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Research Article

A Costing Analysis for Decision Making Grid Model in Failure-Based Maintenance

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Background. In current economic downturn, industries have to set good control on production cost, to maintain their profit margin. Maintenance department as an imperative unit in industries should attain all maintenance data, process information instantaneously, and subsequently transform it into a useful decision. Then act on the alternative to reduce production cost. Decision Making Grid model is used to identify strategies for maintenance decision. However, the model has limitation as it consider two factors only, that is, downtime and frequency of failures. We consider third factor, cost, in this study for failure-based maintenance. The objective of this paper is to introduce the formulae to estimate maintenance cost. *Methods.* Fish bone analysis conducted with Ishikawa model and Decision Making Grid methods are used in this study to reveal some underlying risk factors that delay failure-based maintenance. The goal of the study is to estimate the risk factor that is, repair cost to fit in the Decision Making Grid model. Decision Making grid model consider two variables, frequency of failure and downtime in the analysis. This paper introduces third variable, repair cost for Decision Making Grid model. This approaches give better result to categorize the machines, reduce cost, and boost the earning for the manufacturing plant. *Results.* We collected data from one of the food processing factories in Malaysia. From our empirical result, Machine C, Machine D, Machine F, and Machine I must be in the Decision Making Grid model even though their frequency of failures and downtime are less than Machine B and Machine N, based on the costing analysis. The case study and experimental results show that the cost analysis in Decision Making Grid model gives more promising strategies in failure-based maintenance. *Conclusions.* The improvement of Decision Making Grid model for decision analysis with costing analysis is our contribution in this paper for computerized maintenance management system.

1. Introduction

One of the main challenges in maintenance model is to improve the way we maintain equipment and defend the maintenance decisions. Improved technology and the increased

sophistication of maintenance personnel have led some companies to improve their reactive approach. Proactive strategies utilize preventive maintenance activities to prevent the failures from occurring at an early stage [1]. Reference [2] developed analyses based on polling models, which could be used to obtain system performance metrics when preventive maintenance is conducted. They calculated the weighted sum of mean service waiting times to measure the overall preventive maintenance performance system. Some formulas are given by [2] to estimate preventive maintenance and manufacturing system performance. The preventive maintenance service is based on measurements going beyond a predetermined limit. If a machine cannot hold a tolerance, then other techniques, such as a condition-based maintenance (CBM) and vibration-based maintenance, are initiated. All this maintenance involves costs.

In this study, we make comparison study on various maintenance techniques to estimate the reliability of machineries and embed them into computerized maintenance management system (CMMS). References [3, 4] used stochastic measures to analyze cost in condition-based and failure-based maintenance in gas turbine productions. Bayesian and Proportional hazards model have been used by [5] to analyze cost in preventive maintenance. Later, [6] used mathematical measures to estimate cost in reliability-centred maintenance. They used simulation studies to optimize the plant and wrote a program in computerized maintenance management system. Reference [7] tinted few important reasons on why industries are still lacking on decision support system:

- (i) difficulty to collect raw data;
- (ii) computational complexities;
- (iii) complexity of modelling failure distribution;
- (iv) gap between theory and practice;
- (v) managers are unaware of the various types of maintenance optimization models.

As mentioned, there is little assessment of the successful applications of the maintenance optimization model and they are still underexplored in CMMS. Decision Making Grid model can be used to identify strategies for maintenance decision in CMMS. However, the model has limitation as it considers two factors only, that is, downtime and frequency of failures. We consider third factor, cost, in this study for failure-based maintenance. In this study, we sought to introduce costing formulae for Decision Making Grid model. This will contribute for optimization algorithm development in CMMS.

