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Machine Clustering Analysis for Maintenance Using Decision Making Model

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Abstract: Since daily service on manufacturing system has been conducted by maintenance personnel, their skillfulness has greatly involved the maintenance stage. It is critical for maintenance department in the industries to assume all maintenance data, to process information instantaneously and subsequently to transform it into useful decisions. This work introduces a methodology to utilize available information from failure-based care. The goal of this study is to conduct downtime analysis by describing some observation in one of the food processing company in Malaysia. This study demonstrates how downtime analysis can be conducted to cluster machines using Decision Making Grid model. As a case study, 2014 maintenance dataset is collected from the company and analyzed using DMG. Once analyzed, maintenance strategies are commended to the company to reduce troubleshooting time in their production floor. DMG gives more promising result to analyze and gain strategies for machine maintenance in production floor for little and medium industries. This decision model able to improve the accuracy of maintenance activities for production equipment.

Key words: Multiple Criteria Analysis · Machine Maintenance · Decision Grid · Clustering

INTRODUCTION

Conventional methods of identifying maintenance strategies used in manufacturing for air-conditioning, lighting, automobile, etc. consist mainly of parts replacement and overhaul work based on visual and sensory diagnosis at scheduled inspection periods by maintenance personnel. The work is generally referred to as Time-based maintenance and is a form of preventive maintenance. It is, nevertheless, influenced by the skill levels of the maintenance personnel as well as the disparities in the life spans of the equipment required. In contrast, large-scale manufacturing and steel mills monitor equipment conditions by non-destructive measurement means.

Improved technology and the increased sophistication of maintenance personnel have led some societies to improve their reactive approach. Proactive strategies utilizes preventive maintenance actions to prevent the failures from occurring at an early stage [1]. [2] Developed analyses based on polling models, which could be applied to obtain system performance metrics when preventive maintenance is carried. They estimated the weighted sum of mean service waiting times to assess the overall preventive maintenance performance system.

Many researchers and practitioners are pursuing the growth of various maintenance techniques to calculate the reliability of machineries and embed them into Computerized Maintenance Management System (CMMS). However, [3] found that the majority of commercial CMMS in the market is nonetheless lacking in decision support for management. He has spotlighted one of the causes for this is that managers are unaware of the diverse cases of maintenance optimization models. Another cause is that optimization models have:

- Hard to get new data;
- Computational complexities;
- Complexity to plot failure distribution; and
- Gap between theory and practice.

As noted, there is little assessment of the successful applications of the maintenance optimization model and they are still under-explored in the CMMS. This moves the present research to give more options to the programmers for plugging Decision Making Grid into CMMS.

Related Decision Making Work: There are two ways to diagnosis method of production equipment. One is a

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computer simulation based on machine failures history. This method requires lots of calculations using a mainframe computer and is not applicable to field maintenance work. The other is based along the experimental approach. This method requires lots of experiments to determine the diagnosis parameters. However, the diagnosis procedure is easy and inexpensive. Thus, the experimental approach was taken.

A determination should also count time and operating characteristics, such as processing unit speed, storage capability, network bandwidth, number of guests, etc. Alternatives of hardware, maintenance, expendability should be looked at as well. These may be some of the decision criteria in this lawsuit, where the criteria may vary based on different purpose of the servers. The Multiple Criteria Decision-Making (MCDM) model is the problem-solving model, always used to ascertain the best alternative for the above model.

The example consists of a finite set of alternatives, which decision-makers have to select or rank to a finite set of measures, weighted according to their importance. Then, the model is structured to M alternatives and N decision criteria. Each option can be valued in terms of the decision criteria. After that, the relative importance or weight of each measure can be calculated. Let a_{ij}, where i=1, 2, 3,…, M and j=1, 2, 3,…, N denote the performance value of the ith alternative in terms of the jth criterion. Likewise, let W_j denote the weight of the criterion C_j. Then, [3] gave the essence of the typical MCDM as given in the grid as follows, where A represent alternatives and C is their criteria:

