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Incorporating deep learning data analytics techniques in the optimisation of capacitated planned maintenance

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A B S T R A C T

Manufacturing systems must be supported by the availability of materials, a streamlined production process and a prepared production line to achieve the production target. In a mass customization manufacturing system, the number of machines required for customization is relatively small. Consequently, maintenance on critical machines will impact this manufacturing system the most. Two types of maintenance strategies are implemented: corrective and preventive maintenance. The corrective maintenance requires more resources since the time and cost to repair the breakdown machine will be higher due to fatal failure. For the management to consider preventive maintenance while the binding machines are still operational, it must be equipped with a deep analysis demonstrating that fewer resources will be required. This paper discusses two deep analyses: accurate prediction of the binding machines' breakdown based on Mean Time Between Failure (MTBF) data using a deep learning data analytics technique and optimizing the maintenance total cost in the available capacitated time. The findings and results of this paper show that the proposed deep learning data analytics technique can increase the MTBF prediction accuracy by up to 66.12% and reduce the total maintenance cost by up to 4% compared with the original model.

1. INTRODUCTION

In a mass customisation manufacturing system, there are typically multiple production lines, each of which will produce a distinct product. The availability of materials, a streamlined production process and prepared production line, must support production targets for each type of product. A short production process necessitates a production line with a small number of machines, and one way to improve the readiness of the production line is to perform maintenance on critical machines [1], [2]. There are two types of maintenance strategies in the application, which are corrective and preventive maintenance. The commonly applied maintenance strategy on the critical machines in most manufacturing industries is corrective maintenance as the production is stopped due to the binding machine breakdown and the scarcity of resources available for maintenance. However, corrective maintenance requires medium to heavy maintenance action due to the fatal failure of critical machines.

Consequently, it requires more maintenance resource allocation. Another option is preventive planned maintenance, which conducts the maintenance when the binding machines are still operational and able to produce the products at the standard quality [3], [4]. Therefore, for the management to consider preventive maintenance, it must be equipped with a deep analysis demonstrating that fewer resources will be required.

One of the main issues discussed in the preventive planned maintenance is the prediction of the critical machines breakdown that can be derived from Mean Time Between Failure (MTBF) data. The MTBF data is typically not constant; it varies according to the machine's condition. Since conventional prediction approaches are inconvenient for MTBF prediction, researchers are currently focusing on data analytics techniques. Blumbauskas et al. [5] have implemented big data analytics to develop an intelligent maintenance application. Su & Huang [6] investigated the application of big data analytics for real-time predictive maintenance. Dinis et al. [7] have implemented big data analytics to address the stochastic factors in planned maintenance. Another similar study that implemented big data analytics techniques for product life cycle management and maintenance has been investigated by Zhang et al. [8]. Other applications of big data analytics in supporting maintenance have been investigated by other researchers [9]–[11] From those studies, it is a big opportunity to incorporate big data analytics in preventive planned maintenance analysis.

Maintenance tasks are time-consuming and likely to interrupt the production schedule. Therefore, a maintenance schedule should be planned with available resources to ensure it does not interfere with production activity and is cost-effective [12]. Further, it is called capacitated planned maintenance. In addition, when the MTBF is random, the total cost of maintenance must be estimated by factoring in the probability of machines breaking down before and after their MTBF. Consequently, the total cost formula will combine preventive and corrective maintenance costs based on their occurrence probabilities. The predicted MTBF will be modelled using statistical distributions to respond to that issue. The most implemented statistical distributions in the maintenance study field are exponential and Weibull distributions [13], [14]. However, due to its versatility and relative simplicity, the Weibull distribution proposed by Waloddi Weibull in 1951 was frequently used in maintenance studies. That concept is adopted in this paper in formulating the maintenance total cost.

The primary purpose of maintenance planning is to ensure that the production facilities continue to operate by their manufacturer's specifications. Therefore, increased maintenance performance should bring growing profitability to the industry [15]. Previous researchers have investigated several studies considering available resources in planning maintenance tasks. Kuschel & Bock [16] have researched weighted capacitated planned maintenance by considering period-dependent predetermined time constraints for scheduled maintenance activities. This study's objective is to minimise fixed and variable maintenance costs within a feasible timeframe. A similar study was conducted by Leo & Engell [17], that have analysed the integration of production planning with maintenance planning.