2. Multiple Criteria Decision Making Methods

One of the most common problems in many engineering and business applications is how to evaluate a set of alternatives in terms of a set of decision criteria. For example, let someone intends to set up computer servers. There are a number of different configurations available to choose from. The different operating systems are the alternatives. Here, a decision should also consider cost and performance characteristics, such as processing unit speed, memory capacity, network bandwidth, and number of clients. Alternatives of software, maintenance, and expendability should be considered too. These may be some of the decision criteria for this case, where the criteria may vary based on different purpose of the servers. The multiple criteria decision making (MCDM) model is the problem-solving method, always used to determine the best alternative for the above example.

The model consists of a finite set of alternatives, which decision makers have to select or rank to a finite set of criteria, weighted according to their importance. Then, the model is

structured to M alternatives and N decision criteria. Each alternative can be evaluated in terms of the decision criteria. After that, the relative importance or weight of each criterion can be estimated. Let a_{ij} , where $i = 1, 2, 3, \dots, M$ and $j = 1, 2, 3, \dots, N$, denote the performance value of the i th alternative in terms of the j th criterion. Also, let W_j denote the weight of the criterion C_j . Then, [8] gave the core of the typical MCDM as given in the following multicriteria matrix:

$$\begin{array}{c}
 \text{Alternative} \\
 A_1 \\
 A_2 \\
 A_3 \\
 \dots \\
 \dots \\
 \dots \\
 A_M
 \end{array}
 \begin{array}{c}
 \text{Criterion} \\
 C_1W_1 \quad C_2W_2 \quad C_3W_3 \quad \dots \quad C_NW_N \\
 \left[\begin{array}{cccccc}
 a_{11} & a_{12} & a_{13} & \dots & a_{1N} \\
 a_{21} & a_{22} & a_{23} & \dots & a_{2N} \\
 a_{31} & a_{32} & a_{33} & \dots & a_{3N} \\
 \dots & \dots & \dots & \dots & \dots \\
 \dots & \dots & \dots & \dots & \dots \\
 \dots & \dots & \dots & \dots & \dots \\
 a_{M1} & a_{M2} & a_{M3} & \dots & a_{MN}
 \end{array} \right]
 \end{array}
 \quad (2.1)$$

The decision matrix 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 get a global evaluation for each alternative and a total ranking of the alternatives. Given 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 instance, if the decision problem is to select the best project to be funded, then one is only interested in identifying the best candidate project. In another case, if it is to allocate the budget among a number of competing projects, then one may be interested in identifying the relative importance of each project, so that the budget can be distributed proportionally to the significance of each project.

In a simple MCDM situation, all the criteria are expressed in terms of the same unit, such as Saudi Riyals, hours, and metres. However, in many real-life MCDM problems, different criteria may be expressed in different units. Examples of such units include pound figures, political impact, regional impact, and so forth. These multiple dimensions make an MCDM problem more complicated. That is why research in MCDM is numerous, diverse, and found in many applications, as is shown by the examples given in Table 1.

Reference [17] used multiple criteria evaluation of multifamily apartment block's to benchmark maintenance contractors. They built the model for maintenance contractor evaluation and the determination of its selection. Later, [18] applied the model in Lithuanian case study. Reference [7] introduced another model, Decision-Making Grid (DMG) for similar problem to identify maintenance strategies. He revealed that DMG is the most suitable 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 down in the list and resources can be directed at these new offenders. If this practice is continued from time to time, then all machines will eventually be running optimally.

Table 1: Research on MCDM model.

