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Russian Roulette Reliability

Loading the barrel with statistics and pulling the trigger on Reliability

UNDERSTANDING ALARMING TRENDS IN THE APPLICATION OF STATISTICAL METHODS TO THE ANALYSIS OF PLANT MAINTENANCE REQUIREMENTS

ABSTRACT

Computerization has put massive power and capability into the hands of people from all walks of life. This has provided benefits in the maintenance world in most cases.

Computerization has also opened the doors in areas such as complex statistical analysis through cheap and easy to use software packages. The downside of this is that statistical methods can easily produce the wrong answers. When these tools are applied by people with low statistical literacy[1] then major problems can result, particularly if these methods are incompetently applied to major hazardous facilities. The latter has been observed by the author and that is one of the reasons for this paper.

Of major concern is the abuse of Weibull Analysis method. This method has become popular as a tool for the development of maintenance plans. The method is quick, fun to apply and produces quick results. However most analysts ignore the fundamentals listed below:

- **Data Scarcity** - There is always going to be a problem caused by a lack of reliable and representative data in industrial plants.
- **Mismatched Distributions** - There are many component failure distributions that do not match the Weibull distribution yet Weibull method is applied in many circumstances without hesitation.
- **Multiple Failure Mechanisms** - A single Weibull prediction can only have one Beta (shape) value so it does not cope well with components that have two or more failure mechanisms such as a mix of infant mortality, premature failure and wear out.
- **Irrelevant for Condition Based Maintenance -** Weibull analysis does not assist in the development of condition based strategies unless the inspection task has a low effectiveness level[2]. The outcome of Weibull analysis is always a fixed time replacement program or run to failure. Studies of Nowlan and Heap (1978) and others have proven that this approach has limited merit and can be counterproductive.

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[1] Statistical literacy is a term used to describe an individual's or group's ability to understand statistics.

[2] If the condition based task is highly effective in finding the deterioration, the probability of failure (failure pattern) does not have a noticeable impact on the lowest cost interval of performing that task.

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This paper is written to raise the problem and demonstrate the issues surrounding the misapplication of 'Weibull Analysis. As far as practical, this paper is written for people who have college level mathematics.

The reference to Russian Roulette comes from the use of a roulette table to explain the concepts of statistical methods and the traps that capture statistically illiterate users.

NOTES TO READERS

The field of statistics and mathematical modelling can be complex. This paper is aimed at the practical level. Those wanting a more in-depth explanation of statistics or mathematical modelling are requested to search the web or purchase text books on the subject.

While it is recognized that some failure modes or mechanisms are hidden and that maintenance is necessary to manage them. This paper is focused on evident failures which are failures, that on their own cause some form of material consequence.

The use of Weibull and other Statistical methods has a range of applications. This paper is primarily concerned with the application of these methods to determine the appropriate maintenance strategy for physical assets. It does not make judgment on the use of statistical methods in modelling per se, however if a primary input to the model is based on the maintenance strategy developed, then naturally the paper is relevant in such cases.

THE DATA CONUNDRUM

The conundrum posed by Resnikoff in 1978 very neatly summed up the situation with respect to data and reliability management. He wrote:

> The development of an age-reliability relationship, as expressed by a curve representing the conditional probability of failure, requires a considerable amount of data. When the failure is one, which has serious consequences, this body of data will not exist, since preventive measures must of necessity be taken after the first failure. Thus actuarial analysis cannot be used to establish the age limits of greatest concern - those necessary to protect operating safety."
>
> This contradiction applies in reverse at the other end of the scale of consequences. Failures with minor consequences tend to be allowed to occur precisely because they do not matter very much. As a result, large quantities of historical data are available concerning these failures, which means that there will be sufficient material for accurate actuarial analyses. These may even reveal some age limits. However, because the failures don't matter much, it is highly unlikely that the resulting fixed interval maintenance tasks will be cost effective. So while the actuarial analysis of this information may be precise, it is also likely to be a waste of time.

Then in 1999 Moubray added the following*:*

> Perhaps the most important conclusion to arise from the above comments is that maintenance professionals should turn their attention away from counting failures (in the hope that an elegantly constructed scorecard will tell us how to play the game in the future), towards anticipating or preventing failures which matter.

THE CURRENT TRENDS

Unfortunately, universities, and consultants seem to have taken an opposing view. As software programs that use statistical methods make it easy for anyone to enter some numbers into a software program and create an answer, the growth of statistical methods and their misapplication has now reached disturbing proportions.

The problem is that the people doing the analysis are often ill-informed or completely ignorant of the statistical principles behind the method, the assumptions by which the outcomes are generated and their subsequent limitations. Moreover, many have never heard of terms such as confidence intervals or statistical significance[3]. They believe the answer they create must be correct because it was produced by software developed by highly intelligent people from highly respected companies and lots of intelligent engineers use the software to get results.

The maintenance community should be alarmed by the frequent application of these tools in hazardous facilities by statistically illiterate people.

