Enhancing RBD RAM Analysis using Bayesian Inferencing

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Contents

Abstract:

The life cycle performance of a system or process can be determined through a Reliability Availability and Maintainability (RAM) study. These studies quantify the expected number of failures and repair durations over a defined period. A series of Reliability Block Diagrams (RBDs) enable such studies with each block representing an asset and which holds the reliability distribution for both the probability of failure and expected return to service time after an asset has failed. Typically, the parameters for these reliability distributions are sourced from one of three places: reliability data libraries such as standards, manufacturer data or derived from history for sample assets.

A challenge arises when modelling a system which has not yet been commissioned and there is a need to ensure that the results of the RAM study credibility reflect expected performance. Typically this is when library/textbook or manufacturers values are used in the RAM study. In this work, Bayesian inferencing was used to pool data from in-service assets combining with expert engineering to specify reliability distributions. For each asset class considered in the RBD, two items of information were compiled. The first was performance data for comparable assets with similar operating parameters. The second was adjustment based on the expert engineer's expectations of reliability.

The advantages of using Bayesian inferencing instead of traditional techniques such as the Maximum Likelihood Estimate (MLE) or regression methods to fit reliability distributions is twofold. It allows both historical data and experienced experts' opinions to influence the resulting distributions and it returns a distribution for the parameters instead of a point value such as a single value for shape and scale in a Weibull distribution. Bayesian techniques ensure that where there is limited data, the experience of experts will more heavily influence the resulting distributions. When there is a wealth of data, the influence of this advice is more limited.

As a distribution is returned rather than a point value for the parameters in the reliability distributions, it is possible to perform the RAM study based on not only the assets probable performance but can also consider best and worst-case scenarios. By comparing the results of these scenarios, it is than possible to quantify the sensitivity of the system to variations in component reliability.

Keywords: Reliability Block Diagram, Reliability Availability Maintainability, Bayesian

1 Introduction

The purpose of performing a Reliability Availability and Maintainability (RAM) analysis is to model the performance of a system either to identify improvement opportunities or before construction to estimate performance and evaluate the asset configuration. The outcomes of a RAM analysis are estimates of the probability of the system experiencing a failure or failures and the associated downtime over the time period to be modelled (e.g. one to five years). The results of a RAM analysis are dependent on the configuration of Reliability Block Diagrams (RBDs) and their associated reliability distributions. The purpose of the reliability distributions is to model both the probability of failure typically using either a Weibull or Poisson distribution and the return to service time typically using a Normal or Log-Normal distribution.

One of the major challenges associated with configuring the RBDs is the selection of the parameters that make up each of the reliability distributions including Weibull. When modelling an established system it is possible to use production related data such as SCADA delay records to fit the required reliability distributions. However, when modelling a new or proposed system often we rely heavily on industrial libraries or Subject Mater Experts (SMEs) to suggest values to use in the reliability distributions.

By relying on industrial libraries or SMEs to select values for the reliability distributions, it may not be modelling a true representation of the system thus introducing inaccuracy into the analysis. The use of Bayesian inferencing provides a neat solution to this problem by allowing the combination of industrial libraries or an SMEs experience with any available data to produce the required reliability distributions.

Furthermore, in most RAMs analyses, the sensitivity of the system to changes in asset reliability are unable to be quantified. By using a Bayesian technique, it is possible to determine the uncertainty in the underlying data and then run multiple RAM simulations and quantify the sensitivity of the system to this uncertainty. Modelling the uncertainty in the system also allows assets of increased risk to be identified. An asset with increased risk will be expected to experience greater changes in performance when the uncertainties are modelled.

2 Advantages of Bayesian Inferencing

The use of Bayesian inferencing to fit reliability distributions to industrial data provides several advantages over traditional methods such as Maximum Likelihood Estimate (MLE) or regression fitting. Some of these advantages are:

1. Providing a distribution for the parameters of interest rather than a point value,
2. Enabling the SMEs' experience to influence the model/fitting of the data,
3. Handle gaps in the data (e.g. limited failure data recorded), and
4. Enable pooling of data for similar asset types (e.g. instrumentation).

