

Maintenance management decision model for preventive maintenance strategy on production equipment

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Received: 29 September 2009; Revised: 25 April 2010; Accepted: 23 June 2010

Abstract: In industries, Preventive Maintenance (PM) is not a new practice to minimise the sudden breakdown of production machine. PM will be performed at predetermine intervals to provide a balance between failure cost and component utilisation (aging). However, most of PM interval is based on experience or original equipment manufacturer (OEM) recommendations. Consequently, the benefits from PM are not fully obtained because the current machine state is not considered. The aim of this paper is to propose a maintenance management decision model for PM application. The main objective of the model is to revise the PM interval based on current machine state. The proposed model provides step-by-step procedure from data identification, classification, evaluation until determination of the revised PM interval.

Keywords: Age Replacement Model (ARM); Failure Mode Effect and Criticality Analysis (FMECA); Maintenance management decision model; Machine breakdown; Proportional Hazard Model (PHM)

1. Introduction

In industry, the high rate of production machine breakdown is one of the disturbances on the production floor. This problem affects the profit of the company where the profit cannot be maximised due to increasing production loss and maintenance cost. In most occasions, the machine breakdown is contributed by either single component failure or failures between components (Li and Thompson, 2005). Failure of the component can be divided by sudden and deteriorating types (Moustafa *et al.*, 2004). Sudden failure refers to the immediate failure that occurs without giving any caution or sign, while deteriorating failure is a process of gradually worsening due to complete failure and it usually can be detected by abnormal signals such as vibration, sound etc. In fact, component failure is inevitable and it can be reduced by applying the appropriate and adequate maintenance.

Dhillon (2002) defined maintenance as the combination of activities to restore the component or machine to a state in which it can perform its designated functions. Generally, maintenance can be applied based on two strategies; corrective and preventive maintenance. Corrective Maintenance (CM), also known as run-to-failure or reactive strategy is a traditional strategy that restores (repairs or replaces) the machine or component to its required function after it has failed (Blanchard, 1995). This strategy reflects a high machine

downtime (production loss) and maintenance (repair or replacement) costs due to sudden failure (Tsang, 1995). Moreover, continuous application of CM will affect the machine performance. Therefore, an alternative of CM strategy is by applying the Preventive Maintenance (PM). PM strategy involves the maintenance activities such as preventive repair and preventive replacement that performed before equipment failure (Gertsbakh, 1977; Lofsten, 1999). The goal of PM is to reduce the failure rate or failure frequency of the machine. It contributes to reducing costs, minimising machine downtime (production loss), increasing productivity and improving quality (Usher *et al.*, 1998). The main target of PM is determination of the optimal time/interval to carry out the PM's task (replacement or repair) (Jardine, 1973).

In industry, most of PM (time/intervals) is performed based on the PM manual provided by machine or component (spare parts) manufacturer or original equipment manufacturer (OEM). However, Labib (2004) highlighted that PM should be based on the current state of the machine because each machine may operate in a different environment and failure of the machine (due to component failure) may not have similar occurrence as OEM predicted (only based on component age analysis – wear and tear process). It is also supported by Tam *et al.* (2006a), that PM intervals suggested by spare part manufacturer may not be optimal because the actual operating

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states may be very different and hence the actual outcomes may not satisfy plant requirements. Consequently, the benefits from PM (reducing costs, minimising machine downtime etc) cannot be maximised. Therefore, it is necessary to carry out PM by considering the current machine state. Current machine state refers to the external factors (covariates) such as environmental effect, human skills, product types etc, which contribute to the component failure, while the internal factor refers to the aging of the component, where it is usually measured in the unit of time (Lam and Zhang, 2003). This paper describes the development of a maintenance decision model to revise the PM interval based on current machine state. The proposed model provides a complete guide for maintenance engineers in making the maintenance decisions based on PM strategy in order to reduce machine failure rate. The paper firstly presents a literature review in maintenance categories and current maintenance practices in the case study company in order to identify the needs for the model that has been proposed. This is then followed by a description of model development process. Finally, a case study is presented for validation of the model. The definitions and notations used in this paper are given in Table 1.

2. Maintenance categories: A literature review

Most of maintenance research focuses on maintenance decision making process. According to Tam *et al.* (2006b), maintenance research falls into three categories; maintenance theories, mathematical models and frameworks (management model). Each of these categories provides a different methodology in making maintenance decision.

