Simulation Modeling and Analysis for Productivity Improvement in the Production Line

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Abstract

Lean manufacturing addresses the growing need for all types of organizations that drive process change and performance improvements in their organization environment and supports the evolution toward demand-driven supply networks. Lean principles are derived from the Japanese manufacturing industry. It is the set of "tools" that give contribution in the identification and steady elimination of waste (muda). As waste is eliminated, quality improves while production time and cost are reduced. The key to lean manufacturing is to compress time by eliminating waste and this continually improving the process. Ohno (1988) defines waste as all elements of production that only increase cost without adding value that customer is willing to produce.

The total productive maintenance (TPM) is mostly regarded as an integral part of Lean. TPM originated in Japan in 1971 as a method for improved machine availability through better utilization of maintenance and production resources. TPM uses an overall equipment effectiveness (OEE) index to indicate equipment and plant effectiveness. The technique works to eliminate the six big losses indicated by Nakajima, as down time (caused by equipment failure, set-up and adjustment), speed losses (owed by idling, minor stoppage and reduced speed) and defects (caused by process defects and reduced yield). The Japan Institute of Plant Maintenance promoted TPM which includes the OEE in 1971. In 1988, Nakajima introduced the TPM to the U.S. OEE has since gained a lot of attention as the ultimate performance measure of a piece of equipment.

Sohal et al., (2010), from survey results, found that OEE typically advances from a base measure for efficiency (as its initial purpose), to being a tool to improve effectiveness for analyzing data to support continuous improvement objectives. It's through the identification and elimination of six big losses, namely (i) breakdowns, (ii) setups and changeovers, (iii) running at reduced speeds, (iv) minor stops and idling, (v) quality defects, scraps, yields, reworks, and (vi) start-up losses. The first two affect Availability rate (A), the second two affect Performance efficiency (P), and the last two affect Quality rate (Q). These three OEE elements, since being introduced by Nakajima until this research was conducted, already experienced several improvements involving a weight calculation method for OEE elements.

This study proposes a procedure to obtain weight settings of each OEE element and OEE estimation for productivity improvement in the production line.

The first research proposal is sought to offer a procedure to cover the drawbacks of weighting OEE elements. The research motivation was initiated by several researches of OEE improvement, which met difficulty when determining the proper weight for each OEE element. The calculation results of OWEE and PEE by STP also showed better results than the original OEE for the simulation model case study. From the result analysis, it can be concluded that the outcome of this research experiment can be implemented in OEE with a weighted method, among others; for example, in PEE (Production Equipment Effectiveness) as well as OWEE (Overall Weight Equipment Effectiveness). A simulation model was chosen because it is able to mimic a real production line and therefore act as a suitable experiment tool.

This study provide a lean overview followed by a description of how simulation is being used to enhance lean performance. This study offering simulation as the lean way to implement and accelerate the TPM. The STP (Simulation Taguchi method Procedure) provided characteristic mapping of OEE elements through a response table. Naturally, even though STP seems to be difficult to implement, the outcome is worthwhile. Moreover, the company will have obvious data to consider when making decisions for the improvement of priorities in their production line.

The second research proposal offers OEE enhancement scheme, which provides a company with the appropriate information for decision-making on priority improvement in the production line. By using the Taguchi method and simulation as an experimental tool, this scheme can measure and estimate the contribution for each OEE element to an OEE score. This procedure can be implemented in a specific WS or in a production line if the factory is made up of more than one manufacturing line. They provide measurements for each OEE element in order to observe the extent of the influence the simulation experiment has on the OEE elements and scores.

All of those research proposals are to improve the OEE as a KPI in the factory. In order to meet the objective of the TPM itself, increasing the sustainability of the company by continuous improvements.

Keyword: Overall Equipment Effectiveness (OEE). Total Productive Maintenance (TPM), Simulation modelling, Taguchi method, Experiment design, and Decision support.

Table of Content

List of Figures and Tables

List of Figures

List of Tables Page

Chapter I

Introduction

1.1 Motivation of Study

Organizations look for ways to improve their production and management processes in order to remain competitive in the market. This calls for ways to reduce production cost, enhance productivity and improve product quality.

Productivity is in industrial engineering defined as the relation of output (i.e. produced goods) to input (i.e. consumed resources) in the manufacturing transformation process. Productivity is therefore, on the one hand, closely connected to the use and availability of resources (Tangen, S. 2002). Consequently, organizations must utilize all the available resources efficiently and effectively in order to provide their customers with high quality products at a low price.

Aimed at these motives, many researchers proposed several improvement strategies and tools to satisfy organization’s needs. Such initiatives include Total Quality Management, Quality Awards, Total Productive Maintenance (TPM), and Lean principles (Mandahawi and Obeidat, 2012).

Lean principles are derived from the Japanese manufacturing industry. It is the set of "tools" that give contribution in the identification and steady elimination of waste (muda). As waste is eliminated, quality improves while production time and production cost are reduced.

A list of such lean tools would include SMED, Value Stream Mapping, Five S, Kanban (pull systems), poka-yoke (error proofing), Total Productive Maintenance (TPM), Cell manufacturing, etc. TPM is mostly regarded as an integral part of Lean. TPM originated in Japan in 1971 as a method for improved machine availability through better utilization of maintenance and production resources.

Machine downtimes, low capacity of machines, longer production times, products defects, etc., also clustered as a waste in the company, particularly a waste in production line. The lean manufacturing itself has a principle, doing more, with less of everything; eliminating waste to reduce manufacturing cost. In order to addressed that problems, the TPM program need to be implemented. The maintenance's meaning (based on Oxford dictionary) is the process of preserving a condition or situation or the state of being preserved. Alternatively, the word of maintenance is addressing for sustainability of a system, preserving a desired state or level of performance. Introduction of a TPM program is based on the implementation of a series of steps or pillars. In the Japan Institute of Plant Maintenance (JIPM) presented eight pillars that structure TPM. These eight pillars are shown in Figure 1-1 (Ahuja, and Kamba, 2008).

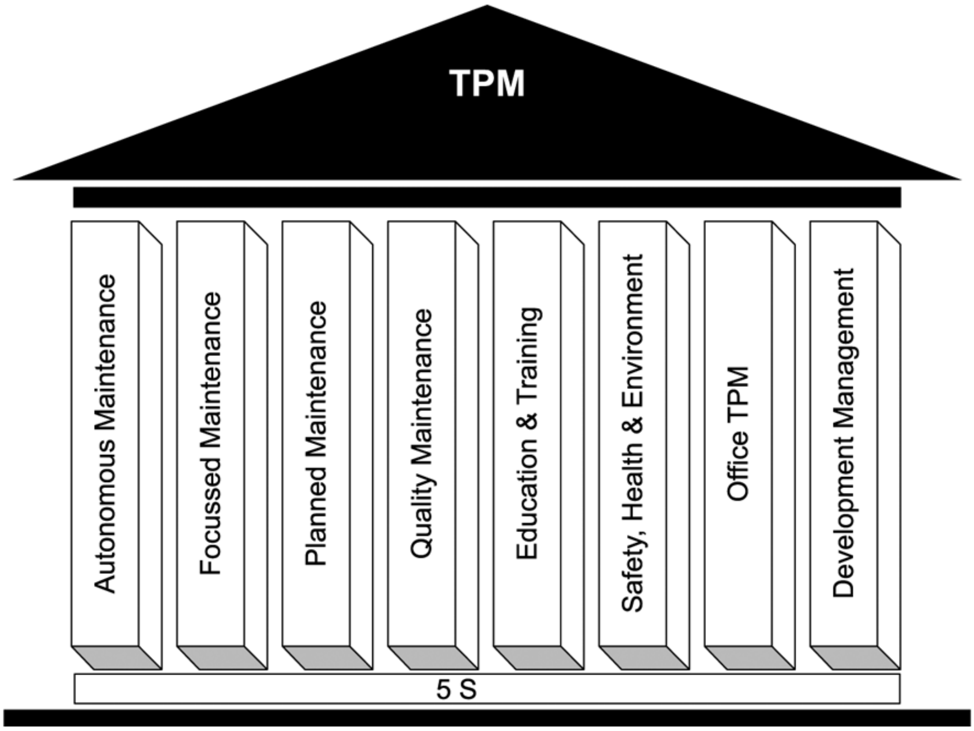
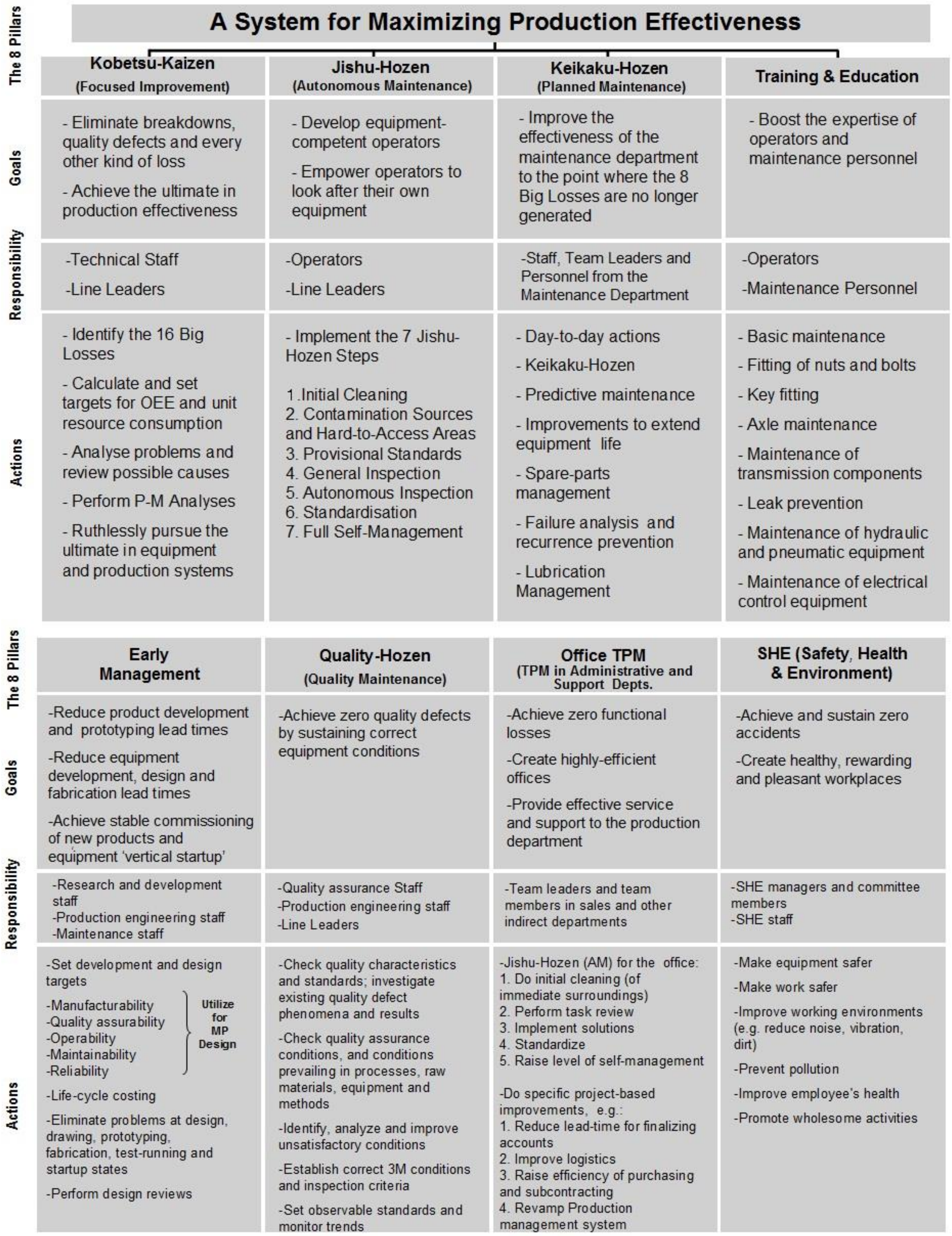


Figure 1-1. Eight Pillars approach for TPM suggested by JIPM



A System for Maximizing Production Effectiveness

The 8 Pillars	**Kobetsu-Kaizen** (Focused Improvement)	**Jishu-Hozen** (Autonomous Maintenance)	**Keikaku-Hozen** (Planned Maintenance)	**Training & Education**
Goals	- Eliminate breakdowns, quality defects and every other kind of loss - Achieve the ultimate in production effectiveness	- Develop equipment-competent operators - Empower operators to look after their own equipment	- Improve the effectiveness of the maintenance department to the point where the 8 Big Losses are no longer generated	- Boost the expertise of operators and maintenance personnel
Responsibility	-Technical Staff -Line Leaders	-Operators -Line Leaders	-Staff, Team Leaders and Personnel from the Maintenance Department	-Operators -Maintenance Personnel
Actions	- Identify the 16 Big Losses - Calculate and set targets for OEE and unit resource consumption - Analyse problems and review possible causes - Perform P-M Analyses - Ruthlessly pursue the ultimate in equipment and production systems	- Implement the 7 Jishu-Hozen Steps 1. Initial Cleaning 2. Contamination Sources and Hard-to-Access Areas 3. Provisional Standards 4. General Inspection 5. Autonomous Inspection 6. Standardisation 7. Full Self-Management	- Day-to-day actions - Keikaku-Hozen - Predictive maintenance - Improvements to extend equipment life - Spare-parts management - Failure analysis and recurrence prevention - Lubrication Management	- Basic maintenance - Fitting of nuts and bolts - Key fitting - Axle maintenance - Maintenance of transmission components - Leak prevention - Maintenance of hydraulic and pneumatic equipment - Maintenance of electrical control equipment

The 8 Pillars	**Early Management**	**Quality-Hozen** (Quality Maintenance)	**Office TPM** (TPM in Administrative and Support Depts.)	**SHE (Safety, Health & Environment)**
Goals	-Reduce product development and prototyping lead times -Reduce equipment development, design and fabrication lead times -Achieve stable commissioning of new products and equipment 'vertical startup'	-Achieve zero quality defects by sustaining correct equipment conditions	-Achieve zero functional losses -Create highly-efficient offices -Provide effective service and support to the production department	-Achieve and sustain zero accidents -Create healthy, rewarding and pleasant workplaces
Responsibility	-Research and development staff -Production engineering staff -Maintenance staff	-Quality assurance Staff -Production engineering staff -Line Leaders	-Team leaders and team members in sales and other indirect departments	-SHE managers and committee members -SHE staff
Actions	-Set development and design targets -Manufacturability -Quality assurability -Operability -Maintainability -Reliability **Utilize for MP Design** -Life-cycle costing -Eliminate problems at design, drawing, prototyping, fabrication, test-running and startup states -Perform design reviews	-Check quality characteristics and standards; investigate existing quality defect phenomena and results -Check quality assurance conditions, and conditions prevailing in processes, raw materials, equipment and methods -Identify, analyze and improve unsatisfactory conditions -Establish correct 3M conditions and inspection criteria -Set observable standards and monitor trends	-Jishu-Hozen (AM) for the office: 1. Do initial cleaning (of immediate surroundings) 2. Perform task review 3. Implement solutions 4. Standardize 5. Raise level of self-management -Do specific project-based improvements, e.g.: 1. Reduce lead-time for finalizing accounts 2. Improve logistics 3. Raise efficiency of purchasing and subcontracting 4. Revamp Production management system	-Make equipment safer -Make work safer -Improve working environments (e.g. reduce noise, vibration, dirt) -Prevent pollution -Improve employee's health -Promote wholesome activities

Figure 1-2. Brief Summary of the eight TPM Pillars by JIPM

In addition, for the brief summary of the eight pillars of TPM can be described in Figure 1-2. All of these pillars are based on continuous improvement philosophy or kaizen (5s), whereby the eight pillars essences are:

1. Jishu Hozen – An Autonomous Maintenance Program
2. Kobetzu Kaizen – Focused improvement. To eliminate major losses to improve production system effectiveness
3. Keikaku Hozen – A Planned Maintenance program for maintenance department
4. Education and Training – Increasing skills of operators and maintenance personnel.
5. Early equipment management – reduce product development and prototyping lead times.
6. Hinshitsu Hozen – Quality Maintenance. Achieve zero quality defects by sustaining correct equipment conditions.
7. Office TPM – TPM in administrative and support departments. Achieve zero functional losses
8. Safety, Health and Environmental Management – achieve and sustain zero accidents.

While the 5S components include Sort (Seiri), set in Order (Seiton), Shine (Seiso), Standardize (Seiketsu), and Sustain (Shitsuke). Together, they provide a methodology for organizing, cleaning, developing, and sustaining a productive work environment (Al-aomar, 2011).

Nakajima S. (1988) identified three main objective of TPM: zero defects, zero breakdowns and zero accidents. These goals are achieved through the implementation of activities planned to increase equipment efficiency, the creation of a program of autonomous maintenance, the establishing of a planned maintenance system, the organization of training course for workers and the design of a plant management system.

TPM uses an overall equipment effectiveness (OEE) index to indicate equipment and plant effectiveness. The technique works to eliminate the six big losses indicated by Nakajima, as down time (caused by equipment failure, set-up and adjustment), speed losses (owed by idling, minor stoppage and reduced speed) and defects (caused by process defects and reduced yield). The Japan Institute of Plant Maintenance promoted the total productive maintenance (TPM) which includes the OEE in 1971. In 1988, Nakajima introduced the TPM to the U.S. OEE has since gained a lot of attention as the ultimate performance measure of a piece of equipment. The OEE involve of three elements, among others: Availability rate, Performance efficiency, and quality rate, as can be illustrated on Figure 1-3 (Shirose and Nakajima, 1992).

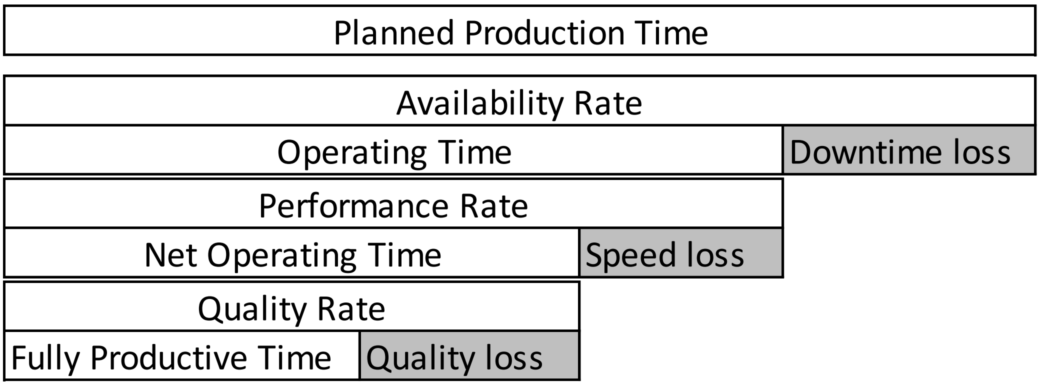


Figure 1-3. OEE Main Element Illustration.

OEE as key performance indicator (KPI) will allow company to focus their efforts on prioritizing and then reduce the classic six big losses of; (1) breakdowns, (2) set-ups and changeovers; (3) running at reduced speeds, (4) minor stops and idling; (5) quality defect, scraps, yield, rework, and (6) start-up losses. The first two losses affect Availability rate, the second two losses affect Performance efficiency, and the last two losses affect the quality rate.

The target of TPM activities is to raise the OEE and labor productivity, eventually to secure the equipment failure zero, defects and rework zero and industrial accident zero (Shirose, 1989) .

TPM initiatives are focused upon addressing the six major losses, and wastes associated with the production systems by affecting continuous and systematic evaluations of production system, thereby affecting significant improvements in production facilities (Gupta et al., 2001).

Performance measurement is one of the most critical subjects for driving business organizations. Firms are unable to identify the increase of competitiveness and profitability, unless they still are aware of their current performance. Additionally, management level can neither manage nor improve an organization if current performance cannot be identified. Therefore, in the last three decades, several frameworks and performance measurements have been developed and implemented.

Generally, there are several different types of performance measurements; such as, financial measures, productivity measures, quality measures and so on. Sohal et al., 2010 from survey result find that OEE typically advances from a base measure for efficiency as the initial purpose, to being a tool to improve effectiveness for analyzing data to support continuous improvement objectives. Even though OEE appears to be a complete performance measurement indicator, it still requires proper modification. Several researches related to OEE improvement have used weighted OEE approach to advance this performance measurement for production line use.

Other research try to use the cost calculation approach to extent the OEE as performance measurement of production line. Since several researches of OEE improvement have met with difficulty when determining the proper weight for each OEE element, and because in OEE, it cannot measure the estimation of improvement and measure how the production cost loss (non-value added cost); this study proposes a new procedure to cover these drawbacks.

1.2 Scope of Study

Motivation to advance the OEE as KPI and decision-making support in order to improve productivity, this study proposes two solutions:

a. Calculation of OEE Weight by Taguchi Method with simulation

It is a proposal of OEE weight calculation in order to obtain more weight value that is more reflect to the real production line through simulation and Taguchi experiment method. Overall Equipment Effectiveness (OEE) is a comprehensive performance measurement that is used to measure equipment effectiveness on the production line. OEE is a Key Performance Indicator (KPI) to measure the implementation of Total Productive Maintenance (TPM). Nevertheless, as the time passes, the usage of OEE is transformed to a system that analyses production data, to identify potential areas of improvement, and support lean initiatives.

Therefore, OEE characteristically advances from being a base measure of efficiency as its initial purpose, to being a tool that improves effectiveness. Even though OEE appears to be a complete performance measurement indicator, it still requires proper modification. Many researches related to OEE improvement have used weighted OEE to advance this performance measurement for production line use.

Until now, only a few researches have been conducted by other researchers related to OEE improvement. Several OEE improvements have included the cost variable into the OEE calculation; others have attempted to develop a new technique to set up the weights of OEE. Since several researches of OEE improvement have met with difficulty when determining the proper weight for each OEE element, this research proposes a new procedure to cover this drawback.

The baseline for weighting OEE elements in this research refers to OEE element characteristics that are obtained by a combined result of simulation and experiment, through the Taguchi method. The research outcome proves that this combination of methods gives a more accurate result for providing characteristic data of a production line related to OEE, and for obtaining a weight calculation of OEE elements.

b. OEE Estimation for Improvement in the Production Line

It is a proposal of OEE estimation for improvement and OEE measurement in order to measure until how far the change will take effect to the production line. The objective of this research is to propose an enhancement of the Overall Equipment Effectiveness (OEE) by including information on OEE estimation, Value Added (VA) cost, and Non-Value Added (NVA) cost through simulation and the Taguchi experimental method.

This additional information can enhance the original OEE as a Key Performance Indicator (KPI) and act as a guide for a company in deciding on the priority improvement required. If a company relies solely on the ordinary OEE calculation, it can only arrive at a decision for priority improvement through the lowest score measured and will be in the dark as to the level of improvement required in the production line. Decision-makers in the company need to consider information other than the OEE score if their intention is to see a profound improvement in the performance of the production line. This research proposes a procedure, which employs simulation and the Taguchi experimental method.

1.3 Thesis Outline

This thesis consists of six chapters. Chapter I presents the introduction of this study including the motivation of work and scope of the research. Chapter II deals with the research background, which includes literature reviews on related topics of the research.

Chapter III discusses the objective of this research regarding to the calculation of OEE weighted by simulation and experiment by Taguchi method. The chapter begins with introduction on procedure to calculate the weight for OEE with weight calculation, followed by experiment design by Taguchi method approach with simulation model of CHM factory as an experiment tool. Finally, the weight calculation of OEE is discussed by using Taguchi method S/N ratio with simulation.

While Chapter IV discusses the OEE estimation in order to improve productivity of production line. The chapter begins with introduction on procedure in order to measure the estimation of OEE, followed by experiment design by Taguchi method approach and development of CHM factory simulation model as an experiment tool. Finally, the estimation of OEE is discussed by using Taguchi method approach with simulation.

Chapter V introduces the development of simulation model for CHM factory, verification, and validation of the simulation model. Furthermore, an overview of CHM simulation model development explanation as an experiment tool and Taguchi method overview.

Chapter VI presents the concluding remarks and summary of the findings of this research. The contributions of this research and recommendations for future works are also presented in this chapter.

Chapter II

Research Background

2.1 An Overview of TPM

In this era of globalisation there are several challenges facing the manufacturing sector. Complexity in taking decisions due to the immense availability of information, randomness in the system which affects performance, heterogeneity in events occurring all make modelling for performance prediction difficult.

According to (Muthiah, & Huang, 2006; Gershwin, 1994, 2000), a manufacturing system is a set of machines, transportation elements, computers, storage buffers and other items that are used together for manufacturing. People are also part of the system. Alternate terms are factory, production system and fabrication facility. Subsets of manufacturing systems, which are themselves systems, are sometimes called cells, work centres or workstations. Excess inventories, long lead times and uncertain delivery dates are caused by randomness and lack of synchronisation. There are only two possible solutions: reduce the randomness (due to machine failures, engineering changes, customer orders and so on) and reasons for the lack of synchronisation (costly set-up changes, large batch machines and others) or respond to them in a way that limits their disruptive effects. Both responses are valid, but they can be, in practice polar opposites. Performance measurement is defined as the process of quantifying the efficiency and effectiveness of action (Tangen, 2003). Slack (2001) mentioned five types of performance objectives based on cost, flexibility, speed, dependability and quality.

The Lean concept came into existence at Toyota Company during the 1930s and mainly after the Second World War. Toyota managers and engineers had benchmarked the Flow Production concept from Ford. After understanding and using the concept, they started to develop and improve it and defined Toyota Production System (TPS), which focuses on elimination of wastes like waste in time as well as resources. TPS is the base of what is known as Lean now. TPM also originated at Toyota but was introduced during the 1970s. Toyota developed the American concept, PM, with focus on Total Employees Participation. Total was added to PM and formed TPM. Production loss is in contrast with right quality, reasonable cost and right time. In this way, Reliable equipment (through TPM) is needed.

TPM is mostly regarded as an integral part of Lean. TPM role in maintenance is similar to TQM in Quality. Lean and TPM comparison reveals that OEE is a part of Lean analysis; also, OEE improvement has a positive effect on Flow and Perfection. Front line asset care affects Flow and Perfection. A systematic approach to maintenance serves Lean principles like Flow and Perfection. Continuous and appropriate training helps in understanding customer value by providing external or internal customers with fewer defective products and positively affects Flow and Perfection. Finally, early equipment management facilitates Flow and Perfection.

2.2 Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation

Nakajima S., (1988), proposed OEE and its feasibility has been proved in various case studies. This original OEE is referred to as Original-OEE in this paper. To extend its feasibility, several ideas have been proposed, such as Production Equipment Effectiveness (PEE), or Overall Weighting Equipment Effectiveness (OWEE). This section covers these three types of OEE that are related to this research.