Apart from the implications on human safety and our environment, the amount of time wasted in such analyses and the subsequent poor outcomes must also be of concern.

UNDERSTANDING STATISTICAL METHODS

HOW STATISTICAL MODELS WORK

Statistics is a mathematical science pertaining to the collection, analysis, interpretation, and presentation of data in a way that it can be used for prediction and forecasting. It is applicable to a wide variety of disciplines, from the natural and social sciences to humanities, government and business. The following paragraphs explain in simple terms how statistical methods are applied.

The first step is to collect data about an event or condition. In maintenance this could be failure data that reports the life of components. Then, a probability pattern or distribution that describes the data in mathematical / probability terms is created from the data collected. The pattern can be drawn on graph paper or remain as a mathematical formula.

These patterns are useful if

- the data collected accurately represents the event being studied, and
- the past or the sample is a good indication of the future.

Once the graph or formula has been created, it can be used to predict future outcomes and probabilities based on different decisions. For example, if there is a lot of failure history about a certain type of component, a mathematical or graphical representation of the failure data can be created and used to predict what percentages of component failures will occur at various times.

[3] When using data to predict future outcomes, the more data and the more closely it follows a given formula, the more accurate a prediction based on that data will be. The confidence of a prediction is based on a term known as the statistical significance. The fewer and more scattered the data, the lower the confidence and statistical significance. The greater the data points and the more aligned they are, the better the confidence or statistical significance. Mathematics can be used to rate the statistical significance of a data set.

If the cost of unexpected component failure and the cost of replacing the component as a planned activity are brought into the equation, the most economical time to replace the item can be evaluated. If the component failure has consequences that are not economic, for example environmental or safety consequences, then the model can be used to determine how the risk of unexpected failure changes with the life of the component and therefore define the life at which the component should be replaced based on the tolerable risk.

DISTRIBUTION PATTERNS

The patterns or distribution that the data forms can emerge in many shapes however a large number of them have similar shapes and characteristics. One of the common distributions is known as the normal distribution or bell curve. This distribution is one where the outcomes of events congregate around a mean or average outcome and there is a scatter that shows events further away from the mean are less likely than the ones closer. The scatter is symmetrical around the mean. An example of the bell curve is shown at Figure 1.

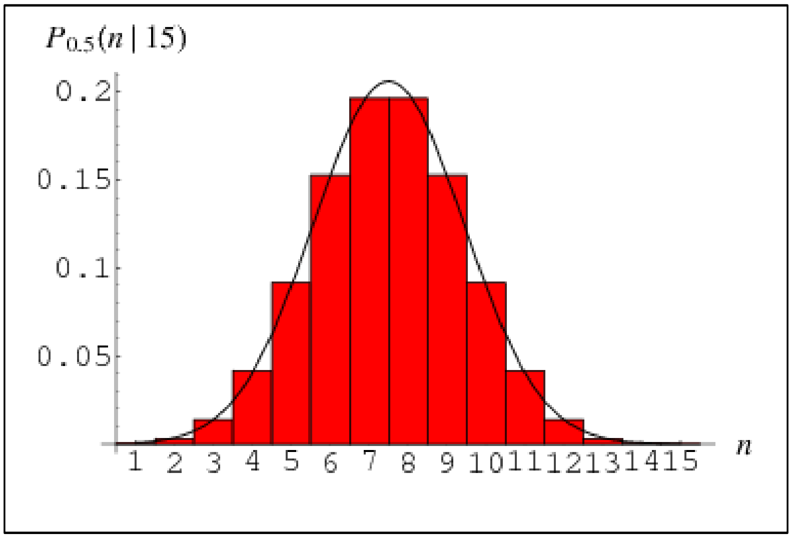

Figure 1 Example of a Normal Distribution

Over the years there have been a large number of distributions created. Names such as “Exponential”, “Log Normal” “Chi-Square” and “Beta” may be known to some of the readers who have studied statistics.

In 1939, a Swedish Engineer named Waloddi Weibull took an interest in modelling distributions relating to machinery / component life. He noted that component failure patterns presented themselves in a wide variety of shapes. Many of these shapes were very different to the normal distribution and other distributions that had been created by other mathematicians. For example a normal distribution did not fit well with infant mortality (high early failure rates), or random distributions (where the chances of failure do not congregate around a mean).

Waloddi Weibull then created a mathematical formula or a distribution that could replicate the typical patterns that were found in component failures. The formula is provided in Figure 2. A graphical explanation is shown in Figure 3.

1.1. The Three-Parameter Weibull Distribution

The three-parameter Weibull *pdf* is given by:

$$f(T) = \frac{\beta}{\eta}\left(\frac{T-\gamma}{\eta}\right)^{\beta-1} e^{-\left(\frac{T-\gamma}{\eta}\right)^{\beta}}$$

where,

$$f(T) \geq 0,\ T \geq 0 \text{ or } \gamma,\ \beta > 0,\ \eta > 0,\ -\infty < \gamma < \infty,$$

and,

- η = scale parameter,
- β = shape parameter (or slope),
- γ = location parameter.

