The Determination of Preventive Maintenance using Simulated Annealing Algorithm based on Weighted Fitness Function

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ABSTRACT

This study aims to determine the machine maintenance schedule. We use the Simulated Annealing Algorithm. Fitness and reliability functions are functions that are used in the optimization process. Several weighting scenarios are done to see the unity of the function. The results of the scenario produce several alternative schedules. This algorithm is implemented on machines that have more than one sub-machine. This sub-machine is a smaller engine system part. This sub-machine also has one particular function. The results of the study show that the optimal engine maintenance period to use is six periods. There are five scheduling scenarios used in this problem. The resulting schedule can increase the value of reliability and can minimize costs.

1. Introduction

Maintenance is an important activity in the manufacturing industry. Preventive maintenance can increase the life of the engine and prevent breakdown. The machine has a breakdown when production and might severe fatal impacts. These impacts include disrupted production processes, lost production, more extended downtime, and expensive repair costs. Regarding the importance of machine maintenance, companies require a maintenance period. However, generally, the maintenance period is only based on the machine book manual. If the machine operates relatively long, the machine experiences an unexpected breakdown. Therefore, the authors propose preventive maintenance based on actual machine breakdown. Hence, the maintenance period does not depend on the manual machine book. Preventive maintenance based on breakdown time data can use the classical approach. Some of these approaches are the age replacement model and block replacement model. The method is used for one sub-machine and provides information on treatment time on the timing of sub-machine replacement. Pan, et al. [1] reviewed preventive maintenance for a single machine. They proposed a single machine scheduling model. The model aims to minimize the average scheduling time. Another approach for determining the maintenance schedule is by using a genetic algorithm. This approach was

applied by Chen, et al. [2]. They used Genetic Algorithms (GA) to schedule preventive maintenance of rocket machines. Ayoobian and Mohsendokht [3] proposed genetic algorithms to schedule maintenance of nuclear power plants. Moinian, et al. [4] developed a genetic algorithm for scheduling maintenance of gas turbine preventive maintenance.

Another type of metaheuristic method is the Simulated Annealing algorithm (SA). SA is a method for solving combinatorial optimization problems. SA discusses randomly to get the optimal solution to a problem. Temperature SA decreases from high to low. The change is expected to get an optimal global solution. Some researchers also have studied preventive maintenance. Shirmohammadi, et al. [5] proposed a non-linear optimization model based on age. It is used to optimize single component preventive maintenance schedules. Moghaddam [6] compared SA with other algorithms such as the Genetic Algorithm (GA) and a Steady State Genetic Algorithm (SSGA). Allaoui and Artiba [7] used a combination simulation model and machine scheduling optimization with more than one objective function. One of the developments of GA is the GA hybrid used by Nguyen, et al. [8]. In actual conditions, optimization using conventional methods does not get convergent results because the objective function is more than one challenge.

Several researchers have researched other metaheuristic algorithms. Azadeh, et al. [9] developed a hybrid metaheuristic algorithm on employee scheduling optimization. The metaheuristic hybrid algorithm also has been used by Pooranian, et al. [10], Allahyari, et al. [11], and Liu and Kozan [12]. Furthermore, Nasir, et al. [13] proposed a spiral adaptive dynamic metaheuristic algorithm. Several researchers have carried out the use of SA in various fields. Vahedi Nouri, et al. [14]used for cases of machines with non-fixed operating times. Wang, et al. [15] applied to the chemical distillation optimization process. Kang and Zhu [16] applied SA to solve the problem of train passenger waiting time. Zhang, et al. [17] used SA to track differences in areas experiencing drought based on time intervals. Jerin Leno, et al. [18] proposed a strategy to increase the convergence of the SA algorithm.

