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RESEARCH ARTICLE

Optimization of Preventive Maintenance Planning for the Motor Cooling System at PLTGU Using Differential Evolution

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Abstract

The determination of the optimal preventive maintenance time of the three-phase induction motor (88WC) during operation at 380V in the cooling system of the Semarang Gas and Steam Power Plant (PLTGU) is achieved by combining the Power-Law Non-Homogeneous Poisson Process (NHPP) model and the Differential Evolution (DE) algorithm to achieve minimum total maintenance cost. The parameters of NHPP, β = 1,75 and η = 7198,99 hours, are estimated using the least squares method from the historical failure data for the 2020–2024 period, which includes recording failures beyond 20.000 operating hours. The DE optimization results indicate that the optimal PM time is 371,60 hours which reduces the total cost from IDR 28.198.935 (for the 500-hour interval) to IDR 20.299.822, thereby achieving cost savings of 38%. The validation process entails the execution of Monte Carlo simulations, encompassing 1.000.000 iterations that culminate in pre-optimization failure probability of 0,56%. Sensitivity analysis using a $\pm$20% parameter variation further substantiates the model's robustness. This data-driven framework is expected to enhance the reliability and cost-effectiveness of the PLTGU cooling system and is scalable to other power-generating facilities.

Keywords: Preventive Maintenance, NHPP, Differential Evolution, PLTGU, Cost Optimization, Monte Carlo Simulation

1. INTRODUCTION

The escalating demand for electricity can be attributed to two major factors: economic growth and urbanization. The data reveals a substantial increase in national electricity demand from 206.6 TWh in 2010 to 283.6 TWh in 2020, with an average growth estimate of 5.5% per year until 2030 [1]. PLTGU, which consists of GTG, HRSG, and STG in a combined cycle power plant, plays a strategic role in maintaining the continuity of the reliability of the Java-Bali power supply. Nonetheless, unplanned production disruptions, including unscheduled downtime, have been shown to have a detrimental effect on costs and result in a loss of production hours.

The efficacy of a given maintenance strategy is of paramount importance to the reliability of power generation plants, particularly with regard to critical components such as cooling systems. Data-driven predictive maintenance has been demonstrated to facilitate proactive maintenance, thereby mitigating the occurrence of failures [2]. Condition-based and reliability-centered approaches have been shown to be effective in the prevention of system damage [3]. This necessity persists even in scenarios dedicated to renewable energy, underscoring the importance of predictive maintenance in addressing operational issues [4]. The capacity to discern failures with precision is paramount for facilitating the formulation of maintenance decisions [5].

The integration of reliability analysis and optimization methodologies, exemplified by Differential Evolution (DE), facilitates the optimization of proactive and efficient maintenance scheduling [6] while concurrently enhancing system reliability through the approximation of failure probability [7]. Such an approach has the potential to minimize downtime and operational expenses [8].

PLTGU Semarang currently implements time-based maintenance (TBM) but has not optimized historical failure data. Consequently, there is a possibility of over-maintenance or under-maintenance. The objective of this study tries to estimate The shape (β) and scale (η) parameters using the Least Squares method within the NHPP framework, forecast the reliability and expected failure for the system adn optimize the preventive maintenance (PM) interval of the three-phase induction motor of the PLTGU Semarang cooling system with the DE algorithm.

The NHPP model is employed to model the failure rate, which varies over time [9]. The parameters β and η are calculated from historical data using the least square technique. The Differential Evolution (DE) algorithm is utilized to ascertain the optimal preventive maintenance interval, with the objective of minimizing the aggregate cost of maintenance, encompassing both preventive and corrective measures.

Several previous studies [10] [11] [12] [13], have not fully integrated cost approaches and algorithmic optimization. And study [14] and [15] utilized NHPP but without focus on maintenance cost effectiveness. This reveals a research gap regarding cost-based and reliability-focused PM interval optimization. This research bridges the existing gap by formulating a model that combines the Power-Law Non-Homogeneous Poisson Process (NHPP) and Differential Evolution (DE) for optimizing the preventive maintenance interval of the cooling motor of PLTGU Semarang to minimize the total cost [16] [17] [18]. The validation process is carried out using Monte Carlo simulations to guarantee the reliability of the optimization results [19].

The method employed is a recursive optimization procedure that is verified using Monte Carlo simulations. Considering this, the objective of this study is to enhance maintenance efficiency, decrease operating expenses, and increase the reliability of PLTGU Semarang's cooling system, as well as to make a valuable contribution towards the advancement of more effective maintenance methods for the power industry in Indonesia

2. METHODOLOGY

Repairable systems, as represented by the induction motor used in the cooling system of PLTGU, exhibit fundamentally different failure behavior compared to non-repairable systems. For non-repairable systems, the incidence of failure marks the end of the component's working life, and reliability studies often use probabilistic distributions such as Weibull, Exponential, or Log-Normal to describe the time to failure [20]. Contrasting with this are repairable systems that enable restoration following a failure but do not necessarily bring back the component to as-new condition. In many instances, the repairs are incomplete (as old), and this necessitates a model capable of capturing the varying failure rates resulting from aging and successive repairs [21].

Unlike the conventional Time-Based Maintenance (TBM) approach, which determines maintenance intervals based on manufacturer guidelines or experiential rules (e.g., every 500 operating hours) without accounting for variations in failure rates, the Non-Homogeneous Poisson Process (NHPP) explicitly models time-dependent failure behavior, where the rate may increase or decrease over time ($\beta \neq 1$). By utilizing the NHPP's Mean Cumulative Function m(t), preventive maintenance (PM) intervals can be tailored to the actual reliability characteristics of the system, thereby minimizing the risk of over-maintenance (i.e., intervals that are too short) and under-maintenance (i.e., intervals that are too long).

The NHPP model is selected as it can represent differences in failure rates among different time intervals, especially in the scenario of minimal repair [22]. This study adopts a quantitative methodology that integrates historic failure data with Power-Law NHPP-based reliability modeling and optimization procedures. Data is gathered from the three-phase induction motor maintenance history in PLTGU Semarang for the years 2020-2024, including operating time to failure, failure mode, and maintenance costs.

The shape and scale parameters of the Non-Homogeneous Poisson Process (NHPP) model are approximated through the least squares procedure, in accordance with the historical data. [23]. Then, to minimize total operating costs, comprising both PM costs and failure costs, the preventive maintenance (PM) interval is optimized through the Differential Evolution (DE) algorithm.