2.2.1 Original-OEE

The original OEE involves three elements defined by Nakajima, S., (1988), as follows; Availability rate (A), Performance efficiency (P), and

Quality rate (Q). The mathematical equation of OEE can be seen in the following equations:

$$OEE = A \times P \times Q \tag{2-1}$$

Where by,

$$A = \frac{(loading\ time - downtime)}{loading\ time} \tag{2-2}$$

$$P = \left(\frac{ideal\ cycle\ time}{actual\ cycle\ time}\right) \times \left(\frac{actual\ cycle\ time \times output}{operating\ time}\right) \tag{2-3}$$

$$Q = \frac{(total\ number\ of\ production - number\ of\ defect\ product)}{total\ number\ of\ production} \tag{2-4}$$

2.2.2 Production Equipment Effectiveness (PEE)

Raouf A., (1994), developed a method of assigning weights to OEE elements, using an analytical hierarchy process. It was introduced as Production Equipment Effectiveness (PEE).

In his research, Raouf described that the traditional means of evaluating maintenance management systems could not yield higher capital productivity. Factors relating to OEE are not equally important in these aspects; however, the difference in weights should be taken into account. Assuming that Availability rate (A) has a weight of k_1, Performance efficiency (P) has a weight of k_2, and Quality rate (Q) has a weight of k_3; where, $0 < k_i < 1$ and $\sum_{i=1}^{3} k_i = 1$.

PEE can be calculated as;

$$PEE = A^{k_1} \times P^{k_2} \times Q^{k_3} \tag{2-5}$$

However, Raouf did not explain specifically how to obtain or calculate the values for k_1, k_2, and k_3.

2.2.3 Overall Weighting Equipment Effectiveness (OWEE):

Wudhikarn, R., (2010)b developed Overall Weighting Equipment Effectiveness (OWEE), which is calculated using the following formula;

$$OWEE = w_A A + w_P P + w_Q Q \qquad (2\text{-}6)$$

Where, w_A is the weight of an element, w_P is the weight of the P element, and w_Q is the weight of the Q element. An authorized person must identify the weight in this equation utilizing the Rank-Order Centroid (ROC). The ROC formula is defined as follows;

$$w_i = \left(\frac{1}{k}\right) \sum_{j=i}^{k} \frac{1}{r_k} \qquad (2\text{-}7)$$

This weight setting calculation is then implemented in equation (2-6). Wudhikarn proposed this method, since the original OEE method did not appropriately prioritize problematic equipment.

Furthermore, Wudikarn regularly described that the lowest OEE machine was primarily selected for improving. However, other studies opined that the lowest OEE machine may not have the highest losses whilst all equal OEE elements do not mean the same losses. After using this indicator and studying several other researches, Wudikarn discovered the problem of weight setting each OEE element. All of these problems will possibly lead to incorrectly prioritized machine improvement decisions. It will specify an equivalent weight in each element, and then, the weighted OEE method is presented and the analytical hierarchy process will be applied to set the weight.

After several improvements of the OEE concept (as described previously), all drawbacks of the improved OEE concept using the weighted method, notify that there is difficulty when determining the weight for each OEE element (Raouf, A., 1994; Wudhikarn, R. et al, 2010a; and Sheu, D.D., 2006). Drawbacks of several OEE concept developments are shown in Table 2-1.

Based on these drawbacks, this research purposes a procedure rectify the weighting method of each OEE element.

Table 2-1. Short resume of OEE concept developments related to this research

No.	Method	Advantage	Drawback
1	Original OEE (Overall Equipment Effectiveness)	Simple indicator that covers comprehensive operational measurement	The weight of each element is equivalent, whilst their losses are totally different. E.g. availability rate associates with time losses, and quality rate is composed of qualitative losses. Because of this, OEE cannot always describe the actual condition of the production line, depending on the case.
2	Productivity Equipment Effectiveness (PEE)	Improvement of the OEE concept. All OEE elements have different weights	It did not specifically describe the calculation to obtain the weight value for each OEE element.
3	Overall Weight Equipment Effectiveness (OWEE)	Improvement of OEE and PEE concepts. Using the Rank-Order Centroid (ROC) method calculation for each weighting of OEE elements	This depends on authorized personnel in order to decide the weight rank for each OEE element. It can be very subjective if not accompanied by accurate data.

2.3 Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line

The role of OEE in performance measurement and decision support will be enhanced if it can provide more information, especially on how improvements can be estimated in relation to cost and OEE element scores. This is relevant because companies regularly measure productivity with due consideration to the operational cost. Several OEE developments related to cost calculations with reference to the OEE elements are as follows:

Wudhikarn et al., (2010) proposed a new indicator that could prioritize problematic machines by showing production loss in a monetary unit through the OEE method. In line with the OEE method, the presented indicator still analyses losses in 3 elements, but reveals the outcome in saving cost instead. The losses in each element are dissimilar and depend on resource usage.

Sheu (2006) proposed the concept and analysis of overall input efficiency (OIE) to complete the calculation of full machine efficiency which the research called total equipment efficiency (TEE). The research revealed that the OEE is apparently only concerned about the output aspect of machine efficiency.

Tekin (2012) developed a methodology called "Analysis of Costs Resulting from Manufacturing Losses" based on the ABC model in order to measure costs resulting from manufacturing losses. The aim of this study was to provide a decision support approach for estimating the cost of tools for the managerial staff of companies to reorder cost reduction priorities and initiate the recovery of manufacturing losses through TPM activities. In this study, the OEE metric was used for identifying the performance of individual manufacturing units.

All these studies shared the same general objective, which was to enhance the OEE concept by including cost calculations in the production process to support decision-making. This is because the OEE is not equipped to measure losses attributed to production costs. It is a rare situation in manufacturing that a 1% downtime loss has the same business or financial impact as a 1% efficiency loss or a 1% quality loss.

The OEE can also serve as a tool for improving the examination of data to support continuous improvement objectives. In an actual situation, decision-makers in a company need to consider much more than just the OEE score. Among others, they need to deliberate on buffer size, number of products, work in progress, queue times, batch size, operator skills, production cost, labour cost, material cost, transport time between workstations (WS) and other issues related to the production line besides machine or equipment capacity. Another aspect that requires consideration is a universal measurement, which is a combination of several measurements. For instance, the cost for machine idle time and work in progress can be combined in a single cost calculation to simplify the measurement process.

Furthermore, by using the procedure proposed in this research, the OEE improvement estimation can be calculated for each OEE element. This estimation will provide information on all OEE element estimations including the level of improvement attained and the amount of value added and non-value added costs involved.

This study focused on OEE estimations with the inclusion of cost calculations. As every production line has its own characteristics, the information obtained should reflect the actual situation in a specific production line. As such, information gathering through the simulation method (which can mimic the actual situation) is most appropriate for this situation. This research also employed the Taguchi method as a statistical experiment to measure the OEE score of each OEE element. A procedure will be proposed whereby more information related to the production line can be included into the OEE concept.

The research focussed on enhancing the OEE through the employment of simulation and a statistical approach by the Taguchi method. This was to provide an estimation of each OEE element for priority improvement decision-making on the production line particularly on production cost calculations.

The crimping manufacturing line (CML) simulation model was developed as an example of the implementation of this procedure. Arena simulation software was employed to develop the CML model. This research was unique because it combined the simulation method and the statistical experimental method to measure the contributions of OEE elements and calculate the production cost. With this procedure, the improvement effect on the OEE can be estimated for each OEE element by cost (value added and non-value added cost) and by OEE scores.

Chapter III

Calculation of Overall Equipment Effectiveness Weight by Taguchi Method With Simulation

3.1 Introduction

The Total Productive Maintenance (TPM) concept was introduced in 1951. TPM can form a foundation for improvements to the entire production process. It has been defined as a set of activities for restoring equipment to its optimal condition and changing the work environment to maintain that condition. In order to measure performance for TPM, Nakajima, S., (1988) introduced Overall Equipment Effectiveness (OEE). Sohal et al., (2010), from survey results, found that OEE typically advances from a base measure for efficiency (as its initial purpose), to being a tool to improve effectiveness for analysing data to support continuous improvement objectives through the identification and elimination of six big losses, namely (i) breakdowns, (ii) setups and changeovers, (iii) running at reduced speeds, (iv) minor stops and idling, (v) quality defects, scraps, yields, reworks, and (vi) start-up losses. The first two affect Availability rate (A), the second two affect Performance efficiency (P), and the last two affect Quality rate (Q). These three OEE elements, since being introduced by Nakajima until this research was conducted, already experienced several improvements involving a weight calculation method for OEE elements.

This research proposes a procedure to obtain weight settings of each OEE element. Differences from previous studies by other researchers already conducted, include the weight proportion determination of OEE elements comes from a mathematical calculation, such as an Analytical Hierarchy Process (AHP) and a weighted signed graph approach, and another method is through a Rank-Order Centroid (ROC) method. This paper presents a weight proportion calculation of OEE elements using a simulation and statistical approach. This procedure was proposed because every production line has its own characteristics or specifications. The simulation method was chosen because it can mimic a real production line. Usually the Taguchi method is used for optimization matter. However in this research The Taguchi method was chosen because it can statistically measure which factor of an OEE element has the highest sensitivity, caused by different level values. Therefore, the weight proportion comes from experimentation of the simulation model of a real production line. The benefit is that it better reflects production line conditions.

3.2 Framework of OEE extension

This section presents a proposed weighted OEE extension using the Taguchi method, based on a process simulation approach. Figure 3-1 shows the framework of this extension, by which the weight calculation of OEE elements can be conducted more effectively than in the other approaches presented in the previous section.

The framework of this extension can be explained as follows - by implementing the OEE concept in the production line, the company can measure the performance of the production line and decide what kind of maintenance program must be employed. However, in order to select the correct maintenance program, a good Key Performance Indicator (KPI) is needed. The OEE concept has already been proven as a feasible KPI of TPM. However, as shown by several researchers lately, it still needs modification. In order to improve the OEE concept, several researches developed a weighted method over the OEE concept. However, it was not easy to select a suitable weighted method. The result of this research provides a calculation that is more accurate (i.e., reflects the real characteristics of a production line) for weighting values of OEE elements. In order to obtain accurate results, this research used simulation and statistical experiments through the Taguchi method. From this procedure, the results can be obtained more accurately than other weighting techniques. Based on this, companies can properly measure their KPIs and correctly prioritize the maintenance program for each machine or equipment (Figure 3-1). In this research, the procedure for weighting OEE elements through simulation and the Taguchi method will be known as the Simulation-Taguchi-Procedure (STP).

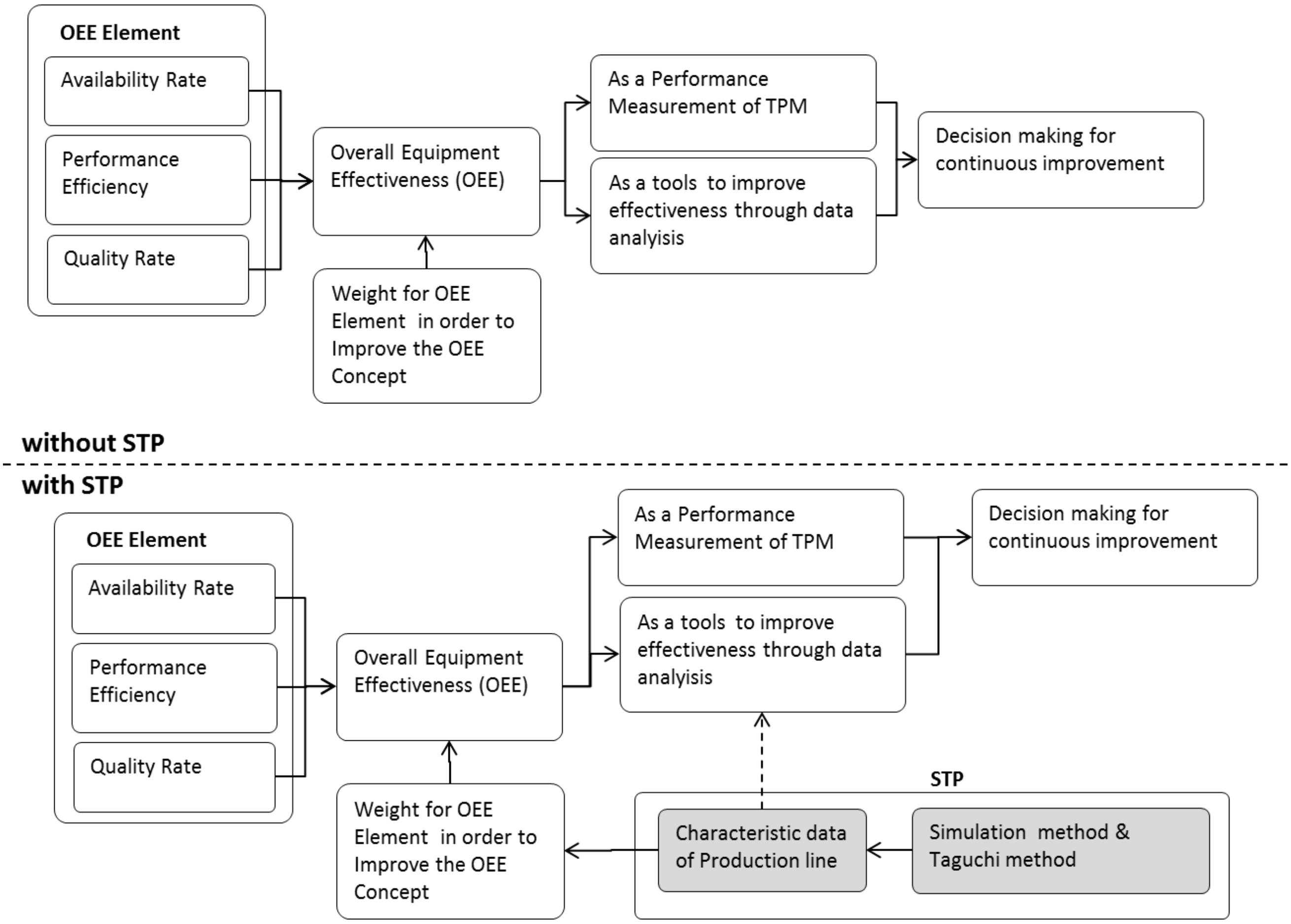


Figure 3-1. Research framework of STP.

This research present a procedure in order to get weight proportion calculation for OEE element which is more reflect to real condition in production line. After the weight proportion calculation for the OEE elements is obtained; then the OEE value can be calculated by manually as well as mention in the several references; based on real data from shop floor directly.

3.3 Experimental Procedure

The research framework is able to develop a procedure to implement the proposed idea. As mentioned previously, the procedure for this research combines simulation and Taguchi methods to measure OEE elements, as illustrated in Figure 3-2.

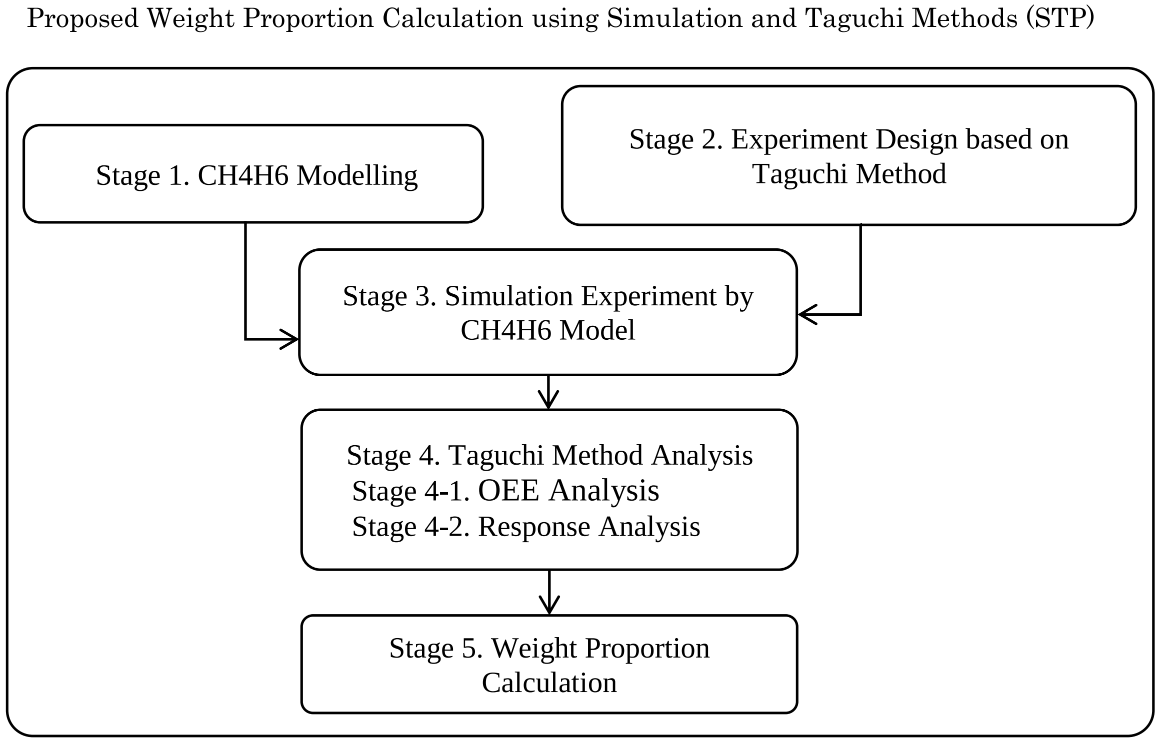


Figure 3-2. Simulation and Taguchi Procedure (STP).

The simulation model acts as an experimental tool to obtain the result using the Taguchi method approach, using Arena Simulation software. The simulation model produces an output based on control factor measurement. The three OEE elements used as control factors for this experiment are Availability rate (A), Performance efficiency (P), and Quality rate (Q). These OEE element's characteristics are observed under various levels of each control factor. The research outputs are original OEE and response table.

The response table can be used to provide data to obtain the weight of OEE elements. All procedures in this experiment will follow stage sequence numbers, as illustrated in Figure 3-2. Research preparation involves stages 1 and 2; implementation of simulation experiment takes place in stage 3. The research result is in stage 4; and is divided into two sub stages, namely OEE calculation and Response analysis. The final stage, weight proportion calculation, is the calculation of weights for OEE elements; based on the results obtained from the response table in stage 4.

3.4 Stage 1 - CH4H6 Modelling

A simulation model was developed using Arena Simulation software, for a coolant hoses manufacturing company (CH4H6 line). The CH4H6 line produces two coolant hose products, namely CH4 and CH6 hoses. The CH4H6 line simulation model was built before the first experiment was conducted. This model consists of five workstations (WS), which carry out the following processes: (WS1) machining, (WS2) deburring, (WS3) crimping, (WS4) testing, and (WS5) marking. The model layout can be seen in Figure 3-3.

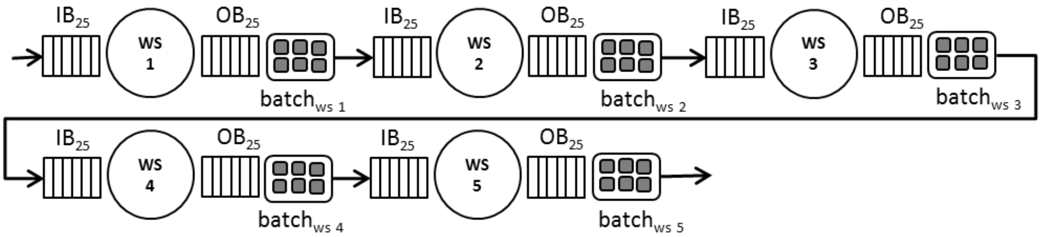


Figure 3-3. Layout model for the CH4H6 manufacturing line.

The CH4H6 line simulation model was developed under the assumption that all time-related modules in the production line use triangular random distribution. All resources work at full capacity. The parameters for the CH4H6 line are as follows: the demand for coolant hose products is 300 units; in detail, 150 units of CH4 and 150 units of CH6. Products per arrival for each product = 150 unit; maximum arrival = 1 unit; WS1 process time $t_{0,1}$ = TRIA(0.5,1,1.5), using triangular distribution; WS2 process time $t_{0,2}$ =

(0.25,0.5,0.75); WS3 process time $t_{0,3}$ = TRIA(0.5,1,1.5); WS4 process time $t_{0,4}$ = TRIA(0.5,0.75,1), WS5 process time $t_{0,5}$ = TRIA(1,1.25,1.5). Change over occurs for every product type in WS1 and WS5; total time for changeover in WS1 is 51 minutes, while in WS5, total time for change over is 24 minutes. The batch capacity in each WS in CH4H6 is 5 units, and buffer capacity for each WS is 25 units. Each WS is handled by one operator. There is no rework product in this production line. Defective products are disposed. The average route time between WS is 0.33 minutes. Work hours in the CH4H6 model are set at 9 hours per day.

Due to the important role of the simulation model in this experiment, it needs to be verified and validated. The purpose of model verification is to ensure that the model is correctly constructed. In other words, verification ensures that the model conforms to its specification and does what it is supposed to do. Model verification was conducted largely by inspection, and consisted of comparing model code to model specification (Altiok, T., and Melamed B., 2010; Kelton W., and Sadowski R., 2009). This research employed Little's Law mathematical equation for model validation:

$$w = \delta .\ \varphi \tag{3-1}$$

Where,

w = the mean number of products in the manufacturing production line (work in progress (wip)–level w in units)

δ = the mean number of products leaving the system per unit of time (throughput δ in Units/time units)

φ = the mean time a lot remains in the system (flow time φ in time units)

The production line consisted of a buffer and a batch for each WS. The waiting time for each product calculation had to consider buffer, batch, process time, and route time. The total mean flow time for each WS can be calculated as follows (Rooda, J.E., and Vervoort, J., 2007):

$$\varphi_{tot} = \varphi_B + \varphi_{Bq} + \varphi_{Bk} + t_0 + t_{route} \tag{3-2}$$

Where,

t_{route} = mean route time between workstations (in time unit)
t_0 = process time for workstations (in time unit)
φ_B = mean flow time for waiting in the buffer (in time unit)
φ_{Bq} = mean flow time for queuing on the inter-arrival of a batch (in time unit)
φ_{Bk} = mean flow time for wait-to-batch time (in time unit)

The total production time can be obtained from the WS with the longest φ_{tot} (WS which causes the most bottlenecks in the production line), multiplied by the total demand/number of batch.

The calculation's result is compared with simulation software and mathematical calculation results. A detailed animation was used to further verify that the model sufficiently replicated the real system. Validation of the model calls for comparing outputs of the simulation to the mathematical calculation. The validation uses a confidence interval of 95% to confirm the result of the simulation model. The simulation result was 834.61 minutes and the calculation was 853.6028 minutes. This shows a similarity of 97.77%, and the calculation result was within a confidence interval 95%, at 692.43-948.31 minutes, which was a valid result.

3.5 Stage 2 - Experiment Design Based on the Taguchi Method

The Taguchi method is based on Orthogonal Array (OA) experiments, which provide a set of well-balanced experiments to use (Taguchi, G., Chowdhury, S. and Wu, Y. 2007). The research objective was to measure OEE element characteristics in the CH4H6 line, using a simulation method, and analyse the results using the Taguchi method. In order to do that, the control factor assigned to the OA for this experiment was related to each

OEE element. Each consisted of three level variations, as seen in the matrix experiment in Table 3-1.

Table 3-1. Matrix Experiment Details

Control Factor in OA	Description of Control Factor	Level 1	Level 2	Level 3
A	Unplanned Downtime Failure in minutes (A)	WS1 TRIA(30, 35 , 40)	WS1 TRIA(35, 40 , 45)	WS1 TRIA(40, 45 , 50)
		WS2 TRIA(15, 20, 25)	WS2 TRIA(20, 25, 30)	WS2 TRIA(25, 30, 35)
		WS3 TRIA(20, 25 ,30)	WS3 TRIA(25, 30 ,35)	WS3 TRIA(30, 35 ,40)
		WS4 TRIA(15, 20, 25)	WS4 TRIA(20, 25, 30)	WS4 TRIA(25, 30, 35)
		WS5 TRIA(10, 15 ,20)	WS5 TRIA(15, 20 ,25)	WS5 TRIA(20, 25 ,30)
B	Performance Efficiency for each WS in minutes (P)	WS1 TRIA(0.5, 0.75 , 1.5)	WS1 TRIA(0.5, 1 , 1.5)	WS1 TRIA(0.5, 1.25 , 1.5)
		WS2 TRIA(0.25, 0.3, 0.75)	WS2 TRIA(0.25, 0.5, 0.75)	WS2 TRIA(0.25, 0.7, 0.75)
		WS3 TRIA(0.5, 0.75 , 1.5)	WS3 TRIA(0.5, 1 , 1.5)	WS3 TRIA(0.5, 1.25 , 1.5)
		WS4 TRIA(0.5, 0.6 , 1)	WS4 TRIA(0.5, 0.7 , 1)	WS4 TRIA(0.5, 0.8 , 1)
		WS5 TRIA(1, 1.2 , 1.5)	WS5 TRIA(1, 1.3 , 1.5)	WS5 TRIA(1, 1.4 , 1.5)
C	Quality Rating (Q)	99%	98%	97%

The variation of control factor will be implemented in the OA experiments. Each experiment simulation runs 10 replications with each control factor variation parameter level. In order to measure the control factor for A, P, and Q, “failure,” “speed loss,” and “product defect” were assigned, respectively, to the CH4H6 line simulation model, in accordance with the levelling of control factors in OA in this experiment.

Consequently, all variation levels used triangular random distribution to make it easier to define where the random failure would occur in the CH4H6 simulation model. It would particularly make it easier to define performance efficiency; since it must reflect the maximum capacity of the machine. An explanation of this can be described as follows; for illustration WS1 TRIA(0.5, 1 , 1.5), WS1 will operate with a minimum time of 0.5 minute per unit, and mostly (average) operate within 1 minute per unit, and a maximum operating time for WS1 of 1.5 minute per unit. The levelling of performance efficiency, as one of the control factors, simply changes the average capacity. Minimum and maximum values did not change for each level. In designing the experiment, an OA was required to conduct the experiment properly. Degree Of Freedom (DOF) calculations determine which OA is going to be used in this experiment (Mason, R. L., and Gunst, R.F., 2003; Taguchi, G., Chowdhury, S. and Wu, Y. 2007). For factors A, B, and C, if the number of levels is n_A, n_B. n_C, the degree of freedom = the number of levels-1; for illustration A=n_A-1. This experiment consisted of three control factors using three levels of variations. The DOF calculation for three control factors can be described as (3x(3-1)) = 6, respectively.