Traditional methods of fitting data to reliability distributions return a point value for each of the parameters that make up the reliability distribution (e.g. shape and scale in a Weibull distribution). A Bayesian approach however returns a distribution for each of the parameters of interest (see Figure 1 and Figure 2 below (Weibull)). The parameter distributions provide insight into the uncertainty in the underlying data and into the quality of the fit. Using a distribution for each parameter also allows for the best, worst and most likely scenarios to be modelled in the RAM analysis. By modelling the best, worst and most likely cases in the RAM analysis we can assess the sensitivity of the system to changes in asset performance and quantified the effect of changes in asset performance.

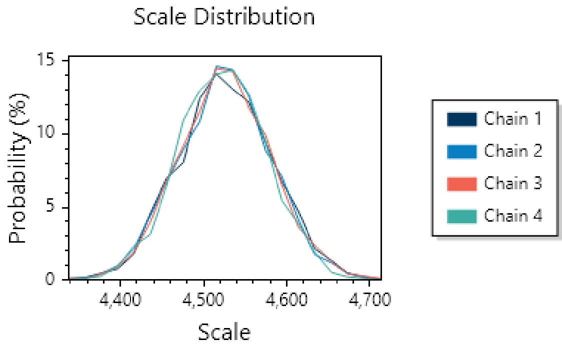

Figure 1 Scale Distribution

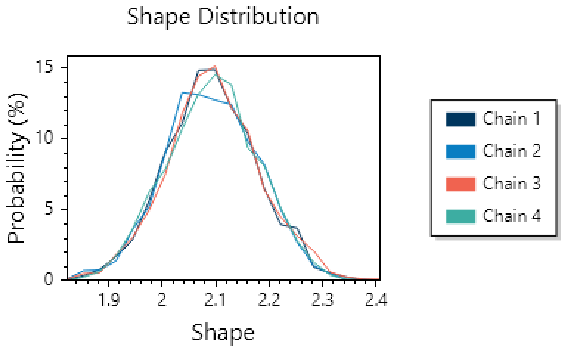

Figure 2 Shape Distribution

For the distributions above the 5th, 50th and 95th percentiles have been extracted. These values are the parameter values that will be passed to the RAMs analysis to determine the number and probability of failure when the simulation is run.

Shape 5th Percentile (Worst Case)	1.967
Shape 50th Percentile (Most Likely)	2.107
Shape 95th Percentile (Best Case)	2.255
Scale 5th Percentile (Worst Case)	4443.526
Scale 50th Percentile (Most Likely)	4535.005
Scale 95th Percentile (Best Case)	4626.543

Table 1 Parameter Distribution Values

Using the parameter distributions the cumulative probability of failure can be generated. Figure 3 below shows the cumulative failure probability with the light blue line represents the most likely case and the shaded area the uncertainty in the fit. The narrowness of the parameter distributions is leading to only a small amount of uncertainty in the cumulative failure probability. This confirms that the underlying data follows a Weibull distribution.

