (interarrival values (TBF_i) are tending to decrease) (system deterioratio

(c) $u < 0$ (interarrival values (TBF_i) are tending to increase) (system improvemen

Figure 5. Formula for calculating the Laplace statistic.

Where:

“u” is the defining indicator whose value will determine the trend the TTSF’s are showing and therefore the behavior of condition of the system over time. “u” is calculated from the TTSF of each of the “n” failures recorded.

For practical purposes we can assume a range from -0.3 to +0.3 to mean lack of trend. In real data tracking we will never get exactly a zero value for “u”.

Once we know graphically or numerically (u statistic) what the trend is we can select the statistical model to use for condition analysis and failure forecasting.
For systems with u≈0 use the Homogeneous Poisson Process model. HPP.
For systems with u>0 or u<0 use the NonHomogeneous Poisson Process model. NHPP.
We shall see both models in later sections.

Example 1:
Calculate the Laplace statistic “u” for systems A, B and C with failure data from table fig. 2.
Results: (actual calculations are omitted due to lack of space)
System A, u = 0.0, System’s condition constant.
System B, u =+2.0, System’s condition deteriorating.
System C, u = -2.0, System’s condition improving.

MTBF TREND ANALYSIS.

In this section we present of trending a system's condition using the MTBF metric.
We know from previous sections that if the system's failure data show that TBF's tend to shorten we can conclude that failures are occurring more and more frequently and since each failure has a TTR which is system's downtime then we have all the ingredients to conclude that our system is deteriorating (example system B from figure 4)
There are many factors that may cause a system to deteriorate. Let's name a few:

1. Aging components with time dependent failure modes.
2. Relaxation of maintenance practices.
3. Inadequate maintenance strategies.
4. Replacement or changing of maintenance crews.
5. Replacement of original components with components of lesser quality.

If however system's failure data show that TBF's tend to lengthen we can conclude that failures are occurring less and less frequently and therefore our systems condition is improving over time (example system C from figure 4)
There are many factors that may cause an improvement in the condition of a system. Let's name a few:

1. Implementation of a new or different maintenance strategy.
2. Reorganization of the maintenance crews.
3. A systems overhaul or general repair.
4. Redesign of a critical component.

Let us define a few common terms:
MTBF - mean time between failures. Is the mean of the sum of all the operating times between failures within a specific time period divided by the number of failures (N) that occurred within that period.
COTn – cumulative operating time to failure Tn
Looking at figure 1 we can define MTBF mathematically:

Figure 8

$$MTBF = \frac{COT_n}{N} = \frac{\sum_{i=1}^{n} TBF_i}{\sum_{i=1}^{n} T_i}$$

We normally include the operating time from time 0 to the first failure in the equation, therefore MTBF strictly speaking is not a true mean, but in the analysis of repairable systems over their long lifespan this difference can be ignored.

Cumulative MTBF – is the cumulative operating time divided into the cumulative number of failures that have occurred at time of failure i including failure i.

let us graph cumulative failures vs. cumulative MTBF for systems A, B & C of previous example.

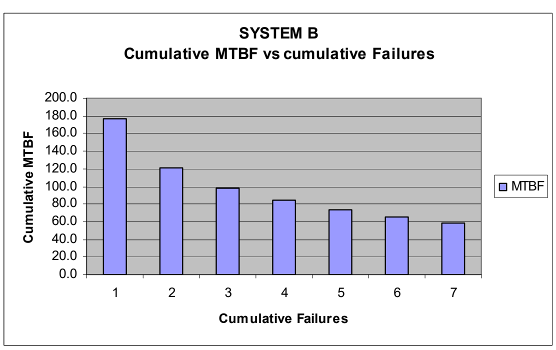

Figure 6

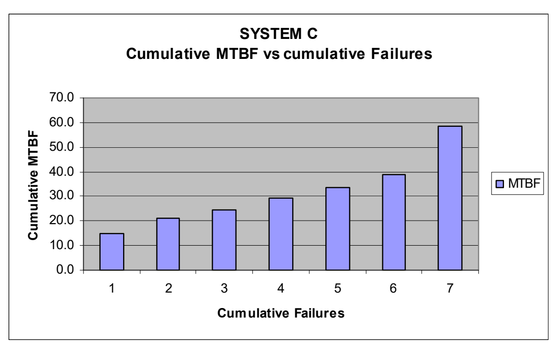

figure 7

From figure 6 we easily see that the cumulative MTBF decreases at each consecutive failure, therefore the trend means that system B is deteriorating over time.