Maintenance theories are concepts of maintenance practice used for continues improvement in an organisation. Total Productive Maintenance (TPM) is an example of maintenance practice concept. In TPM, the involvement of non-technical staff (production operator) is required to do simple maintenance activities. Operators have been trained in making the maintenance decision to solve simple maintenance problems without depending on maintenance staffs (engineers or technicians). This practice indirectly can prevent unexpected breakdowns thus reducing the maintenance cost that amounts to several millions a year. In literature, the application of TPM in industries is well reported. For example, Tsang and Chan (2000) presented the TPM practice in a high-precision machining factory in Mainland China. Sharma *et al.* (2006)

discussed TPM implementation in a semi-automated cell of a company. Ireland and Dale (2001) reported the success of TPM implementation in three companies which attained the Japan Institute of Plant Maintenance (JIPM) award in 1995, 1998 and 1994 for companies A, B and C, respectively. Chan *et al.* (2005) reported that the productivity of an electronics company increased up to 83% after TPM programme is implemented. The challenge of this category is that the complete development and implementation of the maintenance practice concept may take a long period and involve many organisation levels. In other words, this is long-term programmed to achieve a world-class company. Mathematical models (also known as maintenance models) are various tools of maintenance management to solve particular maintenance problems. Age and block replacement models are two well-known maintenance models in PM study to solve repair and replacement problems. In literature, the applications of these models are widely reported. One of them is from Huang *et al.* (1995) that applied age replacement model in order to minimise the cost of failure for a case of drilling tools replacement problem. On the other hand, Bahrami *et al.* (2000) proposed a new perspective of block replacement model applied on machine tool in the crankshaft line at a car engine manufacturing company.

Table 1: The definitions and notations used.

a	A row vector consisting of the covariates
$C(T)$	Cost function at time, T
C_{dt-r}	Cost of downtime due to replacement
C_f	Cost of failure replacement
C_k	Critically index for failure mode k
C_p	Cost of preventive replacement
C_{pro}	Cost of product reject
C_r	Cost of replacement
$F(T)$	Cumulative distribution function
$R(T)$	Reliability function
t	Duration of time used in the analysis (FMECA)
T	Optimum time of replacement
x	A column vector consisting of the regression parameters
α_{kp}	Fraction of the component p 's failure having failure mode k (that is, the conditional probability of failure mode k given component p has failed)
β	Shape parameter of Weibull distribution
β_k	Conditional probability that failure mode k will result in the identified failure effect
θ	Scale parameter of based line lifetime of the critical component
θ_0	Scale parameter of actual lifetime of the critical component
$\lambda(t)$	Based line failure rate (without considering the covariate effects)
$\lambda_0(t)$	Actual failure rate function by considering the covariate effects
λ_p	Failure rate of component p

The main objective of this model is to determine the optimum time of preventive replacement to minimise the total machine downtime. Details application, modification, classification and clarification of these maintenance models are presented by Wang (2002). Although some of the maintenance models that have been proposed provides good results (decision), most of papers have been written for algorithm development purposes only. Therefore, it is difficult to be understood and interpreted by engineers and technicians. Another issue of this category is that most of papers focus only on the models analysis to provide a solution but not the whole process of maintenance decision making such as problem identification, failure analysis and data collection (types of data and sources). This issue highlighted by Dekker (1996), which stated that data is an important element in maintenance decision making and analysing data without knowing the underlying failure mechanisms, improper data collection and classification (censored and uncensored data) can lead to totally wrong results in determining the PM time/interval.

Framework (management model) defines as a guideline, procedure or step-by-step process used to plan or decide for something. The development of a maintenance framework may borrow some ideas from literature and apply some analysis tools from statistical and mathematical theories. Generally, the framework is used to solve the particular problems in a systematic way. Because of this reason, the framework is more practical method to assist engineers and technicians in making decisions. In maintenance application, various maintenance frameworks to solve particular maintenance problems have been proposed. For example Mirghani (2001) proposed a costing framework with the objective of providing reliable, relevant, and timely information about the actual costs and the cost efficiency of planned maintenance jobs. Tan and Kramer (1997) proposed a general framework for preventive maintenance optimization that combines Monte Carlo simula-

tion with a genetic algorithm. The authors claim that the framework is easily integrated with general process planning and scheduling. Labib (1999) proposed a nine-step framework for formulating the appropriate productive maintenance (APM) programme. A modelling tool, called IDEF0, is used to map the whole process of the framework. Tan and Raghavan (2008) proposed a simple practical framework for predictive maintenance (PdM) based on scheduling of multi-state systems (MSS). Through the framework development, various factors influencing PdM-based scheduling are identified and their impact on the system reliability and performance are quantitatively studied.

3. Current maintenance practice in the case study company

The work reported in this paper is carried out at a processing industry located in Penang, Malaysia. This company employs around 1000 workers in various positions from human resource to production. The case study company is a wood-based industry that produces various types of products for daily use. To achieve daily production target, maintenance plays an important role to minimise the rate of machine breakdown.

In this company, PM is not a new practice and most of maintenance staffs (engineers and technicians) are categorised as experience worker where most of them have more than five years work experience. Several discussion and interview sessions among maintenance staffs (engineers and technicians) have been carried out to understand the current practice of PM in this company. Maintenance staffs were asked four main questions based on what, who, when and how during the discussion and interview sessions. Table 2 summaries the answers based on the given questions. Out of the first question, all of the maintenance staffs (engineers and technicians) understood the significance of PM on the shop floor process.