In this article, we use SA for maintenance scheduling. This algorithm was chosen because it was never used in literature before. Annealing is illustrated as a physical process. In the process, the substantial heated until it reaches high temperatures. Furthermore, the solid is slowly allowed to cool. In the process, all particles make themselves slowly reach a low level of energy. The final energy level depends on the temperature and cooling rate. SA is a simulation that starts with a scorching temperature. Next, the simulation will end at a minimum final value. The purpose of this study is to determine the optimal preventive maintenance schedule using SA. The proposed scheduling model is based on cost and reliability weighting match functions. The difference between this research and the previous one weighs and schedules based on the consistency of the algorithm during the treatment period. The treatment period is a concern of the researcher. The schedule formed is recommended for 12 months or more. The schedule was not verified. We need to do Validation for a more extended period. The proposed algorithm uses a match function that matches the company's problems. This study carries out several scenarios of weight reliability and cost.

2. Methods

2.1 Simulated Annealing Algorithm

Optimization in SA used two objective functions. The function is the total cost and reliability function. According to Moghaddam [6], the form of the objective function is shown in equation (1) and equation (2).

$$total\ cost = \sum_{i=1}^{N}\sum_{j=1}^{T}[F_i.\lambda_i((X'_{i,j})^{\beta_i} - (X_{i,j})^{\beta_i}) + M_i.m_{i,j} + R_i.r_{i,j}] + \sum_{j=1}^{T}[Z(1 - \prod_{i=1}^{N}(1 - (m_{i,j} + r_{i,j})))]$$

(1)

$$reliability = \prod_{i=1}^{N}\prod_{j=1}^{T}e^{-\left[\lambda_i\left((x'_{i,j})^{\beta_i} - (x_{i,j})^{\beta_i}\right)\right]}$$

(2)

the notation used in both functions is as follows:

N : number of sub-machines

T : a treatment period

F_i : sub-machines breakdown cost i

β_i : sub-machines shape parameter i

λ_i : $1/\alpha_i$, and α_i : scale parameter

M_i : sub-machines treatment cost i

R_i : sub-machines replacement cost i

Z : downtime fixed cost

$m_{i,j}$: 1 if treatment is carried out and 0 if treatment is not carried out

$r_{i,j}$: 1 if the replacement is carried out and 0 if replacement is not carried out

$X_{i,j}$: $(1 - m_{i,j-1})(1 - r_{i,j-1})X'_{i,j-1} + m_{i,j-1}(\gamma_i.X'_{i,j-1})$; and $0 \leq \lambda_i \leq 1$.

$X'_{i,j}$: $X_{i,j} + \frac{T}{J}$; J is a number of discrete intervals in a period $[0, T]$.

$Z(t)$: normalization factor

$T(t)$: solid temperature

S is an initial scheduling solution

The annealing process is described as a stochastic procedure in a physical phenomenon. The solid undergoes many random transitions from different energy levels to the balance point at each temperature level. The energy level is random so that the opportunity value can statistically describe it. If X states the random energy level of solids with the energy level E, then the chance is written $P(X = E)$ (equation (3)).

$$P(X = E) = \frac{1}{Z(t)}e^{\left(\frac{-E}{K_B T(t)}\right)}$$

(3)

$Z(t)$ is a normalization factor, T(t) is the stable temperature, and K_B is Boltzmann's constant, $1.38064852 \times 10^{-23}$ J/K. The distribution of opportunities is called Boltzmann Distribution. Suppose the temperature of T (t) decreases. In that case, the chance of a balance with a higher energy level has a chance that is not zero. If cooling is rapid, heat balance cannot be achieved at any temperature level, so the solid reaches a meta-stable condition.

In choosing an optimal schedule, researchers used a match function. A match function is a type of objective function that quantifies the optimality of the solution. Matching functions are used for weighting between functions of total costs (total costs) and functions of reliability (reliability) by Moghaddam [6]. Weighting is based on the needs of the company. If the company prefers to issue a higher machine, then the weight of $w2$ is more considerable than $w1$ and vice versa. The matching function is described in equation (4).

$$Fitness_1 = w_1\left(\frac{Total\ Cost}{Cost_{max}}\right) + w_2(-reliability) \tag{4}$$

Where $w1$ and $w2$ is which weight $w1 + w2 = 1$. Total Cost is a function of the total cost, with Costmax the maximum cost value of the process simulated annealing. Reliability is a reliability function which is the second objective function. The SA procedure from Kuo, et al. [19] is shown in Algorithm 1.

