Reliability, Availability and Maintanability Study of A Power Generation Plant

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ABSTRACT

Power generation plants need to produce electricity on a continuous rate to cater for the electricity demand of the public. The performance of the power generation plant could be evaluated in terms of its availability. By performing reliability, availability and maintainability (RAM) study, the performance of the power generation plant could be investigated. By using the failure and repair data of the power plant, Monte-Carlo simulation was conducted to predict the performance of the power plant system for the next 25 years. From the simulation, the system uptime and downtime duration, system availability, failed components list, spare parts list, and labor costing were obtained. Maintenance planning can be planned by using the results obtained from the simulation. The system was observed to have an average availability of 93% for the next 25 years based on the simulation.

Keywords: *Power plant, RAM study, Monte-Carlo simulation, availability, maintenance planning*

1.0 INTRODUCTION

The purpose of a reliability, availability and maintainability (RAM) Study is to identify critical components or subsystem in an operational system by calculating the RAM parameters, which are reliability, availability and maintainability. Through these parameters, the performance of the system can be determined, and any maintenance actions can be planned accordingly for critical components. Reliability, $R(t)$ is defined as the success probability of a component or system until it reaches or exceeds mission time, t. Reliability is commonly quoted as the mean time between failure (MTBF) of a component or system. The MTBF represents the average time taken for the component to reach a failed state. Mathematically, reliability is represented as:

$$R(t) = P(T \geq t) \tag{1}$$

where T is the operating time of the component and t is the mission time.

Availability, A refers to the probability that the system is operable when required. This parameter is used as a performance measure in this study, as it represents the overall percentage of time the system is operable.

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The general equation of availability is given as:

$$A = \frac{\text{Total Uptime}}{\text{Total Uptime} + \text{Total Downtime}} \quad (2)$$

Maintainability, $M(t)$ refers to the probability that the system can be repaired in a specified period of time. This parameter is defined by the mean time to repair (MTTR), which shows the average time taken for a component to be repaired and returned to its operational state. The mathematical expression for maintainability is given as:

$$M(t) = P(T_{\mathrm{r}} \leq t) \quad (3)$$

where T_r refers to the repair time and t is the repair time.

These parameters are predicted for the upcoming years based on the distribution parameters of the current system. The *Monte-Carlo* simulation is conducted to perform the system simulation and to generate the required data. The methodology for this study is derived from past literatures and adapted to the scope of this study.

2.0 LITERATURE REVIEW

2.1 RAM Study in Food Industry

A study conducted by Tsahouras was designed to determine the critical subsystem in each food production line and to determine the trend of the reliability indices generated [1]. Different types of food production lines were reviewed and compared in terms of the RAM indices. Food production lines have systems connected in series configuration, which causes production stoppage if any of the components fails. This study was able to provide a good explanation regarding the concepts in the reliability engineering.

2.2 RAM Study with Compressor as A System

A study by Corvaro *et al*. focuses on reciprocating compressor used in oil and gas industry model API 618 [2]. This study is different from other studies due to the way the system was analyzed. The compressor is assumed as a system with the components of the compressor are modelled as subsystems.

This type of RAM study is identified as subsystem level RAM study as only the compressor is analyzed rather than the whole system, in which the compressor is a subsystem. The aim of the study is to determine the availability of the compressor and then compare its availability with end user site project standard. The identification and ranking of the subsystems that are major contributors towards unavailability is also carried out to enable planning of maintenance activities.

The RAM analysis is carried out in accordance to documents such as maintenance strategy, piping and instrument diagram, process flow diagram, process operations and control philosophy, and maintenance policy. The data used for calculations includes failure rates and model data collected from several sources. The compressor system in this study is assumed repairable, i.e. the components in the compressor are repairable and need replacing only in extreme damage cases. Reliability block diagrams are generated, and the analysis is performed using *Monte Carlo* analysis technique.

2.3 RAM Study of Mining Process

Barbera *et al*. carried out RAM analysis for a copper smelting process in a mining field of Chile [3]. The RAM study process follows the process of data collection, data management, calculation of RAM indicators, and analysis and interpretation of results. The major difference in this literature compared to the previous literatures is in the complexity of the process during data management stage.

In this literature, the data management stage is carried out by separating the subsystems into repairable or non-repairable equipment/components. This process is not seen in other literatures as it is usually assumed that the components of a system is repairable and then the system is modelled using traditional probabilistic distributions (Weibull, Lognormal, etc.). Another difference is the assumption of independent and identically distributed (iid) data. This assumption determines the usage of either traditional approach or stochastic approach to model the distribution of the data. In this literature, the iid data assumption is not made for repairable components so that a more accurate representation of the data can be obtained. Stochastic approach is used to model the data for repairable system so that we can consider the system change in behavior over time as the failure process in a repairable system will be directly related to the failure rate.