The methodology comprising the collection of failure data for a cumulative total of 20.000 operating hours, estimation of reliability parameters through Power-Law NHPP model, optimization of preventive maintenance intervals by the DE algorithm, validation of optimization results through Monte Carlo simulation, sensitivity analysis, and framing of conclusions, Figure 1 shown the flowchart for the method on this study.

The Monte Carlo simulation is employed to test the robustness of the model to stochastic variations in input parameters, and sensitivity analysis is employed to investigate the effect of parameter variations on the optimization outcome. The method is employed to make sure that the resultant PM interval is economically optimal and practicable within the PLTGU system operating regime

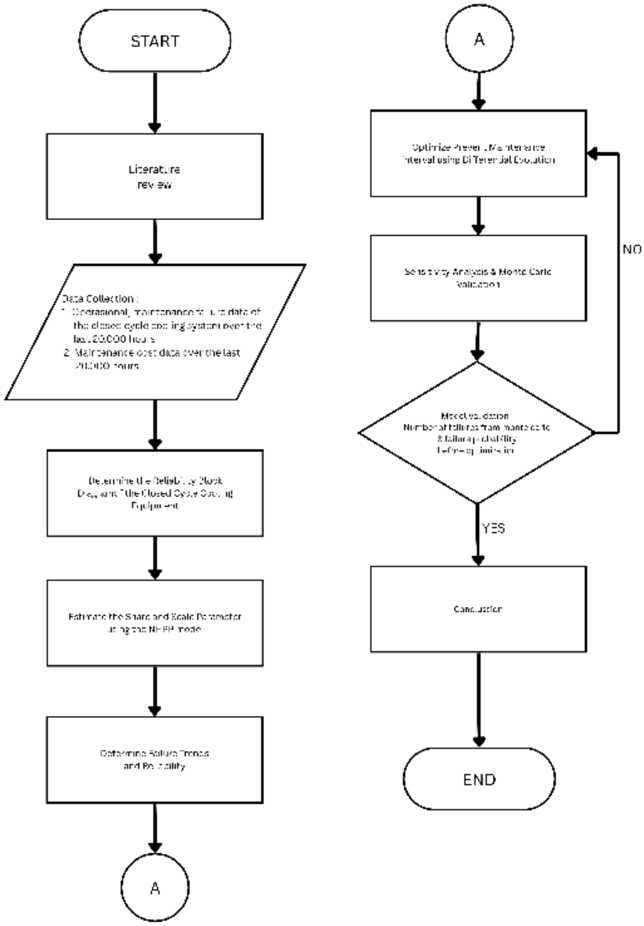

Figure 1. Flowchart for the Study

2.1 Data Collection

The data gathering, maintaining, and analyzing are intended to render the data more structured in form, which aligns with the objectives of statistical analysis [24]. Data utilized in this study are failure history data associated with one of the cooling motors in the PLTGU Semarang cooling system, as presented in Table 1, with a range of 20,000 operating hours for the period 2020–2024. Data contains operating time and failure occurrences (both in operating hours) as shown with table 1. Data undergoes processing and analysis with the aid of statistical techniques and various computer programs.

Table 1. Motor Cooling System Operating Data

Operating Hour	Status	Operating Hour	Status
0	Operating	11000	Operating
1000	Operating	12000	Operating
2000	Operating	13000	Operating
3000	Operating	14000	Operating
4000	Operating	15000	Operating
5000	Operating	16000	Operating
6000	Operating	17000	Operating
7000	Operating	17800	Fail
7200	Fail	18200	Fail
8000	Operating	18500	Fail
9000	Operating	18600	Fail
10000	Operating	18700	Fail
10200	Fail	20000	Operating

The data on operating hours can be utilized to determine availability as shown in equation (1).

$$Availability_{year} \frac{Uptime_{year}}{Uptime_{year} TTR_{year}} \% \tag{1}$$

The data will also show the number of failures of the motor at different operating hours. These data are then used to estimate the NHPP model parameters and determine the optimum PM interval. The data are then estimated by using Minitab software with NHPP model to get the parameters β and η.

2.2 Model Power-Law Non-Homogeneous Poisson Process

Power-Law Non-Homogeneous Poisson Process (NHPP) is a powerful statistical process that can be used to model systems with changing failure rates over time and hence is particularly well-suited to repairable systems like induction motors. NHPP enables failure patterns to be modeled based on historical data, and this enables preventive maintenance intervals to be tailored to the true reliability characteristics of the system [18]. The Power-Law Non-Homogeneous Poisson Process (NHPP) model is used to describe failure rates that change over time and is thus well-suited for systems that undergo aging or wear effects. This model includes two parameters: β, which is the shape parameter, and η, which represents the scale parameter, and both are determined from past failure data. The parameter β measures the rate of change of the failure rate, while η represents the characteristic time scale of the system [25].

Power-Law Non-Homogeneous Poisson Process model is applied to model systems that display an increasing failure rate with respect to age or use. It is assumed that the failures occurring in a specified interval are Poisson distributed, but with the note that the failure rate is non-uniform in the sense that it rises proportionally to time [26].

Parameter estimation of the NHPP model to determine the optimal maintenance interval for preventive maintenance of the cooling motor system of PLTGU from historic failure experience is an important task for predictive system reliability behavior and maintenance interval optimization. The physical meanings and effects of the estimated parameters, β and η, are important and influence the proposed maintenance strategy. In this research, it is the time scale on which failures begin to manifest as significant [25] when the cooling motor is operating, derived from an examination of historical failure data. These parameters are estimated through the least squares technique, which tries to reduce the gap between observed cumulative failure and predicted failures that are calculated according to the NHPP model.

The NHPP model presupposes that failures happen according to a Poisson process, yet the failure intensity varies as a function of operating time. Equation (2) presents the failure intensity function of the Power-Law NHPP

$$\lambda(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{2}$$

Where:

β: Shape parameter, indicating the direction of the system's failure rate

The important interpretation of β, indicated as below:

- If β>1, failure rate increasing with time, most commonly due to wear-out or aging of components.
- If β<1, The failure rate decreases, often due to early repairs (burn-in) or better reliability after component replacements.
- If β=1, The failure rate remains constant, in accordance with a homogeneous Poisson process in which failures are random, without aging tendency.[27]

η: The parameter of scale refers to the typical temporal nature of the system (in hours). In the context of this research, it represents the temporal context at which failures become significant [25] within the operation of the cooling motor, as gleaned from historical failure data.

(t): The real operating time, in hours, is the independent variable in the model.

