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Optimisation of Capacitated Planned Preventive Maintenance in Multiple Production Lines Using Optimisation-in-the-Loop Simulation

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Abstract: In a mass customisation manufacturing system, the production schedule is tailored to the customer's specifications. However, the production system must be accompanied by an effective maintenance program to ensure that the production lines operate as intended. The purpose of this study is to optimise planned preventive maintenance across multiple production lines. An optimised Weibull distribution is proposed to model the machine's Mean Time Between Failures (MTBF), and the total expected maintenance cost is calculated using this distribution, taking into account the probability of the machines remaining operational and failing. Because the optimised Weibull distribution is a continuous distribution, in order to simulate the continuous time domain, it will be divided into several sub-systems and optimised using Bayesian optimisation during simulation. The maintenance scheduling is carried out by considering available time capacity after production scheduling was arranged. The study's findings indicate that the proposed method successfully optimised the planned maintenance schedule without interfering production activity with total cost for the proposed maintenance planning as low as IDR 50.017,75/maintenance unit time.

Keywords: Planned preventive maintenance, MTBF, optimisation-in-the-loop simulation, Bayesian optimisation

1. Introduction

In a mass customisation manufacturing system, there will be multiple production lines, each producing a distinct type of product. Production targets for each type of product must be backed up by material availability, a short production cycle time, and a reliable production line. A short production cycle time requires a production line to contain a few machines, and one way to improve the production line's reliability is to perform maintenance on critical machines [1]. In the most of manufacturing industries, critical machine maintenance is typically performed correctively, that is, to repair the machine after failure. This is done due to the scarcity of resources available for maintenance. In corrective maintenance, the required maintenance action is medium to heavy due to major failure to the machines. Therefore, corrective maintenance is frequently more time-consuming and costly than preventive maintenance. Therefore, to make preventive maintenance an option, it must be accompanied by cost analysis to increase the confidence of management in performing it before the critical machines are failure.

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Maintenance actions should be planned in accordance with available time and other resources to ensure that the machine maintenance schedule does not interrupt the production activity and is cost-effective. One of the main inputs in the maintenance field is Mean Time Between Failures (MTBF) or Mean Time to Failures (MTTF) which is typically not constant; it varies according to the machine's condition. Given that the MTBF or MTTF is stochastic, the randomness of the MTBF or MTTF can typically be modelled using the exponential or Weibull distributions [2], [3]. Due to its adaptability and relative simplicity, the Weibull distribution, proposed by Waloddi Weibull in 1951, was widely applied in maintenance studies.

When the MTBF is random and represented by a probability distribution, then the maintenance total cost must be approximated by taking into account the probability of the machines before and after failure. Consequently, the total cost formula will incorporate preventive and corrective maintenance costs based on their occurrence probability. Since the model for the time-based events in the maintenance is a continuous model and because there is no formal algorithm for optimising the total cost formula, one technique that can be used is optimisation during iterative simulation.

The optimisation used in this study is Bayesian optimisation (BO) as it able to provide a good quality solution by minimising intervention from the system analyser [4]. Besides, from computation point of view, the BO has computation effective since it takes data sample in the objective function evaluation. In the optimisation process, BO aims to find the global optimum through a black-box function *f* over a space *x*, that is $x_{opt} = \arg min_{x \in X} f(x)$. In every iteration, a surrogate function attempts to approximate the *f*(*x*) based on the best evaluation so far. Then, an acquisition function will suggest the most promising points to be evaluated and it makes the BO has effective computation.

2. Related Works

The purpose of maintenance activities is to ensure that all industrial facilities continue to operate in accordance with its manufacturer's specifications, therefore, increased maintenance performance should bring in growing profitability to the industry [5]. However, because maintenance activities require the machine to stop for a period of time, they should be scheduled in accordance with the production planning to avoid impeding the production system's ability to meet its production targets [6]. Study about weighted capacitated planned maintenance by considering period-dependent predetermined time limitations for the scheduled maintenance activities has been carried out by [7]. The objective of that study is to minimise fixed and variable maintenance costs with a feasible schedule. A similar study that integrates production planning with maintenance has been investigated by [8]. In that study, production planning was used to forecast machine degradation, which was then used to determine the maintenance strategy.

Alimian et al. examined parallel-line capacitated lot sizing and scheduling problems by incorporating sequence-dependent setup time and cost, in addition to the preventive maintenance schedule [9]. Zhang et al. conducted research on the optimization of condition-based maintenance in serial machine production systems [10]. Akl et al. were studying another maintenance study that incorporated production resources aspects. In that study, a high-value asset maintenance system was modelled using a novel large-scale discrete event simulation model that considering asset acquisitions factor, maintenance workforce planning, and preventive maintenance scheduling [1]. Ghaleb et al. conducted another study on the integrated production and maintenance scheduling in a jobshop production system. A hybrid genetic algorithm was used in that study to optimise deteriorating machines [11].