2.4 RAM Study of Thermal Power Plant

This literature discusses work done by Adhikary *et al*. [4], and similarly by Eti *et al*. [5], on a coal-fired thermal power plant. This study was carried out to determine the critical subsystems in the power plant and designing their preventive maintenance program. This way, the availability of the power plant can be improved. The subsystems in the power plant is connected in series.

The RAM study process is almost similar to the other literatures: data collection, frequency of failure analysis, data analysis, distribution fitting of data, RAM Indices calculation and preventive maintenance interval (PMI) estimation. The process detailed in this literature, was adapted and used in the study explained in this paper. However, some slight changes were made in terms of assumptions.

In this paper, the system is assumed to be repairable and only components with independent and identical distributed (iid) data are used for analysis. The procedure of the RAM study in this literature is very helpful in providing a framework to design our own RAM study.

Other similar works for power plants are by Eti *et al*. [5], Murtala *et al*. [6] and Sarkar *et al*. [7]. An alternative method for similar study is offered by Suleiman *et al*. [8].

3.0 METHODOLOGY

The general methodology for conducting a RAM study is obtained from the analysis of past literatures. The basic flow is given in Figure 1:

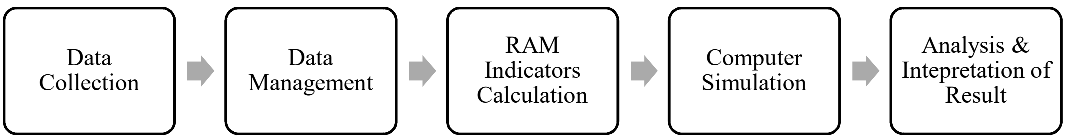

Figure 1: General methodology for conducting a RAM study

In data collection stage or stage 1, failure data needs to be collected from the power plant. The required data are the failure data and repair data. Companies usually employ the usage of maintenance logbook or the usage of computerized maintenance management system (CMMS). The data needs to be collected for a given period.

In data management stage or stage 2, the data needs to be filtered and arranged for analysis. The data needs to undergo frequency of failure analysis, trend test and serial correlation test. In frequency of failure analysis, the components with less number of failure will be eliminated, as the reliability is nearly perfect and the effect on system reliability is negligible. The trend test is conducted to ensure collected data is free of trend, or 'identically distributed'. Identically distributed data shows that the failure rates of the components are constant with no change over the years. Serial correlation test ensures that the failures of components are not interrelated, or 'independent'. The previous failure of a component should not influence the next failure of the same component. This proves a proper repair task has been carried out. Independent and identically distributed (iid) data is a category that will be used to separate the failure data collected.

In the RAM indicator calculations stage or stage 3, data fitting is conducted using goodness-of-fit test to determine the statistical distribution of the collected failure data. iid data can be fitted using the traditional probabilistic distributions such as *Weibull* and *Lognormal*. Meanwhile, non-iid data needs to be fitted using stochastic approach.

In the computer simulation stage or stage 4, the distribution parameters of the components are used to generate simulated data. Inverse transform sampling method is used to randomly pick data from the distribution of each component. The data is then applied to the reliability block diagram (RBD) of the system to generate the system data. The RBD of the system defines the characteristic of the system.

In the analysis stage or stage 5, the results obtained from simulation – system uptime and downtime, system availability and failed components list are used for maintenance planning. The data is used to plan for the labor cost and spare part list.

In this study, data for stage 1-3 was collected from article by Adhikary *et al*. [4]. Stages 4 and 5 were then continued as described above. The data was collected from the power plant maintenance logbook over a 12-year period [4].

3.1 Reliability Block Diagram (RBD) of the power plant system

The components in a power plant are connected in a very complicated manner. RBD is usually generated based on the process flow diagram (PFD) of the power plant. In this study, the components and their connections are identified from the article by Adhikary, *et al*. [4]. The components and their connection are shown in Figure 2.

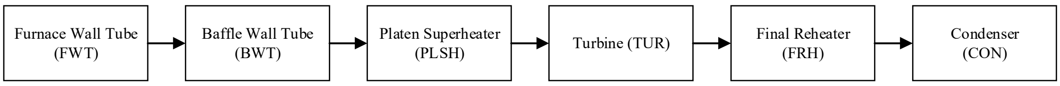

Figure 2: RBD of the system

The RBD shows the components are connected in series. This can be used to determine the characteristic of the system. This system shown will fail if any one of the components fails. This characteristic needs to be accurately represented in the simulation stage.