Figure 2 - Formula for a three parameter Weibull probability density function.

The formula has values that change the shape scale and horizontal starting point. These values and their effect are listed below:

- η (Eta)is the scale or ratio of height to width of the graph
- β (Beta) is the shape parameter that determines whether the graph shows infant mortality, random failures or wear out.
- γ (gamma) is the location parameter which sets the point on the horizontal axis where the graph starts.

So the idea behind Weibull analysis is to obtain a set of reliable failure data that accurately reflects the mechanisms or modes of failure of a component and, on the assumption that the distribution of the data fits the Weibull distribution, create the parameters of scale shape and location presented above.

Once these parameters have been established, then the population of all failure mechanisms, or modes related to the data set obtained, is theoretically defined. Predictions can then be made about future failure rates from which life cycle costs, availability models and a host of other complex problems can be solved. If the failure data fits the Weibull curve, and there is sufficient of it to be confident about the Weibull parameters and that the future is going to be the same as the past, this is a powerful way to make predictions.

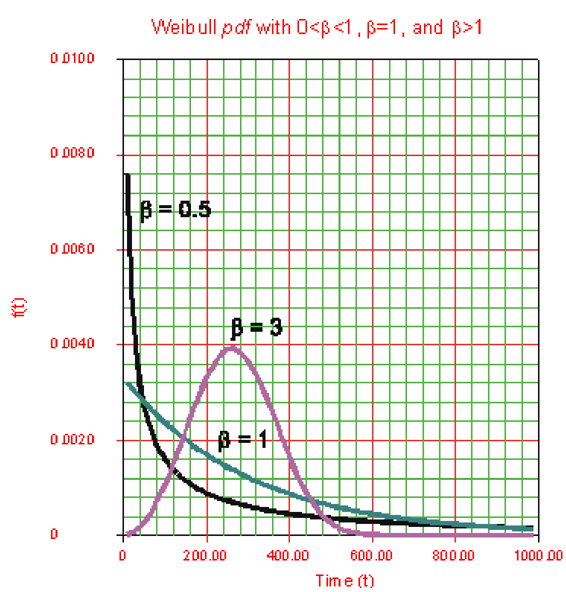

Figure 3 - Illustration of the changes to Weibull probability density function with changes in Beta

THE TRAPS OF WEIBULL STATISTICAL MODELS

OVERVIEW

The traps of Weibull Analysis can be summarized as follows:

1. **Data Scarcity** - There is always going to be a problem with lack of reliable and representative data in industrial plants.
2. **Mismatched Distributions** - There are many component failure distributions that do not match the Weibull distribution.
3. **Multiple Failure Mechanisms** - A single Weibull prediction can only have one Beta (shape) value so it does not cope well with components that have two or more failure mechanisms such as a mix of infant mortality, premature failure and wear out.
4. **Irrelevant for Condition Based Maintenance** - Weibull analysis drives component replacement at fixed intervals. Weibull analysis does not assist in the development of condition based strategies unless the inspection task is not effective[4].

These traps will be explored using two methods. Data Scarcity and Mismatched Distributions traps will be illustrated by using a roulette wheel. The readers will be provided with an example taken from a forum where the forum members were asked to predict a range of parameters of the roulette wheel using Weibull analysis and three data points.

The trap of multiple failure mechanisms will be illustrated using real data of fan belt failures taken from an oil refinery.

The relevance of Weibull for condition based maintenance will be argued based on the work of Nowlan and Heap (1978).

DATA SCARCITY

The massive problem that confronts reliability engineers is the lack of sufficient data to enable a reasonable approximation of the failure pattern and the Weibull parameters. This is the whole point of Resnikoff's (1978) paper.

Unfortunately there has been major misrepresentation of the capability of Weibull Analysis to work where data is limited. Some consultants contend that good assessments can be made with as few as three data points.

One recent example is a case presented at a public forum where the forum member claimed that Weibull analysis using three data points was useful, particularly when safety or environmental problems were the likely outcomes of failure.

[4] If the condition based task is highly effective in finding the deterioration, the probability of failure (failure pattern) does not have a noticeable impact on the lowest cost interval of performing that task.

The following example was used to illustrate the fallacy of this statement.

THE QUESTION

The critical part of the machine the reliability engineer analysing is a component called a Roulette Wheel. The roulette wheel has a failure distribution which, for the sake of this example[5], is set by the numbers on a roulette wheel. The roulette wheel we are using has 37 numbers ranging in sequence from zero to 36. Each number on the roulette wheel represents component life in years. 36 represents the case where the component lasted more than 36 years but less than 37 years. The number zero represents infant mortality which is where the component lasted less than one year.

The challenge is to apply Weibull Analysis to figure out a number of factors about the component failure pattern and then set in place a component replacement program that reduces the chances of in-service failure to 1:10,000 years. The roulette wheel can be run three times so data about three failures can be used as input to the Weibull Analysis[6]. Some of the numbers drawn can be the same.