It is critical to minimise the negative impact of maintenance activities on other facets. Fernández et al. proposed a practical method for dynamic maintenance planning based on Dynamic Risk Assessment (DRA) [12], whereas Abdelkader et al. proposed a multi-objective optimisation for bridge maintenance planning with the goal of minimising traffic disruption duration and environmental impact [13]. Han et al. proposed a multi-objective optimisation model for Preventive Maintenance (PM) planning with the goal of minimising the dynamic characteristics of risk, the conflicting effects of increased risks due to PM, and the maintenance cost [14]. Tao et al. also conducted a study on maintenance planning that included risk-based decision making and resulted in the development of a vehicle health management system [15].

Additionally, a maintenance strategy can be developed in response to the deterioration process. The typical process for making maintenance decisions is to forecast the machine's condition during the deterioration process and then identify and schedule the appropriate maintenance strategy. Zhang et al. proposed a model-based reinforcement learning approach for determining the maintenance actions to be taken for each degradation state at each inspection time during a finite planning period [16]. Rombouts et al. proposed a coordinated maintenance model for a multi-component system with compound Poisson deterioration. In that study, a Semi-Markov system was used to optimize the threshold at which a component is eligible for preventive maintenance if another component requires corrective maintenance [17].

Morato et al. also conducted research on maintenance planning based on the deterioration process. The study's objects are bridges connecting offshore platforms and wind turbines that are subjected to deterioration mechanisms over the course of their operational lives [18]. Rivera-Gomez et al. investigated another type of maintenance planning based on the deterioration process, referred to as age-based maintenance planning. The study's object is an unreliable production line, and the maintenance decision is based on three factors: production, sampling inspection, and age-based maintenance planning [19]. El Hamshary et al. conducted another study in the same field that consider the allocated budget for subway maintenance [20].

The majority of maintenance studies formulated the total cost as a zero-one decision regarding whether to perform planned maintenance activities or not. However, in a stochastic condition where the machines' MTBF is not constant, the time chosen for preventive planned maintenance still has a probability that the machines are already failing and requiring corrective maintenance. As a result, the total cost must be calculated taking into account the cost of preventive and corrective maintenance. In this study, the total cost is formulated by multiplying preventive and corrective maintenance by their probability of occurrence. The MTBF's randomness is modelled using the Weibull distribution, and the decision to perform the maintenance activity is made based on available time capacity and carried out during a simulation. That are what distinguishes this study from previous studies.

3. Models Development

Parameter definition:

t	:	time index
MTBF	:	Mean Time Between Failure
$MTBF_{pred}$	:	Prediction value of MTBF
MSE	:	Mean Squared Error
m	:	machine index
M	:	number of critical independent machines
y	:	maintenance activity
i	:	index of maintenance activity
I	:	number of maintenance activity
pt	:	preventive maintenance duration
ct	:	corrective maintenance duration
pc	:	preventive maintenance cost
p	:	multiplier for corrective maintenance cost relative to preventive maintenance cost
cc	:	corrective maintenance cost $(cc_i = pc_i \times p)$.
N	:	number of *MTBF* data.
r	:	time capacity available
T	:	expected time to replace a machine

Because the shape, scale, and location of the Weibull distribution will be optimised in this study in order to obtain an accurate $MTBF_{pred}$, those values will serve as decision variables.

Decision variables definition:

a	:	Weibull distribution shape value
b	:	Weibull distribution scale value
c	:	Weibull distribution location value
TCprev	:	expected total cost of preventive maintenance
TCcor	:	expected total cost of corrective maintenance
TC	:	expected total maintenance cost
Et	:	expected time to replace the critical machine
v	:	time available
d	:	decision variable indicates running a maintenance activity $(d \in 0/1)$
s	:	number of sub-simulation system

Assumptions:

a. The value of *r* varies between planning periods based on the quantity of time spent on production.

b. As long as the maintenance is still within the coverage period preceding the critical machine failure time, it can be shifted.