3.2 Distribution Parameters

From the data management stage, after performing data fitting using *Kolmogorov-Smirnov* test [4], the distribution of each component shown in Figure 2 can be identified. The data fitting is performed for the failure data (time between failure) and repair data (time to repair)

The distribution parameters for time between failure and time to repair data are shown in Tables 1 and 2, respectively. These parameters were then used in the *Monte-Carlo* simulation to obtain the simulated data for the next 25 years.

3.3 Monte-Carlo Simulation

Monte-Carlo simulation uses random input taken from the distribution if the components and generates the output of the system in the form of system uptime and downtime. Figure 3 shows the basic concept of *Monte-Carlo* simulation.

Table 1: Distribution parameters of components for time between failure (TBF) data

Component	Distribution	Shape Factor	Scale Parameter	Mean (MTBF)
FWT	Weibull	$\beta = 2.010$	$\theta = 8775$ hours	7776 hours
BWT	Lognormal	$1/s = 1.797$	$t_{med} = 13963$ hours	16301 hours
PLSH	Weibull	$\beta = 1.600$	$\theta = 15350$ hours	13762 hours
TUR	Weibull	$\beta = 2.470$	$\theta = 14818$ hours	13144 hours
FRH	Weibull	$\beta = 1.470$	$\theta = 11638$ hours	10533 hours
CON	Weibull	$\beta = 1.190$	$\theta = 2778$ hours	2619 hours

Table 2: Distribution Parameters of components for Time to Repair (TTR) data

Component	Distribution	Shape Factor	Scale Parameter	Mean (MTTR)
FWT	Lognormal	$1/s = 1.330$	$t_{med} = 75$ hours	99.50 hours
BWT	Lognormal	$1/s = 0.950$	$t_{med} = 105$ hours	182.73 hours
PLSH	Weibull	$\beta = 1.990$	$\theta = 235$ hours	208.28 hours
TUR	Lognormal	$1/s = 3.413$	$t_{med} = 143$ hours	148.27 hours
FRH	Lognormal	$1/s = 1.818$	$t_{med} = 128$ hours	148.90 hours
CON	Weibull	$\beta = 0.950$	$\theta = 23$ hours	23.54 hours

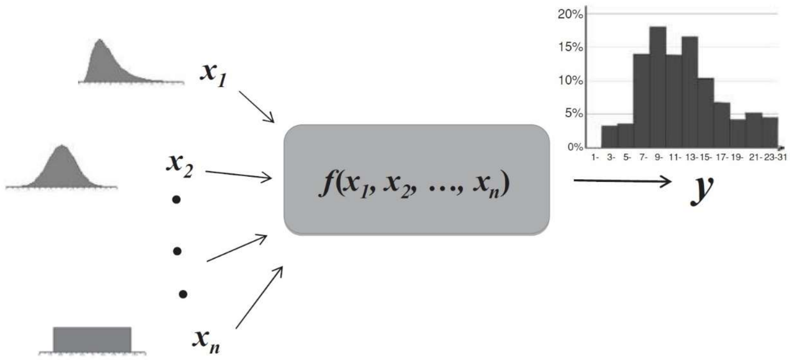

Figure 3: Basic concept of *Monte-Carlo* simulation [9]

The random inputs from each distribution is generated with the inverse transform sampling method [9]. This method randomizes the failure probability for each component and then generated the time data using the cumulative distribution function of the components. Each distribution has its own cumulative distributive function, which depends on the scale parameter and shape factor shown in Tables 1 and 2. The cumulative distributive function of *Weibull* distribution is [10]:

$$F(t) = 1 - e^{-\left(\frac{t}{\theta}\right)^{\beta}} \tag{4}$$

where $F(t)$ is the failure probability, t is the failure/repair time, θ is the scale parameter, and β is the shape factor.

This data generation process was simplified using MATLAB coding. Built-in functions, 'wblrnd' and 'lognrnd' were used to create the random input for the simulation. The inputs were then applied to the RBD of the system to model the system characteristics. This will generate the system uptime and downtime data. By tracking the generated data, we were able to identify the failed component that caused the system failure.

The system simulation was repeated for 25 times, and the results were averaged. The number of failures for each trial is random, therefore, by repeating 25 trials, we can produce stable and accurate results by taking the statistics.

4.0 RESULTS AND DISCUSSION

4.1 Component Time between Failure (TBF) and Time to Repair (TTR) Data

The results obtained from the simulation are the TBF and TTR data for each component. This is the input data for the system simulation. Table 3 shows a sample of generated data for furnace wall tubes (FWT) from its distribution parameters.

