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A Simulation-Based Approach to Assess Eco-Process Innovation Performance

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A Simulation-Based Approach to Assess Eco-Process Innovation Performance

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Abstract. In the recent decade, eco-process innovation practice has been prioritised over other green strategies to help manufacturing firm becoming more sustainable. This paper evaluates the improvement in production cycle time as an outcome of the eco-process innovation, using the actual data of a manufacturing facility. Discrete event simulation approach was adopted to model and simulate the cycle time of previous state and current state of an eco-innovated production line. Result of cycle time per entity revealed a 6% reduction, thus proving that implementation of eco-process innovation could improve the economic performance of manufacturing firm. The study is a small part of a larger research work of which the authors are developing indicators for measuring eco-process innovation performance at firm level.

1. Introduction

Manufacturing refers to the process of transforming input resources such as material, people and machines into products to fulfill human needs and generate wealth for the manufacturer. However, manufacturing processes has indirectly resulted to degradation of the environment due to their side produces such as waste, emissions and other unfavorable outputs. Numerous approaches have been adopted by manufacturers to obtain the most optimized production operations, yet associated with minimal environmental unfavorable impacts. The incorporation of eco-innovation practice into the manufacturing processes (known as eco-process innovation) is an effective initiative to achieve the intended eco-friendly results [1][2][3]. [4] View of eco-process innovation as the changes of existing production methods or addition of new processes to minimize the environmental impacts. Moreover, it relates directly to operations activities and concerned with process upgrades or introduction of new techniques and technology into production operations [5][6] which improve resources consumptions and production efficiency, thereby leading to waste and cost reduction [4][7]. In agreement to [8], this study refers to eco-process innovation as any eco-innovation taking place in the production processes which are aimed at an improved economic, environmental and social performance of the firm. However, this study is primarily concerned with the economic aspect of eco-process innovation performance, specifically indicated by production cycle time.

Development and refinement of effective mechanisms to assess eco-process innovation performance is of vital importance for various reasons such as benchmarking [12], improvement plan design [13] and provide stakeholders with information on firms' actual eco-innovation performance [10][14]. Recently, some researchers and practitioners have developed instrument for measuring performance of eco-process innovation implemented in manufacturing firms [4]. However, such efforts are scattered and

various measuring approaches emerged. Some scholars proposed a conceptual framework and instruments while others have attempted to validate the eco-process innovation performance measure through empirical study. Interestingly, in connection to the empirical studies, most studies adopted perceptual approach and very limited studies undertook operational approach of measuring the eco-process innovation performance [8]. Hence, the latter approach was deployed in this study. The aim of this study is to measure the improvement in production cycle time brought by eco-process innovations, using the real operational data of a Malaysian electronic component manufacturing facility. Discrete event simulation (DES) approach was used to model and simulate the changes in cycle time of production processes, which have been eco-innovatively improved by the company. No attempt was made to analyze and select the best eco-process innovations as the focus of this study was not on proposing the most optimized processes or ranking of eco-innovation processes in the case study company. Rather this study was to validate the appropriateness of production cycle time to indicate the performance of eco-process innovations by using actual eco-process innovations data obtained from the company.

2. Literature Review

Conceptually, at micro level, economic performance is defined as a firm's influences on its stakeholders' economic condition and on the condition of economic systems of local, national and global level [15]. Adoption of eco-process innovation has a significant positive impact on a firm's costs [16][17][18]. One well-known early study that is often cited is that of [19], who provided a valuable insight into the positive relationship between eco-process innovation and the firms' economic achievement that is the competitive advantage. They recommended manufacturers to invest in performing eco-friendly process changes to stay competitive in the industry. Similarly, more recent studies such as by [20], [21] and [6] have also measured the economic component of eco-process innovation performance. The authors highlighted the need for manufacturers to pursue eco-process improvement activities due to the fact that such environment-oriented initiatives contribute to better firm's economic achievement. Furthermore, literature demonstrated that production efficiency found to be relevant to represent the economic aspect of eco-process innovation. Production efficiency is the outcome of standardized and balanced processes and job procedures, shorter production cycle time and lead time, more effective use of resources [22], reduced inventory level and space required, and better process flexibility [23]. For the purpose of this study, production cycle time was used to indicate the economic performance of eco-process innovation carried out in the case study company. Production cycle time refers to the total time taken to perform series of steps in a process to produce a product including the transfer, waiting and queue time in between and at each process [24].