Ghaleb et al. [18] investigated the integration of production scheduling and maintenance planning in a job shop environment. In that study, degrading machines were optimized using a hybrid genetic algorithm. Another study that considered the machine condition in planning has been investigated by Zhang et al. [19]. The optimisation of condition-based maintenance in serial machine production systems was examined in that study. Alimian et al. [20] investigated parallel-line capacitated lot sizing and scheduling problems by incorporating sequence-dependent setup time and cost and the preventive maintenance schedule. Akl et al. [21] have studied a maintenance study that accounts for production resources. In this study, a high-value asset maintenance system was modelled using a novel large-scale discrete event simulation model and simulated by incorporating multiple aspects, including asset acquisitions, maintenance workforce planning, and preventive maintenance activity scheduling.

Today, big data analytics has received significant attention from researchers to enable a manufacturing system to become intelligent [22], [23]. In terms of reliability engineering, which sometimes requires an MTBF-based analysis, big data analytics present a significant opportunity for improving MTBF prediction. One of the factors that cause big data analytics to have superior prediction is the deep learning technique as the data recogniser. Susto et al. [24] have implemented a multiple classifier machine learning methodology for Predictive Maintenance. In that study, a set of inputs was classified using the proposed machine learning method related to

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operational cost and failure risk. With the widespread adoption of big data analytics, the deep learning-based data analysis process has been standardised, including data collection, analysis, storage, and querying. Therefore, there are currently a variety of commercial and open-source platforms that can be used to conduct big data analytics. Sahal et al. [25] have studied several open-source platforms to be matched with the requirements of a predictive maintenance use case. The result of the study shows that an open-source platform must be combined with other platforms to increase the capability for the predictive maintenance use case. Other researchers who have implemented big data analytics for maintenance [26].

The advantage of big data analytics in providing accurate predictions for the future has been utilised by previous researchers in the maintenance engineering field [5]. The performance of the deep learning technique as the tool in big data analytics for prediction and classification has been tested in other fields with superior results. This empirical proof supports that big data analytics can be implemented in maintenance engineering, usually containing machine failure prediction. Solomon et al. [27] have implemented a deep learning technique using a Multi-Layer Perceptron network to predict burglaries. The data in that study came from several contexts that prove the proposed deep learning technique can provide a high-accuracy prediction. Cheng et al. [28] used a deep learning technique for labelling or classification. The study object is sheep behaviours, and the output of the prediction system is very potential to be used as the basis of breeding management and monitoring animal welfare. Another similar study that implemented a deep learning technique for labelling or classification agriculture has been investigated by Raei et al. [29]. The object of that study is an agriculture irrigation system, and the proposed architecture for the deep learning technique is convolution network architecture with the U-net method.

Most studies in the maintenance field implemented a statistical distribution directly to model the randomness of the MTBF with less effort to improve the accuracy of the MTBF prediction. On another side, studies on maintenance engineering that implemented big data analytics did not consider the expected total maintenance cost of expected preventive and corrective maintenance costs. Furthermore, most studies in maintenance formulated the total cost as a zero-one decision regarding whether to perform planned maintenance activities. That method is incompatible with stochastic maintenance conditions that must consider the cost of preventive and corrective maintenance at a time. In this study, the MTBF will be first predicted using deep learning data analytics, and then the stochastic factor will be modelled using Weibull distribution. The total cost is formulated by multiplying preventive and corrective maintenance by their probability of occurrence. It will be optimised using an evolutionary algorithm by considering the available time to conduct the maintenance activities. Therefore, an optimum and feasible maintenance schedule for all binding machines can be obtained. That is what distinguishes this study from previous similar studies.

2. RESEARCH METHODS

The following notations to develop the optimisation of the maintenance case are used:

t:	index for time
MTBF:	Mean Time Between Failure
MTBF	: The predicted MTBF
MSE	: Mean Squared Error
m	: index for machine
M	: number of critical independent machines
y	: maintenance activity
i	: maintenance activity index
I	: number of maintenance activity
pt	: duration to carry out preventive maintenance task
ct	: duration to carry out corrective maintenance task
pc	: cost to carry out preventive maintenance task
pl	: estimated multiplier for corrective maintenance cost from preventive maintenance cost
cc	: cost to carry out corrective maintenance task $(cc_i = pc_i \times pl)$.
N	: number of *MTBF* historical data.
r	: available time capacity
T	: expected time to replace a machine

In the Weibull distribution, the shape, scale, and location values will be determined based on the result of the deep learning method; therefore, those values will serve as decision variables. The following definitions apply to all of the decision variables.

