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Structured maintenance engineering policy development based on a production machine process perspective

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Abstract

Purpose – The purpose of this paper is to present the development of a maintenance engineering policy in the context of a decision support model based on a production machine process perspective.

Design/methodology/approach – The structure of the policy is called the maintenance decision support (MDS) model, which consists of three steps: initial setup, deterioration monitoring, and decision making. A detailed presentation of each step of the proposed model together with a real case example from the pulp manufacturing industry proves the applicability of the model.

Findings – Validation of the proposed MDS model is as follows. In Task 1 of Step 1, the cutting, sealing, and perforating line processes are classified as critical machining processes. The analysis of Task 2 of Step 1 found that cutting knife, bearing, and motor are classified as the components that most possibly contribute to the cutting appearance quality. In Task 3 of Step 1, it was found that the cutting knife is classified as a maintenance-significant component with non-repairable and single-component type characteristics. The result of Step 2 suggested that at the 29th hour of operating time, the decision of do-something was suggested. In the following step (Step 3), for the case of the cutting knife, which has been classified as a non-repairable type component, the decision to perform preventive replacement of cutting knife is recommended to be carried out at the 29th hour of operating time.

Research limitations/implications – The uniqueness of this model is that it systematically considers different machinery component(s) characteristics, including single- and multiple-component cases, repairable and non-repairable types, and functional or/and physical failure types, to make maintenance decisions.

Practical implications – The proposed MDS model provides a systematic guideline for identifying, evaluating, and monitoring, which makes maintenance-related decisions. Three significant maintenance decisions can be determined based on the proposed MDS model, which includes an appropriate time-to-perform maintenance, correct maintenance actions to be performed, and the right component required for maintenance (for multi-component cases).

Originality/value – One of the vital elements in considering the production machine process perspective toward the development of the MDS model is the need to use product output/quality characteristics for machine deterioration-monitoring and decision-making processes.

Keywords Decision support system, Maintenance policy, Condition monitoring, Industry application, Production machine perspective

Paper type Research paper

1. Introduction

In present industries, maintenance is one of the important support functions for production machine systems to reduce costs, protect commercial margins, and enhance productivity (Cholasuke *et al.*, 2004). The implementation of a proper maintenance policy that maximizes

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the availability and efficiency of the machine is a major challenge for maintenance engineers. The application of a preventive maintenance (PM) strategy is the primary key to maximize the availability and efficiency of a production machine by minimizing unplanned or corrective maintenance. Two PM techniques that are widely discussed in the literature are time-based maintenance and condition-based maintenance. Many comprehensive discussions on this concept, principle, and technical processes have been presented by researchers (Ahmad and Kamaruddin, 2012a, b).

A proper maintenance policy based on PM strategy is characterized by the occurrence of few corrective maintenance events despite the performance of minimal maintenance actions (Cooke and Paulsen, 1997). PM should only be performed when needed or just before the machine equipment fails. Thus, the costs of unexpected failure can be minimized and the machine lifetime can be fully utilized. In reality, designing and developing a proper maintenance policy using the PM strategy on a complex system is not a simple task. For complex systems, like a production machine, no general, formal, or flexible maintenance techniques can be used for all types of problems and situations because a production machine is typically structured and connected with numerous sub-systems and components, each with its own functions, characteristics, and failure behavior. Viles *et al.* (2007) highlighted a unique maintenance policy that combines different maintenance techniques and concepts must be used on the basis of certain objective, situations, and specific needs for companies. In other words, it is concerned with designing and developing a proper maintenance policy in the form of a maintenance decision support (MDS) model.

Previous studies on the development of structured MDS for specific cases and perspective were available from a few researchers. For example, Waeyenbergh and Pintelon (2009) developed a structured maintenance policy to systematically identify and make maintenance-related decisions on the basis of an optimization approach. Utne *et al.* (2012) presented a decision support model for condition monitoring methods selection. Elhdad *et al.* (2013) proposed a framework for process monitoring and maintenance to ensure that decision makers have sufficient information to make the right decision at the right time. Mendes and Ribeiro (2014) proposed a quantitative method for supporting the preparation or review of an equipment maintenance plan in a just-in-time production scenario. Faccio *et al.* (2014) introduced a new quantitative framework to develop optimal maintenance policies by using several cost models. The proposed framework is developed based on the framework introduced by Waeyenbergh and Pintelon (2002) with improvements in the final steps for the economic evaluation of different maintenance policies. Martinez *et al.* (2013) introduced a logical support method for maintenance management decision making, namely, graphical analysis for maintenance management. A detailed application of this method based on two case studies of slurry pumps in a mining plant located in Chile is presented in Barberá *et al.* (2014).

Previous literature shows that research on the development of MDS is still limited. A study of the literature revealed that each proposed MDS model is unique from one to another, as each is developed based on a specific case scenario, cost-effective purpose, comprehensiveness, graphical approaches, and is user-friendly. Other researchers have proven that policies are applicable based on the case studies presented. In other words, it is clear that there is no generic maintenance policy that is appropriate for all cases due to uniqueness and complexity.