From figure 7 we easily see that the cumulative MTBF increases at each consecutive failure, therefore the trend means that system C is improving over time.

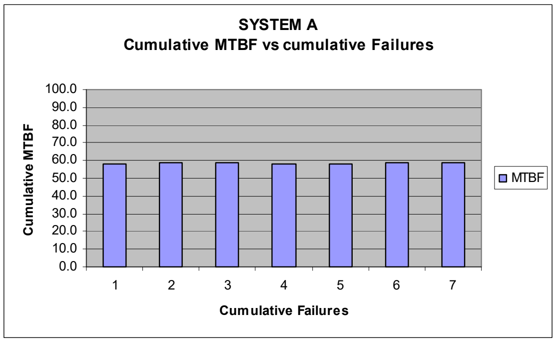

Figure 8

From figure 8 we see that the cumulative MTBF remains constant at each consecutive failure, therefore there in no trend and that means that the condition of system A is neither deteriorating nor improving over time.

The constant MTBF over time reminds us that MTBF = $1/\lambda$ and this corresponds to the exponential distribution, as we shall see in a later section.

CONDITION AND FAILURE FORECASTING.

When we speak of forecasting the future condition and failure behavior of a system, we are basically referring to:

1. Forecasting the number of failures in a specific future time period.
2. Calculating the probability of failure of a system at a specific future point in time.
3. Showing graphically what the future trend of the machine will look like.

There are two methods that we can use depending on the type of trend that the TTSF's and TBF's show.
If the system data shows no trend we call that a Homogeneous Poisson Process (HPP)and we can use the Poisson's and the exponential distributions for forecasting.

If the system's failure data shows either an increasing or decreasing trend we call that a Non-homogeneous Poisson Process (NHPP) and we can use the Power Law Process for forecasting.

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HOMOGENEOUS POISSON'S PROCESS MODEL (HPP)

When the failure TBF's show no trend, that is when the Laplace statistic is close to 0 and the cumulative MTBF is constant one can use Poisson's process to model the systems failure behavior.
The Poisson process is characterized by the number of failures observed over a period of time (t) having a Poisson distribution:

$$p_n(t) = \frac{e^{-\lambda t}(\lambda t)^n}{n!} \qquad n = 0, 1, 2, \ldots$$ Figure 9

Where:
n = Number of failures expected.
$\rho_n(t)$ = probability of observing n failures in time t
λ = constant rate of occurrence.

Refer to reference 1 for a complete explanation of the HPP.

We also know that for a Poisson distribution with λ constant the MTBF is also constant and: λ = 1/MTBF
Since we know the MTBF from our previous calculations we can calculate the system's λ
We can now estimate the expected number of failures N(t) over time t:

$$N(t) = \lambda t = (1/MTBF)t$$ Fig. 10

Example 2:
Forecast the number of expected failures of system A for the following year.
Taking the data of system A (fig. 4A) we calculate the MTBF=410/7=58.6 days and λ = 1/MTBF =1/58.6=0.0171
Expected no. of failures N(365)= λt = 0.0171x365= 6.24 failures.

From here we could diverge and do a number of forecasts such as; probability of failure in a month of continuous operation or the reliability for the year if we stock 4 spares for the component that fails. These calculations are out of the scope of this article.

NON-HOMOGENEOUS POISSON'S PROCESS MODEL (NHPP)

When the failure TBF's show an increasing or decreasing trend, that is when the Laplace statistic is less than -0.3 or greater than +0.3 such as systems B & C one can use the Power Law process to model the systems failure behavior.