The number of experiments must be higher or the same as the number of degree of freedom calculations. Based on the DOF calculation, the OA that is suitable for this experiment is $L_9(3^4)$. This means that this OA consists of 9 experiments, with three levels of each control factor, with a maximum of 4 control factors or interactions that can be assigned to OA. The experiment uses 3 control factors for OEE element measurement (i.e., availability, performance, and quality). It does not matter if this experiment only uses 3 columns of the array (i.e., 3 factors control). The other column (the 4th column) in $L_9(3^4)$ is used as an empty column (Chao-Ton Su, 2013).

The Taguchi method in this research is not applied roundly, since the aim of this research is to observe OEE elements, which have a major influence based on variation of control factor level. The optimization step in the Taguchi method (the final step) was not conducted, because it was unnecessary to predict the optimum condition for random failure. Obviously, the optimal condition is without random failure occurs. Another reason was that this research utilizes simulation software to obtain the characteristics of production line data. Furthermore, the Taguchi method usually defines the uncontrollable (noise) factors in an experiment. The Taguchi method provides signal to noise ratio (S/N ratio) calculation in the experiment. Since this experiment was conducted through simulation software, the uncontrollable factors were not considered. The S/N ratio provides a measure of the impact of noise factors on performance. The larger the S/N ratio, the more robust the product is against noise. There are 3 S/N ratios of common interest for optimization of Static Problems, 1) Smaller the better; For the case of minimizing the performance characteristic; This is usually the chosen S/N ratio for all undesirable characteristics like “defects“, for which the ideal value is zero. 2) Nominal the best; this case arises when a specified value is most desired, meaning that neither a smaller nor a larger value is desirable. The objective for the response is to achieve a target or nominal value; most parts in mechanical fittings have dimensions which are nominal-the-best type. 3) Larger the better; for the case of maximizing the performance characteristic; when an ideal value is infinite. And it is defined to decrease variability when maximizing the response.

Therefore, analysis of variance (ANOVA) and S/N ratio calculation for larger the better scheme was applied in this experiment (equation 3-3), because the parameter measurement is OEE score. Let n is number of data, and y_1, y_2, .. y_n is the data points.

$$\frac{S}{N} = \eta \text{ dB} = -10\text{Log}\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{3-3}$$

3.6 Stage 3 - Simulation Experiment by CH4H6 Model

The simulation of the CH4H6 line was conducted through nine experiments; corresponding with OA, each experiment ran for ten replications. The simulation employed Arena Simulation software Ver. 13.9. The outcome from this experiment was divided into two main parts, namely OEE analysis and Response analysis. The final stage was the weight proportion calculation, which was proposed as a procedure (STP) for weighting OEE elements based on machine or equipment characteristics obtained from previous stages.

3.7 Stage 4 - Taguchi Method Analysis

3.7.1 Stage 4 – 1. OEE Analysis

OEE calculations and S/N ratio for each experiment are shown in Table 3-2. The Availability rate average and the Performance efficiency average varied for each experiment. For Quality rate, the result was averaged from varying results of 97 to 99%, based on the matrix experiment shown in Table 3-1. Table 3-3 provides ANOVA calculation results for all WS in CH4H6 line. The results show that quality element have significantly contribute in this experiment (P values). ANOVA calculation in this research was using confidence level 95%. For OEE element calculations (as shown in Table 3-2), the CH4H6's OEE average score for the overall experiment was 52.5%. Table 3-2 also provides OA experiment results (values of 1, 2, or 3 are level values for each control factor - refer to Table 3-1). The highest OEE score was obtained in experiment 8, with the condition of A in level 3, P in level 2, and Q in level 1. From this table, it can be seen that the higher OEE score, the higher S/N ratio score (consider the negative value).

Table 3-2. Average OEE calculation result for each experiment

No. EXP	A	P	Q	Availability Rate	Performance Efficiency	Quality Rate	OEE Average	S/N ratio (dB)
1	1	1	1	95.7%	55.9%	99.0%	52.9%	-6.8755
2	1	2	2	95.6%	56.3%	98.0%	52.7%	-6.90924
3	1	3	3	95.5%	56.5%	97.0%	52.4%	-6.96771
4	2	1	2	94.5%	56.5%	98.0%	52.3%	-6.9758
5	2	2	3	94.7%	56.6%	97.0%	52.0%	-7.02698
6	2	3	1	94.7%	56.0%	99.0%	52.4%	-6.95372
7	3	1	3	93.7%	57.7%	97.0%	52.4%	-6.96481
8	3	2	1	93.8%	57.5%	99.0%	53.3%	-6.80809
9	3	3	2	93.7%	56.4%	98.0%	51.8%	-7.06709
Average for Experiment				94.7%	56.6%	98.0%	52.5%	-6.94988

Table 3-3. ANOVA for All Workstations in CH4H6 Line

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Availability	2	0.006987	0.006987	0.003493	0.86	0.539
Performance	2	0.010502	0.010502	0.005251	1.29	0.437
Quality	2	0.022554	0.022554	0.011277	2.76	0.266
Residual Error	2	0.008158	0.008158	0.004079		
Total	8	0.048201				

Theoretically, the ideal condition is supposed to be where all control factors are in level 1. This possibility was caused by the use of triangular random distribution in the simulation model.

3.7.2 Stage 4 – 2. Response Analysis

The results of the simulation experiment are shown in Table 3-4 as a response table. This response table is the overall experiment's result (S/N ratio), grouped by average results for each level, and for each control factor. The Delta in Table 3-4 implies a different value from all levels for each control factor. This can be obtained from the calculation of maximum value minus the minimum value for each level of control factor.

It appears as if each control factor is being measured for its sensitivity, how high the variation (delta) obtained will be, because of changes for each level of control factor. In other words, this response table can describe which factor has the highest sensitivity through its levelling parameter.

Table 3-4. Response results by S/N ratio (dB) for OEE elements for the CH4H6 line and Weight Proportion Calculation

Level	**Availability Rate**	**Performance Efficiency**	**Quality Rate**
1	-6.917	-6.939	-6.879
2	-6.986	-6.915	-6.984
3	-6.947	-6.996	-6.987
Delta	0.068	0.081	0.107
Rank	3	2	1
Weight Proportion Calculation by S/N Ratio			
Total of Delta	Availability Rate	Performance Efficiency	Quality Rate
0.26	26.56%	31.64%	41.80%

The quality rate has the highest delta value in the CH4H6 line, followed by Performance efficiency and Availability rate. This result indicates that any improvement related to quality rate in the CH4H6 line will affect the

OEE score significantly more than the other OEE elements. The weight proportion calculation (which will be discussed in the next section of this research) is a calculation of weight for each control factor.

3.8 Stage 5 - Weight Proportion Calculation

The proposed idea for weighting OEE elements in this research experiment, based on the response shown in Table 3-4, describes that the first rank mean OEE element has a significant result, based on changes in the level of control factor in this experiment. A total of the delta calculation is needed to obtain a weight percentage for each OEE element. A simple mathematical equation for this stage can be described as follows:

$$w_A = \frac{\Delta_1}{\sum_{i=1}^{3} \Delta_i} \tag{3-10}$$

$$w_P = \frac{\Delta_2}{\sum_{i=1}^{3} \Delta_i} \tag{3-11}$$

$$w_Q = \frac{\Delta_3}{\sum_{i=1}^{3} \Delta_i} \tag{3-12}$$

Where, w_A is the weight of the availability rate element, w_P is the weight of the performance efficiency element, and w_Q is the weight of the quality rate element. In addition, Δ_1, Δ_2, and Δ_3, are the deltas for A, P, and Q, respectively. For all weight values, $w_A + w_P + w_Q = 1$. The calculation for weighting OEE elements from the response table's result is shown in Table 3-4; in the weight proportion calculation section. This table describes how to obtain the weight for each OEE element from the simulation experiment's results. The same procedures can also be used to calculate the OWEE and PEE for each WS (as shown in Table 3-5).

The calculation of weighting OEE for OWEE by STP is specifically different from PEE by STP; even though the outcome is similar. All OWEE calculations used Equation 6. For PEE calculations, Equation 5 was used, while values for $k_1 = w_A$, $k_2 = w_P$, and $k_3 = w_Q$, were obtained from the weight proportion calculation for each WS, from the response table's results. For the original OEE calculation, Equation 1 was used, based on OEE elements from experiment results.

3.9 Evaluation of Weight Proportion for OEE Elements

For the evaluation of weight proportion, compared to other techniques, each method of OWEE, PEE, and original OEE is shown in Table 3-5. OWEE and PEE by STP use the weighting OEE element calculation based on Table 3-4 procedures for each WS calculation.

Meanwhile, OWEE and PEE (without STP) weight calculations used the ROC method in other research as reference for weighting OEE elements (Wudhikarn, R., 2010b), with the assumption that the weighting value was different for each OEE element. The results calculation comparison from OWEE and PEE by STP rank showed similar results. Meanwhile, OEE and PEE (without STP) show lesser value percentage scores in each WS. Table 3-5 shows that the highest result for OEE measurement was OWEE by STP, followed by PEE by STP, and original OEE.

Table 3-5. Calculation comparison for each OEE WS From OWEE, PEE, and Original OEE

Workstation	OEE Original	OWEE by STP	OWEE without STP	PEE by STP	PEE without STP
WS1	58.30%	85.86%	77.00%	84.49%	75.50%
WS2	58.30%	86.01%	76.10%	84.35%	74.30%
WS3	29.10%	76.13%	57.00%	67.73%	48.60%
WS4	43.70%	81.06%	66.50%	77.01%	62.30%
WS5	72.90%	90.97%	85.30%	90.48%	84.70%
Average	52.46%	84.01%	72.38%	80.81%	69.08%

Even though the value difference of weight was less for each WS. The comparison result of original OEE versus OWEE by STP, or PEE by STP (shown in Table 3-5) surprisingly shows a very different result; particularly for WS3, where difference score was very high. WS3 was the assembly crimping station for the CH4H6 line. This result was possibility influenced by other areas of the production line (i.e., crimping manufacture), which supported the crimping parts for the crimping process on the CH4H6 line. Interestingly, WS that had a change over in the CH4H6 line were WS1 (51 minutes for each change over) and WS5 (24 minutes for each change over), had a higher OEE score. This indicates that the changeover in WS1 and WS5 had less influence on the OEE score in the CH4H6 line.

The result comparison (shown in Table 3-5) specified the importance of this experiment's results, and was used as a baseline to calculate the weight for other OEE elements. Furthermore, the outcome shows that STP can be implemented to calculate the weight of OEE elements for OWEE, as well as PEE, in each WS. Furthermore, this also indicates the importance of data provided by the simulation and the experiment, for considering decisions of priority improvement in the production line.

In conclusion, we recognize that the STP can obtain more detail value than other weighting techniques when implemented in PEE, as well as in OWEE, in the CH4H6 line. The baseline for weighting OEE elements in this research refers to the response of the simulation experiment through the Taguchi method; which shows different values (delta) for each OEE element and for each group level.

3.10 Other Experiments of Weight Proportion for OEE Elements

This research also provides another implementation of STP in another manufacturing line. This paper presented the Crimping Manufacturing Line (CML) as another example. Compared to CH4H6, which had five WS, the CML consisted of three WS processes, namely Machining; Testing, and Marking. The procedure of weight proportion calculation was the same as with STP. The matrix experiment table for CML can be seen in Table 3-6.

Table 3-6. Matrix experiment details for CML

Name	Control Factor	Level 1	Level 2	Level 3
A	Unplanned Downtime Failure (in minute) for each workstation, using triangular distribution	WS1 TRIA(30, 45 , 60)	WS1 TRIA(45, 60 , 75)	WS1 TRIA(60, 75 , 90)
		WS2 TRIA(15, 20, 30)	WS2 TRIA(20, 25, 30)	WS2 TRIA(25, 30, 40)
		WS3 TRIA(20, 30 ,40)	WS3 TRIA(30, 40 ,50)	WS3 TRIA(40, 50 ,60)
P	Performance Rating for each workstation (in minute) using triangular distribution	WS1 TRIA(0.5, 1 , 2.5)	WS1 TRIA(0.5, 1.5, 2.5)	WS1 TRIA(0.5, 2 , 2.5)
		WS2 TRIA(0.5, 0.75, 3)	WS2 TRIA(0.5, 1.5, 3)	WS2 TRIA(0.5, 2 , 3)
		WS3 TRIA(1, 1.25 , 3)	WS3 TRIA(1, 1.75 , 3)	WS3 TRIA(1, 2.25 , 3)
Q	Quality Rating	99%	98%	97%

Table 3-7. Average OEE Calculation Result for the Crimping Manufacturing Line (CML)

No. EXP	A	P	Q	Availability Rate	Performance Efficiency	Quality Rate	OEE Rate	S/N Ratio (dB)
1	1	1	1	92.48%	52.58%	99.00%	48.35%	-6.87783
2	1	2	2	92.43%	49.93%	98.00%	44.92%	-7.51744
3	1	3	3	93.08%	46.11%	97.00%	42.06%	-8.08891
4	2	1	2	90.76%	53.56%	98.00%	47.35%	-7.05947
5	2	2	3	90.56%	50.38%	97.00%	43.65%	-7.76627
6	2	3	1	91.11%	46.70%	99.00%	41.58%	-8.18858
7	3	1	3	88.45%	55.53%	97.00%	46.47%	-7.22213
8	3	2	1	88.64%	50.55%	99.00%	42.50%	-7.99799
9	3	3	2	89.15%	45.99%	98.00%	40.49%	-8.41992
Average OEE's value for 3 WS				**90.7%**	**50.1%**	**98.0%**	**44.2%**	**-7.68206**

The results of STP are shown in Tables 3-7 and 3-8. This template table is the same as the previous one. Table 3-7 shows that the lowest OEE element in the CML was performance efficiency, with the highest OEE value for experiment number 1. Table 3-8 also shows the OEE element with the highest sensitivity if there is level changing in the experiment, which was performance efficiency.

Table 3-8. Response result OEE element by S/N (dB) ratio for the Crimping Manufacturing Line and the Weight Proportion Calculation

Level	Availability Rate	Performance Efficiency	Quality Rate
1	-7.495	-7.053	-7.688
2	-7.671	-7.761	-7.666
3	-7.88	-8.232	-7.692
Delta	0.385	1.179	0.027
Rank	2	1	3
Weight Proportion Calculation			
Total of Delta	**Availability Rate**	**Performance Rate**	**Quality Rate**
1.591	24.20%	74.10%	1.70%

Table 3-8 also provides a calculation for the weight proportion calculation of OEE elements. The results of weighted OEE element calculations (based on Tables 3-7 and 3-8) can be described as follows; $w_A = 24.20\%$; $w_P = 74.10\%$; and $w_Q = 1.70\%$. In addition, the average Availability rate = 90.72%; Performance efficiency = 50.10%; and Quality rate = 98%. The weighted OEE value by using OWEE was 60.7% while by using PEE was 58.5%, compared to the original OEE value of 44.2%. Tables 3-7 and 3-8 clearly show the benefit of using STP. It also shows that STP can be implemented to other cases.

Chapter IV

Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line

4.1 Introduction

Manufacturing systems often operate at less than full capacity while producing quality products. Among the many reasons for low productivity are: incompatible design specifications, frequent occurrences of product defects, high machine downtime, low operator skills, etc.

Low productivity increases the operational cost, and it comes as no surprise that manufacturing companies are very much concerned about the effective utilization of the available resources. Other significant problems related to low productivity include unfulfilled customer demands and longer lead-times. In order to increase productivity, a company will generally conduct an improvement program aimed at reducing machinery downtime, increasing operator skills or machine capacity, reducing product defects, etc. That program is known as Total Productive Maintenance (TPM). The goal of TPM is to increase the productivity of the equipment in a plant by involving all the employees from the various departments (production, maintenance, technical services, stores, etc.) in the process. The most effective way to maximize output is to remove the barriers that stand in the way of equipment effectiveness. The lean manufacturing philosophy takes the same route by striving to increase efficiency through waste reduction. Similarly, ineffective machines and equipment can also be considered as ‘waste’. While the TPM model provides a quantitative metric for measuring the productivity of specific production equipment, it has been observed that an appropriate measurement is required for the problem identification in order to improve and increase productivity. This entails the establishment of suitable metrics for measurement (Raja and Kannan, 2007).

Some researchers are in agreement that Total Productive Maintenance

(TPM) is a reliable tool for the enhancement of equipment effectiveness and equipment output. The findings indicate that TPM not only increases the efficiency and effectiveness of manufacturing systems, but also prepares the plant in general to engage in globally competing economies (Singh and Singh, 2012).

There are six major causes for the loss of effectiveness in TPM. These are set-up and adjustments, equipment failure, reduced speed, idling and minor stoppages, reduced yield (from start up to stable production), and process defects. According to (Nakajima, 1988; Wang, 2005), the first two are downtime losses as they reduce the availability of the equipment, the next two are considered as speed losses as they reduce the performance level of the system, while the last two are categorized as defect losses or rejected low quality products.

Overall Equipment Effectiveness (OEE) is a performance indicator that covers the measurement of the six major causes for the loss of effectiveness in TPM. The OEE directly measures product quality, loss and the ability to deliver according to a schedule (Singh and Singh, 2012). Before the advent of OEE, only availability was considered in equipment utilization and this resulted in the overestimation of equipment utilization. The OEE methodology is a proven approach for improving the overall performance of equipment (Badiger et al., 2008). From a survey, (Sohal et al., 2010) found that the OEE has typically advanced from a base measure for efficiency as the initial purpose, to being a tool to improve effectiveness for analysing data, to supporting continuous improvement objectives.

The original OEE involved three elements which have been defined by Nakajima (1988) as: (A) Availability rate, (P) Performance rate, and (Q) quality rate. OEE percentages have become a metric to compare current equipment performance to world-class performance. The measure of 85% equipment effectiveness has become known as a “world-class OEE”. Once used as a benchmarking score for “world-class”, the OEE has eventually become a way to compare one piece of equipment with another, even though the equipment performs different functions in different processes or even if the equipment is located in a different plant. The OEE was designed and developed to characterize and communicate the major equipment-related losses.

4.2 Research Objective

This research proposes a procedure to enhance the OEE through simulation and a statistical experiment by the Taguchi Method. With the improvement, the OEE can provide more information to support the decision-makers in a company, especially those in the middle management at the tactical level such as production managers, production supervisors, etc.

4.3 Proposal of Research Framework

Generally, the framework of this research (Figure 4-1) is to provide a combination of simulation experiments that can deliver information that is useful for determining the priority of improvement.

The information outcomes consist of the data measurements of each OEE element contribution, the value added cost and non-value added cost utilising the OEE scoring procedure. This additional information goes a long way in determining the improvement priority of the machine or equipment. With the OEE calculation alone, only the element with the lowest score is identified, and there is no guarantee that any improvement to this element will lead to a favourable result. On the other hand, the additional information from the research procedure will include the level of improvement of each OEE element and its effect on the OEE score. This is very useful when it comes to decision-making for priority improvement in the production line.

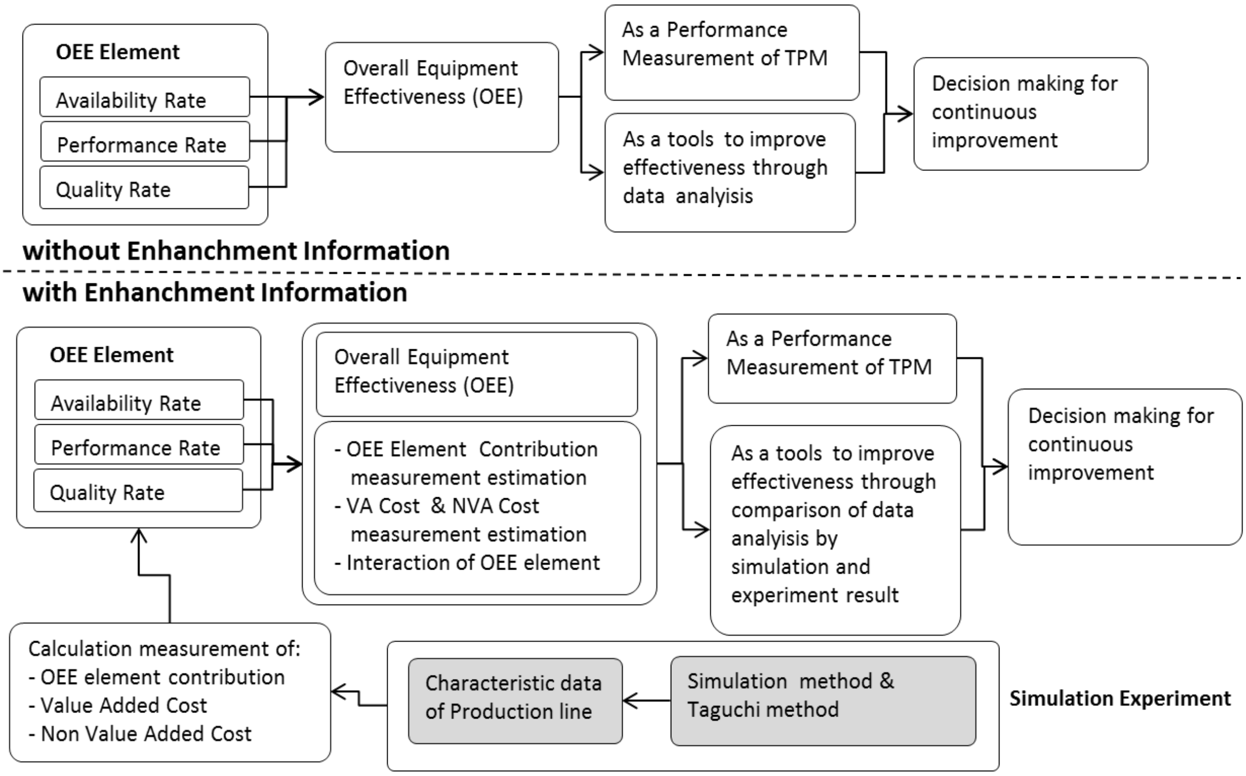


Figure 4-1. Proposal for Research Framework

4.4 Research Methodology

The research methodology was a combination of simulation and the Taguchi experimental method. A simulation model of the CML served as an experimental tool while the Taguchi method served as an experimental method. Two types of measurements were employed in this experiment. The first used the OEE score for each workstation (WS) and each experiment, while the second was by cost measurement. The cost measurement was again divided into two types of measurements; value added cost and non-value added cost (McNair et al., 2001). The cost measurement will be explained in more detail in the simulation section. The cost budgeting assumption for defining the operational cost for each product was provided in the simulation software. Each procedure in this research will be explained in stages (Figure 4-2).

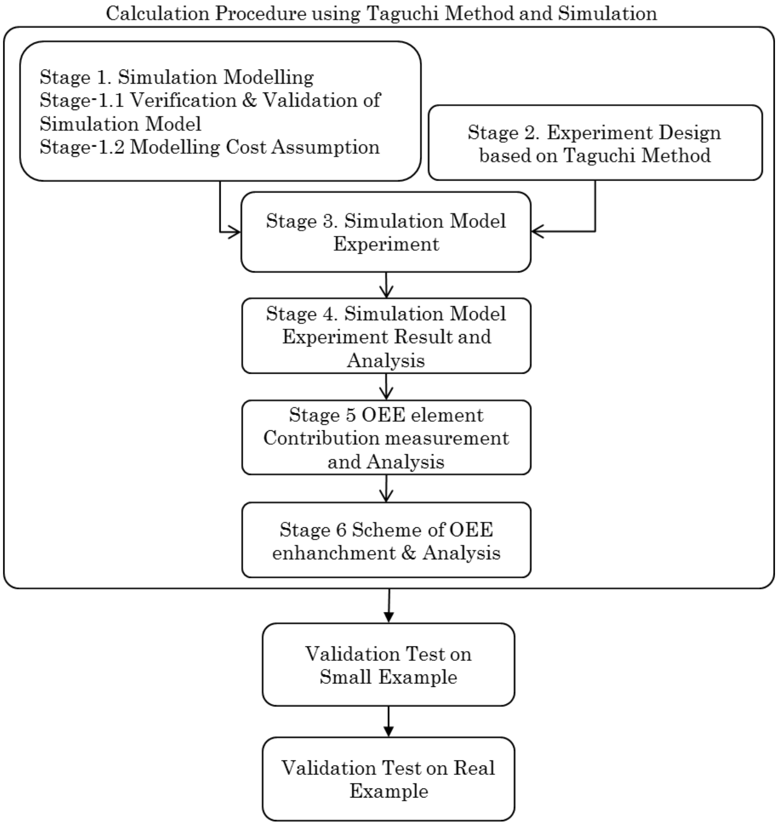


Figure 4-2. Proposed Procedure Research

The research procedure was grouped into several stages (within the large rectangle in Figure 4-2). In order to ensure that the procedure was valid, after the calculation procedure was completed, it then continued with a validation on a small example (on a single WS) and the last validation was on a real example. This paper presents two types of real examples from the manufacturing line. The first one (CML) is included in the research methodology. In addition, the other one is the CH4H6 line that produces two types of coolant hoses that will be explained in another part of this paper.

4.4.1 Stage-1 Simulation Modelling

The research focus will be on the crimping manufacturing line (CML) for all coolant hoses in Section 2 (Figure 4-3). The CML supports two production lines together with Sections 3 and 4 for each coolant hose type of crimping material. A simulation model was developed using the Arena Simulation

Software for a Coolant Hoses Manufacturing (CHM) company. This factory consists of six sections. Four sections are production lines which produce Coolant Hose#4(CH4), Coolant Hose#6(CH6), Coolant Hose#8(CH8), and Coolant Hose#10(CH10), while two sections are warehouses for storage as seen in Figure 4-3. The CML simulation model was built before the experiment commenced. This model consisted of three workstations (WS) where the procedures for machining, testing and marking were carried out. The layout of the model can be seen in Figure 4-4. The parameters for the CML were as follows: The demand for coolant hose products was 600 units comprising 300 units of coolants CH4 and CH6, and 300 units of coolants CH8 and CH10. The product time between arrivals was 120 minutes.