The parameter estimation of the NHPP model for establishing the preventive maintenance interval of the cooling motor system of PLTGU from historical failure data is necessary to forecast the reliability behavior of the system and optimize the maintenance interval. The parameters η and β, which were estimated, have a significant role in establishing the suggested maintenance strategy.

The Mean Cumulative Function (MCF), *m*(t), represents the expected number of failures which occur by a specific time (t). This function is ascertained using equation (3)

$$m(t) = \left(\frac{t}{\eta}\right)^{\beta} \tag{3}$$

where dan β are the parameter model that need to be estimated [19].

MCF is a significant component of reliability analysis as it provides the shape of the anticipated failure frequency over time period It plays a key role in determining the best PM interval because a high failure rate will increase CM costs as well as downtime. Aside from this, the system reliability function, R(t), which provides the probability that the system won't fail up to time (t), may be obtained using equation (4).

$$R(t) = e^{-m(t)} = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \tag{4}$$

The reliability function provides an important metric / measurement for evaluating the effectiveness of preventive maintenance practices. The NHPP model has been used widely in reliability analysis of complex systems, particularly where the failure rate is not constant over time. The model allows accurate prediction of future failure rates, which is essential in effective maintenance planning.

To determine the goodness of fit of the Power-Law Non-Homogeneous Poisson Process (NHPP) model to the historical data, a group of goodness-of-fit statistics is employed, which consists of the Sum of Squared Errors (SSE), Total Sum of Squares (SST), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Collectively, these statistics offer a quantitative judgment of the predictive model's accuracy relative to real data. The Sum of Squared Errors (SSE) quantifies the squared deviation of the actual number of failures from the model predictions. The Total Sum of Squares (SST) quantifies the total variance in the observed data compared to its mean. SSE, SST, MSE, RMSE, and R^2 are estimated based on equation (5).

$$SSE = \sum_{i=1}^{n}[N(t_i) - m(t_i)]^2 \tag{5}$$

Where:
$N(ti)$: The actual number of failures observed at time t_i
$m(ti)$: The expected number of failures from the NHPP model at time t_i

$$SST = \sum_{i=1}^{n}(y_i - \bar{y})^2, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{6}$$

Where
y_i : Cummulative observation
$\bar{y}$: Average observation

$$R^2 = 1 - \frac{SSE}{SST} \tag{7}$$

$$MSE = 1 - \frac{SSE}{n} \tag{8}$$

$$RMSE = \sqrt{MSE} \tag{9}$$

Low value of SSE indicates that the model predictions are close to the actual data, meaning that the model parameters are accurate and the model can be trusted in making decisions, e.g., optimization of preventive maintenance (PM) interval. SSE is most widely used as a measure of goodness-of-fit within literature to contrast how well the NHPP model fits real data [28]. Application of combining SSE, RMSE, and R^2 is most used in verifying NHPP models that have been estimated via the least squares approach [29].

Together with Non-Homogeneous Poisson Processes (NHPP), historical data enables additional analysis, for instance, computation of Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), and MTBF itself. MTBF, or the average time between failures of a system or unit, is a significant parameter in reliability analysis [30]. MTBF can be approximated through equation (10).

$$MTBF = \frac{1}{n}\sum_{i-1}^{n}(t_i - t_{i-1}), t_0 = 0 \tag{10}$$

where:

- t_i : The time of occurrence of the *i-th* failure
- t_{i-1} : The time of the previous failure
- n : The total number of failures observed during the observation period

A larger value of MTBF indicates a greater system reliability to proceed with operations prior to the occurrence of the next failure [31].

Other than MTBF, Mean Time To Repair (MTTR) is also a very critical metric in determining the reliability of repairable systems. MTTR is the mean time to repair the system after a failure occurs and is utilized to measure the effectiveness of the system or maintenance crew in recovering the operational states as quickly as possible. The recovery process of the system is more efficient if the value of MTTR is lower. MTTR (Mean Time To Repair) can also be calculated in this research, which is the average time taken for the repair of a system after failure. The measurement formula of MTTR is provided in equation (11)

$$MTTR = \frac{1}{n}\sum_{j-1}^{n} TTR_j \tag{11}$$

Where:

- TTR_j : The repair time for the j_{-th} failure
- n : The total number of failure events that require repair

A lower MTTR indicates the ability of the system or maintenance team to restore operations efficiently [32].

2.3 Algorithms and Differential Evolution (DE) Optimization

The Differential Evolution (DE) algorithm is a population-based optimization algorithm inspired by evolutionary mechanisms to find optimal solutions in search spaces [23]. The method operates by applying a population of candidate solutions or individuals that change over time via mutation, crossover, and selection mechanisms.

DE consists of four main components: initialization of the population, mutation, crossover, and selection, which are executed iteratively to reach the optimal solution. DE is less complex in composition than other techniques such as Genetic Algorithm or Simulated Annealing but is highly effective regarding convergence as well as searching the solution space [33].

The optimization begins with the creation of an initial population, which is composed of several potential solution vectors (individuals) scattered randomly in the given parameter space. The mutation operation generates a new vector by adding the difference between two vectors chosen randomly from the population to the target vector. Crossover incorporates features of the mutated vector and the target vector for the generation of a trial vector. The objective function used is total operating cost that considers both PM cost and repair cost resulting from failures. The **objective function** in this study is shown by equation (12) are for the cost optimization.

$$C(t) = \frac{C_{PM} + C_{labor\_pm}}{t} + (\frac{m(t)}{t}).(C_{CM} + C_{DT}.T_{CM} + C_{labor\_cm}) \tag{12}$$

where:

C_{PM}	**: Cost of preventive maintenance (PM) material, such as replacement of lubricants, bearings, or other minor components carried out periodically to prevent failure (specified from company records, 2024).**
C_{labor_pm}	: Labor cost for PM, calculated based on technician wages per maintenance session, typically a few hours. This is a low cost because PM is scheduled and does not require special skills (specified from company records, 2024)
C_{CM}	: Labor cost of corrective maintenance (CM), expressed in terms of technician salaries per maintenance session, which is longer than PM. This costs more than PM due to the unplanned nature and the need for more specialist expertise (specified from company records, 2024).
C_{DT}	: Downtime cost, or the loss in production per hour when PLTGU is unavailable due to motor failure. This cost is high because downtime can cause disruption in electricity supply and significant financial losses ((specified from company records, 2024))
T_{CM}	: Mean Time To Repair (MTTR), the average time taken for corrective repair following failure, based on PLTGU Semarang's historical data.
C_{labor_cm}	The labor cost for CM
$m(t) = \left(\frac{t}{\eta}\right)^{\beta}$	: The cumulative expected number of failures up to time t calculated from the NHPP model
t	: The PM interval in hours, and the optimization variable in this study.