Algorithm 1 Simulated Annealing (SA) Algorithm
Begin Simulated Annealing
k=0
Select $T_{initial}$ and T_{final} if the termination criterion involves T_{final}
Randomly produce an initial solution x_0 from S
Determine the fitness value of the initial solution $f_0 = C(x_0)$
While a sufficient number of times to ensure a near-equilibrium condition, do
Randomly select a transition $x_k = y$ and compute $\Delta C = C(y) - C(x_k)$. If $\Delta C \leq 0$, Accept the transition. if $\Delta C > 0$, accept the transition with probability $Pr_k(\Delta C) = e^{\left(\frac{-\Delta C}{T_k}\right)}$, moreover, reject it with probability $1 - Pr_k(\Delta C)$
If the transition is accepted, update $x_k = y\ and\ f_k = C(y)$. (To accept or reject the transition with $\Delta C > 0$, First generates a random number p from (0,1). If $p \leq Pr_k(\Delta C)$, accept the transition; otherwise, reject it)
$k = k + 1$. Find T_k from T_{k-1} , based on the rule for decreasing the control parameter T
$x_k = x_{k-1}, f_k = f_{k-1}$
End while
End Simulated Annealing

2.2 Experimental Procedures

This study used several ASA inputs presented in Table 1. The initial temperature was the initial condition of the iteration. The final temperature was the final value intended from the iteration of the simulated annealing algorithm. At the same time, the iteration rate was 99%, which indicates that the iteration was carried out carefully.

Table 1. SA Variable Input

Variable Input	Score
Number of Sub-machines	4
Treatment period	6
Initial Temperature	10^6
Final Temperature	10^{-6}
Geometric Decreasing Rate	0,99

This algorithm was implemented to determine preventive maintenance scheduling for HPFQ machines. The machine has four sub-machine as sub-machine Press, Loader, Ejector, and Heating. The analysis was carried out at the time of breakdown. The data were tested for distribution compatibility and estimated parameters. The parameter time of breakdown is one of the inputs in the SA. The distribution comes from data on the time of sub-machine breakdown that has been collected by Giovani [20]. Table 2 describes the distribution of breakdown time for each sub-system along with the estimated parameters. Table 2 shows that sub-machine breakdown time is Weibull distribution and cost.

Table 2. Time of Sub-system Breakdown Distribution and Costs

Sub machines	Breakdown Distribution	Estimated Parameter		Cost (IDR)		
		alpha (scale parameter)	beta (shape parameter)	Breakdown (Fi)	treatment (Mi)	Replacement (Ri)
Press	Weibull	115.0032	1.4694	9,744,352.94	33,096.95	2,297,539.26
Loader	Weibull	131.4796	1.2005	7,599,827.10	29,295.04	1,008,442.96
Ejector	Weibull	122.0742	1.8763	7,225,662.70	28,811.67	743,037.95
Heating	Weibull	591.6664	2.5168	15,200,098.11	34,845.00	7,359,973.60
Fixed cost downtime (Z_i) = IDR 4,500,000,-						

Several experiments were carried out to obtain optimal total costs. Eleven trials were carried out to obtain the Total Cost Based on the Combination Weight of the Match Function. Furthermore, 11 experiments were carried out to obtain the reliability function based on weight matching functions. Each experiment used cost weights ($W1$) and different reliability ($W2$). Furthermore, the researcher provides several proposed preventive maintenance scenarios.

3. Result and Discussions

The results of several trials can be seen in Fig. 1 and Fig. 2. These present a weighting simulation with various combinations. Fig. 1 shows that the cost weight ($W1$) is increased and the weight of reliability is lowered ($W2$). The combination of the two weights results in a total cost that tends to decrease. This result proved research from Moghaddam [6]. Fig. 2 shows a decreasing trend in reliability [6]. The experiment in Fig. 2 also used the same weighting scenario as the experiment in Fig. 1.

