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Mathematical Modeling with Sem – PLS in Elimination of Six Big Losses to Reduce Production Cost of Steel Factories

Erry Rimawan, Untung Mardono, Humiras Purba
Magister of Industrial Engineering
Mercu Buana Univercity, Jakarta, Indonesia

Abstract:- Increasing productivity is very important for companies to achieve success in their business processes. The concept of Total productive Maintenance (TPM) has been used by various companies to increase production operational productivity so that production processes become more efficient and produce sustainable corporate profitability performance. The steel processing industry is one of the capital-intensive industries where 80% of the production costs are in raw materials and energy, so the success of eliminating Six big losses is a key factor in success for reduce the production cost. This paper proposes a methodology for evaluating the effectiveness of production operational systems using a mathematical model in eliminating six big losses which are the 3 main components of OEE (Availability, Performance rate and Quality rate). Mathematical models in the eliminating six big losses are obtained by processing operating data for 3 (three) years and using the PLS SEM as the data processing software. The findings in this paper reveal that the OEE variable with 3 (three) indicators : Availability, Performance rate and Quality rate that are significant to the level of machine productivity, decreased production costs. From the mathematical equations generated from SEM PLS analysis, it provides information that the priority to eliminating of Six Big Losses: Reduce the downtime losses, reduce quality losses and Reduce speed losses.

***Keywords**:- Six Big Losses, TPM, SEM-PLS, Profitability.*

I. INTRODUCTION

According to Prasetyo (2010), the strength, robustness of the iron and steel industry owned by a country is one indicator that shows the strength and failure of a country's economy in the present and future. The Chinese state is currently undoubtedly the condition of the strength and ability of its economic movement, where China is currently the largest producer of the world's iron and steel industry.

Indonesia's economic growth was strongly influenced by the national steel industry. Where is the link between the national steel industry is very strong with other industries (backward and forward linkages), such as with the machinery industry and the transport equipment industry and others. As shown that the increase in steel sector production can affect the input-sector demand of 1.2744 according to the results of backward linkages analysis. This means that every increase in the steel sector output is Rp. 1 will increase the demand for inputs from other sectors by Rp. 1,2744. The electricity and gas energy sector is a major contributor to input for the steel sector production. While the results of forward linkages analysis on the steel sector is 1.0203 (Hasni, 2011)

In 2013 Indonesia's steel consumption amounted to 61.6 kg per capita. To be able to become a developed country, Indonesia must have an annual per capita consumption of 500 Kg. With annual consumption of steel per capita still low, Indonesia still needs at least 120 million tons of steel production capacity to sustain consumption of 500 kg per year per capita (World Steel Association,2014)

Steel consumption in Southeast Asian countries as shown in Figure 1 :

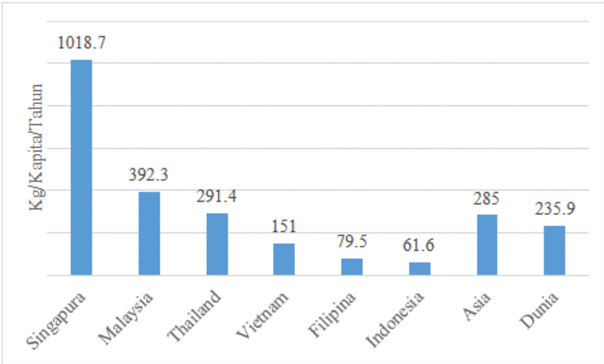

Fig 1:- Steel consumption in Southeast Asian countries (Source: World Steel Association, 2014)

The national profile steel mill production capacity is 2,381 million tons while the national demand is 1,023 million tons (Statistical Years book SEAISI,2016).

With the imbalance in Supply-Demand and steel products, the China-ASEAN free trade agreement (CAFTA) and investment plans for the construction of integrated steel plants by Chinese investors in Indonesia will force domestic steel products to make improvements and innovation in the production process to produce quality products at a cost competitive and profitability.

