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# An application of association rule mining in total productive maintenance strategy: an analysis and modelling in wooden door manufacturing industry

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## Abstract

One of the challenges in the implementation of Total Productive Maintenance (TPM) in the manufacturing industry is a slow managerial decision-making to respond the condition in the factory. This research investigates the answers of these challenges by analysing and modelling the equipment condition and the response of actions required in a wooden door manufacturing industry. TPM implementation in this company has deployed the Overall Equipment Effectiveness (OEE) measurement as an indicator of the equipment utilization and condition. Through an analysis and modelling of the OEE value obtained from the factory, the formulation of Association Rule Mining (ARM) aims to find a rule that shows the well computed relationship between measurable indicators of OEE with the response of action required to take in certain condition of machine utilization. Results obtained from ARM accelerate the decision to establish an appropriate TPM management strategy based on the rules. The generated dynamic rules form and facilitate the process of decision-making by related stakeholders. Furthermore, relying on these rules the action taken by the company induced to a higher reliable and increasing the effectiveness of response and efficiency of time and costs.

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*Keywords:* Overall equipment effectiveness; association rule mining; data mining; total productive maintenance

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## 1. Introduction

As one of the global company in wooden door manufacturing industry, CII sells high-variation products that are

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fully exported across the world to fulfil market demand. With limited number of machine and limited production capacity, this high-variation production leads to higher changeover rate in the main factory. To adjust the production machine from one type of product to another one, the machine must be turned off which resulted to a higher downtime. Early 2015 data from maintenance department in CII shows that 33% of planning production time is the downtime. Higher percentage of downtime in this company results to a slower production rate and higher overtime.

In fact, CII management has been implemented a Total Productive Maintenance (TPM) program to maintain the factory plant and its equipment. TPM is manufacturing program designed primarily to maximize the effectiveness of equipment by participation and motivation of the entire workforce [1]. TPM strategy implemented in this company is a benchmarked strategy from another manufacturing company. But, due to lack of human resources, the implemented strategy could not significantly affect the machine performance. According to these condition, there is a necessity to perform an improvement to the TPM strategy in CII to make it fit and suit with company condition.

The strategy developed in this research to improve the TPM in CII is predictive maintenance. This research focused on predictive maintenance than other maintenance strategy, like autonomous maintenance and preventive maintenance, due to the capability of data mining technique to supports the development of predictive maintenance to improve plant and machine condition in industry [2]. Using measurable parameters when breakdown is eminent, predictive maintenance intends to make an intervention to the machine itself or related factors before harmful events may occur [3]. It mean there is a requirement of data-driven technique like data mining to process inputted data and make the prediction well targeted.

One of data mining techniques is Association Rule Mining (ARM). Actually, the prototypical application of ARM is market basket analysis to mine the sets of items that are frequently bought together at a supermarket by analyzing the customer shopping. ARM has a capability to show the dependencies between attributes and define it in association rules [4]. ARM could clarify the relationship between the parameters and the observed variable with the intervention response that will be taken by the related stakeholder and present it in a model consisted by association rules.

Based on motivation above, the main objective of this research is to solve the problem in CII with research approach as formulated as: 1) to identify the effectiveness of used machine, 2) to develop association rules of observed variables and intervention responses, 3) to develop a model of the maintenance strategy. The maintenance strategy developed by this research aims to support the decision-making process in management of CII, and other related stakeholder like maintenance department.

## 2. Methodology of research

To accomplish the research objectives, a methodology was designed with research approach. The research methodology represented in **Fig. 1**.

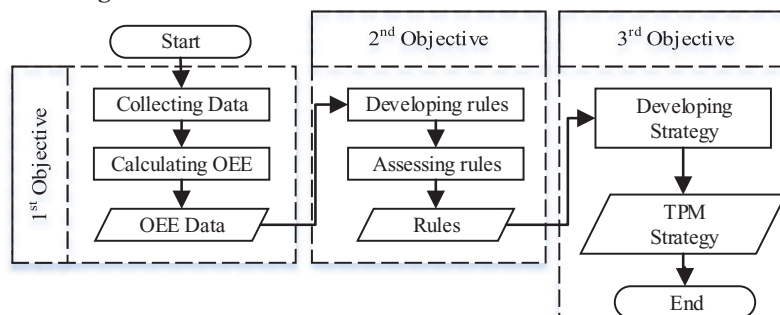


Fig. 1. Research Workflow

The research starts with the collecting machine condition data from moulding machine as sample used equipment. Then, the collected data processed with Overall Equipment Effectiveness (OEE) method to identify machine effectiveness as presented in Section 3. Afterward, using Association Rule Mining (ARM), the OEE data assigned to binary through discretization and processed with apriori algorithm to get rules of data as presented in Section 4. To