We believe that there is a need for a structured maintenance policy development from other perspectives so that it can be effectively applied for specific cases. Therefore, the current study presents the development of a structured MDS model based on a production machine process perspective. One of the vital elements in this perspective is the need to use product output/quality characteristics for machine deterioration-monitoring and decision-making processes. A detailed discussion regarding the motivation and the uniqueness of maintenance engineering problem in production machine perspective has been presented in

Ahmad and Kamaruddin (2012a). The proposed MDS model provides a systematic guideline for identifying, evaluating, and monitoring, which makes maintenance-related decisions. Three significant maintenance decisions can be determined based on the proposed MDS model, which includes an appropriate time-to-perform maintenance, correct maintenance actions to be performed, and the right component required for maintenance (for multi-component cases).

The remainder of the paper is organized as follows. Section 2 presents the technical features of the proposed MDS model. This section is also the main part of this paper as each step of the MDS model is described in detail and its applicability is presented based on a case study in the pulp manufacturing industry. Section 3 provides our summary, conclusions, and recommendations for possible future research.

2. Structure of MDS model

Figure 1 presents the general structure of the proposed MDS model, where it can be divided into three main steps:

(1) Step 1: Initial setup: this stage is concerned with the process of identifying the most significant problem to be solved and understanding and classifying its characteristics. In other words, this step will answer the question where and how to start performing PM program?

(2) Step 2: Deterioration-monitoring process: this stage systematically and continuously monitors the deterioration process of targeted component(s), namely, maintenance significant component (MSC), and predicts its future trend conditions. At this stage, two initial decisions will be decided as follows: do-nothing or do-something.

(3) Step 3: Decision-making rules: this stage is concerned with the specific maintenance decision rules if the result of Step 2 is a do-something decision. At this stage, a simple set of rule-based algorithms are proposed.

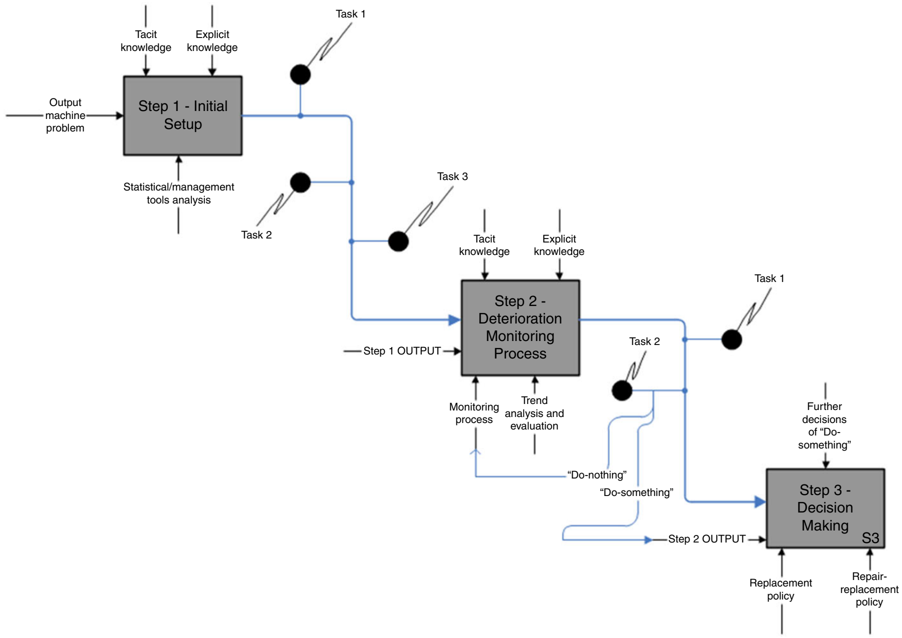

Figure 1.
Structure of maintenance decision support (MDS) model

A detailed description of each step is presented in the following sub-sections. A case study of the pulp product manufacturing industry is used to illustrate the applicability of each step of the proposed model.

Brief introduction of the case study is as follows. The company of pulp product manufacturing considered in this study is located in the North Peninsula of Malaysia. This company is capable of operating 24 hours in three shifts and is supported by more than 1,000 full-time workers. The company's primary products are various types of tissues for daily use. This company has two types of production plants. The first production plant, known as front-of-line, processes the raw materials for tissue and produces the semi-finished product called "jumbo roll." The second production plant, known as end-of-line (EOL), processes the semi-finished product into a finished tissue product that is ready for market.

The production machines in EOL are fully automated to perform many machine processes. The first machine process is embossing, which forms a particular pattern on the surface of the tissue using an embossing method. The second machine process is a perforating line process, which forms the dash-line on the surface of the tissue. The next machine process is the rewinding process, which refers to the roll-up, during which a sheet of tissue is rolled into a log roll scale with a specific thickness. Once the rewinding process is completed, the log-rolled sheet of tissue undergoes the next machine process, sealing. The sealing process glues the top sheet of the log-rolled tissue. This process is followed by the cutting process, for which the log roll is cut into small-sized rolls, called final rolls. The final machine process is the packaging process, where a certain number of final rolls are packed as a ready-to-market product. Figure 2 shows the results of each machining process in the EOL production line.

