

RAM analysis applied to decommissioning phase: Comparison and assessment of different methods to predict future failures

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ABSTRACT: Reliability Engineering methods are applied throughout asset lifecycle, but the greatest challenge is in decommissioning phase, as it requires the equipment degradation after repair and its effects on system operational availability to be considered in order to better predict future equipment performance.

In order to predict future failures and define critical equipment it is necessary to take into account the positive or negative maintenance effect on equipment reliability. Therefore, the Reliability Growth Analysis (RGA) applied to a repairable system can be performed to predict the cumulative number of failures, considering the degradation effect of repairable equipment.

Despite RGA being the best approach, in some cases it is necessary to consider the system configuration modelling RBD (Reliability Block Diagram) and perform a direct simulation to predict system operational availability and expected number of future failures. Therefore, the General Renewal Model is required to define the restoration factor of each equipment item in order to take into account the degradation effect on equipment performance and apply these factors to RBD configuration in order to predict the system operational availability and future expected number of failures with respect to the degradation effect. The restoration factor is minted to give values between zero and one. In other words, a restoration level between “as bad as old” and “as good as new”. The RGA model deems the restoration levels as “as bad as old” and “as good as new” and “better than as good as new”. Therefore, the proposal methodology predicts the restoration factor from the RGA model, based on a likelihood method. In addition, the expected number of future failures is determined by comparing the prediction results from RGA model (Crown AMSAA Model) and direct simulation which considers the restoration factor.

The main objective of this paper is to present these particular reliability engineering methods and demonstrate the application on an asset case study in decommissioning phase. The simulation for cumulative time as well as a specific period of four months was carried out in order to predict the effect of critical failures on system operational availability during a specific range of time.

1 INTRODUCTION

The RAM analysis is a recognized management and engineering discipline for the purpose of guaranteeing the specified functionality of a system over its complete lifecycle. RAM analysis also aims to ensure the operation, maintenance and disposal costs remain below the acceptable level, by establishing the relevant performance characteristics at the beginning of the procurement cycle, and through monitoring and control of their implementation throughout all asset life cycle phases (Vozella, 2006).

The general definition of reliability used throughout industry and quoted in many engineering books published on this subject follows the example as taken from MIL-STD-785:

Reliability: the ability of a product to perform a required function under given conditions for a given time interval.

Availability: ability of an item to be in a state to perform a required function under given conditions at a given instant of time or over a given time interval, assuming that the required external resources are provided.

Maintainability: a state in which an item can perform a required function, when maintenance is performed under given conditions and using stated procedures and resources.

Despite the RAM analysis being the most common method utilized by reliability engineers, most of time the degradation caused by equipment age and maintenance effects is not taken into account. In many cases, the reliability data are obtained from

a generic database concerning constant failure rate, and the equipment failure-rate data obtained are treated as an average (Gerbec, M. et al. 2010).

The null hypothesis of the HPP (Homogeneous Poisson Process) with the alternative being a NHPP (NonHomogeneous Poisson Process) is defined by a trend test such as the Laplace Test or the Military Handbook test (Lindqvist, et al. 2006).

The degradation effect must be taken into account to represent the increasing number of asset failures during asset wear out. Whenever this type of degradation is not represented by “Direct simulation”, the equipment is considered as good as new after repair.

The RAM analysis performed concerning decommissioning phase must take into account the degradation effect in order to predict the future failures of the assets.

Indeed, nowadays many RAM analyses use data from generic databases (exponential PDF) that in most of cases will not represent the real performance of the system assessed. In addition, these databases do not consider the restoration factor or the different PDFs (probability density functions) which are more applicable to failure modes in the analysis.

This paper will discuss the importance of considering the restoration factor by comparing the reliability growth analysis (Crow AMSSA Model) and General Renewal Model when performing a RAM analysis to predict system performance by applying a case study concerning decommissioning phase.

2 RAM ANALYSIS IN DECOMMISSIONING PHASE

In order to understand the application of RAM analysis in asset decommissioning phase it is necessary to first understand the asset management concept, as well as how reliability engineering is applied during asset lifecycle.

Asset Management is defined as the best practices applied during asset lifecycle in order to achieve the best performance result. Indeed, such practices are carried out with support of a leader at different organizational levels, specifically strategic, tactical and operational.

Therefore, different reliability engineering methods must be used in different asset lifecycle phases, as shown in Figure 1. The optimal asset performance is achieved when most early life failures are eliminated during design phase, which enables excellent performance during operational phase. This is shown by the green bathtub curve in Figure 1, representing a lower failure rate, or in other words, higher reliability.