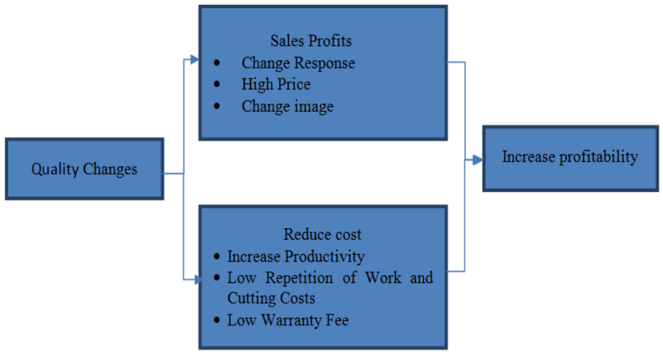

Fig 2:- Quality gives way to change profitability (Source : Heizer, 2001)

To achieve good engine performance and minimize losses, improvement activities are needed which aim to eliminate Six Big Losses which is the biggest problem in the performance of an engine (Vijayakumar & Gajendran, 2014).

In this study the author will determine the indicators of the six big losses that significantly affect the effectiveness of production operations with SEM PLS and provide recommendations for improvements that must be made so that productivity increases, decreased production costs and increase the performance of the company's profitability.

II. LITERATURE REVIEW

A. Quality, Productivity& Profitability

- Quality is defined as the ability of a product or service to meet the desires of its customers (P. Tampubolon, 2004). And according to Heizer (2001), building quality is a way for a company to create profitability, as described in Figure 2.
- Mali (1978) states that productivity is not the same as production, but production, quality performance, results, are components of productivity efforts. Thus, productivity is a combination of effectiveness and efficiency
- The profitability of a company is measured by using the difference between the selling price and the cost of goods sold (HPP). Profitability is the ability of a company to make a profit in relation to sales (Santoso, 2001)

B. Cost Quality

Cost of Goods Sold is all costs incurred in a production process in producing a product until it is ready for sale. The HPP is composed of the following costs:

➢ *Direct Material Costs*

Represents all costs for obtaining raw materials up to materials ready for use which include: Price of raw materials, transportation costs, storage and others.

➢ *Direct labor costs*

Is a part of the wages or salaries of all workers involved in the manufacture of products, the sequence of certain jobs, or the provision of certain services.

➢ *Over Head (OH) Factory Costs*

Defined as indirect raw materials, indirect labour and other factory expenses that are not easily identified or charged directly to specific jobs, products and the ultimate target of costs. Costing OH takes into account 2 characteristics, which relate to a special relationship between the cost of OH and the product itself and the amount of production volume. Based on OH's relationship with the number of production volumes, OH costs can be fixed, variable or semi variable

To reduce overall costs and increasing revenue from this operation, one common methodology used in decision making is the optimization model (Muñoz-Villamizar, A. at. All, 2018)

C. TPM (Total Productive Maintenance)

TPM is a concept that aims to improve production performance by maintaining equipment. TPM has been developed by Japan since 1960 and 1970, which is based on the concept of Preventive Maintenance and Productive Maintenance or commonly abbreviated as PM developed in the United States (King, 2009).

4 stages of TPM development include (Nakajima, 1988):

- Breakdown Maintenance
- Preventive Maintenance
- Productive Maintenance
- TPM (Total Productive Maintenance)

TPM is an innovative approach to maintenance that optimizes the effectiveness of equipment, eliminates damage, and encourages autonomous maintenance by operators through daily activities that cover all relevant employees

D. Six Big Losses

In every equipment performance, of course there are losses that occur in operation, this is described into six major losses on equipment by Nakajima (1988), including:

➢ *Downtime Losses (Loss of Termination / Unused Time)*

- *Equipment Failure (Breakdown)*

Equipment Failure is damage to equipment consisting of two types, namely sporadic failure and chronic failure. Sporadic failure is a sudden engine failure, usually this damage can be identified and repaired. Conversely, chronic failure is a type of minor damage to equipment, but when damage occurs we cannot clearly identify the cause and the resulting impact is insignificant.

- *Set up and Adjustment Losses*

This is the time used to install, adjust and adjust the engine parameters to get the desired specifications when first starting to produce certain components / products. In addition, Garvin (1988) offers eight product quality dimensions as defined from the customer's perspective: performance, features, reliability, conformance, durability, marketing, aesthetics, and perceived quality.

- *Speed Losses*
- *Idling and Minor Stoppages*

Idling Losses occur when the equipment or machine stays on but does not produce output, such as delays in material supply, etc. While Minor Stopping Losses is a stop that occurs on the equipment in a short time due to temporary problems, such as a component malfunction, quality problems that occur during the process etc.