Steps for developing Weibull probability distribution is as follows:

Step 1 : sort ascending the $x_m, m \in = 1, 2, \dots, M$

Step 2 : calculate rank probability (*p*) of the $MTBF_{tm}$ using Equation 1.

$$p_{MTBF_{tm}} = \frac{i - 0.5}{N}, t \in 1, 2, \dots, N; m \in 1, 2, \dots, M \quad (1)$$

Step 3 : determine *b* value using Equation 2:

$$b = \frac{\left[N \times \sum_{t=1}^{N} MTBF_{tm}\,(w_i)^{\frac{1}{a}}\right] - \left[\left(\sum_{t=1}^{N} MTBF_{tm}\right) \times \left(\sum_{t=1}^{N}(w_{tm})^{\frac{1}{a}}\right)\right]}{N\sum_{t=1}^{N}(w_{tm})^{\frac{2}{a}} - \left[\sum_{t=1}^{N}(w_{tm})^{\frac{1}{a}}\right]^2}, m \in 1,2,\ldots,M \qquad (2)$$

Where:

$$w_{tm} = ln\left(\frac{1}{1 - p_{MTBF_{m}}}\right), m \in 1,2,\ldots,M$$

Step 4 : determine *c* value using Equation 3:

$$\boldsymbol{c} = \frac{\left[\sum_{t=1}^{N} \boldsymbol{MTBF_{tm}} \times \sum_{t=1}^{N}(\boldsymbol{w_{tm}})^{\frac{2}{a}}\right] - \left[\left(\sum_{t=1}^{N} \boldsymbol{MTBF_t} \times (\boldsymbol{w_t})^{\frac{1}{a}}\right) \times \sum_{t=1}^{N}(\boldsymbol{w_t})^{\frac{1}{a}}\right]}{\left[\boldsymbol{N} \times \sum_{t=1}^{N}(\boldsymbol{w_t})^{\frac{2}{a}}\right] - \left[\left(\sum_{t=1}^{N}(\boldsymbol{w_t})^{\frac{1}{a}}\right)^2\right]}, \boldsymbol{m} \in \boldsymbol{1}, \boldsymbol{2}, \ldots, \qquad (3)$$

The determined *a, b*, and *c* values will be used calculate the $MTBF_{pred}$ value using Equation 4.

$$MTBF_{pred_{tm}} = c + b \times \left[ln\left(\frac{1}{1 - p_{MTBF_{tm}}}\right)\right], t \in 1,2,\ldots,N; m \in 1,2,\ldots,M \qquad (4)$$

To obtain an accurate $MTBF_{pred}$ value, the independent variable, that is *a*, will be optimised with the goal of minimising the *MSE*, as defined in Equation 5.

$$\boldsymbol{MSE_m} = \frac{\sum_{t=1}^{N}\left(\boldsymbol{MTBF_{tm}} - \boldsymbol{MTBF_{pred_{tm}}}\right)^2}{\boldsymbol{N}}, \boldsymbol{m} \in \boldsymbol{1}, \boldsymbol{2}, \ldots, \boldsymbol{M} \qquad (5)$$

The main objective of this study is to optimise the expected total maintenance cost, which is defined in Equation 6 as the sum of the expected total cost of preventive maintenance and the expected total cost of corrective maintenance. The optimisation takes into account the availability of time resources during the production activity in order to ensure that the solution is feasible to implement.

$$Min\ TC = \frac{TC_{prev_m} + TC_{cor_m}}{Et_m}, m \in 1,2,\ldots,M \qquad (6)$$

The TC_{prev_m} is computed by multiplying maintenance activity with maintenance activity cost, as defined in Equation 7.

$$\boldsymbol{TC_{prev_m}} = \sum_{i=1}^{I} \boldsymbol{y_{im}} \times \boldsymbol{pc_{im}}, \boldsymbol{m} \in \boldsymbol{1}, \boldsymbol{2}, \ldots, \boldsymbol{M} \qquad (7)$$

The TC_{cor_m} is computed by multiplying cost of corrective maintenance with the probability of the machine breaking down, which is derived from the Weibull distribution's cumulative probability. Equation 8 shows the formula to compute the TC_{cor_m}.

$$\boldsymbol{TC_{cor_m}} = \boldsymbol{cc_c} \times \boldsymbol{F(T)_m}, \boldsymbol{m} \in \boldsymbol{1}, \boldsymbol{2}, \ldots, \boldsymbol{M}$$
$$\boldsymbol{F(T)_m} = \{\boldsymbol{1} - \boldsymbol{e}^{-\left(\frac{\boldsymbol{MTBF_m} - \boldsymbol{c}}{\boldsymbol{b}}\right)^{a}}, \boldsymbol{if\ MTBF_m} > \boldsymbol{c}\ \boldsymbol{0}, \boldsymbol{otherwise} \qquad (8)$$

In Equation 6, the Et_m is calculated by summing the cumulative probability to carry out preventive and corrective maintenance, as depicted in Equation 9.

$$Et_m = \left(\int_0^{T_m} MTBF_m \times f(MTBF_m)dMTBF_m\right) + \left(T_m \times (1 - F(T)_m)\right) \qquad (9)$$

According to assumption *a*, the planned maintenance will be considering available time since it was used for production activities. According to assumption *b*, if the available time for conducting planned maintenance during the optimum period is insufficient, the period will be shifted to the alternate period with still considering the *TC*. That condition is defined in Equation 10.

$$pt_{im} \times y_{im} \times d_t \leq r_t, m \in 1, 2, \dots, M \tag{10}$$

4. Optimisation in-the-Loop Simulation

Due to the fact that BO uses sample data to evaluate the objective function and the objective function in this study is a continuous function, a simulation will be used to discretise the objective function in order to make the computation more efficient. To have a shorter period in the simulation, a hierarchical decomposition concept as implemented by Zhou, Li and Lin [21] is adopted. The T will be divided into s groups and all of the groups will be simulated simultaneously and the result will be combined again in order to have an integrated analysis. Fig. 1 shows the mechanism of the proposed simulation and Fig. 2 shows the optimisation during simulation.