The three numbers drawn must be used to work out the following information:

- The component Mean Time Between Failure (MTBF) (The average of all the numbers on the roulette wheel).
- Whether the failure distribution is Normal, Weibull, Exponential or Chi-squared or any other distribution (What is the distribution of the roulette wheel numbers)
- If the pattern is Weibull, the parameters Eta and Beta and Gamma for the roulette wheel numbers
- The component replacement frequency to reduce the chances of unexpected failure to 1 failure in 10,000 years (If the roulette wheel was run millions of times, what would be the number from the roulette wheel that would have only had 1/10,000 of all numbers below it.)

[5] Even though many may have difficulty with the concept that the roulette wheel failure rate is determined by its numbers, the connection is not relevant to this illustration. What we are trying to determine, is the effectiveness of Weibull analysis to predict component failure characteristics from small data samples – in this case three.

[6] The author realizes that the roulette wheel numbers are discrete variables whereas the Weibull probability density function is a continuous variable. In the author's opinion, this does not impact the argument presented.

THE ANSWER USING THREE DATA POINTS

The answer that came back from a willing participant was as follows:

Using a single zero roulette wheel with numbers from 0-36 (I know how many numbers there are and what the highest number is) the numbers drawn were:

21, 33 and 29

The average of all the numbers represented on the single zero roulette wheel = 18

The average number of those numbers drawn = 27.66

If these numbers represented a 'component failure' we would be looking at wear out.

Eta = 30.41

Beta = 4.096

The Author's analysis of this result using RCM Cost Software and the Weibull function in MS Excel tells us the change out life to reduce the component failing down to 1/10,000 years would be 3.21 years.

WHERE THIS ANSWER IS WRONG

If the component was changed out at 3.21 years then it would be the same as the probability of getting a number less than 3.21 on our roulette wheel. There are four numbers less than 3.21. They are 0, 1, 2, and 3. So actual probability of failure at age 3.2 or 1 is around 4/37 which is near enough to 1 in 10. This is a massive error – the question asks for a 1:10,000 year chance and the analyst uses Weibull analysis and produces a result that is 1:10 year chance.

HOW THIS ANALYSIS WENT WRONG - SAMPLE SIZE - THREE DATA POINTS IS NEVER ENOUGH

The answers to the question given showed how terribly wrong an estimate based on three data points could be. The statement could be proven wrong by using a variety of statistical methods, however, this paper is going to show the problem by conducting a number of trials. This method of evaluation is preferred because it does not require knowledge of complex mathematics.

To understand if this was a "once off" error 13 more random trials were conducted. The results are presented in the following paragraphs

In Figure 4, the results showed two of the sample sets said the roulette wheel was a skewed bell curve whose failure rate peaked at about 8 years and then reduced gradually over a long period.

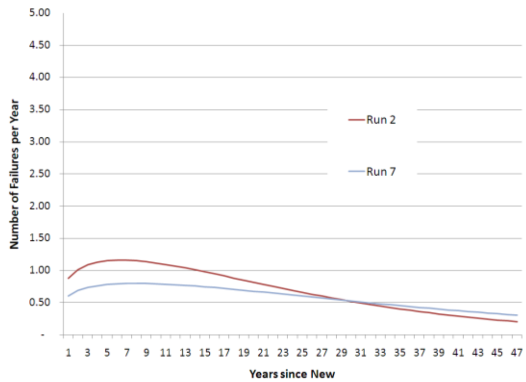

Figure 4 - Illustration of some of the Weibull analysis runs that showed Skewed distribution

Figure 5 shows that four of the sample sets said that the roulette wheel was heavily biased towards infant mortality.

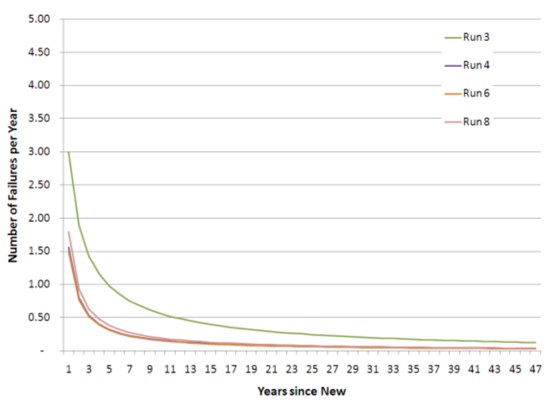

Figure 5 - Illustration of some of the Weibull analysis runs that showed infant mortality distribution

In Figure 6, the analysis came to the conclusion that the roulette wheel was biased towards wear out. This pattern accounted for half of the outcomes. Some of the bias was strong as indicated by the runs that had peaks of over four failures in one year.