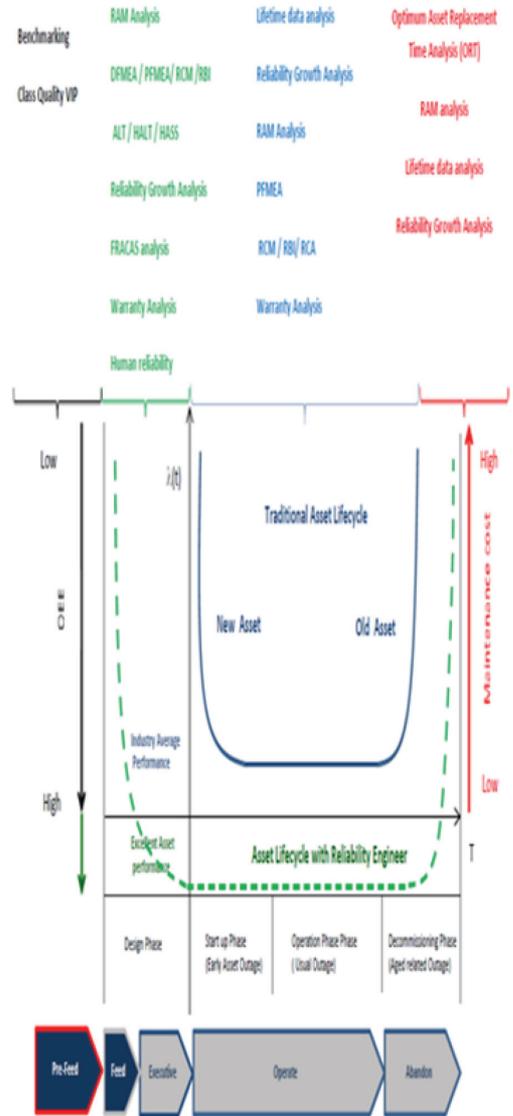


Figure 1. Asset Management Source: Calixto, E. 2014.

In order to achieve optimal performance, it is necessary to implement different methods throughout asset lifecycle. Indeed, all efforts begin in design phase, applying different qualitative (DFMEA, RCM, RBI, HALT, FRACAS, human reliability) and quantitative (RAM, ALT, Reliability Growth analysis and warranty analysis) methods. The main objective of these methods is to identify the early-life failure during design and eliminate them whenever it is possible. During operational phase, different qualitative (PFMEA,

RCM, RBI) and quantitative (Lifetime data analysis and RAM analysis) methods must be utilized to maintain asset performance until the end of asset life, when decommissioning of the equipment is defined and supported by RAM analysis, ORT (Optimum Replacement Time) and Reliability Growth analysis.

The Optimum replacement time for all equipment must be analyzed in order to reduce operational cost, maintain high availability of the system and below the acceptable risk level for failure.

The decommissioning phase is the most challenging in terms of RAM analysis because it requires different analyses to be performed, such as Reliability Growth Analysis, General Renewal Model and the usual Lifetime data analysis during the lifetime data analysis step in order to predict the future system performance.

In addition, in some cases, it is also important to carry out the Optimum Replacement Time analysis in order to define when it is best to replace equipment based on operational cost analysis.

In general terms, the RAM analysis methodology applied for decommissioning phase can be defined by the following steps represented in Figure 2.

Regarding decommissioning phase, it is very important to take into account the equipment age in order to predict future failures that will reduce system performance in decommissioning phase. Therefore, it is important to perform the Reliability Growth Analysis (RGA) using the Crow AMSAA method, as well as performing the General Renewal Model in order to accurately predict the expected number of future failures.

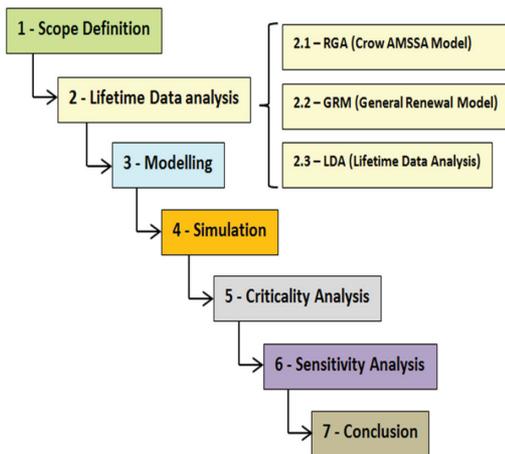


Figure 2. RAM Methodology in decommissioning phase.

