Research Article

A Hybrid Simulation Study to Determine an Optimal Maintenance Strategy

Ig. Jaka Mulyana, Ivan Gunawan, Yunia Vera Angelia , Dian Trihastuti

Universitas Katolik Widya Mandala Surabaya, Jl. Kalijudan 37, Surabaya, 60114, Indonesia

ARTICLE INFORMATION

KEYWORD

CORRESPONDENCE

Phone : +62818507566
E-mail : ivangunawan@ukwms.ac.id

A B S T R A C T

With the increasing complexity of the process industry, having excellent maintenance management is essential for manufacturing industries. Various parts that interact and interdependent with each other make a well-planned maintenance strategy is one of the major challenges faced by industry. The whole system could be interrupted just simply because of the failure of a component. Therefore, a review of a maintenance strategy must be done from a system perspective. It is suggested that the optimal preventive maintenance time interval is not only determined by the lowest maintenance cost of each machine but also its impact on the whole system. Two main indicators that can accommodate the system perspective are reliability and revenue. A large number of machines and the array of machines can be synthesized using reliability indicators. Moreover, the creation of maximum revenue is always the main goal for a business. Therefore, in this study, the best maintenance strategy will be determined from the revenue obtained by a process industry which operates a well known flour mill in Surabaya. A hybrid approach is proposed using Monte Carlo simulation to observe the machine individually from which the results are reviewed using the application of System Dynamics. From three improvement scenarios, a scenario 2 with a recommendation of setting the preventive maintenance time interval considering resource availability, was finally chosen because it was able to generate the highest revenue at the end of the period.

INTRODUCTION

The characteristics of industry significantly influence its maintenance policy [1]. Process industry is considered a complex system including various parts and subsystems, which are intertwined with each other. A failure of one part may result in the whole system disruption. However, we cannot simply halt the main system to perform a maintenance task. Ideally, performing maintenance tasks should follow a predetermined schedule, which has considered various factors of the system. Such consideration should also be applied in determining the maintenance strategy for the supporting system. In other words, the maintenance strategy for the supporting system must follow the pattern of the main system. However, finding an appropriate maintenance strategy is a challenging task. The maintenance strategy referred to in this study is 'what tasks on which machine' and 'when will it be executed'. Therefore, determining a maintenance strategy for each system in process industries is important and must be considered systemically [2].

Researches on maintenance strategy has been applied in various disciplines. However, most of the literatures emphasized more its application to the main system while paying less attention to the supporting system. Telford et al. [3] proposed a condition based maintenance program in the oil and gas industry and focused only on the components of the main system. Braaksma et al. [4] discussed asset maintenance in five process industries but the study only emphasized on the main systems. Ighravwe et al. [5] proposed a model to optimize the maintenance workforce in a brewery industry with a focus on its three main production lines. Due to the lack of studies in maintenance strategy for the supporting system, this research addresses the system perspective to develop a maintenance strategy that considers the supporting system.

There are two types of maintenance strategies. The first one is corrective maintenance (CM) or repair. CM is conducted after a failure occurs and intends to restore the overall functioning of the system. The second type is preventive maintenance (PM). PM is conducted even if the system is still running normally in order to avoid failure or breakdown. PM can be a condition-based or time-based approach. While the condition-based PM is determined according to the results of the system's state monitoring; the time-based PM or planned preventive maintenance (PPM) is conducted at scheduled times or periodically [6]. In this study, the time interval of PPM will be analyzed for each machine before determining the well-suited maintenance strategy for all machines. The time interval of PPM will affect the proportion of CM and PPM. The right proportion between CM and PPM will lead to the optimal maintenance cost of each machine. However, if there is more than one machine working in parallel, determining the PPM time interval of each machine must consider resource availability. The optimal PPM's time interval for a machine may not necessarily provide the lowest cost. Therefore, comprehensive analysis of PPM's time interval for all machines is required.

Monte Carlo Simulation (MCS) is one of the favorite methods in the maintenance studies [7] - [9]. It becomes popular because of its flexibility in handling the uncertainty of non-linear problems. However, MSC has some limitations. MSC can only address a small space of problems and cannot show the exact optimal point. To tackle such limitation, some studies combined MSC with other methods known as hybrid simulation-analytical modeling [10] and [11].

In fact, analyzing a complex system requires an improvised method in order to develop a simpler, more natural and more efficient model. Therefore, it is of advantageous to integrate two or more simulation methods [12]. Combining two or more simulation approaches in addressing such issue is called a hybrid simulation model. Hybrid simulations enhance the understanding of complex systems because problems can be investigated from different perspectives.

There are four types of method combination which are categorized as a hybrid [13]: a) Sequential: two or more different single method execute sequentially (but only once), a result of one method becomes the input to the other; b) Enrichment: there is only one dominant method and the others are to support or to enrich the analysis; c) Interaction: there are two or more single methods that are equally important and interact cyclically; and d) Integration: Combining two or more methods so perfectly that it is difficult to know when one method ends and when another method starts.

In general, there are four general approaches in building simulation model which are MCS, Discrete Event Simulation (DES), System Dynamics (SD), and Agent Based Modeling (ABM). Compared to MCS and DES, the use of SD and ABM in maintenance studies is less popular [14]. ABM can be ruled out because it is a relatively new method. On contrary, MCS and DES are popular in maintenance studies because some events in the maintenance system are discrete, such as an unexpected failure. Moreover, the maintenance system can be viewed from a system perspective because there are many continuous and interacting processes, such as the availability of maintenance resources and the financial aspects [15]. While MCS is only able to solve problems with low to medium abstraction, SD can reach higher abstractions. SD is more appropriate for analyzing complex systems that are characterized by feedback loops. Therefore, SD can provide a system perspective in overcoming a problem. SD has also been used in several maintenance studies as demonstrated in [16] and [17]. Thus, the use of SD will eliminate the limitation of MCS.