Table 2: Summary of questions and answers in discussion and interview sessions.

Questions	Answers (important point only)
1 What do you understand (significance) about PM strategy?	PM is the proactive activities to reduce the rate of machine failure
2 Who are involved in PM decision and activities?	- Long-term maintenance decision (e.g. one year budget) will made by manager - Major maintenance decision on shop floor will be decided by engineers - Minor decision and hand-on actions will be carried out by technicians
3 How is PM activity performed?	The work list of PM (spare part list and time to perform PM) is decided by engineer then it will be given to technician for practice
4 When is PM activity carried out?	PM activities are carried out at predetermined intervals based on experience or based Original Equipment Manufacturer (OEM) recommendation

All of them agreed that PM is a proactive strategy to reduce the rate of machine failure through preventive activities such as repair, replacement, adjustment, cleaning etc. Out of the second question, maintenance manager is responsible for long-term decisions, for example one-year budget for the cost of PM spare parts, while engineers and technicians are responsible for current maintenance problems on the shop floor including PM programme. This answer implies that engineers and technicians play an important part to plan and implement the PM in order to maximise the efficiency of production process.

Out of the third question, engineers are responsible to plan detailed activities of PM such as where, what and when to carry out the PM, while technicians will implement everything that has been planned by engineers. This answer shows that the effectiveness of PM to production machine process depends on the decision made by the engineers. Out of the final question, the interval (time) of PM is based on experience or Original Equipment Manufacturer (OEM) recommendation. This answer shows the drawbacks of current PM practice in this company. In reality, PM interval based on experience or OEM recommendation is not always effective (maximise PM benefits) because it is not taking into account the current machine state (operating).

The conclusion from this interview and discussion sessions is that the scientific approach is necessary to improve the effectiveness of PM practice. Therefore, the development of a management model to revise the PM interval based on current machine state is required.

4. Maintenance management decision model

The proposed maintenance management decision model is structured based on three basic steps; problem identification, critical component evaluation and maintenance decision as shown in Figure 1. The details of each step are described in the following sections. The main objective of the proposed model is to provide step-by-step procedure to determine the PM interval by considering the current machine state (external factor).

4.1. Step 1: Problem identification

Defining and understanding the problem accurately is the first important step of the proposed model. In reality, failure of the component is the main reason for the machine to breakdown. Component(s) failure that results in high machine downtime or cost (due to machine breakdown) is classified as critical components. The objective of this step is to perform failure mechanism analysis in order to identify possible external factors (covariates) that contribute to the component failure and classify the censored and uncensored data. The process of this step is shown in Figure 2. Referring to Figure 2, failure mechanism analysis is carried out by using a well-known tool; Failure Mode Effect and Criticality Analysis (FMECA). Through FMECA, identification of the possible external factors (covariates) and classification of the censored and uncensored data can be performed systematically. Classification of censored and uncensored data is based on failure modes records and criticality index calculations.

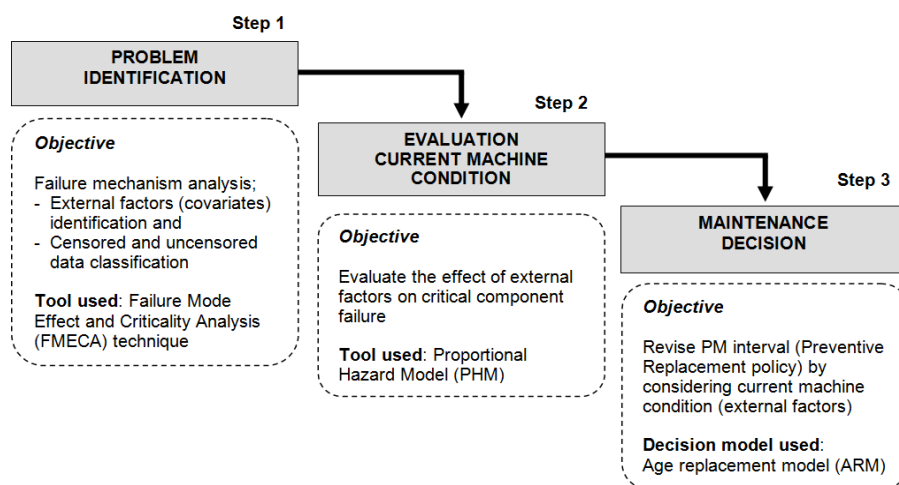


Figure 1: The general structure of the maintenance management decision model.