2.1 Step 1: initial setup

The objective of this stage is to identify the sub-system(s) that are maintenance-importance, which will be the focus. Then, from this sub-system, the component(s) failures that affect the machine output (product quality) characteristics measures are further determined. This step comprises three tasks as follows: identification of the critical machining process (CMP), further CMP analysis, and the identification of the MSC.

2.1.1 Task 1 – identification of the CMP. The uniqueness of the proposed MDS model is that it starts investigating the production machine maintenance problem by looking at the output/quality characteristics of the final product that has been produced. This is similar with a reversed engineering approach. In Task 1, useful sources of information that are based on product inspection records and a simple statistical tool, such as Pareto Analysis (PA) can be used to identify CMPs. Based on the case study used, Task 1 was started by listing all output characteristics of the final roll product. Five types of main output characteristics of the final roll product are routinely evaluated by the product quality inspector as follows:

(1) cutting appearance quality (result of the cutting process);

(2) cutting length (result of the cutting process);

(3) embossing appearance quality (result of the embossing process);

(4) perforating line appearance quality (result of the perforating line process); and

(5) sealing appearance quality (result of the sealing process).

Three months of data based on these five types of output characteristics are used for Task 1 analysis to extract valuable information for the identification of CMPs. The primary objective is to identify the significant output characteristic problems in the machining processes for the final roll product. As proposed in Task 1, the objective can be achieved by applying PA. The results from PA indicated three significant output characteristic problems that usually

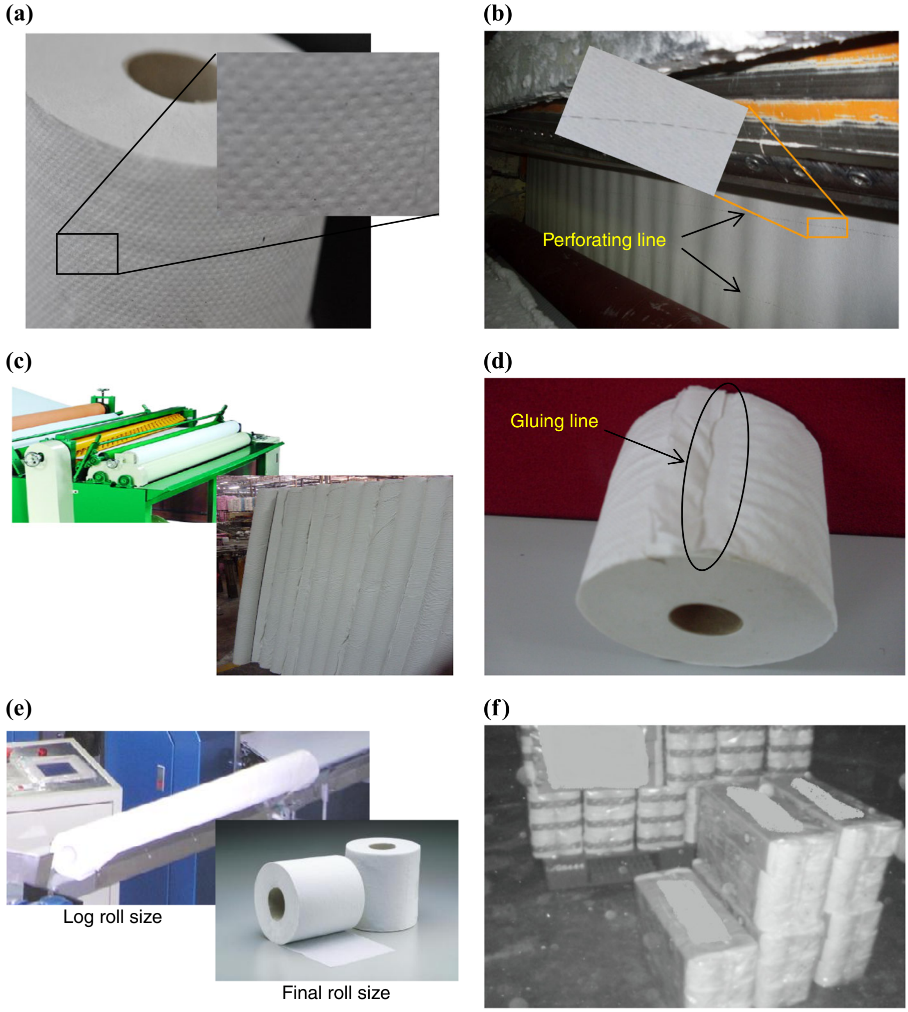

Figure 2. Machine processes in the EOL production line

Notes: (a) Emboss pattern – result of the embossing process; (b) perforating line – result of the perforating line process; (c) log roll product – result of the rewinding process; (d) gluing line – result of the sealing process; (e) log roll to final roll sizes – result of the cutting process; (f) Ready-to-market product – result of the packaging process

occurred in the production of the final roll. These three problems include cutting appearance (43.3 percent), sealing appearance (31.2 percent), and perforating line appearance qualities (17.2 percent). These product output characteristic problems resulted from the deterioration or problems during the cutting, sealing, and perforating line processes. Therefore, on the basis of the analysis of Task 1, these three machine processes are classified as CMPs and are considered for further analysis. For simplicity, only a cutting process case (due to highest percentage of cutting appearance) is considered for further analysis.