Hybrid simulations are still rarely exploited to solve maintenance problems. In the last five years, there are only two studies found using hybrid simulations. Oleghe and Salonitis [18] used a hybrid simulation (SD and DES) as a decision-making tool in improving Total Productive Maintenance (TPM). Then, Linnéusson et al. [19] used a hybrid simulation (Multi Objective Optimization (MOO)-SD-DES) to support the development of maintenance strategies.

Considering the above mentioned individual advantage of MCS and SD, in this study MCS and SD are applied simultenously to analyze the influence of maintenance strategy in the process industry. The combination of MCS and SD in tackling maintenance issues is rarely used, and to the best of our knowledge, the integration of these two methods to develop maintenance strategy in the process industries has not been explored. Therefore, in the proposed hybrid simulation work, the methods of MCS and SD are combined in such a way that MCS is used to find the possible alternatives of PPM time interval for each machine, and SD then reviews the results of the MCS using the perspective of the whole system to find the optimal solution.

The problem situation being modeled is a packing department of a well-known flour mill in Indonesia. The packing department is an important supporting system of the flour mill. This department has three types of machines: scales, carousels, and sewing. From the initial observation, sewing machines were chosen as the research subject because these machines have the highest rate of failure. The packing department consists of 13 sewing machines. Based on the data obtained, the critical components of the sewing machines are scissors and throat plate. If there is a problem with the scissors, it may cause knitting jams, imprecise cut of yarn, and in the worst case, break the shear drive. Similarly, if there is a problem with the throat plate, it may cause knitting failure, and even break the throat plate. The packing department is one of the important links in the flour mill because it is strongly related to the distribution process. The factory could not distribute its products if the packaging process is hampered.

The flour mill is categorized as a process industry. Therefore, the determination of maintenance strategy in each department will affect the whole system. The hybrid simulation is used to analyze the influence of the maintenance strategy in the packing department to ensures that the best strategy is determined from a system perspective. Thus, the response variable in this study is the system revenue. The decision variable is the PPM time interval of each component of the individual sewing machine.

Reliability is one indicator in determining the effectiveness of the maintenance strategy. The concept of Reliability Centered Maintenance (RCM) has been widely used in various studies [20] and [21]. This RCM concept is adapted in the proposed hybrid simulation study using MCM and DES sequentially to accommodate 13 sewing machines that work in parallel. Secondary data from the past record of flour mill is used in MCS to obtain the input data for the SD model. To address the evidence unavailability of direct link between the PPM time interval of each component of the individual sewing machine and the revenue as the financial indicator, the SD model is developed to determine maintenance strategy according to the best trade-off condition between those two variables.

A sequential hybrid simulation (MCS and SD) is believed to be able to solve the problem of determining optimal preventive maintenance schedules with an integrative system perspective. Thus, the prosed study is not only an appropriate to solve the stated problem but also can contribute to providing knowledge on the use of hybrid simulations in maintenance-related studies.

This paper consists of three more sections. Section 2 describes the detailed methods we have used. To provide a complete overview of our hybrid simulation method, we divided Section 2 into four sub-sections: data collection, research design, MCS process, and SD process. Section 3 describes the details of the process industry investigated, MCS results, SD results, and the discussion of the results. Finally, Section 4 summarizes the conclusions and provides some premises for future research.

METHODS

This section is divided into four sub-sections: data collection, research design, Monte Carlo simulation process, and System Dynamics process.

Data Collection

Secondary data related to the operations of the packing department in 2018 was collected from the flour mill using the haphazard approach. The data was selected and reorganized as needed. From the results of observations and data analysis using Risk Priority Number (RPN), the research subject was selected. It is found that the scissors and the throat plate of the sewing machines are the most frequent causes for the system failure, thus they are selected as the research subjects. Afterwards, the data was sorted and processed to obtain the cause of failure, time-to-failure (TTF), time-to-repair (TTR), and maintenance cost that would be used in MCS. In addition, more comprehensive financial data was also collected to run the SD simulation.

Research Design

Distribution fitting was carried out for the historical data of each sewing machine using Weibull++. Then, the distribution of each sewing machine was used in the MCS spreadsheet. Experiments using PPM with various time intervals data were carried out to find the bath-up curve of each sewing machine from the perspective of maintenance cost. The bath-up curve would be the basis for generating the alternatives of PPM time interval for each machine.

