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HOW STATISTICS CAN BECOME A BETTER FRIEND IN SUPPORTING EFFICIENT ISSUES MITIGATION

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Abstract

Mathematics is the method that we use to describe the world around us, implementing the discoveries within physics, chemistry and other sciences in ways that make it possible to generate predictions of what we need, or wish, to know: international flight times and flight fuel requirements, bridge strength requirements, distances to nearby stars, storage life of a lube oil during certain conditions and turbine blade life. However since models are just models and not the truth itself, they vary in accuracy and are sometimes simply not right. Statistics is often used as a measure to follow-up and to quantify how well a model works for a particular purpose. However as has been shown over and over again statistics, unless used with caution and insight, can provide inconclusive, useless or even misleading results. Statistical analysis also often suffers from incomplete data and biased presumptions. This paper describes examples of what can happen when statistics is applied to a gas turbine blade with multiple failure modes. In particular, the result of different ways to model infant failure is studied with the goal to understand if certain failure distribution data found on the Internet can be reproduced with physically sound assumptions, thereby making them understandable and useful for design improvements. The paper shows some necessary factors to consider in particular when the presence of infant or early wear-out failures in the underlying data is suspected.

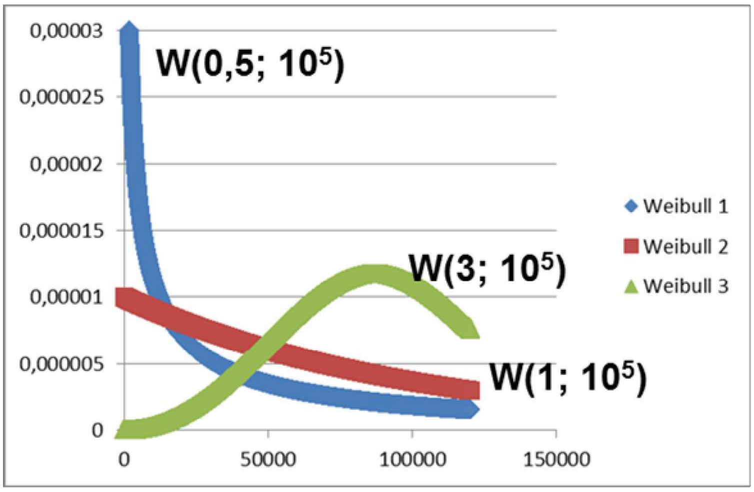

Figure 1: Weibull 2-parameter failure frequency distribution

0 NOMENCLATURE AND DEFINITIONS

CPD	*Combined Probability Distribution* **-** the probability distribution resulting from combining multiple failure modes acting on a part into a single distribution using a weakest link assumption
Failure	Any state resulting in a part being removed from service before reaching its maximum allowable service life
Failure data	Data describing the condition of equipment related to a failure
Failure mechanism	A degradation mechanism that can cause a part to fail
Failure mode	Effect which caused the part to fail
FMEA	*Failure Mode and Effects Analysis*
MTBF	*Mean Time Between Failure*
Prognostics	Structured methodology to predict progression of failure modes in parts
R quality parameter	Relative least squares parameter used as convergence criterion for SWD calculation. Relative means that each least squares deviation is divided by the target value, thereby increasing the importance of low probabilities.
Scale parameter	Second Weibull parameter determining the "time" needed to reach a certain probability
Shape parameter	First Weibull parameter determining the rate of change in probability as function of "time"
SWD	*Suggested Weibull Distribution* – target function used to identify a Weibull distribution representing the combined part probability distribution CPD
$T_{50\%}$	Time to 50% failure probability – measure used in this report to present the relative deterioration rate for the different analyzed cases. $T_{50\%}$ is used instead of MTBF since it is less sensitive to time step length than MTBF and is therefore much easier to work with. It will show similar relative impact as MTBF but the absolute numbers will be

	different. The calculation of corresponding MTBF is left as an exercise to the interested reader.
"time"	Weibull input parameter. "time" is a quantifiable parameter that is identical for all data in the analyzed dataset and is used to measure service time and maintenance intervals.
Weibull distribution	Statistical probability distribution. The Weibull distribution was originally suggested as a useful distribution for fatigue and failure data and has seen extensive use. It exists in two distinct versions, the two-parameter and three-parameter Weibull distributions. In this paper only the two-parameter Weibull distribution will be applied.
λ	*Lambda* – Failure frequency defined as the inverse MTBF: MTBF = $1/\lambda$