Being recognized as the most widely used approach of simulation in operational studies which include semiconductor's manufacturing operation [25], DES is an application that is known fit for modelling a specific well-defined production system as it allows for the provision of statistically valid quantitative assessment of performance indicators of the system. Extensive research have been conducted on simulating and optimizing manufacturing system using DES to achieve a better manufacturing performance. However, studies on the application of DES method to assess the performance of eco-process innovations in manufacturing systems are very few. This includes [26] study, who applied DES method to perform cost-time profile analysis, discovered hybrid lean and eco-process innovation implementation lead to reduction in operational cost of an automotive manufacturer. Their manufacturing system model was tested using various sources of data namely historical data, expert consultants' interview and shop floor measurement. Later, [27] used similar method in their study of energy efficiency in a vehicle assembly line. Using real production data gathered from the computerized enterprise resource planning (ERP) system, findings indicated that eco-process innovation resulted in cost and energy saving.

3. The assessment of production cycle time

The measure of production cycle time was based on the real production processes and other operational data which was collected from a case study company. The company has been an innovator and leader in Malaysian electronic components manufacturing industry for more than 40 years. Its products range is varieties of standard and customized power inductors, common mode chokes and transformers for applications in automotive, industrial, medical and alternative energy sectors. Eco-process innovation in the company did not taking place randomly, but accompanied with proper plans, certain financial and other resources allocation, and reliable support system.

A production line of producing common mode choke has been investigated owing to the largest demand of its product model, hence, one of the long runs production line. Most tasks in the line were previously performed manually and relied too much on human labor. Then, the processes have been gradually transformed, taking continuous process improvement approach into consideration to enhance their performance. The production operation starts when the copper wires are fed into the system and ends when the finished chokes are packed and waiting for collection by the warehouse department.

Arena Version 15 simulation software (Academic License) package of Rockwell Automation was utilized to construct the simulation models of production system in which eco-process innovations have taken place. Luminea et al [28] recommended the use of Arena software compared to other simulation tools due to its capability of better modelling and experimentation function.

3.1. Data collection and sampling procedure

In order to ensure the structure and logic of real production system is precisely represented by the Arena modules, numerous types of data and collection approaches were employed. Generally, three types of data were collected from the relevant departments in the case study company:

i. Structural data for designing the simulation model structure and visualizing the studied production processes such as production line layout, process flow chart and process operation instruction.

ii. Process parameters refer to factory and operational data such as production schedule, process cycle time, types and quantity of resources, production yields and rejects and etcetera.

iii. Process parameter relationships to visualize the interdependencies of the parameters. This include data on process improvement projects such as changes details and improvement results.

The aforementioned data were collected through multiple methods such as:

a. Documentation which includes production line control plan (includes information on the process flow and the conducted process improvements) and operation instruction card (OIC).

b. Historical records such as production planning and schedules, the resources used and production yields records, and innovation and creative circle (ICC) project reports.

c. Discussions, verbal reports and open dialogs with all relevant personnel involved in the production line operations such as the operations manager, assistant production manager, industrial engineer, process engineers, lean engineer, quality assurance engineer, technical support technicians, production line supervisor, line leaders and process operators.

d. Direct observations that involve observations of the production line layout, operation methods, production processes run, transfer of the work-in-progress (WIP) in between processes, and operator's working condition.

e. Direct measurement of processes cycle time by conducting time study on all process operations in the investigated production line. During the time study, the process operations performed by both the operators and machines were recorded using video camera device to allow for the repetitive play, fast-forward or fast-rewind of the video so as to accurately determine processes cycle time or review of any other details of the tasks completion.

The following formula which suggested by [29], was used to compute the minimum sample size of readings or cycles to ensure the representativeness of the cycle time inputs used in simulation models to reflect the actual cycle time of the processes.

$$n = \left(\frac{40\sqrt{n'\sum x^2 - \left(\sum x\right)^2}}{\sum x} \right)^2 \qquad (1)$$

where, n is the sample size, n' is the number of readings taken in the preliminary measure, $\sum$ is the sum of values and x is the value of the readings. Preliminary measure of cycle time was performed on each processes, whereby the readings then were used to compute the appropriate sample size for the actual measure of cycle time.

