Determining Optimum Maintenance Interval of Critical Equipment in Geothermal Power Plant Based on Reliability Value and Cost Ratio

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Abstract

Geothermal industry unit capital cost and electricity tariff has been competing with lower-cost power generators. This situation has challenged all people that work for the industry to optimize their plant reliability, increase revenue, and reduce cost. Maintenance activities can be considered a critical process which can be very costly if those activities are not managed properly. Part of maintenance management is to determine the optimal maintenance interval with the lowest maintenance cost. This paper determines the optimal maintenance interval of the most critical subsystem in a big-scale geothermal generation facility in Indonesia. The most critical subsystem of the facility is chosen based on reliability value. One of the tools chosen in the industry as a framework for evaluating system reliability is Reliability Block Diagram (RBD). Based on RBD, the most critical sub-system is the Cooling Tower Structure System which consists of two equipment, the Cooling Tower Fan, and the Cooling Tower Structure. The optimum maintenance of the Cooling Tower Fan was calculated using the total cost model equation. Sensitivity analysis is also carried out in this paper to determine the cost ratio at which maintenance cost and failure cost calculations must be calculated in detail. To obtain optimum maintenance intervals with a certain confidence interval value, the data resampling with the bootstrap method is applied to the equipment failure data due to the limited amount of data. The difference in maintenance interval value between the original data and the bootstrapped data is relatively small with a maximum of 5.1% difference.

Keywords
The geothermal power plant, Reliability Block Diagram, Optimum maintenance interval, Bootstrapping.

1. Introduction

Indonesia is a country located on the boundary of the Indo-Australian and the Eurasian tectonic plate. Those tectonic plates generate numerous active volcanoes stretching from Sumatera up to Sangihe Island, resulting in many high-enthalpy geothermal resources in these areas. The geothermal resource potential of Indonesia is approximately 24 000 Mwe (Fauzi 2015). This huge resource can be an alternative to replace fossil-based thermal power plants for generating electricity and reducing carbon emissions.

Compared with an oxyfuel power plant, the geothermal power plant has a higher upfront capital cost. The most likely investment cost for a 40 MW unit of a geothermal power plant is 57.6 million $ with upper and lower limits 79.1 and 44.9 million $ respectively. This gives the cost range of 1122 –1992 $/kW with the most likely value of 1440 $/kW (Stefansson 2001). Compare with an oxyfuel power plant retrofitted from a typical traditional 2×600MW power plant, the unit capital cost is 4926.30 RMB/kW (Fan et al. 2020) or 734 $/kW. The investment cost of an oxyfuel power plant is almost a half of geothermal power plant.

This situation has concluded that only by optimizing plant reliability, decreasing operating costs, and increasing revenue, the geothermal power plant can compete with another thermal power plant in the whole life cycle cost. Robertson and Jones (2004) surveyed maintenance costs for various industries and showed that maintenance costs are ranging from 2% (light manufacturing) to 90% (equipment-intensive industry and utility sector) with an average of 20.8% of the total operating budget. Based on that survey, it will be significant savings in maintenance costs if the operation team can make the right and opportune maintenance decisions (Jardine and Tsang 2013). One of the important maintenance decisions is determining the optimum maintenance interval that minimizes maintenance cost.

Due to the large quantity of geothermal power plant equipment, this paper will focus on generating facility equipment and calculating the optimum maintenance interval of critical system equipment based on reliability value. The reliability value of generating facility equipment was determined by actual failure data and was analyzed by Reliability Block Diagram (RBD).

1.1 Objectives

Many factors affect the determination of the right maintenance interval, including the availability of spare parts and consumables, manpower, production demand, availability of tools and heavy equipment, contract availability, and many others. One factor that is also important to determine the optimal maintenance interval is the probability of failure of equipment and how much the cost of failure is compared to the cost of maintenance.

This research has two main objectives as following:

1. Determine the optimum maintenance interval of geothermal power plant critical equipment based on equipment reliability and the ratio between failure costs and maintenance costs.
2. Determine the maintenance interval with a certain confidence interval by using bootstrap data resampling.

To achieve the objectives of this research, several steps must be taken, these steps are: developing RBD from a geothermal generating facility which describes the reliability relationship between components, generating failure distribution of each equipment from failure data, and testing the distribution fits, determining the most critical system equipment based on reliability value, determining the optimum maintenance interval of critical equipment and resampling the failure data to get the maintenance interval with the certain confidence interval value.

2. Literature Review

This paper structured the literature review into four subsections. Subsection 1 describes the brief concept of reliability including the methodologies to analyze the system reliability model. Subsection 2 describes the type of maintenance strategy and common method to determine the optimum maintenance interval. Subsection 3 shows how reliability analysis is applied in various industries. The last subsection describes the statement of the art of this research.

2.1 Reliability

The term "Reliability" has been rising as a fundamental attribute for the operation of any modern technological system (Zio 2009). The simplest definition of reliability is the probability of a successful operation (Stapelberg 2009). USA military standard (M1L-STD-721B) has defined the complete definition as stated, "Reliability is the probability that an item will perform its intended function for a specified interval under stated conditions".