Indeed, these methods are applied for single equipment and components but it is a very important result for comparison with the Monte Carlo (MC) Simulation result from RAM analysis. In fact, the best approach is to carry out RGA analysis and then adjust the MC simulation for each equipment item.

Despite a good approach, the software packages which perform system direct simulation (Monte Carlo simulation) have some limitations and are not able to predict the exact expected number of failures predicted by RGA. Indeed, it is possible to take into account the restoration factor predicted by the General Renewal Model, but it is only possible to have equipment in the state “as good as new” or “as bad as old”.

Theoretically, this is the best condition that some equipment can achieve in terms of performance after preventive or corrective maintenance, but in some cases it is possible to have reliability growth. This is achieved by swapping internal components for more reliable ones or even modifications which increase equipment reliability when performed.

3 RELIABILITY GROWTH ANALYSIS

The Crow AMSAA model was introduced by Dr. Larry H. Crow in 1974 in order to be applied to product improvement assessment during design phase. Nowadays, this model is also applied during the operational phase of asset life cycle to assess the equipment degradation over time, as well as the effect of maintenance on repairable equipment in order to predict future failures.

The Crow AMSSA is a statistical model which uses the Weibull failure rate function to describe the relationship between accumulated time to failure and test time, being a Non-Homogeneous Poisson Process Model. This approach is applied in order to demonstrate the effect of corrective and preventive actions on reliability when a product is being developed or for repairable systems during operation phase (Crow, 2012). Thus, whenever improvement is implemented during test (Test-Fix-Test) or maintenance, the Crow AMSAA model is appropriated to predict reliability growth and expected cumulative number of failures. The expected cumulative number of failures is mathematically represented by the following equation:

That is approximately:

$$E(N_i) = \int_0^T \rho(t) dt \quad (1)$$

$$E(N) = \lambda T^\beta \quad (2)$$

The Crow AMSAA Model assumes that intensity failure is approximately Weibull failure rate, thus intensity of failure on time is:

$$\rho(t) = \frac{\beta}{\eta^\beta} T^{\beta-1}$$

where initial failure rate as:

$$\lambda = \frac{1}{\eta^\beta}$$

If cumulative failure rate is approximately failure intensity we have:

$$\lambda_i = \beta \lambda T^{\beta-1}$$

The equation above describes failure intensity during the test and depends on the β value increasing, decreasing or staying constant through time. It's very important to bear in mind that β in the Crow AMSAA Model describes intensity failure behavior and does not have same meaning as the Weibull PDF shape parameter.

An example of an application of this methodology is demonstrated in Figure 3, which shows the

cumulative number of failures over time for different compressors.

In Figure 3, for each compressor, there are different β and λ values, which describe the effect of improvement actions as well as the cumulative failure rate.

In fact, β is a shape parameter of Intensity Failure Function in the Crow AMSAA Model. Thus, in this model when $\beta > 1$, reliability decreases through time because failure intensity is increasing. In other words, corrective product actions are not improving the product. When $\beta < 1$, intensity of failure decreases through time; in other words, reliability is increasing. Therefore, corrective product actions are improving product reliability. When $\beta = 1$, there's no improvement or product reliability degradation. In this case, the product behaves as if no corrective action takes place and intensity failure is constant through time. The Growth rate in the Crow AMSAA Model is $1-\beta$.

The Crow AMSSA model is the best model to predict future failures and analyse the effect of maintenance and operational environment on equipment performance. Indeed, Power Law processes (Crow AMSAA Model) are often sufficient for simple reliability studies, but in the case of complex system, there is a need for more complex model (Verrier, V. et al. 2010).

Indeed, it is not possible to use the Crow AMSAA model to predict the expected number of future failures for different equipment in complex configurations. In this case, it is necessary to represent complex systems with an RBD model.

Once the system is represented by RBD and the direct simulation is performed to predict the expected number of future failures, it is necessary to take into account the degradation factor that will be explained in the next section.