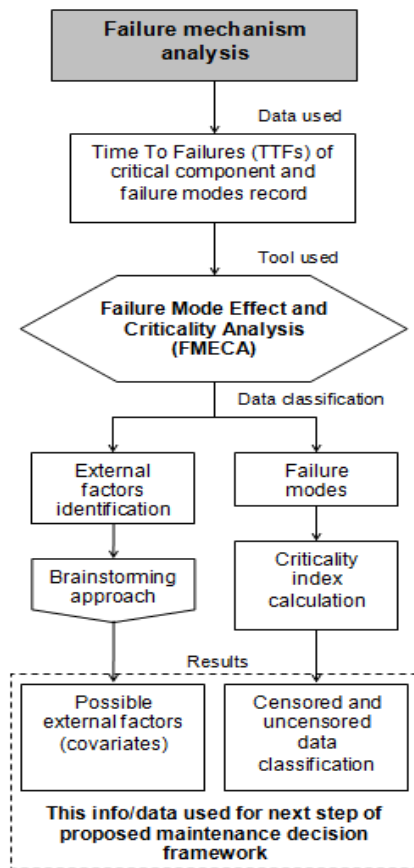


Figure 2: The process of failure mechanism analysis.

The criticality index of each failure modes is calculated using the following formula (Ebeling, 1997).

$$C_k = \alpha_{kp} \beta_k \lambda_p t \quad (1)$$

The data used in FMECA are Time to Failures (TTFs) of the critical component along with failure modes records and the possible external factors (covariates) that contributes to the critical component failure. The identification of possible external factors (covariates) is carried out through brainstorming approach among experts such as maintenance technician, engineers and experience operators. The information (data) of the identified covariates and censored and uncensored data classification then will be used for further analysis in the next step of the proposed model.

4.2. Step 2: Critical component evaluation

In this step, the possible covariates that have been identified at previous step along with censored and uncensored data will be evaluated. In other words, it will determine how much (effect) the operating condition (refers to the identified covariates) contributes to the failure of

the critical component based on the value of covariates parameters. The evaluation process in this step is shown in Figure 3.

Referring to Figure 3, the Proportional Hazard Model (PHM) is used to evaluate the effect of covariates (identified at previous step) on critical component failure. Generally, PHM is a regression type model that is widely applied in failure time analysis in order to evaluate or estimate the relationship between two variables (Coit and English, 1999). One of the advantages of PHM is that it is an excellent exploratory data analysis technique that always gives a reasonable measure of the importance of the covariates (external factor) (Newby, 1994). Generally, PHM can be presented in the following form:

$$\lambda_0(t) = \lambda(t) \exp(a, x) \quad (2)$$

where “ a ”, is a row vector and “ x ” is a column vector consisting of covariates and regression parameters, respectively. The basic assumption of PHM is that the actual hazard rate (failure rate), $\lambda_0(t)$ of a component is the product of a baseline (time-dependent) hazard rate $\lambda(t)$ and positive (time-independent) functional term $\exp(a, x)$, basically time independent to the effects of a number of covariates.

Baseline hazard rate is the failure rate without considering covariates effect (only internal factor effects - aging and accumulative wear), while the observed (actual) hazard rate, $\lambda_0(t)$ is the failure rate that is considered by covariates effect. The effect of covariates may increase or decrease the actual hazard rate. The environmental effects such as dust and heat commonly found in industries may increase the component hazard rate, while the best maintenance activities may decrease the component hazard rate.

The data used for PHM analysis are Time to Failures (TTFs) of the critical component along with censored and uncensored classification and codification of identified covariates. The parameters of identified covariates are obtained by maximising the likelihood function given by Kalbfleisch and Prentice (1980). Then, the significant test on the covariates parameters is carried out, where if the value of significant test is less than 0.05, the covariates parameters have a significant contribution (effect) on critical component failure and vice versa.

For the covariates that have a significant contribution, its parameter values are used further in maintenance decision process to determine more realistic (by considering current machine state) PM interval.