A functional form of the time variant rate of occurrence of failure ρ(t) is the intensity function:

$$\rho(t) = a\, b\, t^{b-1} \qquad a, b > 0$$ Fig.11

The parameters α and b can be estimated using the Maximum Likelihood Method as shown later. (References 1 & 2)
Once these parameters are estimated we can forecast the expected number of failures N(t) in any interval from 0 to t:

$$N(t) = \hat{\alpha} t^{\hat{b}}$$ Fig. 12

Two cases have to be considered when estimating parameters α and b:
First case is when the observed interval is time terminated. That is when we are asked to do a forecast on a specific point in time where no failure has occurred and there has passed some time as of the last failure.

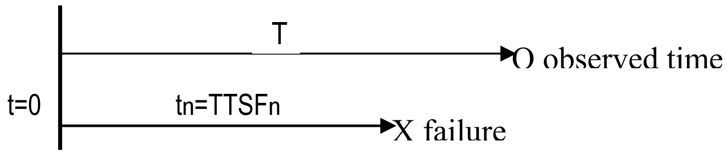

Fig. 13

Where:
T = Observed system time.
t_n = Observed time to last failure n. ($TTSF_n$ in fig. 1)

Second case is when the observed interval is failure terminated. That is when we are asked to do a forecast at the time when the failure occurred. The observed time is equal to the time to the last failure n.

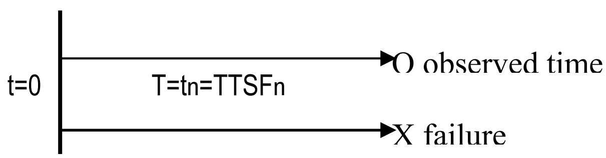

Fig. 14

First Case. Time terminated parameter maximum likelihood estimate.

$$\hat{b} = \frac{n}{n \ln T - \sum_{i=1}^{n} \ln t_i} \qquad \hat{a} = \frac{n}{T^{\hat{b}}}$$

Fig. 15

Where:
n = total number of failure events.
t_i = Observed time to failure i. ($TTSF_i$ in fig. 1)
ln = natural logarithm

Estimated instantaneous rate of occurrence of failure ρ(t) can be calculated and plotted from equation fig. 16

$$\hat{\rho}(T) = \hat{a}\hat{b}T^{\hat{b}-1}$$

Fig. 16

And the instantaneous MTBF can be calculated and plotted from equation fig. 17

$$\text{MTTF}_i = \frac{1}{\hat{\rho}(T)}$$

Fig. 17

Second Case. Failure terminated parameter maximum likelihood estimate

$$\hat{b} = \frac{n}{(n-1)\ln t_n - \sum_{i=1}^{n-1} \ln t_i} \qquad \hat{a} = \frac{n}{T^{\hat{b}}}$$

Fig. 18

Estimated instantaneous rate of occurrence of failure ρ(t) can be calculated and plotted from equation fig. 16 and the instantaneous MTBF from equation fig. 17

Example 3. Failure terminated:
From the failure data of system B estimate α and b and give a forecast of the number of failures for the next year after the last failure at tn=410, if no action is taken and the present trend continues. That would be 410d +365d = 775 days.
Results:
After performing the calculations with equations of fig. 18 (which are omitted to save space) we get the following results: Parameters; b= 3.42, $\hat{\alpha}$=0.00000001, N(775) ≈ 62 failures (from 0 to 775d) less the failures occurred from 0 to 410d N(410) = 7 therefore for the following year 365 days after day 410 the expected failures will be approximately 55 failures.

Example 4. Time terminated:
From the failure data of system C estimate α and b and give a forecast of the number of failures for the next year if the last failure occurred one month (30d) ago and the present trend continues.
Results:
After performing the calculations with equations of fig. 15 (which are omitted to save space) we get the following results: Parameters; b= 0.67, $\hat{\alpha}$=0.12120442, N(805) ≈ 11 failures (from 0 to 805d) less the failures occurred from 0 to 410d N(410) = 7 therefore for the following year 365 days after day 440 the forecasted failures will be approximately 4 failures.