3.2. Input data analysis

The collected raw data were examined to determine if they can be used directly (deterministic or non-random data) or need to be fitted to a probability distribution (stochastic or random data). Data such as number of entities per arrival and number of resources are clearly deterministic. Whereas the cycle time of certain processes such as curing, cooling and packaging was found to be deterministic since they were performed over a fixed period of time. In curing process for instance, parts were cured in oven over a constant time duration. Concerning the stochastic cycle time, variability in data was captured to justify model validity by running the goodness-of-fit test to probability distribution using Input Analyzer (a separate application of Arena software). Decision on the goodness-of-fit test for stochastic cycle time input data was made based on the guidelines provided by [30], who recommended three numerical measures which represent the fit quality of a particular probability distribution such as shown in the distribution summary and fit all summary report provided by the Input Analyzer:

i. Square error - smaller value demonstrates a good fit to the distribution. Larger value means the fitted distribution is further away from the actual data, hence having a poorer fit to the distribution.

ii. Chi-Square and Kolmogorov-Smirnov (K-S) - corresponding p-value that is greater than 0.05 provides a fair degree of confidence that the fitted distribution is a good representation of the actual data.

The fitted probability distribution and the associated goodness-of-fit test measures are summarized in Table 1.

3.3. Models development

In order to analyze the impact of changes in the production cycle time brought by the eco-process innovations, the production line was visualized in two separate models: previous state which illustrates the production line before the eco-process innovations took place, and current state which shows the production line after the eco-process innovation implementation.

3.3.1 Modelling the previous state. The previous production line consists of 20 processes arranged in a single line assembly with no re-entrance back to the same process. The previous state model is depicted in **Error! Reference source not found.**.

3.3.2 Modelling the current state. The eco-process innovations were defined using parameters in two forms of change in the current state model, namely structural and quantitative change. Structural change refers to the change of model structure such as the process sequence. The quantitative change, on the other hand, involves the change of quantitative input or parameter values of the model such as the resources quantity [26]. Table 2.2 provides a summary of the detail eco-process innovations taken place in the production line and the respective modelling change.

Table 1. Summary of fitted probability distribution and the associated goodness-of-fit test measures

No.	Process		Probability Distribution	Value/Expression	Square Error	Corresponding P-Value
1.	Stripping & cutting		Uniform	UNIF(57.5, 59.5)	0.180000	Chi-square: 0.253
2.	Wire pre-soldering		Triangular	TRIA(1.28, 1.4, 2.61)	0.001979	Chi-square: > 0.75 K-S: > 0.15
3.	Winding	Manual	Uniform	UNIF(14.5, 19.5)	0.045000	Chi-square: 0.586
		Auto	Uniform	UNIF(10.5, 13.5)	0.046667	Chi-square: 0.248
4.	Forming		Uniform	UNIF(10.5, 13.5)	0.086667	Chi-square: 0.0785
5.	Wire pre-chopping		Triangular	TRIA(2.5, 3.5, 4.5)	0	Chi-square: 0.75
6.	Header assembly		Triangular	TRIA(6.5, 9.85, 10.5)	0.002815	Chi-square: > 0.75
7.	Dressing		Uniform	UNIF(5.5, 9.5)	0.047778	Chi-square: 0.136
8.	Tinning	Manual	Triangular	TRIA(13.5, 13.9, 17.5)	0.064228	Chi-square: 0.19
		Auto	Triangular	TRIA(18.5, 18.6, 23.5)	0.039220	Chi-square: 0.226
9.	Cleaning & adjustment		Uniform	UNIF(6.5, 8.5)	0.002222	Chi-square: 0.728
10.	Epoxy application		Uniform	UNIF(6.5, 8.5)	0.020000	Chi-square: 0.285
11.	Fixturing		Triangular	TRIA(2.08, 2.22, 3.52)	0.079012	K-S: > 0.15
12.	Curing	1	Deterministic	8s	NA	NA
		2	Deterministic	4.25s	NA	NA
13.	Cooling	1	Deterministic	8s	NA	NA
		2	Deterministic	8s	NA	NA
14.	Wire chopping		Triangular	TRIA(3.28, 3.71, 4.72)	0.294093	K-S: > 0.15
15.	Part number marking		Triangular	TRIA(45.5, 54, 56.5)	0.073213	Chi-square: 0.397
16.	Visual mechanical inspection		Triangular	TRIA(19.5, 20.4, 29.5)	0.015538	Chi-square: 0.345
17.	Final test		Uniform	UNIF(5.5, 7.5)	0.005000	Chi-square: 0.681
18.	Packing		Deterministic	1.0s	NA	NA