2.1.2 Task 2 – further CMP analysis. The objective of Task 2 is to identify the possible machine component(s) that contribute to the output characteristic problems identified in Task 1.

In Task 2, it can be easily conducted if tacit knowledge (experts or experienced workers) for understanding CMP is available. From experience, experts may directly suggest a possible component(s) that affects certain product output problems. On the other hand, this task is challenging if tacit knowledge is unavailable or vague. Nevertheless, the objective of this task may be accomplished with the aid of some management analysis tools, such as the cause-consequences analysis (CCA).

CCA is a tool for failure analysis used to explore all the possible causes and consequences of problems (e.g. oil leakage) in a system. CCA is a team activity using a brainstorming approach to investigate a specific problem by focusing on its causes and consequences. Table I summarizes the steps for using the CCA application in the proposed MDS model.

In Step 1, the leader of the team activity clarifies the output characteristics problem as identified in Task 1. In Step 2, the workers involved with CCA give their initial opinion based on experience on the possible components that contribute to the problem stated in Stage 1. In this step, the leader lists down all the possible components suggested by the team. In Step 3, the evaluation of the degree of contribution of each component listed in Step 2 to the defined problem is measured using scale numbers. In other words, each participant evaluates each component and its contribution to the problem. The numbering scales that can be used in the evaluation are as follows: 5 = highly contributes to the problem, 3 = moderately contributes to the problem, and 1 = minimally contributes to the problem. In Step 4, the overall scale value given by each participant involved in the CCA activity is determined by averaging all the scales given in Step 3. On the basis of Step 4, the component (s) that has/have high average values can be classified as the component(s) that contribute(s) to the significance of the problem stated in Step 1.

For the case of cutting processes, Table II summarizes the result of CCA. The validation result of Task 2 shows that the cutting knife, transmission belt, bearings, and motor were identified as the possible components that affect the cutting appearance quality. The evaluation result given by the technical staff (evaluators A, B, and C) is as follows: cutting knife (5.00),

Step 1	The critical output characteristic (e.g. cutting surface appearance and surface roughness level, diameter of work piece, and so on) is identified
Step 2	All possible components that may contribute to the problem stated in Step 1 are listed
Step 3	The degree of contribution of each component listed in Step 2 to the problem stated in Step 1 is measured using scale numbers. For example, 5 = highly contributes to the problem 3 = moderately contributes to the problem 1 = minimally contributes to the problem
Step 4	The overall scale value given by each worker involved in the CCA activity is determined by averaging all the scales given in Step 3

Table I. Steps of cause-consequences analysis (CCA)

CMP	Output characteristic problem	Possible components that contribute to output characteristic problem	Evaluation scale Evaluator A	B	C	Average evaluation scale
Cutting process	Cutting appearance quality	Cutting knife	5	5	5	5.00
		Transmission belt	3	1	1	1.67
		Bearing	3	5	3	3.67
		Motor	5	3	3	3.67

Notes: Evaluation scale: 5 = highly contributes to the output characteristic problem, 3 = moderately contributes to the output characteristic problem, 1 = slightly contributes to the output characteristic problem

Table II. Result of CCA

bearing (3.67), and motor (3.67), which are classified as the components that most possibly contribute to cutting appearance quality. Once the analysis of Task 2 is completed, the validation of the initial setup step is followed by the analysis of Task 3.

2.1.3 Task 3 – identification of the MSC. After identifying the possible components that contribute to the output characteristics problems (in this case if more than one component is identified), the next task is to narrow the scope of the problem by identifying MSC and classifying its characteristics. The motivation of this task is that although more than one component contributes to the output characteristics problems identified, not all these components are equally important for maintenance (Waeyenbergh, 2005). In other words, the machinery component(s) that is/are worthwhile for a specific maintenance program has/have to be investigated from an economical perspective or based on economic consequences. Thus, the identification of the component(s), also known as MSC, is necessary. MSC can be identified using a simple cost analysis (CA) by considering some failure consequences (production loss, P_l) and maintenance costs parameters, M_c (Hu *et al.*, 2009). Using a simple CA, total cost, T_C based on a year can be estimated using the following equations:

$$T_{C/\text{year}} = M_{c/\text{year}} + P_{l/\text{year}} \tag{1}$$

$$M_{c/\text{year}} = \left(\frac{365}{L_{c/\text{day}}}\right) \times M_{c/\text{cycle}} \tag{2}$$

$$P_{l/\text{year}} = \left(\frac{365}{L_{c/\text{day}}}\right) \times \left(D_{t/\text{hour}} \times PD_{t/\text{hour}}\right) \tag{3}$$

The component(s) that show(s) significant total costs per year $T_{C/\text{year}}$ can be classified as the MSC. Once the MSC is finalized, its characteristics are identified to determine the appropriate maintenance decision direction. The following are the two types of MSC characteristics considered. Table III shows their definitions.