Criterion

$$
\begin{array}{cc}
\textbf{Alternative} & \begin{array}{cccccc} C_1W_1 & C_2W_2 & C_3W_3 & \cdots & C_NW_N \end{array} \\
\begin{array}{c} A_1 \\ A_2 \\ A_3 \\ \cdots \\ \cdots \\ \cdots \\ A_M \end{array} &
\begin{bmatrix}
a_{11} & a_{12} & a_{13} & \cdots & a_{1N} \\
a_{21} & a_{22} & a_{23} & \cdots & a_{2N} \\
a_{31} & a_{32} & a_{33} & \cdots & a_{2N} \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
a_{M1} & a_{M2} & a_{M3} & \cdots & a_{MN}
\end{bmatrix}
\end{array}
$$

The grid is constructed, complete with the priority rating of each alternative with respect to each criterion, using a suitable measure. The evaluation ratings are then aggregated, taking into account the weights of the criteria, to engender a global valuation of each alternative and a total ranking of the options. From the above decision matrix, the decision problem considered in this study is how to determine which is the best alternative with the N decision criteria combined. For example, if the decision problem is to select the best project to be funded, one is just interested in naming the best candidate project. In another shell, if it is to allocate the budget among a number of competing projects, one may be interested in identifying the comparative importance of each project, so that the budget can be given out proportionately to the signification of each task.

In a simple MCDM situation, all the criteria are expressed in terms of the same unit, such as Malaysian Ringgit, hours, meters, etc. However, in many real-life MCDM problems, different measures may be extracted in different units. Cases of such units include pound figures, political impact, regional impact, etc. These multiple dimensions make an MCDM problem more complicated. That is why research in MCDM is numerous, diverse and institute in many applications, as is evidenced aside the examples given in Table 2. [4] Revealed that the DMG is the most suited model for continuous improvement in MCDM by identifying top ten worst production machines. This is because when machines in the top ten lists of worst performers have been appropriately dealt with, then others will move downward in the list and resources can be directed at these new offenders. If this pattern is carried on from time to time and so all machines will eventually be working optimally. In another attempt, [5] commented that AHP is the sole model in MCDM that is capable to conduct pairwise comparisons of attractiveness and use default measurement scales. [5] Also, comments that AHP is the most famous MCDM technique in their research.

Decision Analyses: Many researchers use Decision-Making Grid (DMG) on managing equipment in the production area. Among those, at that place are three selected reviews that are worth discussing under this sub-division. In the first, [6] has introduced the DMG model to help maintenance management identify breakdown maintenance strategies. In short, DMG is a control chart in two-dimensional matrix forms. The columns of the matrix show the three criteria of the downtime, whilst the rows of the matrix show another three criteria of the frequency of all failures. DMG model consists of these three steps:

- Criteria analysis;
- Decision mapping; and
- Alternative decision.

Here, a better maintenance model for quality management is formed by handling both the rows and columns of the matrix respectively. The matrix offers an opportunity to determine what maintenance strategies are needed for decision-making, such as to practice Operate To Failure (OTF), Fixed-Time Maintenance (FTM), Skills Level Upgrade (SLU), Condition-Based Maintenance (CBM) or Design-Out Maintenance (DOM).

The second important review was undertaken by [4], in which implementation of DMG in CMMS was discussed in particular. They expanded the hypothesis of the maintenance maturity grid and implemented it into a magnetic disc brake pad manufacturing company in England. The outcomes can provide maintenance policies in the respective working group in production lines, to achieve their common goal to cut downtime. Later, [3], in the third review, comprehended the model and demonstrated the hybrid intelligent approach using the DMG and fuzzy rule-based techniques. In this work, the DMG is employed in small and medium food processing companies to identify maintenance strategies and more detail is available in the following chapters.

DMG is used in this work as the model is flexible and considers OTF, FTM, SLU, CBM, DOM, TPM and RCM strategies in the same grid. The model is able to analyze multiple criteria and is the best choice when the number of machines is less than fifty [7]. It can be utilized to discover the top ten problematic machines on the production level with various system conditions. This is with regards to failures such as fatigue, imbalance and misalignment.