1 INTRODUCTION

In order to validate life predictions, and in particular prognostics life predictions, there is a desire to compare predictions with available service data. In practice service data is rarely collected primarily with this purpose. Furthermore, the data commonly consists not mainly by pure wear-out failures but a mixture of parts not passing acceptance criteria during status inspections, infant failures, maintenance errors, random failures, mixed human errors and complex multi-cause errors with many different root causes where the wear-out mechanisms considered by the prognostics methods may or may not have played a role. There is also a share of parts passing one or several cycles of operation with intermediate repairs, often with gaps in service and/or repair scope history documentation. Due to the complex nature of service data, these data will need careful processing and interpretation before they can be compared with the predictions. This paper presents a study carried out under the assumptions that Weibull analysis is an established method to analyze and interpret failure data and to predict future failures, that the variation in life of typical gas turbine wear-out failure mechanisms can be represented sufficiently well by Weibull distributions and that the failure modes of typical gas turbine blades can be ordered into a set of independent distributions with known asymptotic shape. The purpose of this study is to investigate a) the impact of operation and different operation history on failure distributions, b) the outcome of three different ways to model the impact of non-conforming parts on fleet data, and c) how the quality of statistical predictions can be estimated, all under the assumption that failure descriptions are missing or inconclusive.
The work presented here is an extension of the work presented in GT2015-43572, [1].

2 CHALLENGES WITH SERVICE DATA AND MAIN WORK HYPOTHESIS

In order to make good comparisons between the predicted and real condition of a part, there is a chain of data that has to be maintained. Ideally all data from full design specification, allowable design variability, expected failure modes, prognostics descriptions of how damage will accumulate as function of operation, detailed data on how the equipment has been operated, detailed data of operating environment including weather as well as air quality, records on handling and any maintenance actions – or lack thereof – on not only the part itself but the equipment as a whole, previous repair and inspection data including variability in processes and probability of detection and as precise as possible records of any observations – expected or not – on the part is needed. In practice it is usually not possible to collect all this data, and in fact much of the data is only needed in certain situations. On the other hand, much of the data cannot be collected afterwards. Therefore, a "sufficiently good" process is necessary from the beginning that collects as much data as is "affordable" and "practical". Standards such as ISO 14224 [2] and ISO 3977-9 [3] are intended to help analysts to collect data systematically in formats that can be shared with others and that will maximize usability of the data with reasonable effort. Methods of risk analysis such as FMEA and various root cause analysis methods can also implicitly be helpful due to their explicit or implicit requirements on data. Most of these methods are covered by multiple standards for the interested reader – however the standards tend to be application specific or adapted to national regulations. It is expected that many major companies use in-house, product and application specific, versions of the methods to ensure that specific quality requirements can be met. One example of a seemingly more general FMEA standard is IEC 60812, [3]. One of the driving forces behind this paper is to use statistical approaches to develop a better understanding of how much loss of data quality actually affects the desired comparison between theory and practice, with the goal to understand how knowledge can be extracted from small and fragmented data sets, and to understand how various gaps in data can best be bridged. The hypothesis behind the work is that each failure mode has a characteristic statistical shape that is determined by the underlying physical damage mechanisms, or a combination of shapes, each of which is representative for its development during one phase of its total development. Refer e.g. to the crack initiation and crack propagation phases that in sequence constitute a fatigue failure mode. If said hypothesis is valid then it should be possible to describe actual failure data reasonably well with a proper, physically based combination of failure modes. An important part of the knowledge generation is therefore to understand how phenomena like operation conditions and different types of failures will change the appearance of the resulting failure distribution.

3 DESIGN CASE – THE PART TO BE STUDIED

The subject of the study is a hypothetical air-cooled turbine blade closely resembling a real turbine blade in a Siemens gas turbine. The blade is assumed to have three independent wear-out failure modes that are dependent on the same "time" parameter x and have identical Weibull parameters at design conditions. In addition, a fourth infant failure mode is available to simulate the presence of a load-independent infant failure mode in a certain fraction of the blade population. At non-design conditions the prognostics algorithms will treat the different failure modes independently, resulting in different failure characteristics. If the failure modes are independent then it is assumed that the failure probability after time x can be described using a standard weakest link assumption, that is

$$P_f(x) = 1 - \Pi_i(1-P_{f,i}(x)) \qquad (1),$$

where $P_{f,i}(x)$ is the probability of failure due to failure mode i after time x.