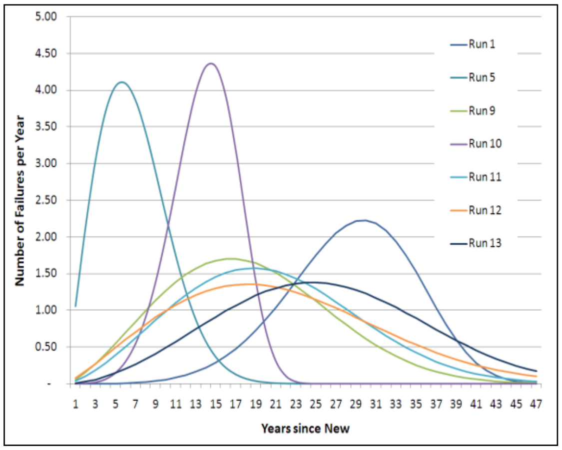

Figure 6 - Illustration of some of the Weibull analysis runs that showed wear out distribution.

Even more alarming was the variety of predictions about the where the MTBF occurred. A visual assessment shows that MTBF ranges from about five to over 30 years.

The conclusion that can be drawn here is that the sample size of three does not provide a consistent answer so it is not practical to use this method with only three data points.

MISMATCHED DISTRIBUTIONS

Following on from the above example, it is known that the numbers on the roulette table are not biased. The chances of the ball landing on one number are the same as they are on any other number. The number generation is random. It is also known that the numbers do not extend past 36.

However, strange as it might seem, when these numbers describe component failures, the component's failure pattern is not random. This is because the definition of random failure rate is that every surviving component has the same probability of failure. This means the same *percentage* of surviving components that fail in every period is constant. For example 10% of surviving components could fail every period for there to be a random failure pattern.

It does not mean that the same number of components fail each period.

The roulette wheel in this exercise is being used as the life and when the life data is put on a graph, it does not match the random failure distribution.

So if the example started with 36 components and they failed randomly with one in every 36 (2.87%) failing each year, when the numbers of survivors or the living population reduced, the numbers of failures would also reduce. This comparison is shown in Figure 7.

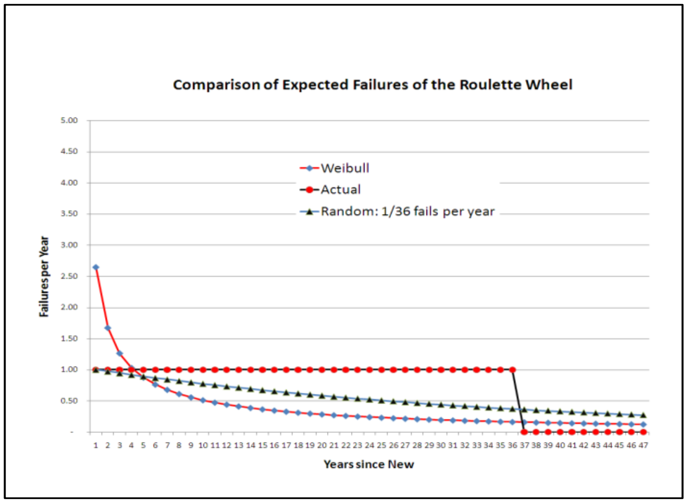

Figure 7 - Illustration of three failure distributions

In Figure 7 the real numbers of failures are represented by the "Actual" lines. This line stays constant at 1 failure per year until the 37th year and thereafter when there are no failures. This is the distribution of the Roulette wheel.

The line represented by "Random" represents the rate of failure if the failure pattern were truly random. This pattern is quite different to the Actual pattern of the Roulette wheel and illustrates why the failure pattern generated by the Roulette wheel is not a random pattern.

The third pattern represented by the "Weibull" line is the failure rate that the Weibull distribution would show if a number close to zero were entered as well as the integers 1 to 36. This graph is obviously not the same as either of the other two graphs on the chart.

The most interesting of the discrepancies is that there is a significant variance between the Weibull interpretation of the roulette wheel failure pattern compared to the real failure pattern. Even though the full set of numbers has been entered into Weibull, the Weibull graph has no similarity to the real set of figures.

This is a very clear example of one of the traps of Weibull analysis; that being the assumption that a Weibull distribution can be used for any set of data. The assumption is false.

MULTIPLE FAILURE MECHANISMS

The following example has been taken from real data from a refinery. The data is the failure data from a turbine exhaust fan belt. The turbine exhaust is fitted with many fans.

The failure rates are shown in Figure 8.