Factories have to strictly follow manufacturer specification or study their best-known practice to improve these factors. Nevertheless, this will definitely increase their maintenance cost. Process flow in the useful life cycle of machines in SMI is shown in Figure 1. We also learned that the maintenance team can learn from the defect during the diagnostic and repair phases, to continually restructure some improvement strategies in other phases. Further study on failure modes and event analysis can detect how bad the defect characteristics are. Then, recommendations can be prepared to improve the equipment's reliability during its life span.

In this field, further analysis on FBM or the diagnosis and repair box in Figure 1 is investigated by formal interviews with minor and medium food-processing industries. The aim of the consultations is to uncover some fundamental risk factors that delay FBM. The elements are placed with the Fishbone analysis using an Ishikawa diagram, as depicted in Figure 2. Then, some schemes are recommended to reduce FBM time, such as:

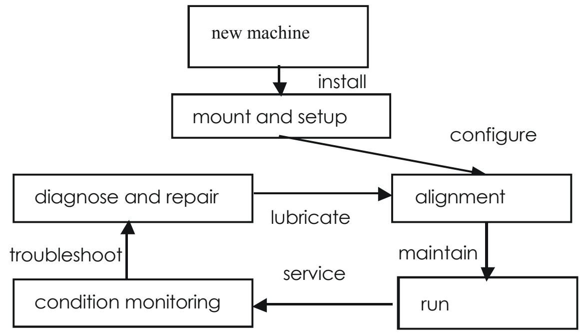

Fig. 1: Machine Useful Life Cycle

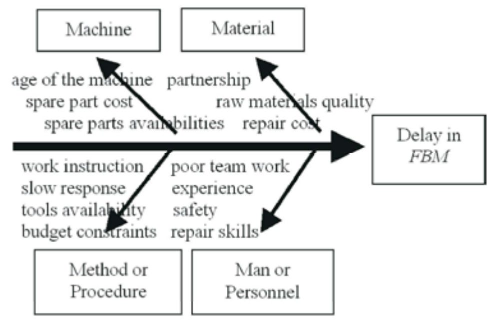

Fig. 2: Maintenance Delay Factors

- Reset preventive maintenance schedule;
- Use good parts for replacement;
- Use good tools for repair and collaboration; or
- Restructure man-hours of repairing the equipment.

Risk factor analysis of the machines always conducted to research the general renewal process for repairable systems using a general likelihood function formulation for single and multiple systems with the time truncated data and failure truncated data to estimate parameters [8]. However, [8] used only one parameter, i.e. failure time in their analytic thinking, which is insufficient to improve maintenance strategies. [9], [10] recommended decision control chart in itself in two-dimensional matrix forms. The pillars of the matrix indicate the three touchstones of the downtime, while the rows of the matrix show another three criteria of the frequencies of the failures. A better maintenance model for quality management can be formed, by handling both the rows and columns of the matrix respectively. The matrix offers an opportunity to determine what maintenance strategies are needed for decision-making, such as to practice OTF, FTM, SLU, CBM or DOM. The ground substance can also be used to determine what maintenance concepts are useful for each defined cell of the matrix, such as the Total Productive Maintenance (TPM) or Reliability Centered Maintenance (RCM) approaches.

Table 1: Decision-Making Grid [3]

	Downtime		
Frequency	Low	Medium	High
Low	OTF	FTM1	CBM
Medium	FTM2	FTM3	FTM4
High	SLU	FTM5	DOM

DMG Evaluation: The top ten machines that met both criteria, i.e. downtime and frequency are then associated with the grid, as shown in Table 1, with respect to the multiple criteria, as follows [4]:

- OTF: Machine is very rarely gave way. Once failed, the downtime is short;
- FTM1, FTM2, FTM3, FTM4, FTM5: Failure frequency and downtime are almost at moderate cases;
- SLU: Machine is always failing, but it can be fixed quickly;
- CBM: Machine is very rarely failed. But once failed, it exacts a long time to get it backwards to normal operation; and
- DOM: Machine is always neglected. Once failed, it accepts a longer time to get it backwards to normal functioning.