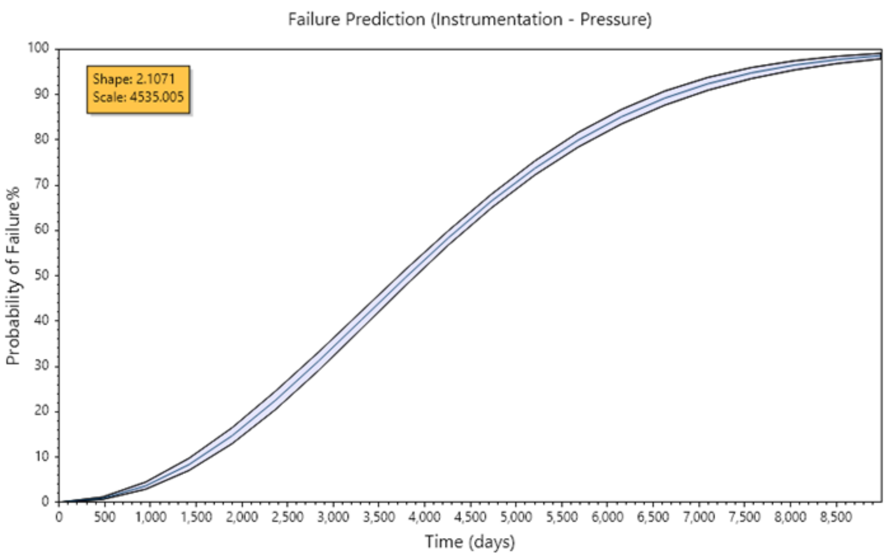

Figure 3 Weibull Distributions

The second advantage of using a Bayesian technique is that it allows SMEs to influence the fitting of the distribution to the available data. This is done by allowing them1 to suggest what the parameter distributions should look like before the model sees the data. These assumptions are called the Bayesian priors.

The influence that the SME assumptions have on the model is heavily dependent on the volume of data available. Where there is a wealth of data available, the SMEs influence is minimised or even negligible. However, where there are gaps or limited data available, the SMEs opinion will have a greater influence on the model.

Furthermore, when there is limited data available to fit a distribution traditional methods tend to struggle and result in large uncertainties or unusual results. When this is the case, RAM analysis are forced to depend heavily on SME knowledge or industrial library values rather than real life data. This approach however does not consider:

- Any bias in then SMEs experience.
- The uniqueness of each business or sites operational environment or tempo.
- An evidence based approach.

Another advantage of using Bayesian techniques is that it allows data from similar assets or asset classes to be pooled together. When the data is combined from multiple assets or asset classes, this is called hierarchical modelling. Hierarchical modelling can be used when there are gaps in the data or to enhance the accuracy of the fitting of the distribution.

When performing hierarchical modelling it is possible to see how each of the assets or asset classes is affecting the fit of the distribution. Figure 4 shows how each of the four instrument asset classes has affected the fitting of the Weibull scale parameter.

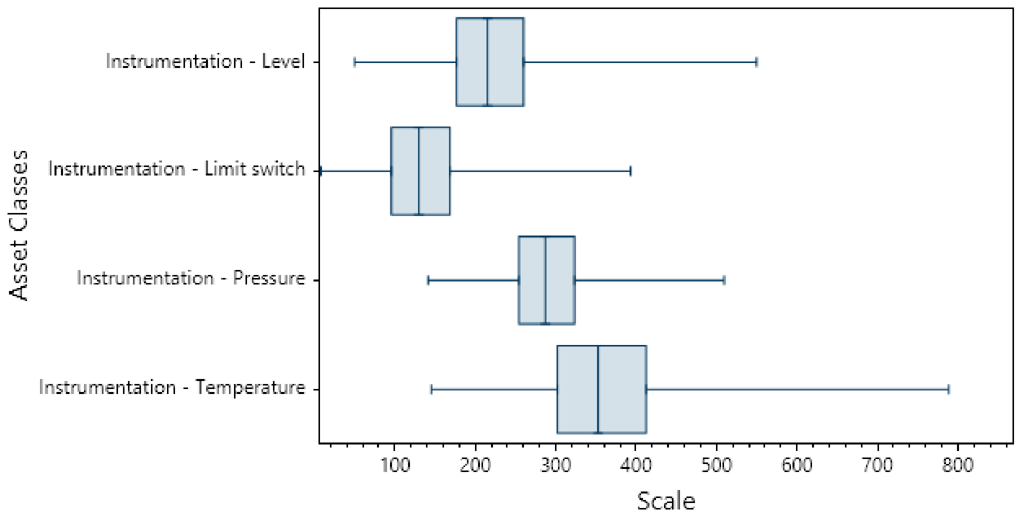

Figure 4 Hierarchal Modelling (Weibull Scale Parameter)

Hierarchal modelling also provides insight into how assets or asset classes are performing compared to each other. In Figure 4 we can see that the limit switch has the shortest MTBF and the temperature instrument has the longest. Using this information we are also able to make decisions about how we pool our data. In this case we may decide that the performance of the pressure and temperature instrumentation at this site is similar enough to pool the data but exclude the level and limit switches.