Several methodologies are used to analyze the system reliability model, but two types of analysis are often used to model a system's reliability behavior, Fault Tree Analysis (FTA) and Reliability Block Diagrams (RBD) (Ram 2013). FTA is the analysis that uses a graphical method that models how failures propagate through the system and how component failures lead to system failures (Ruijters and Stoelinga 2015). A reliability block diagram (RBD) is a graphical analysis that expresses the system as a connection of several components based on reliability relation (Guo and Yang 2007). Those type of analysis has a similar method that uses a graphic to describe the connection between components and to show how the failure of each component affects the whole system.

Traditional FTA can only model systems in which a combination of failed components results in a system failure, regardless of when each of those component failures occurred. In a complex system, the failure of the whole system may not happen if the failure of each component occurs in a different order of sequence. To adopt this phenomenon, Dynamic Fault Tree (DFT) has been studied as an extended version of traditional FTA (Ruijters and Stoelinga 2015).

2.2 Maintenance Interval

The Failure and erosion of system components are inevitable and because of this condition, a comprehensive structure for their maintenance is a crucial issue (Enjavimadar and Rastegar 2022). Three types of maintenance strategies are common in industrial applications. The first type is corrective maintenance as the simplest strategy of maintenance which is only conducted when a component failed. The second type is preventive maintenance or time-based maintenance which is conducted at a certain frequency or time before the component fails without considering the component's condition. The last one is predictive maintenance or condition-based maintenance which is conducted frequently but need to consider the component condition before carrying out further maintenance action.

This research focuses on preventive maintenance activity, that repairs or replaces a component at a certain interval. How to find the right maintenance interval has been a question for many people involved in maintenance organizations because the maintenance interval has a significant impact on the overall maintenance cost. Jardine and Tsang (2013) have explained how to determine the optimal maintenance interval based on failure data of equipment, failure costs, and maintenance costs. BULUT and ÖZCAN (2021) used a cost ratio curve in the Weibull shape parameter and cost ratio chart to determine the optimum maintenance interval for hydroelectric power plant equipment.

The maintenance interval is difficult to set at a fixed time without tolerance because many factors influence planning a maintenance job, including production demand, availability of spare parts and labor, and others that can make the maintenance interval slightly shift. Because of these factors, it would be better if the maintenance interval is determined within a certain range. Due to limited failure data from equipment, determining the maintenance interval with a certain range will be difficult. One method to obtain a maintenance interval with a certain range is data resampling using the bootstrap method. Bootstrap is a resampling method that involves the extraction of a bootstrap sample of size n with the original data of the original sample. The samples are used to test the statistical characteristics of the unknown distribution, such as mean, variance, standard deviation, and confidence interval (Zhang et al. 2019). There are two types of bootstrap method, parametric bootstrap which use assumed distribution data to be resampled, and non-parametric which used original data to be resampled and then found the statistical characteristic.

Doss and Chiang (1994) have developed two types of new bootstrapping methods that have been applied to a simple RBD system, namely: Model-Free and Model-Based. Marks et al. (2014) have also analyzed the bootstrapping method for more complex RBD systems with a new method to eliminate resampling errors.

2.3 Reliability Analysis in Application

Reliability analysis has been widely applied in various industrial fields. In the food industry, reliability analysis uses to determine periodic maintenance and scheduling and managing the appropriate maintenance policy in cheddar cheese manufacturing plant (Tsarouhas 2022). In the energy sector like the oil and gas industry and power, reliability analysis has been used to optimize system availability. Many subsystems in a thermal power plant such as the water circulation system (Jagtap et al., 2021), and coal handling unit (Kumar and Ram 2013) have been studied to determine the reliability parameter and the critical subsystem (Adhikary et al. 2012). Reliability analysis has also been applied to determine optimal preventive maintenance for the Well Barrier Element components in the oil and gas industry (Siswanto and Kurniati 2018).

In renewable energy, reliability analysis has been used to identify the critical subsystem and improve the system reliability of grid-connected solar photovoltaic systems (Sayed et al. 2019). Reliability analysis has also been applied to the geothermal industry by using Monte Carlo simulation (Popescu et al. 2003) and stochastic evaluation (Felea et al. 2014). In the renewable energy industry, most reliability studies are using non-actual reliability data, such as general reliability databases, literature reliability data, or using random number generators to generate reliability random variables.

2.4 Statement of the Art

From the literature review, it can be concluded there is only a little research on the reliability analysis of geothermal power plants. Research on reliability analysis of geothermal power plants has also not shown a reliability relationship between the components. Reliability analysis of geothermal power plants also still uses random values as failure data and not actual maintenance data. This research used actual data taken from CMMS.

This study uses a reliability block diagram to describe the reliability relationship between components. The system to be studied is the generating facility in the geothermal power plant. Generating facility was chosen as the system under study because it is an important system in geothermal power plants to convert geothermal steam into electricity. The generating facility also has a more complete component reliability relationship to be described in RBD, namely series, parallel, and k-out-of -n operations.