[4] Listed the importance of CMMS, but it seems to be employed less often as a tool for analysis and maintenance coordination. It happens to only be a data storage in which to keep equipment information and its maintenance activities. Thus, [3] makes a real good improvement of CMMS by using a formalized decision analysis approach based on multiple criteria and DMG, to detect the worst production machines. The policy stresses the fact that the best insurance is the one that maximizes profit. DMG approach used as a visual tool in their CMMS to obtain a good decision support organization. They have gone through the CMMS with DMG in one of the brake pad manufacturing companies in England. By having impact studies, manufacturing managers may be more comfortable in making investments in maintenance.

In fact, the machines are supposed to be barred from the DMG model in the following cycle. This is due to a diminution in the maintenance cost, even though their frequencies of failures are still eminent. The cost is reduced as the operators managed to fix the problem, with no maintenance escalation to technicians or contractors. Otherwise, the blocks of the grid are occupied and other machines with a higher cost of failure cannot be fitted into the DMG for the next cycle.

Machine Clustering With DMG: Some of the major expenses incurred in manufacturing industries are associated with repairs and the replacement of failed parts [10]. When the failure takes place, the affected production time is considered as a portion of the losses. Corrective maintenance activities are executed to reestablish the system to a reasonable operating state. Transportation, tools and machines used for repair and calibration are considered as expenses too. Next, preventive maintenance takes place at regular intervals to reset the system to a sound working condition.

[10] set the random variables, u and v, to be the lifetimes after *PM* and *CM* respectively. Their known parameters are $f_u(u)$ and $f_v(v)$ respectively, with the distributions as follows [4]:

Gamma: $$f(t) = \frac{e^{-\frac{t}{b}} t^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)}, \quad t > 0;$$ or

Weibull: $$f(t) = \frac{e^{-\frac{t^{\alpha}}{\beta}} \alpha t^{\alpha-1}}{\beta}, \quad t > 0;$$ or

Log-normal: $$f(t) = \frac{e^{-\frac{1}{2\beta}(\log t - \alpha)^2}}{t\sqrt{2\pi\beta}}, \quad t > 0$$

[11] and [12] used the hazards function, $\lambda(t) = \lambda_0(t)e^{\delta' y}$ where t measures the time since the most recent event with the baseline hazards function. Observe that the exponential distribution is a limiting case of the Gamma and Weibull as $\alpha \to 1$. Assume that the downtimes corresponding to *PM* and *CM* are r and s respectively, with associated costs being c and d respectively. These prices include the price of parts, labor and downtime. Then, we can figure the cost of PM in the interval length of it. First, allow r units of downtime for *PM* and generate observation u from new function $f_u(u)$, to represent a typical lifetime following *PM*. From the observation, [10] noted that the interval is complete and the total cost incurred is c, if $(r + u) \geq t$. Otherwise, if $(r + u) < t$, we should add a *CM* downtime s. If $(r + u + s) \geq t$, the interval is complete with a cost of $(c + d)$.

Otherwise, if $(r + u + s)$, an observation v_1 is generated from $f_v(v)$, to represent a typical lifetime following *CM*. Let this process continue, generating *CM* lifetimes v_1, v_2, v_3... until this interval is complete and calculate the total cost, v_1 for the interval in the same manner [4]. By having completely simulated a *PM* interval of length t, we repeat this procedure m times and determine the total cost for these simulated intervals for $k_1, k_2, ..., k_m$. Then, the average total cost is [10]:

$\bar{k} = \frac{1}{m}\sum_{i=1}^{m} k_i$, for the selected maintenance interval length.

Based on the dialogue with *SMI* staffs, they highlighted that there are many cases where *FBM* charges by contractors are not uniform and expensive. Let k and l be vectors. Let embrace $machine_i$ with higher cost, where *SMI* manager is unhappy with the charges to vector *k*. whereas, $machine_i$ with a specified range and where the manager can tolerate the charges assigned to vector l. Thus, more examination should be conducted on all machines rolled under vector k. From the formal interview, we found that the *SMI* have been given the catalogues of the machine's with the price list of every replacement parts by supplier or manufacturer. As of service charge, every contractor has their own hourly charge rate stated in the service agreement.