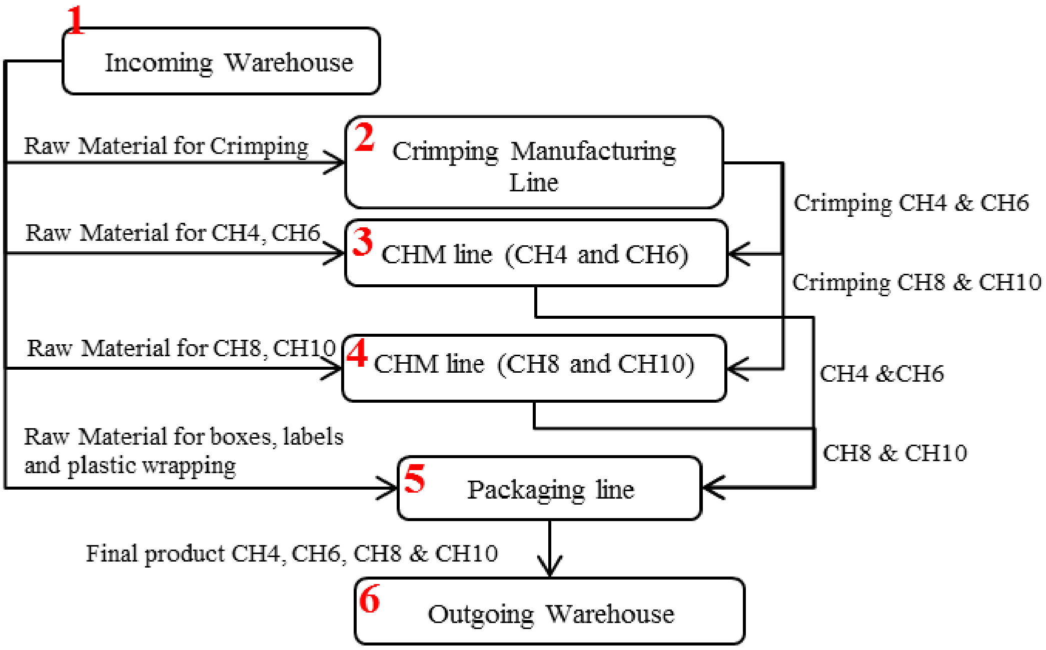


Figure 4-3. Flow diagram of CHM factory floor for all sections

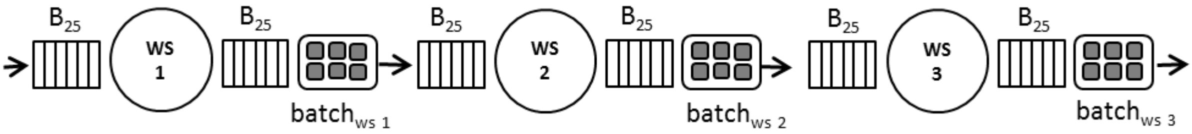


Figure 4-4. Model layout for the Crimping Manufacturing Line (CML).

Product per arrival for each product = 100 units; maximum arrival = 3 units; using triangular random distribution (TRIA), the annotation representing the random distribution TRIA(min value, most value, max value), WS1 process time t0,1 = TRIA(0.5,1,1.5); WS2 process time t0,2 = (0.5,0.75,1); WS3 process time t0,3 = TRIA(1,1.25,1.5). A changeover occurred for every product type in WS1 and WS3; the total time for the changeover in WS1 was 40 minutes, while in WS3, the total time for the changeover was 20 minutes.

The batch capacity in each WS in the CML was 5 units, and the buffer capacity for each WS was 25 units. Each WS was handled by one operator. The route time between the WSs was 0.3 minutes. The work hours in the CHM model were set at 9 hours per day. The simulation runs were replicated 10 times.

4.4.2 Stage -1 .1 Verification and Validation of the Simulation Model

The significant role of the simulation model in this experiment required that it be verified and validated. The purpose of model verification is to ensure that the model is correctly constructed. Verification ensures that the model conforms to its specifications and performs to expectations. This is conducted largely by inspection, which involves ensuring that the model code corresponds to the specifications (Altiok, T., and Melamed B. 2010; Kelton W., and Sadowski R., 2009). This research employed Little's mathematical equation for validating the model (Rooda and Vervoort, 2007):

$$w = \delta . \varphi \tag{4-1}$$

Whereby;

w = The mean number of products in the manufacturing production line (work in progress (wip)–level w in units)

δ = The mean number of products leaving the system per unit of time (throughput δ in units/time units)

φ = The mean time a lot remains in the system (flow time φ in time units)

The production line consisted of a buffer and a batch for each WS and the calculation for the waiting time for each product had to consider the buffer, batch, process time, and route time. The total mean flow time for each WS can be calculated as follows:

$$\varphi_{tot}=\varphi_{B}+\varphi_{Bq}+\varphi_{Bk}+t_{0}+t_{route} \tag{4-2}$$

Whereby;

t_{route} = route time between workstations (in time unit)

t_0 = process time for workstation (in time unit)

φ_B = mean flow time for waiting in buffer (in time unit)

φ_{Bq} = mean flow time for queuing on the inter-arrival of a batch (in time unit)

φ_{Bk} = mean flow time for wait-to-batch time (in time unit)

The total production time could be calculated by multiplying the WS with the longest φ_{tot} (the WS which caused the most bottlenecks in the production line) with the total demand/number of batches. The result was then compared to the results from simulation software and mathematical calculations. A detailed animation was used to further verify that the model sufficiently replicated the real system.

Table 4-1. Validation of CML (Section 2 in CHM) Simulation model

Name in CHM	Simulation Result (in minute)	Calculation Result (in minute)	Confidence interval range 95%	Stated
CML	385.59	380.0199	342.13-519.58	Valid

The validation of the model called for comparing the outputs of the simulation process to mathematical calculations. The calculated results of the validation can be seen in Table 4-1. The validation used a confidence interval of 95% for confirming the results of the simulation model.

4.4.3 Stage - 1 .2 Modelling Cost Assumption

This research analysis also included the cost for measuring the production line performance. Several cost assumptions needed to be declared in the simulation, and some of cost assumptions that were used in this experiment are described in this section. Other information that required consideration were: the demand was for 600 units; with the assumption that the crimping price in the market was $9 or ¥843 (assumption $1= ¥93.67); the total price was calculated as ¥843 x 600 unit = ¥505,818. The lead time for fulfilling the demand was 27 work hours (three days), the total number of workers in the shop floor was 5, and the work hours per day was 10 hours inclusive of a 1 hour rest allowance (540 minutes of effective work hours).

Table 4-2. Budgeting Assumption for Simulation of CML model

Budget Item	%	Yen per hours	Yen per Unit
% budget for Worker	25%	¥936.70	¥42.15
% budget for direct material	10%	¥3.12	¥84.30
% budget for holding cost	5%	¥1.56	¥42.15
% budget for VA Process	10%	¥3.12	¥84.30
% budget for waiting Cost	5%	¥1.56	¥42.15
% budget for transport	5%	¥ 1.56	¥42.15
TOTAL	65%		

Table 4-3. Cost Assumption Definition in Simulation Model for WS

Type of Cost	Role Definition in Simulation model	Assumption Value	Remarks
Busy/Hour	Cost per hour of a resource (machine or equipment) that is processing an entity. The resource becomes busy when it is originally allocated to an entity and becomes idle when it is released. During the time when it is busy, cost will accumulate based on the busy/hour cost.	¥ 936.70	VA Cost
Idle/Hour	Cost per hour of a resource that is idle. The resource (machine or equipment) is idle while it is not processing an entity. During the time when it is idle, cost will accumulate based on the idle/hour cost.	¥936.70	NVA Cost
Per Use (per product)	Cost of a resource (machine or equipment) on a usage basis, regardless of the time for which it is used. Each time the resource is allocated to an entity, it will incur a per use cost.	¥ 42.15	VA Cost

The percentage cost allocation for each budget item came from the total price calculated (¥505,818) multiplied by the percentage budget cost for each item, whereas the percentage value for each budget item was assumed. Based on this information, the cost assumption for production was calculated as shown in Table 4-2.

For the role definition in the simulation, each cost assumption from Table 4-2 was assigned to an entity product as can be seen in Table 4-3 and Table 4-4. Generally, there are two types of operational costs: the value added cost (VA), and the non-value added cost (NVA). The VA costs are those that evolve in relation to any activity that generates added value for the product.

Examples of these activities are the main production process and the transportation of products to the next WS. As for the NVA, the costs evolve according to any activity that does not provide any added value to the product. Examples of these activities are idle operators and waiting. These two types of costs are assigned to each entity (product) and each WS (Machine or equipment). The cost in each WS and the entity product are displayed in Tables 4-3 and 4-4. The term 'entity' is used in the simulation model of the CML and is assigned the same meaning as product.

Table 4-4. Cost Assumption in Simulation Model for Each Product

Type of cost	Role Definition in Simulation model	Assumption Value	Remarks
Holding Cost/Hour	Hourly cost of processing the entity through the system. This cost is incurred when the entity is anywhere in the system.	¥1.56	NVA Cost
Initial VA Cost (per product)	Initial cost value that will be assigned to the value added cost attribute of the entity. This attribute accrues the costs incurred when an entity is spending time in a value added activity.	¥84.3	VA Cost
Initial Waiting Cost (per product)	Initial cost value that will be assigned to the waiting cost attribute of the entity. This attribute accrues the costs incurred when an entity is spending time in a wait activity, e.g. waiting to be batched or waiting for resource(s) at a Process module.	¥42.15	NVA Cost
Initial Transfer Cost (per product)	Initial cost value that will be assigned to the transfer cost attribute of the entity. This attribute accrues the costs incurred when an entity is spending time in a transfer activity.	¥ 42.15	VA Cost

4.4.4 Stage - 2 Experiment Design Based on the Taguchi Method

The Taguchi method was developed by Genichi Taguchi of the Nippon Telephones and Telegraph Company, Japan. It is based on an orthogonal array experiment which provides a set of well-balanced experiments.

The research objective is to measure the characteristics of the OEE elements in the CML using the simulation method, and analysing the results with the Taguchi method. To accomplish this, the control factors in this experiment were in relation to the OEE elements of (A) availability rate, (P) performance rate, and (Q) quality rate, with two variation levels each, as can be seen in Table 4-5. The variation in the control factors were implemented in the Orthogonal Array (OA) experiments. Each experiment simulation ran 10 replications with each control factor variation. In order to measure the control factors for A, P, and Q with regard to “failure,” “speed loss,” and “product defect”, these OEE elements were respectively assigned to the CML simulation model in accordance with the levelling of the control factors in the OA experiments.

Consequently, all the variation levels utilised triangular random distribution to make it easier to define the location where random failure would occur in the CML simulation model. The performance efficiency would be particularly easy to define as it would reflect the maximum capacity of a machine.

Table 4-5. Matrix Experiment for CML

Name	Control Factor	Level 1	Level 2
A	Availability (A) for each WS, using Triangular Distribution	WS1 TRIA(30, 45 , 60)	WS1 TRIA(45, 60 , 75)
		WS2 TRIA(15, 20, 30)	WS2 TRIA(20, 25, 30)
		WS3 TRIA(20, 30 ,40)	WS3 TRIA(30, 40 ,50)
P	Performance (P) for each WS, using Triangular Distribution	WS1 TRIA(0.5, 1 , 2.5)	WS1 TRIA(0.5, 1.5 , 2.5)
		WS2 TRIA(0.5, 0.75, 3)	WS2 TRIA(0.5, 1.5, 3)
		WS3 TRIA(1, 1.25 , 3)	WS3 TRIA(1, 1.75 , 3)
Q	Quality (Q)	95%	99%

An explanation on this is as follows: As illustrated by WS1 TRIA(0.5, 1, 2.5), WS1 will operate with a minimum time of 0.5 minutes per unit, and mostly (average) operate within 1 minute per unit, with a maximum operating time of 2.5 minutes per unit. The levelling of performance efficiency occurred as one of the control factors only changed the average capacity. The minimum and maximum values did not change for each level. In designing the experiment, an OA was required to conduct the experiment properly. The Degree Of Freedom (DOF) calculations determined which OA was to be used in this experiment (Mason, R. L., and Gunst, R.F., 2003; Taguchi, G., Chowdhury, S. and Wu, Y. 2007).

For factors A, B and C, if the number of levels was n_A, $n_B.n_C$, the degree of freedom = the number of levels-1, as illustrated by $A=n_A-1$. This experiment consisted of three control factors with two variation levels. The DOF calculation for the three control factors and the three interactions (AxP, AxQ, and PxQ) can be described as (3x(3-1)) + (3x(2-1) x(2-1)) = 6, respectively. The number of experiments must be higher or equivalent to the degree of freedom calculations. Based on the DOF calculation, the OA that was deemed suitable for this experiment was $L_8(2^7)$. This OA consisted of eight experiments with two levels for each control factor and a maximum of 7 control factors or interactions. This experiment used two control factors for measuring the OEE elements of availability, performance and quality. It was immaterial that only three columns of the array (three control factors) were used and the 7th column in $L_8(2^7)$ was left empty (Chao-Ton Su, 2013). The Taguchi method was not applied roundly because the main objective was to identify the OEE element with the highest contribution based on variations in the control factor level. Hence, in this research, the Taguchi method was not used for optimization. The measurement of the VA and NVA costs for each WS and each product utilised the OEE scoring procedure.

4.4.5 Stage -3 Simulation Model Experiment

The simulation of the CML was conducted in eight experiments. Each experiment was replicated ten times corresponding to the OA The simulation employed the Arena simulation software ver. 13.9. The outcome from this experiment was divided into an experimental result analysis and a response analysis, which were related to the OEE element contribution measurement.

4.4.6 Stage -4 Simulation Model Experiment Result and Analysis

Table 4-6 and Table 4-7 reflect the outcomes of the experiments. Table 4-6 describes each variation, including the OEE value for each WS for all the experiments. Figure 4-3, which is an illustration of Table 4-6, helps to simplify the description. As can be seen in Figure 4-3 and Table 4-6, the average OEE score for all the WSs for the highest condition of OEE values was attributed to the first experiment and the lowest to the eighth experiment. For the VA cost, the lowest condition was attributed to the first experiment and the highest to the fourth experiment. As for the NVA cost, the lowest condition was attributed to the first experiment and the highest to the eighth experiment. From Table 4-6 and Figure 4-3, it can be deduced that the OEE scores for all the WSs, and the NVA costs for all the WSs were in a vice versa situation where the experimental results were concerned. It should be noted that the high OEE score did not guarantee that the Value Added (VA) cost would display the same condition in the experimental results. From Table 4-6 and Figure 4-3, it can be assumed that the higher the OEE score, the lower the NVA cost. However, more data from this experiment was required to verify this assumption.

The lowest condition for OEE values in the CML model simulation was located in WS2 (Table 4-7). This table also reveals that WS3 recorded the highest OEE score with the lowest NVA cost and the highest VA cost. These results were in accordance with those in Table 4-6.

On the other hand, while WS2 recorded the lowest OEE score, it did not have the highest NVA cost. WS2 and WS1 recorded slightly different OEE scores and this could be due to the “random effect” between replications. However, significant differences were observed between WS3 and WSs 2 and 1 for OEE scores, VA costs, and NVA costs. The OEE score fluctuation in the experiments for each WS is shown in Figure 4-5. This graph is an illustration of Table 4-6. Low OEE scores were evident for experiments three, five and eight.

The third experiment was mostly influenced by the performance and availability condition in Level 2, the fifth experiment was mostly influenced by the performance condition in Level 2, while the eighth experiment - which recorded the lowest OEE score - was mostly influenced by the availability condition in Level 2 (Table 4-5 matrix of the experiment). Figure 4-5 reveals that the availability element was the dominating condition in this research.

Table 4-6. Orthogonal Array Experiment

EXP	A	P	Q	OEE WS1	OEE WS2	OEE WS3	OEE Average ALL WS	VA Cost All WS	NVA Cost All WS
1	1	1	1	31%	29%	52%	37%	¥118926	¥24522
2	1	1	2	27%	25%	45%	33%	¥119657	¥36990
3	2	2	1	24%	22%	40%	29%	¥124220	¥40653
4	2	2	2	29%	27%	48%	35%	¥124907	¥25705
5	1	2	1	24%	23%	41%	29%	¥124235	¥39038
6	1	2	2	29%	27%	49%	35%	¥124602	¥28225
7	2	1	1	25%	23%	41%	30%	¥119751	¥40243
8	2	1	2	22%	20%	36%	26%	¥120016	¥52542

Table 4-7. Average OEE element scores for each WS

Average for	Availability	Performance	Quality	OEE	VA Cost	NVA Cost
WS1	87%	33%	97%	26%	¥39,147.5	¥13,604.0
WS2	94%	28%	97%	25%	¥39,724.6	¥13,026.8
WS3	92%	52%	97%	44%	¥43,167.1	¥9,358.9

As mentioned earlier, the VA cost is closely related to all activities in the WSs that are linked to the main production activity. As illustrated in Figure 4-6, it appears that the VA cost was dominated by the performance element as the VA cost rose in tandem with a longer duration of the performance element.

This was clearly evident from the third to sixth experiment. This result can be verified by referring to Table 4-6, where in experiments three to six, the performance element condition in Level 2 displayed a longer process time in each WS.

In Figure 4-6, it can be observed that the highest OEE score (WS3) came with the highest VA cost. Figure 4-7 shows the NVA cost for each WS and reveals that the NVA cost at each WS for each experiment was higher than the VA cost in Figure 4-6.

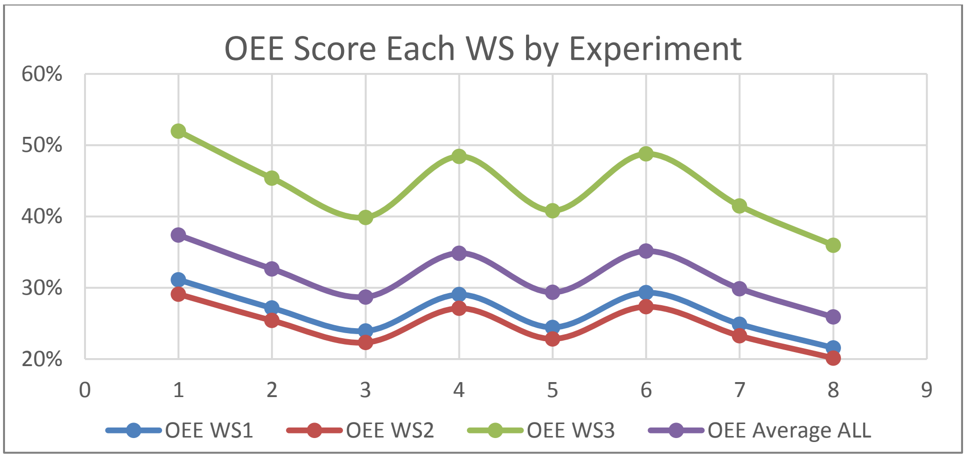


Figure 4-5. OEE Measurement Experiments

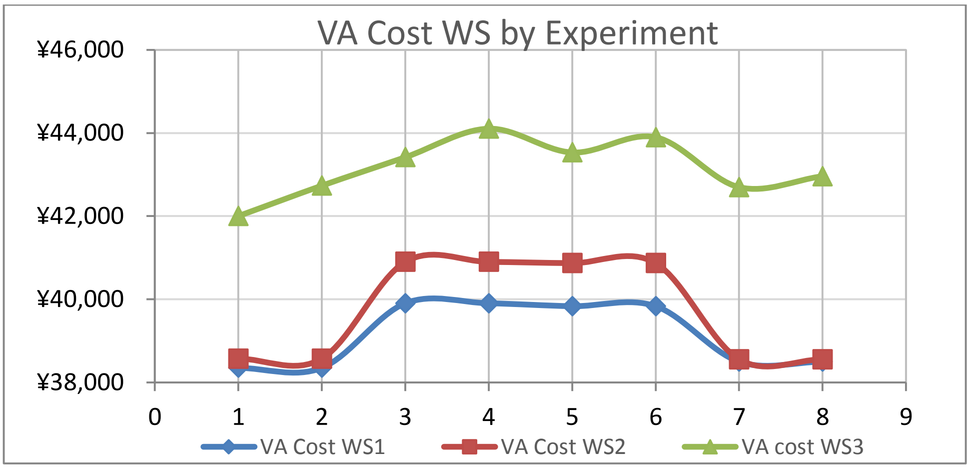


Figure 4-6. VA Cost for each WS

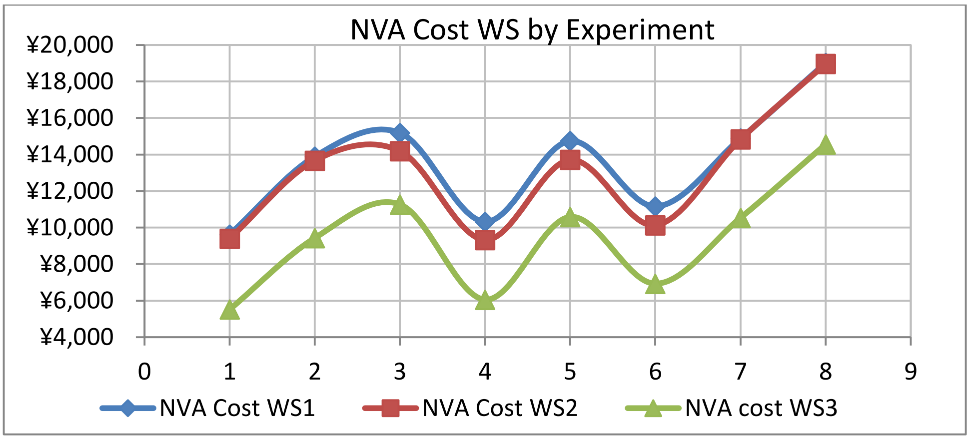


Figure 4-7 NVA Cost for each WS

If Figure 4-7 (NVA cost) were to be compared with Figure 4-5 (OEE score), the configuration of the graph would appear to be contradictory. This signifies that the lower the OEE score, the higher the NVA cost value, and vice versa.

4.4.7 Stage -5 OEE Element Contribution Measurements and Analysis

The purpose of this stage was to identify the OEE element with the highest influence on the OEE score. There were three types of measurements for this experiment, as mentioned earlier. The first measurement was by the OEE score, as shown in Table 4-8; the second measurement was by the VA cost, as shown in Table 4-9; and the third measurement was by the NVA cost, as shown in Table 4-10. The OEE measurement displayed in Table 4-8 shows that the availability element had the highest delta value for the gap between Level 1 and Level 2, while the performance element had the lowest delta value. The measurements in Table 4-8 are the OEE scores for all the WSs. The delta value denoted that if the availability element was switched from Level 1 to Level 2 or from Level 2 to Level 1, then the difference in values (delta) of OEE was 3.8%. The delta value shows only the absolute difference in values between each level. The delta value of 3.8% from Level 1 to Level 2 should be considered a negative value because the OEE score was reduced from 33.7% to 29.8%. The performance and quality elements displayed contradictory values as they increased from Level 1 to Level 2. As such, the OEE scores will be enhanced with the increments appearing on each delta value.

Table 4-8. Mean Response Experiment for OEE in All WS

Level	Availability	Performance	Quality
1	33.7%	31.5%	31.4%
2	29.8%	32.0%	32.2%
Delta	3.8%	0.6%	0.8%
Rank	1	3	2

Table 4-9. Mean Response Experiment for VA Cost in All WS (in JPY)

Level	Availability	Performance	Quality
1	121855	119588	121783
2	122223	124491	122295
Delta	368	4903	512
Rank	3	1	2

Table 4-10. Mean Response Experiment for NVA Cost in All WS (in JPY)

Level	Availability	Performance	Quality
1	32194	38574	36114
2	39786	33405	35866
Delta	7592	5169	248
Rank	1	2	3

However, these results would depend on how the experiment was designed. Nevertheless, it is clear that with this procedure, the OEE element contribution to the OEE score can be measured by a simulation experiment. In Table 4-9, the OEE element was measured by the VA cost (in JPY currency). Each delta value reveals that the performance element had the highest difference value followed by the quality element and finally the availability element. This indicated that the VA cost was the highest contributor to the performance element of the OEE. In other words, the delta value influenced the performance element more than the other elements.

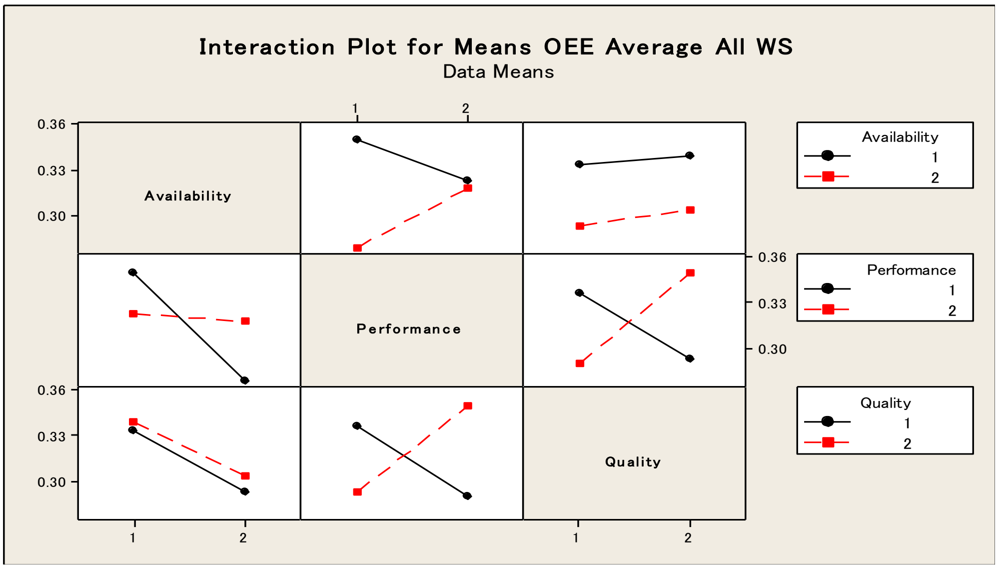


Figure 4-8. Interaction plot for Mean OEE All WS by Experiment

In Table 4-10, the OEE element was measured by the NVA cost (in JPY). As can be seen, the highest delta value was the availability element, followed by the performance element. These two elements displayed a high proportion of delta values compared to the quality element. This showed that the availability element made the highest contribution to NVA cost, followed by the performance element. The research outcome from the Taguchi method also provided an interaction plot between the control factors. Figure 4-6 illustrates the interaction plot between all the OEE elements in this experiment. The purpose of this interaction plot is to identify the control factors (OEE element) that interact with each other by referring to the graph lines of each OEE element. If the graph lines are parallel to each other, it can be assumed that no interaction exists. Non-parallel lines or intersecting lines indicate that there is a significant interaction between the control factors (Vuchkov, I.N., and Boyadjieva N.L., 2001). As can be seen in Figure 4-8, the availability and performance elements, as well as the performance and quality elements were not parallel to each other. This revealed that there was interaction between these control factors. However, there was no indication of any interaction between the elements of availability and quality.