The goal of this strategy is to optimize the preventive maintenance (PM) interval for optimizing the overall costs of the system that includes PM costs, repair costs (CM), and related downtime using the Differential Evolution (DE) algorithm. In the context of PM interval optimization, the DE algorithm is utilized for determining the PM interval that successfully reduces the total operational costs by considering PM costs, repair costs, and downtime costs.

The cost optimization function consists of two primary elements:

- $\frac{C_{PM}+C_{labor\_pm}}{t}$; PM unit cost per time, decreasing with greater interval (t) as PM frequency decreases.

- $\left(\frac{m(t)}{t}\right) \cdot (C_{CM} + C_{DT} \cdot T_{CM} + C_{labor\_cm})$; which increases with increasing interval(t), because the expected number of failures *m(t)* increases by the NHPP model.

The process of applying Differential Evolution (DE) involves:

1. **Population Initialization** Here in the present work, the population at the beginning is 50 members within the provided interval of T and the search boundaries of T (T_{min} dan T_{max}).
2. **DE Algorithm Parameters** The following DE parameters are utilized:
   - **Mutation Factor (F)** The parameter F= 0.8, determines the degree of changes (shifts) generated by the mutation operator. The value 0.80 implies that the mutation vector changes by 80% of the difference between two random solutions.
   - **Crossover Probability (CR)** Controls the probability with which each element of the solution will be put through mutation based on the mutation vector rather than retaining the initial value. A value of 0.9 indicates that 90% of the genes in the new proposed candidate solution come from the donor vector.
   - **Maximum Number of Generations (G_{max})** The maximum number of evolutionary cycles is specified. The procedure stops either at the 200th generation or at the fulfilment of another convergence criterion.
   - **Enhancement Acceptance Threshold** (tol = 0.01)
   - If the improvement (or decrease) in the optimal cost function value between generations is less than 0.01, it is considered that the saturation level has been reached, thereby making it possible to halt the evolutionary process prematurely.
3. **Evolutionary Cycle for Every Generation** For every solution X_i in the population:

   a) Mutation Operator
      - Select three indices r1, r2, r3≠i randomly
      - The donor vector is created as equation (13)

   $$V_i = X_{r_1} + F(X_{r_2} - X_{r_3}) \tag{13}$$

   This donor vector employs the difference of two arbitrary solutions to search the decision space

   b) Crossover Operator
      - For every solution element j, create the trial vector $U_{i,j}$ based on the principle from equation (14)

   $$V_{i,j} = \left\{ V_{i,j} \quad \text{if } random \ \leq \ CR, X_{i,j}, \ otherwise \right\} \tag{14}$$

   A high probability ensures most of the new genes come from the donor vector but retains a small segment of the old genes to ensure diversity.

   c) Selection Operator
      - Compute the average cost per hour for U_i and the previous solution X_i.
      - Choose the option with the lower cost value to move to the next generation

$$X_i^{next} = \{U_i, if\ C(U_i) < C(X_i),\ X_i,\ otherwise.\} \tag{15}$$

Where:

$- X_i$	: Current solution vector i .
$- X_{r1}, X_{r2}, X_{r3}$	: Three random solutions (indices\distinct from i)
$- V_i$	: Donor vector of the mutation $X_{ri} + F(X_{r2} - X_{r3})$
$- F$	: The mutation factor, which control the scale of shift.
$- CR$	: Crossover probability, the probability of a member from the donor vector crossover into the trial vector.
$- U_i$	: The trial vector, achieved through the crossover of V_i dan X_i
$- U_{i,j}$	: The $j - th$ entry of U_i.
$- X_i^{next}$	: The solution that proceeds to the next generation, chosen between between Ui and Xi based on the cost function value.

4. **Maximum Iterations and Final Results**

The evolution process then continues until the maximum number of generations G_{max} or the fitness improvement is less than the tolerance (fitness<tol). The optimal best solution T_{opt} is selected as the individual with minimum cost throughout the entire evolution.

This strategy is substantiated by research form study [34] [35], which show the efficiency of Differential Evolution (DE) in determining the best maintenance schedule in power generation systems. The parameters chosen for DE (F, CR, and NP) have been shown to yield convergent results after a reasonable number of iterations.

This compromise results (trade-off) in a globally minimum non-linear cost function corresponding to the optimal PM interval. Optimization aims to determine the best value of t that would minimize C(t) in equation (12) and maintain low costs of PMs and failure risks. This study applies PLTGU Semarang's actual operational data to estimate the cost parameters such that the model can reflect real operational conditions.

2.4 Monte Carlo Simulation

In the present study, Monte Carlo simulation is utilized for assessing the performance of the preventive maintenance (PM) interval developed by optimization based on Differential Evolution (DE). The simulation is aimed at calculating the probability of failure and the average operating costs per hour within the framework of system uncertainty, such as uncertainties in operating conditions, load, and repair quality.

The basic model employed is the Non-Homogeneous Poisson Process (NHPP) with a power-law failure intensity function. The simulation method incorporates a time transformation derived from the cumulative distribution function (CDF) of the NHPP, which described in equation (16)

$$F(t) = 1 - e^{-m(t)}; M(t) = \left(\frac{t}{\eta}\right)^{\beta} \tag{16}$$

To simulate the random failure times, we use the inverse transform sampling method as in equation (17). The method uses the cumulative distribution function (CDF) of the NHPP model to calculate the failure times. By using the inverse of the CDF on random numbers that are uniformly distributed, we can simulate random failure times based on the failure rate specified by the NHPP model. This method helps in simulating the failure events over time and shows how reliable the system is and how it fails in the simulated model

$$T = \eta \cdot (-\, lnU)^{1/\beta}, U \sim Uniform(0, 1) \tag{17}$$

The simulation is carried out for M=10^6=1.000.000 runs. In a run, failure time T_j is calculated repeatedly until the cumulative time exceeds the T_{PM} interval. If there is one or more failures prior to the T_{PM} interval, such a run is tallied as a "failure."

The estimate for how many failures happens before PM is obtained with equation (18)

$$p^{\wedge} = \frac{Total\ failure\ from\ iteration}{M} \tag{18}$$

Monte Carlo simulation was utilized because it can deal with complex distribution models like NHPP quite easily and can also consider the uncertainties of system parameters [36]

2.5 Sensitivity Analysis

The Differential Evolution (DE) algorithm is a population-based optimization algorithm inspired by evolutionary mechanisms to find optimal solutions in search spaces [23]. The method operates by applying a population of candidate solutions or individuals that change over time via mutation, crossover, and selection mechanisms.