Table 2. Eco-process innovation and the respective modelling change

Eco-Process Innovation (EPI)	Type of Model Change	Model Change
EPI#1 - Efficient Equipment Manual to auto winding jig	Quantitative	Shorter process cycle time
EPI#2 - Process Automation: Manual to auto tinning machine	Quantitative	Shorter process cycle time
EPI#3 - Process Integration: Curing 1 & Curing 2	Structural	Reduced process from 2 to 1
EPI#4 - Process Integration: Cooling 1 & Cooling 2	Structural	Reduced process from 2 to 1
EPI#5 - Efficient Equipment: Video to Laser Jet Printer	Structural	Rearranged process sequence

    The first improvement involved the use of pneumatic winding jig to replace the manual jig in winding process. In tinning process, auto tinning machine has been introduced to improve the process which previously done manually. Both process improvements have resulted in shorter cycle time. Apart from that, curing 2 and cooling 2 process were removed from the line due to the replacement of Video Jet Printer with Laser Jet Printer. The use of more efficient printer to mark the part number has eliminated the need for the marked parts to be cured and cooled for the second time. The implementation of these eco-process changes has reduced the total number of processes in the line to 18, which potentially lead

to more resources saving such as equipment, operator, energy, material, space and etcetera. The current state model is shown in Figure 2.2.

3.4. Model assumptions

The models were run in steady state simulation setup with 10 replications; warm-up period 10,000 seconds; 5 days which equals to one week of production operation (159,000 seconds) replication length and 8.50 hour per day. The warm-up period was set to eliminate the start-up or initialization bias. Arena clears up the statistics during the warm up period for summary report and starts the statistic collection after the warm up period ends [30]. The warm-up period of both models was identified by performing multiple replications of preliminary runs and analyze the statistical plots of saved data in Output Analyzer (a separate application of Arena software).

The actual run of both models were carried out with the following assumptions:

i.   The eight hours and fifty minutes of production operation per day have excluded the breaks.

ii.   The provision of materials at processes workstation was done by the material handlers, who are not performing the process operations.

iii. No entity transfer has been set up due to the very short time taken per entity, hence it was considered and included in the process cycle time.

3.5. Model verification and validation

Models' structural were verified by comparing them with the processes sequence in the actual production line in addition to the line leader's verification (of the case study company) on the correctness of the structural logic to represent the production line under investigation. Besides that, error messages were eliminated during the simulation run by referring to the suggested possible causes and solutions, and improving the models accordingly. The generated SIMAN coded files were also reviewed to check the detail modules setting so as to identify any errors. Last but not least, the animation running was also helpful in checking the models' logic.