3 Application of Bayesian Inferencing

The Bayesian inferencing techniques described above were applied to a gas transmission offtake station, a delivery station and a pipeline that had completed its initial design. This system has a range of asset classes including:

- Values,
- Instrumentation,
- Control and communication,
- Pipework, and

- Electrical distribution.

The purpose of performing the RAM analysis on the system was to determine if it would be capable of reaching the desired reliability and availability before the design was locked and construction began. The project team decided that rather than use library values in the analysis, they wanted to use existing asset data. The assumption made was that the assets to be installed would be maintained and operated in a way similar to its existing asset base and thus could be expected to have similar performance characteristics.

Ideally in a RAM analysis delay/fault data from the SCADA system is used to determine the reliability and availability of the system. In this case however accessing the required data from the SCADA system was practicable and did not contain faults data for all of the assets classes that needed to be modelled. As a result the decision was made to use the historical work order data from the organisations CMMS. The data available in the CMMS also had the advantage of being able to align with blocks within the RBDs.

Using work order data instead of delay/faults data from the SCADA system posed some added complexity and affect the results of the RAM study. Unlike SCADA data it was difficult to determine if a corrective work order was in the result of a failure or a condition based repair conducted as a result of an inspection. As a result, the decision was made to assume that all corrective work orders were a result of a failure with the understanding that this would make the system appear less reliable than it might realistically be.

The other factor that needed to managed was the return to service time. The decision was made to fit a Log-Normal distribution to the work associated with the corrective work orders. Then as neither of the delivery stations had a permanent on-site trades and additional two hours was added to the Log-Normal mean parameter to account for the expected response/travel time.

4 Configuration of Bayesian Models

Figure 5 shows the process used to perform the Bayesian inferencing for both normal and hierarchical modelling.

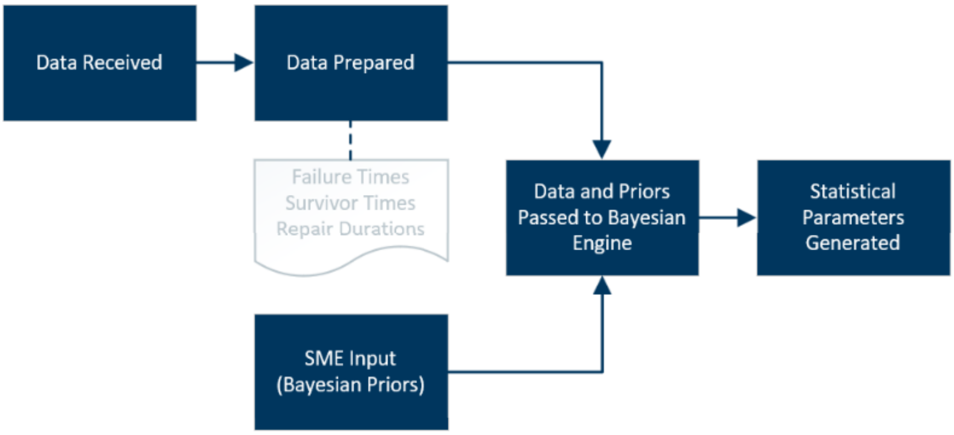

Figure 5 Process for Bayesian Inferencing

Once the data has been extracted from the source system (i.e. SCADA or an EAM) it needed to be prepared for processing. As part of the data preparation process the asset classes of interest were identified from the RBDs and the mapped to the data. After this for each asset in the data set a series of failure survivor times were calculated. A failure time is the time between the asset being installed/commissioned and its first failure and then the time between subsequent failures. The survivor time is the time from the last failure to the data extraction date or if the asset has not experienced a failure, the time between install/commissioning date and the data extraction date.

As the Weibull distribution was used to represent the reliability of the system, it is critical to use both failure and survival times in fitting the distribution. In most cases when a Weibull distribution is fitted only the failure times are used, this can lead to the assets having an under represented reliability. This was particularly true in this case where the systems assets are inherently reliable and do not experience a large number of failures.