At this point we can estimate the Reliability of the system at different times between failures. We can calculate the time to the next failure. We can also plot the graph of cumulative time vs instantaneous rate of occurrence of failure ρ(t) and cumulative time vs instantaneous MTBF. These tasks are outside of the scope of the present article.

CROW AMSSA method for system condition monitoring and system failure forecasts.

It has been known for some time that when failure cumulative time is plotted vs. cumulative failures on a log-log scale the plot should be a straight line if the intensity function model applies to the process.
The basic equation for the cumulative number of failures is:

$$N(t) = \hat{\alpha} t^{\hat{b}} \qquad \text{Fig. 19}$$

Taking natural logarithms of equation fig. 18 yields:

$$\text{Ln } N(t) = \ln \alpha + b \ln t \qquad \text{Fig. 20}$$

This implies that equation fig. 20 should plot as a straight line.
Let take systems A B & C failure data from our example and plot it on 1x1 scale, log-log paper. (EXCEL was used for the plot of figs.21 and 21a)

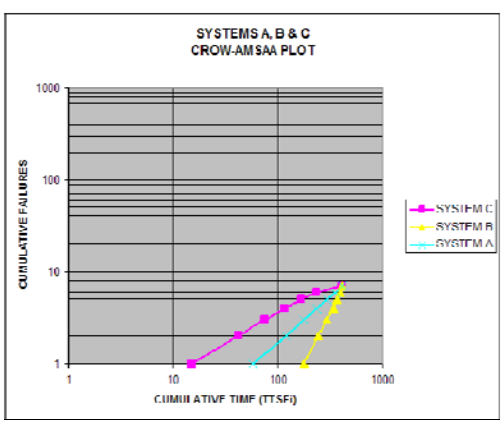

Fig. 21

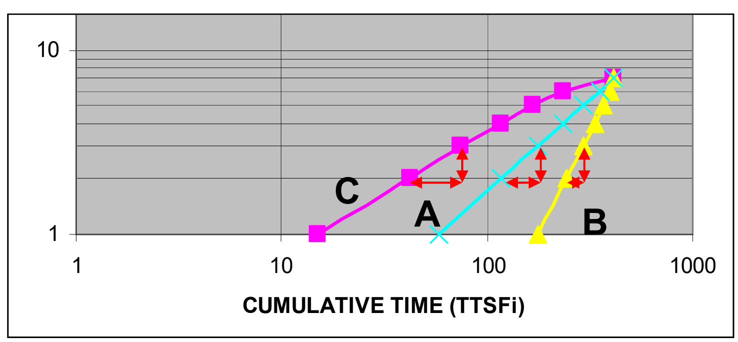

Fig. 21a, Zooming on the line plots.

From fig. 21a we can see that the data of all 3 systems plot as straight lines meaning that the model applies. Graphically we can estimate b from the slope Y/X of the line plotted. If we measure the slope of system A we see that it approximates 1, the slope of B ≈ .5 and the slope of C ≈ 2. We can therefore give the following interpretation to the values of b :

If b ≈ 1 the systems condition is constant. Homogeneous Poisson process.

If b > 1 the systems condition is deteriorating. NonHomogeneous Poisson process.

If b < 1 the systems condition is improving. NonHomogeneous Poisson process.

This model is called the Crow-AMSSA model and was originally developed by J.T Duane at the Army Materials Systems Analysis Activity for reliability growth trending. The latter contributions by Dr. Larry Crow won him the name.

Parameter estimating for the Crow-AMSSA model.
We can estimate parameters α and b using the Maximum likelihood estimate for the NHPP. Therefore the equations of figs. 15 and 18 apply for both α and b

The following plots of failure data of systems A, B, and C were generated with software WinSMITH Weibull for easiness of plotting. Some authors use different notations for the parameters: β for b and λ for α. But be careful not to confuse with β and λ in Weibull analysis.