| Researcher | Focus | Application | Approach |
|------------|---|---|---|
| [9, 10] | Design, development, and implementation of CMMS with criteria analysis and decision mapping customized features on maintenance maturity grid and decision analysis | Automotive sector | Mathematical formulas DMG |
| [11] | Development of procedure and algorithm to evaluate alternatives in flexible manufacturing system | Mathematical analysis and simulation | MCDM algorithm with fuzzy data |
| [7, 12] | Development of hybrid intelligent approaches systematic analysis of the system with combination on multiple criteria analysis and fuzzy rule-based techniques | Mathematical calculation and simulation using fuzzy logic | DMG multiple criteria decision analysis fuzzy logic rules |
| [13, 14] | Solution to perform a multivariate design and multiple criteria analysis of alternate alternatives based on the enormous amount of information. Development of multivariate design method and multiple criteria for a building refurbishment's analysis | Public building of Vilnius Gediminas Technical University | Decision-Making matrix Weightage analysis |
| [15] | Optimization framework on optimal maintenance planning arrangement of maintenance schedules for PM by considering few criteria: availability, maintenance cost, life cycle costs, and tolerance level | Paper production, nuclear production plant | Multiple-objective genetic algorithm MATLAB toolbox |
| [16] | Survey result to show the applicability of an approach based on a combination of distribution-free tolerance interval and genetic algorithms for testing and maintenance optimization of safety-related systems | Simulation using Monte Carlo and genetic algorithm | Multiple-objective genetic algorithm |

3. Decision-Making Grid Model

There are many researchers who have studied the DMG and apply it in the equipment management area. We extended the study of these three selected reviews. In the first, [9] 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 criterions of the downtime, whilst the rows of the matrix show another three criterions of the frequency of the failures. The model consists of these three steps:

- (i) criteria analysis;
- (ii) decision mapping;
- (iii) decision support.

Here, 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 decide what maintenance strategies are needed for decision-making, such as to practice OTF, FTM, SLU, CBM, and DOM.

The second important review was undertaken by [10], in which implementation of DMG in CMMS was discussed in detail. They extended the theory of the maintenance maturity grid and implemented it into a disk brake pad manufacturing company in England. The results can provide maintenance policies in the respective functional group in production lines, to achieve their common goal to reduce downtime. Later, [7], in the third review, comprehended the model and demonstrated the hybrid intelligent approach using the DMG and fuzzy rule-based techniques. In this study, the DMG is extended with costing analysis in small and medium food processing companies to identify the maintenance strategies.

DMG is used in this study 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 [19]. It can be used to detect the top ten problematic machines on the production floor with several system conditions. This is with regards to failures such as fatigue, imbalance, misalignment, loosened assemblies, and turbulence, which can occur in rotational or reciprocating parts such as bearings, gearboxes, shafts, pumps, motors, and engines. Identifying the top ten problematic machines is in alignment with the 80-20 rule.

The rule states that 80% of the problems arise from the same 20% of the root causes. In another word, once 20% of the root cause had been fixed, then 80% of the problem is resolved. The application of the model can have a breakthrough performance, as it fulfils the purpose of the model to map machines into a certain grid in a matrix and suggests the appropriate maintenance strategies to comply with.

4. Preliminary Analysis

In this research work, we conducted formal interviews with multinational bearing manufacturers in Malaysia. We asked about the customers' complaint about their production parts performance after the sales. They gave feedback on the reason why the warranty period of certain parts is one year, but there are still cases of the failure of parts within eight months of the product's deployment. Based on the manufacturer's records, 14% of the parts' failure before expiry of the warranty is due to contamination in the equipment usage area. Another 34% is due to a fatigue where equipment is utilized for too long and 16% of these defects are due to poor fitting during installation. The highest remaining portion is 36%, due to routine maintenance. The technical team highlighted that the highest proportion of routine maintenance is due to these factors:

- (i) low quality of the lubrication oil;
- (ii) lubrication quantity is too little or over the given specification limit;
- (iii) preventive maintenance frequency is too frequent or very rare;
- (iv) incorrect tools are used for repair and preventive maintenance;
- (v) poor technician skills.

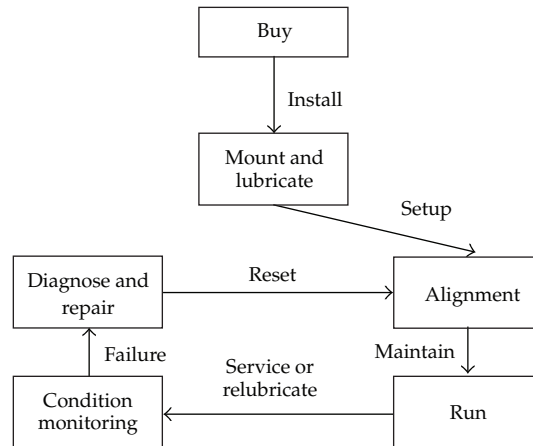


Figure 1: Machine useful life cycle.