Once the failure and survival times had been prepared the priors for each asset class were established. To establish the priors a variety of sources were used including SME experience and published industrial reliability data.

To conduct the Bayesian inferencing a sampling process was used, the table below details the key parameters passed to the sampling algorithm.

Sampling Parameter	Value
Burn in samples	1000
Samples	2000
Chains	4

Table 2 Bayesian Sampler Key Parameters

In most cases there was enough data available for each asset class to ensure that the prior distributions selected had little to no impact on the final/posterior distributions. Conservative prior distributions were usually selected and the final/posterior distributions moved away from the prior distributions.

The Weibull posterior distributions had typically shape factors of above thee and scales above three years. This was mostly driven by the long survival times where assets have not experienced a failure whilst in service. The table below provides and overview of the posterior distributions for a sample of asset classes.

Asset Class	Shape 5th Percentile	Shape Median	Shape 95th Percentile	Scale 5th Percentile	Scale Median	Scale 95th Percentile
Air Compressors	1.558	2.181	2.92	3397.188	3556	3710.189
Electrical - Distribution	1.818	3.315	4.37	2936.272	3196.61	3327.333
Meter – Coriolis	2.063	2.974	3.979	4351.256	4518.59	4683.383
Valve - Control	3.962	4.469	5.014	4130.637	4238.175	4349.133
Instrumentation - Pressure	1.967	2.107	2.255	4443.526	4535.005	4626.543

Table 3 Asset Class Posteriors

5 Application of Bayesian Posteriors to the RBD

The RBD model was initially populated using median values from the Bayesian analysis and the reliability and availability simulations executed. The reliability simulation was run over a one year period and the availability simulation over a five year period.

Figure 6 and Figure 7 below provide an example of one of the RBD used to model the filtration system within the stations. Figure 6 shows the results of the reliability simulation when the median posterior values, are used and Figure 7 when the 5th percentile values are used. For the median posterior values a reliability of 97.18% is achieved and when the 5th percentile values are used, a reliability of 97.88% is achieved.

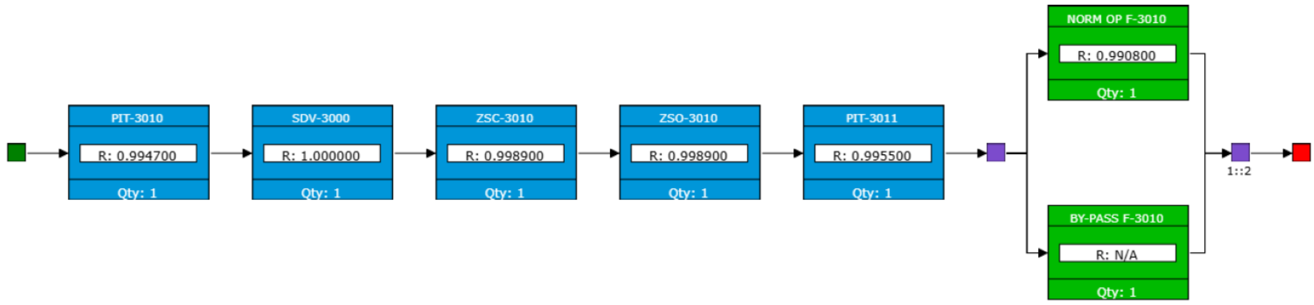

Figure 6 Gas Filtration System Reliability (Median Parameters)