- *Reduced Speed*

Is a loss caused by the speed of equipment that is operated under a predetermined standard, this is caused by several factors such as mechanical problems, nonstandard raw material, setting the machine that is not according to procedures that make the speed of the machine or equipment decreases.

- *Quality Losses*
- *Defect in Process*

It is a waste of time to produce a bad product and rework when the machine is running continuously after adjusting and adjusting the equipment.

- *Reduced Yield*

This loss is a loss caused by a product that is not in accordance with the standard. So that the reduced number of outputs is appropriate for the quality of the product.

With this, the calculation of the Six Big Losses above can help to identify the losses that occur in the machine so that it affects the OEE value.

E. PLS-SEM

Structural Equation Model (SEM) alternative method Partial Least Square (PLS) is one of the analytical tools that is often used in developing a predictive linear causality model between cooperative networks as a predictive latent variable (Xi) with innovation and performance as bound latent variables (Yi) who have non-parametric properties in situations of high complexity with the support of weak theory (Nurwullan,2015).

Structural Equation Modelling (SEM) is a multivariate data analysis method used in this study and can be used as a data source (Statsoft, 2013). SEM can also be used in solving problems for latent variables that cannot be calculated and difficult to measure (Wong, 2013).

There are two approaches to SEM: The first approach is the widely applied covariance- based SEM (CB-SEM). CB-SEM has been widely applied in the field of social science during the past several decades, and is still the preferred data analysis method today for confirming or rejecting theories through testing of hypothesis, particularly when the sample size is large, the data is normally distributed, and most importantly, the model is correctly specified. That is, the appropriate variables are chosen and linked together in the process of converting a theory into a structural equation model (Hair et. al.., 2011).

PLS handle all types of data, from nonmetric to metric, with very minimal assumptions about the characteristics of the data (Hair et. al.., 2010). Also it handles both reflective and formative constructs and all recursive models are identified. However, many industry practitioners and researchers note that, in reality, it is often difficult to find a data set that meets these requirements. Furthermore, the research objective may be exploratory, in which we know little about the relationships that exist among the variables. In this case, researchers can consider PLS.

The second approach is Partial Least Squares (PLS), which focuses on the analysis of variance and can be carried out using PLS-Graph, Visual PLS, Smart PLS, and Warp PLS. PLS is a soft modelling approach to SEM with no assumptions about data distribution. Thus, PLS-SEM becomes a good alternative to CB-SEM when the following situations are encountered (Wong, 2010):

- Sample size is small.
- Applications have little available theory.
- Predictive accuracy is paramount.
- Correct model specification cannot be ensured.
- Definition of Normal Distribution is free.

It is important to note that PLS-SEM is not appropriate for all kinds of statistical analysis. Researchers also need to be aware of some weaknesses of PLS-SEM, including:

- High-valued structural path coefficients are needed if the sample size is small.
- Problem of multi co linearity if not handled well.
- Since arrows are always single headed, it cannot model undirected correlation.
- A potential lack of complete consistency in scores on latent variables may result in biased component estimation, loadings and path coefficients.
- It may create large mean square errors in the estimation of path coefficient loading.

In spite of these limitations, PLS is useful for structural equation modelling including formative indicators in applied research projects especially when there are limited participants and that the data distribution is skewed, e.g., surveying female senior executive or multinational CEOs (Wong, 2011). PLS-SEM has been deployed in many fields, such as behaviour sciences, marketing, organization, management information system, and business strategy.

III. RESEARCH MODEL AND RESEARCH HYPHOTESIS

Based on the review of the literature presented, the research model is proposed where 3 OEE variables are Availability with indicator L12, Performance rate with indicator L34 and Quality rate with indicator L56. These 3 indicators represent of the six big losses: Equipment Failure (Breakdown), Setup and adjustment losses, Idling and Minor Stoppage, Reduced Speed, Defect in Process, Reduced Yield that will affect the level of productivity, decrease in production costs and performance of the company's profitability shown in the figure 3.