Companies have to strictly follow manufacturer specification or study their best-known practice to improve these factors. However, this will definitely increase the maintenance cost. When the machines deploy in SMI, they follow an important process in their flow of the useful life cycle, which is shown in Figure 1. We also discovered that the maintenance team can learn from the defect during the diagnostic and repair phases, to continuously restructure some improvement strategies in other phases. Further study on failure modes and effect analysis can detect how bad the defect characteristics are. Then, recommendations can be given to improve the equipment's reliability during its life span.

In this study, further analysis on FBM or the diagnose and repair box in Figure 1 is investigated by formal interviews in small and medium food processing industries. The purpose of the interviews is to reveal some underlying risk factors that delay FBM time. The factors are identified with the Fishbone analysis using Ishikawa diagram, as shown in Figure 2. Then, some strategies can be executed to reduce FBM time, such as

- (i) improve preventive maintenance strategies;
- (ii) use good quality replacement parts;
- (iii) use good tools for repair and collaboration;
- (iv) restructure man-hours on repairing the equipment.

However, most of the time, implementing these strategies will increase the maintenance cost. Reference [20] proposed some structures for maintenance policy decision strategies, that is, when to practice UBM, CBM, or FBM at any phase of the machine's life cycle. Reference [21] suggested more measurement of service processes studies using mathematical models. Reference [22] used systematic mathematical measurements on covariates, illustrated by the use of the semiparametric, multistate hazards model for transition, and reverse transition among more than one transient state, which emerged from follow-up studies.

Reference [23] used the proportional-hazards model to analyse transitions in human contraceptive recovery over time and to illustrate the score test on testing the equality of parameters for models on transitions and repeated transitions. Then, [24] employed the competing risk model proposed by [23], to estimate the risk factors that delay the equipment's downtime. Reference [24] estimated the relationship between repair time and various risk

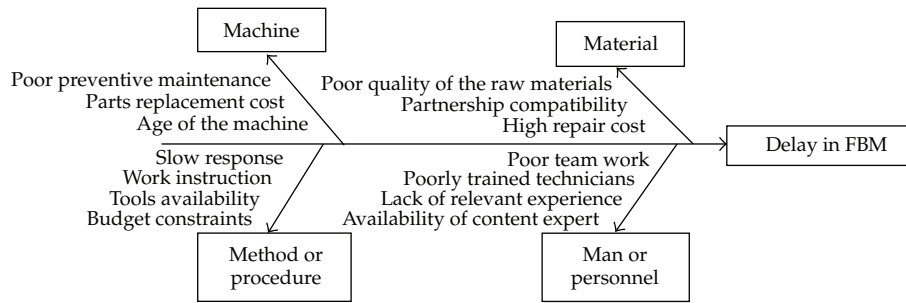


Figure 2: Ishikawa diagram.

factors of interest, including underlying characteristics of the technicians, that is, their age, experience, and qualifications.

Reference [25] analysed downtime of the machines by exploring the general renewal process for repairable systems. They used the Kijima Model II to model complex repairable systems. A general likelihood function formulation for single and multiple systems with the time-truncated data and failure-truncated data is applied to estimate parameters, using Weibull software. However, [25] used only one parameter, that is, failure time in their analysis, which is insufficient in the proposed study.

Reference [26] defined DMG as a control chart in itself in two-dimensional matrix forms. The columns of the matrix show the three criteria 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 decide what maintenance strategies are needed for decision making, such as to practice OTF, FTM, SLU, CBM, or DOM. The matrix can also be used to decide what maintenance concepts are useful for each defined cell of the matrix, such as the TPM or RCM approaches. References [26, 27] have described an application of AHP for selecting the best maintenance strategies. Later, [7] mentioned that the DMG analysis is a very important measure prior to the AHP analysis.