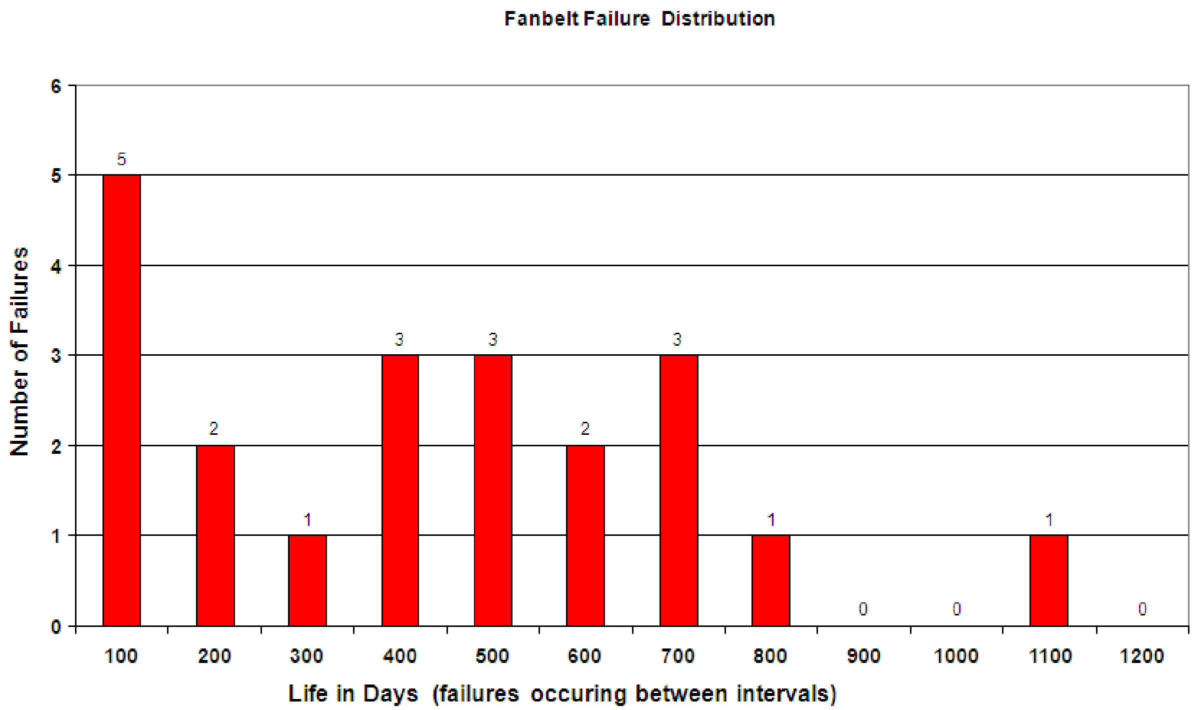

Figure 8 - Illustration of a failure distribution of fan bets from a gas turbine exhaust system

The graph shows the number of failures between each increment of 100 days. For example, in the first 100 days, there were five belt failures. Between 100 and 200 days there were 2. The total number of failures recorded was 21.

There is one anomaly at 1100 days. The mechanics at this refinery said that this data point was probably due to the failure being recorded against the wrong fan. It is highly unlikely that one fan belt survived twice the life of most of the others.

If one were to put these numbers and some cost information into a Weibull software program, the outcome would be an irrelevant change out scenario, where as the real answer is to recognize the various failure mechanisms in the data set.

The first one is easy. The infant mortality mechanism is due to poor installation and early belt stretch.

The second and third are interrelated. One mechanism is premature belt failure due to sheave condition and the other is normal wear. It is not easy to separate them so Weibull of itself would be unable to provide a satisfactory solution using the available data to predict the failure pattern attributable to wear alone.

So the conclusion here is that a Weibull analysis of data that has multiple failure mechanisms is an inappropriate method. It is often far better to take the data to the people who are working on the equipment and ask them some questions about what might be causing the various patterns.

IRRELEVANCE TO CONDITION BASED MAINTENANCE

For many years engineers considered that all equipment generally has some form of wear out pattern (Moubray 1999). This meant that engineers believed that equipment was not likely to fail for a period of time and that at some point, failures would begin to occur. Because of this notion, maintenance engineers sought to figure out the safe life of components and then deploy a program where the components were overhauled or replaced on a fixed time basis regardless of their condition. This was expensive because components that were in good condition were replaced with abundant useful life remaining. It did not seem to matter about the lost life because the belief was that failure was inevitable and the cost of lost production outweighed the cost of the new or overhauled parts.

This thinking ignored the reality that intrusive maintenance induced failure to otherwise serviceable systems. Anecdotal evidence of this result eventually prompted a review. Through the 1960' and 70's, the aviation industry began to question this approach. As a result of concerns about airline maintenance costs and safety in the early 1970's, the United States Department of Defense commissioned United Airlines to study the maintenance effectiveness of the airline company. United Airlines engaged Stanley Nowlan and Howard Heap who commenced the study in 1974 and finished in 1978. One of the key initiatives was gathering the failure data from United Airlines and assembling this into failure patterns. The failure patterns Nowlan and Heap generated from the data are shown in Figure 9.