α : shape value in the Weibull distribution
β : scale value in the Weibull distribution
γ : location value in the Weibull distribution
TCp : expected preventive maintenance total cost
TCc : expected corrective maintenance total cost
TC : expected maintenance total cost
v : available time
d : decision variable to conduct maintenance tasks ($d \in 0/1$)
Et : expected time to carry out the planned maintenance tasks.

Assumptions:

a. The value of r in each production planning period varies according to the time remaining after production activities have been completed.
b. The maintenance task schedule can be shifted as long as it is within the coverage period before the critical machine breakdown time.

In this study, a conventional approach which uses Weibull distribution to model the stochastic of the MTBF will be compared with the result of the MTBF prediction using the deep learning method. Therefore, the algorithm for developing Weibull probability distribution is also proposed as follows:

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

Step 2 : Calculate the rank probability (p) of the $MTBF_{tm}$. The objective step is to give a score to the sorted MTBF proportionally according to the amount of data. Therefore, the p will be the function of the proportion value and number of data, as shown in the following formula:

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

Step 3 : determine β value, which is the first auxiliary variable to predict the MTBF. This variable represents the scale parameter in the Weibull distribution of the predicted MTBF. Therefore, β is the function of the range of the predicted MTBF divided by the cumulative distribution of the predicted MTBF, as shown in the following equation (2).

Step 4 : determine γ value, the second auxiliary variable to predict the MTBF. This value represents the threshold of the predicted MTBF. Therefore, this variable is the function of the cumulative MTBF based on their cumulative probability divided by their probability of occurrence, as shown in the following equation (3).

$$\beta = \frac{\left[N \times \sum_{t=1}^{N} MTBF_{tm}(w_i)^{\frac{1}{\alpha}}\right] - \left[\left(\sum_{t=1}^{N} MTBF_{tm}\right) \times \left(\sum_{t=1}^{N}(w_{tm})^{\frac{1}{\alpha}}\right)\right]}{N\sum_{t=1}^{N}(w_{tm})^{\frac{2}{\alpha}} - \left[\sum_{t=1}^{N}(w_{tm})^{\frac{1}{\alpha}}\right]^2}, m \in 1, 2, \dots, M \quad (2)$$

Where:

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

$$\gamma = \frac{\left[\sum_{t=1}^{N} MTBF_{tm} \times \sum_{t=1}^{N}(w_{tm})^{\frac{2}{\alpha}}\right] - \left[\left(\sum_{t=1}^{N} MTBF_t \times (w_t)^{\frac{1}{\alpha}}\right) \times \sum_{t=1}^{N}(w_t)^{\frac{1}{\alpha}}\right]}{\left[N \times \sum_{t=1}^{N}(w_t)^{\frac{2}{\alpha}}\right] - \left[\left(\sum_{t=1}^{N}(w_t)^{\frac{1}{\alpha}}\right)^2\right]}, m \in 1, 2, \dots, M \quad (3)$$

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The β, and γ values will be used to calculate the *MTBFp* by assuming the *MTBFp* has a threshold value of γ and increase non-linearly according to the scale value (β). Therefore, the *MTBFp* will be calculated using the following formula:

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

The independent variable that is α will be optimised with the objective function is minimizing the *MSE*, as defined in the following formula:

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

Step 1 and Step 2 is the requirement to the deep learning technique used in this study is from the Recurrent Neural Network (RNN) technique and is known as Gated Recurrent Unit (GRU) as proposed by Cho et al. [30]. In the maintenance study field, the MTBF data is recorded continuously; however, each event is separated by time. Therefore, the GRU technique is used because it has a procedure to recognise a data pattern separated by time. In the GRU technique, two gates will be used to address dependencies when the algorithm is trying to recognise the data pattern. The first gate is called the reset gate to anticipate the short-term dependencies while the second gate is called the update gate to anticipate long-term dependencies. The mechanism of the GRU used in this study is adapted from the one proposed by Zhang et al. [31], as shown in Fig. 1.