We have discovered from the interviews and survey that the optimization strategies in SMI should not be based solely on the machines' downtime and frequency of failures. Yet, another important factor, the cost of maintenance, should be considered seriously for FBM jobs in SMI. Once the most problematic machines with higher maintenance costs have been identified, then further decision analysis is conducted to improve their time-based maintenance by

- (i) identifying candidates (machines) for the DMG model using cost analysis,
- (ii) extending the DMG model suggested by [7, 10] by incorporating it with the costing analysis,
- (iii) giving appropriate suggestions on maintenance strategies.

The combination of the results is important as a membership function, to derive fuzzy logic rules for maintenance policy and decision making, as suggested by [7].

Table 2: Decision Making Grid [26].

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

5. DMG and Costing Evaluation

References [7, 10] have demonstrated DMG as a powerful model in CMMS to analyse raw data for strategic decision making. Reference [26] considered the top ten worst production machines based on two criteria: downtime and frequency of failures. Then, they mapped those machines into DMG and recommended appropriate maintenance strategies depending on the location of the machines in the grid.

The top ten machines that meet both criteria are then associated in the grid, as shown in Table 2, with respect to the multiple criteria, as follows [26]:

- (i) OTF: machine is very seldom failed. Once failed, the downtime is short;
- (ii) FTM1, FTM2, FTM3, FTM4, FTM5: failure frequency and downtime are almost at moderate cases;
- (iii) SLU: machine is always failed, but it can be fixed quickly;
- (iv) CBM: machine is very seldom failed. But once failed, it takes a long time to bring it back to normal operation;
- (v) DOM: machine is always failed. Once failed, it takes a longer time to bring it back to normal operation.

Reference [28] listed the importance of CMMS, but it appears to be used less often as a tool for analysis and maintenance coordination. It happens to only be a data store in which to keep equipment information and its maintenance activities. Thus, [26] makes a very good improvement of CMMS by using a formalized decision analysis approach based on multiple criteria and DMG, to find the worst production machines. The policy emphasizes the fact that the best policy is the one that maximizes profit. Reference [29] designed a computer-aided integration of maintenance in their model.

Later, [10] embedded [26] DMG approach as a visual tool in their CMMS to obtain a good decision support system. They have implemented the CMMS with DMG in one of the brake pad manufacturing companies in England. Reference [30] identifies the importance of the study by measuring the relationship between maintenance strategies and performance. Reference [30] discovered a strong positive relationship between maintenance strategies and performance. By having impact studies, manufacturing managers may be more comfortable in making investments in maintenance.

Reference [31] applied [10, 26] approaches by implementing DMG in one of the food processing companies in Malaysia. They discovered that the DMG analysis creates more opportunities in CMMS to be transparent to the entire production workforces, instead of only the maintenance team. The increased usage of data mining and DMG analysis in CMMS by personnel outside maintenance function may have a good potential to improve maintenance strategies and equipment utilization.

Another important criterion, that is, cost of the failure analysis prior to DMG association, is considered in this research work. For instance, if we look at SMI operation in Malaysia, they tend to outsource most of the corrective maintenance work to contractors. From the SMI management view, the machine is not considered as the worst machine if the cost impact to the factory is minimal. However, if the cost impact is high, then the machines are considered to be the worst, even if their frequencies of failures are lower. Moreover, cost is always a crucial factor for production during this recent economic depression.

References [7, 31] recommended upgrading operators' technical skills in repairing the machines in the FTM1, FTM2, and SLU regions, as shown in Table 2. This will reduce the cost of maintenance in the long term, because operators are able to fix the problem without any escalation to the technicians. Hence, waiting time for technicians is eliminated. When the DMG analysis is conducted again in the next cycle, those machines in the FTM1, FTM2 and SLU regions in the previous cycle will most likely appear again in the DMG model, as the frequency of failures is still high [31]. This could be misleading because analyses are executed regardless of costing evaluation.