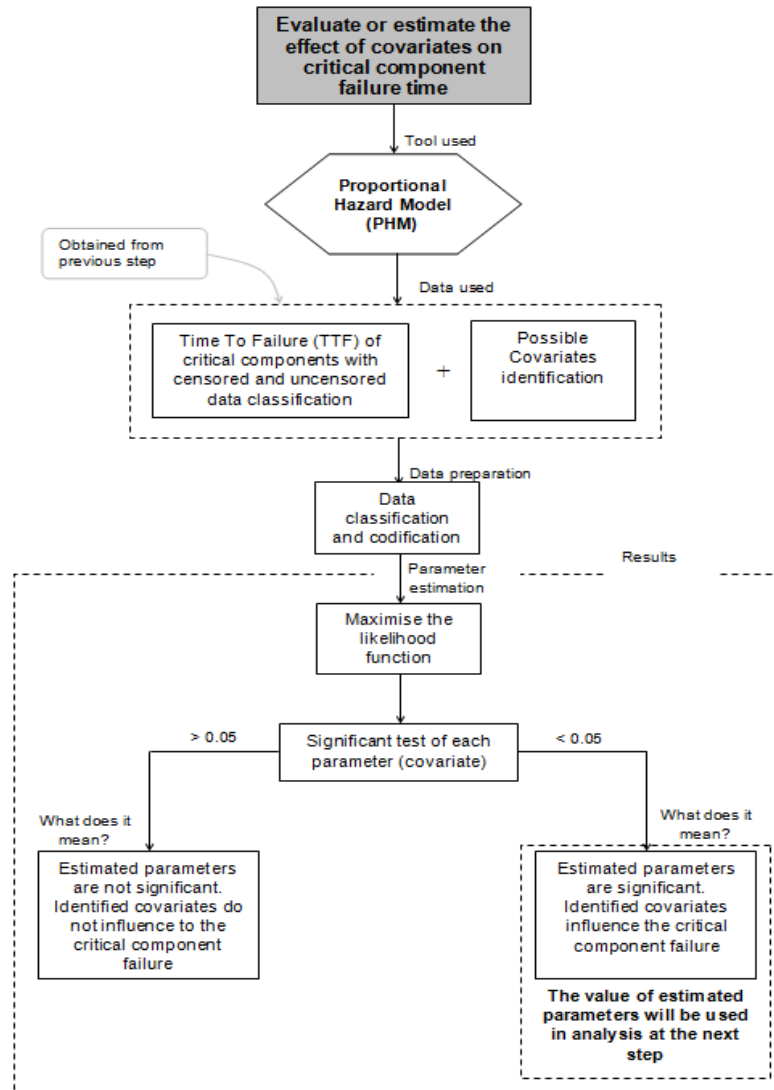


Figure 3: The process of critical component evaluation.

4.3. Step 3: Maintenance decision

Maintenance decision is the final step of the proposed model. The process of maintenance decision is illustrated in Figure 4. The first process is to test the failure times (refers to TTFs) of the critical component in terms of their trend and correlation. The result of this test is used to decide the modelling tool (either power law model or renewal model) for fitting the failure time distribution based on Weibull distribution model. Weibull distribution model is used in fitting the failure time distribution because it is flexible (versatile) distribution model and most commonly used in failure time analysis (Ghodrati and Kumar, 2005). The data for fitting the failure time distribution are TTFs of the critical component along with censored and uncensored classification, which are obtained from the first step.

The result of fitting the failure time distribution is the shape parameter, β of the Weibull distribution. The value of shape parameter depicts the states of the critical component whether in decreasing failure rate ($\beta < 1$), constant failure rate ($\beta = 1$) or increasing failure rate ($\beta > 1$). If the value of shape parameter is less than or equal to 1, the value of Mean Time To Failure (MTTF) is used as maintenance decision (PM interval). However, if the value of the shape parameter is more than 1 (increasing failure rate), PM strategy is beneficial and cost effective. Then, more realistic PM interval (based on preventive replacement policy) is determined by considering the current machine state (covariates).

Without considering the current machine state, the lifetime of the critical component is denoted by, θ (based line lifetime), where provided by OEM or experience.