The SD approach started with developing a conceptual model in the form of a causal loop diagram (CLD). CLD shows the relationship between the elements in the system. The complexity of the system observed is reflected in the number of loops in the CLD. The CLD was then translated to be a stock flow dia-
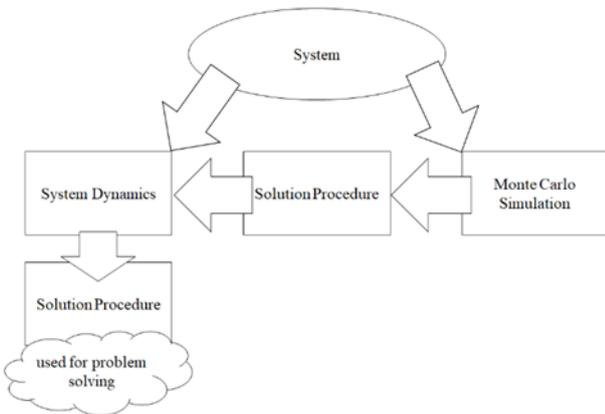

Figure 1. The Concept of the Hybrid Simulation in This Study
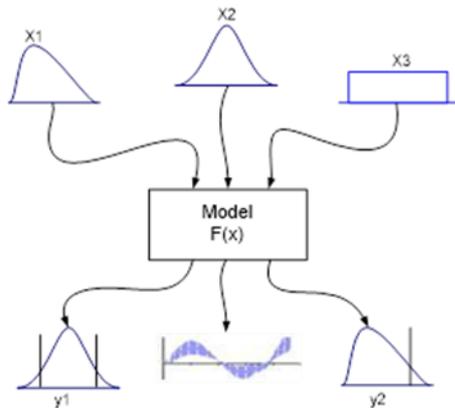

Figure 2. Schematic Showing the Principal of Stochastic Uncertainty Propagation

gram (SFD) as a basis for running the simulation. STELLA software was used to run the SD simulation. The simulation model had been validated before it was used to run the improvement scenarios. The improvement scenarios were generated using the reference of each sewing machine's bath-up curve. The result is an optimal maintenance strategy for all sewing machines in the packing department from the system perspective. The proposed hybrid concept is categorized as a sequential hybrid simulation and is shown in Figure 1.

Monte Carlo Simulation

The application of MCS is to set the PPM time interval based on random events. MCS provides an approach to estimate the total maintenance cost per hour rate. Technically, MCS is a technique in choosing random numbers (as inputs) from probability distribution to run the simulation process [22]. Random numbers are used as indicators of systems failure which is represent the real system condition. This method shows us how the random variation of the failure probability (F(t)) influences the reliability of the modeled system. Figure 2 illustrates the random variation of the input parameters and their influence.

Moreover, it also shows how a set of input variables (X1, X2, X3) becomes a set of output variables (Y1, Y2) through the simulation process. The simulation will generate data used to represent probability distributions, reliability predictions, tolerance zones, and confidence intervals [23]. In this study, the input variables are TTR and TTF of each component of each sewing machine. These input variables are used in the simulation process of some possibilities of the PPM time interval. The expected simulation output is the total maintenance cost per hour rate.

MCS process is presented in detail to allow this simulation to be reproduced. There are seven steps used in this process. Each step is described in detail as follows:

1. Check the distribution fitness of TTR and TTF data by examining the AvGOF, AvPlot, dan LKV value.

2. Determine the PPM time interval (T_p) and the number of replications required (N). In this study, the PPM time intervals for the scissors is 10 hours while the PPM time intervals for the throat plates was 100 hours. The number of iterations (N) for each T_p is 500 times.

3. The failure time (T_i) is calculated using Equation (1) if the TTF distribution is Weibull 3, or using Equation (2) if the TTF distribution is Weibull 2. F(t) is the probability of failure. F(t) in the equation is replaced with a random number between 0 -1.

$$T_i = \gamma + \eta \left(\ln \left(\frac{1}{1 - F(t_i)} \right) \right)^{\frac{1}{\beta}} \tag{1}$$

$$T_i = \eta \left(\ln \left(\frac{1}{1 - F(t_i)} \right) \right)^{\frac{1}{\beta}} \tag{2}$$

4. Compare T_i and T_p. When $T_i > T_p$, the component succeeds to operate without failure. However, the component reaches its maintenance time (T_s) and it needs to maintain for the T_{ppm}. In this study, T_{ppm} for the scissors and the throat are 0.05 hours (3 minutes) and 0.75 hours (45 minutes), respectively. These were determined based on field observations.

When $T_i < T_p$, the component fails to operate for T_p and can only operate during its failure time (T_f). Consequently, it needs to repair for corrective maintenance time (T_{cm}). The T_{cm} is calculated either using Equation (3) (for Weibull 3) or Equation (4) for Weibull 2. M(t) is the probability of restoring components in the available time. M(t) in Equation (3) and (4) are replaced with a random number between 0 - 1.

$$T_{cm} = \gamma + \eta \left(\ln \left(\frac{1}{1 - M(t_i)} \right) \right)^{\frac{1}{\beta}} \tag{3}$$

$$T_{cm} = \eta \left(\ln \left(\frac{1}{1 - M(t_i)} \right) \right)^{\frac{1}{\beta}} \tag{4}$$

5. Compute the total cost per hour. When $T_i > T_p$, the preventive cost (C_{ppm}) is calculated using Equation (5).

$$\begin{aligned} C_{ppm} \\ = \left(T_{ppm} . (\text{labour cost per hour} \\ + \text{lost opportunity cost}) \right) + \text{utility cost} \\ + \text{component replacement cost} \end{aligned} \tag{5}$$

When $T_i < T_p$, the corrective maintenance cost (C_{cm}) is calculated. The equation used to calculate the corrective cost shown in Equation (6).

$$\begin{aligned} C_{cm} \\ = \left(T_{cm} . (\text{labour cost per hour} \\ + \text{lost opportunity cost}) \right) + \text{utility cost} \\ + \text{component replacement cost} + \text{quality cost} \end{aligned} \tag{6}$$

6. Compute the total component operation time (T_{opr}) and total simulation time (T_{clock}). After deriving the value of T_i, T_{cm}, and T_{pm}, the T_{opr} and T_{clock} are determined using Equation (7) and (8), respectively.