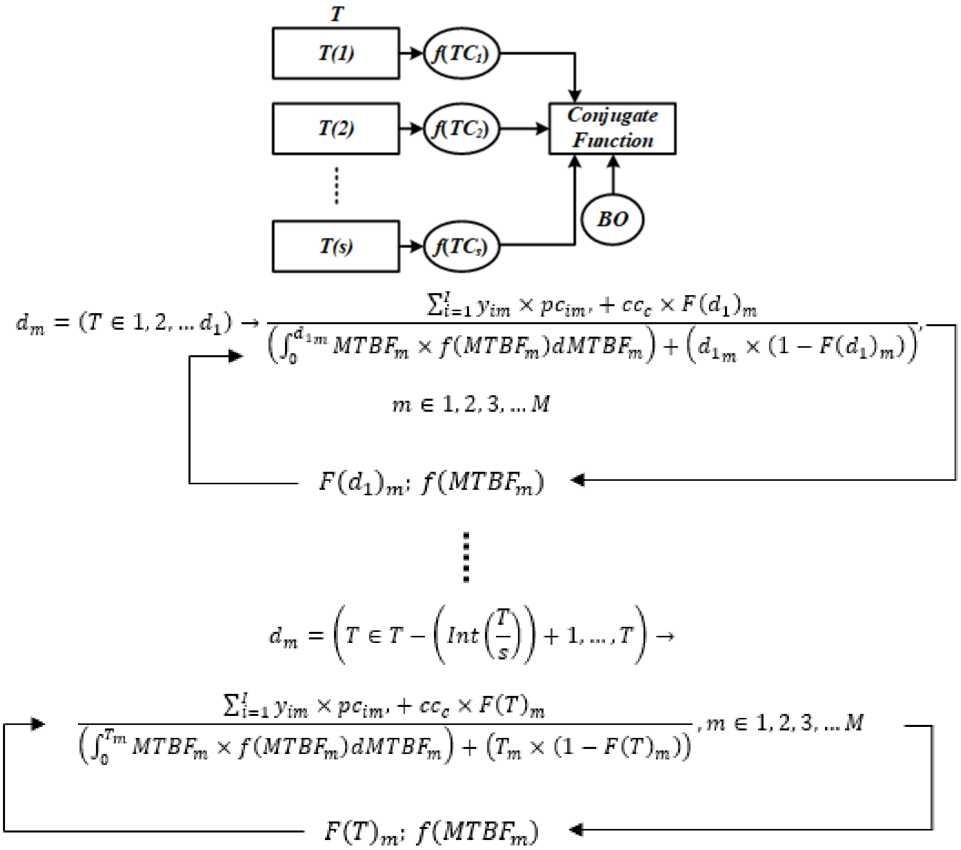

Fig. 1 - Mechanism of the proposed simulation

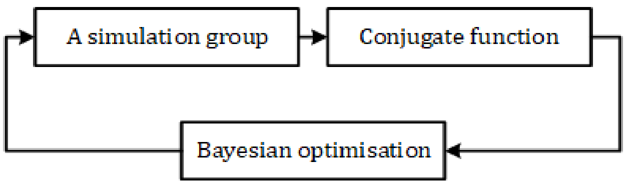

Fig. 2 - Mechanism of the optimisation during simulation

5. Case Study

This study took place in a manufacturing industry in Indonesia. The company has implemented a mass-customisation concept; therefore, the inventories are held in the form of semi-finished products. The company produces 12 types of products and the customisation of the semi-finished products to become final products is processed by a different production line consisting of 2 machines. The parameters values and the historical data on MTBF for the critical machines are as follows:

M = 12, I = 5, p = 5, $N_m = (20\ 20\ 20\ 20\ 20\ 20\ 20\ 20\ 20\ 20\ 20\ 20)$, s = 3.
$MTBF_1 = (30\ 26\ 23\ 23\ 29\ 30\ 30\ 26\ 25\ 23\ 26\ 25\ 24\ 24\ 27\ 30\ 26\ 30\ 28\ 23)$,
$MTBF_2 = (22\ 19\ 21\ 17\ 19\ 21\ 17\ 19\ 21\ 25\ 22\ 17\ 22\ 23\ 23\ 19\ 23\ 23\ 18\ 18)$,