An investigation of characteristics of creep, oxidation and fatigue properties of gas turbine blade materials indicate that the Weibull shape parameter is fairly constant for a specific failure mechanism, and that the shape parameters for all three failure mechanisms are in the range of 3 – 7. In order to give a brief description of what 3 or 7 means, a Weibull shape parameter of 3 means that a risk increase from 10% to 20% probability of failure corresponds to a 28% increase in life. In contrast, with a Weibull shape parameter of 7, an increase from 10% to 20% probability of failure corresponds to only an 11% increase in life. For the purpose of this study it has been assumed that each of the three failure modes on the blade has a Weibull shape parameter of 3. Further, also for the purpose of this study, the scale parameter for all three failure modes has arbitrarily been assigned the value of 100000 at a known reference condition. These parameters do not correspond to any known Siemens gas turbine design of today. The characteristics of the prognostics algorithms have been taken from a real turbine blade and can therefore not be revealed in this paper. Finally, a blade set is assumed to consist of 50 blades. All these assumptions can have a considerable impact on the calculated numbers, and any conclusions and intended applications of this study will have to consider this fact.

Calculating non-design point failure characteristics of the part is done in the following way:

1. Using the prognostics algorithms, calculate the relative amount of accumulated damage xi for each individual failure mode after time x

2. For each failure mode, calculate $P_{f,i}(x_i)$ and use (1) to calculate the probability of failure $P_f(x)$ for the part as a whole

3. Visualize the resulting probability distribution

4 Use a relative least squares sum R together with graphical comparison to estimate the Weibull parameters of same distribution

The least squares sum $R = \Sigma\ ((P_f(x)-P_{est}(x))/P_f(x))^2$ for all time steps x. It appears that by using the relative least squares R instead of a straightforward least squares the focus on the lower probability range, where one is normally most interested, will be stronger. Judging whether a particular R value is good or bad has to consider the number of time steps and is really only used as a relative measure.

4 SCOPE OF THE STUDY

The purpose of this study is to contribute to the understanding of what kinds of efforts and skills are necessary in order to get reliable results out of investigations of service experiences. Specifically, the contributions have been limited to answering the following questions, under the assumptions described above and taking into account the outcome from the previous results reported in [1]:

1. How will the failure distribution and $T_{50\%}$ change if infant failures are represented by an operation condition independent, statistically independent, infant failure mode?

2. How will failure distribution and $T_{50\%}$ change if early failures are instead represented as wear-out failure modes with a shorter characteristic life?

3. Can the suggested failure distributions represent public internet data on gas turbine blade characteristics sufficiently well? Are there any models that appear less useful in this context?

4. From a gas turbine plant maintenance perspective, how can the results be used?

5 IMPACT OF OPERATIONAL CHANGES ON FAILURE DISTRIBUTION

The wear-out failure modes of the hypothetical blade are described by a Weibull distribution with parameters (3, 100000) at reference conditions, corresponding to 21582 time units to 1% failure probability per individual failure mode. At non-design conditions the 100000 units of “time” will be consumed with different rates for each failure mode. As a consequence the failure probabilities after time x will be different for each failure mode. In order to understand how this will affect the failure distribution three different operation conditions have been analyzed using Siemens proprietary prognostics algorithms for a similar part. The conditions cannot be revealed in detail – however it can be stated that each of them is based upon a unit operating at a fixed condition somewhere within the 50 – 105% nominal power output range in a simple-cycle application and fall within the normal regime of operation for mechanical drive applications. Both Case A and Case B fall within realistic conditions for base load power generation near or at design conditions. Case C is a part load case that resembles a pipeline application in a temperate climate. The relative life consumption rates for the failure modes at Cases A, B and C are shown in Table 1.

Table 1. Relative life consumption rates for Cases A, B, C

Case	FM1	FM2	FM3	FM4*
A	1,00	1,00	1,00	1,00
B	0,489	0,503	0,473	1,00
C	0,027	0,03	0,026	1,00

* = Note: In this study FM4 will only be used to represent a load-independent infant failure mode.

In summary, the conclusions from the previous study were:

- If the shape parameter is the same for all present failure modes, then the CPD will follow the same shape parameter

- In order to correlate observed failure times to predictions per failure mode, it appears that "all" data needs to be available in "perfect" condition, including complete operation history, complete knowledge of all failure modes, and models describing the impact of all present and previous non-conformities in parts performance and unit configurations.

- Observation of the shape parameter appears to be a useful method to determine whether infant, random or wear-out failures dominate the failure rate for a particular part or sub-system

- Surprisingly, the value added from running all parts to failure appears to reduce the quality of shape-based predictions. Rather contradictory, the first few per cents of the failure distribution appears to provide the most value.

- More work is needed to understand how service experience can be used to extrapolate conclusions from one operation regime to another

- More work is also needed to understand how detailed operation experienced data analysis can be transferred to decision support data useful for the operation and maintenance of individual gas turbine plants.