$$T_{opr} = \sum_{i=1}^{N} (T_f + T_s) \tag{7}$$

$$T_{clock} = \sum_{i=1}^{N} (T_f + T_s + T_{ppm} + T_{cm}) \tag{8}$$

7. Conduct the cost analysis. This analysis is based on three cost variables i.e., corrective maintenance cost per hour (C_{cm}/hour), preventive maintenance cost per hour (C_{ppm}/hour), and the total maintenance cost per hour (TC/hour). These three variables are calculated using the following equations.

$$C_{cm}/\text{hour} = \frac{\sum_{i=1}^{N} C_{cm}}{T_{clock}} \tag{9}$$

$$C_{ppm}/\text{hour} = \frac{\sum_{i=1}^{N} C_{ppm}}{T_{clock}} \tag{10}$$

$$\text{TC/hour} = C_{cm}/\text{hour} + C_{ppm}/\text{hour} \tag{11}$$

Cost analysis is the most important stage of this study because it allows us to know the trade-off between determined maintenance time interval (Tp) and the total maintenance cost per hour (TC/hour). Consequently, the maintenance schedule are set to achieve the most efficient cost.

System Dynamics Process

The first step after understanding the problem situation is to build the mental model or the conceptual model. The proposed tool for building a mental model or a conceptual model in the SD is a CLD. It is suitable segment in the SD process because the CLD is able to represent interdependencies and feedback

Table 1. Polarity Explanation

Symbol	Interpretation
X → Y (+)	If X increases, then Y increases
	If X decreases, then Y decreases
X → Y (-)	If X increases, then Y decreases
	If X decreases, then Y increases

processes which are the main concept of SD [24]. A CLD consists of variables connected by arrows showing causal relationships among the variables. Furthermore, at each causal relationship, the polarity is determined. The polarity can be positive or negative depending on how the dependent variable respond to the independent variables (see Table 1).

At least there must be a loop in a CLD, either a reinforcing loop or a balancing loop. A reinforcing loop occurs if the multiplication of polarity signs shows a positive result. This indicates that the variables in the loop will grow exponentially. A balancing loop occurs if the multiplication of polarity signs shows a negative result. A balancing of loop will lead to a steady condition. Complexity occurs when there is a combination of reinforcing loops and balancing loops so the results cannot be predicted.

After a CLD has been established, it is then translated into an SFD. Although a CLD is a powerful tool in representing the system thinking, the CLD does not represent a stock and flow concept, which is one of the core concepts of SD. A CLD shows qualitative relationships while SFD contains quantitative operational variables that make it possible to run a simulation. A stock becomes a major element in an SFD because it represents the status of the observed system. This is represented by a rectangle. In addition, there is an inflow represented by a pipe that leads to the stock and outflow represented by a pipe coming out of the stock. Other important elements are valves, clouds, and converters. Valves serve to control the flow. Clouds show the source and the sink. Converters are components of a system of which the values are obtained from other components of the system through computational procedures. In a system simulation, one of the advantages of SD is the flexibility in swapping the dependent and independent variables to see the system behavior.

RESULT AND DISCUSSION

The process flow in the packing department begins with the process of weighing the flour at the scales section. Then, it is distributed on the carousels which act as intermediaries so that the flour can easily get into the package. After the flour fills the sack, it is sewn with sewing machines (see Figure 3). Data shows that these sewing machines are the most frequent cause of downtime in the packing department (see Figure 4). However, the number of failures alone often does not represent the risk of failure as a whole. Therefore, it is necessary to involve an analysis of the risk of failure with RPN which is the result of multiplication of occurrence (O), severity (S), and detection (D). Each component consists of 10 scales. In occurrence, scale 1 represents 'never occurs' and scale 10 represents 'always occurs'. In severity, scale 1 represents 'no impact' and scale 10 represents 'a very severe impact'. In detection, scale 1 represents 'very easy detection' and scale 10 represents 'a very severe impact'. In detection, scale 1 represents 'very easy detection' and scale 10 represent "it
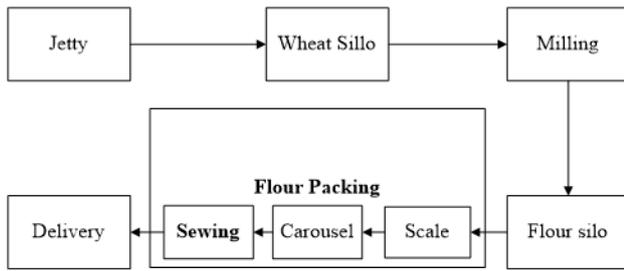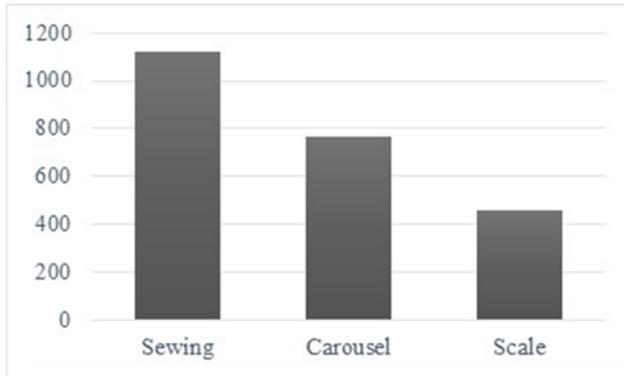
Figure 3. The Process under Study

Figure 4. The Amount of Downtime for Each Type of Machine

cannot be detected'. The results of the RPN calculation of each machine show that the sewing machine still ranks first (see Table 2). Furthermore, a bigger problem may arise if the flour silo is unable to accommodate the output of the milling process. Therefore, the critical components of a sewing machine are scissors and throat plate. The causes of downtime and preventive action can be seen in Table 3.