accomplish 3<sup>rd</sup> objective, the rules got from ARM developed to model to be evaluated and to show the association of machine condition and applied management strategy in TPM as presented in Section 5.

### 3. Identification of machine effectiveness

In order to answer the first research objective, the calculation of OEE is required to identify the effectiveness of the moulding machine. The moulding machine has been chosen as research target due to its importance as component profiler that make this machine has high changeover rate. The data used in this analysis is secondary data collected from CII production department record. First, the data was processed with OEE measurement. OEE is a key performance index to measure the effectiveness of the used equipment, plant, or machine [5]. The formula of OEE is shown below.

$$OEE = A \times P \times Q \quad (1)$$

Wherein:

A : availability (%)

Pe : performance efficiency (%)

Qr : quality rate (%)

Availability means the actual available time to produce goods using a machine. Performance rate shows the products produced according to the available time. Then the quality rate concludes the good products produced along the available time into OEE score [6]. Each of the factors that compose the OEE formula can be calculated by processing production data and machine condition.

$$A = OT \div POT \quad (2)$$

Wherein:

OT : operating time (minutes)

POT : planned operating time (minutes)

$$Pe = RRR \div IRR \quad (3)$$

Wherein:

RRR : real run rate (pieces/minutes)

IRR : ideal run rate (pieces per minutes)

$$Qr = GP \div TP \quad (4)$$

Wherein:

GP : good product (pieces)

TP : total product (pieces)

The calculation of OEE shows that OEE of CII moulding machine only reach 51%, with availability 67%, performance 80%, and quality 98%. The comparison between the calculation result with manufacturing company average in the world and world-class standard defined by JIPM in Fig. 2, shows that OEE in CII cannot reach world average mainly due to its availability. To find out the causes of this availability, a Six-Big Losses assessment was conducted using data of 12 days records as sample. Pareto chart that shows this assessment result shown in Fig. 3.

■ Moulding Machine ■ World Class ▨ World Average

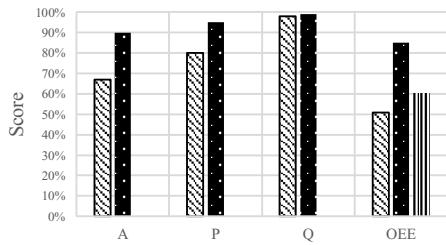


Fig. 2. OEE comparison chart

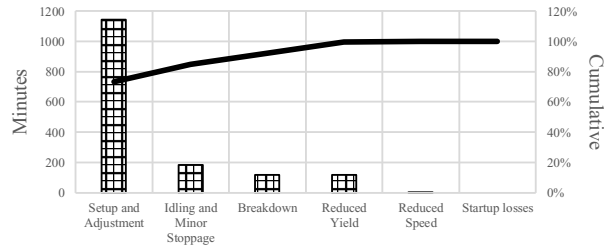


Fig. 3. Six-Big losses Pareto chart

Based on these assessment, main cause of availability loss in CII moulding machine (about 73%) is setup and adjustment loss usually caused by stoppage due to pre-production set-up or changeover while in production time, or in this case as adjustment time for changing cutter blade in moulding machine to fit demanded door component specification. A fishbone diagram to identify the source of the problem of setup and adjustment loss is shown in Fig. 4.