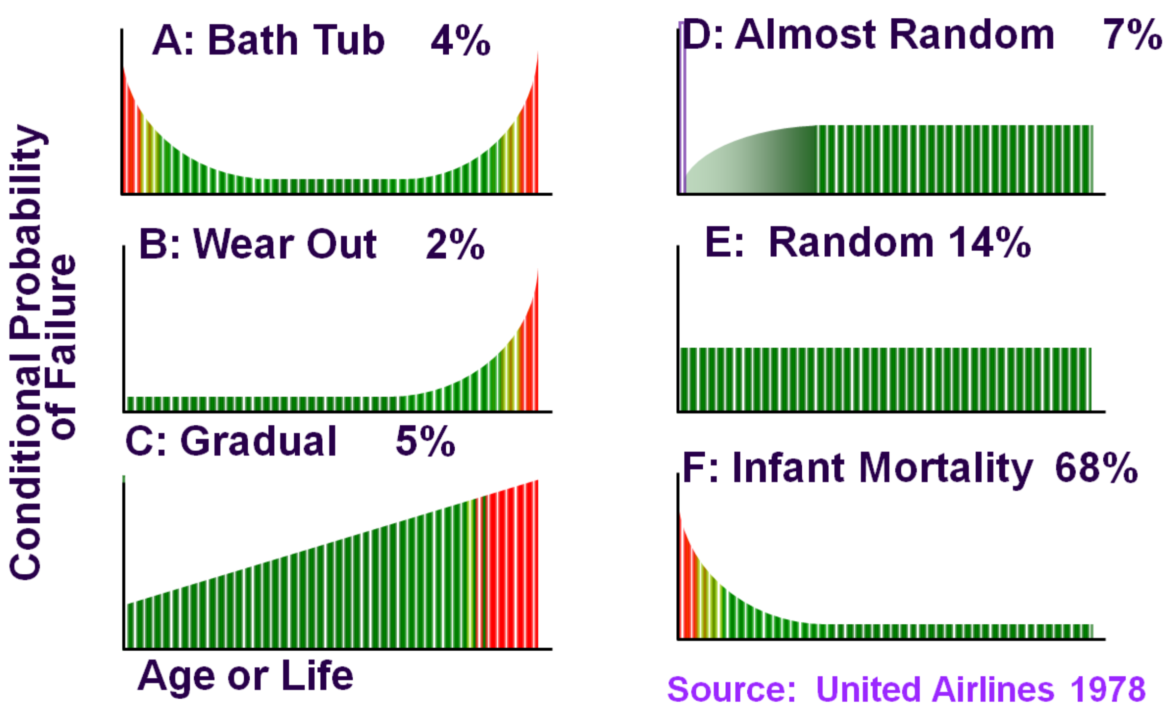

Figure 9 - Failure patterns derived from United Airlines by Nowlan and Heap (1978)

This study and the information produced from it have been widely circulated in the maintenance engineering profession and is probably the most significant study in the history of maintenance engineering.

The Nowlan and Heap analysis found that in the aviation industry, few failures behaved in definite wear out patterns.

The results showed that the majority of failures (68%) had a dominance of infant mortality (Pattern F). Another 14% of failures were observed to be completely random (Pattern E).

This data strongly suggests that in the aviation industry at the time, the majority of failure was caused by the act of maintenance itself. It follows that if most failures occur after overhaul or component replacement then doing more of these activities would result in more failures.

The data from the Nowlan and Heap study had identified that overhaul as a preventive maintenance practice has limited usefulness.

This left Condition Monitoring, as the primary means of preventing equipment failure but Condition Monitoring was not technically feasible for equipment; specifically for equipment that without signs of deterioration or where deterioration was close to sudden.

The alarming conclusion was that a certain level of component failure was inevitable.

The work showed that the maintenance strategy needed to change from one which was highly based on fixed time overhaul to one based on plant condition.

The adoption of statistical methods as the primary means of determining maintenance strategy drives to an overhaul policy. The evidence above illustrates the downside of overhaul policy. This means that the use of statistical methods to develop maintenance strategy should be carefully considered.

SIMPLE METHODS OF MAINTENANCE STRATEGY DEVELOPMENT

The reality is that maintenance analysis of evident failure modes is not difficult. It does not have to rely on failure data and statistical methods.

For evident failure modes, there are only a few basic concepts to learn and knowing these will provide a strong baseline for improving the time taken and the accuracy of the analyses and the acceptance of it by the workforce.

The following is a suggestion on how to assess evident failure modes without a heavy reliance on statistical methods.

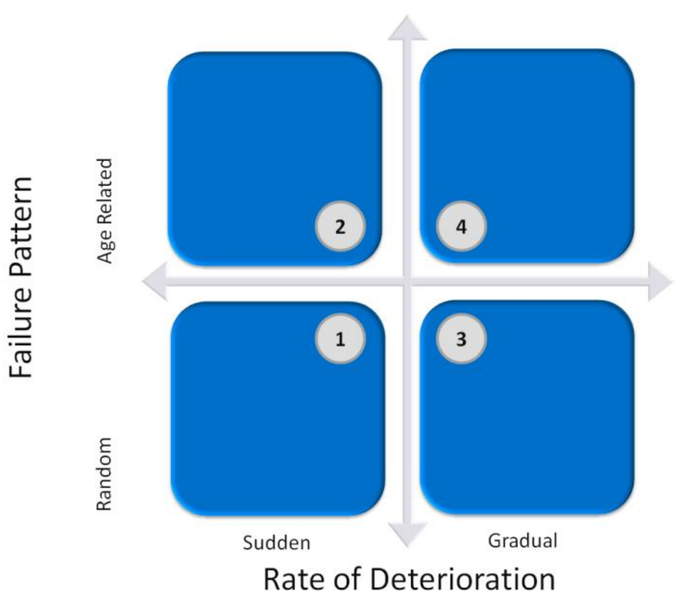

Figure 10 - Matrix of Options for Selecting Maintenance Strategies

THE BASICS OF WHAT DRIVES FAILURE

The failure patterns of any physical asset are set by two things. They are set by the way the asset is designed and the way, or the conditions under which, it is operated. The latter is often called the operating context.