A Sensitivity analysis is performed to see how changes in parameters affect the optimal PM interval. The parameters that are considered for sensitivity analysis are NHPP model's β and η parameters, along with C_{PM}, C_{CM}, C_{DT}, and T_{CM}. Each of these parameters is changed by ±20% of its normal value.

The results of the sensitivity analysis will provide the extent to which the optimal solution fluctuates as the parameters of the model fluctuate. If the optimal solution does not change significantly despite these fluctuations, then it is considered robust and reliable.

Sensitivity analysis shows which factors have the most impact on the optimal solution and gives guidance on how risks and uncertainties are to be dealt with in maintenance planning. Sensitivity analysis is one way of monitoring the effect of varying input parameters on optimization results. We will be able to determine which parameters have the largest impact on total cost and optimum PM interval and provide an indication of how sensitive the model is to data uncertainties from this analysis.

Sensitivity analysis is also important to determine that the suggested solution is still the best alternative under different operating conditions that can occur [37].

3. RESULT

3.1 Repairable System Analysis

Table 2 shows the historical failure data of one of our cooling motors in the PLTGU Semarang cooling system over 20000 operating hours for the years 2020 to 2024.

Table 2. Failures Over Time in Repairable Systems

Repairable System Failure Data	
Operating Hour	**Year**
7200	2022
10200	2023
17800	2024
18200	2024
18500	2024
18600	2024
18700	2024

Table 2 data indicates that the motor failed many times within various operating hours, depicting a growing failure rate over time. Figure 2 plots the relationship between event times and failures. Data concerning Uptime, TTR, and N_fail are acquired from the system's log sheet. Using this data, the MTTR and Annual Availability are computed using equations (11) and (1), respectively, and are presented in Table 3.

Table 3. Repairable Systems Performance Profile

Repairable System Performance Profile					
Year	**Uptime**	**TTR(hour)**	**N_fail**	**MTTR**$_{year}$	**Availability**$_{year}$ **(%)**
2020	654,72	0	0	0	100
2021	4.401,42	0	0	0	100
2022	3.197,55	104,72	1	104,7167	96,8289447972
2023	7.247,80	168,45	1	168,45	97,7286364402
2024	4.404,90	1.644,67	5	328,93334	72,8134793522

After that, the global MTTR and MTBF of the system are estimated using equations (10) and (11), and the results are presented in Table 4

Table 4. MTTR and MTBF

	value(hour)
MTTR	200,70
MTBF	2671,43

The data are used to estimate the parameters of the NHPP model and compute the PM interval. Data are then estimated using Minitab software according to the

NHPP model, where the parameters β and η are found from Table 5.

Table 5. Software estimation for parameter shape and scale

Parameter	Estimate
Shape (β)	1,75261
Scale (η)	7198,99

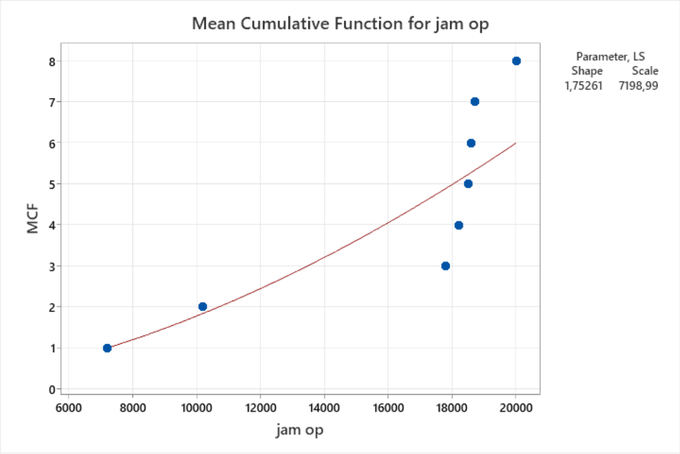

Figure 2. Mean Cumulative Function from operating hour data

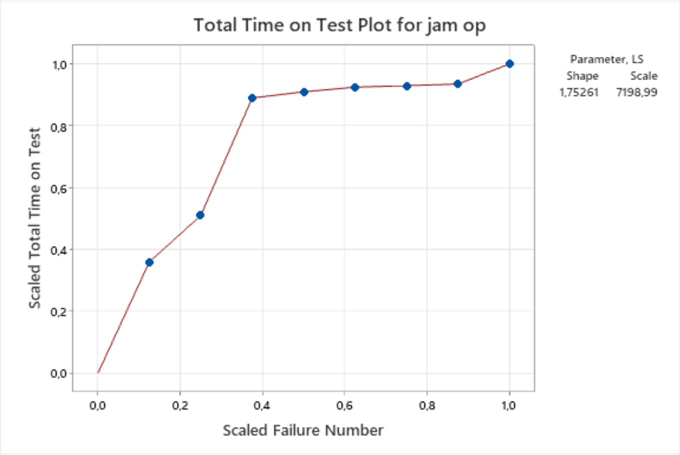

Figure 3. Scaled Failure Number for operating hour data

3.2 Power-Law Non-Homogeneous Poisson Process (NHPP) Parameter Estimation

The estimation results of NHPP parameters using the least squares method from the cooling motor system 88WC historical failures in PLTGU are presented in Table 5 with **Shape (β) = 1,75261** and **Scale (η) = 7198,99**. This is a case of increasing failure rate over time, which may be due to wear-out or aging of components.