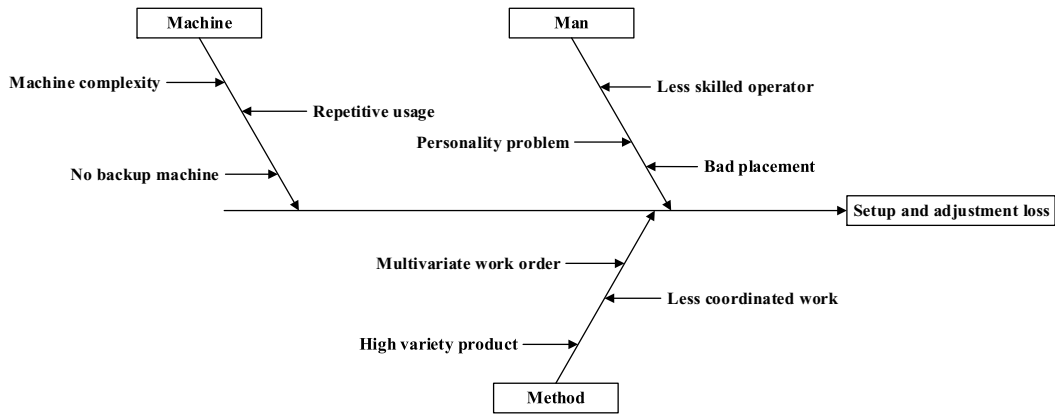


Fig. 4. Causal-effect (Fishbone) diagram

OEE calculation, Six-Big Losses assessment, and source problem identification using fishbone diagram was aimed to identifying used machine condition, and provide a better visualization of current machine state. In the next phase of this research, a strategy to resolve the solution of this condition was developed using data processed in this phase and processed with ARM.

#### 4. Association rule mining

The second phase of this research is developing rules using ARM. ARM start with mining frequent items with their support values using frequent item mining algorithm like Apriori algorithm. This algorithm works over numeric or non-numeric data because the data itself will be converted into code [4]. All of the attributes were pre-processed with discretization in a certain range. Measurable parameter like OEE measurement result was converted into antecedent code, while response activities converted into consequent code. The data of each attributes was compiled and converted into discrete binary data. Then, after combining the item-sets to combination 2-item sets up to 4-item sets, Apriori algorithm formed candidate item set, then it generated large item set consist of rules [7]. Each combination

generally called as transaction.

To ease the combination process using Apriori algorithm, every attributes has been grouped into certain range and labeled through discretization. Discretization, also called binning, converts numeric attributes into categorical ones. Discretization can also help in reducing the number of values for an attribute, especially if there is noise in the numeric measurements [4]. The measurable parameter of moulding machine has been determined as rule antecedent, while response activities of CII management has been determined as rule consequent.

Table 1 If (Antecedent) label

| If (Antecedent)              |            |       |  |        |       |                           |          |       |
|------------------------------|------------|-------|--|--------|-------|---------------------------|----------|-------|
| Parameter                    | Range      | Label | Parameter                                      | Range  | Label | Parameter                 | Range    | Label |
| Setup and Adjustment per day | 0-25% DT*  | S1    | Availability (Av) per day                      | 0-40   | A1    | Quality rate (Qr) per day | <90      | Q1    |
|                              | 26-50% DT  | S2    |  | 40-60  | A2    |                           | 90-95%   | Q2    |
|                              | 51-75% DT  | S3    |  | 60-90  | A3    |                           | 95-99%   | Q3    |
|                              | 76-100% DT | S4    |  | >90%   | A4    |                           | >99-100% | Q4    |
| Material Delay per day       | 0-25% DT   | M1    | Performance efficiency (Pe) Occurrence per day | 0-40   | P1    | OEE per day               | 0-40%    | O1    |
|                              | 26-50% DT  | M2    |  | 40-60  | P2    |                           | 41-60%   | O2    |
|                              | 51-75% DT  | M3    |  | 60-95  | P3    |                           | 61-85%   | O3    |
|                              | 76-100% DT | M4    |  | >5%    | P4    |                           | >85%     | O4    |
| Break Down per day           | 0          | B1    | Setup Occurrence per day                       | 0-5 x  | C1    |                           |          |       |
|                              | 1x         | B2    |  | 6-15 x | C2    |                           |          |       |
|                              | >1x        | B3    |  | >15 x  | C3    |                           |          |       |

\*DT=Down Time

The used attribute in antecedent code is determined according to the OEE calculation of field data. While according to the requirement analysis using fishbone diagram in previous phase, the response target has been determined into three object: the moulding machine itself, the machine operator, and the used method included the implemented production strategy. The response activities has been classified by defining the source problem into an actionable activities, as presented in Table 2.