In fact, the machines are supposed to be excluded from the DMG model in the next cycle. This is due to a reduction in the maintenance cost, even though their frequencies of failures are still high. 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.

6. Machine Prioritization for the DMG

Some of the major expenses incurred in manufacturing industries are related to repairs and the replacement of failure parts. When the failure occurs, the affected production time is counted as a part of the losses. Corrective maintenance activities are performed to restore 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 good working condition.

Reference [4] defined 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]:

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

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

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

Reference [4] 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. Note that the exponential distribution is a limiting case of the Gamma and Weibull as $\alpha \rightarrow 1$. Suppose that the downtimes corresponding to PM and CM are r and s , respectively, with associated costs being c and d , respectively. These costs include the cost of parts, labour, and downtime. Then, we can estimate cost of PM in the interval length of t . 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, [4] commented that the interval is complete and the total cost incurred is c if $(r + u) \geq t$. Otherwise, if $(r + u) < t$, then we should add a CM downtime s . If $(r + u + s) \geq t$, then the interval is complete with a cost of $(c + d)$.

Table 3: The conjunction truth table [32].

| M | N | $m \wedge n$ |
|-----|-----|--------------|
| 1 | 1 | 1 |
| 1 | 0 | 0 |
| 0 | 1 | 0 |
| 0 | 0 | 0 |

Alternatively, if $(r + u + s) < t$, then 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, \dots until this interval is complete, and calculate the total cost, v_1 , for the interval in the same manner [4]. 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, \dots, k_m . Then, the average total cost is [4]

$$\bar{k} = \frac{1}{m} \sum_{i=1}^m k_i, \quad (6.1)$$

for the selected maintenance interval length.

Let \mathbf{k} and \mathbf{l} be vectors. Let us include *machine* _{i} with higher cost, where SMI manager is unhappy with the charges to vector \mathbf{k} , whereas *machine* _{i} with a specified range and where the manager can tolerate the charges assigned to vector \mathbf{l} . Thus, more investigation should be conducted on all machines rolled under vector \mathbf{k} .

Let x_i be the actual unit price of the replacement part, and then x_c is the unit price of the replacement part stated in the catalogue. Likewise, let y_i be the actual labour or service charge for the repair work, and let y_c be the labour or service charge stated in the service agreement. Then, rules of inference can be used to tie the equivalence together. When any failure of the *machine* _{i} occurs, proposition of the maintenance cost is assigned to vectors \mathbf{p} and \mathbf{q} as follows:

If $(x_i + y_i) > (x_c + y_c)$, then

add *machine* _{i} to \mathbf{p} ,

else add *machine* _{i} to \mathbf{q} .

Note that machines with unexpected or higher costs are rolled under \mathbf{p} . Let m and n be propositions, denoted by $m \wedge n$. Let m be the hypothesis, where m is equal to 1 if adding *machine* _{i} to \mathbf{k} , means FBM cost is expensive, whereas n is the hypothesis, where n is equal to 1 if $(x_i + y_i) > (x_c + y_c)$, where add *machine* _{i} to \mathbf{p} . The conjunction of $m \wedge n$ is true when both m and n are true and is false otherwise. We can prove this conjunction using the truth table given by [32] as shown in Table 3.