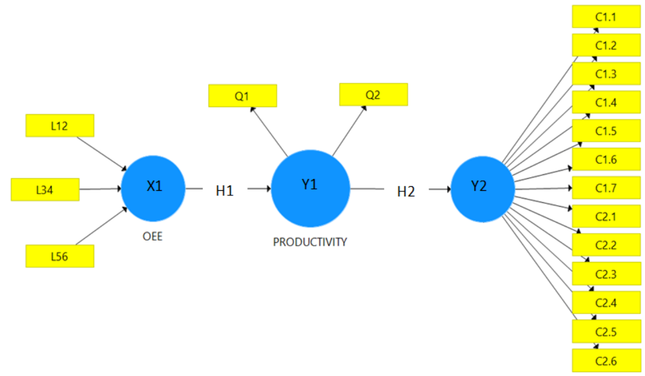

Fig 3:- Research Model

The research hypothesis determines that there are critical factors that affect the operational effectiveness of production, namely productivity that will affect the size of each cost item and the company's profitability performance. In view of that, research hypotheses are as follows:

- H1: OEE will have a positive effect on plant productivity performance.
- H2: Plant Productivity will have a positive effect/ reduce cost.

IV. METHODOLOGY

To test the hypothesis of this study, the production operational manifest data is used with a minimum of 30 pieces of monthly operating performance data from a steel processing plant and testing this research model refers to Smart PLS 3.0, by implementing a road weighting scheme. We adopted two step approaches (Anderson & Gerbing, 1988). The first step is confirmatory factor analysis. In this step researchers can confirm reliability and validity. The second step is to analysis structural equation models to assess the research hypothesis

V. RESULT

A. Evaluation on the Final Outer Model (Indicator of Reliability and Validity)

No.	Criteria	Rule of thumbs	Research Result Value
1	Composite Realibility (CR)	> 0.8	Y1 = 0.822 (reliable) ; Y2 = 0.939 (reliable)
2	Average Variance Extracted (AVE)	> 0.5	Y1 = 0.698 (valid) ; Y2 = 0.711 (valid)
3	Outer Loadings	> 0.7	Q1 = 0.857 ; Q2 = 0.813 C1.1 = 0.994 ; C1.2 = 0.985 ; C1.3 = 0.997 ; C1.4 = 0.974 C1.5 = -0.841 ; C1.6 = 0.985, C1.7 = 0.967 ; C2.1 = 0.961 C2.2 = 0.884 ; C2.3 = -0.261 ; C2.4 = 0.975 ; C2.5 = -0.022 C2.6 = -0.047
4	Discriminant Validity		Fornell-Larcker Criter... Cross Loadings

	COST	OEE	PRODUKTIVITY
COST	0.843		
OEE	-0.626	0.695	
PRODUKTIVITY	-0.648	0.783	0.836

Table 1. Criterion value of research model measurement results (final outer)

Test reliability and validity of the measurement model is done to ensure that the reflective model that is built has fulfilled the requirements as a reliable and valid measurement model. This test uses a correlation between indicators with construct scores indicated by the value of the loading factor. Indicators with high loading factors have a higher contribution to explain the latent construct.

It is essential the reliability and validity of the latent variables to complete the examination of the structural model. The following tables shows the various reliability and validity items that we check and report when conducting a PLS-SEM (see Table1).

Indicators that have reflected the construct consistently and stably with the loading factor> 0.8 are Q1, Q2, C1.1, C1.2, C1.3, C1.4, C1.5, C1.6, C1.7, C2.1, C2.2, C2.3, C2.4, C2.5, C2.6,unless the indicator C2.3, C2.5 and C2.6can be deleted. Composite reliability (ρc) Y1and Y2 are valued above 0.8, meaning that having internal consistency is very satisfying. AVE values for Y1 and Y2 are above 0.5, meaning that each latent construct has a valid measurement model.

AVE values for Y1 and Y2 are above 0.5, meaning that each latent construct has a valid measurement model. The value of cross loading or indicator correlation to the latent construct is greater than the correlation value of the indicator to other constructs, so that the validity of the measurement model is fulfilled. The discriminant criteria for Fornell-Larcker, Square Root of AVE are marked by the AVE root of each construct compared to the value of the interconnection correlation. The AVE root value of each construct is greater than the mean interconnection correlation, all constructs in the estimated model meet the criteria for discriminant validity.

B. Inner Model Evaluation Evaluation (Results of Bootstrap Method Resampling Analysis)

The inner model describes the relationship between latent constructs, in this study only looked at the indirect relationship between X1, Y1and Y2 (Figure 2). The structural model or inner model is evaluated by looking at the level of variance described, namely the criteria for testing the inner model through five conditions, namely the criteria for R2, Goodness of fit (GoF), effect size f2, prediction relevance (Q2), estimation of path coefficients, and estimated stability who tested using the t-statistical test through the re sampling method or Bootstrap.