Distribution Fitting

The distribution fitting was conducted on TTF and TTR of each type of component: scissors and throat plate. The distributions of TTF of each sewing machine which was caused by the failure of scissors are dominated by Weibull 3. Whereas the distributions of TTF of each sewing machine which was caused by the failure of the throat plate are dominated by Weibull 2. The result of distribution fitting can be seen in Table 4 and Table 5.

Table 2. RPN of Each Machine

No.	Machine	O	S	D	RPN	Rank
1	Scale	4	8	7	224	2
2	Carousel	6	5	5	150	3
3	Sewing	8	6	7	336	1

Table 3. The Cause of Downtime and The Preventive Action

Component	Cause of downtime	Preventive action
Scissors	Knitting jam	Lubricating
	Imprecise cut of yarn	Cleaning and resetting
	Broken scissors drive	Replacing the component
Throat plate	Knitting failure	Tightening the bolts and fixing the position
	Broken throat plate	Replacing the component

Table 4. Scissors' TTF Distributions

Sewing Machine	TTF Distribution
201	Weibull 3 (2,536; 4,76; 100,65)
202	Weibull 3 (3,5641; 79,005; 85,906)
203	Weibull 3 (3,024; 68,377; 95,02)
204	Weibull 3 (1,9146; 31,448; 10,05)
205	Weibull 3 (2,032; 56,621; 98,41)
206	Weibull 3 (2,9058; 61,004; 105,39)
306	Weibull 2 (6,9662; 167,61)
305	Weibull 3 (2,0036; 47,989; 106,72)
301	Weibull 3 (1,525; 31.32; 106,39)
406	Weibull 3 (1,9859; 36,323; 99,851)
405	Weibull 3 (1,3457; 31,151; 110,32)
404	Weibull 2 (9,0213; 151,76)
401	Weibull 3 (3,2875; 69,903; 86,987)

Table 5. Throat Plate's TTF Distributions

Sewing Machine	TTF Distributions
201	Weibull 2 (8,738; 1823,9)
202	Weibull 2 (15,633; 1652,4)
203	Weibull 2 (12,455; 1564,1)
204	Weibull 2 (4,7969; 1623,5)
205	Weibull 2 (4,1983; 1757,4)
206	Weibull 2 (10,275; 1778,5)
306	Weibull 3 (4,5783; 740,55; 735,97)
305	Weibull 3 (2,6929; 983,69; 834,53)
301	Weibull 3 (21,384; 4337,7; -2565,3)
406	Weibull 2 (7,9644; 1269)
405	Weibull 2 (14,678; 1585)
404	Weibull 2 (15,122; 1695,5)
401	Weibull 2 (6,2994; 1476,3)

After finding the distribution of TTF of each component in each machine, it continued by looking at the TTR distribution of each component in each machine. TTR distributions of the scissors can be seen in Table 6 and TTR distributions of the throat plates can be seen in Table 7. Even though, the TTR distributions of the scissors of each sewing machine are similar, researchers still insisted on using the specific distribution of each sewing machine in the simulation. This is necessary because the TTR distributions of the throat plate in each sewing machine have a high variation.

Monte Carlo Simulation

As explained in the Method section, MCS will be used to build bath-up curves that show the relationship between the PPM time interval and the maintenance cost. Since the simulation clock (Tclock) is not the same for each experiment, we used total maintenance cost/hour (TC/hour) as a comparable indicator. The total maintenance cost/hour is the sum of PPM cost/hour and CM cost/hour. Therefore, the maintenance cost/hour represents the total maintenance cost for maintaining the

Table 6. Scissors' TTR Distributions

Sewing Machine	TTR Distributions
201	Weibull 2 (3,7647; 0,26953)
202	Weibull 2 (3,3611; 0,2587)
203	Weibull 3 (3,024; 68,377; 95,02)
204	Weibull 2 (3,6787; 0,24535)
205	Weibull 2 (3,6997; 0,24342)
206	Weibull 2 (3, 7579; 0,24111)
306	Weibull 2 (3,5445; 0,23705)
305	Weibull 2 (3,3463; 0,24169)
301	Weibull 2 (3,7317; 0,24826)
406	Weibull 2 (3,401; 0,25598)
405	Weibull 2 (3,5079; 0,25315)
404	Weibull 2 (3,2573; 0,23953)
401	Weibull 3 (1,6994; 0,10171; 0,11548)

Table 7. Throat Plate's TTR Distributions

Sewing Machine	TTR Distributions
201	Weibull 2 (10,664; 1,9794)
202	Weibull 2 (7,01; 1,8549)
203	Weibull 3 (2,5478; 1,4658; 0,75688)
204	Weibull 2 (3,4834; 1,9418)
205	Weibull 2 (4,3108; 1,5691)
206	Weibull 2 (5,7284; 2,0756)
306	Weibull 2 (4,017; 1,8552)
305	Weibull 2 (5,1359; 1,5312)
301	Weibull 2 (7,5109; 1,7851)
406	Weibull 2 (6,1479; 1,9171)
405	Weibull 2 (7,0137; 1,6046)
404	Weibull 2 (12,968; 1,5683)
401	Weibull 2(7,0218; 1,7081)

component for each PPM time interval. It is called a bath-up curve because the maintenance cost/hour curve has a pattern like a bath-up or a boat. When PPM time interval is very tight, PPM will be done more frequently and cause high PPM costs. On the other hand, when the PPM time interval gets longer, the PPM cost will decrease but, CM cost starts to increase. The longer the PPM time interval, the higher the CM cost (see Figure 5 and Figure 6). Therefore, the optimal PPM time interval is obtained when the total sum of PPM cost and CM cost is at the lowest condition. The bath-up curves of the maintenance cost/hour for sewing machine 201 can be seen in Figure 7 and Figure 8. The same process was duplicated for all sewing machines.