3.3 Intensity Function

Finally, the intensity function (or failure rate) of the Power-Law NHPP model is calculated using equation (1) for which the Shape parameter (β) = 1,75261 and the Scale parameter (η) = 7198,99.

$$\lambda(t) = \frac{\beta}{n}\left(\frac{t}{n}\right)^{\beta-1}$$
$$\lambda(1000) = \frac{1{,}75261}{7198{,}99}\left(\frac{1000}{1{,}75261}\right)^{1{,}75261-1} = 0{,}0000553112$$

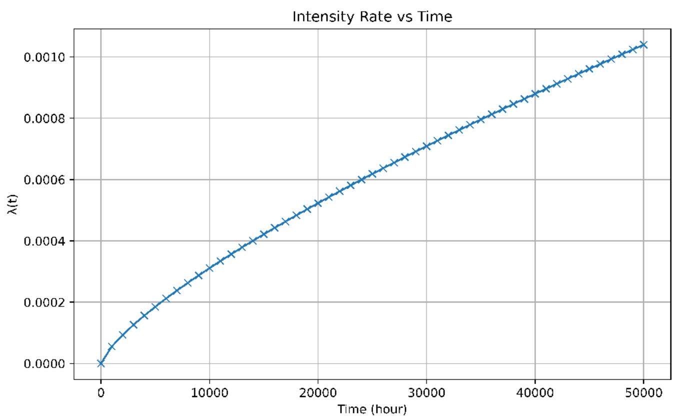

Figure 4. Plot intensity rate vs time

The calculated failure rate =0,0000553112 is for 1000 hours of operation, that is, at t = 1000. Then, the intensity function will be extrapolated to 40000 hours of operation as forecast, and the results are shown in Table 9

3.4 Mean Cumulative Function dan Reliability

MCF is a crucial component of reliability analysis as it provides an understanding of the expected failure frequency over a specified time interval. This information is necessary in determining the ideal PM interval because a higher failure frequency will lead to increased corrective maintenance (CM) cost and downtime. Further, the reliability function of the system, R(t), is the probability that the system is free from any failure until time (t). MCF and reliability are estimated by equations (2) and (3) based on the already estimated shape (β) and scale (η) parameters. A reliability plot is then generated as figure 5 from the calculations.

$$m(t) = \left(\frac{t}{\eta}\right)^{\beta}$$
$$m(1000) = \left(\frac{1000}{7198,99}\right)^{1,75261} = 0,0316063796$$
$$R(t) = e^{-m(t)}$$
$$R(t)e^{-m(1000)} = 0,9688878811 \approx 97\%$$

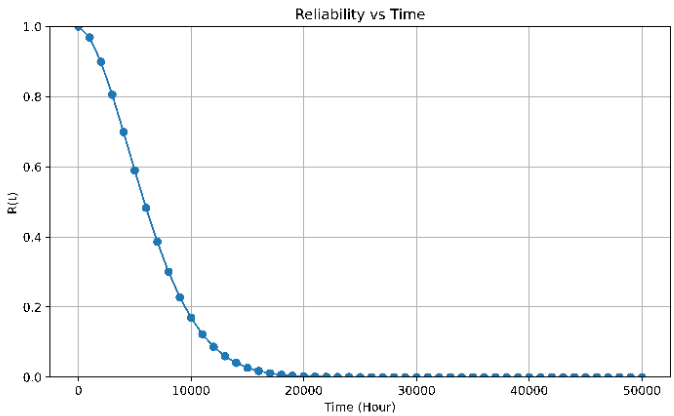

Figure 5. Plot reliability vs time

The computed MCF and Reliability values are 0,0316063796 and 0,9688878811, or 97%, at 1000 hours of operation (t = 1000). The intensity function is calculated up to 40000 hours of operation as a forecast, which is presented in Table 9.

3.5 Model Validation and Parameters

To evaluate how well the Power-Law NHPP model fits the historical data, some goodness-of-fit criteria are employed, i.e., Sum of Squared Errors (SSE), Total Sum of Squares (SST), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The description of the historical data is shown in Table 6.

Table 6. Study Observation Data Recap vs MCF

i	Failure time (t)	Cumulative Observation (y_i)	MCF ($m(t)$)
1	7200	1	1,000245533
2	10200	2	1,8403030630
3	17800	3	4,8753944421
4	18200	4	5,0687364104
5	18500	5	5,215852203
6	18600	6	5,265291312
7	18700	7	5,314930176

From the summary in Table 4, the mean observation asi $\bar{y}$ is calculated as $\bar{y} = \frac{1+2+3+4+5+6+7}{7} = 4$. Subsequently, $\mathbf{N}_{ti}$ and $\mathbf{N_{ti}}^2$ are calculated to obtain the value of SSE as presented in Table 7. SSE is then calculated using equation (4), SST using equation (5), R^2 using equation (6), MSE using equation (7), and RMSE using equation (8). The results of the calculations are presented in Table 8.

Table 7. SSE calculation result

	Validation Parameter SSE Recap		
y_i	m(t)	N_{ti}	N_{ti}^{2}
1	1,000245533	-0,000245533	$6{,}03 \times 10^{-8}$
2	1,840030630	0,159969370	0,0255899
3	4,875394421	-1,875394421	3,5161340
4	5,068736104	-1,068736104	1,1421481
5	5,21852203	-0,215852203	0,0466046
6	5,265291312	0,734708688	0,5398197
7	5,314930176	1,685069824	2,8394660

Table 8. Validation Result

Validation Parameter	Value
SSE	8,110740695
MSE	1,158677242
RMSE	1,076418711
R2	0.7104
%Error	15,38%

The total SSE approximately ≈ 8,11 is the summation of all discrepancies between observed failure counts (y_i) and model-predicted values $m_{(ti)}$. The smaller the SSE, the better the model fit; the 8,11 values on a scale of 7 data points suggests the squared error is acceptable for a repairable system. The mean squared error per observation (MSE) is approximately 1,16 failures. This means, on average, the squared error per observation is approximately ≈ 1,16. The square root of MSE (RMSE) is approximately ≈ 1,08 failures. Practically speaking, this means that on average the difference between the model prediction and actual number of failures is approximately 1 failure per observation point. The coefficient of determination, $R^2 \approx 0{,}71$, indicates that approximately 71% of the variability in the occurrence of failure is accounted for by the Power-Law NHPP model. The other 29% is due to factors outside the system or random variation. The model is "adequate" for the reliability data of a repairable system. The ratio error, i.e., the root means square error (RMSE) relative to the maximum failure value of 7 or the mean value of 4, is between 15% and 27%. Based on the maximum value, the RMSE value of 0,7 is about 15,4%. It indicates that the mean prediction error is just about 15% of data scale. Expected failure over reliability is shown in Figure 6, and a summary of the system analysis is provided in Table 9.