The optimum maintenance interval is determined using the total maintenance cost equation which is based on the failure distribution of the equipment and the cost ratio between failure costs and maintenance costs. Sensitivity analysis is also carried out in this paper to determine the cost ratio at which maintenance cost and failure cost calculations must be calculated in detail because if there is a small change in the cost ratio, the maintenance interval can shift by a large value.

In this research, resampling failure data using the bootstrap method was carried out to determine the optimum maintenance interval within a certain range. In this range, the maintenance interval number is the optimum value at a predetermined confidence interval.

3. Methods

The research methodology can be divided into 3 major stages, namely reliability analysis, optimum maintenance interval, and data bootstrapping. This research methodology can be seen in Figure 1 below.

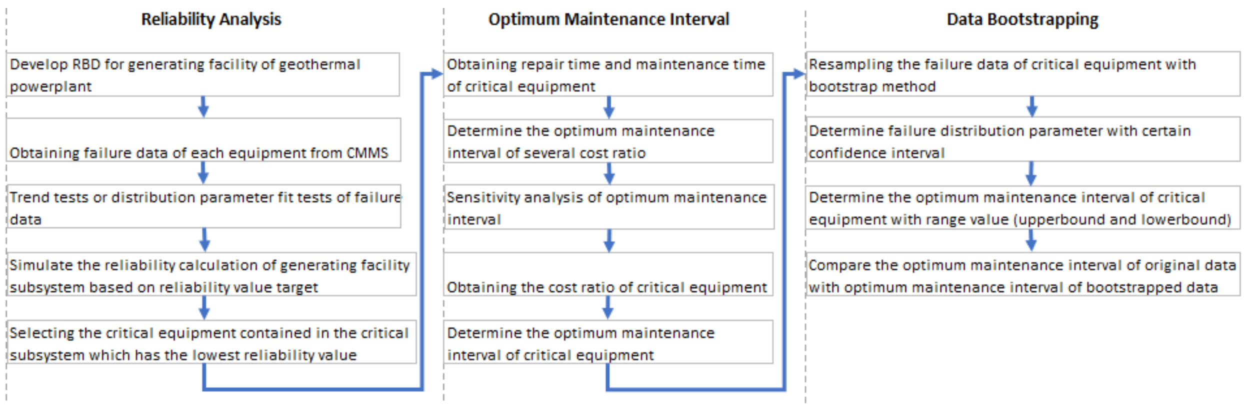


Figure 1. Research Methodology

3.1 Reliability Analysis

In this research, the first step in reliability analysis is to construct an RBD from a generating facility. The generating facility of a geothermal power plant starts with steam entering the turbine control valve and ejector system until the electricity generated enters the electric substation. There are 34 types of major equipment that make up 24 subsystems in the generating facility. Those subsystems can be divided into two types, namely electrical system and mechanical system that is connected in series relation which can be seen in Figure 2.

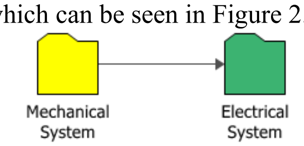


Figure 2. System in generating facility.

There are 16 subsystems in the mechanical system and 8 subsystems in the electrical system which can be seen in Figure 3 and Figure 4. In this subsystem, several types of equipment are connected to other equipment in a reliability relationship.

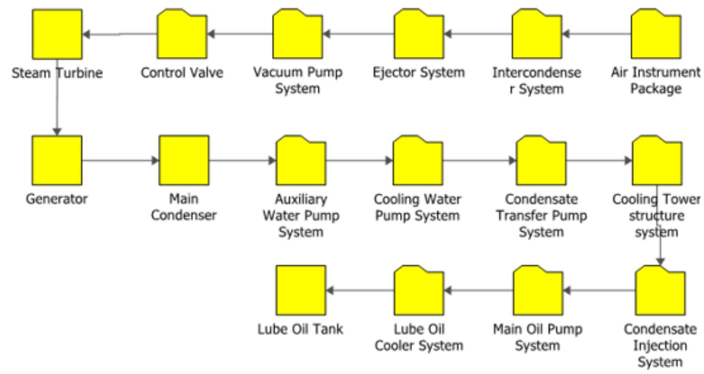


Figure 3. Mechanical subsystems

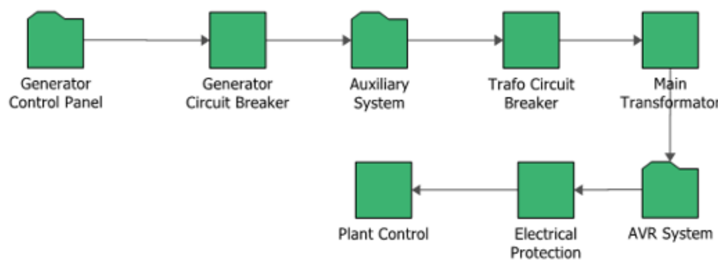


Figure 4. Electrical subsystem

Three types of configurations are commonly described in the RBD, namely: series configuration, parallel configuration, and k-out-of-n operation configuration. Let