6 OPERATION INDEPENDENT INFANT FAILURES

On the Internet, there are claims that gas turbine blades and vanes can display typical shape parameters of 1,6 with a range between 0,9 – 2,7, and scale parameters of 125000 with a range between 10000 and 160000. Unfortunately it is not clear whether the numbers are collected for e.g. first-stage blades only, or are suggested to be valid for any blade or guide vane. In particular the scale parameter must be valid only for a mix of early-stage parts since the life times quoted as scale parameters are in the range of normal service times for power turbine blades in a range of gas turbines known to the author. In any case it would be interesting to see how much of the variation in primarily shape, but to a lesser extent also in scale, parameters that can be explained by datasets with mixed operation conditions, and some infant failures.

Load-independent infant failures are modelled with standard infant failure mode shape parameter of 0,5 and two different scale parameters: 50000, corresponding to 50% of blades failed after around five years of operation, and 1000000, corresponding to 50% of blades failed after around 100 years. While it can appear questionable to call 50% of parts failed after 120 years a case of infant mortality, the results will show why this case was tested.

The sensitivity of parts performance were analyzed as function of load cases A, B, C and a mixture of 20%, 60% and 20% blade sets operated in each load case, respectively. The fraction of parts with the infant failure mode active was also varied from 0% to 100%. The results are illustrated in Figure 2 below. From the Figure it is obvious that if more than a few per cent of the blades suffer from an infant mortality failure mode, even one with a considerable scale parameter, there will be a dramatic impact on the life expectancy of said parts. The main reason is that with 50 blades per set, the failure probability per blade set will correspond to the combined failure rate of all the blades.

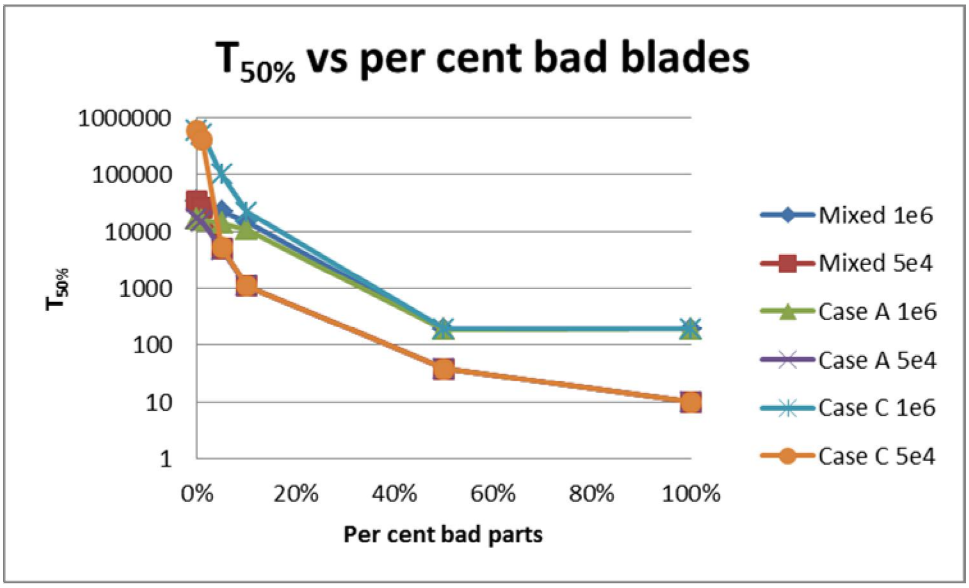

Figure 2: Time to 50% failure probability for blade sets with load-independent infant failure mode

Observations – operation independent infant failure rate

The following observations appear relevant for pure infant failure modes in gas turbine blades.

- If failure is interpreted as something that makes the unit inoperable, then an amount of such blades above 1% or so would cause immediate failures all over the fleet. It appears that a Weibull scale parameter of 10 to 1000 would be representative for the resulting blade set characteristics. Interestingly, this happens even with a scale parameter of 1000000 hours.
- It would therefore appear that infant failure models for gas turbine blades and vanes are only applicable for very severe, rare production faults that may sneak through quality control, and possibly for failures that are easily spotted but do not have immediately catastrophic consequences.