For the case of the cutting process, the result of CA found that only a cutting knife will give significant cost effect at RM209,875.00. Thus, a cutting knife is classified as an MSC with non-repairable and single-component type characteristics (Table III).

2.2 Step 2: deterioration-monitoring process

After the MSC and its characteristic types are selected and identified in Step 1, the deterioration-monitoring process for the MSC (Step 2) is conducted. Step 2 monitors the deterioration of the MSC and predicts its future trend conditions and evaluation. Two tasks are involved in this step, the first task is available data identification and the second task is future trend forecasting and condition evaluation. Figure 3 shows a flowchart of Step 2.

Characteristic of MSC		Definition
Structure types	Single component	MSC consisting of only one component
	Multiple components	MSC that consisting of more than one component
Design types	Repairable	Component that can be repaired for functional recovery after each failure, instead of being discarded (Crow, 1974)
	Non-repairable	A component that cannot be repaired (only replaced) once it failed and is consequently discarded (because repair is physically unfeasible or non-economical) (Louit *et al.*, 2009)

Table III.
Definition of MSC characteristics

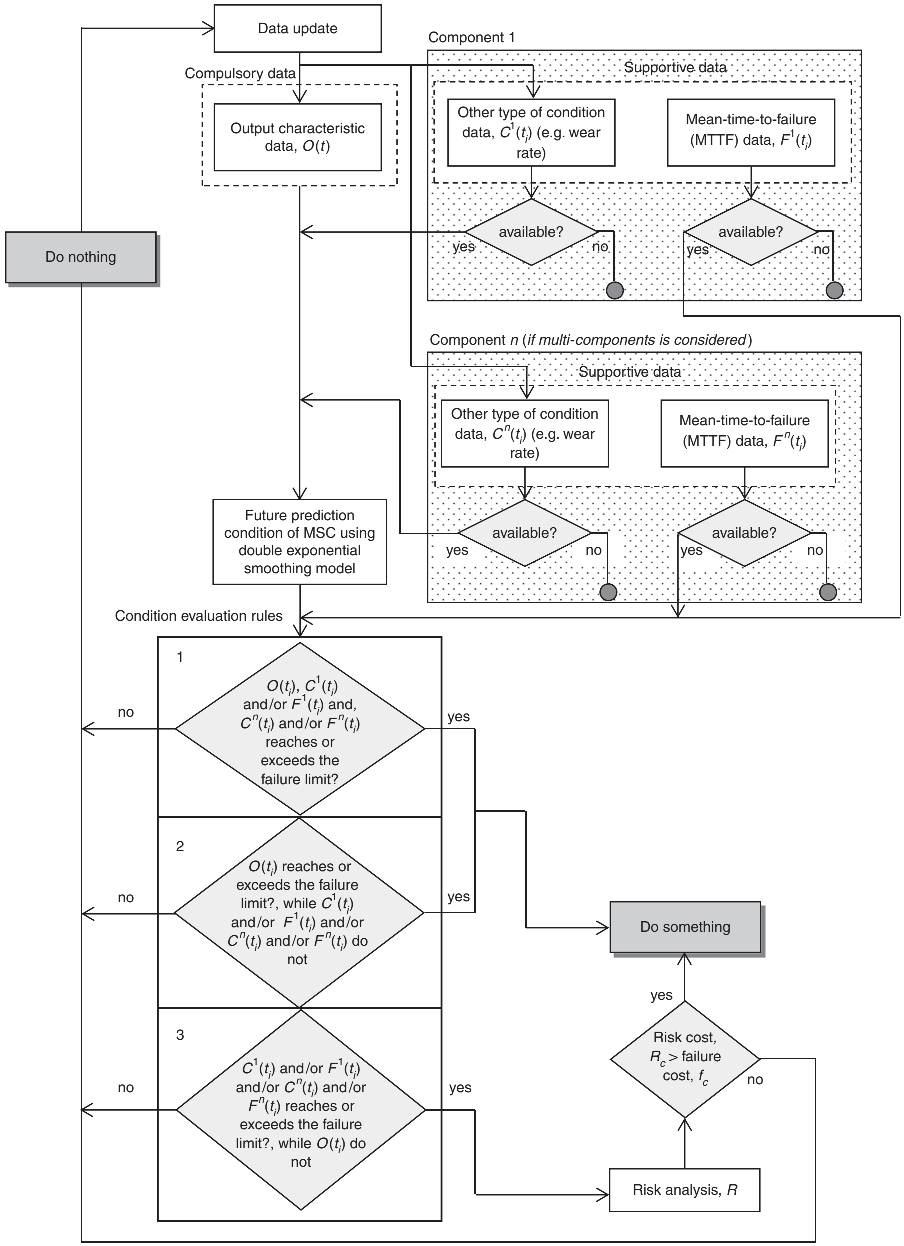

Figure 3.
Detail flow of step 2

2.2.1 Task 1 – available data identification. Data are an important requirement for any special maintenance program for maintenance decision making. In maintenance research, data can be classified into first- and second-level data. Waeyenbergh and Pintelon (2002) defined first-level data as data recorded while system installation (e.g. original equipment manufacturer (OEM) recommendation or ISO standards) and second-level data as data recorded during the chain of normal work (e.g. actual operating condition or worker experiences).

In the proposed MDS model, three types of data can be used for deterioration-monitoring and decision-making processes. The first type of data is machine output measured as explained before. The second type of data are the condition parameters from the physical changes of the components (e.g. vibration, wear, and sound, among others). The third type of data is the time-to-failure (TTF) to estimate the value of mean-time-to-failure (MTTF), which is the data measured using a time scale. The first type of data can be classified as second-level data, whereas the last two types of data can be grouped either as first or second levels of data. The details of each type of data are presented as follows.

Machine output. Machine output characteristic(s) data are necessary because they present the trend of MSC deterioration in the actual failure perspective (Ahmad and Kamaruddin, 2012a). Machine output measures refer to one of the condition monitoring (CM) parameters that can be represented by the form of variables (e.g. length or width, temperature, and volume) and attributes (e.g. degree of cleanliness, dirtiness, and abnormal color).