4 GENERAL RENEWAL PROCESS

The General Renewal Model (Kijima I and II) was proposed by Kijima and Sumita in 1986. The Kijima Model, known as "General Renovation Process" or "General Renewal Process", is based on component virtual life concept. This method considers the reduction in component age when an intervention is performed; it can be described in two forms:

⇒ Age re-establishment based in last intervention (Kijima I);

⇒ Age re-establishment based in all intervention (Kijima II);

In first case, the "Model Kijima I" assumes that reestablishment of component age occurs only for the last repair. Therefore, the model assumes that the "ith" repair does not remove all reliability

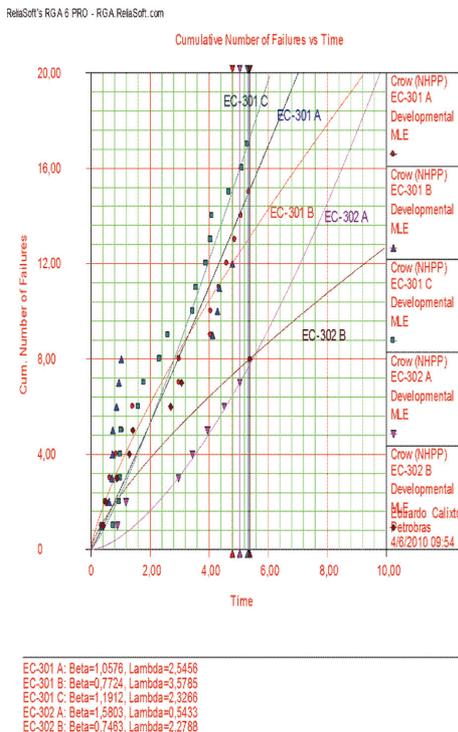


Figure 3. Reliability Growth Analysis. Source: Calixto E, 2011.

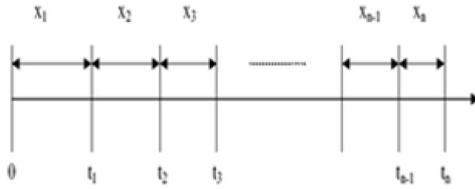


Figure 4. General renewal model.

losses until the “ith” failure. Therefore, if “ t_i ” is time between failures, the component age through time is represented by equation:

$$V_n = V_{n-1} + qX_n \quad (3)$$

where,

X_n = time between (n – 1)th and a nth failure

q^n = restoration factor

V_n = age in time n

V_{n-1} = age in time n–1.

In the second case, the Model Kijima II assumes that re-establishment of component age occurs for all failures throughout component life since the first repair. Thus, this model regards that the “ith” repair remove all reliability losses until “ith” failure. Therefore, the component age through time is represented by equation:

$$V_n = q(V_n + X_n) \quad (4)$$

Figure 4 graphically represents the concept of the General Renewal Model that takes into account the effect of maintenance. The Kijima factor applied in the case study was defined using the software “Weibull 9.0” based on the likelihood method applied in Crown AMSSA Model parameters.

5 LIFETIME DATA ANALYSIS

In order to define equipment, product and services reliability it is necessary to collect historical failure data and treat them statistically.

Therefore, the first step in a lifetime data analysis study is to know how failures occur through time; this is critical for definition of indexes such as failure rate, reliability, availability, reliability through time, in order to support decisions in defining best time to inspection), and maintenance, to check if equipment achieves reliability warranty requirement and to support information to new projects.

Indeed, the decisions based on reliability are based on lifetime data analysis results. This analysis requires historical data about failure modes and

repair time. The failure mode is the way that the equipment or product lost part or total capacity to carry out their function.

Therefore, understanding the type of data required is the first step in the lifetime data analysis process. Essentially, the type of data sample can be grouped or not grouped, meaning that reliability is predicted based on only one equipment item or based on a group of similar equipment. In most cases, when equipment from a process plant is being assessed, the sample is not grouped because, when comparing the equipment to the sample from a similar process plant, factors such as maintenance policy, operational environment and process variation affect equipment reliability differently.

Regarding the data, it is important to understand how data are recorded. Indeed, the data can be complete, right suspension, left suspension, in interval, or a combination of such configurations.

The next step is to apply different goodness of fit methods, such as Rank regression and Maximum Likelihood, to estimate the PDF parameters as well as the best PDF which fits the data assessed.

The final product of lifetime data analysis is the PDF and its parameters that best fit the failure or repair data assessed, as shown in Figure 5.