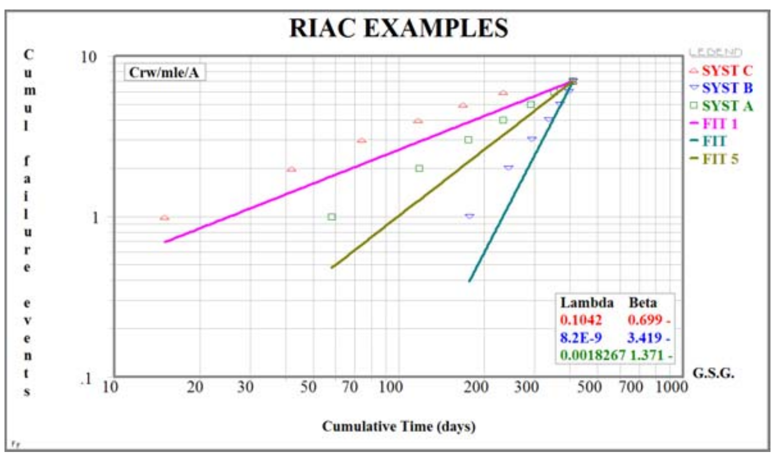

Fig. 22. Plot generated with MLE method.

Plot of Fig. 22 shows the points and the line fits. As well as the estimates of β and λ for time terminated case. We an appreciate that the fit lines drawn with the estimated parameters do no coincide exactly with the data points this is because with few point (10 or less) there is considerable difference from the actual values when using MLE. As the number of data points increase this difference becomes smaller and tends to 0.
The new handbook AMSAA TR-652 and std. IEC1664 present an unbiased method for determining the parameters β (b)and λ (α) and take into account this difference. The plot of fig. 23 was generated using the IEC unbiased method.

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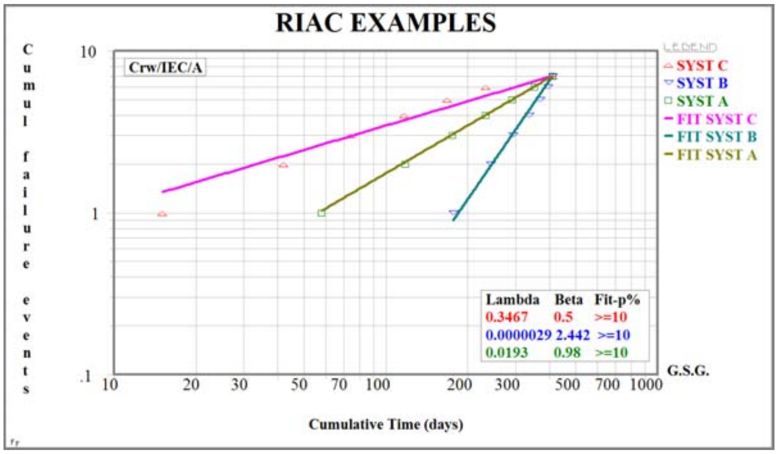

Fig. 23 Plot generated with unbiased method.

We can see that there is a better fit but the parameters differ from the MLE method. Generally the MLE values are on the conservative side making β (b) steeper. We can usually live with this, but we can use a correction multiplier $\left(\frac{n-2}{n}\right)$ to approach the results of the unbiased method when we have 10 or less data points.

Fig. 24 taken from reference 2 shows the difference in β (b) estimation between the 3 commont methods; RR rank regression, MLE and the IEC unbiased method.