Physical changes parameter. The physical change parameter of the MSC is another type of data that can increase the reliability of the deterioration-monitoring and decision-making processes. The data can be classified as common CM parameters with examples such as vibration, acoustic, wear rate, and temperature levels. In the proposed MDS model, this type of data is classified as supportive data, in such a way that if it is available in the real case, the decision will be more reliable. Otherwise, the decision can still be made by relying on machine output data. The failure limit of this type of data can be determined based on either worker experiences or on OEM or ISO standards.

TTF. TTF is another type of supportive data that can be used in deterioration-monitoring and decision-making processes. TTF is a time-based type of data that is measured based on a time scale. Moreover, TTF can comprise alternative data if the data in the physical change parameter are not available in real industrial cases because of impractical issues and high monitoring costs (e.g. sensors, data acquisition, analysis, and expert training, among others). The TTF data estimate the value of (MTTF), which can be determined using two methods. The first method relies on worker experience and the second method is performed through replacement record analysis, where the value of MTTF can be statistically estimated based on the Weibull distribution functions as follows (Ebeling, 1997):

$$\mathrm{MTTF} = \hat{\theta}^{-}\left(1+\frac{1}{\hat{\beta}}\right) \tag{4}$$

$$b = \hat{\beta} = \frac{\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} x_i^2} \tag{5}$$

$$a = \bar{y} - b\bar{x} \tag{6}$$

$$\hat{\theta} = e^{-\left(\frac{a}{\beta}\right)} \tag{7}$$

$$\mathrm{TTF}, (x_i) = \ln t_i \tag{8}$$

$$y_i = \ln \ln\left[\frac{1}{(1-F(t_i))}\right] \tag{9}$$

$$F(t_i) = \frac{i-0.3}{n+0.4} \tag{10}$$

Once the mandatory data (output characteristics) and available supportive data (physical change parameter and/or MTTF) are obtained, the data are further analyzed to extract useful information on MSC conditions.

In the case of cutting processes, where the cutting knife was classified as an MSC with non-repairable and single-component type characteristics, Task 1 of Step 2 found that the data of machine output for the cutting knife is the surface appearance quality of the cutting process (Figure 4). These data were classified under the attribute type. The level of surface appearance quality was measured by a scale system currently used by the quality control department of the case study company. Four scales were used as follows: scales 1, 2, 3, and 4, which indicate the cutting appearance quality as "very good," "good," "ok," and "bad," respectively. The acceptance limit of this scale system is determined by scales 1, 2, and 3, which indicate that the product is acceptable, whereas scale 4 indicates that the product has to be rejected.

The data of physical parameter for the cutting knife is also identified to be available. The data are the physical changes of wear rate, that is, the effects of wear and tear on the cutting process (Figure 5). These data were collected using a measuring tape and were based on the diameter reduction of the cutting knife. On the basis of current practice of the case study company, the cutting knife is considered failed (reaches the failure limit) if its diameter reaches or exceeds 525 mm. In addition, the case study company currently uses wear-rate monitoring to make replacement decisions regarding the cutting knife.