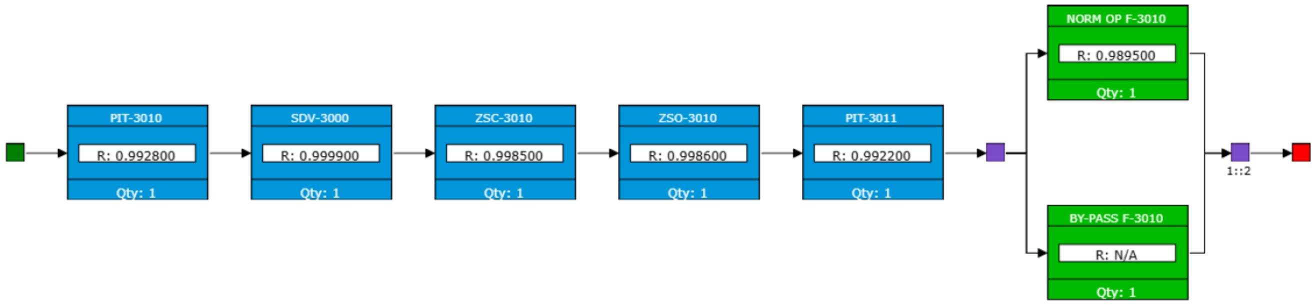

Figure 7 Gas Filtration System Reliability (5th Percentile Parameters)

By comparing each of the blocks in Figure 6 and Figure 7, we were able to determine that the reliability of the filtration system is being influenced by the reliability of the instrumentation asset classes. This was a trend seen across both the gas offtake and receiving stations.

Comparison of the results also revealed that the reliability of the electrical power supply system was heavily influenced by changes in electrical switch and distribution board reliability. The reliability of the electrical power supply system dropped from 99.91% to 95.78%.This drop can be seen in Figure 8 with a wide range in the 95% confidence interval.

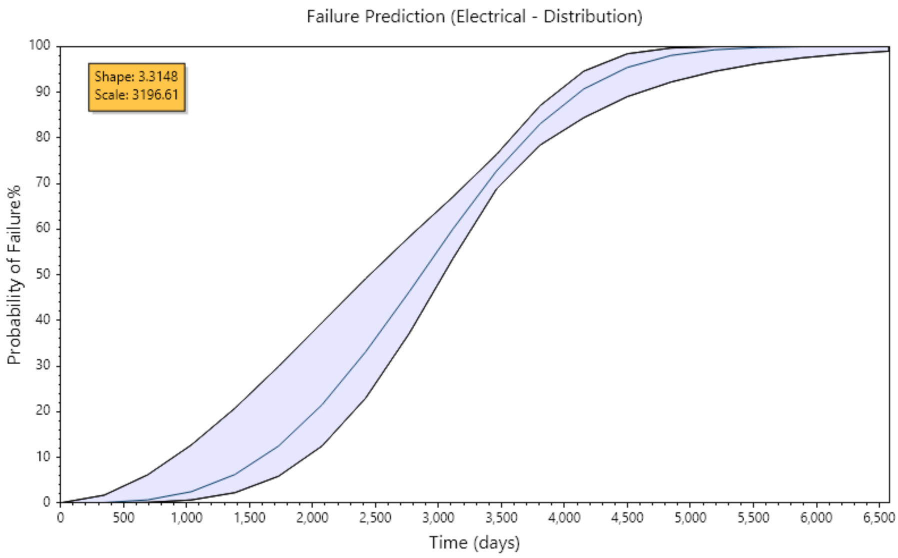

Figure 8 Electrical - Distribution (Cumulative Probability of Failure)

With the median posteriors resulting in a system reliability meeting the target, it was decided that there was no need to model the 95th percentile posteriors as this would add little to the analysis or conclusions.

Analysing the results of the RAM modelling we were able to determine which asset classes were the drivers of potential reliability issues within the system. As a result of this, changes to the configuration and control logic of the gas delivery and offtake stations were able to be made. A major change to the configuration of the control logic was adding additional protection logic to prevent superfluous station trips. The most likely cause of these trips was identified as loss of signal of a valve position switch, so additional logic to protect against this issue was recommended. Other recommendations included:

- Addition of a voting system,
- Addition of flow control logic (e.g. open switch experiences a loss of signal but there is no flow downstream and the close position switch reads the valve as closed), and
- Installation of valve position potentiometers to add additional redundancy into the system.