4.4.8 Stage -6 Schemes of OEE Enhancement &Analysis

The scheme of the OEE enhancement was set up through a combination of simulations and the Taguchi method as described in Table 4-11, while the experimental outcome for this scheme is exhibited in Table 4-12. The first part of this scheme consisted of calculations to acquire the OEE score by multiplying each OEE element. The OEE calculation was carried out based on the current state or the worst condition of the experiment if the matrix of the experiment (with availability and performance in Level 2 and quality in Level 1) was referred to. The positive (+) and negative (-) signs reflect an improvement or a decline from the current condition (the worst condition) after the simulation experiment. Therefore, the altered condition (from the worst condition to the good condition) of the availability element in this simulation experiment changed its position from Level 2 to Level 1. This was the same for the performance element. However, the level of the quality element was changed from Level 1 to Level 2. These transformations in the condition of the elements would be utilised as a foundation for improvement. The second part of this scheme involved the OEE element contribution through simulation and experiments, where the value for each (ΔA, ΔP, and ΔQ) was obtained from delta values (Table 4-8). The OEE estimation for each OEE element can be calculated by adding each OEE element to a delta value. This is because the Taguchi experiment measurement utilises the OEE score. From the delta value for each OEE score, the balance of each OEE element can be revealed and the contributions of the OEE elements can be ascertained by level altering. The third part of this scheme was the OEE element measurement by VA cost and NVA cost. The result of the delta value of the VA cost balance in Table 4-11 refers to the delta value in Table 4-9, while the delta value of the NVA cost balance refers to the delta value in Table 4-10. This scheme provides additional statistical information on the OEE elements through simulation and the Taguchi experimental method.

Table 4-11 Scheme for OEE Enhancement by Simulation and Experiment

OEE Calculation	Availability	Performance	Quality	OEE
	A	P	Q	AxPxQ
OEE Element Contribution Measurement by Simulation Experiment				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	OEE Estimation
	(+/–) ΔA	(+/–) ΔP	(+/–) ΔQ	
OEE + Δ (OEE estimation) by each OEE element	OEE+ΔA	OEE+ΔP	OEE+ΔQ	OEE+ΔA +ΔP + ΔQ
VA Cost & NVA Cost Measurement by Simulation Experiment for Each OEE Element				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	Cost Estimation
VA Cost Balance	(+/–) VA(ΔA)	(+/–) VA(ΔP)	(+/–) VA(ΔQ)	VA(ΔA +ΔP + ΔQ)
NVA Cost Balance	(+/–) NVA(ΔA)	(+/–) NVA(ΔP)	(+/–) NVA(ΔQ)	NVA(ΔA +ΔP + ΔQ)

With this information, the decision-makers in the company will be able to consider several options when making decisions on priority improvement for the production line. This scheme can be implemented on a specific WS (small scale) or for WSs in general (large scale). This depends on the needs of the company. Obviously, the decision made by the company will depend on its main objective. Through this scheme the company will be able to measure the extent of the change in each OEE element and how far the contributions of these elements affect the VA and NVA costs.

Table 4-12 Result of Simulation and Experiment by Using the Scheme

OEE Calculation	Availability	Performance	Quality	OEE
	94%	28%	97%	24.7%
OEE Element Contribution Measurement by Simulation Experiment				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	OEE Estimation with All Δ OEE element
	(+) 3.8%	(-) 0.6%	(+) 0.8%	
OEE +Δ (OEE estimation) by each OEE element	28.5%	24.1%	25.5%	28%
VA Cost & NVA Cost Measurement by Simulation Experiment for Each OEE Element				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	Cost estimation
VA Cost Balance	(-) 368	(-) 4903	(+) 512	(-) 4759
NVA Cost Balance	(-) 7592	(+) 5169	(-) 248	(-) 2671

This scheme can also estimate the OEE increments through simulation and the Taguchi method. Obviously, companies would expect high returns in terms of improvement in the production line to justify the expenditure involved.

In Table 4-12, WS2 was used as reference for the scheme because it had the lowest OEE score (the worst case). As can be seen, this scheme can provide a contribution measurement for each OEE element and also a measurement of estimation by level varying. It also makes available the VA and NVA cost measurements for the OEE score estimation. This additional information will go a long way in helping decision-makers in the company to conduct an effective evaluation on priority improvement.

4.5 Implementation on Other Case Studies

In order to ensure that the model developed could be applied in other situations or scenarios, this research also tried this scheme on other production lines. This part focussed on the CH4H6 line that produced two types of coolant hoses, hose#4 and hose#6. This model consisted of five workstations (WS), which carried out the following processes: (WS1) machining, (WS2) deburring, (WS3) crimping, (WS4) testing, and (WS5) marking. The layout of the model can be seen in Figure 4-9.

The CH4H6 line simulation model was developed under the assumption that all time-related modules in the production line use triangular random distribution. All resources worked at full capacity. The parameters for the CH4H6 line were as follows: the demand for the coolant hose products was 300 units; in detail, 150 units of CH4 and 150 units of CH6.

The products per arrival for each product = 150 unit; maximum arrival = 1 unit; WS1 process time $t_{0,1}$ = TRIA(0.5,1,1.5), using triangular distribution; WS2 process time $t_{0,2}$ = (0.25,0.5,0.75); WS3 process time $t_{0,3}$ = TRIA(0.5,1,1.5); WS4 process time $t_{0,4}$ = TRIA(0.5,0.75,1), WS5 process time $t_{0,5}$ = TRIA(1,1.25,1.5).

A changeover occurred for every product type in WS1 and WS5; the total time for the changeover in WS1 was 51 minutes, while in WS5, the total time for the changeover was 24 minutes.

The batch capacity in each WS in CH4H6 was 5 units, and the buffer capacity for each WS was 25 units.

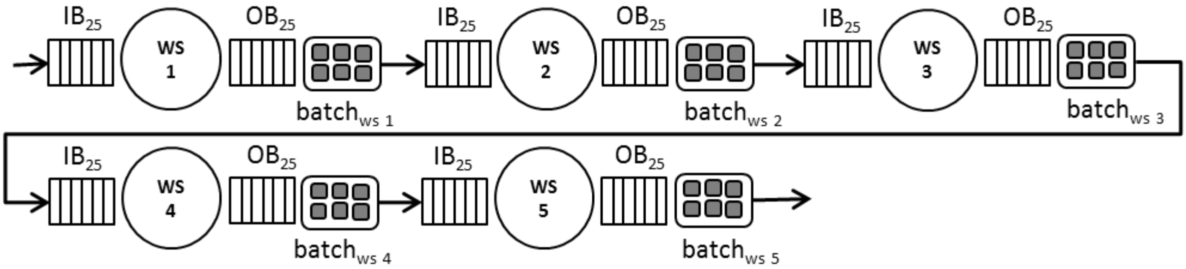


Figure 4-9. CH4H6 Line Model Layout

Each WS was handled by one operator. There was no reworked product in this production line. Defective products were disposed. The average route time between WS was 0.33 minutes. The work hours in the CH4H6 model were set at 9 hours per day.

This simulation model had been verified and validated in the same way as the verification and validation of the CML.

The experiment was conducted in the $L_4(2^3)$ orthogonal array with ten replications for each experiment.

The scheme of the OEE enhancement can be seen in Table 4-13. It can be implemented for other case studies, even with different simulation models and different experimental designs by using the Taguchi method approach.

Table 4-13. OEE Enhancement Scheme on CH4H6 line

OEE Calculation	Availability	Performance	Quality	OEE
	93.8%	15.6%	97%	14.15%
OEE Element Contribution Measurement by Simulation Experiment				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	OEE Estimation with All Δ OEE element
	(-) 0.9%	(+) 2.0%	(-) 0.9%	
OEE +Δ (OEE estimation) by each OEE element	14.06%	16.15%	14.06%	14.13%
VA Cost & NVA Cost Measurement by Simulation Experiment for Each OEE Element				
Balance for each different level (Δ)	ΔAvailability	ΔPerformance	ΔQuality	Cost estimation
VA Cost Balance	(-) 296	(-) 929	(+) 214	(-) 1011
NVA Cost Balance	(-) 2412	(-) 1668	(+) 2291	(-) 1798

Table 4-13 indicates that the focus of improvement in the CH4H6 line would be the performance element. In addition, the OEE estimation after only the performance improvement by this condition in the experiment increased by 2.0%. Moreover, the VA cost and NVA cost reduction could be estimated for each element only or for all OEE elements.

Chapter V

Coolant Hose Manufacturing Factory Model Development And an Overview of Taguchi Method

5.1 Overview of CHM factory

In this study, Coolant Hoses Manufacturing (CHM) simulation model served as an experiment tools. The process model of CHM factory was developed using simulation software (Rockwell Arena 13.9) as shown in Figure 5-1. The model is based on CHM factory, produces four types of coolant hose products, which are called CH4, CH6, CH8 and CH10 (Figure 5-2).

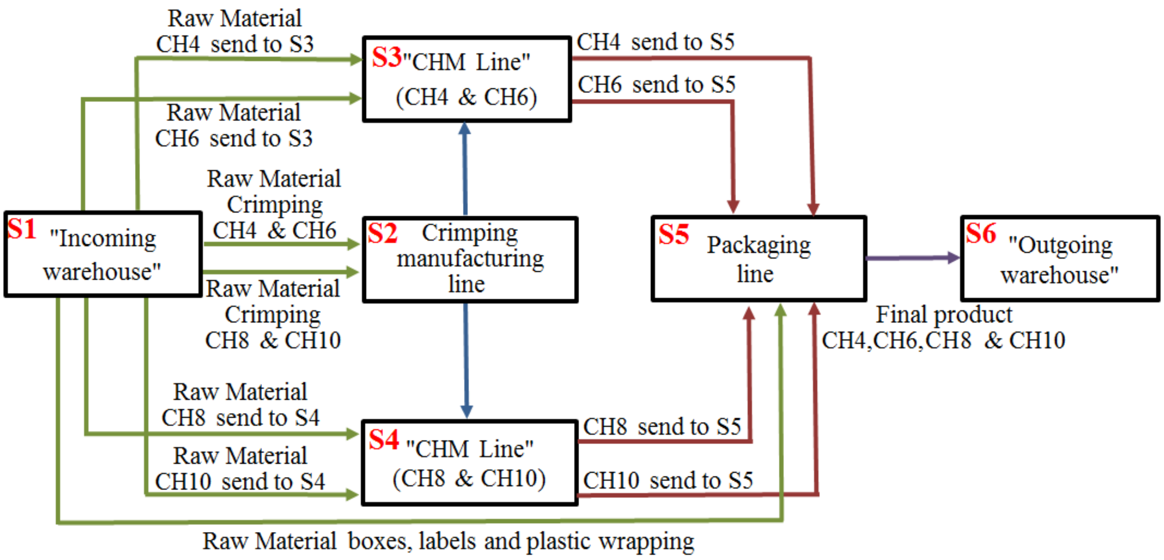


Figure 5-1. Process model of CHM factory floor

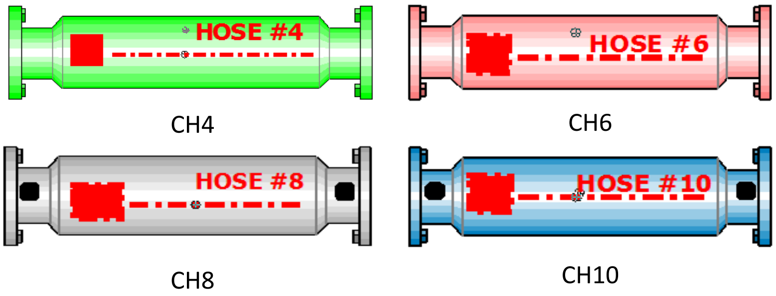


Figure 5-2. Four types of coolant hose product of CHM factory

The factory floor is divided into six sections from Section 1(S1) to Section 6(S6). S1 is the supplier section, which supplies raw materials to S2, S3, S4, and S5. Then, S2, S3, S4 and S5 supply their processed parts to S3/S4, S4, S5 and S6, respectively.

Average product demand for each section is 150 units. The factory is consist only one shift for nine hours operation. Material handling of these parts in production lines is performed by either forklift or trolley. Table 5-1 shows these conditions.

Table 5-1. Manufacturing conditions

From	To	Material	Distance (m)	Material Handler
S1	S2	Raw Material Crimping CH4&CH6 and CH8&CH10	50	Forklift
	S3	Raw Material CH4&CH6	50	Forklift
	S4	Raw Material CH8&CH10	50	Forklift
	S5	Raw Material Wrapping/Packaging/Labelling	50	Forklift
S2	S3	Crimping CH4&CH6	25	Trolley
	S4	Crimping CH8&CH10	25	Trolley
S3	S5	CH4 & CH6	25	Trolley
S4	S5	CH8 & CH10	25	Trolley
S5	S6	Final Products	25	Trolley

5.2 CHM Factory Simulation Model

The numbers of WS in each section are three WSs in S2, five WSs in S3, six WSs in S4, and three WSs in S5. Each of these WS is operated by one operator, who is assigned with certain tasks. Changeover (C/O) operation is scheduled in S2, S3 and S4 because of die switches for product type change in the production line. Based on the aforementioned details, layouts of CHM factory were created. From these layouts, model logics were developed for each section. As for the sections with C/O operation schedule (S2, S3 and S4), sub models of the C/O process were also created. Figure 5-3 and Figure 5-4 shows the snapshot in the CHM simulation model by using Arena Simulation software. For Figure 5-4 utilizing the zoom function in order to the user can focus on one section only. Therefore, the user can see the detail process of each

WS in a section. The detail scene is useful to watch the work in progress queue or buffer in each WS, or to see the bottleneck in the section.

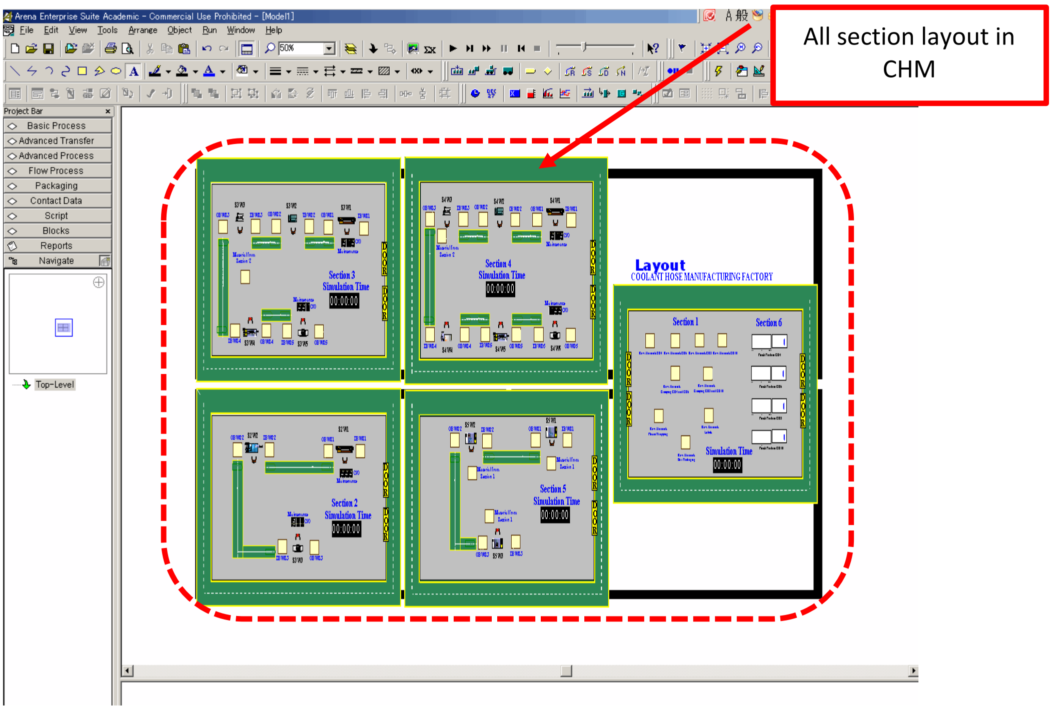


Figure 5-3. All Section Layout in CHM

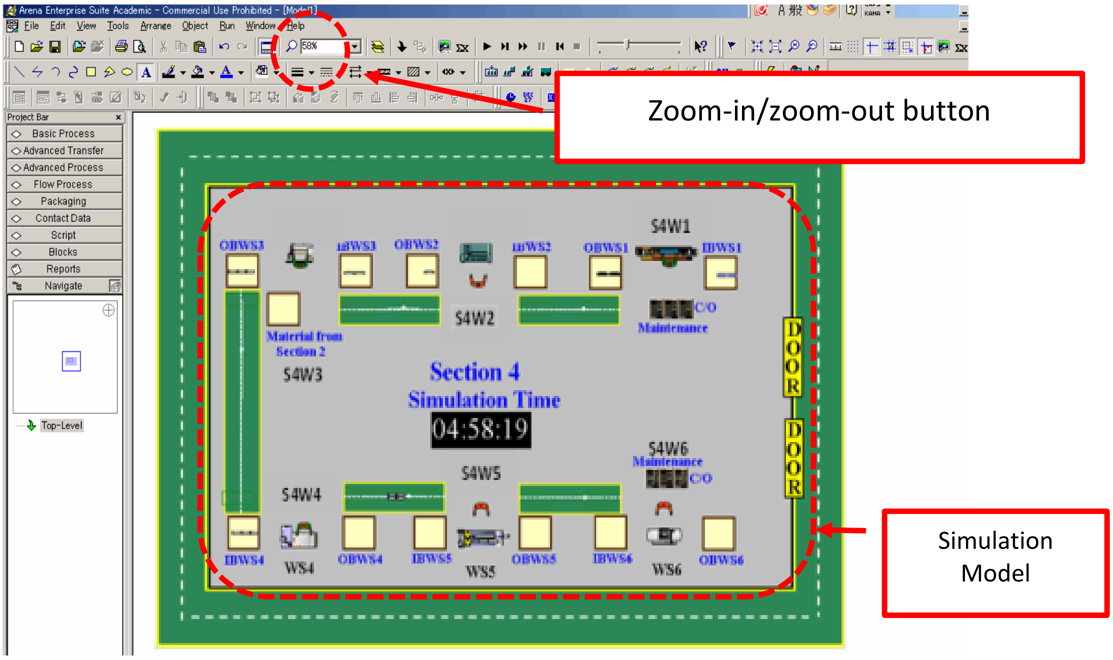


Figure 5-4. Example Snapshot of a Section in CHM

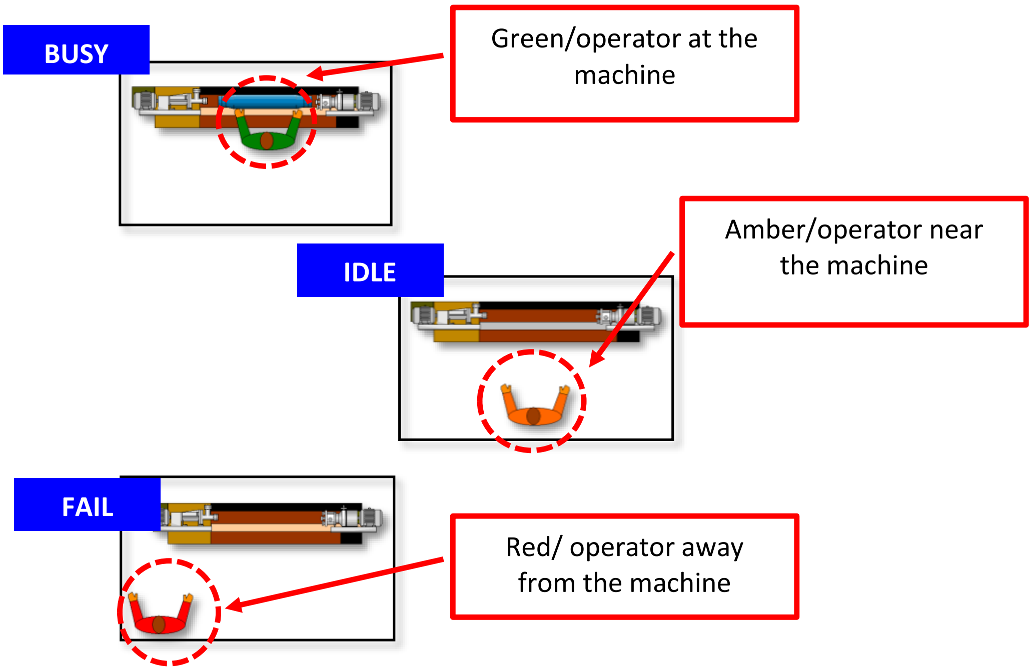
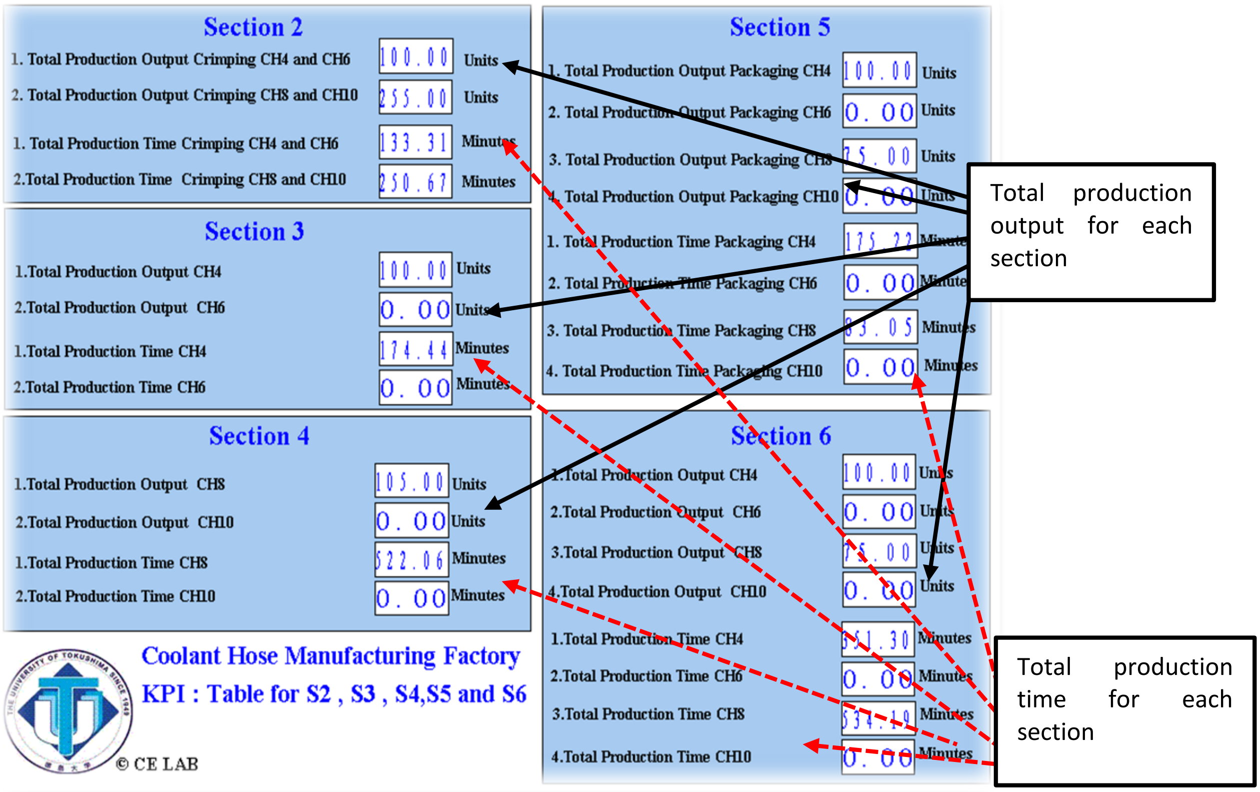


Figure 5- 5. Task status function in WS



Section 2

1. Total Production Output Crimping CH4 and CH6	100.00	Units
2. Total Production Output Crimping CH8 and CH10	255.00	Units
1. Total Production Time Crimping CH4 and CH6	133.31	Minutes
2.Total Production Time Crimping CH8 and CH10	250.67	Minutes

Section 3

1.Total Production Output CH4	100.00	Units
2.Total Production Output CH6	0. 00	Units
1.Total Production Time CH4	174.44	Minutes
2.Total Production Time CH6	0. 00	Minutes

Section 4

1.Total Production Output CH8	105.00	Units
2.Total Production Output CH10	0. 00	Units
1.Total Production Time CH8	522.06	Minutes
2.Total Production Time CH10	0. 00	Minutes

Coolant Hose Manufacturing Factory
KPI : Table for S2 , S3 , S4,S5 and S6
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Section 5

1. Total Production Output Packaging CH4	100.00	Units
2. Total Production Output Packaging CH6	0. 00	Units
3. Total Production Output Packaging CH8	75.00	Units
4. Total Production Output Packaging CH10	0. 00	Units
1. Total Production Time Packaging CH4	175.22	Minutes
2. Total Production Time Packaging CH6	0. 00	Minutes
3. Total Production Time Packaging CH8	83.05	Minutes
4. Total Production Time Packaging CH10	0. 00	Minutes

Section 6

1.Total Production Output CH4	100.00	Units
2.Total Production Output CH6	0. 00	Units
3.Total Production Output CH8	75.00	Units
4.Total Production Output CH10	0. 00	Units
1.Total Production Time CH4	551.30	Minutes
2.Total Production Time CH6	0. 00	Minutes
3.Total Production Time CH8	534.19	Minutes
4.Total Production Time CH10	0. 00	Minutes

Total production output for each section

Total production time for each section

Figure 5- 6. Table of KPI status function (Total production output & Total production time)