Table 2 Then (consequent) label

| Then (Consequent) |                             |       |
|-------------------|-----------------------------|-------|
| Response target   | Response activities         | Label |
| Machine           | Targeted Machine Monitoring | X1    |
|                   | Full Performance Monitoring | X2    |
|                   | Planned Maintenance         | X3    |
| Man               | Operator Evaluation         | Y1    |
|                   | Operator Shifting           | Y2    |
|                   | Operator Training           | Y3    |
| Method            | Prioritize One Type Product | Z1    |
|                   | Work-Order Evaluation       | Z2    |
|                   | Management Meeting          | Z3    |

The result of discretization then has been represented in binary database. A binary database is a binary relation on the set of tids (transaction identifiers) and items [4]. If certain value in an attributes has been qualified into certain discrete range, the value will be represented as true value (1), while the rest of other range will get false value (0). The example of binary table is presented in Table 3.

Table 3 Availability score represented in binary table

| Availability | 0-40 | 40-60 | 60-90 | >90% |
|--------------|------|-------|-------|------|
| 65%          | 0    | 0     | 1     | 0    |
| 74%          | 0    | 0     | 1     | 0    |

|     |   |   |   |   |
|-----|---|---|---|---|
| 53% | 0 | 1 | 0 | 0 |
| 81% | 0 | 0 | 1 | 0 |
| 55% | 0 | 1 | 0 | 0 |
| 84% | 0 | 0 | 1 | 0 |

To generate the rules, each antecedent has been combined with consequent, with limitation 4-set combination. The example of antecedent-consequent combination is presented in Table 4. The result of this combination is 30228 rules.

Table 4 Combination of antecedent A-P-Q and consequent X-Y-Z

| 2-set combination | 3-set combination | 4-set combination |
|-------------------|-------------------|-------------------|
| A1→X1             | A1-P1→X1          | A1-P1-Q1→X1       |
| A1→Y1             | A1-P2→Y1          | A1-P1-Q2→Y1       |
| .....             | .....             | .....             |
| A3→Z3             | A3-Q3→Y3          | A3-P3-Q3→Z3.      |

Although there are many rules obtained, most of the rules were discarded or eliminated due to their low value with rule assessment. Rule assessment is a method consist of different rule interestingness measures to quantify the dependence between the antecedent and consequent [8]. There are 4 measures used in this assessment: support, confidence, lift, and bond. As example an association rule  $X \rightarrow Y$ , where X is antecedent and Y is consequent, the support (sup) of this rule is defined in (5). With  $|t(XY)|$  is a total of transaction contain both X and Y in a combination. Relative support (rsup) or support value compared relatively to the size of database was defined in (6), with  $|D|$  is a total of transaction in database.

$$sup(X \rightarrow Y) = sup(X \cap Y) = |tXY| \tag{5}$$

$$rsup(X \rightarrow Y) = sup(X \cap Y) / |D| \tag{6}$$

Confidence (*conf*) of a rule is the conditional probability that a transaction contains the consequent Y given that it contains the antecedent X.

$$conf(X \rightarrow Y) = sup(X \cap Y) / sup(X) \tag{7}$$

Lift of a rule is a ratio of the observed joint probability of X and Y to the expected joint probability if they were statistically independent.

$$lift(X \rightarrow Y) = conf(X \rightarrow Y) / sup(Y) \tag{8}$$

Bond shows the strength of item set with comparing conjunctive (combination contain only true value) and disjunctive (total of all combination) of each transaction.

$$bond(X \rightarrow Y) = conjunc(X \cap Y) / disjunctive(X \cap Y) \tag{9}$$

Using trial and error method, the user threshold has been determined. The minimum relative support, confidence, lift, and bond used in this research is 0.2, 1, 2, and 0.2. By using this threshold, the rule assessment was resulting 83 qualified rules. **Table 5** below shows the summary of top 10 qualified rules ranked by bond.