The Probability Density Function (PDF) describes the possibility of events occurring

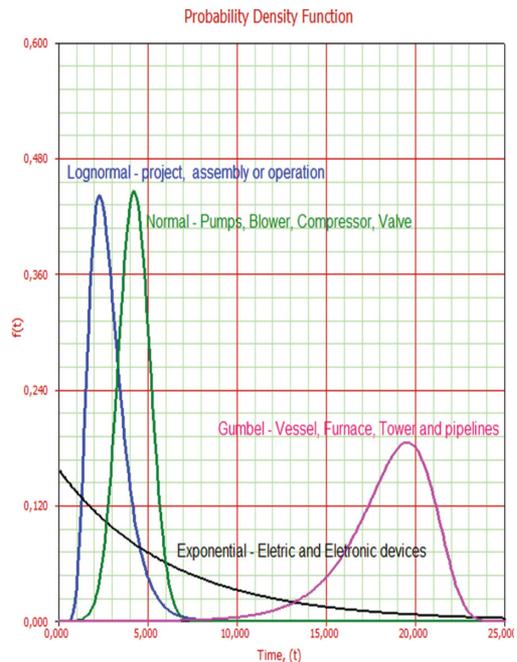


Figure 5. Oil and Gas equipment PDF. Source: Calixto E, 2012.

through time. In equipment life cycle analysis, it describes failure or repair time occurrence through time. This provides good information to a maintenance and reliability professional to make decisions regarding maintenance policy, inspection policy and failure behavior. However, in order to make these decisions, other indexes are required, such as failure rate and reliability function. Figure 6 summarizes the main steps of lifetime data analysis.

Despite a very important method, the lifetime data analysis does not consider the effect of maintenance on equipment degradation. In fact, when applying the PDF parameters to RBD models and then running the direct simulation in RAM analysis, the following events will be similar to the first one.

Therefore, it is important to take into account the degradation effect analysis which is defined by applying the General Renewal Model and Crow AMSSA model, as will be demonstrated in the next section.

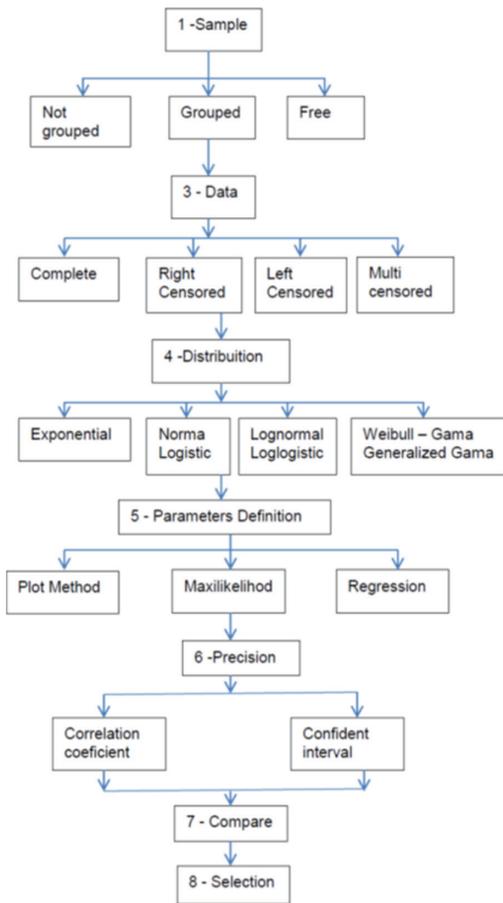


Figure 6. Lifetime data analysis steps.

6 COMPARING DIFFERENT METHODS

In order to predict future failures, it is necessary to take into account the positive or negative maintenance and environment effect on equipment reliability. Therefore, the Reliability Growth Analysis (RGA) can be performed to predict the cumulative number of failures regarding the degradation effect on repairable equipment. The second option is to perform the General Renewal Method to predict the restoration factor and apply it to the RBD for each equipment item or failure mode and run the direct simulation.

In the first case, in order to predict future failures, the Reliability Growth Analysis (Crow AMSSA Model) is applied to define the improvement or degradation in each equipment item as well as taking into account the effect of corrective and preventive maintenance.

This analysis is the most accurate in predicting future failures because it considers all positive or negative effects on equipment performance.

Certainly, the ideal situation is performing this analysis for each component, but due to a lack of precise information in the historical data archive, the analysis is carried out at the equipment level. Figure 7 shows an example of an RGA carried out for a blower.