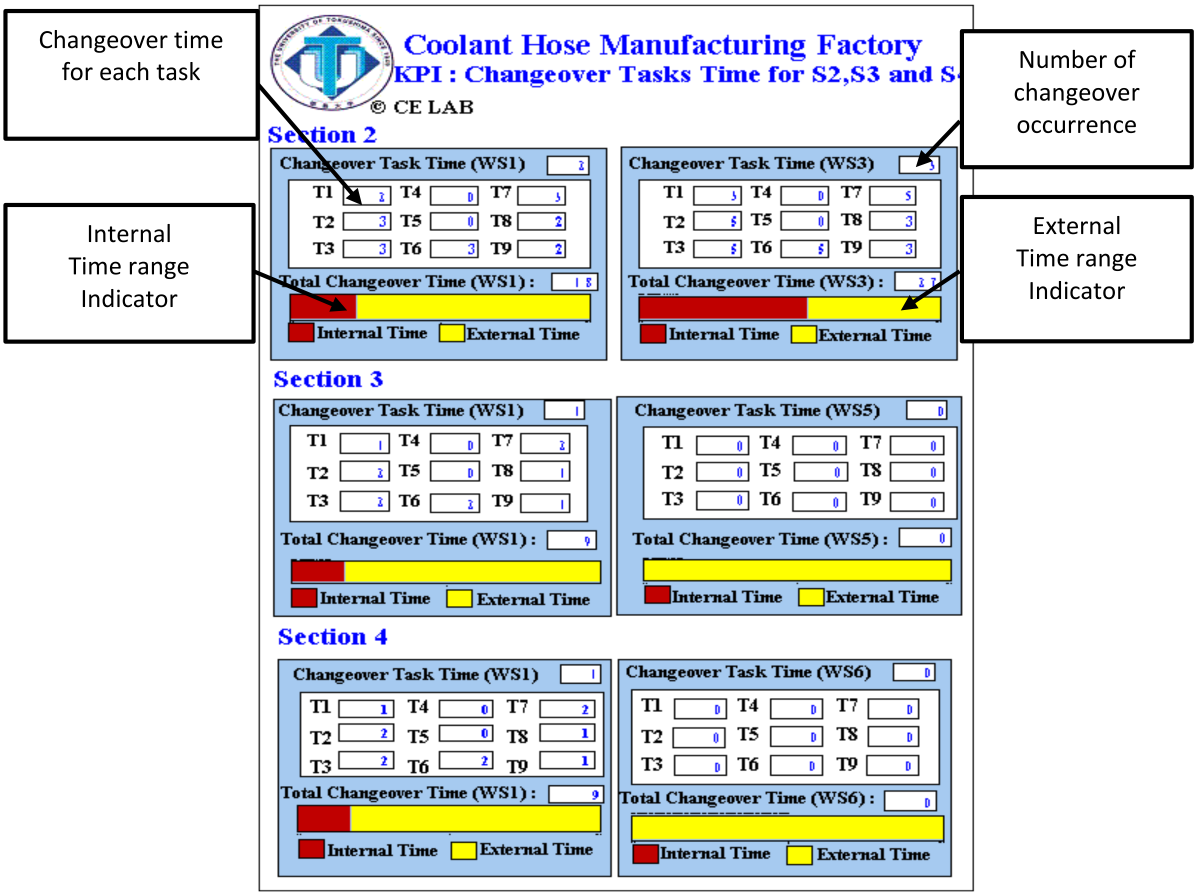


Figure 5- 7. Table of KPI status function (changeover)

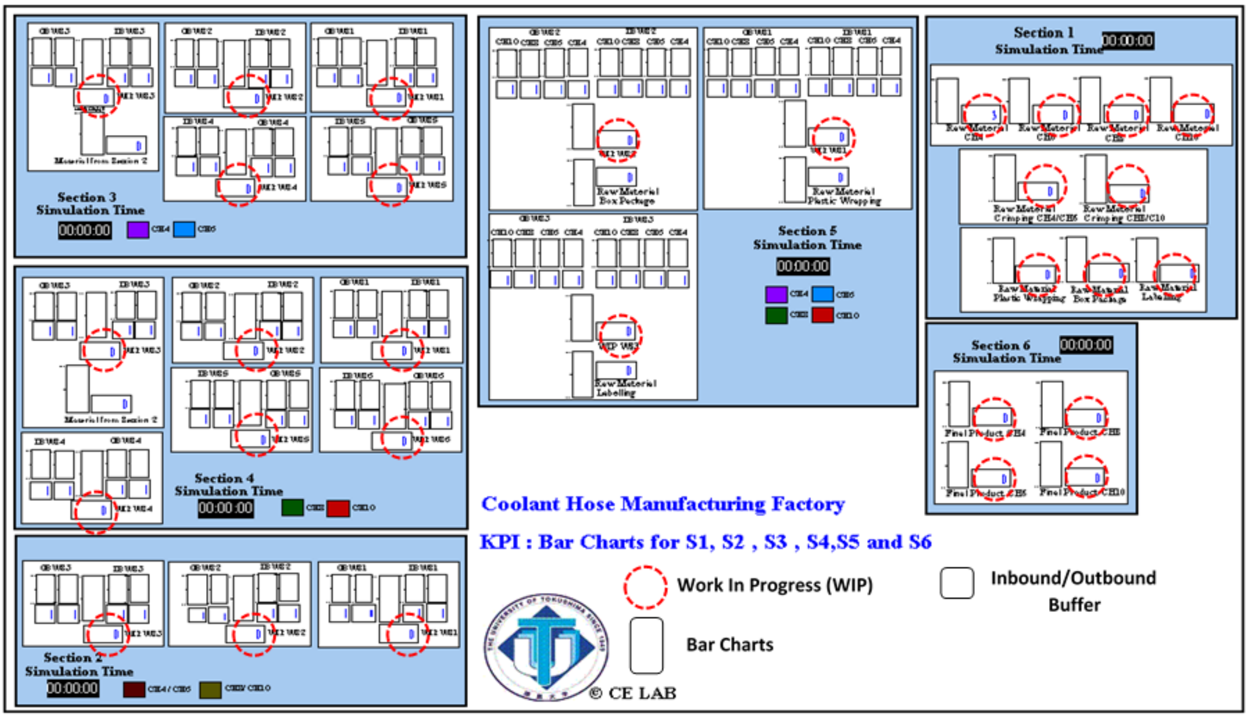


Figure 5- 8. Bar charts of KPI status function

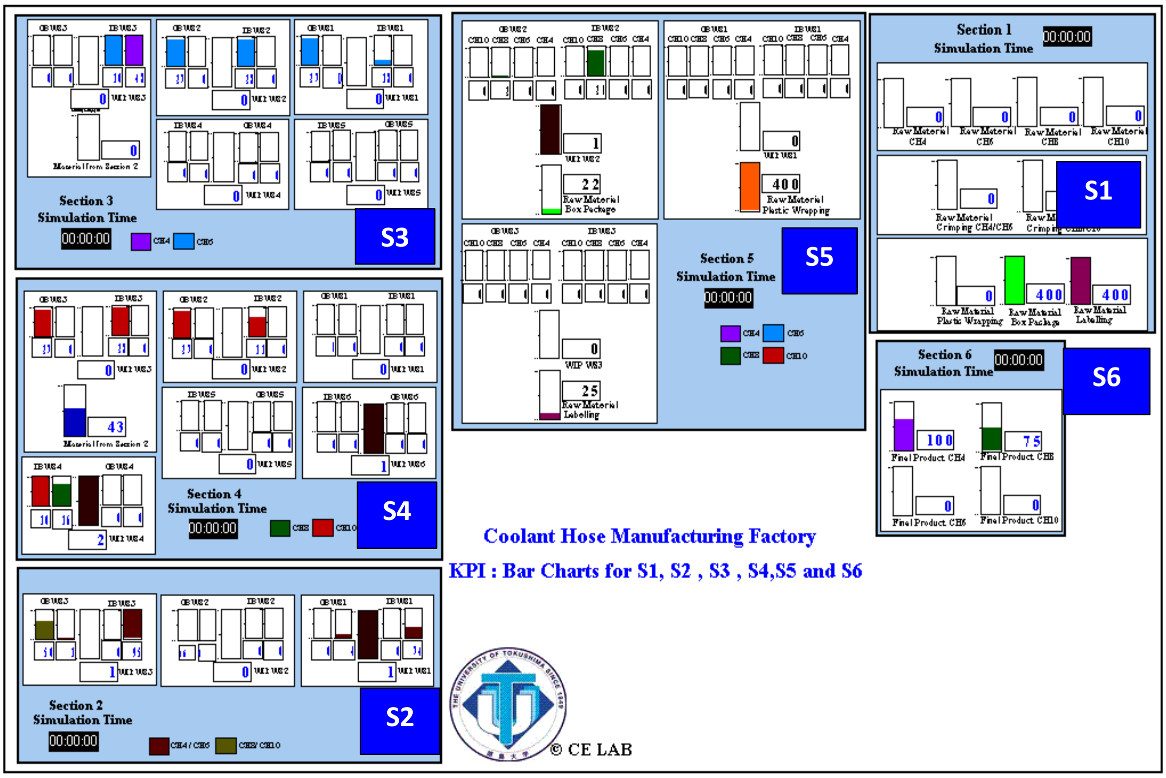


Figure 5- 8a. Real time snapshot of KPI Status function

The task status functions of each WS provides three status illustrations i.e. busy, idle, and fail to represent operator status in every workstation in the factory (Figure 5-5). The three task statuses of operator are differentiated by means of colours and locations of the operator from the machine. By observing these status illustrations, the users are able to understand the changing task status in real time during simulation runs. Once they understood the problem at the workstation, they can resume viewing the layout view by clicking on the zoom-out button. Following that, the user prompted to utilise the KPI (Key Performance Indicators) status function to acquire more information on the existing problem (Figure 5-6 until Figure 5-8a). The CHM simulation model was designed based on a certain assumptions; all workstations operate at full capacity; all workstations have triangular distribution process time; product arrival time is based on a deterministic arrival pattern; and all results are reported at a confidence interval level of 95%. Simulation based on the model provides quantitative information, such as total production output, total production time as seen on Figure 5-6.

Figure 5-6 is describing the measurement of total production time and total production output in unit for each section. While Figure 5-7 describes the animation measurement of change over for each section. Because each section (except inbound warehouse, outbound warehouse, and packaging line) is handle two types of product. Furthermore, in some machines in each section need to be change the setup or tools in order to precede the entire demand product. For Figure 5-8 is describe the KPI's for all WS in the CHM factory. This KPI measure not only the buffer or number of WIP (Work in Progress) in each WS, how many inventory in the warehouse (inbound and outbound), total time production in each WS, however it also measure the smoothness of material flow in the assembly WS. All of this animation measurement is used in order to verifying and validating the simulation model of CHM factory. As mentioned before, KPI values in this simulation model are generated and updated in real time during simulation. This way, users could understand the effectiveness of LM tools by a trial-and-error use of simulation and by conducting what-if analysis. In addition, for visual understanding of KPI, bar charts of KPI table are also available during simulation (Figure 5-8).

The implemented animation, which represents the model logic, is to ensure that the model is error-free. Verification of the model was proved by tracing all the products from the point of their creation (S1: Incoming warehouse) to the point of their disposal from the system (S6: Outgoing warehouse) to ensure that the simulation model closely approximate the real system.

Generally, simulation model of each section of CHM factory is created using a set of simulation modules (model logic). Each module is used for different purposes. Batch Module and Separate Module are used for managing batch of product in the production lines while Process Module is used for processing the products. Hold Module represents inbound and outbound buffer in the production line. The details regarding all modules used to develop the CHM factory simulation model are as follows:

1. Create Module: This module is the source of product creation in the simulation model. It provides time distribution and quantity of product arrival.
2. Batch Module: This module is used to manage batch of product. The batch capacity for each WS in this factory may vary. However, for most WS in CHM factory simulation model, the batch capacity is 5 units.
3. Separate Module: This module is used to separate products from batch form.
4. Hold Module: This module is used to manage buffer in CHM factory model based on certain inferred conditions. An example of inferred condition for buffer release is: "NQ (Seize Operator WS1 Hose#4_Hose#6.Queue) == 0 && NQ (Outbound buffer Hose#6 at WS1.Queue) <= 25".
5. Process Module: This module is used to represent the processing of products in WS. The module includes information on resources and process time of the products. In CHM factory simulation model, process time is in the form of triangular distribution and operators are the resources.
6. Station Module: This module is used to represent certain landmark in the CHM factory simulation model.
7. Route Module: This module is used together with Station Module to transfer product from one station to another.
8. Assign Module: This module is used to customize product with attribute, variable, product type and picture following the requirement of the production line.
9. Decide Module: This module is used to decide on production processes based on inferred condition. For example, in CO process, Decide Module is used to determine the time for die switch for product type change in the production lines, and another thing is, decide module is used to clustered the entities to each type in the buffer of each workstations (WS).
10. Match Module: This module is used as a main controller of the queue of products. This module is paired with Hold Module in order to manage the queue accordingly.

5.2.1 CHM factory simulation model : S1 and S6

Section 1 (S1) function is as an inbound warehouse for CHM. It is keeping all material in one place, and ready to send to production floor as it's needed. The transportation that used to send the material of coolant hoses to production floor is using forklift.

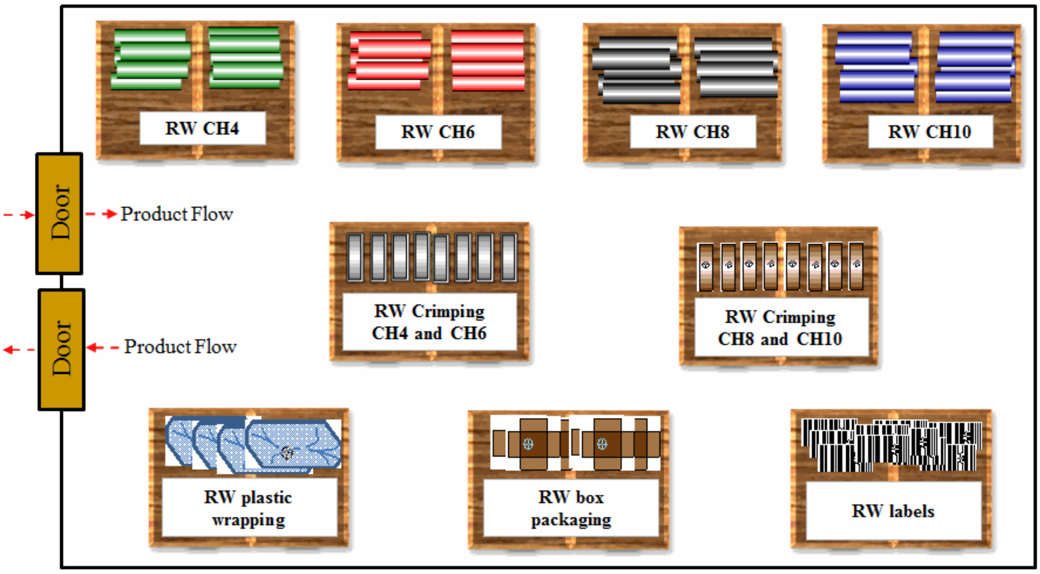


Figure 5-9. Model layout of S1 (Incoming warehouse)

The layout model for S1 can be seen on Figure 5-9. In addition, for the model logic of S1 can be seen on Figure 5-10. The model logic for the inbound warehouse consists of create module, assign module, hold module, batch module, and route module.

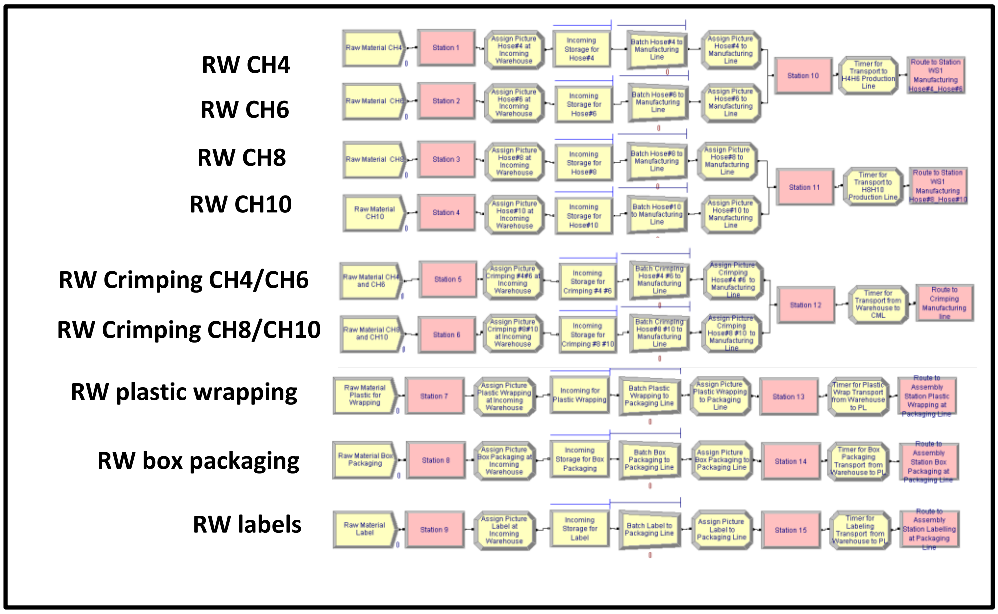


Figure 5-10. Model logic of S1 (Incoming warehouse)

Create module function is to make entities as demand requested (150 units) of raw material for each type of coolant hoses. For the assign module, function in this section is to change the entity picture for each of type materials based on the condition in the warehouse.

The first assign module in each line is to change the entities picture in the single form. While the second assign module is to change the entities picture in the group form.

Furthermore, the third one is to add label time attribute to each entity in order to measure the transport time. To transport the material to the production line this model using route module, which is, defined as a forklift for transport the material in the production line.

The station module is used in order to using its pairing with route module. The batch module is used for batching process or grouping processes in order to make it easier to send the entities by using the forklift.

For the outbound warehouse consists of statistic module, station module, separate module, decider module, and dispose module.

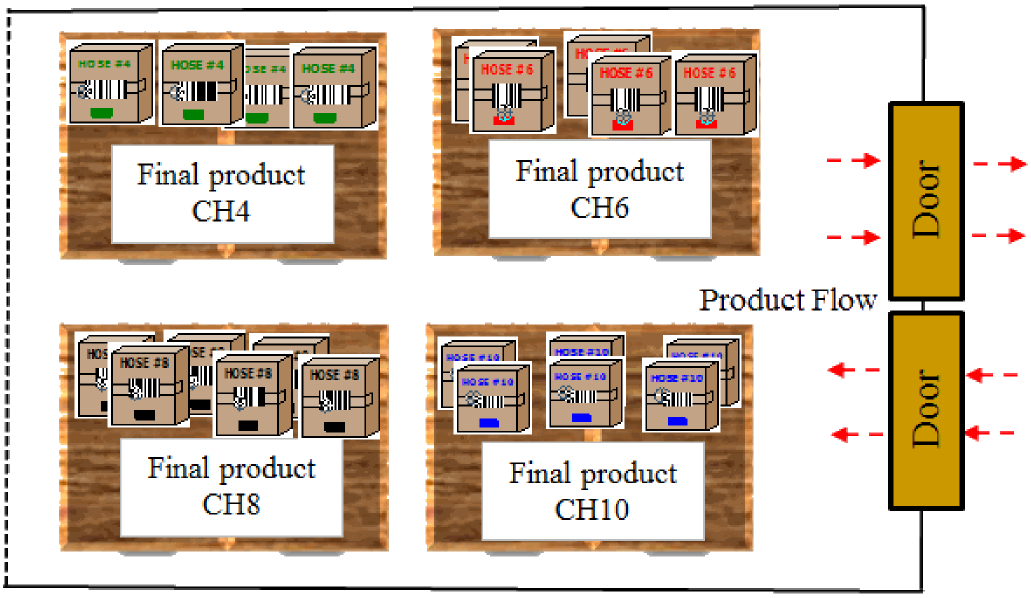


Figure 5-11. Model layout of S6 (Outgoing warehouse)

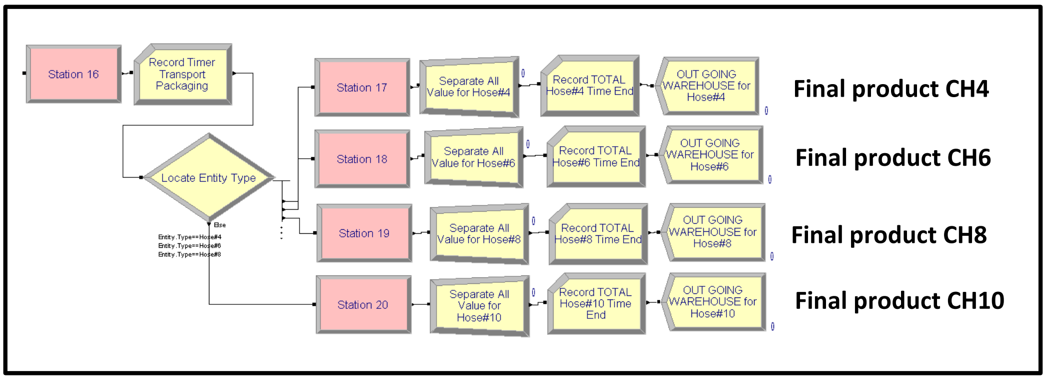


Figure 5-12. Model logic of S6 (Outgoing warehouse)

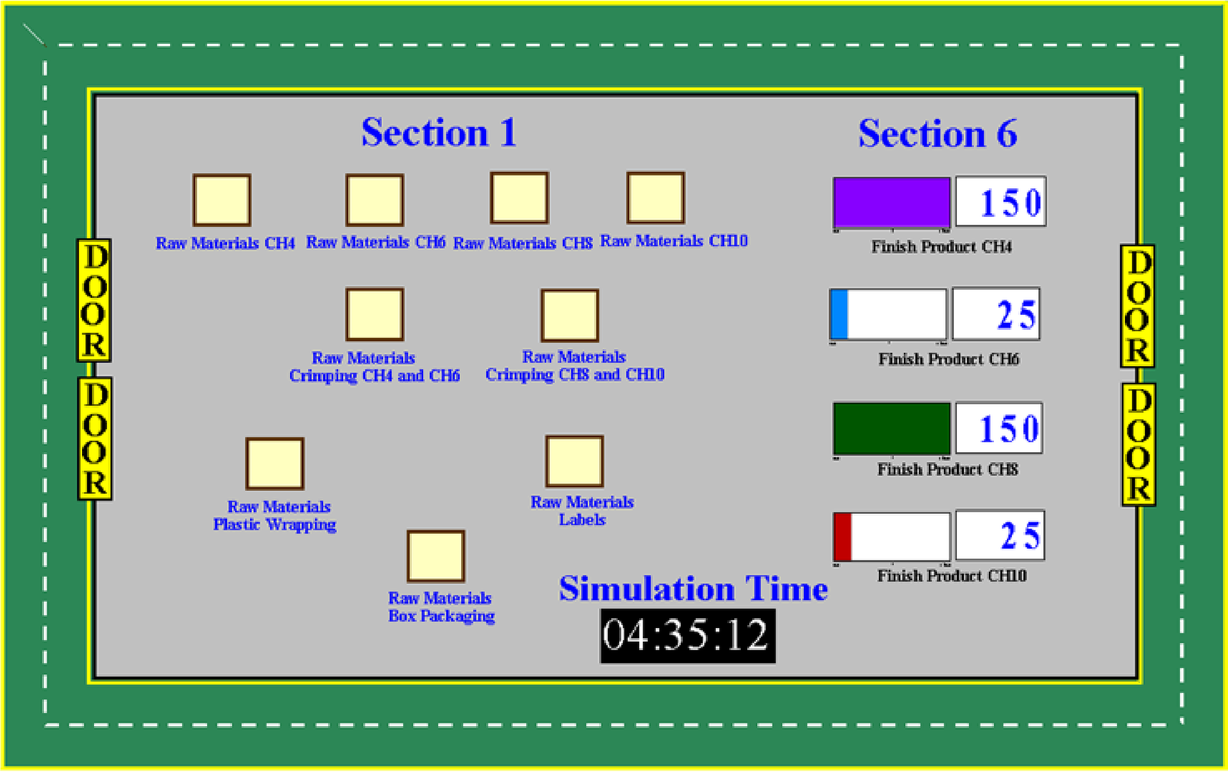
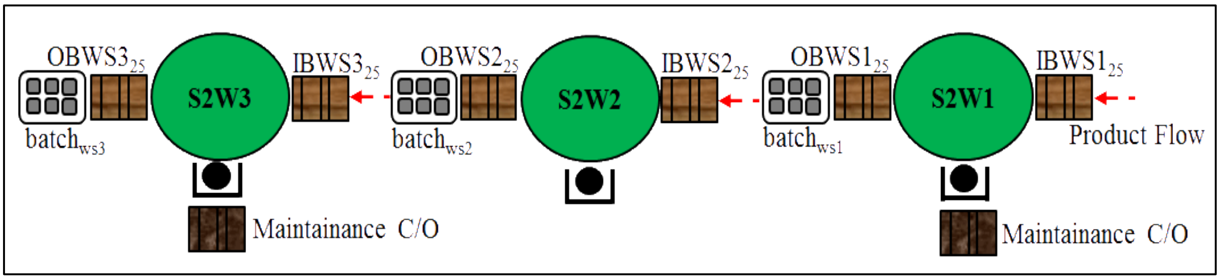


Figure 5-13. Snapshot of S1 and S6

The statistic module is used in order to measure the transport time from the packaging line to outbound warehouse. The station module is used in pairs with route module from the previous packaging line (Figure 5-11 and Figure 5-12). The separate module is used for separate the entities product from grouped item to single item before they are sending to the customer. For Figure 5-13 is illustrating the real-time snapshot when the simulation model is running. All the measurement in this section (S1 & S6) shows the number of unit entities in each type of product. In section 1 the measurement shows number of raw material inventory, while in the section 6 shows the finish product that already sent to the customer for each type of product. In addition the simulation time also shown. All this measurement in this section can be used as performance indicator for managing the inventory in the warehouse.

5.2.2 Section 2 CHM Factory

Section 2 (S2) is describe the crimping manufacturing line (CML) that is produce the crimping part for the coolant hoses for each size. This section is very critical to CHM factory. Because this line is related to two other production line, which produce coolant hose#4, coolant hose#6, coolant hose#8, and coolant hose#10. If this line is not operating normally then the whole production process in all production line in the CHM factory will be prolong.



**Changeover (C/O): for product switch in production line*

Figure 5-14. Model layout of S2

The CML supports two production lines together with Sections 3 and 4 for each coolant hose type of crimping material. A simulation model was developed using the Arena Simulation Software for a Coolant Hoses Manufacturing (CHM) company.

This factory consists of six sections. Four sections are production lines which produce Coolant Hose#4(CH4), Coolant Hose#6(CH6), Coolant Hose#8(CH8), and Coolant Hose#10(CH10), while two sections are warehouses for storage as seen in Figure 5-13.

The CML simulation model was built before the experiment commenced. This model consisted of three workstations (WS) where the procedures for machining (S2W1), testing (S2W2) and marking (S2W3) were carried out. The layout of the model can be seen in Figure 5-14.

The parameters for the CML were as follows: The demand for coolant hose products was 600 units comprising 300 units of coolants CH4 and CH6, and

300 units of coolants CH8 and CH10. The product time between arrivals was 120 minutes.