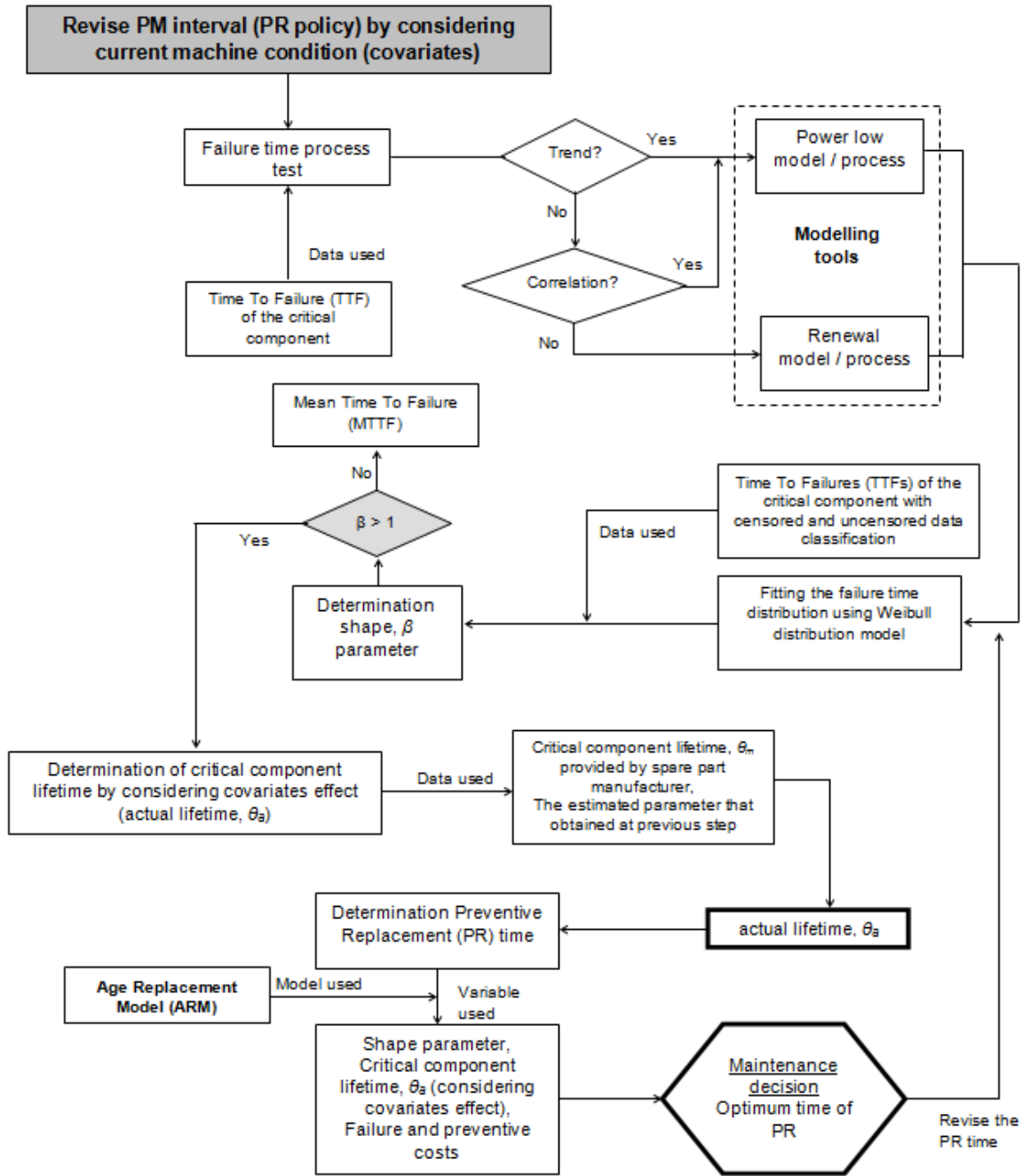


Figure 4: The process of PM interval determination.

For more realistic case, the effect of covariates on critical component lifetime should be taken into account in revising PM interval. Therefore, by using the covariates parameter obtained at the previous step (critical component evaluation) and the based line of the critical component lifetime (provided by spare parts manufacturer), the actual lifetime θ_a is obtained by using Equation (3) (Ghodrati and Kumar, 2005).

$$\theta_0 = \theta \left(\exp \left(\sum_{j=1}^n a_j x_j \right) \right)^{-\left(\frac{1}{\beta}\right)} \quad (3)$$

The next process is to determine the optimum time of Preventive Replacement (PR) by using Age Replacement Model (ARM). This is shown in Equation 4.

$$\min : C(T) = \frac{C_f F(T) + C_p R(T)}{\int_0^T R(t) dt} \quad (4)$$

According to Jiang *et al.* (2006) age replacement model is more useful in practical application and it gives more benefit in terms of

cost saving. The main objective of this model is to determine the optimum time, T by minimising the cost function, $C(T)$. The application of the ARM by using Weibull distribution model is shown in Equation (5).

$$C(T) = \frac{C_f \left(1 - e^{-\left(\frac{T}{\theta_0}\right)^\beta} \right) + C_p \left(e^{-\left(\frac{T}{\theta_0}\right)^\beta} \right)}{\int_0^T e^{-\left(\frac{t}{\theta_0}\right)^\beta} dt} \quad (5)$$

To solve the ARM in Equation 5, four input parameters: failure cost, C_f , preventive replacement cost, C_p , actual component lifetime, θ_0 and shape parameter, β are required. The failure and preventive replacement costs can be determined based on Equation (6) and (7). The actual component lifetime is obtained by using Equation (3). Meanwhile, detail calculation of shape parameter is given in (Ebeling, 1997).

$$C_f = C_r + C_{dt-r} + C_{pro} \quad (6)$$

$$C_p = C_r + C_{dt-r} \quad (7)$$

Where, C_r is the cost of replacement, C_{dt-r} is the cost of downtime due to the replacement and C_{pro} is the cost of product reject.

5. Model validation

The proposed maintenance decision model has been applied at one of the production machines in a processing industry. The subject (critical component) used in this case study is transmission belt where it contributed to high rate of machine failures. Currently, the company implements the PM program (preventive replacement) that provided by OEM, however it does not help much reducing the rate of unplanned maintenance (failures). Therefore, the proposed model is used to revise their PM program (based on PR policy) by considering the current machine state. The sources of the data used in the analysis are composed from the Computerised Maintenance Management System (CMMS) data base and also maintenance records from the shop floor. The results of each maintenance decision model steps are presented in the following sections.

5.1. Failure mechanism analysis result: Step 1

The process of failure mechanism analysis is given in Figure 2. The heart of this step is the use of FMECA, thus the identification of the possible external factors (covariates) and classification to the censored and uncensored data can be performed systematically.

The result of FMECA is shown in Table 3. It shows that, through brainstorming approach among the expert staffs (technicians, engineers, and operators) the possible external factors (covariates) that contribute to transmission belt failure are dust effect, product types and pulley tension. Then, via maintenance records, the failure modes at each failure time have been identified and the criticality index of each failure modes is calculated to classify censored and uncensored data (failure time).