$MTBF_3 = (16\ 13\ 15\ 14\ 15\ 13\ 16\ 13\ 14\ 15\ 13\ 13\ 17\ 15\ 17\ 17\ 13\ 14\ 14\ 15)$,
$MTBF_4 = (31\ 27\ 27\ 30\ 27\ 33\ 31\ 28\ 29\ 27\ 29\ 28\ 29\ 30\ 30\ 29\ 31\ 30\ 31\ 30)$,
$MTBF_5 = (14\ 17\ 13\ 16\ 12\ 13\ 13\ 15\ 14\ 16\ 12\ 14\ 13\ 14\ 13\ 14\ 13\ 15\ 17\ 14)$,
$MTBF_6 = (13\ 9\ 13\ 13\ 9\ 12\ 8\ 9\ 13\ 13\ 10\ 8\ 9\ 11\ 10\ 13\ 11\ 9\ 13\ 9)$,
$MTBF_7 = (14\ 11\ 8\ 12\ 12\ 12\ 12\ 9\ 8\ 13\ 14\ 7\ 7\ 7\ 14\ 11\ 8\ 14\ 11\ 12)$,
$MTBF_8 = (10\ 11\ 10\ 11\ 9\ 12\ 11\ 12\ 9\ 9\ 11\ 11\ 12\ 9\ 10\ 10\ 10\ 10\ 10\ 11)$,
$MTBF_9 = (11\ 10\ 12\ 9\ 12\ 10\ 10\ 12\ 12\ 12\ 9\ 12\ 9\ 10\ 12\ 12\ 11\ 12\ 10\ 9)$,
$MTBF_{10} = (9\ 9\ 6\ 8\ 8\ 9\ 7\ 7\ 6\ 9\ 6\ 7\ 7\ 6\ 7\ 6\ 6\ 8\ 7\ 7)$,
$MTBF_{11} = (16\ 17\ 17\ 17\ 15\ 17\ 15\ 13\ 13\ 17\ 15\ 15\ 13\ 16\ 16\ 17\ 16\ 16\ 15\ 16)$,
$MTBF_{12} = (22\ 23\ 21\ 18\ 20\ 19\ 21\ 18\ 18\ 21\ 20\ 18\ 18\ 22\ 20\ 23\ 19\ 19\ 22\ 20)$,

$$y_{im} = \begin{pmatrix} 1\ 1\ 1\ 0\ 1;\ 0\ 1\ 0\ 1\ 1;\ 1\ 0\ 1\ 0\ 1;\ 1\ 1\ 1\ 1\ 0;\ 1\ 0\ 1\ 1\ 1;\ 1\ 0\ 1\ 0\ 1; \\ 0\ 1\ 1\ 1\ 1;\ 0\ 1\ 0\ 1\ 0;\ 1\ 0\ 1\ 1\ 0;\ 0\ 1\ 1\ 0\ 1;\ 0\ 1\ 1\ 1\ 1;\ 1\ 1\ 1\ 1\ 1 \end{pmatrix},$$

$$pt_{im} = \begin{pmatrix} 30\ 25\ 20\ 0\ 10;\ 0\ 40\ 0\ 15\ 5;\ 40\ 0\ 25\ 0\ 10;\ 30\ 10\ 10\ 25\ 0;\ 40\ 0\ 5\ 10\ 15;\ 10\ 0\ 20\ 0\ 15; \\ 0\ 20\ 10\ 5\ 5;\ 0\ 15\ 0\ 30\ 0;\ 60\ 0\ 15\ 30\ 0;\ 0\ 10\ 5\ 0\ 15;\ 0\ 25\ 10\ 15\ 10;\ 10\ 20\ 30\ 15\ 10 \end{pmatrix},$$

$$pc_{im} = \begin{pmatrix} 5000\ 10000\ 25000\ 0\ 7000;\ 0\ 12000\ 0\ 8000\ 8000;\ 5000\ 0\ 20000\ 0\ 9000; \\ 7000\ 12000\ 25000\ 8000\ 0;\ 6000\ 0\ 23000\ 7000\ 8000;\ 8000\ 0\ 22000\ 0\ 10000; \\ 0\ 13000\ 25000\ 7000\ 9000;\ 0\ 10000\ 0\ 8000\ 0;\ 6000\ 0\ 26000\ 7000\ 0; \\ 0\ 11000\ 27000\ 0\ 8000;\ 0\ 8000\ 22000\ 5000\ 7000;\ 7000\ 9000\ 23000\ 6000\ 8000 \end{pmatrix},$$

After MSE optimisation of the value of *a*, *b* and *c* through the steps for creating Weibull probability distribution, the result is shown in Table 1. Fig. 3 and Fig. 4 shows the Weibull distribution of every MTBF's machine after all of the simulation groups are combined.