After the MTBF is predicted using the GRU deep learning technique, all Weibull parameters will be redetermined, including the TCp, TCc and TC, to know the benefit of using the deep learning technique in improving the maintenance cost performance. The expected maintenance total cost is defined in the following formula as the sum of the TC_p and the TC_c.

$$Min\ TC = \frac{TC_{p_m} + TC_{c_m}}{Et_m}, m \in 1,2,\ldots,M \quad (6)$$

The TC_{p_m} Is computed by multiplying maintenance activity with maintenance activity cost, as formulated in the following formula:

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

The TC_{c_m} is computed by multiplying the cost of corrective maintenance with the probability of the machine getting breakdown obtained from the cumulative probability of the Weibull distribution. Equation 8 shows the formula to compute the TC_{c_m}.

$$TC_{c_m} = cc_c \times F(T)_m, m \in 1,2,\ldots,M$$
$$F(T)_m = \begin{cases} 1 - e^{-\left(\frac{MTBF_m-\gamma}{\beta}\right)^{\alpha}}, if\ MTBF_m > \gamma \\ 0, otherwise \end{cases} \quad (8)$$

In (6), the Et_m is computed by summing the cumulative probability of preventive and corrective maintenance, as defined in the following equation (9).

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

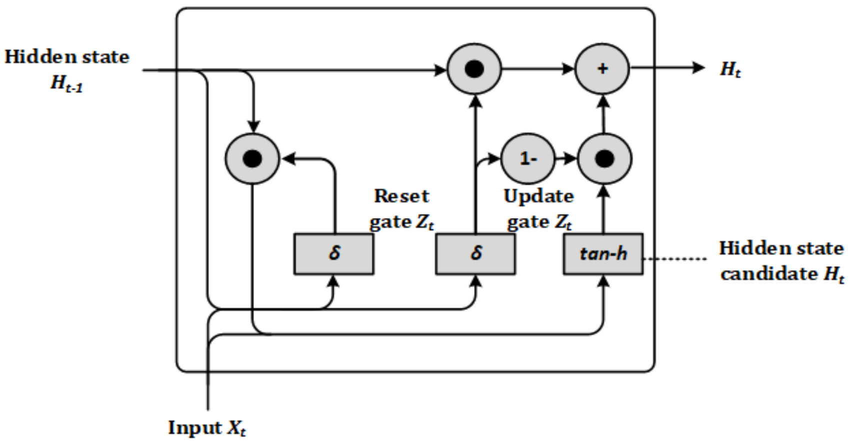

Fig. 1. Mechanism of the GRU as the deep learning algorithm

With reference to assumption a, the planned maintenance will consider the available time allocated for production activities. According to assumption *b*, if the available time during the optimum period for performing planned maintenance is insufficient, the maintenance task schedule will be shifted to the alternate period by considering the minimum *TC*. That condition is defined in the following formula:

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

3. RESULTS AND DISCUSSION

This study was conducted in an Indonesian manufacturing industry. Due to the company's implementation of mass customisation, the inventory is held in the form of semi-finished products. The company manufactures twelve distinct types of goods, with a separate production line containing two machines handling the customisation of semi-finished goods into finished goods. The following are the parameter values extracted from the system:

M = 12, I = 5, pl = 5, $N_m = (200\ 200\ 200\ 200\ 200\ 200\ 200\ 200\ 200\ 200\ 200\ 200)$.

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

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

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

The GRU deep learning is implemented using Python programming language while the optimisation of the Weibull distribution is conducted using built up Evolutionary Algorithm in the Microsoft Excel Solver. The non-zero result for *d* variables based on the conventional Weibull distribution is as follows:

$d_{1_{152}} = 1;\ d_{2_{111}} = 1;\ d_{3_{83}} = 1;$
$d_{4_{180}} = 1;\ d_{5_{78}} = 1;\ d_{6_{55}} = 1;$
$d_{7_{50}} = 1;\ d_{8_{62}} = 1;\ d_{9_{60}} = 1;$
$d_{10_{38}} = 1;\ d_{11_{90}} = 1;\ d_{12_{118}} = 1.$

Table 1. Comparison result of the conventional and GRU deep learning-based Weibull distribution

m	**Conventional Weibull Distribution**					**GRU Deep Learning-based Weibull Distribution**		
	α	***β***	***γ***	**MSE**	***TC***	***γ***	**MSE**	**TC**
1	2.150	8.662	21.211	0.850	49644.29	22.000	0.650	47696.67
2	2.771	9.106	14.459	0.500		14.657	0.320	
3	2.771	5.298	11.115	0.450		11.667	0.080	
4	3.100	6.665	24.799	0.450		25.474	0.090	
5	4.046	6.860	9.037	0.450		9.332	0.210	
6	1.870	5.622	7.568	0.800		8.136	0.500	
7	1.870	7.502	6.554	1.250		6.936	0.600	
8	1.870	2.996	8.704	0.550		9.237	0.070	
9	9.504	10.388	1.761	0.450		1.993	0.100	
10	6.967	7.299	1.190	0.400		1.509	0.150	
11	4.187	6.275	10.927	0.550		11.642	0.110	
12	2.491	6.095	16.238	0.450		16.882	0.120	
			Average	0.596		Average	0.250	