R_s = System reliability
R_i = Unit *i* reliability
n = Total number of units in parallel
k = Minimum number of units required for system success
R = Unit reliability

In a series configuration, a failure of any equipment results in the failure of the entire system. System reliability of series configuration can be calculated by using Equation (1).

$$R_s = \prod_{i=1}^{n} R_i \tag{1}$$

In a parallel configuration, a system needs at least one equipment survived for the system to survive. System reliability of parallel configuration can be calculated by using Equation (2).

$$R_s = 1 - \prod_{i=1}^{n} (1 - R_i) \tag{2}$$

The k-out-of-n operation configuration requires at least k equipment to survive out of the total n parallel equipment for the system to survive. System reliability of k-out-of-n operation configuration can be calculated by using Equation (3).

$$R_s(k, n,\ R) = \sum_{r=k}^{n} \binom{n}{r} R^r (1 - R)^{n-r} \tag{3}$$

After the RBD is developed, the failure distribution of each equipment is determined as the input of each block. Failure distribution can be determined from the time between failure data of each equipment obtained from the actual CMMS data. The actual CMMS data used in this study is failure data from 2006 to 2021. The time between failure data needs to be tested using a trend test or distribution fit test to determine the fittest distribution function and parameter value. This research uses the Anderson-Darling test of Minitab software to test the data and uses a p-value of 0.05 to accept the distribution function and parameter value. If the failure data has a p-value of more than 0.05, then Ho that the data follows the distribution is acceptable. This research used Maximum Likelihood Estimation (MLE) method to estimate the parameter value of the distribution.

An example of the results of the distribution fit test of vacuum pump separator failure data can be seen in Figure 5 with the selected distribution function is the gamma distribution with a p-value > 0.250.

Goodness of Fit Test

Distribution	AD	P	LRT P
Normal	1,864	<0,005	
Box-Cox Transformation	0,774	0,041	
Lognormal	0,774	0,041	
3-Parameter Lognormal	0,628	*	0,345
Exponential	1,798	0,014	
2-Parameter Exponential	1,163	0,055	0,018
Weibull	0,498	0,214	
3-Parameter Weibull	0,519	0,198	0,086
Smallest Extreme Value	6,374	<0,010	
Largest Extreme Value	0,566	0,150	
Gamma	0,453	>0,250	
3-Parameter Gamma	0,454	*	1,000
Logistic	0,727	0,034	
Loglogistic	0,787	0,023	
3-Parameter Loglogistic	0,724	*	0,674
Johnson Transformation	0,487	0,214	

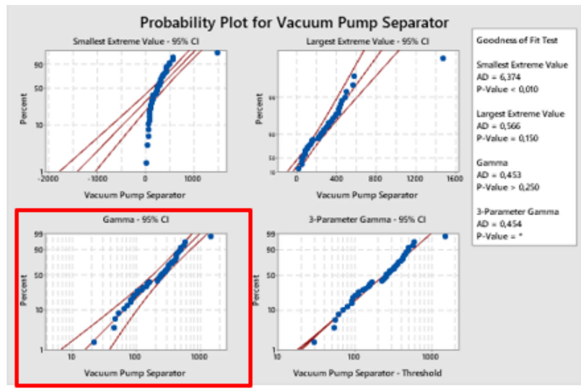


Figure 5. Distribution fit test of vacuum pump separator.

The distribution function and parameter value are used as input into the block on each equipment. After all the distribution functions are entered into each block, the system reliability simulation is run based on the system reliability target values which range from 0.99 to 0.80. The selected critical equipment is the equipment contained in the critical subsystem that has the smallest reliability value.

3.2 Optimum Maintenance Interval

Optimum maintenance intervals can be determined using the total cost maintenance equation which can be formulated by Equation (4) below (Jardine and Tsang 2013).

$$C(t_p) = \frac{C_p R(t_p) + C_f[1 - R(t_p)]}{(t_p + T_p)R(t_p) + \int_o^{t_p} tf(t) + T_f[1 - R(t_p)]} \tag{4}$$

Where:

$C(t_p)$	= Total cost per unit time	t_p	= Time interval
C_f	= Cost of failure	$R(t_p)$	= Reliability at t_p
C_p	= Cost of preventive maintenance	T_p	= Preventive maintenance duration
$f(t)$	= Failure probability distribution function	T_f	= Failure duration

Preventive maintenance cost and failure cost have been obtained but the value has not been shared due to confidentiality. This research proposed variable *r* as the ratio between failure cost and preventive maintenance cost. Equation (4) can be modified by dividing the right side and left side of the equation with C_p which can be seen in Equation (5).

$$\frac{C}{C_p}(t_p) = \frac{R(t_p) + r[1 - R(t_p)]}{(t_p + T_p)R(t_p) + \int_o^{t_p} tf(t) + T_f[1 - R(t_p)]} \tag{5}$$

Where:

r $= C_f / C_p$

The optimum maintenance interval is calculated with various cost ratio *r* values ranging from 2 to 80 with a period of eight years to perform a sensitivity analysis. Sensitivity analysis is conducted to determine the cost ratio at which maintenance cost and failure cost calculations must be calculated in detail because if there is a small change in the cost ratio, the maintenance interval can shift by a large value. The final step of this analysis is to calculate the optimum maintenance interval for critical equipment with the actual *r* value.