At this point, both propositions have to be considered and fulfilled. The rationale behind this m is the maintenance department decision either charge is expensive or exceptional, whereas n is the comparison of price between actual and expected from the price catalogue listed by supplier or manufacturer. In brief, both m and n conditions have to be fulfilled. Then, those machines appeared in vector \mathbf{k} and \mathbf{p} are candidates in the DMG model. In brief, we improve DMG model by this algorithm:

Table 4: Machine failures.

| ID | Freq | Downtime | MDT | Std dev | MTBF |
|----|------|----------|-------|---------|---------|
| A | 1 | 2.00 | 2.00 | — | 6238.00 |
| B | 3 | 89.15 | 29.72 | 19.03 | 2050.28 |
| C | 8 | 193.20 | 24.15 | 1.02 | 755.85 |
| D | 2 | 13.10 | 6.55 | 6.57 | 3113.45 |
| E | 5 | 33.00 | 6.60 | 11.05 | 1241.40 |
| F | 16 | 249.53 | 15.60 | 10.29 | 374.40 |
| G | 5 | 129.26 | 25.85 | 1.40 | 1222.15 |
| H | 30 | 737.19 | 24.57 | 1.11 | 183.43 |
| J | 5 | 73.35 | 14.67 | 13.01 | 1233.33 |
| K | 3 | 54.14 | 18.05 | 14.57 | 2061.95 |
| L | 1 | 8.41 | 8.41 | — | 6231.59 |
| M | 19 | 188.40 | 9.92 | 13.02 | 318.51 |
| N | 9 | 63.48 | 7.05 | 9.36 | 686.28 |
| P | 2 | 33.08 | 16.54 | 20.53 | 3103.46 |

- (i) evaluate maintenance cost for $machine_i$,
- (ii) assign the $machine_i$ to vector \mathbf{p} , \mathbf{q} , and \mathbf{k} ,
- (iii) build criteria analysis matrices for machines in vector \mathbf{p} and \mathbf{k} ,
- (iv) conduct decision mapping analysis,
- (v) suggest decision support strategies for $machine_i$.

We wrote visual basic code to execute these formulae in our decision support system to estimate the maintenance cost.

7. Empirical Results

As a case study, the present study observed the maintenance operation in a food processing company in Malaysia, with the main characteristics being as follows:

- (i) reliability: they must work for ten hours a day, six days a week, and based on demand;
- (ii) every machine may have a different frequency of failures. Once failed, it has a different downtime, including waiting and repairing time;
- (iii) machines operate in serial lines to manufacture seven types of products in different volumes.

The machines' operation and failures are observed, and real dataset is collected. The machine name (ID), frequency of failure (Freq), downtime, mean downtime (MDT), standard deviation (Std dev), and mean time between failure (MTBF) of the machines are given in Table 4.

In this research work, the DMG model is proposed to visualize machine maintenance in its production lines. The DMG model introduced by [26] is used, where two major factors of machine failure, that is, frequency of failure and downtime, are considered. The factors are

Table 5: DMG analysis.

| Frequency | Downtime | | |
|-----------|-------------|-------------|-------------|
| | Low | Medium | High |
| Low | <i>J, K</i> | <i>G, B</i> | |
| Medium | <i>N</i> | | <i>C</i> |
| High | | <i>M</i> | <i>H, F</i> |

Table 6: DMG before costing analysis.

| Frequency | Downtime | | |
|-----------|----------------|----------|----------|
| | Low | Medium | High |
| Low | <i>B, H, N</i> | <i>G</i> | |
| Medium | <i>J</i> | <i>A</i> | <i>E</i> |
| High | | | <i>M</i> |

separated into three different criterions, that is, high, medium, and low. Let h be the highest value and let l be the lowest value in the list:

$$\begin{aligned}
 \text{High boundary} &= h, \\
 \text{Medium/high boundary} &= h - \frac{1}{3}h, \\
 \text{Low/medium boundary} &= h - \frac{2}{3}h, \\
 \text{Low boundary} &= l.
 \end{aligned} \tag{7.1}$$

A query instruction is developed in CMMS to select the top ten machines that have the highest frequency of failures. Likewise, the top ten machines having the highest downtime are selected from the CMMS. Subsequently, the machines are categorized using formulae in (7.1). Reference [26] listed three steps in DMG development:

- (i) criteria analysis: establish a Pareto analysis of the two factors: frequency of failure and machine downtime,
- (ii) decision mapping: Those machines that meet both criteria in step (i) are then mapped into the two-dimensional matrix as shown in Table 5,
- (iii) once mapping has been finalized, the decision is developed by comparing the two-dimensional matrix with DMG shown in Table 2.