As seen in Figure 7, the lowest maintenance cost/hour for maintaining the scissors in sewing machine 201 is at the PPM time interval of 80 hours. Then, the maintenance cost/hour starts to rise again because of the increase of CM cost/hour. Moreover, as seen in Figure 8, the lowest maintenance cost/ hour for maintaining the throat plate in sewing machine 201 is at the PPM time interval of 1.000 hours. After 1.000 hours, the maintenance cost/hour starts to increase again because of the increase of CM cost/hour.
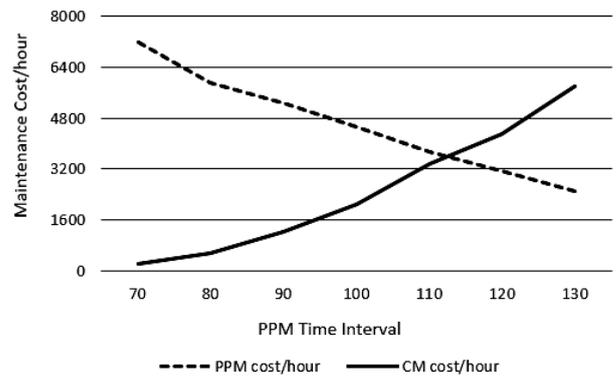

Figure 5. The Movement of CM Cost and PPM Cost for Scissors in Sewing Machine 201
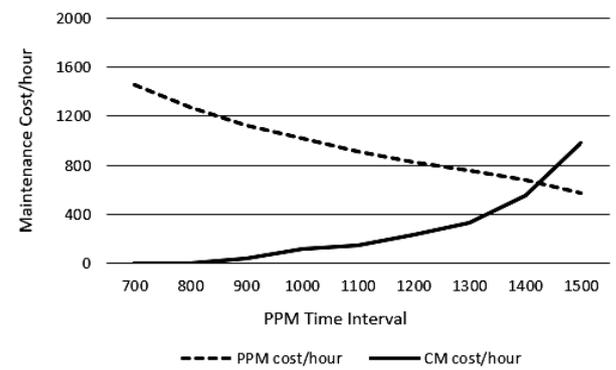

Figure 6. The Movement of CM Cost and PPM Cost for Throat Plate in Sewing Machine 201
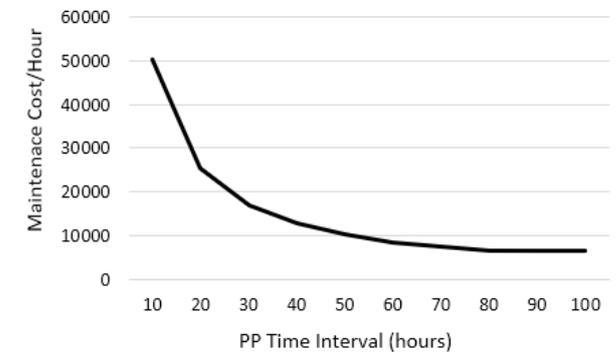

Figure 7. The Bath-Up Curve of Maintenance Cost/Hour for Scissors in Sewing Machine 201
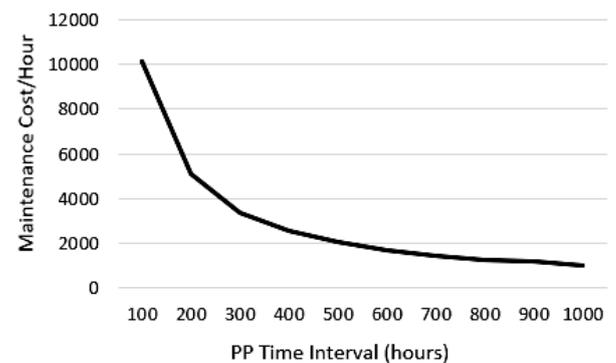

Figure 8. The Bath-Up Curve of Maintenance Cost/Hour for Throat Plate in Sewing Machine 201

Table 8. The Reliability and The Maintenance Cost/Hour of Each PPM Time Interval for Scissors in Sewing Machine 201

PPM Time interval (hours)	Reliability (r_n)	TC/hour (Rp.)
50	1,00	10.114,85
60	1,00	8.430,47
70	0,991	7.397,09
80	0,973	6.476,48
90	0,936	6.541,55

Table 9. The Reliability and The Maintenance Cost/Hour of Each PPM Time Interval for Throat Plate in Sewing Machine

PPM Time interval (hours)	Reliability (r_n)	TC/hour (Rp.)
700	1,00	1.453,80
800	1,00	1.272,24
900	0,997	1.169,18
1000	0,998	1.030,35
1100	0,985	1.058,38

Table 10. The Summary of The MCS Result for Scissors and Throat Plate in All Sewing Machines

Sewing Machine	Optimal PPM time interval for scissors (hours)	Optimal PPM time interval for throat plate (hours)
201	80	1000
202	120	1200
203	110	1100
204	70	700
205	140	700
206	110	1200
306	120	900
305	90	900
301	70	1500
406	90	700
405	90	600
404	110	1300
401	100	500

The result of the MCS study is not only the bath-up curves that can provide information about PPM time intervals and their relationship with the maintenance costs, but also the reliability indicator for each PPM time interval that will be used in SD. The example of reliability indicators for the scissors and the throat plate in sewing machine 201 can be seen in Table 8 and Table 9. A summary of the MCS study for the optimal PPM time intervals of each component in each sewing machine can be seen in Table 10.