3.3 Data Bootstrapping

This study uses non-parametric bootstrap by resampling the actual failure data of critical equipment to obtain the optimum maintenance interval within a certain range. In this range, the maintenance interval number is still the optimum value at a predetermined confidence interval. The steps for bootstrapping of actual failure data $(x_1, \ldots\ldots, x_n)$ are as follows:

- Simulate k samples of size n by randomly sampling among the available data (with replacement).
- Calculate the distribution parameter value θ using the MLE method in each of the k samples $\hat{\theta}_1^*, \ldots\ldots, \hat{\theta}_k^*$.
- Find the distribution parameter value at a certain confidence interval.

Pattengale et al. (2010) reviewed the standard text of Bootstrap that suggests choosing a sufficiently large number of data resampling without addressing exact bounds. Efron and Tibshirani (1994) suggest that 500 data resampling is sufficient for the general standard bootstrap method in most cases. This research simulated 1000 times data resampling with MATLAB software and use alpha 0.05 (95% confidence interval) to find the distribution parameter then calculate the maintenance interval lower bound and upper bound and compare it with the maintenance interval that uses original data.

4. Data Collection

Reliability analysis relies on historical data, and the collection of these data represents the first step (Garmabaki et al. 2016). Failure data can be collected from three sources: the Computerized Maintenance Management System (CMMS) for actual failure data, the general reliability database, and literature reliability data.

After collecting the reliability data, this data needs to be processed by testing the trend data before selecting the best fit of life distribution. Common analytical trend tests such as Laplace, Anderson-Darling, and The Mann test can be utilized to determine the existing trends in inter-failure times (Garmabaki et al. 2016).

This research used the actual failure data from CMMS. The failure data can be defined from the corrective work order of CMMS. Corrective work order contains a lot of information including equipment number, failure description, duration, start date, and finish date. Some equipment that did not have a failure history is considered to have a static reliability value of one. This research uses the Anderson-Darling test of Minitab software to test the data and uses a p-value of 0.05 to accept the distribution function and parameter value.

5. Results and Discussion

5.1 Reliability Analysis and Critical Equipment

After the failure data for each equipment is obtained, the time between failure data needs to be tested using a trend test or distribution fit test to determine the fittest distribution function, and parameter values were defined by MLE. Test results of 33 equipment can be seen in Table 1 below.

Table 1. Distribution fit test and parameter value

No	Model Name	Distribution	Model Unit	Parameter 1	Parameter 2	Parameter 3	P-value
1	Vacuum Pump Separator	Gamma	Day (day)	5.054033743	1.77393		>0.250
2	Air Compressor	Lognormal	Day (day)	5.60722	1.4633		0.315
3	Air Dryer	Lognormal	Day (day)	5.40449	1.04959		0.439
4	Seal Water Separator Pump	Lognormal	Day (day)	5.45418	0.93288		0.767
5	EHC	2P-Weibull	Day (day)	2.61066	500.18344		>0.250
6	Steam Turbine	Normal	Day (day)	7530.333398	507.59268		0.545
7	Cooling Tower Fan	3P-Weibull	Day (day)	1.23236	636.54088	14.39004	0.5
...	....	......	......	......	......	......	......
28	Insulated Phase Busduct	Never Failed					
29	Plant Control	Never Failed					
30	Main Transformer	2P-Weibull	Day (day)	2.5411	850.3031		>0.250
31	Electrical Protection System	Never Failed					
32	Transformer Circuit Breaker	Never Failed					
33	Ejector	Exponential	Day (day)	1974.85714			0.305

All distribution functions and parameter values are used as input into the block on each equipment. After all the distribution functions are entered into each block, the system reliability simulation is run based on the system reliability target values which range from 0.99 to 0.80 by using Blocksim Reliasoft. The result of the simulation can be seen in Table 2.

Table 2. Reliability value of generating facility

Block	Reliability					
Generating Facility	0.99	0.97	0.95	0.9	0.85	0.8
Mechanical System	0.993875	0.978566	0.962175	0.919283	0.874868	0.830408
Control Valve	0.999662	0.999102	0.998593	0.997369	0.996143	0.994902
Steam Turbine	1	1	1	1	1	1
Generator	1	1	1	1	1	1
Air Instrument Package	0.999185	0.99693	0.994547	0.988359	0.981996	0.975633
Intercondenser System	0.99869	0.997275	0.996195	0.993967	0.992036	0.990277
Ejector System	0.999586	0.999134	0.998786	0.998062	0.997428	0.996848
Vacuum Pump System	0.998503	0.994241	0.989432	0.976122	0.961698	0.946811
Main Condenser	1	1	1	1	1	1
Condensate Transfer Pump Syst	1	0.999739	0.998825	0.995768	0.992379	0.988929
Condensate Injection System	0.999998	0.999919	0.999628	0.997585	0.993456	0.987396
Cooling Tower structure system	0.998308	0.992259	0.985942	0.970044	0.95419	0.938649
Cooling Water Pump System	0.999928	0.9998	0.999681	0.999393	0.999105	0.998815
Auxiliary Water Pump System	1	1	1	1	1	1
Lube Oil Tank	1	1	1	1	1	1
Lube Oil Cooler System	1	1	1	1	1	1
Main Oil Pump System	1	0.999987	0.999991	0.999995	0.999939	0.999842