The treatment period applied to the multi-subsystem SA case is six months. After that period, the maintenance schedule is changed every time the program starts. The researcher also proposed five scheduling possibilities. The schedule can be seen in Table 3, Table 4, Table 5, Table 6, and Table 7. There are several actions taken based on the proposed schedule. These actions are Replacement (R), Maintainance (M), and no action is needed (-).
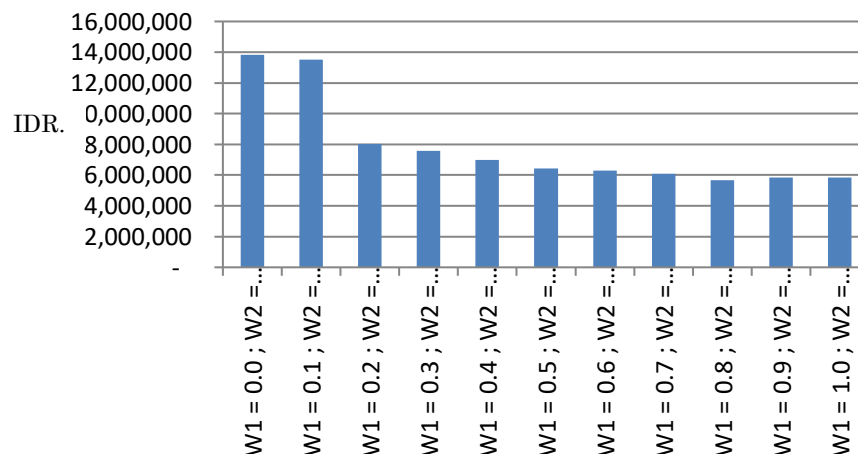

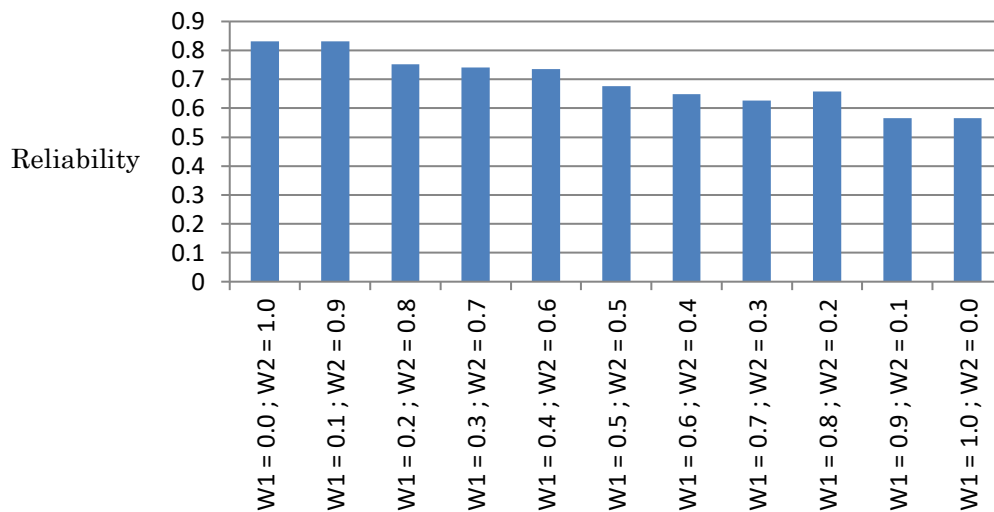Fig. 1. Total Cost Based on Combination Weight Matching Function

Fig. 2. Reliability based on the combined weight of the match function

Table 3. Preventive Maintenance Schedule Scenario 1 (W1 = 0.0; W2 = 1.0)

Sub machines	Month					
	1	2	3	4	5	6
Press	R	R	R	R	R	M
Loader	R	R	R	R	R	M
Ejector	R	R	R	R	R	M
Heating	R	R	R	R	R	M

Table 3 shows a preventive maintenance schedule with maximum weighting on reliability (W1 = 0.0; W2 = 1.0). The weighting does not consider the cost element in its match function. Using this weighting, the sub-system component must be replaced from the 1st month to the 5th month. Whereas in the 6th-month, treatment was taken. The total cost incurred to carry out maintenance using the scheduling is IDR 13,829,600 with the resulting reliability of 83.07%.