System Dynamics

CLD represents the mental model or the conceptual model of the SD simulation. CLD describes the relationship among the elements which are involved in the system under observation. The proposed CLD for the maintenance system study can be seen in Figure 9. Afterward, the CLD was translated to become an SFD as is shown in Figure 10.

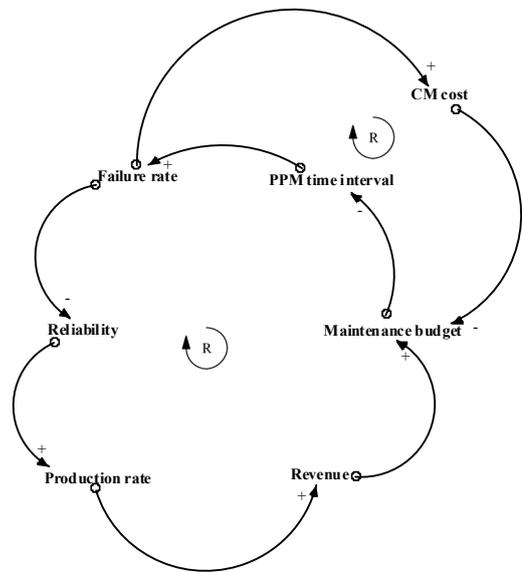There are two reinforcing loops in the CLD. The first one is

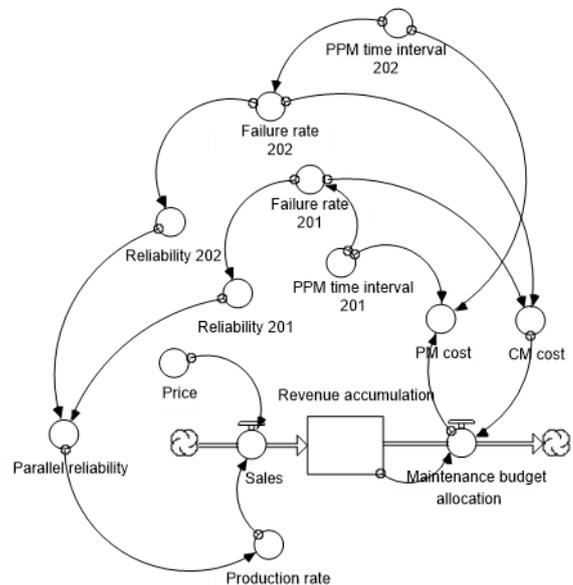Figure 9. The Causal Loop Diagram (CLD)

Figure 10. The Stock Flow Diagram (SFD)

Revenue > (+) Maintenance Budget > (-) PPM time interval > (+) Failure rate > (-) Reliability > (+) Production rate > (+) Revenue. This relationship can be explained as the revenue of the system will be allocated as a maintenance budget to pay the PPM cost. With a high allocation of the maintenance budget, PPM can be done more frequently so that it is done at a shorter interval. PPM time interval will affect the failure rate. The more frequent PPM is done, the lower the failure rate. A low failure rate will increase reliability. The higher reliability will cause an increase in the production rate which will increase the revenue as well.

The second reinforcing loop is Maintenance Budget > (-) PPM time interval > (+) Failure rate > (+) CM cost > (-) Maintenance Budget. This relationship explains that the income from the system will affect the maintenance budget allocation of the packing department. The higher the maintenance budget allocation, the more frequent PPM can be done, thus the shorter intervals are performed. The relationship also shows that PPM will affect the failure rate. The more frequent PPM is done, the lower the failure rate. A low failure rate will reduce

CM cost. Low CM cost will not significantly reduce the maintenance budget that has been allocated for PPM.

Although both of these loops are reinforcing loops of which result can be predicted, the model provides information about improvement scenario that will provide the highest exponential revenue increase of the proposed improvement scenario candidate. Therefore, it does not make the SD become meaningless. Figure 10 represents the simplification of the SFD with involving only two sewing machines. Revenue in the CLD was set as 'stock' in the SFD. The inflow is sales, while the maintenance budget allocation is the outflow. This system will review the revenue at the end of the simulation period.

Reliability, which is one indicator in the maintenance system, was chosen in this study because it can capture the condition of 13 sewing machines that work in parallel. The parallel reliability in the stock flow diagram is calculated by Equation (12).

$$R_p = 1 - (1 - r_1)(1 - r_2) \dots (1 - r_n) \tag{12}$$

Validation

Model validation was done by running the simulation on the initial condition and comparing the results with historical data using the paired t-test with α = 5%. The test result shows that there is no significant difference between the results of the simulation model and the historical data. Therefore, the model is confirmed valid. The real data set used as a basis for validation cannot be displayed in this paper at the request of the organization.