Block	Reliability						System Level
Generating Facility	0.99	0.97	0.95	0.9	0.85	0.8	Power Plant
Electrical System	0.996102	0.991243	0.987343	0.978994	0.971525	0.96459	Primary System
Generator Circuit Breaker	1	1	1	1	1	1	Primary Sub-system
Auxiliary System	0.997161	0.993307	0.99042	0.984347	0.978968	0.974004	
Trafo Circuit Breaker	1	1	1	1	1	1	
Main Transformator	0.999896	0.999721	0.999576	0.999245	0.998926	0.998615	
Electrical Protection	1	1	1	1	1	1	
Plant Control	1	1	1	1	1	1	
Generator Control Panel	1	1	1	0.999997	0.999993	0.999985	
AVR System	0.999181	0.998241	0.997575	0.996224	0.995063	0.99401	

From Table 2 above, the Auxiliary of the electrical system has the lowest reliability value when the reliability target of generating facility is 0.99, but at the rest reliability target value (0.97-0.8), Cooling Tower Structure System in Mechanical System has the lowest reliability value. In this research, the equipment selected to calculate the optimum maintenance interval is the equipment on the Cooling Tower Structure System. Cooling Tower Structure System has two equipment, the Cooling Tower Fan and the Cooling Tower Structure, each of which is arranged in a series configuration, and both are arranged in a 5-out-of-6 operation configuration. The configuration of the Cooling Tower Structure System can be seen in Figure 6.

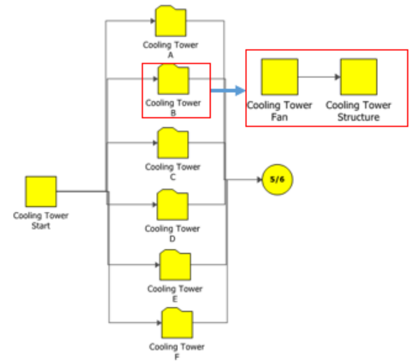


Figure 6. Cooling Tower Structure System configuration

The cooling tower is the most important equipment in the cooling process of a geothermal power plant. The cooling water from the cooling tower flowed into the main condenser to condense the steam and maintain the condenser pressure to remain a vacuum. Cooling tower failure will cause the cooling water temperature to increase and can reduce power generation significantly. This research focuses on the Cooling Tower Fan equipment. Based on the distribution fit test, the Cooling Tower Fan distribution function of the original data is a three-parameter Weibull with a p-value of 0.5.

5.2Optimum Maintenance Interval Result

Before the optimum maintenance interval of the Cooling Tower Fan, the mean time to repair after failure and time duration for preventive maintenance need to be defined by data from CMMS. The value of the mean time to repair after failure and time duration for preventive maintenance can be seen in Table 3.

Table 3. Maintenance duration

Equipment	Mean time to repair after failure (T_f)	Preventive maintenance duration(T_p)	Unit
Cooling Tower Fan	40.53	8	hour

The calculation results from Equation (5) for the Cooling Tower Fan equipment for various values of r that range from 2 to 80 and time interval t_p from 1 to 2920 days (eight years) can be seen in Figure 7. The optimal maintenance interval is t_p when C/C_p is at its minimum value.