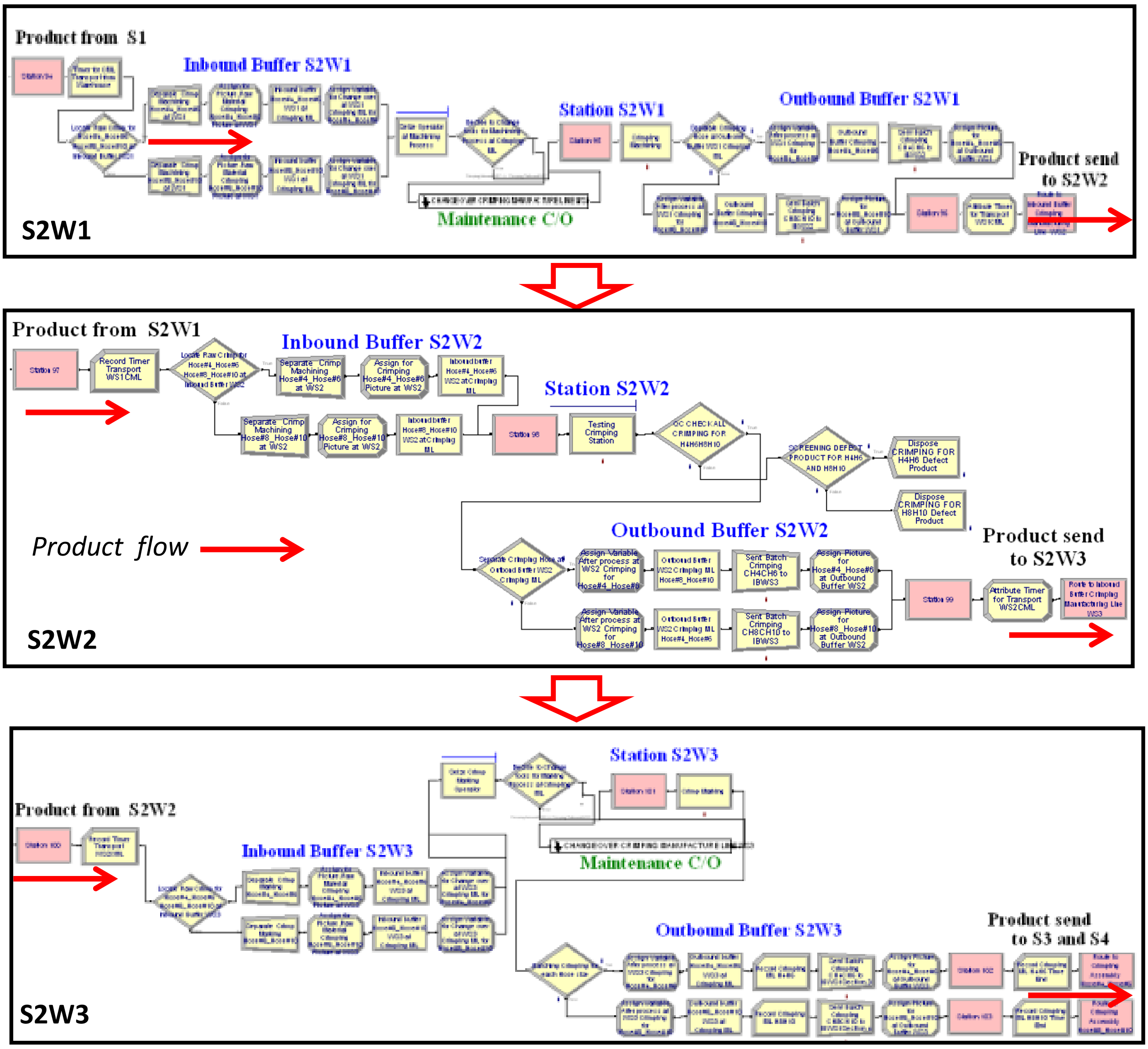


Figure 5-15. Model logic of S2

Product per arrival for each product = 100 units; maximum arrival = 3 units; using triangular random distribution (TRIA), the annotation representing the random distribution TRIA(min value, most value, max value), WS1 process time $t_{0,1}$ = TRIA(0.5,1,1.5); WS2 process time $t_{0,2}$ = (0.5,0.75,1); WS3 process time $t_{0,3}$ = TRIA(1,1.25,1.5).

A changeover occurred for every product type in WS1 and WS3; the total time for the changeover in WS1 was 40 minutes, while in WS3, the total time for the changeover was 20 minutes. The batch capacity in each WS in the CML was 5 units, and the buffer capacity for each WS was 25 units.

One operator handled each WS. The route time between the WSs was 0.3 minutes. The work hours in the CHM model were set at 9 hours per day. The simulation runs were replicated 10 times.

The model logic for CML as can be seen on Figure 5-15 and change over sub model of CML can be seen on Figure 5-16. For Section 2 (S2) simulation real time snapshot can be seen on Figure 5-17.

Table 5-2 is describing how the entities form change from initial process until its ready to send to CH4H6 line, Coolant hoses size 4 (CH4) and size 6 (CH6), or CH8H10 line, coolant hoses size 8 (CH8) and size 10 (CH10).

The entities transformation during its process is arranged by assign module in each WS. In CML there are two output line, one line is go to CH4H6 line, the other one is go to CH8H10 line.

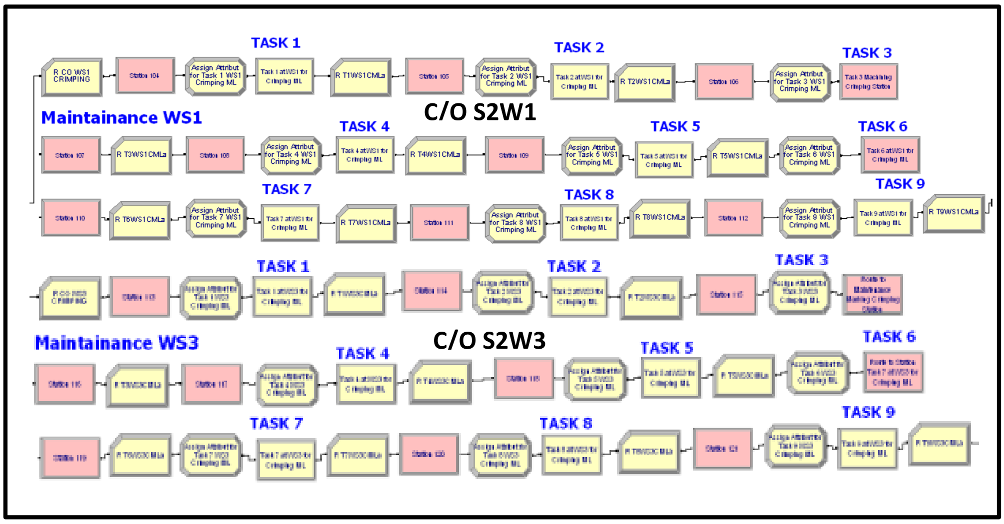
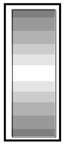
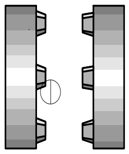
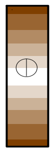
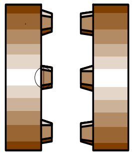
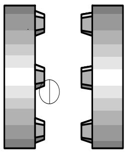
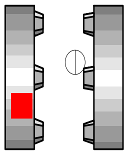
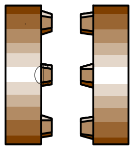
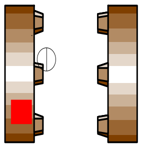
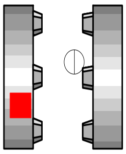
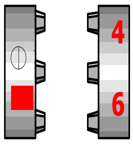
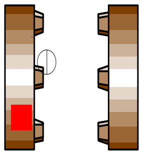
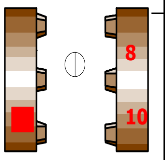


Figure 5-16. Sub-model of C/O for S2W1 and S2W3 at S2

Table 5-2. Product of S2

Before Process	Workstation	After Process	Before Process	Workstation	After Process
	**S2W1**			**S2W1**	
	**S2W3**			**S2W3**	
	**S2W3**			**S2W3**	

**Product crimping CH4 and CH6*

**Product crimping CH8 and CH10*

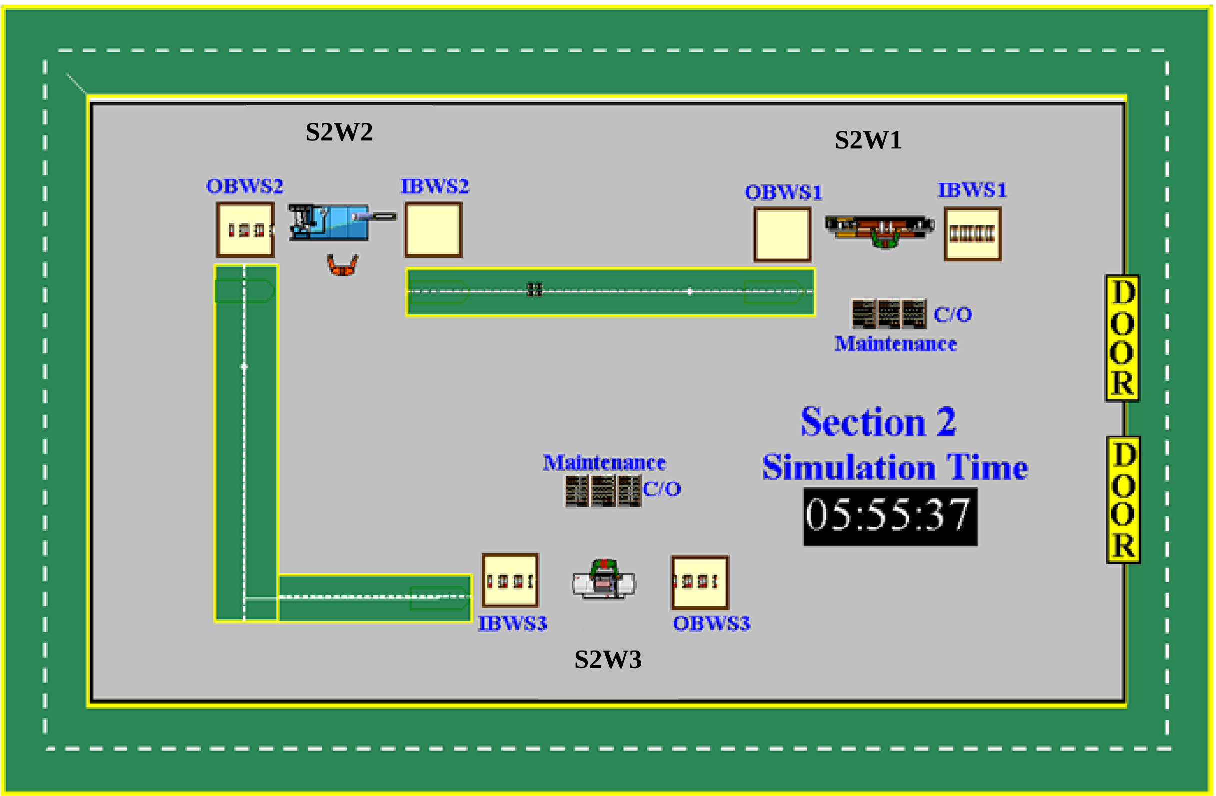
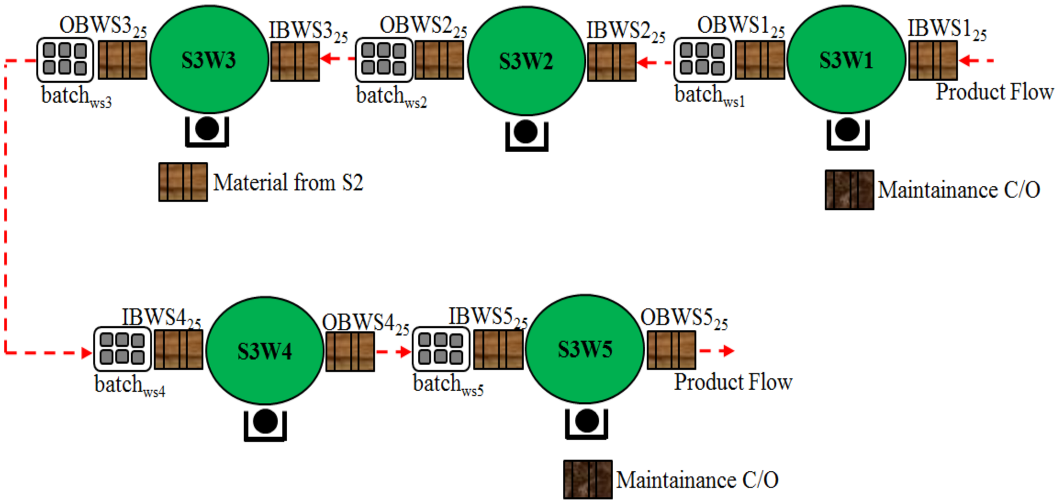


Figure 5-17. Snapshot of S2

5.2.3 Section 3 CHM Factory

The CH4H6 line produces two coolant hose products, namely CH4 and CH6 hoses. The CH4H6 line simulation model was built before the first experiment was conducted. This model consists of five workstations (WS), which carry out the following processes: (WS1) machining, (WS2) deburring, (WS3) crimping, (WS4) testing, and (WS5) marking.

The model layout can be seen in Figure 5-18. The CH4H6 line simulation model was developed under the assumption that all time-related modules in the production line use triangular random distribution. All resources work at full capacity.



**Changeover (C/O): for product switch in production line*

Figure 5-18. Model layout of S3

The parameters for the CH4H6 line are as follows: the demand for coolant hose products is 300 units; in detail, 150 units of CH4 and 150 units of CH6. Products per arrival for each product = 150 unit; maximum arrival = 1 unit; WS1 process time $t_{0,1}$ = TRIA(0.5,1,1.5), using triangular distribution; WS2 process time $t_{0,2}$ = (0.25,0.5,0.75); WS3 process time $t_{0,3}$ = TRIA(0.5,1,1.5); WS4 process time $t_{0,4}$ = TRIA(0.5,0.75,1), WS5 process time $t_{0,5}$ = TRIA(1,1.25,1.5). Change over occurs for every product type in WS1 and WS5; total time for changeover in WS1 is 51 minutes, while in WS5, total time for change over is

24 minutes.

The batch capacity in each WS in CH4H6 is 5 units, and buffer capacity for each WS is 25 units. One operator handles each WS.

There is no rework product in this production line. Defective products are disposed. The average route time between WS is 0.33 minutes. Work hours in the CH4H6 model are set at 9 hours per day.

The model logic of section 3 CHM factory can be seen in the Figure 5-19 for all WS (S3W1-S3W5) and for detailed changeover in S3W1 and S3W5 can be seen in Figure 5-20. Each WS is using buffer as a temporary work in progress (WIP) queue.

The changeover is done when material product is not identical with the intended tools. S3W3 is an assembly WS, because the crimping process requiring the crimping part that produced by CML (S2). Since of this problem, if the CML is overdue, then WIP queue will be very high in this WS.

For Table 5-3 illustrating the entities form transformation during the all process in the CH4H6 line.

Real time simulation snapshot is illustrated in Figure 5-21. The animation of buffer, entities transported, WS status, and simulation time is also provided in this snapshot. It is very useful to track the bottleneck and the condition in the “real” production line.

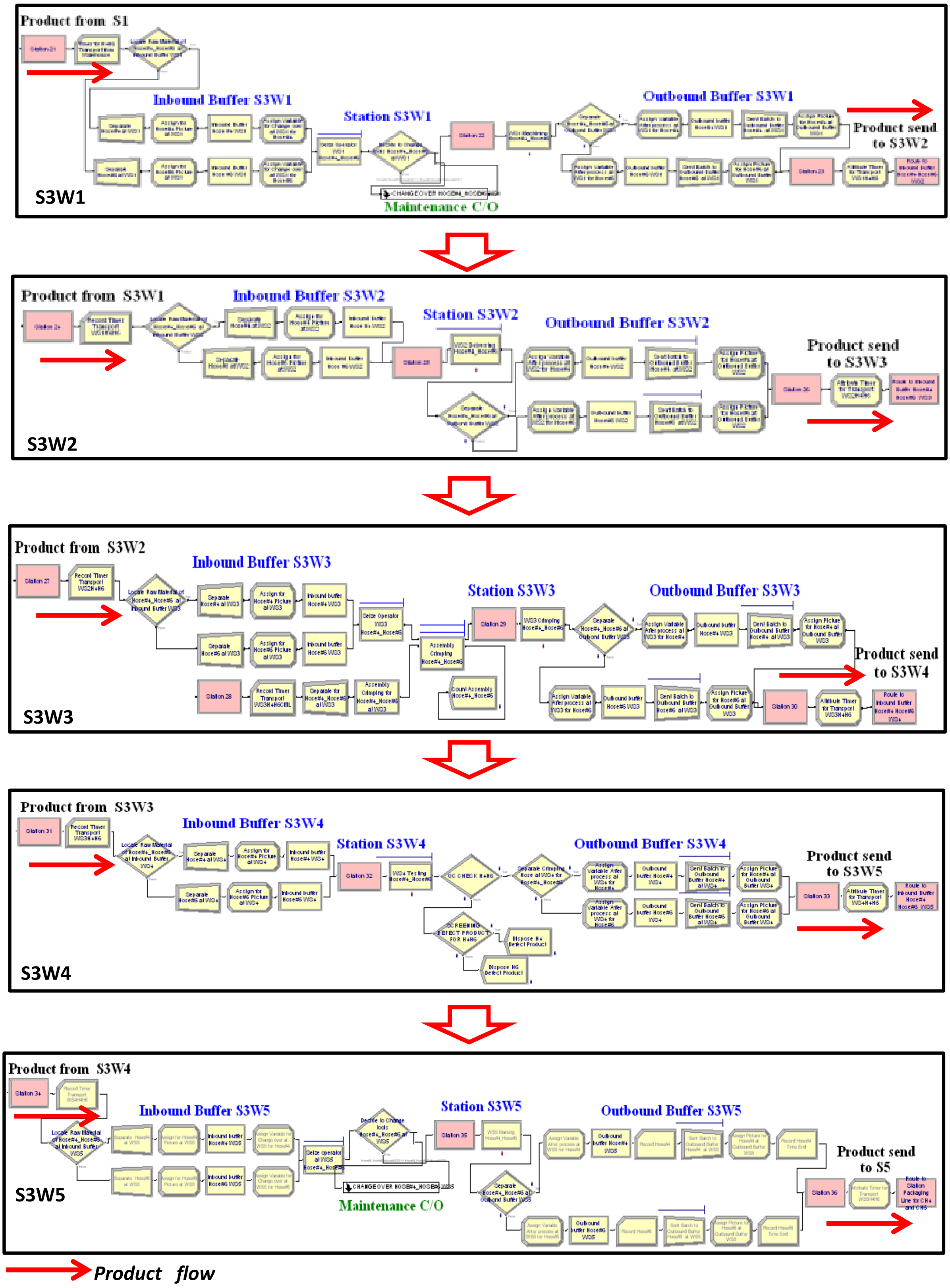
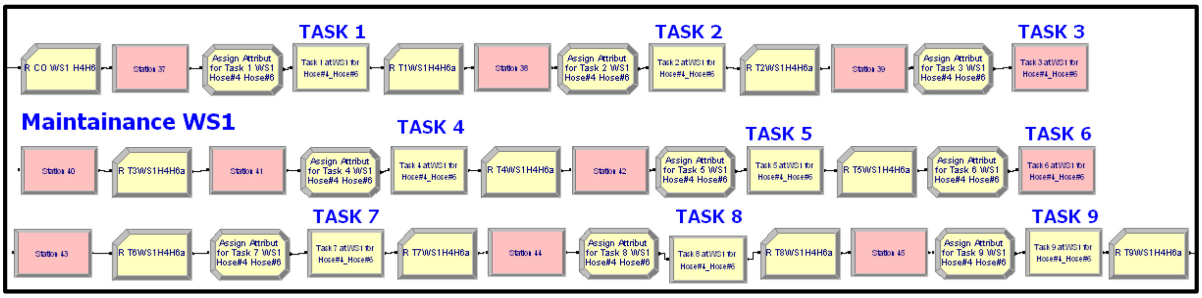
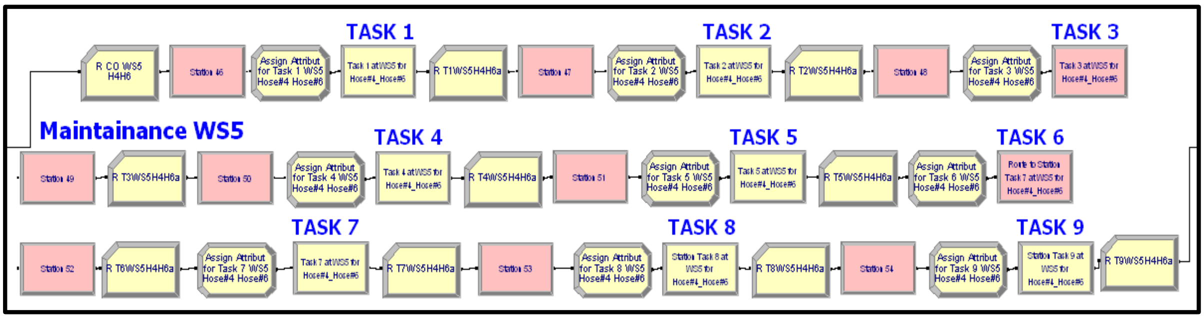


Figure 5-19. Model logic of S3



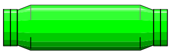
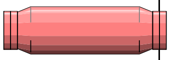
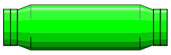
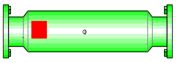
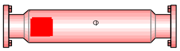
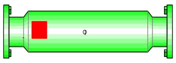
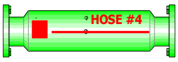
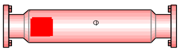
Changeover S3W1



Changeover S3W5

Figure 5-20. Sub-model of C/O for S3W5 at S3

Table 5-3. Product of S3

Before Process	Workstation	After Process	Before Process	Workstation	After Process
	**S3W1**			**S3W1**	
	**S3W2**			**S3W2**	
	**S3W3**			**S3W3**	
	**S3W4**			**S3W4**	
	**S3W5**			**S3W5**	

**Product CH4* **Product CH6*

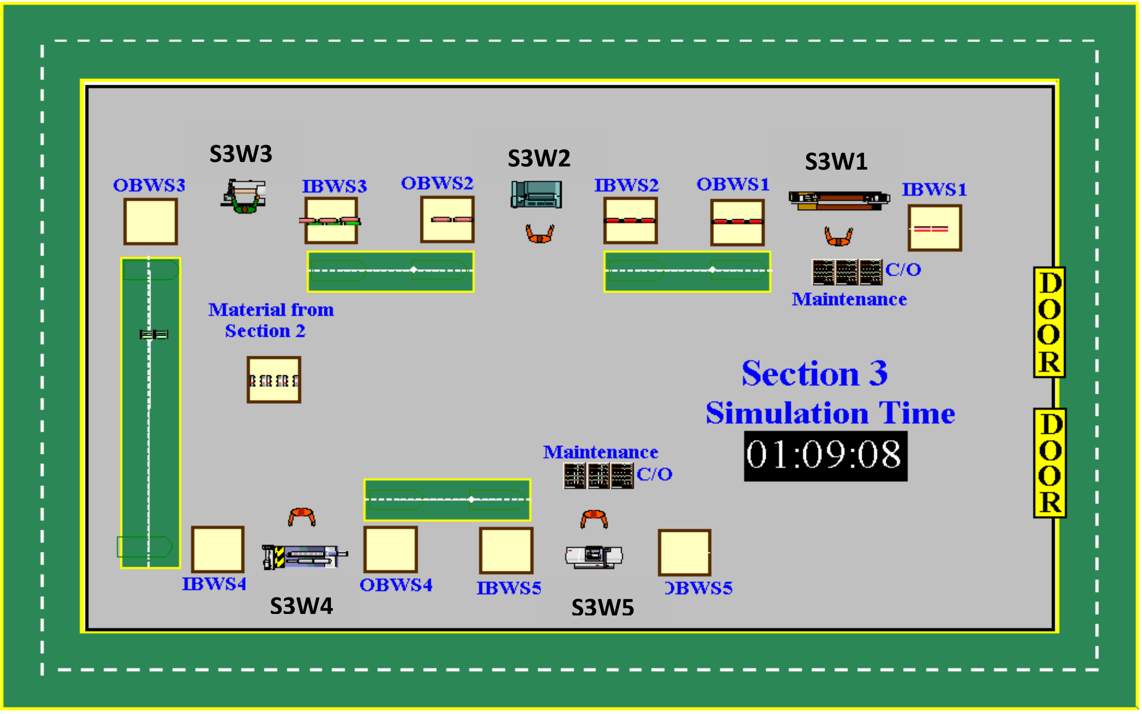


Figure 5-21. Snapshot of S3

5.2.4 Section 4 CHM Factory

The next section in CHM factory is CH8H10 line (S4) which is CH8 & CH10 production line layout (Figure 5-22). S4 consists of six WS namely S4W1 (machining), S4W2 (deburring), S4W3 (crimping), S4W4 (welding), S4W5 (testing) and S4W6 (marking). Similar to S2 and S3, each WS in S4 is operated by one operator. Based on triangular distribution, the process time for S4W1 is TRIA (0.5, 1 , 1.5); S4W2 TRIA (0.25, 0.5 , 0.75); S4W3 TRIA (0.5, 1 , 1.5); S4W4 TRIA (2, 3 ,4); S4W5 TRIA(0.5, 0.75 , 1) and S4W6 TRIA(1, 1.25 , 1.5). S4 produces two types of products namely CH8 and CH10. CO process occurs in S4W1 and S4W6 that requires 51 minutes and 24 minutes to be completed respectively. The batch capacity of each WS in S3 is 5 units and the buffer capacity for inbound and outbound is 25 units. CH8 and CH10 produced by S4 are sent to S5 (packaging line).

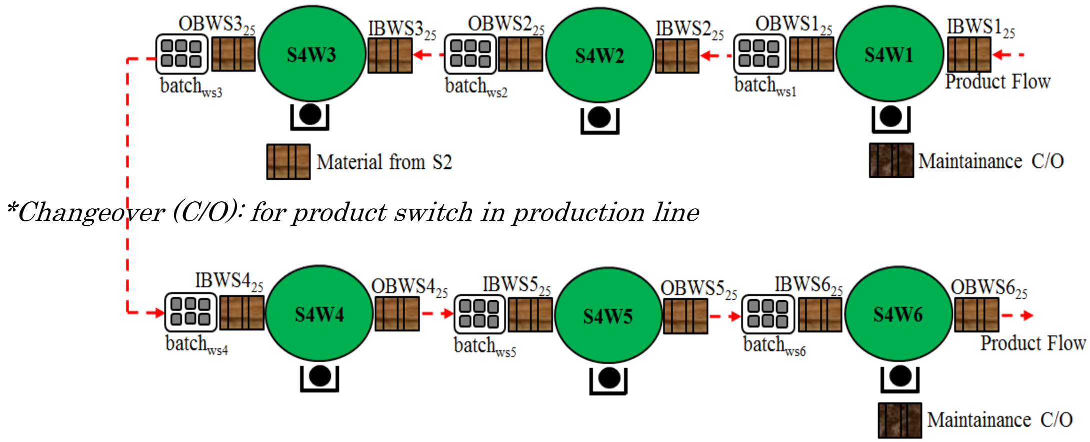


Figure 5-22. Layout of S4

The difference between CH4H6 line compare to CH8H10 line is the CH8H10 line provide welding process in their manufacturing line. Which is add one more WS and of course add one another operator and machine in this production line. The changeover process is similar to the CH4H6 line. Because machining process and marking process using the same machines.