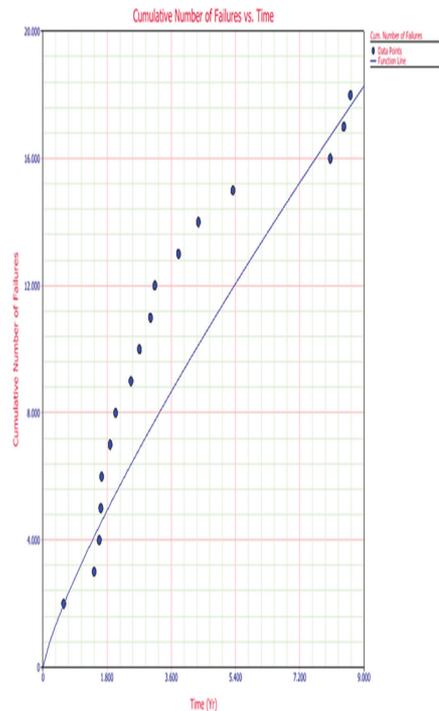


Figure 7. RGA analysis.

The cumulative number of failures during the assessed period is exactly what it is recorded on the database. In addition, the beta parameter, $\beta > 1$, indicates that reliability of this Blower decreases over time ($\beta = 1.74$).

Similar analyses were carried out for other equipment in order to define the cumulative number of failures, as well as to evaluate the effect of maintenance and operational environment by assessing the beta parameter value.

Regarding the second option, the General Renewal Model which defines the type of restoration factor (Kijima I or II) can also be applied. Indeed, this analysis might be adjusted to achieve similar results provided by RGA analysis in terms of cumulative number of failures. Considering that the restoration factor is on the maximum, 1 (100% of restoration), some adjustment is necessary when adjusting the GRM based on RGA results. This adjustment is based on the assumption that the RGA represents the best prediction of future failures. Once the equipment needs to be assessed in the context of a system and not individually, it is necessary to define the PDF and restoration factor for each one and then input the values into the RBD model.

Table 1 shows an example of the final reliability data as result of the RGA, GRM and LDA analyses.

The final step is to validate the reliability database presented in Table 1 by performing individual Direct Simulations (Monte Carlo—MC) in order to check if the PDF and restoration factor were adjusted well to the RGA model prediction. Therefore, the simulation was performed for 10, 15 and 20 years. Table 2 shows an example of future

predictions for some equipment, comparing the RGA and MC methods result.

Tank 1 was assessed only through the MC method because the small number of failures does not enable the RGA analysis. The pumps were assessed by both methods and achieve a similar expected number of failures.

Finally, this approach was applied to all Boiler systems. Thus, it was demonstrated that the PDF and restoration factor were accurate enough to predict future number of failures by the MC method, as the RGA method produced similar results. The next section demonstrates the Boiler system modelled by RBD (reliability diagram block) and the final direct simulation results.

7 RAM ANALYSIS IN DECOMMISSIONING PHASE CASE STUDY

In order to demonstrate the importance of all methods described in previous section, the RAM analysis performed to assess the Boiler system in decommissioning phase will be carried out. The main objective is to define the critical equipment in terms of performance and support decision about which one must to be taken place for a new one.

In this particular case, the boiler system may cause loss of production in the whole refinery in case of outage during winter time. Therefore the RAM analysis took into account the simulation for a specific range of time that in this case is winter time.

Table 1. Reliability data base.

Equipment	Failure	Repair	Kijima factor		Crow AMSSA model					
			Type	q	RF	λ	β			
Tank 1	PDF 2	Parameter (year)	PDF	Parameter (hours)		Type	q	RF	λ	β
	Gumbel	μ σ 7.48 0.01	Normal	μ σ 120 20						
Pump 2	PDF 2	Parameter (year)	PDF	Parameter (hours)		Type	q	RF	λ	β
	Weibull	β η γ 0.56 0.695 0.052	Constant	Repair time 24						
Pump 3	PDF 2	Parameter (year)	PDF	Parameter (hours)		Type	q	RF	λ	β
	Weibull	β η γ 0.47 0.46 1.35	Constant	Repair time 24						
Pump 4	PDF 2	Parameter (year)	PDF	Parameter (hours)		Type	q	RF	λ	β
	Weibull	β η 0.7285 0.564	Constant	Repair time 24						
Pump 5	PDF 2	Parameter (year)	PDF	Parameter (hours)		Type	q	RF	λ	β
	Weibull	β η 0.6363 0.8888	Constant	Repair time 24						
						I	0	1	1.4076	0.5716

Table 2. RGA × MC.