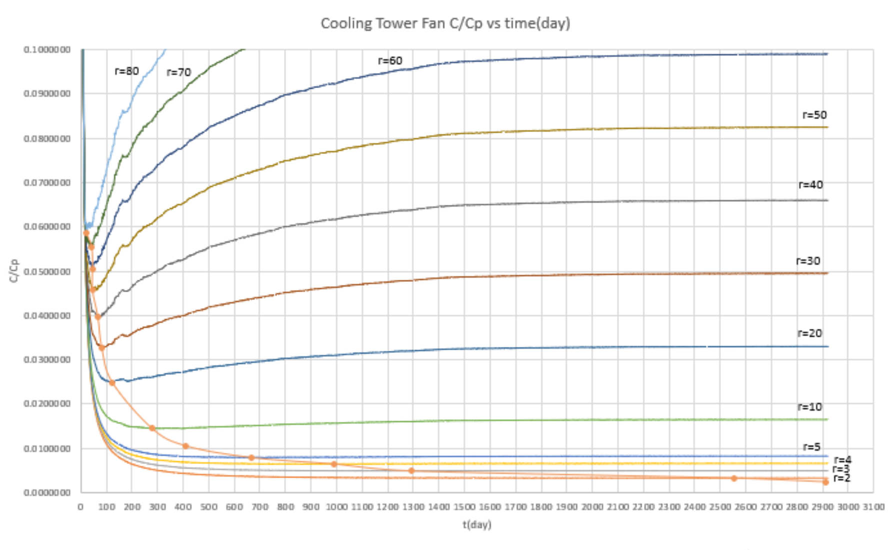


Figure 7. Cooling Tower Fan cost maintenance calculation

The graphic of optimum maintenance interval at various cost ratios *r* of Cooling Tower Fan equipment can be seen in Figure 8. In Figure 8, the optimum maintenance interval increases when the cost ratio decreases.

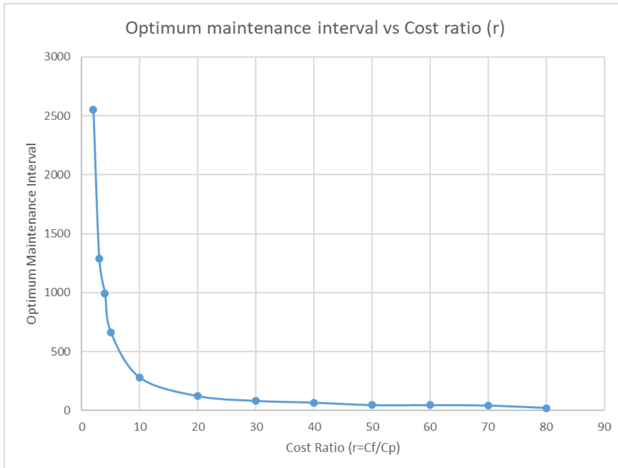


Figure 8. Optimum maintenance interval vs Cost ratio

From Figure 8 above, it can also be seen that there are several values of cost ratio which, when shifted, will not significantly shift the optimum maintenance interval value. The optimum maintenance interval sensitivity to cost ratio can be seen in Figure 9

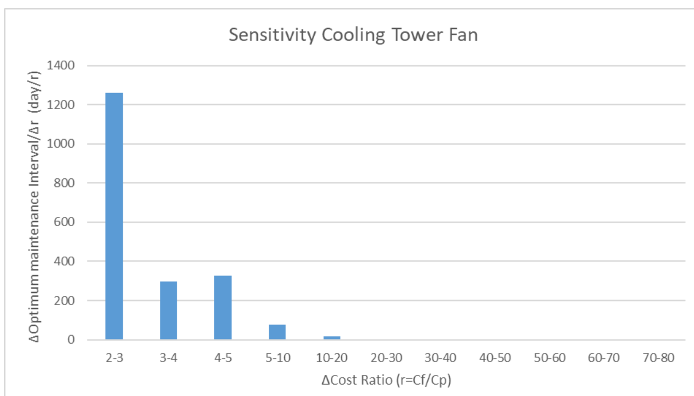


Figure 9. Optimum maintenance interval sensitivity

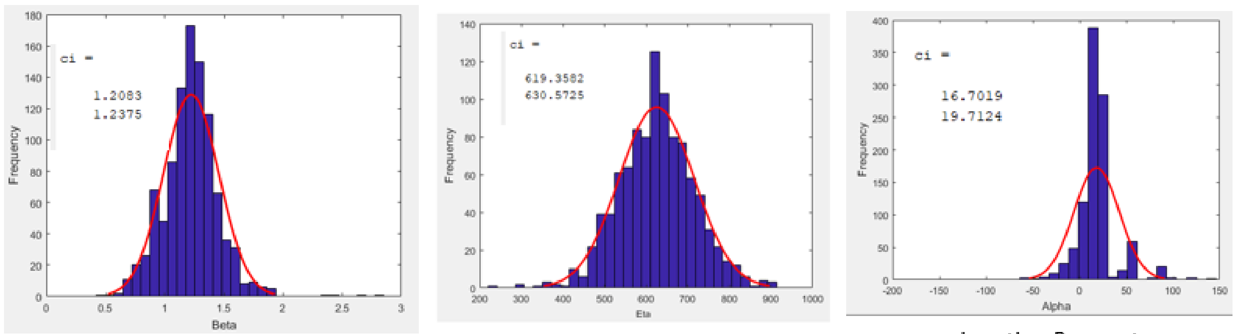
From Figure 9 above, the highest shift in maintenance intervals is in the cost ratio range between 2-3, so in that range, the calculation of failure costs and preventive costs must be calculated carefully and in detail. The shift in the maintenance interval at a cost ratio above 10 is not significant compared with changes in the cost ratio.

The cost ratio value for the Cooling Tower Fan equipment is 6.896. With this cost ratio value, it is found that the optimum maintenance interval of the Cooling Tower Fan is 412 days.