Table 3: Sample generated data for furnace wall tubes (FWT), first trial

TBF (hours)	TTR (hours)
6210.2237	92.7766
3003.9586	99.8483
3391.5974	136.8222
4332.6458	82.6455
20334.7361	46.1057

Using this data and generated data for all the components, we could model the behavior of the system. If any one of the components fails at a specific time, the system will also fail at the same time as the components which made up the system are arranged in series. The number of generated data for each trial is different as the data sampling process is randomized.

4.2 System Uptime and Downtime

System uptime and downtime results were generated using the MATLAB coding, which mimic the characteristic of the system specified in the RBD of the system in Figure 2. A sample of the system uptime and downtime graph is shown in Figure 4.

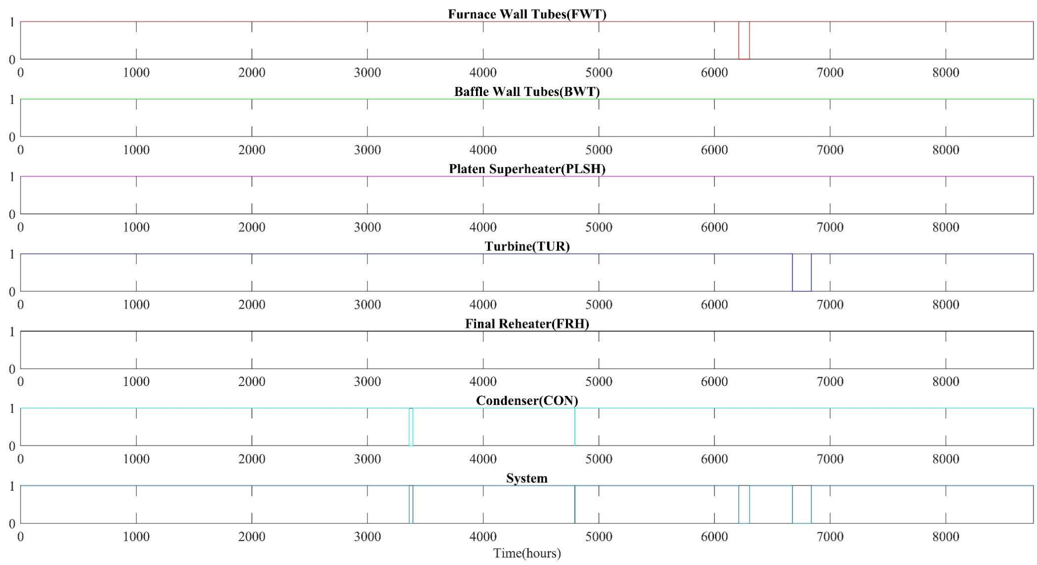

Figure 4: Sample of components and system uptime and downtime for first year, first trial

From Figure 4, we could determine the component responsible for each of the system failure. This shows that the MATLAB coding was able to successfully portray the characteristics of the system. From this result, we could obtain the system availability and failed components list for each year.

An important aspect to note in this graph is that the repair operation was done when failure has occurred. This shows that from simulation, we could predict the corrective maintenance schedule for the components and the system.

4.3 System Availability

By using the information generated for system uptime and downtime and applying the formula in Eq. (2), we could calculate the system availability for each year. The calculation is performed for each year and for each trial. The average, maximum and minimum availabilities for each one year can be obtained from the 25 trials.

Table 3: Sample of system availability on yearly basis

Year	1	2	3	4	5	…	25	25-year Average
Average	0.9616	0.9275	0.9418	0.9383	0.9291	…	0.9305	0.9319
Max	0.9987	0.9692	1.0000	0.9773	0.9782	…	0.9810	0.9433
Median	0.9650	0.9365	0.9512	0.9442	0.9352	…	0.9410	0.9332
Min	0.8825	0.8444	0.8376	0.8662	0.8567	…	0.8070	0.9202

From Table 3, we could observe that, on average, the system has more than 90% availability on a yearly basis. The same is true for the 25-year average availability of the system. The availability is presented in form of average, maximum, median and minimum to provide a better statistical information about the availability. This is because from the 25 trials conducted, we obtain different results for each trial and this method could give us a range of availability to measure our system. For example, for year 1, we could see that the availability has a range of 88.25 % to 99.87% with average of 96.16%. This way, the worst-case scenario for the system during year 1 can be identified as having availability of 88.25%.

This result can be linked to failed component list to identify the components that can cause the system availability to deteriorate. From the results, we can conclude that the system has a high availability, but there are rooms for improvements. To improve the system availability, we need to increase the system uptime (the time which system is in operation). One way to improve system availability is by performing preventive maintenance on predicted failing components.