Equipment	10 years		15 years		20 years	
	MC	RGA	MC	RGA	MC	RGA
Tank 1	MC 1	RGA 1.99	MC 1.99	RGA 2	MC 2	RGA
Pump 2	MC 9.7	RGA 8.89	MC 14.09	RGA 10.98	MC 18.3	RGA 12.76
Pump 3	MC 4.24	RGA 3.15	MC 6.44	RGA 4.28	MC 8.56	RGA 5.28
Pump 4	MC 15.37	RGA 12.88	MC 22.6	RGA 19.3	MC 29.91	RGA 25.27
Pump 5	MC 9.06	RGA 8.87	MC 13.23	RGA 12.13	MC 17.42	RGA 15.24

In addition, the LDA, RGA and GRM are part of “RAM model in decommissioning phase” as shown in Figure 2 and such accuracy was demonstrated on Figure 7, Table 1 and 2.

Once the lifetime data analysis step is complete the following step is to Model the RDB and perform the direct simulation.

Figure 8 shows the Boiler System RDB (RDB BQR software) which basically has two subsystems that are Hot Water Boiler and Hot Water Distribution.

The Hot Water Boiler subsystem is represented by the RBD (RDB-BQR software) in Figure 9. In this case, all equipment has standby configuration that enable a high operational availability. Despite high operational availability, the operational cost is high due to number of failures in such equipment.

Figure 10 shows the Hot Water Distribution Subsystem RBD (RDB BQR software) which has the pipes 1, 7 and 8 as the most critical in terms of boiler system unavailability.

After modeling the system the next step is to carry out the direct simulation (MC-Monte Carlo). In this particular case, for the cumulative time of 8 years the boiler has 97.48% of operational availability. The most critical equipment are the pipes 1, 7 and 8 because are those which presents the lower operational availability that is 97%, 97,1% and 97.4% respectively.

Based on simulation result, the future loss of production was predicted based on failure on critical pipes (1,7 and 8). The simulation to predict future loss of production regarded that once the pipes fails during the winter such pipes will be out until the end of the winter. That is a worse scenario as shows picture 11. From the top t the bottom, the first red line represents the pipe 1 shutdown during the winter time. The second red line show the impact of such failure in the boiler system that will be unavailable during the winter once the pipe 1 shutdown.

Based on Boiler system direct simulation, was recommended to take place those critical pipes

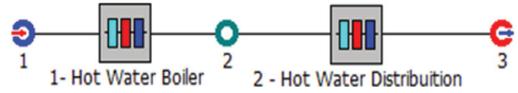


Figure 8. Boiler system.

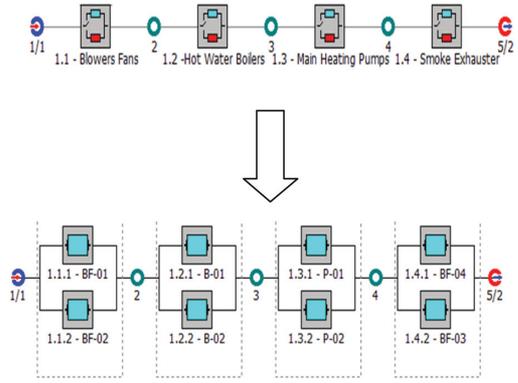


Figure 9. Hot water boiler subsystem.

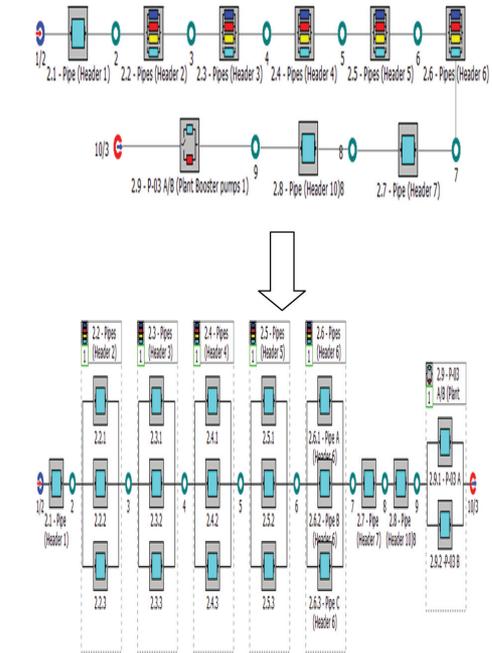


Figure 10. Hot water distribution subsystem.

because based on direct simulation prediction the chance to have such pipe failure during the winter time is 60%. Such probability regards all type of failures on pipes. In case of corrosion, the probability reduces for 10%.