The result of criticality index shows that most of the failures (transmission belt) are due to 'loss grip' failure mode (uncensored data) and the rest are due to 'break' failure mode (censored data). Table 4 shows the summary of the information obtained in this step.

Referring to Table 4, twelve numbers of failure (time-to-failure) are involved in this study. It is found that two failure modes of transmission belts that have been recorded are due to 'break' and the other ten failure modes are due to the 'loss grip'. The information presented in Table 4 will be analysed further in order to evaluate the effects of external factors to transmission belt failure. The detail is given in the following section.

5.2. External factor evaluation on critical component: Step 2

In this step, the significant contribution of identified covariates on component failure is determined by using Proportional Hazard Model (PHM). For this purpose, the identified covariates are codified into quantitative form. Table 5 shows the codification of identified covariates based on description given in Table 6.

The evaluation result using PHM is presented in Table 7. It shows that, only the covariates RCOMP and DUST are found to have a significant effect (contribution) on the transmission belt failure based on the p-value (less than 0.05). The parameter of covariate RCOMP is -0.943, while the parameter of covariate DUST is -1.032. The values of both parameters then have been used to determine the revised PR time.

Table 3: Result of FMECA.

Critical Component	Failure mode	Failure cause		Failure effect	Failure rate, λ_p	β_k	α_{kp}	time, t	Criticality index, C_k
		Internal factor (normal effect)	External Factor (covariate)						
Transmission Belt	Loss grip	Wear & tear	Dust	The pulley can't be moved	$\lambda_p = \text{no. of failure}$		$\alpha_{kp} = \text{no. of failure}$	371	8.31
			Product types (hard & soft)	Cutting process can not operate	Total no. of working day		Total no. of failure		
			Pulley tension (unstable bearing)			1.0	= 10/12		
			2.7×10^{-02}						
	Break	Wear & tear	Dust	Component damage	$\lambda_p = \text{no. of failure}$		$\alpha_{kp} = \text{no. of failure}$	371	0.068
			Product types (hard & soft)	Cutting process can not operate	Total no. of working day		Total no. of failure		
			Pulley tension (bearing)		= 2/371	0.20	= 2/12		
			5.4×10^{-03}		0.17				

Table 4: Summary of the information obtained in step 1.

No of Failure	Time Between Failure (working days)	Censored and Uncensored data	Failure mode	Possible Covariates
1	28	0	Loss grip	
2	52	0	Loss grip	
3	42	1	Break	
4	8	0	Loss grip	Dust
5	14	0	Loss grip	
6	13	0	Loss grip	Product types (hard & soft)
7	47	0	Loss grip	
8	38	0	Loss grip	
9	25	0	Loss grip	Pulley tension (unstable bearing)
10	12	0	Loss grip	
11	50	1	Break	
12	42	0	Loss grip	

Uncensored = 0
Censored data = 1

Table 5: Failure times of transmission belt and codified values of influencing covariates.

No of Failure	Time Between Failure	Censored & Uncensored data	Covariate		
			RCOMP	DUST	PRODT
1	28	1	-1	-1	0.6
2	52	1	1	1	0.4
3	42	0	-1	1	0.4
4	8	1	-1	-1	0.3
5	14	1	-1	-1	0.6
6	13	1	-1	-1	0.6
7	47	1	1	1	0.5
8	38	1	1	-1	0.6
9	25	1	1	-1	0.4
10	12	1	-1	-1	0.8
11	50	0	1	-1	0.6
12	42	1	-1	1	0.6
Total			- 2	- 4	6.4
Average			- 0.167	- 0.333	- 0.533

[- < 0.5 < +]

Table 6: Description of the covariates codification.

Coding Covariate	-1 (bad condition)	+1 (good condition)
Dust factor (DUST)	The component exposed to extreme dust condition without any preventive action (cleaning)	The component is recorded for cleaning activity
Related component factor (RCOMP)	The related component (example: the bearing in a pulley for supporting the belt operation) is NOT replaced together with the component (transmission belt)	The related component (example: the bearing in a pulley for supporting the belt operation) is replaced together with the component (transmission belt)
Product type factor (PRODT)	This covariate was formulated in continuous form and it is based on the product types which are "hard and soft". For example, assumed that the failure time of the component (transmission belt) is 10 days, then the types of product that are produced each day (failure time = 10 working days) is recorded. For example, 3 days have produced soft types of product and 7 days have produced hard-types of product. Therefore, this covariate (PRODT) is codified as 0.7 (percentage), referred to hard-type product. It is because, transmission belt needs more force (more risk to fail) to process the hard type product compared to the soft type product.	

Table 7: Estimation of covariates effect on transmission belt failure using PHM.