4.4 Failed Component List, Spare Part List and Inventory Planning

From the generated system uptime and downtime, we could retrace the component that causes system failure. This data could be used to prepare for spare parts list, inventory planning and budgeting. In this project, the failed component is listed on a maximum number basis, because we could not calculate the average components required on yearly basis. Due to random data generation, the failure number in each trial is different causing this problem to arise. Therefore, using the maximum number of failed components as a measure, we could prepare for the worst-case scenario among the 25 trials.

This is also part of the maintenance planning, where this information can be used as expected number of failures for each year. By obtaining this list of failed components, we could prepare for the worst-case scenario of the system. The sample of the list of failed components is provided in Table 4:

Table 4: Sample of maximum failed component on yearly basis

Failed component	Year 1	Year 2	Year 3	Year 4	…	Year 25	Total by component
FWT	2	3	3	3	…	2	35
BWT	1	1	1	1	…	2	18

PLSH	1	2	2	1	…	2	19
TUR	1	1	1	2	…	2	17
FRH	1	2	1	2	…	2	25
CON	5	6	5	6	…	6	97

We could use this list as the required spare part list and plan our inventory accordingly. The spare part list obtained would be based on the worst-case scenario of the system, as the failed component count is determined on maximum basis from all 25 trials. Therefore, the probability that the number of failure and the number of spare parts required exceeding the maximum limit is very low. This ensures that we would have adequate amount of spare parts prepared for each year and any excess spare part can be used in the upcoming years.

In this study, we could not identify the specific spare part for each subsystem due to lack of data. The generated list of spare parts provides only the required number without any reference to any specific parts, as it is derived from the maximum failed component list provided in Table 4. The spare parts list can be used to predict the spare part cost if we can obtain the cost of the specific failed part of each component.

4.5 Labor Cost

Another use of the maximum failed component list is to determine the labor cost required to perform the repair operation. We could not estimate the spare part costs, as we do not have the required data. In this study, the time required for each repair operation is assumed as the MTTR of each component, as shown in Table 2.

In this study, assumption is made on the required number of technicians for each repair task and the hourly pay rate for a maintenance technician. Each repair task is assumed to be performed by a technician. This assumption is made because we do not have the nature and complexity of the failure, as repair task with higher complexity will require more number of technicians. The pay rate for a maintenance technician is assumed to be RM 20.50/hour. By using the MTTR, maximum failed component list, and pay rate, we could estimate the required labor cost on a yearly basis as

$$\text{Labor cost per component} = \text{MTTR} * \text{Pay Rate} * \text{No. of Failure} \tag{5}$$

The labor cost shown in Table 5 can be used as a budget planning for the power plant. Table 5 shows only the cost involved from the actual repair time involved, whereas in actual scenario, the repair time will involve administration delays, logistic delays and many more. The total cost for repair should also include the spare part costs.

Table 5: Sample of maximum labor cost on yearly basis

Component	Year 1	Year 2	Year 3	Year 4	…	Year 25
FWT	4079.50	6119.25	6119.25	6119.25	…	4079.50
BWT	3745.97	3745.97	3745.97	3745.97	…	7491.93
PLSH	4269.74	8539.48	8539.48	4269.74	…	8539.48
TUR	3039.54	3039.54	3039.54	6079.07	…	6079.07
FRH	3052.45	6104.90	3052.45	6104.90	…	6104.90
CON	2412.85	2895.42	2412.85	2895.42	…	2895.42
Total Cost (RM)	20600.04	30444.55	26909.53	29214.35	…	35190.30

5.0 CONCLUSION

Reliability, availability and maintainability (RAM) study was conducted on a power generation plant. Preliminary data was obtained from an article because we could not obtain the failure data. By applying the reliability concepts, the reliability block diagram (RBD) was obtained from the process flow diagram (PFD) of the power plant. The RBD of the power plant is identified to be in series, which means that failure of any component in the system will result in the failure of the system. The distribution parameters of the components in the system is obtained from the article as well. *Monte-Carlo* simulation was then conducted using MATLAB programming for 25-year lifetime based on 25 trials for every one-year operation. The results obtained from the simulations were the simulated component time between failure (TBF) and time to repair (TTR), and the simulated system data. From there, we were able to determine the availability of the system for overall of 25 years and on a yearly basis. The system has a 25-year average availability ranging from 92.02% to 94.33% with an average of 93.19%. The system data was also used to determine the list of maximum failed component for each year. This list is used to determine the spare parts lists and to calculate the labor cost for repair operation. Some basic maintenance planning was also discussed based on the results obtained.

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