Table 9. System Analysis Recap

System Analysis Recap				
$t_{(hour)}$	Intensity $\lambda(t)$	Availability$_{year}$ (%)	Reliability ($R(t)$)	Expected failure ($m(t)$)
0	0	100	1	0
1000	0,000055311200	99,3656599190	0,96888788110	0,031606379600
3000	0,000126082200	98,5540173088	0,80562178490	0,216140896100
5000	0,000184944000	97,8789561038	0,58954071250	0,528411498600
7000	0,000238032500	97,2701066327	0,38591808020	0,952130159500
10000	0,000311037500	96,4328435822	0,16908439000	1,777357339700
13000	0,000378678200	95,6571016182	0,06002235950	2,813038127200
15000	0,000421581200	95,1650654705	0,02695589630	3,613553219900
17000	0,000463073000	94,6892134786	0,01112652080	4,498423760100
19000	0,000503359200	94,2271888010	0,00423216060	5,465042625600
20000	0,000523100700	94,0007819112	0,00253314500	5,978293662400
25000	0,000618397600	92,9078622899	0,00014565760	8,834251667800
30000	0,000709012300	91,8686417723	0,00000526470	12,154495795900
35000	0,000795909800	90,8720513851	0,00000012210	15,918195331200
40000	0,000879747000	89,9105580296	0,00000000180	20,108502840200

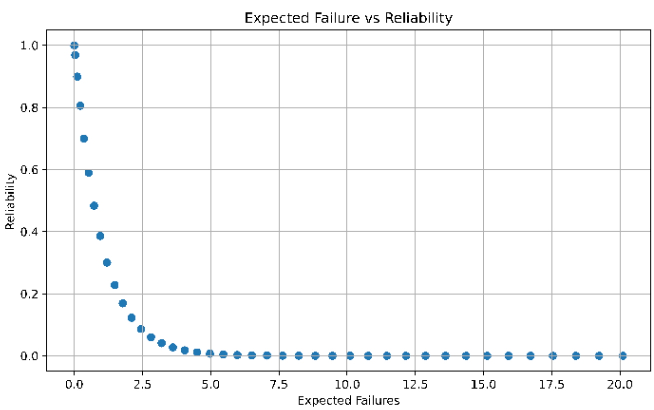

Figure 6. Expected failure vs Reliability

3.6 Optimization Using Differential Evolution Algorithm

The Differential Evolution algorithm is used to optimize the function from equation (12). In this study, the optimization is carried out using Python software, with input data provided in Table 10.

Table 10. Data parameter Input for Optimization

Parameter Input Data		
Parameter	**Value**	**Remarks**
β	1,75261	Parameter shape
η	7198,99	Parameter scale
C_{PM}	8.000.000	PM Cost per event (IDR)
C_{CM}	40.000.000	CM Cost per event (IDR)
C_{DT}	10.000.000	Downtime cost per hour (IDR)
$C_{LABOR.Tech}$	40.000	Technician cost per hour (IDR)
$C_{LABOR.AS.Tech}$	15.000	Assistant Technician cost per hour (IDR)
N_{tech}	2	Number of Technician (People)
N_{Astech}	4	Number of Assistant Technician (People)
T_{PM}	5	PM Duration (hour)
T_{PM_old}	500	Interval PM (hour)
T_{CM}	200,7	MTTR / CM Duration (hour)
T_{Min}	100	Lower Bound of PM Interval (hour)
T_{Max}	50.000	Upper Bound of PM Interval (hours)
N_{sim}	1.000.000	Number of Simulations for Monte Carlo

Table 11. DE Optimization Result

DE Optimization Result		
Iteration	**PM Interval (hour)**	**Cost per Hour (IDR)**
1	136,015916324	78.652,5577794853
2	490,721000000	56.182,8349760817
3	440,661264529	55.379,5280136585
4	415,602153864	54.882,0710082142
5	376,498755269	54.631,2637216776
6	374,399013549	54.628,9102553112
7	374,399013549	54.628,9102553112
8	374,399013549	54.628,9102553112
9	374,399013549	54.628,9102553112
10	373,520080622	54.628,3028340961
11	373,520080622	54.628,3028340961
12	372,1625173808	54.627,8081802478
13	372,1625173808	54.627,8081802478
14	371,6041270191	54.627,7622970472
15	371,6041270191	54.627,7622970472

Based on the given input parameters, equations (13), (14), and (15) were solved using Python software to obtain an optimal value of approximately $T_{OPT} \approx 371{,}61$

hours and a corresponding cost per hour of 54627,76 IDR. Therefore, the total cost of one PM cycle at T = 371,61 hours is 20.300.014,80 IDR. This gives a difference of total cost per hour of 1770,11 IDR, which represents a cost saving of 3,14% when the optimal PM interval is used. The cost savings here are consistent with the total cost of a single PM cycle at the extended interval of 28.198.935,37 IDR, that is, the cost is lowered by 38,9%. The DE optimization iterations and PM comparison are displayed in Table 11 and Table 12, respectively, while the graphical illustration of the DE iterations is presented in Figure 7. The PM cycle interval using T_{OPT} is also presented in Table 13.

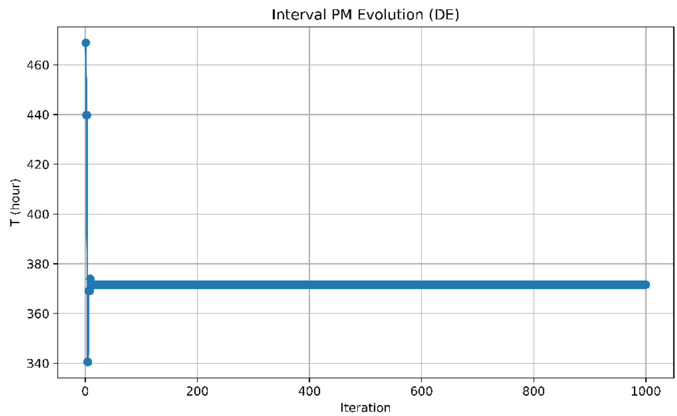

Figure 7. DE iteration Plot

Table 12. Summary of Comparison with Optimal T

Summary				
	T_{PM_old}	T_{OPT}	**Deviation**	**Remarks**
PM Interval	500 hours	371,61 hours	128,39 hours	Shorter Interval
Total Cost per hour	56.397,87 IDR/hour	54.627,76 IDR/hour	1770,11 IDR/hour	3,14% Cheaper
Total Cost per PM cycle	28.198.935,37 IDR	20.300.014,80 IDR	7,898,920.56 IDR	38,9% Cheaper
PM Cost per hour	17400,00 IDR/hour	23411,88 IDR/hour	-6011,88 IDR/hour	34,55% More Expensive

Table 13. Enhanced PM Cycle with T_{opt} Interval

Enhanced PM Cycle with TOPT			
Cycle	T	Reliability (R(t))	Expected failure (m(t))
1	371,6061934	0,994425491	0,005590104200
8	2972,849547	0,808374907	0,212729334000
9	3344,455741	0,769954928	0,261423301300
10	3716,061934	0,730259988	0,314354660400
15	5574,092901	0,527758822	0,639115877100
20	7432,123868	0,347372069	1,057358828100
25	9290,154835	0,209615239	1,562481624000

3.7 Monte Carlo Simulation

With these parameters thus determined, shape (β) = 1,75261 and scale (η) = 7198,99, and the optimum PM interval T_{OPT} = 371,61 hours calculated using the Differential Evolution algorithm, the Monte Carlo verification is carried out on a computer program, phyton specifically with the Weibull distribution function (*weibull_min*). The simulation then runs for 1.000.000 iterations, and the failure number is compared with T_{OPT}. The probability is then estimated from equation (18) yielding the value of 0,005585, or 0,5585%.