7 OPERATION DEPENDENT EARLY WEAR-OUT FAILURES

Considering the extreme effect of traditional infant failure models on data, it appears necessary to test other failure models that can possibly help understanding how shape factors in the order of 0,9 to 1,6 can be considered feasible for gas turbine parts. In literature a concept of early wear-out failures is also suggested, resulting in a bathtub curve with an additional bump near the end of the infant failure or burn-in phase, [4]. See Figure 3 for a comparison of bathtub versus rollercoaster curves. In order to test the rollercoaster approach, two hypotheses for early wear-out of blades were tested. Both assume that a fraction of the blades in the population will have properties lower than the standard blades. This reduction is modelled as a reduction in scale parameter. For the purpose of this study, the reduction is simulated by dividing the blades with reduced properties into ten groups with a linear life reduction factor. Both a linear and a triangular distribution among the different groups were tested. The parameters are shown in Table 2. Finally, in real situations the non-conformance of parts is often due to irregularities in the manufacturing process, resulting in a strong correlation in characteristics to other parts manufactured at the same time, so-called batch effects. Therefore, set characteristics were evaluated both assuming all blades from same property group and assuming totally randomly distributed blades.

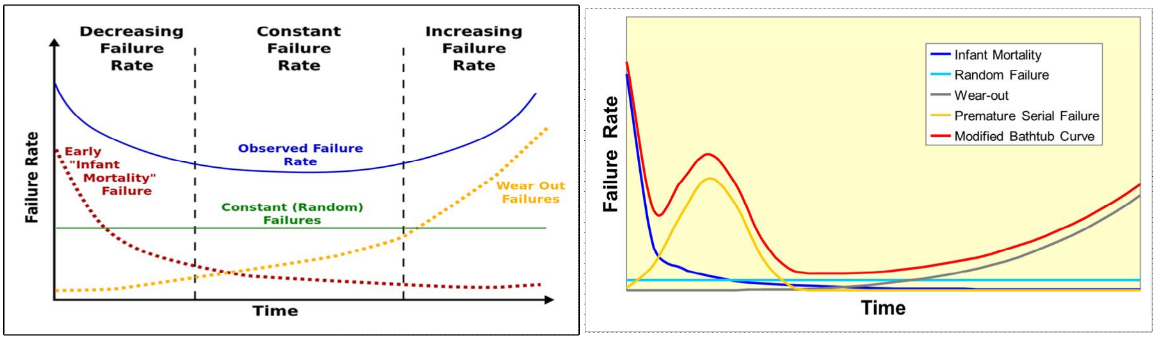

Figure 3: Bathtub vs Rollercoaster failure rate distributions

Table 2. Early wear-out life impact factors

Group	1	2	3	4	5	6	7	8	9	10
Life factor	0,1	0,2	0,3	0,4	0,5	0,6	0,7	0,8	0,9	1,0
Group weight triang.	0,01	0,03	0,05	0,07	0,09	0,11	0,13	0,15	0,17	0,19
Group weight linear	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1	0,1

Finally, it was assumed that all failure modes were affected the same way – that is, all three failure modes are scaled according to the same life impact factor.

Results – triangular distribution in reduction of properties

The results are shown in Table 3 as CPD Combined Probability Distribution estimates for Case A and for the mixed operation case, and as $T_{50\%}$. Results are shown for 0% to 100% non-conforming blades.

Table 3A. CPD parameters for triangular distribution, mixed operation case. Randomly distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	2,3	17000	13600	2,76
50	2,5	19000	15200	2,26
10	2,4	31000	24800	1,96
5	2,4	35000	28000	1,84
1	2,5	37000	29600	1,3
0	2,6	37000	29600	1,08

Table 3B. CPD parameters for triangular distribution, mixed operation case. Batch distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	1,9	28000	22400	1,06
50	2	33000	26400	0,82
10	2,3	37000	29600	0,91
5	2,3	39000	31200	1,44
1	2,6	36000	28800	1,22
0	2,7	37000	29600	1,68

Table 3C. CPD parameters for triangular distribution, Case A operation case. Random distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	3	7000	5600	0,03
50	2,9	9000	7200	0,04
10	2,7	15000	12000	0,29
5	2,9	16000	12800	0,04
1	3	18000	14400	0,08
0	3	19000	15200	0,09

Table 3D. CPD parameters for triangular distribution, Case A operation case. Batch distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	2,2	13000	10400	0,14
50	2,3	16000	12800	0,08
10	2,6	19000	15200	0,07
5	2,9	18000	14400	0,15
1	3	19000	15200	0,1
0	3	19000	15200	0,01

Observations – triangular distribution

The following observations were made in the triangular distributions results:

- R quality parameter is much lower for the Case A data than for the mixed operation data
- The influence on shape parameter from bad parts is stronger for batch distributed parts, but the influence on scale is smaller. This applies for both Case A data and mixed operation data.
- Ideally the probabilities with 0% faulty blades should be identical, and the same applies for the R parameter values. There is however a tiny difference in the fourth decimal in the numerical data. Although not confirmed the author expects that this is a numerical issue caused by the different numeric involved when assuming random and batch distribution of bad blades, respectively.
- The observed range of shape values is 1,9 – 3,0.