5.3 Data Bootstrapping Result

It is very difficult for the maintenance team to carry out maintenance activities at regular intervals without any tolerance. The next question is whether there is tolerance in the maintenance interval timeframe and whether within that range the maintenance interval is still the optimal value at a certain confidence interval. To answer this question, this research conducted data resampling using the bootstrap method. Bootstrapping is done 1000 times and uses alpha 0.05 (95% confidence interval) to find the distribution function parameter value boundaries on that interval.

The Cooling Tower Fan distribution function of original data is a three-parameter Weibull function with shape parameter 1.23, scale parameter 636.54, and location parameter 14.39. The original failure data has 55 data in size and bootstrapped data size is 55000 after bootstrapping 1000 times. Parameter values of bootstrapped data can be seen in Figure 10.



Shape Parameter   Scale Parameter   Location Parameter

Figure 10. Parameter values of bootstrapped data

A comparison of parameter values between the original failure data and bootstrapped data can be seen in Table 4. The parameter values of the bootstrapped data which produce a lower reliability curve (higher shape parameter, lower scale parameter, and lower location parameter) are named bootstrapped data lower parameters, and vice versa the parameter values of bootstrapped data that produce a higher reliability curve (lower shape parameter, higher scale parameter, and higher location parameter) is named as bootstrapped data lower parameter.

Table 4. Parameter values comparison of Cooling Tower Fan

Cooling Tower Fan	Parameter Values		
	Shape Parameter (β)	Scale Parameter (η)	Location Parameter (α)
Original Failure Data Parameter	1.23	636.54	14.39
Bootstrapped Data Lower Parameter	1.24	619.36	16.70
Bootstrapped Data Upper Parameter	1.21	630.57	19.71

5.4 Validation of Optimum Maintenance Interval of Bootstrapped data

After all parameter values are obtained by the bootstrap method, the optimum maintenance interval value of bootstrapped data can be compared with the original failure data as shown in Table 5.

Table 5. Optimum maintenance interval comparison of Cooling Tower Fan

Data type Cooling Tower Fan	Optimum Maintenance Interval (r=6.896)	Unit	Cost/day (Cp=18337.94)	Unit	Different with original data (Percent)
Original Data	412	Days	193.73	USD/Day	
Bootstrapped Data Lowerbound	391	Days	197.03	USD/Day	5.1%
Bootstrapped Data Upperbound	410	Days	194.51	USD/Day	0.5%

In table 5 above, the optimum maintenance interval value on the original failure data is outside the maintenance interval range on bootstrapped data with the largest difference of 5.1%. The graphic of the optimum maintenance interval at various cost ratios (*r*) of Cooling Tower Fan equipment with original data and bootstrapped data can be seen in Figure 11. So, it can be concluded that there is no significant difference in the results of calculating the optimum maintenance interval using original failure data or bootstrapped data.

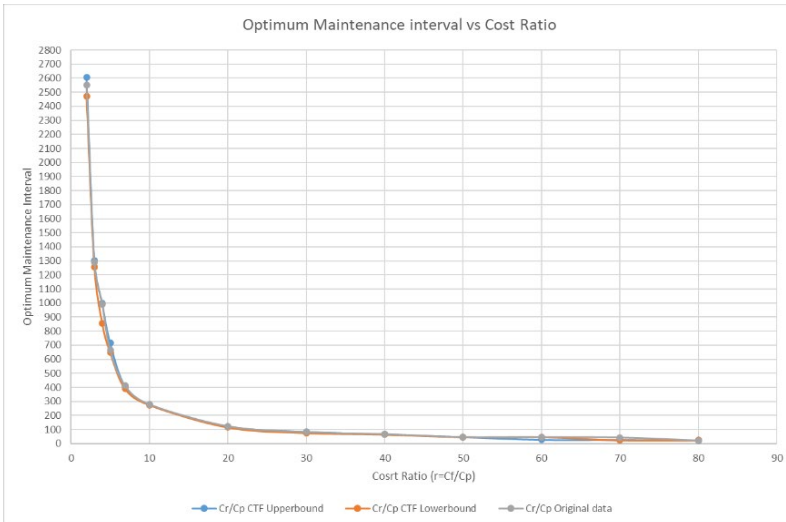


Figure 11. Optimum maintenance interval vs cost ratio (original data and bootstrapped data)

6. Conclusion

With this research, it is possible to select the critical subsystem and equipment based on its reliability value and the target value of the reliability of the whole system. This research provides an alternative on how to determine the optimum maintenance interval and provides a method for determining the maintenance interval in a certain range with a predetermined confidence interval.

One of the critical equipment in the geothermal power plant is Cooling Tower Fan. The Cooling Tower Fan has an optimum maintenance interval is 412 days with a cost ratio of 6.896. Based on bootstrap data resampling, the range of optimum maintenance interval is 391-410 days with a 95% of confidence interval.

As a continuation of this research, future studies about the different resampling methods, higher confidence interval of data resampling, combination with the condition monitoring and inspection interval and total cost of all maintenance strategies (Predictive, Preventive, and Corrective), will make essential contributions to the maintenance and reliability organizations.

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Biographies

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