Monte Carlo simulation of 1.000.000 runs has a failure probability of 0,005585 (0,5585%) before reaching the 371,60-hour interval. This very low probability guarantees that the optimum interval is reliable under actual operations, lessening the chances of sudden failures that lead to expensive downtime. The confidence level is 95%.

The Cumulative Distribution Function (CDF) may then be determined by inserting the result into equation (16), deriving a function for CDF against time, as indicated in Figure 8. And the U shape visualization for minimal cost shown in figure 9

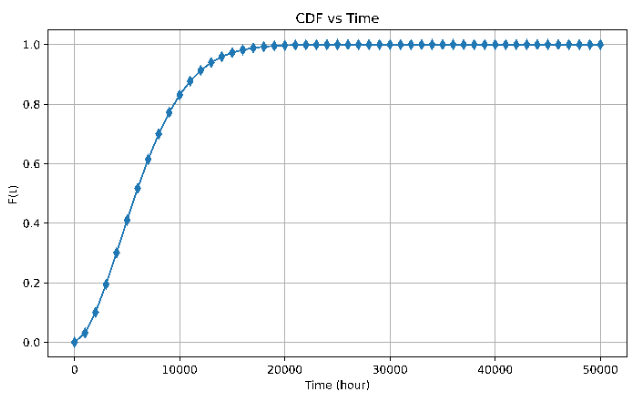

Figure 8. CDF vs Time

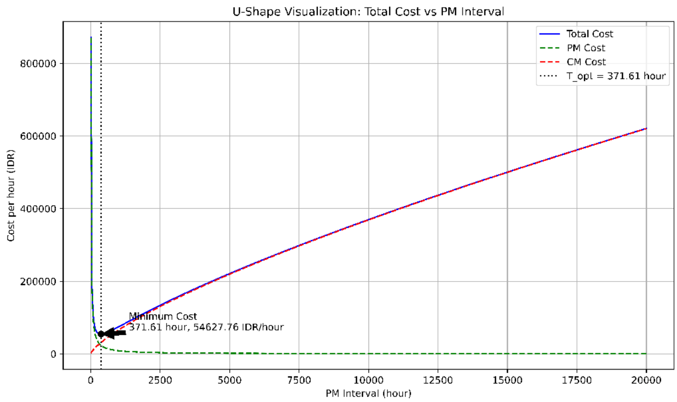

Figure 9. U shape visualization

3.8 Sensitivity Analysis

This sensitivity analysis is performed to understand how changes in key parameters affect the total cost per hour in the maintenance planning model. Each parameter will be varied by ±20%, as shown in Table 14.

Table 14. Model Sensitivity Analysis

Sensitivity Analysis ±20%			
Parameter	**Value**	**T_{OPT} (hour)**	**Cost per hour(IDR)**
C_{PM}	6.000.000,00	425	49245,72067
C_{PM}	10.000.000,00	330	60009,80392
C_{CM}	32.000.000,00	350	54507,4176
C_{CM}	48.000.000,00	390	54748,10699
C_{DT}	8.000.000,00	430	48589,46688
C_{DT}	12.000.000,00	320	60666,05772
T_{CM}	160,56	420	48589,46688
T_{CM}	240,84	330	60666,05772
β	1,40	600	111494,784
β	2,10	250	34474,54145
η	5759,19	320	69540,25254
η	8638,79	420	46100,51871

1. Effect of Preventive Maintenance Cost (C_{PM})
   - A rise in the expense that is associated with preventive maintenance directly contributes to a rise in the expense incurred per hour. This is a logical occurrence, as higher preventive maintenance expenses contribute to operating costs despite its goal of reduce the chance of equipment failure.

2. Effect of Corrective Maintenance Cost (C_{CM})
   - The impact of this change is relatively small compared to the effect of changes in C_{PM}, indicating that the cost per hour is less sensitive to variations in C_{CM}. This could be since corrective maintenance occurs less frequently than preventive maintenance in this model.
3. Effect of Downtime Cost (C_{DT})
   - The high sensitivity to the cost of downtime indicates that C_{DT} has a significant effect on operational expenses (cost), particularly in systems focused on high availability, such as power plants.
4. Effect of Mean Time To Repair (T_{CM})
   - Longer repair times will significantly add costs per hour, perhaps because of greater production losses due to extended downtime.
5. Effect of Parameter Shape (β).
   - The failure rate of the system, Parameter is a very sensitive parameter. A lower value of means a stable failure rate and hence higher cost per hour in this case. A larger means a rapidly increasing failure rate, which can lower the cost per hour, perhaps by allowing more effective scheduling of maintenance.
6. Effect of Parameter Scale (η)
   - Smaller value of η causes failures to happen earlier, thereby raising the cost per hour. A larger η postpones failures from occurring, thereby lowering the cost per hour of operation.

4. CONCLUSION

The shape (β) and scale (η) parameters were estimated using the Least Squares method within the NHPP framework, based on historical failure data exceeding 20,000 operating hours., the estimated values were β=1.75261 η=7,198.99, indicating an increasing failure rate over time.

The system's reliability is predicted to decline exponentially as operating hours increase, while the expected cumulative number of failures continues to rise. This pattern highlights the necessity of adapting preventive maintenance (PM) intervals in accordance with the actual reliability behaviours of the system.

This study also demonstrates that reducing the PM interval using the Power-Law NHPP model and DE algorithm can optimize the operation cost of the PLTGU cooling system by over 38%. The derived optimal PM interval is 371,60 hours. Validation via Monte Carlo simulation and sensitivity analysis proves the reliability and robustness of the optimum solution. Despite a significant variation in parameters (±20%), TOPT varied only by approximately ±20%. This indicates the solution's insensitivity to reliability and cost parameter uncertainty.

From the results of this research, it is advised to apply the ideal preventive maintenance interval proposed in the cooling system of the PLTGU Semarang. Furthermore, the method established here can be modified to be applied in other power generation systems and other equipment

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