Results – linear distribution in reduction of properties

The results are shown in Table 4 as CPD Combined Probability Distribution estimates for Case A and for the mixed operation case, and as $T_{50\%}$. Results are shown for 0% to 100% non-conforming blades.

Table 4A. CPD parameters for linear distribution, mixed operation case. Randomly distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	2,7	7000	5600	2,71
50	2,5	10000	8000	2,4
10	2,5	18000	14400	2,66
5	2,6	21000	16800	3,42
1	2,5	32000	25600	1,83
0	2,7	36000	28800	1,41

Table 4B. CPD parameters for linear distribution, mixed operation case. Batch distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	1,5	24000	19200	1,95
50	1,7	31000	24800	1,5
10	2	39000	31200	0,3
5	2,2	37000	29600	0,47
1	2,5	37000	29600	0,86
0	2,7	37000	29600	1,68

Table 4C. CPD parameters for linear distribution, Case A operation case. Randomly distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	2,1	6000	4800	1,02
50	2,5	6000	4800	0,41
10	2,6	10000	8000	0,49
5	2,7	12000	9600	0,38
1	2,7	17000	13600	0,19
0	3	19000	15200	0,09

Table 4D. CPD parameters for linear distribution, Case A operation. Batch distributed blades

Per cent bad blades	CPD shape	CPD scale	T50%	R quality parameter
100	1,6	10000	8000	0,34
50	1,6	16000	12800	0,37
10	2,1	20000	16000	0,43
5	2,4	20000	16000	0,37
1	2,7	20000	16000	0,15
0	3	19000	15200	0,01

Observations – linear distribution

The following observations were done in the linear distributions results:

- R quality parameter is generally lower for the Case A data than for the mixed operation data
- The influence on shape parameter from bad parts is stronger for batch distributed parts, but the influence on scale is smaller. This applies for both Case A data and mixed operation data.
- The impact of failures on the scale parameter is much stronger than for the triangular distribution, in particular for randomly distributed bad blades
- Ideally the probabilities with 0% faulty blades for batch and random failure distributions should be identical, and the same applies for the R parameter values. There is however a tiny difference in the fourth decimal in the numerical data. Although not confirmed the author expects that this is a numerical issue caused by the different numeric involved when assuming random and batch distribution of bad blades, respectively.
- The observed range of shape values is 1,5 – 3,0.

Frequency plots and what they tell

In order to get a more easily understandable overview of the different probability distributions, frequency plots of set failure distributions were generated for a couple of cases for both triangular and linear distribution of low-performing, or bad, blades. Figure 4 shows frequency plots for the triangular distribution, while Figure 5 shows frequency plots for the linear distribution.

The frequency plots show the transition from distributions dominated by bad blades to the distribution for normal blades.

- There is a considerable difference between random and batch-wise distribution of bad blades. It is clear that knowledge of the degree of batch correlation can help improving reliability predictions.

- It is clearly obvious that there is no way to align a single failure distribution to the data for the mixed operation case, unless there are a lot of bad blades around – preferably randomly distributed.

- If the mode of operation is known, like for Case A data, a Weibull wear-out distribution can describe the data quite well

- For really high numbers of bad blades, a graphical examination would indicate that an infant failure Weibull distribution could describe all but the very earliest part of the failure distribution for batch distribution of failures.