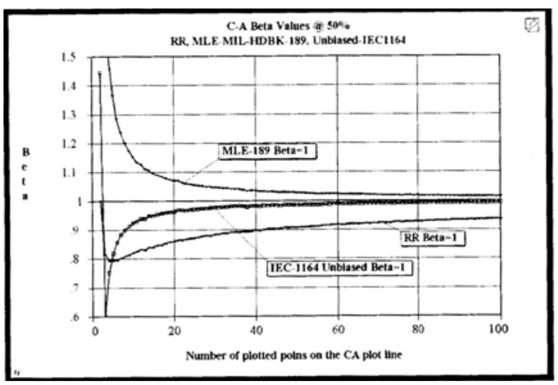

Fig. 24 Taken from reference 3.

For Failure forecasting when using a Crow-AMSSA approach can be done graphically by projecting the fit lines into future times or we can use the method of example 2 and equation fig, 10 for systems with β (b) ≈1 or the methods of examples 3 and 4 with equation fig,12 for systems with β (b) >1 or β (b) <1.

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CASE HISTORY #1

Plant: Gas processing plant
Equipment: liquefied gas centrifugal pump BA1061A
Criticality of equipment: High. Consequences affects personal and environmental safety.
Time Interval analyzed: From January 2000 to May 2006
Length of interval observed: 77 months
Total failures observed: 28
Overall "u" calculated = 4.24 > 0 system is deteriorating and follows a Nonhomogeneous Poisson Process.

In the early part of 2006 management requested a complete failure investigation due to the high incidence of failures in the battery of 4 pumps BA1061A,B,C,D. Coincidently I was presenting a reliability seminar in May 06 at their plant and at that time and the attendees suggested we analyze this case as part of the seminar exercise.

We drew 2 graphs; a cumulative time vs. cumulative failures plot Fig. 25 and a MTBF trend graph fig. 26:

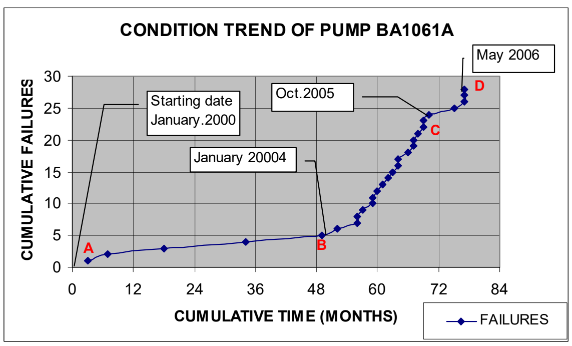

Fig. 25

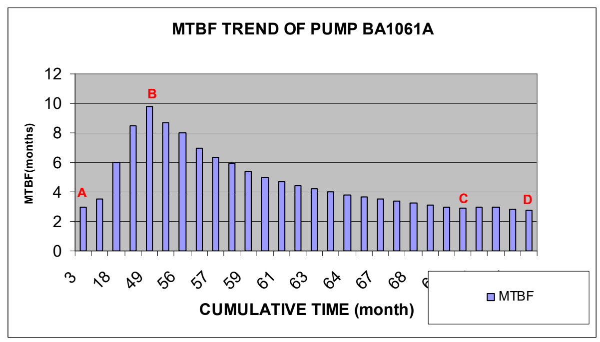

Fig. 26

<u>Observations made from the plots:</u>

1. We can see that the plot fig. 25 does not form a smooth curve but shows a number of discontinuity points; A, B, C & D.
   Point A – First failure recorded (March 2000) after the initiation date of the observed interval.
   Point B - Cusp. Abrupt upwards change in slope. January 2004.
   Point C - Cusp. Abrupt change in slope. October 2005.
   Point D - Last failure recorded (May 2006) and termination of the analyzed interval.
2. We divided the overall graph into 3 distinct and obvious behavior intervals for analysis.
   Interval A-B: slope b not too steep. 5 failures in 49 months and MTBF = 9.8 months.
   Interpretation: we can assume the MTBF and b slope to be the baseline condition.
   Cumulative MTBF from fig. 26 is equal to 9.8
   Interval B-C: slope has changed to steeper b. 20 failures in 21 months. MTBF≈1 in that interval.
   From fig. 26 the cumulative MTBF decreased to 2.92 months.
   Obviously some change occurred in this period that caused the increase of failures and reduction in MTBF and b. It was our job to find out what caused the change.
   Interval C-D: Shows an increase in TBF (5 months) between failures 24 and 25 but after a 2 month period we get 3 failures 26,27,& 28 in the same month (May 2006). The MTBF in that period decreased to 1.75 months.
   Interpretation: The critical situation has not really changed much from interval B-C.