Concerning the models' validation, the goodness-of-fit tests done on the stochastic cycle time data using Input Analyser application helped to provide valid Arena expression, and to paste directly into the models. In addition to that, the simulation run results of both models were compared to the data collected from the real production line. The comparison revealed a minimal difference, thus validated the developed models.
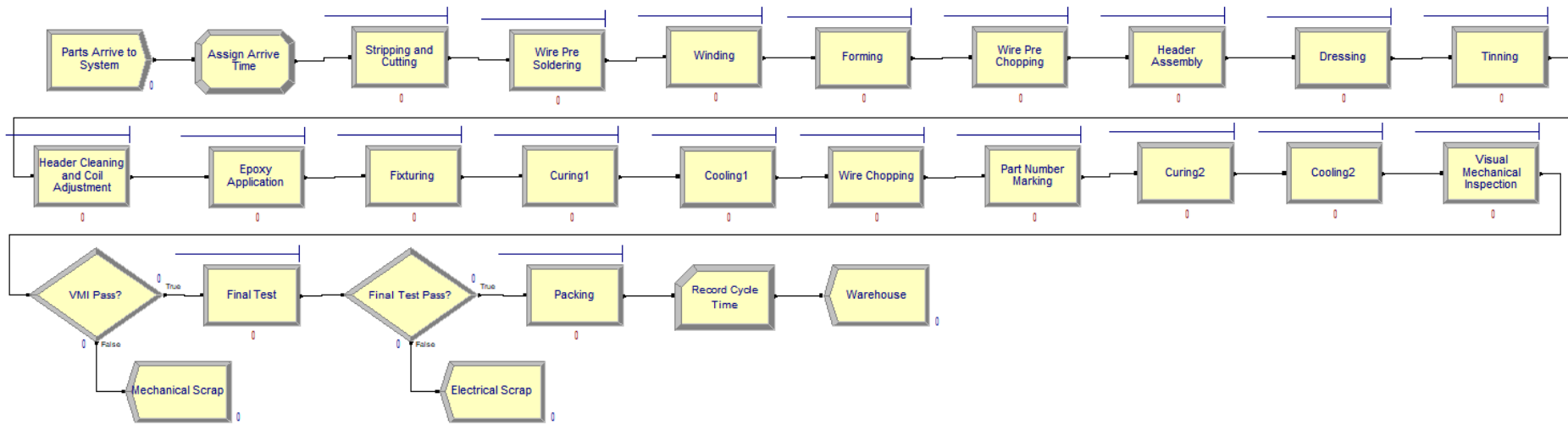
Figure 1. Previous state of production line model
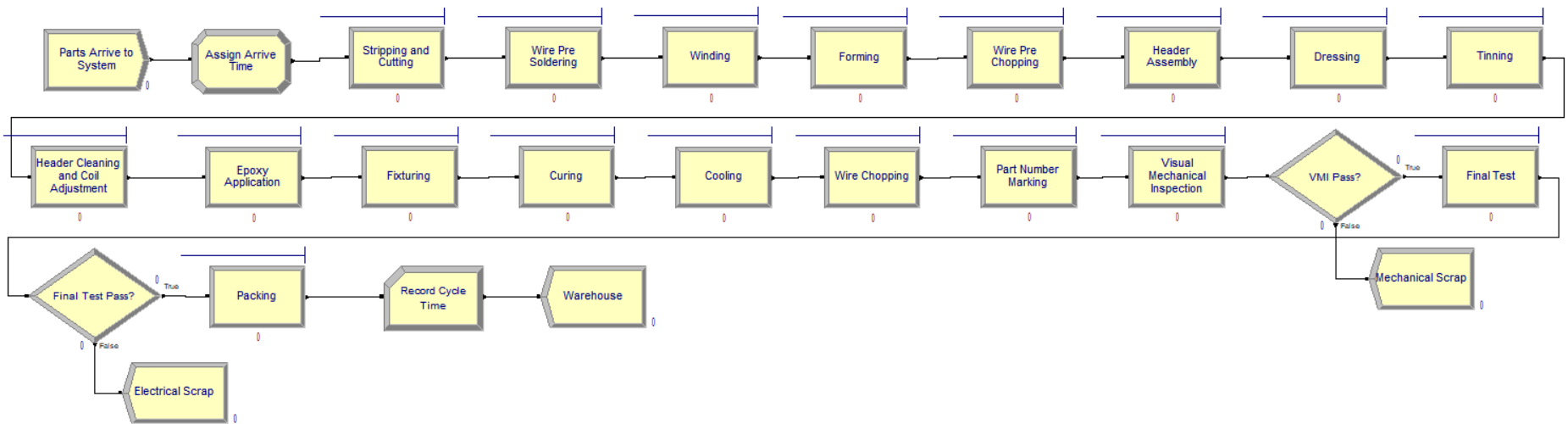
Figure 2. Current state of production line model

3.6. The improvement results

The simulation results of cycle time per entity (product) in both previous and current state models are summarized in **Error! Reference source not found.**3.

Table 3. Simulation results of cycle time per entity

Record Cycle Time	Previous State	Current State
Average	260.02s	244.57s
Half-width	0.12	0.07
Minimum Average	259.73s	244.44s
Maximum Average	260.22s	244.73s

The total cycle time per entity in the production system (i.e. the specified time interval between arrivals of entities to the record cycle time module set after the packing process) has reduced for about 15.45 seconds from 260.02 seconds to 244.57 seconds. This result clearly demonstrated that the implementation of eco-process innovations improves the production cycle time, in this case by 6% for each unit of product. Therefore, with 2,459 units of product out of the system in 5 days of production operation, 37,992 seconds or 10.55 hours of operation period have been saved. The shorter production cycle time reflects a more efficient production operation, as the outcome of the continuous eco-innovations done on the selected processes.

4. Conclusion

This paper has addressed the evaluation of cycle time improvement of a production line resulting from the implementation of eco-process innovations. DES approach was adopted to model and simulate the previous state and current state of the production line to measure the difference in the total cycle time of each entity. Simulation results have reported shorter cycle time of each product unit in the studied production line due to the series of eco-innovative process improvements.

This study has provided with deeper insights into the operational approach of measuring the improvements brought by eco-process innovation, using the real production data. Besides that, it has pointed out the potential use of simulation method to measure eco-innovation performance in electronic components manufacturing settings. This study focuses on only one indicator of economic performance of eco-process innovation (i.e. production cycle time). The simulative study of other economic indicators such as waste rate and resources utilization can be performed in future. The conduct of similar study in other industries such as palm oil and chemical industry might also reveal interesting results due to their different characteristics of production operations.

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