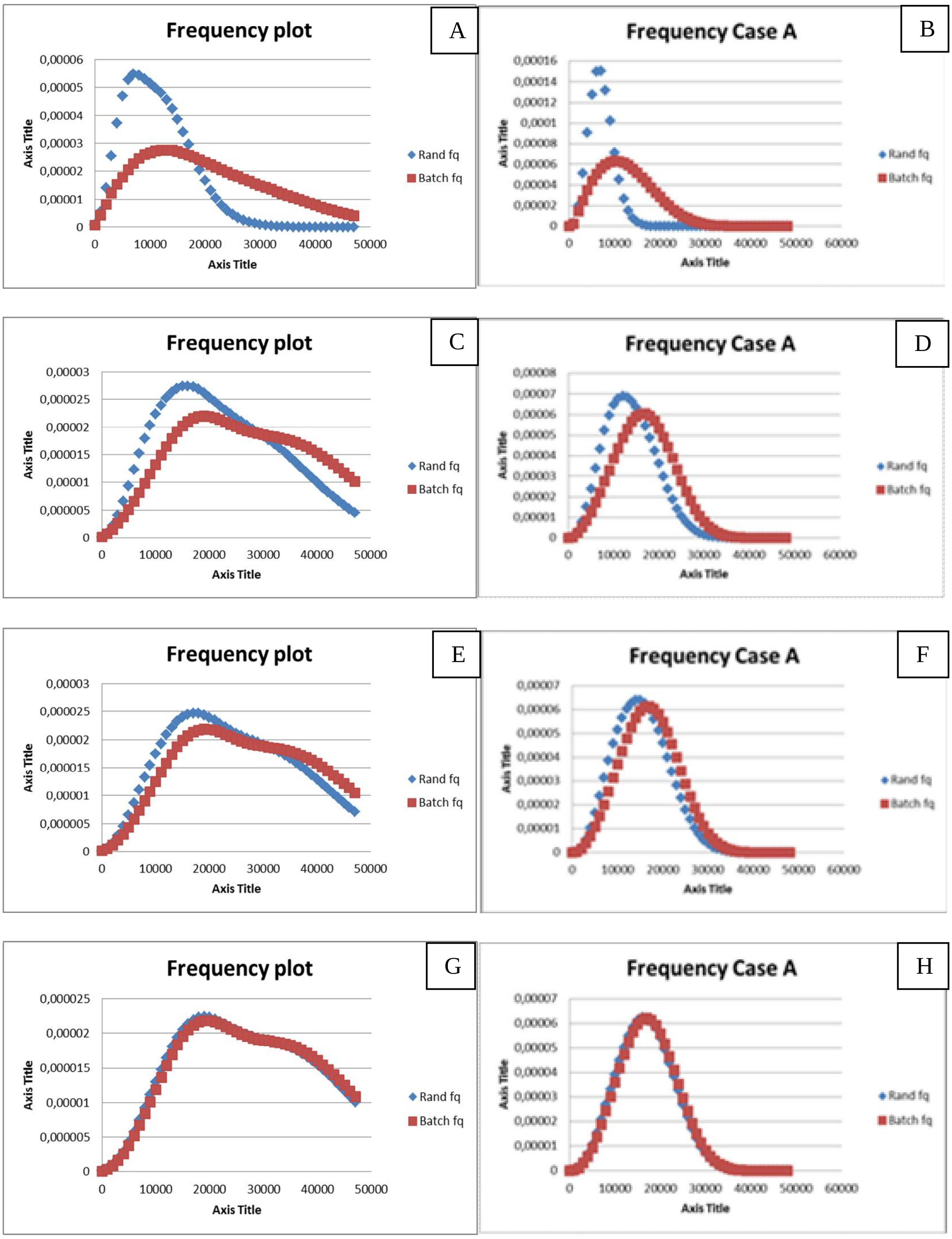

Figure 4A-H: Failure frequency distributions for triangular bad parts distribution, Mixed operation cases (left column) and Case A operation (right column), for, in top – down order, 100% - 10% - 5% - 1% bad blades.