Final Model Summary using PHM				
Parameter	Estimate	S.E.	t-ratio	p-value
RCOMP	-0.943	0.472	-1.998	0.046
DUST	-1.032	0.490	-2.104	0.035
95.0 % Confidence Intervals Final Estimation				
Parameter	Estimate	Lower	Upper	
RCOMP	-0.943	-1.868	-0.018	
DUST	-1.032	-1.993	-0.071	

Table 8: Parameters used for ARM solution.

Parameter required	Value	Description
Shape parameter	2.1	Component in deteriorating state
Actual scale parameter (actual component lifetime)	27.6	Determined by using Equation 3 (base line lifetime is, 35 days)
PR cost (ratio)	1	Component cost + downtime cost
Failure cost (ratio)	3	Component cost + downtime cost + product reject cost + labour cost
Revise PR interval, T	21 days	PR interval by considering current machine breakdown

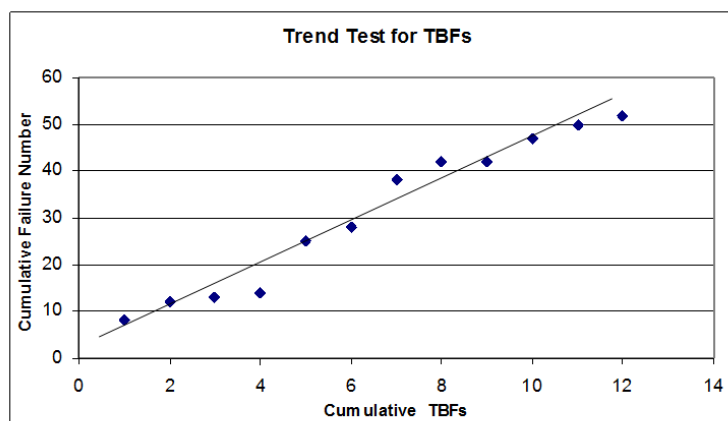


Figure 5: Trend test for transmission belt - no trend.

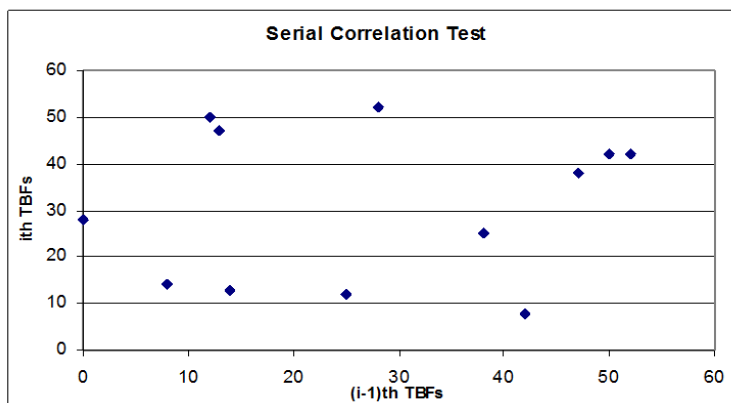


Figure 6: Serial correlation test for transmission belt - no correlation.

5.3. Determine the preventive maintenance decision: Step 3

The result of failure time process test is shown in Figures 5 and 6. It shows that the trend (liner line) and the correlation (no correlation) of the failure time (refers to TTFs) follows the renewal model. The results confirmed the theory where the failure time of non-repairable component (transmission belt is non-repairable component) usually follows the renewal model [26]. Then, Weibull distribution model has been applied in fitting the failure time of the transmission belt. The result shows that the shape parameter is 2.1 and it implies the component in deteriorating state (increasing failure rate). Therefore, the application of PM based on Preventive Replacement (PR) policy is beneficial.

By using Age Replacement Model (ARM) and parameters listed in Table 8, the revised PR interval is determined.

The results show that the revised PR interval by considering current machine state is 21 days. Compared the old PR interval, 35 days, the revised PR interval implies a reasonable decision to improve the machine reliability (to reduce failure rate) because two covariates (RCOMP and DUST) are identified to have the significant contributions to the component failure.

6. Conclusion

This paper presents a maintenance management decision model to revise PM interval by considering current machine state for the case of non-repairable components. The proposed model is based on three steps; problem identification, critical component evaluation and maintenance

decision. In the first step, failure mechanism analysis is carried out using FMECA tool to identify the possible external factors (covariates) and classify the censored and uncensored data in a systematic way. Based on information obtained from step 1, the second step of the proposed model evaluates the effects of external factors (covariates) on the critical component by using Proportional Hazard Model (PHM). In the third step, by considering the effect of external factors (covariates) on the critical component failure (based on parameter values) that obtained from step 2, the PM interval based on PR policy is revised. The main advantage of the proposed model is that it provides step-by-step process in maintenance decision making by considering the current machine state. The proposed model will help the maintenance manager or engineer to revise the PM interval based on realistic environment for more effective maintenance decision. In addition, the effectiveness of the proposed model will be tested for different types of case studies such as for the case of non-repairable and multiple types. This will be the future work of this study.

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