Table 1 - Optimised a, b and c value

Machine	*a*	*b*	*c*	MSE
1	2.150	8.662	21.211	0.850
2	2.771	9.106	14.459	0.500
3	2.771	5.298	11.115	0.450
4	3.100	6.665	24.799	0.450
5	4.046	6.860	9.037	0.450
6	1.870	5.622	7.568	0.800
7	1.870	7.502	6.554	1.250
8	1.870	2.996	8.704	0.550
9	9.504	10.388	1.761	0.450
10	6.967	7.299	1.190	0.400
11	4.187	6.275	10.927	0.550
12	2.491	6.095	16.238	0.450

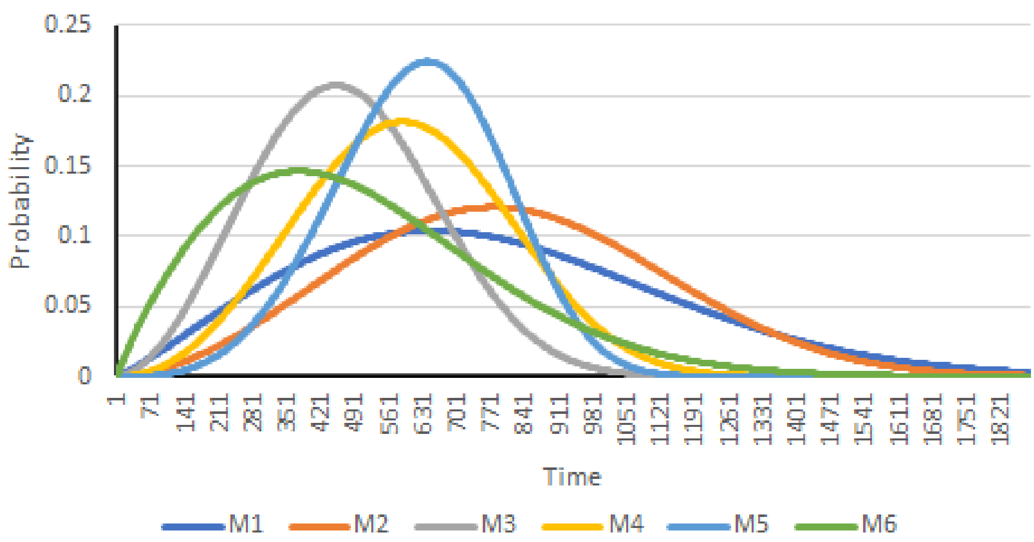

Fig. 3 - Weibull distribution of machine-1 to machine -6

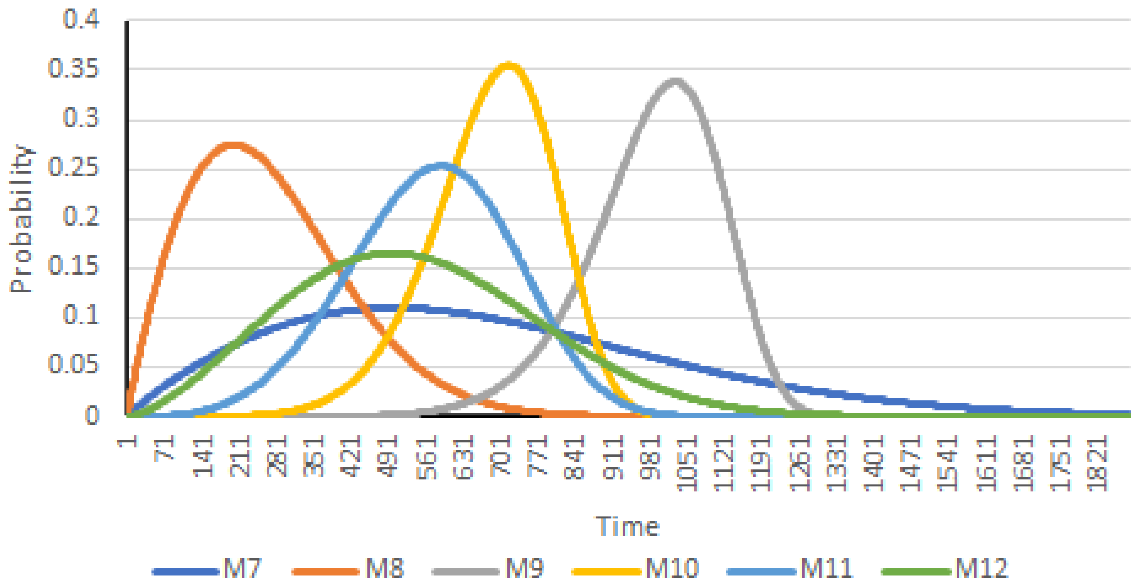

Fig. 4 - Weibull distribution of machine -7 to machine -12

The conjugate function in the BO is determined by adding a penalty value to the objective function when the available time at the chosen maintenance period is insufficient. Therefore, the conjugate function would enable the BO to find global optimum and feasible solution for the planned maintenance problem. After optimisation, the non-zero value of the d_{m_t} variables that represent the planned maintenance schedule is as follows:

$$d_{1_{153}} = 1;\ d_{2_{110}} = 1;\ d_{3_{85}} = 1;\ d_{4_{183}} = 1;\ d_{5_{78}} = 1;\ d_{6_{57}} = 1;\ d_{7_{49}} = 1;\ d_{8_{63}} = 1;\ d_{9_{57}} = 1;\ d_{10_{40}} = 1;\ d_{11_{88}} = 1;\ d_{12_{120}} = 1$$

Searching performance of the proposed BO during optimisation process is shown in Fig. 5 while Fig. 6 shows the comparison between required planned maintenance duration and the available time resources. Table 2 shows the maintenance schedule and estimated failure time for every machine. Optimum TC after optimisation is $\text{IDR } 50.017{,}75 / _{maintenance\ unit\ time}$.

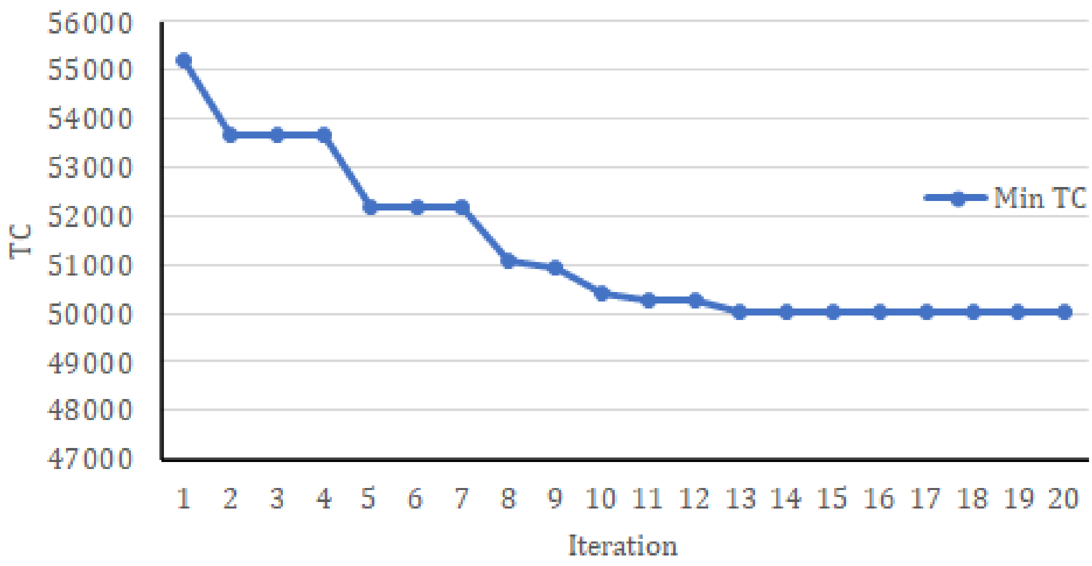

Fig. 5 - Searching performance of the proposed BO during optimisation process

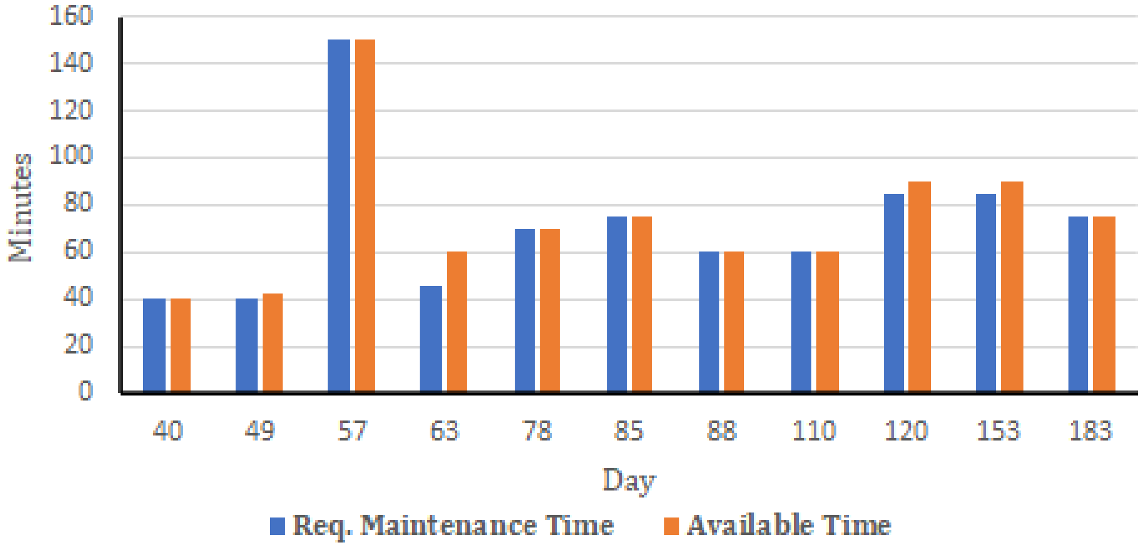

Fig. 6 - Comparison between required planned maintenance duration and the available time resources

Table 2 - Planned maintenance schedule and estimated failure time of every machine

Machine	Maintenance Schedule Day	Estimated Failure Day
1	158	194
2	110	156
3	85	110
4	183	215
5	78	109
6	57	80
7	49	81
8	63	75
9	57	85
10	40	59
11	88	118
12	120	149

6. Discussions

The efficacy of the proposed model will be demonstrated by comparing its total cost performance with the current total costs incurred in the manufacturing industry under consideration. Currently, as with the majority of other manufacturing systems, the implemented maintenance strategy is corrective maintenance, and the estimated total cost for this strategy can be calculated by presuming that maintenance is performed only when the machines break down. The time when the machines break down can be estimated based on their average MTBF value and Table 3 displays the average MTBF value for each machine as well as the *TC* incurred during that time period.

Table 3 - Corrective maintenance schedule day and the TC

Machine	Maintenance Schedule Day	*TC*
1	185	4609.553
2	144	4399.485
3	103	7472.91
4	206	5569.377
5	99	9444.88
6	76	12883.98
7	76	17304.98
8	73	5958.576
9	76	10207.1
10	40	59
11	88	118
12	120	149
	Total	112876.6

Taking into account the *TC* for all of the machines, then the proposed solution can reduce the *TC* for all of the machine by $\frac{(112876.6-50017.75)}{112876.6} \times 100\% = 55.69\%$. As illustrated in Figure 6, the solutions provided by the proposed optimisation-in-the-loop simulation technique are feasible; the required maintenance time can be covered by available time. However, there are periods when available time is critical and there is no possibility for extended maintenance times. As a result, overtime payment for maintenance personnel may be considered in the next study. According to the results in Table 