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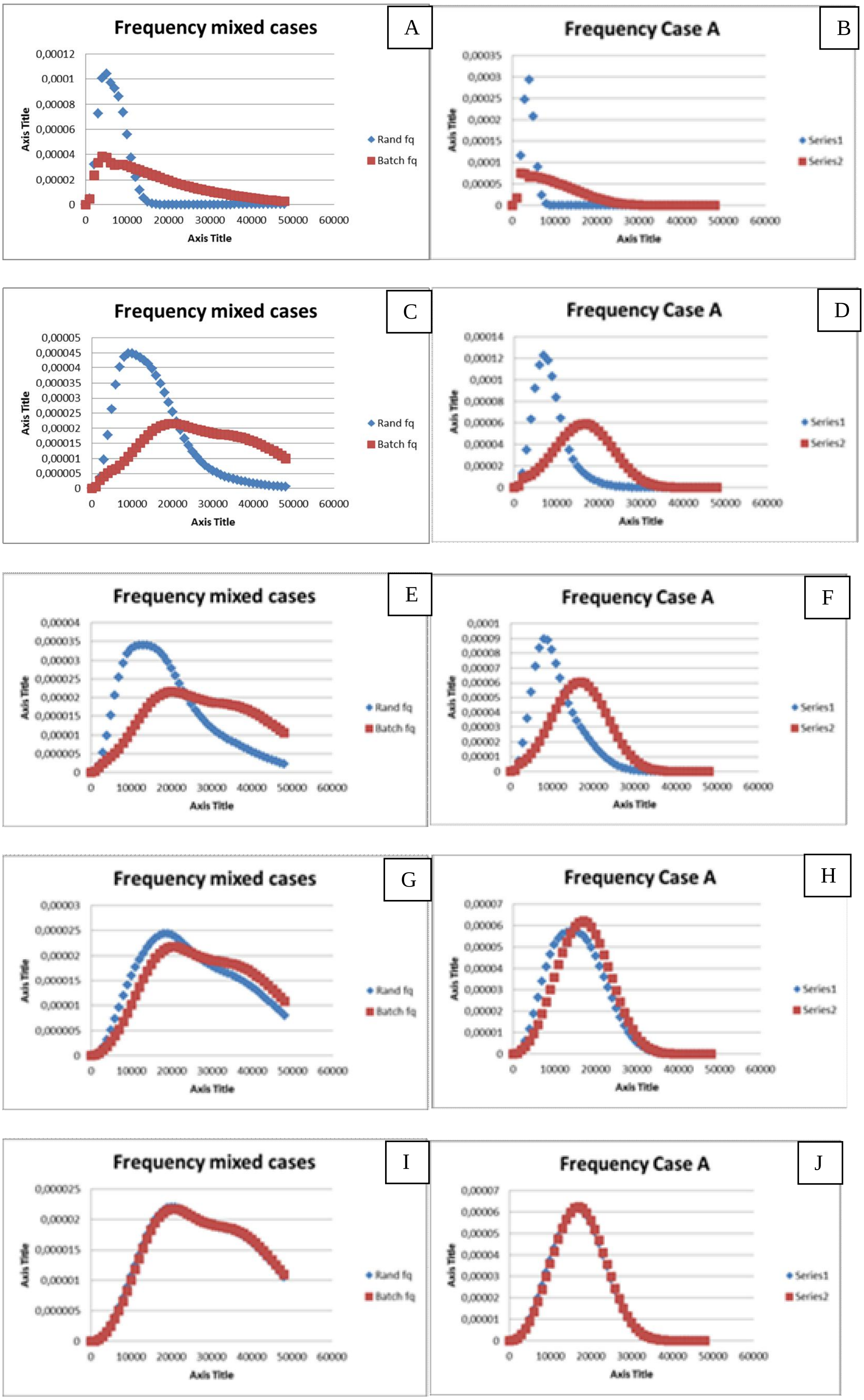

Figure 5A-J: Failure frequency distributions for linear bad parts distribution, Mixed operation cases (left column) and Case A operation (right column), for, in top – down order, 100% - 10% - 5% - 1% - 0,1% bad blades

8 CONCLUSIONS, SUMMARY AND OPEN ISSUES

The Weibull distribution is an amazing tool and can, by a skilled reliability analyst, be useful in many situations. However like most easily applicable methods it also has its drawbacks. Most of all, a solid understanding of the nature of the problem to be modelled is necessary or the conclusions, although statistically reasonable, may be totally misleading. The results presented in this paper suggest three conclusions that could be of relevance for gas turbine reliability assessment, in particular when operation experiences should be evaluated and compared with design calculations.

Firstly, although Weibull shape parameters down to 0,9 are quoted on the internet it seems very difficult to reproduce such results. The main reason appears to be the tremendous effect of the fact that there are many blades of the same design in each engine, making it very unlikely that all those blades together will survive for very long.

There are two factors that can make it possible to reproduce these results, either by assuming that only a small fraction of all the blades are affected by the infant failure mode, or by looking into the definition of failure. It appears plausible that a production error could cause e.g. early loss of coating on a blade according to an infant failure model. If the loss of coating is immediately visible but not immediately critical to failure, one could speculate that this could be observed as infant failures in data. The appearance of the resulting failure distribution would require quite complex simulations of first the coating loss distribution, then the resulting early wear-out damage development, and finally the effect of inspections and probability of detection on observability of the damage. This is a subject for further work.

Secondly, in the case that all parts are not typical samples from the same Weibull distribution, the effects of the variation in characteristics have to be considered. This applies e.g. to the observed batch effects that are visible even with very small amounts of bad parts in the observed population.

Thirdly, none of the early-wearout models tested were able to generate a rollercoaster-type failure distribution. It is left for further work to investigate if this can be explained by another – reasonable – early wearout model, or if it is rather connected to inspection frequencies and the definition of failure as not meeting originally intended life span, including not passing rejection criteria with an unknown remaining life to failure.

It appears that among the necessary requirements for a straightforward, successful and physically sound Weibull analysis one should include: proper selection of a relevant and easily collectable “time” parameter, and the presence of one single dominant failure mode. Although many engineering items fulfil these requirements, this is unfortunately not the case for gas turbine hot section parts. It appears that there is still much to learn before design predictions and operation experience data for gas turbine hot parts can be directly compared with confidence.

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