Another type of cutting knife data available for collection is the TTF data, which was collected from the maintenance record regarding the cutting knife replacement activity. The analysis of TTF data toward the determination of MTTF is conducted using Equations (4)-(8). Based on the calculation, the value of the cutting knife MTTF is 30 hours of operating time. This value indicates that, based on the statistical analysis using the exponential distribution function, 30 hours of operating time is the interval by which the cutting knife

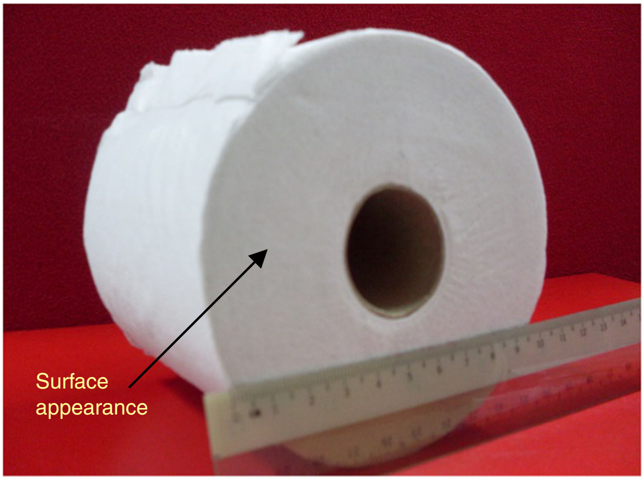

Figure 4.
Surface appearance quality of the cutting process

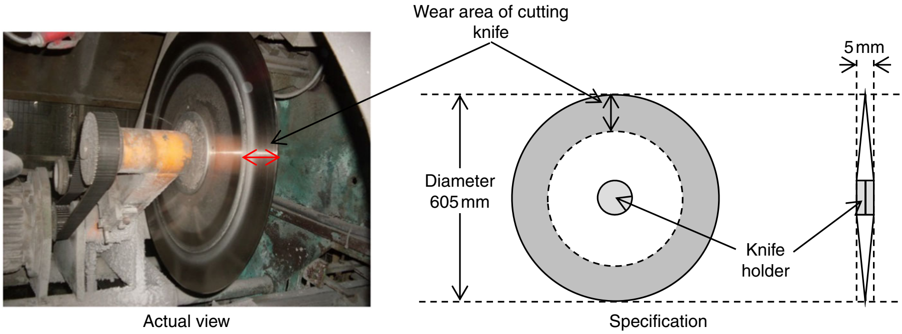

Figure 5.
Wear area on cutting knife

reaches the failure limit. In other words, 30 hours is the average time by which the cutting knife needs to be replaced.

2.2.2 Task 2 – future trend forecasting and condition evaluation. After determining the types of available data and defining the failure limit, the second task of Step 2 is future trend forecasting.

In the proposed MDS model, the method used in the deterioration-monitoring process is the future-condition-prediction-based (FCPB) method and detailed characteristics of the method were discussed in Ahmad and Kamaruddin (2012b). The heart of the FCPB method is the future condition trend forecasting process. The exponential smoothing (ES) method is one of the possible approaches that can be used to forecast future trends. The application of the ES method in the proposed MDS model is motivated by some practical considerations as follows (Makridakis and Wheelwright, 1987):

(1) smoothing models are relatively simple and easy to understand for users;

(2) only limited data storage and computational effort are required; and

(3) predicted values based on the ES method are accurate compared with more complex forecasting methods.

The most appropriate forecasting model under the ES method that can be particularly applied in this task is the double exponential smoothing (DES) model. The DES model is a forecasting model under the ES method that is specifically used to forecast a future point based on a non-linear trend model. The DES model can be presented as follows (Makridakis and Wheelwright, 1987):

$$e_t = X_t - \ddot{X}_{t-1}(1) \tag{11}$$

$$S_t = S_{t-1} + \phi T_{t-1} + h_1 e_t \tag{12}$$

$$T_t = \phi T_{t-1} + h_2 e_t \tag{13}$$

$$\ddot{X}_t(m) = S_t + \sum_{i-1}^{m} \phi^i T_t \tag{14}$$

By applying the DES model in the current task, the most important value is the forecast value made at the end of t for m steps, $\ddot{X}_t(m)$, and is presented in Equation (14). This value then will be evaluated using condition evaluation rules as proposed in Figure 3. It follows by initial decision of do-something or do-nothing action.

If the predicted MSC condition follows rules 1 and 2 ("yes" direction), then the do-something decision is suggested. Otherwise, the do-nothing decision is made, which means that the MSC is classified to be in good condition and may still be used in the machine operation. If the predicted MSC condition follows rule 3, risk analysis (RA) is conducted. RA estimates the appropriateness of deciding whether to do-nothing or do-something. Quantitatively, the risk of a component toward failure can be calculated by multiplying the probability of failure with the consequences of failure (Ananda and Maiti, 2008). In the proposed MDS model, RA refers to the cost of risk calculated based on the probability concept of failure and the cost of failure as follows.