2, the maintenance schedules for all machines are completed prior to the expected failure date. This implies that preventive planned maintenance is recommended for all critical machines in order to keep the total expected maintenance cost to a minimum. The effect of the *c* variable in the Weibull distribution on the *MTBF* prediction accuracy and the *TC* is also examined in this paper. The study is conducted by attempting to minimise the MSE_m value of the $MTBF_{predm}$ by optimising the value of the *c* variable while maintaining the values of the *a* and *b* variables constant. After obtaining the optimal value for the *c* variable, the TC will be optimised again, and the result is shown in Table 4.

Based on the Table 3, in this study, the *c* variable value has an effect to the accuracy of the MTBF prediction, however, it does not have an effect to the maintenance decisions and the total maintenance cost. This study considers the time constraint and the probability of asset failure, both of which have an effect on the cost of corrective maintenance. These two factors significantly differ from the previous study because they were not factored into the total estimated maintenance cost as in the study by Akl et al. (2022). The majority of studies that integrated maintenance with production planning did so by incorporating the maintenance schedule into production planning. This study is unique in that production planning has already been completed in order to meet customer orders, and maintenance has been optimised based on remaining available time capacity.

Table 4 - Effect of the c variable value to the MTBF prediction accuracy and the TC

m	**Current**			**New**		
	c	***MSE***	***TC***	***c***	***MSE***	***TC***
1	21.211	0.850	50.017,75	21.992	0.750	50.017,75
2	14.459	0.500		14.632	0.450	
3	11.115	0.450		11.564	0.150	
4	24.799	0.450		25.454	0.150	
5	9.037	0.450		9.312	0.250	
6	7.568	0.800		8.006	0.700	
7	6.554	1.250		6.906	0.800	
8	8.704	0.550		9.176	0.100	
9	1.761	0.450		1.963	0.300	
10	1.190	0.400		1.469	0.250	
11	10.927	0.550		11.543	0.150	
12	16.238	0.450		16.682	0.200	

Note: Dimension of the *TC* is per maintenance unit time

7. Conclusion

It can be concluded that the optimised Weibull distribution successfully models the randomness of the machine's MTBF, and that the total estimated maintenance cost can be formulated using that distribution by incorporating both expected preventive and corrective maintenance costs and their probabilities. Additionally, the proposed BO-based simulation is effective at solving the estimated total maintenance cost optimisation model.

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