The task of the reliability professional is to understand the failure characteristics of the asset and determine what can and should be done to manage the consequence of the failure.

MECHANISMS OF FAILURE

Mechanisms of failure describe the way in which equipment fails. Examples of mechanisms of failure are wear, fatigue, corrosion and contamination. There are of course many more.

There are only two ways to prevent the unexpected failure of these mechanisms. Both of these require the failure mechanism to be removed before it creates a breakdown. One way (Condition Based Maintenance (CBM)) is to check the component for deterioration or decay. The other way (Fixed Time Replacement) is to replace the component regardless of the evidence of the failure mechanism, at a fixed life based on the assumption that the component will always survive to the replacement life.

For these two methods to be successful, either of two important characteristics of failure mechanisms needs to be understood. These are

- For CBM, the rate of decay, and
- For FTR, the age at which failure occurs or the age to which all components will survive.

These failure mechanisms are important because of the following

If the mechanism deteriorates gradually, then in many cases the condition can be determined and some assessment made about the remaining life of the component. In this case, we can determine the condition of the component and avoid ultimate failure by removing the component before it fails. The failure pattern in this situation is irrelevant to the selection of the interval unless the inspection task has a low effectiveness.

If the failure pattern, or the age at which the conditional probability of failure[7] is known, and it is known that the component suffering the mechanism of failure has a safe life before which time no or very few failures will have occurred, then we can prevent the breakdown.

CONDITION BASED MAINTENANCE

Some failure mechanisms deteriorate very quickly or even instantly (for example when an incandescent light globe fails it fails rapidly) and others deteriorate gradually (when a fluorescent light tube loses brightness it does so gradually over time). Failure mechanisms that deteriorate gradually allow a form of maintenance that monitors the equipment for signs of the onset or the degree of such deterioration with the intent of replacing the item sometime before it is considered to have failed. This form of maintenance is known as condition based maintenance, condition monitoring or predictive maintenance.

[7] The conditional probability of failure is the probability of failure of a component at a point in time given that (if it has) it has already survived to that point in time.

FIXED TIME REPLACEMENT

Some failure mechanisms when plotted against the events which drive deterioration show patterns. If the failure mechanism has a pattern that shows increasing probability of failure with age, then this information can be used to replace the component before it fails. If the failure is random (the chance of failure is the same at any age) or only occurs early in life (commonly known as infant mortality) then it is not possible to reduce the risk of failure by a component replacement program based on the age or use of the equipment.

In fact, if there are a number of infant mortality failure mechanisms that cause a component to fail, then any attempt to reduce the risk of component failure by fixed time component replacement will have the opposite effect.

These two simple characteristics, the rate of decay and the failure pattern form the basis of what maintenance and reliability is all about. Failure mechanisms can be random or age related and they can deteriorate over time or deteriorate suddenly. These characteristics can be visualized in a four quadrant matrix shown in Figure 10.

To explain the options in words we can say that if a failure mechanism is random and sudden, then there is no age at which a component change will reduce the risk of failure and there is no deteriorating condition that can be measured to predict the failure. These are called Quadrant 1 failures.

With all other failure mechanisms, the failure can be prevented either through condition monitoring, fixed interval replacement regardless of condition or in the case of Quadrant 4 failure mechanisms, both options.

From this platform of understanding, maintenance and reliability professionals can take a logical and pragmatic approach to managing the risk of plant failure. Without this understanding, maintenance management will be a hit and miss affair and a suboptimal set of operating economics will result. In the worst case, misunderstanding can have serious safety and environmental implications.

CONCLUSION

The successful application of statistical methods requires an abundance of relevant failure data that conforms tightly to a Weibull or other statistical distribution.

In the vast majority of cases in industry, that body of data does not exist.

Furthermore, the value of statistical methods in the determination of maintenance strategy is limited to the low percentage of components that have a safe life that can be well defined and where the cost of replacement parts is low.

The combination of the two factors so critical to the appropriate application of statistical methods means that statistical methods, at best, become a minor element of maintenance strategy determination projects.

The increase in popularity of such methods, particularly by those who lack knowledge of statistical methods, is a serious problem facing the maintenance engineering profession. The wrong or misguided application of these methods, where analysts are happy to guess data or introduce it from unrelated sources to create maintenance policies for hazardous facilities needs to be stopped before disaster happens.

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