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

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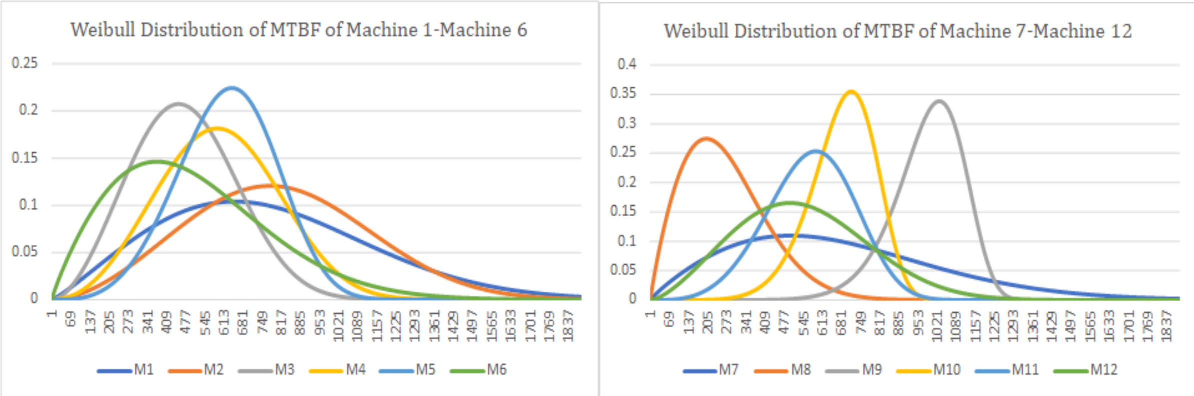

Fig. 2. Weibull distribution graphs of the machines

While, the non-zero result for d variables based on the GRU deep learning-based Weibull distribution is as follows:

$$d_{1_{151}} = 1;\ d_{2_{111}} = 1;\ d_{3_{82}} = 1;$$
$$d_{4_{179}} = 1;\ d_{5_{78}} = 1;\ d_{6_{54}} = 1;$$
$$d_{7_{49}} = 1;\ d_{8_{62}} = 1;\ d_{9_{59}} = 1;$$
$$d_{10_{37}} = 1;\ d_{11_{90}} = 1;\ d_{12_{117}} = 1.$$

Comparison of the result of the conventional Weibull distribution and the GRU deep learning-based Weibull distribution is shown in Table 1. Based on the Table 1, it can be seen that the GRU deep learning technique is able to improve accuracy of the *MTBF* prediction up to $\frac{(0.596-0.250)}{0.596} \times 100\% = 66.12\%$ and the *TC* up to $\frac{(49644.29-47696.67)}{49644.29} \times 100\% = 4\%$.

The primary contribution of incorporating the deep learning technique in this study is to enhance the *MTBF* prediction's accuracy. Nonetheless, it also affects the *TC*, and this phenomenon can be explained using the graphs of the Weibull distribution of critical machines shown in Fig. 2.

Fig. 2 demonstrates that the majority of Weibull curves for critical machines are skewed to the left, indicating that preventive planned maintenance is preferable for minimising the expected *TC*. However, because the Weibull curves for machines 9, 10, and 11 are relatively centred, the likelihood that these machines will break down when their maintenance tasks are scheduled remains high. In such a scenario, the expected *TC* will be greater; however, when the *MTBF* prediction can be improved using the proposed deep learning technique, the likelihood of machines break down will be lower, resulting in a lower expected *TC*.

4. CONCLUSION

On the basis of the preceding explanation, it can be concluded that the proposed optimisation model for preventive planned maintenance can be used to optimise the case under consideration with feasible maintenance schedule. When the expected total maintenance cost is modelled by taking into account the probability of performing both preventive and corrective maintenance, an increase in the accuracy of *MTBF* prediction using deep learning data analytics results in a decrease in the expected total maintenance cost.

From a managerial perspective, the MTBF prediction using deep learning can be used to predict and anticipate machines failure to keep the production lines up. The proposed optimisation model can be used to determine maintenance schedule based on time available. For future research, it is recommended to focus on the order allocation and schedule for each machine, which affect the machine's reliability. Thus, the trade-off between order fulfilment and machine maintenance can be resolved

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