3. Fig. 27 shows a Crow-AMSAA plot of the data generated by WinSmith software and parameters estimated with the IEC method.

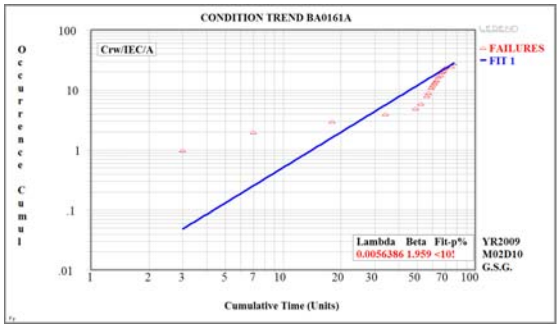

Fig. 27

Failure analysis.

The first step in the analysis of the root cause would be to classify the different failures in interval B-D into distinct failure modes (using CMMS codes or RCM codes) and draw a Pareto plot to show the failure modes that constituted the greatest frequency in that interval and the component affected, thereafter use traditional Weibull analysis or another method to dig into the life behavior of the component. It is outside of the scope of this article to go into this analysis so we'll just mention the results of the failure investigation.

Results of the failure analysis.

The failure mode that represented about 80% of the total failures was "leaking mechanical seals" and the components involved were the mechanical seals. Performing the same condition trend analysis for the 3 other redundant pumps BA1061B,C & D gave similar results for the same time periods although the other 3 pumps showed less seal failures because pump A was the one that had the most operating hours.

An exhaustive investigation was conducted to check the 3 most likely possibilities that might have caused the increase in leaks.

a. Changes in the crews that carried out the replacements.
b. Changes in the procedure to replace the seals.
c. Changes in specification of the mechanical seals.

The investigation disclosed that at approximate the same time that the failures started occurring (time B) the purchasing department had changed the supplier of mechanical seals from the original OEM to another vendor with another make, due to a lower price. This change was made without consulting with either engineering or maintenance and was never reported until after the investigation was carried out.

Corrective Action:

The decision was made to go back to the OEM for mechanical seals supply. This reversal would go slow due to the bureaucracy in the organization.

Failure forecasting.

As part of the exercise during the seminar in May 06 we made a forecast of the number of expected failures N(7) for the remainer of the year (next 7 months) considering the present trend continued. We made an approximation by considering the failure data from interval t=0 to D as time terminated.

a. We calculated statistic "u" ≈ 4.24 > 0 therefore we considered a NHPP model.
b. We calculated parameters $\alpha \approx 0.00153448$ and $b \approx 2.26$ and using equation fig. 12 we calculated N(7)≈6 failures for the remainer of the year.

We also forecasted the time to the next failure (tx) by using equation fig. 12 and solving for time tx. The result was tx= 1.2 months.
As a follow up I called the plant in early December to check how they were doing and at that time they had recorded 7 more failures, pretty close to our estimated 6 and were in the process of going back to the OEM supplier of the mechanical seals.

Lesson learned form this case:
In this case condition trend monitoring was used reactively, about 21 months after the abrupt negative change in TBF after time B. If condition trend monitoring had been used proactively as a routine monitoring tool the decrease in TBF could have been detected earlier about 3 or 4 months after the initiation of the negative trend and the duration of the critical condition before corrective action was undertaken could have been reduced by about 17 months.

FINAL CONCLUSION:
Condition trend monitoring should be used as an everyday proactive tool in order to detect negative trends allowing early corrective actions that will reduce failure occurrences with the associated downtime and financial consequences.
It is an easy tool to use and can be executed with EXCEL or with any other simple plotting software.

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