Note that Machine *B*, Machine *C*, Machine *F*, Machine *G*, Machine *H*, Machine *J*, Machine *K*, Machine *M*, and Machine *N* are mapped into the DMG in Table 5.

After giving the recommendation and restructure maintenance strategies, we collected the longitudinal data again and the DMG model is shown in Table 6. Note that Machine *A*, Machine *B*, Machine *E*, Machine *G*, Machine *H*, Machine *J*, Machine *M*, and Machine *N* are mapped into the DMG table. The analysis was obtained before introducing the cost parameter.

Queries on raw data from CMMS are retrieved from time to time to discover knowledge for good decision making. We obtained all machines in vector \mathbf{k} . Subsequently, we

Table 7: Machine priority for DMG analysis.

| Vector | Machine |
|----------|-------------------------------------|
| <i>P</i> | <i>A, C, D, E, F, G, H, I, J, M</i> |
| <i>Q</i> | <i>B, K, L, N, O, P, Q, R, S, T</i> |

Table 8: DMG based on 2006 after costing analysis.

| Frequency | Downtime | | |
|-----------|-------------|-------------|----------|
| | Low | Medium | High |
| Low | <i>D, I</i> | <i>C, H</i> | |
| Medium | <i>J</i> | <i>A</i> | <i>G</i> |
| High | <i>F</i> | <i>E</i> | <i>M</i> |

calculated the FBM cost for individual *machine_i* in vector **k** using Boolean algebra formulae in (6.2). Visual basic script is run to categorize the machine. As a result, machine with higher cost rolled under vector **p** as shown in Table 7. Machines in vector **p** are candidates for DMG, whereas machines in vector **q** should be excluded from the DMG model.

In the case study, machines in vector **p** are given priority to be fitted into the DMG model as shown in Table 7. Note that Machine *C*, Machine *D*, Machine *F*, and Machine *I* are excluded from DMG in Table 6, even though their maintenance cost is higher than Machine *B* and Machine *N*. Based on Table 7, Machine *C*, Machine *D*, Machine *F*, and Machine *I* have a higher priority to be mapped in the DMG for maintenance strategy and decision-making consideration. In contrast, Machine *B* and Machine *N* should be excluded from DMG, as the operators are able to fix the problem and their maintenance cost is therefore reduced. Machine *E* and Machine *G* have changed position in Table 8 because it is compared with other machines, that is, Machine *C*, Machine *D*, Machine *F*, and Machine *I*, which do not exist in Table 6. This is the evidence which shows that the DMG analysis in Table 8 provides a more promising result compared to that shown in Table 6.

The above costing analysis is more practical, where Machine *C*, Machine *D*, Machine *F* and Machine *I* must be in the model even though their frequency of failures and downtime are less than Machine *B* and Machine *N*. This is because they have a higher maintenance cost compared to Machine *B* and Machine *N*, as shown in Table 7. To be more transparent, it is worth displaying the DMG matrix in Table 8, complete with the machine images or using colour codes on the production floor. The visualization will help to get more attention from the production team of the machines' performance. Perhaps this will alert them to any failures of the worst performing machines in their production plant.

8. Conclusion

This paper demonstrated how the costing analysis prioritize machine for DMG. The Ishikawa diagram is used to select the problematic machines by looking at their maintenance cost. The rules are used to categorize the machines into lower and higher maintenance cost. The results presented show that cost model can be used in failure-based maintenance systems, as it provides a powerful tool for taking into account the interaction between the frequency of failures and downtime. Using this repositioning into DMG model, managers are able to select maintenance policies more economically. Beyond improving the quality of decisions, the DMG can better support the maintenance team to decide on several maintenance strategies.

Further research is needed to adequately quantify the parameters in the above rules for different machines.

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