If $O(t_i)$, $C(t_i)$, and $F(t_i)$ are available:

$$R_{\text{cost}} = \left(\frac{O(t_i)+C(t_i)+F(t_i)}{3}\right) \times C_f \tag{15}$$

If only $O(t_i)$ and $C(t_i)$ are available:

$$R_{\text{cost}} = \left(\frac{O(t_i)+C(t_i)}{2}\right) \times C_f \tag{16}$$

If only $O(t_i)$ and $F(t_i)$ are available:

$$R_{\text{cost}} = \left(\frac{O(t_i)+F(t_i)}{2}\right) \times C_f \tag{17}$$

$$C_f = C_{\text{Main}} + C_{\text{Down}T} \tag{18}$$

Once the risk cost is calculated, it will be compared with the overall unexpected failure cost, C_f. If the risk cost is equal to or more than the failure cost ($R_{\text{cost}} \geqslant C_f$), the do-something decision is recommended. Otherwise, the do-nothing decision is suggested. Table IV shows the series of decisions made through forecasting and evaluating processes based on RA. The result of Table IV indicates that at 29th hour of operating time the decision of do-something is suggested.

2.3 Step 3: decision making

The final step of the proposed MDS model is the decision-making step, which is concerned on further maintenance decision making. For the non-repairable type component, do-something directly refers to the maintenance decision of preventive replacement. For the case of the

Operating time, t_i	24	25	26	27	28	29	30	31
Data monitoring				Forecast values				
$Q(t_i)$	0.595	0.617	0.639	0.662	0.684	0.706	0.729	0.751
$C(t_i)$	1.11	1.16	1.21	1.26	1.31	1.36	1.41	1.46
$F(t_i)$	0.800	0.833	0.867	0.900	0.933	0.967	1.000	1.033
Decision	DN	DN	DN	DN	DN	DS	DS	DS
Risk cost (RM)	1670	1740	1811	1881	1951	2022	2093	2163

Notes: DN, do-nothing; DS, do-something

Table IV. Series of decisions made based on RA cutting knife, which has been classified as a non-repairable type component, the decision of do-something at 29th hour of operating time meant that the preventive replacement of cutting knife is recommended to be carried out at that operating time.

On the other hand, two possible maintenance decisions are involved for a repairable type of component, namely, to repair or to replace. The motivation of this scenario is that the cost and effect of each maintenance action (repair or replace) varies. The cost toward the repair decision is usually cheaper than the cost for replacement, whereas the effect from the repair action is not a perfect (as-good-as-new) maintenance decision compared with the replacement decision (Ebeling, 1997). Therefore, the most appropriate decision for the repairable component case, whether to repair or replace, is relevant.

In the proposed MDS model, the maintenance decision toward the repairable type of component is solved based on the repair limit policy. The repair limit policy is one of the practical repair policies that can be applied in a real industrial case (Wang, 2002). Hence, this policy is used in the current study. The repair limit policy is the calculation of the total maintenance cost per lifecycle of components, considering the number and total cost of repairs performed during its lifecycle (Wang, 2002). In the proposed MDS model, the analysis of the repair limit policy is shown below.

The total maintenance cost $T_{\text{cost}}^{\text{unext}-f}$ along its lifecycle is given by:

$$T_{\text{cost}}^{\text{main}} = C_{pR} + \sum C_{pr} \tag{19}$$

$$C_{pR} = C_R + C_{mdt}^{pR} \tag{20}$$

$$C_{pr} = C_r + C_{mdt}^{pR} \tag{21}$$

The total unexpected failure cost $T_{\text{cost}}^{\text{unext}-f}$ is given by:

$$T_{\text{cost}}^{\text{unext}-f} = C_R^{unp} + C_{rew} + C_{proRej} \tag{22}$$

$$C_R^{unp} = C_R + C_{mdt}^{R} \tag{23}$$

The rule of the maintenance decision based on the repair limit policy is that if the total maintenance cost $T_{\text{cost}}^{\text{main}}$ along its lifecycle reaches or exceeds the total unexpected failure cost $T_{\text{cost}}^{\text{unext}-f}$ limit; then, the preventive replacement decision is preferred. Otherwise, the preventive repair decision is carried out.

On the other hand, MSC also can be classified as a multi-component structure. In fact, the maintenance problem for a multi-component structure is more challenging to solve compared with that of a single-component structure. In the maintenance decision aspect, the MSC toward the multi-component structure deals with the decision to either replace or repair and with the selection of the right component for maintenance action. The detail discussion for this particular case application is given in Ahmad and Kamaruddin (2013).

3. Conclusions and further research

This paper presented a quantitative maintenance engineering policy that was developed and based on a production machine perspective. The structure of the policy is called the MDS model, which consists of three steps; and each step has its own objectives and particular processes. A detail presentation of each step of the proposed model together with a real case example from the pulp manufacturing industry proves the applicability of the model. Future work on simple deterioration monitoring flow and its condition evaluation rules has been proposed in this paper which can be converted to a computerized version of the decision support system. Therefore, this will create a fully automated decision support system that significantly supports a maintenance engineering team in monitoring the production machine processes toward making the maintenance decisions at the right time and for the right component(s) of the machine.

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