Table 4. Preventive Maintenance Schedule Scenario 2 (W1 = 0.1; W2 = 0.9)

Sub machines	Month					
	1	2	3	4	5	6
Press	R	R	R	R	R	-
Loader	R	R	R	R	R	-
Ejector	R	R	R	R	R	-
Heating	R	R	R	R	R	-

Table 4 shows the weighted preventive maintenance schedule W1 = 0.1; W2 = 0.9. This weighting gives a higher weight to reliability and gives a small weight to the cost of the match function. If using this weighting, the components in the sub-system must be replaced from the 1st month to the 5th month. While in the 6th month there is no need to take care measures. The total cost for maintenance using the scheduling is IDR 13,517,400 with reliability equal to the first weighting scenario of 83.07%.

Table 5 shows the preventive maintenance schedule with weighting on the cost component, which is 0.2 and 0.3. If using this weighting, the component in the sub-system must be replaced in the 2nd and fourth months. Furthermore, sub-systems do not need to take care of actions. The total cost incurred for maintenance using the scheduling ranges from IDR 7,572,400 – IDR 8,038,600 with a reliability of 74.01% - 75.20%.

Table 5. Preventive Maintenance Schedule Scenario 3 (W1 = 0.2; W2 = 0.8) and (W1 = 0.3; W2 = 0.7)

Sub machines	Month					
	1	2	3	4	5	6
Press	-	R	-	R	-	-
Loader	-	R	-	R	-	-
Ejector	-	R	-	R	-	-
Heating	-	R	-	R	-	-

Table 6 shows the preventive maintenance schedule by weighting the enlarged cost component from 0.4 to 0.8. If using this weighting, then the component in the sub-system must be replaced in the 3rd month. The total costs incurred for maintenance use the scheduling between IDR 5,653,420 - IDR 6,996,660 with reliability 62.72% - 73.59%.

Table 6. Preventive Maintenance Schedule Scenario 4 (W1 = 0.4; W2 = 0.6) and (W1 = 0.8; W2 = 0.2)

Sub machines	Month					
	1	2	3	4	5	6
Press	-	-	R	-	-	-
Loader	-	-	R	-	-	-
Ejector	-	-	R	-	-	-
Heating	-	-	R	-	-	-

Table 7. Preventive Maintenance Schedule Scenario 5 (W1 = 0.9; W2 = 0.1)

Sub machines	month					
	1	2	3	4	5	6
Press	-	-	-	-	-	-
Loader	-	-	-	-	-	-
Ejector	-	-	-	-	-	-
Heating	-	-	-	-	-	-

At weighting W1 = 0.9 and W2 = 0.1, based on the schedule formed in Table 7. The researchers found no need to take action for over six months because using scenario 5. The scenario requires submissions with minimum reliability. Although the costs incurred are maximum, but do not affect the minimum target reliability. So that SA does not recommend taking care of actions.

4. Conclusion

This study concludes that the SA method is helpful in preventive maintenance determinations. In some experiments, the combination of the weight of the match function resulted in a total cost and reliability that tended to decrease. Based on the analysis results using a weighting match function, there are four HPFQ machine maintenance preventive schedule scenarios. Each scenario has cost consequences and the value of the reliability/reliability of the machine. Further research can examine how long-term preventive maintenance scheduling uses SA to produce a consistent schedule. The researcher can use simulations of the breakdown time distribution parameters to see the behavior of the scheduling.

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