Table 5 Top 15 rules ranked by bond

| oN. | rSup | Conf | Lift | Bond | If (Antecedent)           |                           |                           | Then (Consequent)            |
|-----|------|------|------|------|---------------------------|---------------------------|---------------------------|------------------------------|
|     |      |      |      |      | 1 <sup>st</sup> Condition | 2 <sup>nd</sup> Condition | 3 <sup>rd</sup> Condition | Response                     |
| 1   | 0,25 | 1,00 | 2,22 | 1,00 | OEE 40-60%                |                           |                           | Work-Order Evaluation        |
| 2   | 0,30 | 1,00 | 3,33 | 1,00 | OEE 60-85%                |                           |                           | One-Type Focusing Production |
| 3   | 0,30 | 1,00 | 4,00 | 1,00 | OEE <40%                  |                           |                           | Management Meeting           |
| 4   | 0,30 | 1,00 | 2,22 | 0,67 | Setup Occurrence 1-5x     |                           |                           | Targeted Machine monitoring  |
| 5   | 0,30 | 1,00 | 2,50 | 0,63 | Av 40-60%                 |                           |                           | Planned Maintenance          |
| 6   | 0,30 | 1,00 | 2,22 | 0,57 | Setup Occurrence 6-15x    | OEE 40-60%                |                           |                              |
| 7   | 0,30 | 1,00 | 3,33 | 0,50 | Av 60-85%                 | OEE 60-85%                |                           |                              |
| 8   | 0,30 | 1,00 | 2,22 | 0,50 | Setup Occurrence 1-5x     | OEE 60-85%                |                           |                              |
| 9   | 0,30 | 1,00 | 2,22 | 0,44 | Pe 60-90%                 | OEE 40-60%                |                           |                              |
| 10  | 0,30 | 1,00 | 2,22 | 0,42 | Setup Occurrence 1-5x     | Av 60-85%                 |                           |                              |

**5. Maintenance strategy development**

Using 83 qualified rules from ARM computation, a model of maintenance strategy was developed. Basically, three types of maintenance exist, namely corrective, preventive, and predictive maintenance. In this model, the antecedent of the rules consists of measurable parameters that describe the machine condition, up to three condition, while the consequent of the rules consists of responds to be taken if the condition in antecedent was occurred.

For instance, if condition of the machine, in this case moulding machine, was showed OEE value 40-60%, then the management should conduct a work-order evaluation. OEE with value below 60% is lower than world average OEE. Manufacturing company with high changeover rate like CII maybe has low OEE due to the current work-order. So, to prevent further decreasing in OEE value, the work-order should be evaluated.

Based on this model, improvement of TPM strategy in CII is expected. Using the model as a tool to help in decision making process, management of CII can make a decision easier to solve machine-related problems with considering the qualified rules. The implementation of ARM to develop TPM strategy is very potential. To implement ARM model to develop TPM strategy for other machine in CII or even in another manufacturing company, the management can change used attributes and data in ARM so it will generated rules that fit and suit with the machine condition itself. The advantage of this model is generated dynamic rules that always updated by the data changing comparing to other strategy development tool like Analytic Hierarchy Process that uses static data [2]. Besides that, as one of data mining technique, the implementation of ARM to the TPM is a right choice, due to its ability to handle big-data with high velocity and volume that is generated by machine condition.

**6. Conclusion and recommendation**

This paper presents a novel implementation of data mining techniques to solve real industry problem especially in machine maintenance in a wooden door manufacturing industry targeting moulding machine. The OEE calculation of moulding machine shows a machine availability loss due to low effectiveness caused by high setup and adjustment loss. The deployment of ARM using a’ priori algorithm and generates 30228 if-then rules. Rule assessment has conducted to qualify rules using user threshold to limit support, confidence, lift, and bond value which resulted 83 qualified rules for predictive maintenance strategy. As recommendation, the model itself can be mounted to software. Using if-then rules generated by ARM, an if-else looping algorithm can be developed to mount the model to the

software of mobile apps to make it more user-friendly, flexible, and increase the usability. The OEE measurement and data acquisition improved by using sensor in the machine.

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