In this procedure, a large number of subsamples (for example, 500) are taken from the original sample instead of the standard bootstrap, which at the time gives a significant value of the structural rate. Bootstrap results near normality of data. After the bootstrap procedure is complete, the results can be obtained as follows.

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After selecting the path for the model in, we can use the external model by checking the T-statistics in the "External Content (Means, STDEV, T-Values)" window. As presented in Table 3, three of the T-statistics are greater than 1.96, we can say that the outer loading of the model is very significant. So Y1 and Y2 are adopted. All of these results are the basis of PLS-SEM in our study. The results of PLS SEM are launched in Figure 5.

Mean, STDEV, T-Values, P-... | Confidence Intervals | Confidence Intervals Bias ... | Samples | Copy to Clipboard: Excel Format | R Format

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
OEE -> PRODUKTIVITY	0.783	0.782	0.111	7.083	0.000
PRODUKTIVITY -> COST	-0.635	-0.728	0.087	7.298	0.000

Table 2. Result of PLS – SEM

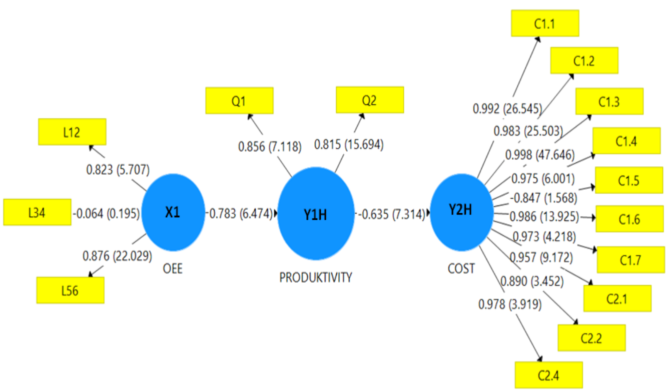

Fig 5:- Path model and PLS – SEM Estimate

Constructs Productivity (Y1) has a value of R2 0.613, which means that the variability or diversity of productivity constructs can be explained by L12(Availability), L34 (Performance rate), L56 (Quality rate), Q1 (volume production) & Q2 (yield production) with 40.2% while 59.8% is explained by other latent variables outside this study. Construct Cost (Y2) has a value of R2 0.404, which means that the variability or diversity of constructs can be explained by C1.1 - C1.7, C2.1, C2.2 and C2.4 with 40.4%, while 59.6% explained by other latent variables outside the study.

Estimation of path analysis coefficient, at the significant level of 5% of all t-statistics values from the re sampling of the bootstrap method in the latent construct Y1 (Productivity) and Y2 (Cost) is greater than t-table (1.96), so the construct the construct has a significant effect.

From the original sample value or estimation coefficient X1 to Y1 gives a positive value of 0.783, while Y1 to Y2 have negative effects with value weights of -0.635. Answering hypothesis 1, 2 with an increase in OEE will increase productivity, reduce production costs.

So from the above PLS analysis can be written mathematical equations influence six big losses indicators namely L12 (Availability), L34 (Performance rate), L56 (Quality rate) on the variables OEE (X1), Productivity (Y1) and Cost (Y2), as follows:

X1 = 0.823L12 + 0.064L34 + 0,876L56
Y1 = 0.783X1
Y2 = -0.635Y1

VI. CONCLUSION AND IMPLICATION

The purpose of this research is to enable companies that can survive and develop in accordance with the indicators that there are six major losses to OEE, productivity, production costs and from the results of the analysis seen from 3 (three) indicators from OEE variable is the first role in engine availability, both improving quality (reducing defects & rework) and improving engine level performance (engine speed).

In the analysis of this study using the second generation multivariate data analysis method, namely Partial Least Square Structural Equation Modeling (PLS-SEM) which has been widely applied in various Business studies, focusing on Partial Least Squares (PLS) which is one of the path modeling. With little data availability, PLS-SEM is able to handle the inadequacy of the data. And from the existing path modeling and the relationship of each variable has provided information with a fairly good level of significance and accuracy.

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