Iprovement Scenario

There are three possible improvement scenarios generated to determine the best maintenance strategy from a system perspective. Scenario 1 uses the optimal interval time for all machines obtained from the MCS study without considering the availability of the resource (see Table 10). If the resource is not available or insufficient at the PPM execution, a penalty fee will be charged. Furthermore, scenario 2 considers the availability of the resource so that it may not use the optimal PPM time interval, but choose a PPM time interval that still shows a low maintenance cost/hour by referring to the bath-up curve. Meanwhile, scenario 3 only applies to CM. The resource mentioned could mean spare parts or maintenance personnel. Simulations for the three scenarios were carried out for a year and the results can be seen in Table 11.

The best scenario is considered from the potential revenue of the packing department. As can be seen in Table 11, the highest potential revenue is obtained if the packing department runs scenario 2: setting the PPM time intervals based on the consideration of resource availability. However, the revenues do not reflect the real conditions because this study only used a sample of one type of machine involving two types of components. Revenue is just an indicator to justify which scenario is best. Table 10 shows the PPM time interval used in

Table 11. The Simulation Result of Each Improvement Scenario

Scenario	Revenue	PPM Cost	CM Cost
1	613.127.530	6.521.157	83.642.915
2	1.084.493.000	6.852.892	62.322.847
3	548.832.715	0	98.715.917

Table 12. PPM Time Interval in Scenario 2

Sewing Machine	PPM time interval for scissors (hours)	PPM time interval for throat plate (hours)
201	80	1100
202	130	1300
203	110	1200
204	50	800
205	150	700
206	90	1500
306	140	1000
305	160	900
301	70	1600
406	60	600
405	170	500
404	120	1400
401	100	400

scenario 2 for each component in each sewing machine. Then, the maintenance schedule can be arranged based on Table 12.

CONCLUSIONS

The proposed method has been proven able to determining the best maintenance strategy of a department in the process industry. In the packing department of the flour mill, the sewing machine is one of the most frequent machines experienced downtime. The critical components of this machine are scissors and throat plate. An examinationof the maintenance strategy was conducted on 13 sewing machines that work in parallel. This was carried out by an 'in-depth' study for each machine and the results were reviewed from a system perspective. The 'in-depth' study used MCS, whereas the system' perspective study implemented SD. The result of MCS study became the input of SD so that it could be calleda hybrid simulation. In SD, simulations were performed on three improvement scenarios. The simulations were run for a year to see which scenario that could provide the highest potential revenue. As a result, scenario 2 was chosen as the best scenario. This scenario suggests that the maintenance schedule should focus on arranging the maintenance period of the scissors and throat plate components for all machines by considering the resource availability.

The results of this study can be applied directly by the flour mill observed and the methods used can provide insight on how to use a hybrid simulation in a maintenance study. The guidance for further research is to involve all machines and all components in a department. The more data collected, the more comprehensive the SFD model is. Therefore, it is highly recommended for companies to adopt maintenance information systems such as the Computerized Maintenance Management System (CMMS).

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NOMENCLATURE

T_p	PPM time interval of each component of each machine
N	Number of replications
T_i	Failure time

T_p	PPM time interval of each component of each machine
N	Number of replications
T_i	Failure time
F(t)	Probability of failure
γ	The location parameter of Weibull distribution
η	The scale parameter of Weibull distribution
β	The shape parameter of Weibull distribution
T_s	Tp when $T_i > T_p$
T_{ppm}	TTR when $T_i > T_p$
T_f	T_i when $T_i < T_p$
T_{cm}	TTR when $T_i < T_p$
M(t)	Probability of restoring component in available time
C_{ppm}	PPM cost
C_{cm}	CM cost
T_{opr}	Total operation time
T_{clock}	Total simulation time
TC/hour	Total maintenance cost per hour
R_p	Reliability parallel

AUTHOR(S) BIOGRAPHY

Ig. Jaka Mulyana

Ig. Jaka Mulyana is a Senior Lecturer in Industrial Engineering Department, Widya Mandala Surabaya Catholic University Surabaya Indonesia. He earned B.S. in Agricultural Industrial Technology from Gadjah Mada University Jogjakarta Indonesia and Masters in Industrial Engineering from Sepuluh Nopember Institute of Technology Surabaya Indonesia. He has published journals and conference papers. His research interests include quality engineering, lean manufacturing and supply chain management.

Ivan Gunawan

Ivan Gunawan is a lecturer in Industrial Engineering Department-Universitas Katolik Widya Mandala Surabaya (UKWMS). He received a bachelor's degree in Industrial Engineering from UKWMS, a master's degree in Technology Management from Institut Teknologi Sepuluh Nopember (ITS), and a doctor's degree in Logistics and Supply Chain Engineering from ITS. His research interests are in food supply chain and quality management. He has published in Supply Chain Forum: An International Journal, Industria, and Widya Teknik. He actively joins international conference related to his field, i.e. IEEM. During past few years, he has provided lectures in statistical quality control, operations research, and simulation.

Yunia Vera Angelia

Yunia Vera Angelia was born on June 8th, 1998 in Mataram. She holds B.S degree in Industrial Engineering from Universitas Katolik Widya Mandala Surabaya. Her research interest is in maintenance management. During her college, she had become a tutor for operations research.

Dian Trihastuti

Dian Trihastuti received her PhD in Industrial Manufacturing and Systems Engineering from University of Missouri. She is working as a lecturer in Industrial Engineering department, Widya Mandala Catholic University. Her research interest includes sustainable supply chain, facility location and planning, input-output modelling, and logistics management.