6 Refinement of Bayesian Inferencing in RBD Modelling

In the current application the 5th, median and 95th percentiles of the parameter distributions are used to model the uncertainty in asset performance. The drawback of this approach is it assumes that the assets performance neatly fits one of these one of these distributions. The performance of the 5th, median and 95th percentiles can differ significantly, Figure 9 shows how the shape of the cumulative probability of failure changes depending on the values selected. The 95th percentile experiences an increased rate of asset failures as the asset ages where the 5th percentile has a greater probability of infant mortality.

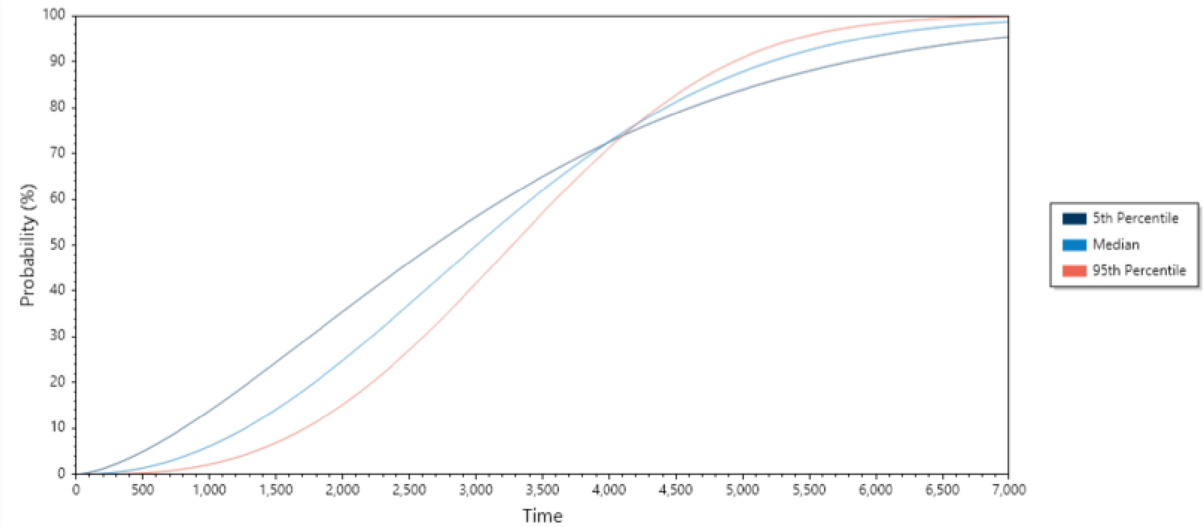

Figure 9 Percentile Comparison (Cumulative Probability of Failure)

An improved method of applying the uncertainty to the RBDs would be to refit a Weibull distribution to the upper and lower confidence limits on the probability of failure graph produced by the Bayesian inferencing (i.e. the top and bottom of the shaded area in Figure 8). This would better reflect the uncertainty within the results of the Bayesian inferencing and account for a wider range of uncertainty.

7 Conclusion

In this application Bayesian inferencing was used to fit Weibull and Log-Normal distributions to enable a RAMs analysis to be completed. The use of these fitting techniques and the resulting distributions could also be used in other reliability applications such as maintenance optimisation and life cycle costing.

In the case of maintenance optimisation, one potential application is the adjustment of inspection frequencies based on the rate at which repair work is generated. By modelling the time between conditions-based repair being identified and assessing the frequency at which inspections are taking place the probability of identifying a fault at an inspection can be quantified. This approach could then be combined with the cost of performing the inspection to develop a cost probability for a range of inspection frequencies. This could then be combined with the probability of a failure occurring in service and the lost revenue and return to service cost to establish a risk cost based inspection frequency.

Bayesian inferencing can also be used to determine the expected arrival rate of events. These events can be anything from faults and delays in a SCADA system to corrective work orders in an EAMs. By applying this methodology to arrival rates, the number of expected events over a period can be modelled. This can then be used to:

- Determine if the asset has begun to deteriorate.
- Calculate the expected downtime and when that downtime will be experienced.
- Benchmark the performance of a fleet of assets against each other.