Empirical Results: As a case study, we have conducted research on maintenance operation in a food-processing company in Malaysia, with the assumption as follows:

- Reliability: the company work for ten hours a day, six days a week and based on demand;
- Each machine may have a different frequency of failures. Whenever failed, it has a different downtime, includes waiting and repairing time; and
- Machines operate in serial production lines to manufacture 7 types of products in different volumes.

Useful information, especially on costing, is obtained from the department's staff and technicians. The machines' operation and failures are observed and real data is collected for the whole period of year 2014. In this research, the *DMG* model is deployed to visualize machine maintenance in its production lines. The *DMG* model considers 3 major factors of machine failure, *i.e.* frequency of failure, repair time and downtime. The factors are separated into 3 different criteria, *i.e.* high, medium and low. Let *h* is the highest value and *l* is the lowest value in the array:

$$\text{High boundary} = h \quad (1)$$

$$\text{Medium/high boundary} = h - \frac{1}{3}h \quad (2)$$

$$\text{Low/medium boundary} = h - \frac{2}{3}h \quad (3)$$

$$\text{Low boundary} = l \quad (4)$$

Table 2: DMG based on 2014 Dataset

	Downtime		
Frequency	Low	Medium	High
Low	*M*	*B, J*	
Medium	*N*		*K*
High			*F, H*

A structured query instruction is developed in *CMMS* to select the top 10 machines that have the highest frequency of failures. Likewise, the top 10 machines having the highest downtime are selected from the *CMMS*. Subsequently, the machines are listed 3 steps in *DMG* development:

- Criteria Analysis: Establish a Pareto analysis of the 2 factors: frequency of failure and machine downtime,
- Decision mapping: Those machines that meet both criteria in step (i) are then mapped into the two-dimensional matrix as shown in Table 2 and
- Once mapping has been finalized, the decision is developed by comparing the two-dimensional matrix with *DMG* shown in Table 1.

The DMG analysis has been conducted using dataset in 2014, as shown in Table 2. Notice that only Machine *F,* Machine *H,* Machine *J,* Machine *K,* Machine *M,* Machine *N* and Machine *K* are mapped into the DMG table as appeared to be the most problematic machines in terms of their frequency of failures and downtime hours.

Machine failure results given in Table 2. The result is compared with the DMG in Table 1. The result shows that machine M is very seldom failed. Once failed, the downtime is very short. Failure-based maintenance is suitable for the machine M, which is been categorized in OTF region.

Fixed-time maintenance should be conducted to Machine B, J, N and K. Failure frequency and downtime are almost at the moderate region. The questions such as who is supposed to operate, when to troubleshoot and what to fix first, should be revised as suggested by [3]. Further analysis able to find the right time to conduct the maintenance on the machines in this group.

Our findings also show that Machines further analysis of Machines F and H with a reliability measure is required. Brainstorming to find a failure mode, severity of failure and its occurrence, should be conducted to detect the root causes as these machines fall under DOM grid. Next, major design projects need to be executed immediately, or predictive-maintenance monitoring equipment installed. We have suggested production emergency response team to be formed for the machines in this grid. Also any emergency indicators should be triggered immediately to alert production technical folks, whenever these machines fail. Consequently, it is recommended that the maintenance engineers to conduct thorough analysis of Machines F and H, which includes failure mode, effect and costing analysis to estimate how many losses there have been to the production floor.

CONCLUSION

Decision making analysis poses a continuing challenge to maintenance management in all types of organization. In this paper, DMG model relating the maintenance action in failure-based problem is presented. The Ishikawa diagram is used to identify risk factors in maintenance by looking at troubleshooting delay. The rules are used to cluster the machines into their respective grids in DMG and suggest the maintenance strategies. The failure-based maintenance records analysed by considering both factors, frequency of failures and downtime. Using this re-positioning into DMG model, we are able to recommend maintenance strategies for machines in the production floor. Next, maintenance engineers are able to select maintenance policies precisely.

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