The sensitivity case regarding new subsystems was carried out and in this case the operational availability will achieve 99.92% of operational availability for the next five years if the Hot Water Boiler remains the same and a new Hot Water Boiler will take place. Whether all system be replaced for a new one the operational availability will be 100% in the next 5 years.

The important aspect related decision in decommissioning phase is the Optimum Replace time assessment that defines when each equipment item must be replaced due to the increase operational cost. Regarding this analysis, the boilers must be replaced at 2.34 years because despite not cause impact on system operational availability due to standby configuration the operational cost increase on time as shows the Figure 12.

Similar OPT assessment was carry out for other equipment of Hot Water Boiler in order to define which one must be replaced for the new one due

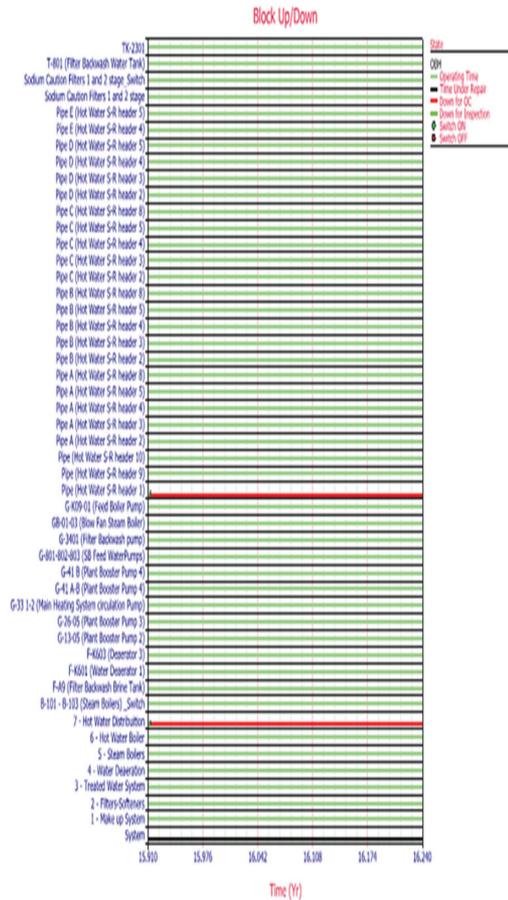


Figure 11. Loss of production during winter.

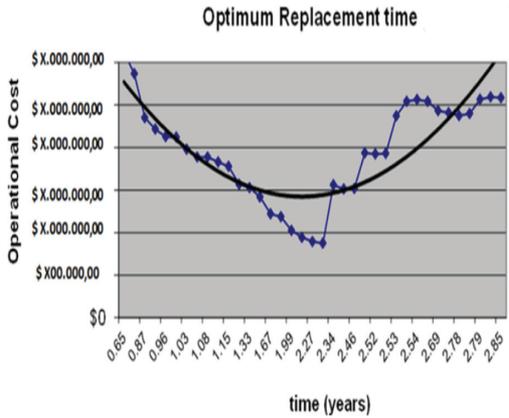


Figure 12. Optimum replace time—water boiler.

to increasing operational cost. In this particular case, because of redundancy configuration the equipment has no impact on Hot Water Boiler operational availability but have high operational cost related to failures.

8 CONCLUSION

The main objective of this paper was to demonstrate the importance of RAM analysis to support decisions regarding asset improvement during decommissioning phase.

In addition, the paper has demonstrated the importance of restoration factors in predicting the future failures of assets that require additional models such as the General Renewal Model and Crow AMSSA model.

The Direct Simulation (MC-Monte Carlo) and CROW AMSAA model were compared and demonstrated to achieve similar results related to equipment future failure prediction. It is important to highlight that it is only possible when is regarded the restoration factor in Direct Simulation and the PDF as well as Restoration factor are adjusted to predict the similar number of failure obtained on the Crow AMSSA method.

In this particular case study, the simulation during a specific range of time (winter) allows prediction of the loss of production. These model characteristics are not present in all software packages, but must be considered as an opportunity to improve, in order to enable simulations for a specific period of time.

The Decommissioning phase is critical in the asset lifecycle and an accurate decision about which equipment must or must not be replaced should be supported by the best Reliability Engineering methods.

The Optimum Replace Time method is not applied in many cases and must be considered in decommissioning phase for all equipment, even for those that do not have a direct impact on system availability in of the event of failure. In many cases the operational cost increases with time, making the asset inefficient from an economic point of view.

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