The model logic that used on the Arena simulation software for Section 4 can be seen on Figure 5-23. Figure 5-24 and Figure 5-25 illustrating the sub model detail for S4W1 and S4W6 changeover machine.

The changeover stage is similar to Section 3. Whereby the nine tasks sequence is need to be done in order to change the tools. The same operator does the changeover in each WS.

If the tool is not for intended material, then changeover is to be done. That is how the changeover works in each WS on CHM factory simulation model.

Table 5-4 illustrating how the entities form change in the S4 during the simulation run. The form change is assigned in each WS by utilizing the assign module with respect along the process sequence. The change of entities picture in this CHM is very useful when verifying the CHM model.

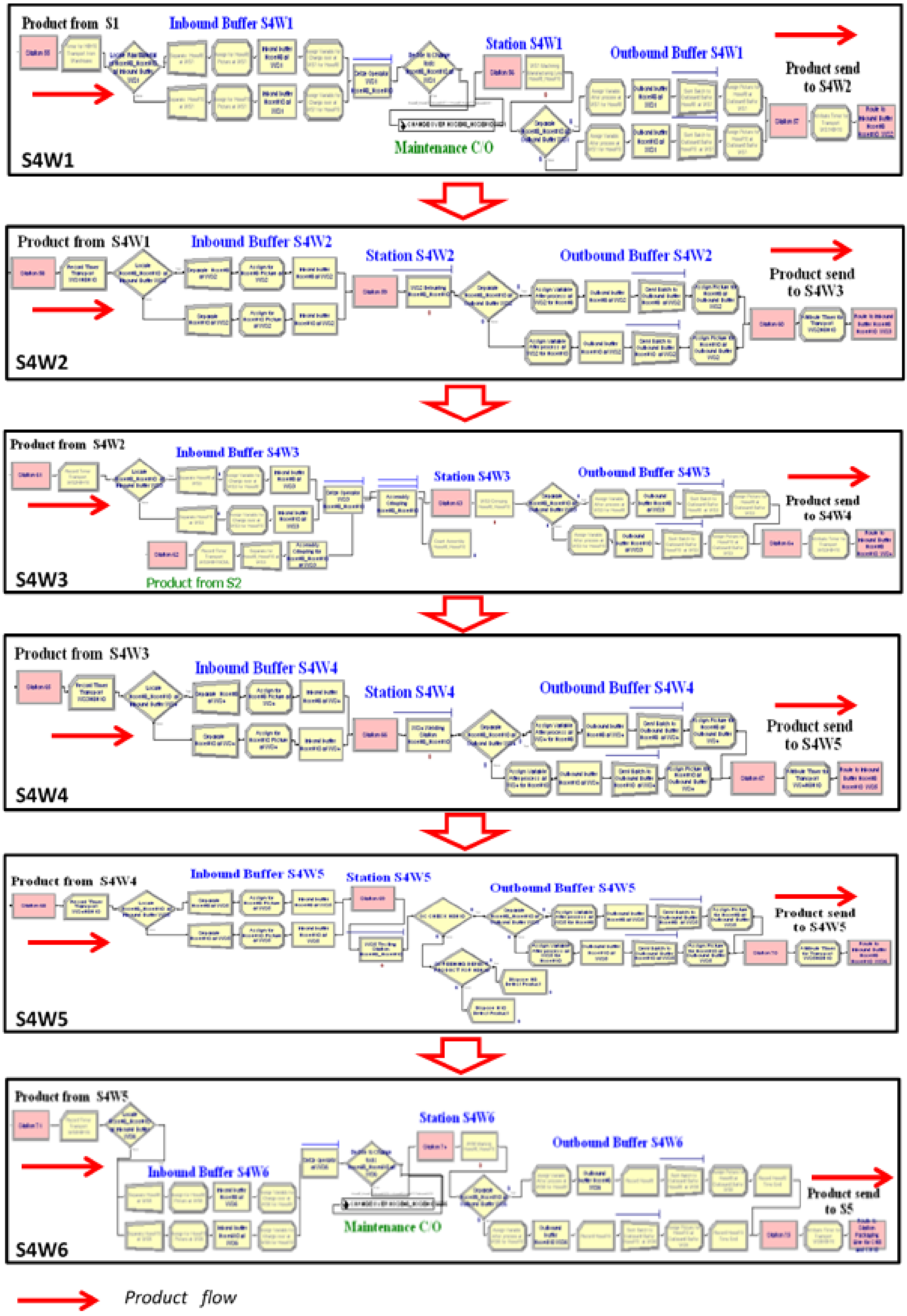


Figure 5-23. Model logic of S4

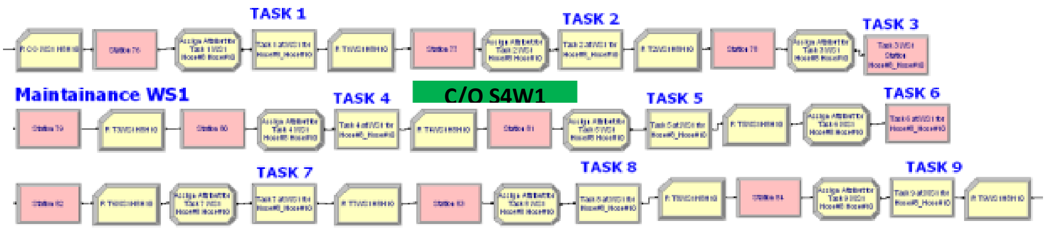


Figure 5-24. Sub-model of C/O for S4W1 at S4

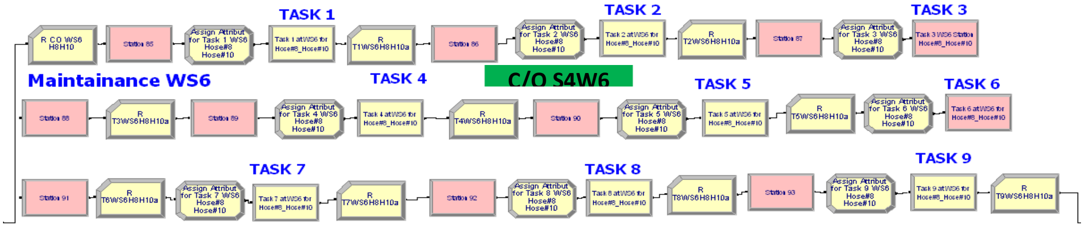
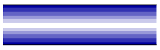
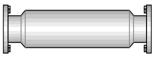
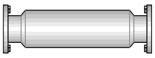
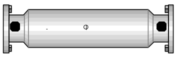
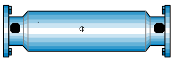
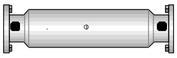
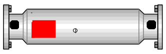
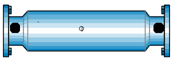
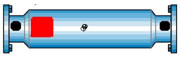
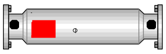
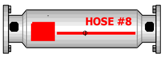
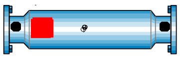
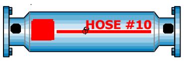


Figure 5-25. Sub-model of C/O for S4W6 at S4

Table 5-4. Product of S4

Before Process	Workstation	After Process	Before Process	Workstation	After Process
	**S4W1**			**S4W1**	
	**S4W2**			**S4W2**	
	**S4W3**			**S4W3**	
	**S4W4**			**S4W4**	
	**S4W5**			**S4W5**	
	**S4W6**			**S4W6**	

**Product CH8* **Product CH10*

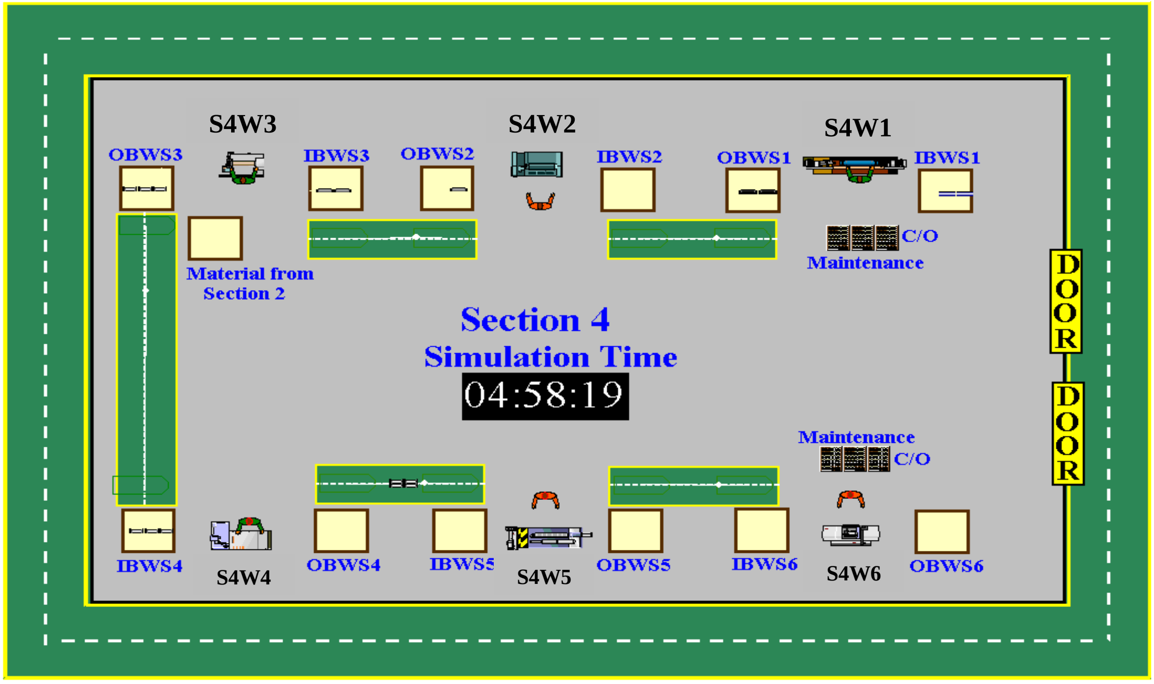
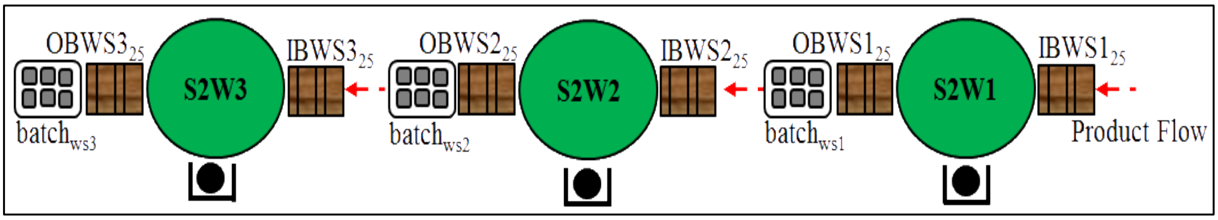


Figure 5-26. Snapshot of S4

Figure 5-26 illustrating the real snapshot of S4 when the model simulation run. The animations are including buffer animation, routing animation, resources animation, and simulation time. All this animation is purpose to made the verification and validation easier. In addition, with this animation the bottleneck in the production line can be visualized.

5.2.5 Section 5 CHM Factory

Section 5 (packaging line) are assembly processes. All assembly processes in WSs in this section are related with Section 1 regarding assembly-packaging materials. All processes are plastic wrapping (S5W1), box packaging (S5W2), and labelling (S5W3). The raw materials for assembly process is sent from inbound warehouse directly, while the main part of coolant hoses are from CH4H6 line and CH8H10 line. Consequently in S5 there are four types of coolant hoses being packaged. The model layout for packaging line can be seen on Figure 5-27, while the model logic is on Figure 5-28. In assembly line, this CHM factory utilizing match module. The match module in this CHM is work as pair entities. The entities will not proceed to the next WS if the other parts from inbound warehouse (S1) that is required still unavailable.



**Changeover (C/O): for product switch in production line*

Figure 5-27. Layout of S5

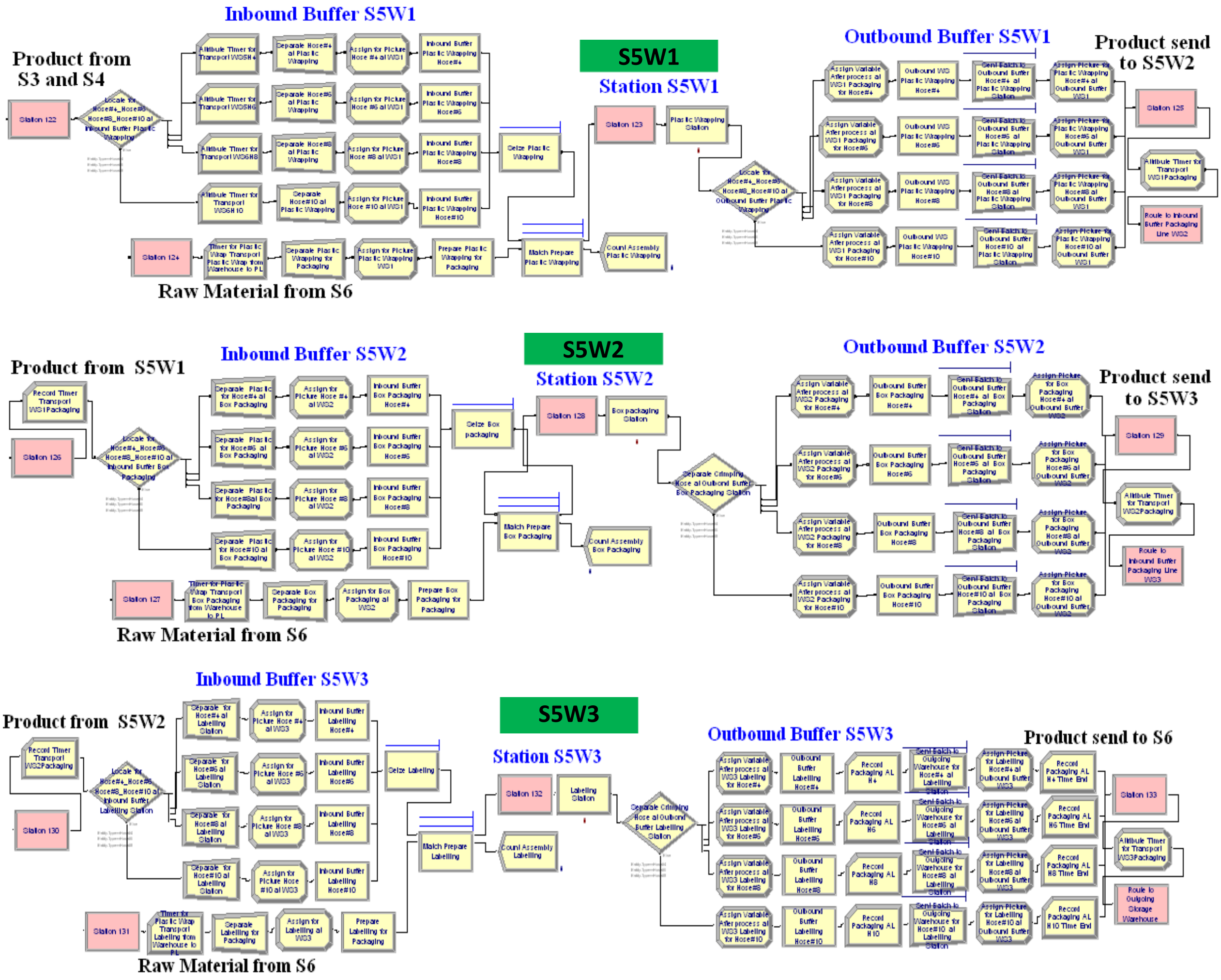
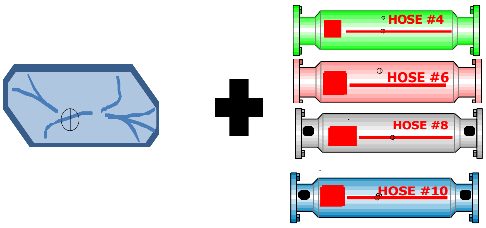
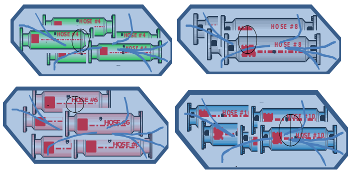
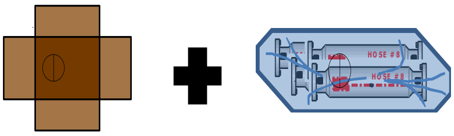
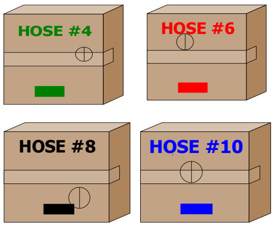
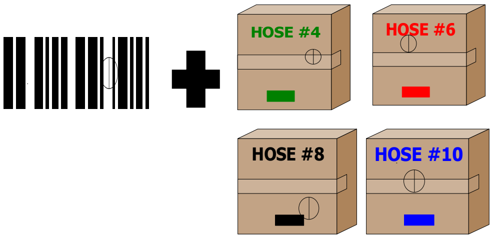
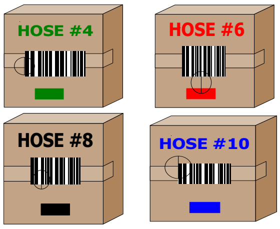


Figure 5-28. Model logic of S5

For Table 5-5 is visualize the change of the entities pictures for each process and each type. The assign module is utilizing the changing of the entities picture for each type of coolant hoses.

Table 5-5. Product of S5

Before Process	Workstation	After Process
	**S5W1**	
	**S5W2**	
	**S5W3**	

5.3 Verification and validation of CHM factory simulation model

Since the importance role of the simulation model in this experiment, its need to be verified and validated. The purpose of model verification is to ensure that the model is correctly constructed. In other words, verification ensures that the model conforms to its specification and does what it is supposed to do. Model verification is conducted largely by inspection, and consists of comparing model code to model specification (Altiok, T., and Melamed B. 2010; Kelton W., and Sadowski R., 2009). This research employs Little's Law mathematical equation for validating the model, (Rooda and Vervoort, 2007):

$$w = \delta.\, \varphi \tag{5-1}$$

Whereby;

w : The mean number of products in the manufacturing production line (Work in progress – wip – level w in units)

δ : The mean number of products leaving the system per unit of time (Throughput δ in units/time units)

φ : The mean time a lots remains in the system (flow time φ in time units)

The production line consist of buffer and batch for each WS, and then the calculation for waiting time for each product must consider for buffer, batch, process time, and route time. The total mean flow time for each WS can be calculated as follow:

$$\varphi_{tot} = \varphi_B + \varphi_{Bq} + \varphi_{Bk} + t_0 + t_{route} \tag{5-2}$$

Whereby

t_{route} = route time between workstation (in time unit)

t_0 = process time for workstation (in time unit)

φ_B = mean flow time for waiting in buffer (in time unit)

φ_{Bq} = mean flow time for queuing on the inter-arrival of a batch (in time unit)

φ_{Bk} = mean flow time for wait-to-batch time (in time unit)

The mean flow time for waiting in buffer, can be calculated from:

$$\varphi_B = \frac{c_a^2 + c_0^2}{2} . \frac{u}{1-u} . t_0 \tag{5-3}$$

For the queuing time on the inter-arrival time of a batch φ_{Bq}, can be calculated from:

$$\varphi_{Bq} = \frac{c_{a,b}^2 + c_0^2}{2} . \frac{u}{1-u} . t_0 \tag{5-4}$$

To calculate the wait-to-batch time:

$$\varphi_{Bk} = \frac{k\text{-}1}{2} . t_a \tag{5-5}$$

Whereby, from equation (5-1) until (5-5), the notation will be:

φ_B : The mean waiting time in buffer (in time units)
c_a^2 : The squared coefficient of variation of inter arrival time
c_0^2 : The squared coefficient of variation of process time
t_0 : Process time at WS (in time units/unit product)
k : number of units in a batch (in unit product)
u : The utilization of workstation
t_a : Inter arrival time (in time units)
$c_{a,b}^2$: The squared coefficients of variation of inter arrival time of a batch

For utilization u, can be obtain from:

$$u = \frac{T_{non\ idle}}{T_{total}} = \frac{t_a}{k.t_0} \tag{5-6}$$

Whereby:

$T_{non\ idle}$: denotes the time the machine is not idle during a total timeframe (in time units).
T_{total} : total timeframe (in time units).

c_a^2 and c_0^2 can be obtain from calculation of variant of its data divided by its squared time:

$$c_0^2 = \frac{s_0^2}{t_0^2} \tag{5-7}$$

$$c_a^2 = \frac{s_a^2}{t_a^2} \tag{5-8}$$

s_0^2 And s_a^2 can be obtaining from variant equation:

$$s_a^2 = s_0^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{5-9}$$

However because in this research using Triangular distribution for its entire simulation model, the variant calculation becomes this one:

$$s_a^2 = \frac{1}{18}(a^2 + b^2 + c^2 - ab - ac - bc) \tag{5-10}$$

$$t_0 = \frac{1}{3}(a+b+c) \tag{5-11}$$

Whereby:

a : minimum value of time range (in time units)

b : mode of time range (in time units)

c : maximum value of time range (in time units)

For the squared coefficients of variation of inter arrival time of a batch$c_{a,b}^2$:

$$c_{a,b}^2 = \frac{s_a^2}{t_a^2} = \frac{k.s_a^2}{(k.t_a)^2} = \frac{1.s_a^2}{k.t_a^2} = \frac{c_a^2}{k} \tag{5-12}$$

To distinguish notation between coefficient of variation for buffer process and batch process, then $c_a^2 = c_{a,l}^2$. For the coefficient of variation of the batch leaving the machine and entering the next machine for a batch c_d^2, (for the next workstation, c_d^2 will also as a coefficient of variation for inter arrival $c_{a,l}^2$):

$$c_d^2 = u^2 . c_0^2 + (1 - u^2) . c_a^2 \tag{5-13}$$

To calculate total production time, can be obtained from WS with longest φ_{tot} (WS which cause most bottleneck in production line) and then multiply it with total demand/number of batch. From here, the total production time was calculated.

The calculation result however compared between results from simulation software and mathematical calculation. A detailed animation was used to further verify that the model sufficiently replicated the real system. Validation of the model calls for comparing outputs of the simulation to mathematical calculation. The calculation result of validation can be seen on Table 5-6. The validation also use confidence interval of 95% for confirm the result of simulation model.

Table 5-6. Validation of CHM factory model

Section in CHM Factory	Average Simulation Throughput Time (in minute)	Calculation Result (in minute)	Confidence interval range 95%	Stated
CML	430.86	380.0199	368.12-493.59	Valid
CH4H6	820.37	853.6028	692.43-948.31	Valid
CH8H10	780.7	853.6	633.18-928.22	Valid
Packaging Line	147.565	148.533	107.82-187.3	Valid

5.4 Experiment Design by Taguchi Method

5.4.1 Why Taguchi Method?

Taguchi method uses orthogonal array to execute experiments and to analyse results. Using orthogonal array can substantially reduce the time, cost of developing a new product or technique, and thereby increase the competitiveness of the product in the open market. Taking the L_{12} (2^{11}) orthogonal array as an example, the initially required 2^{11} = 2,048 sets of experiments can be significantly reduced to 12 sets while achieving similar results to a full factorial experimental set-up.

Furthermore, interaction amongst factors could be evenly distributed to each column, ensuring the effect of interaction is minimized. Orthogonal arrays consist of inner and outer columns, the former assigned with control factors while the latter with input signal and noise factors.

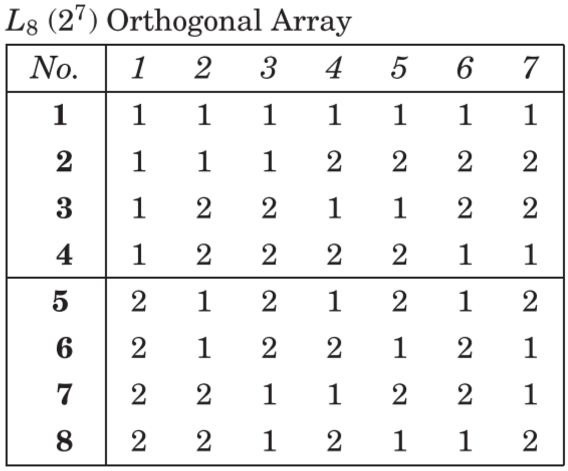
The principle behind the Taguchi method is to subject the design parameters to the tests of the noise factors to obtain optimised control factors that are effective in combating the influence of the noise factors acting on the product quality. This ensures the robustness of the system (Chen et al., 2010).

Even though not all the procedure in the Taguchi method is implemented in this study, however, almost all procedure is using the methodology of Taguchi method. The detail will be conveyed on other part.

5.4.2 An Overview of Taguchi Method

The Taguchi method is based on Orthogonal Array (OA) experiments, which provide a set of well-balanced experiments to use (Taguchi, G., Chowdhury, S. and Wu, Y. 2007). In this study, the research objective was to measure OEE element characteristics. Coolant Hoses Manufacturing (CHM) factory is serve as an experiment tool in this research. Orthogonal Arrays (OA) are a special set of Latin squares, constructed by Taguchi to lay out the product design experiments. By using this table, an orthogonal array of standard procedure can be used for a number of experimental situations. Consider a common 2-level factor OA as shown in Table 5-7 below.

Table 5-7. An Example of Orthogonal Array



L_8 (2^7) Orthogonal Array

No.	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

Taguchi divided the factors affecting any system into two categories: control factors and noise factors. Control factors are factors affecting a system that are easily set by the experimenter. For example, if in a chemical process the reaction time is found to be a factor affecting the yield, then this factor is a control factor since it can be easily manipulated and set by the experimenter. The experimenter will chose the setting of the reaction time that maximizes the yield. Noise factors are factors affecting a system that are difficult or impossible to control. For example, ambient temperature may also have an effect on the yield of a chemical process, but ambient temperature could be a noise factor if it is beyond the control of the experimenter. Thus, change in ambient temperature will lead to variations in the yield but such variations are undesirable.

Taguchi method divides all problems into 2 categories - static or dynamic. While the Dynamic problems have a signal factor, the Static problems do not have any signal factor. In Static problems, the optimization is achieved by using 3 Signal-to-Noise ratios, among others: smaller-the-better, larger-the-better, and nominal-the-best. In Dynamic problems, the optimization is achieved by using 2 Signal-to-Noise ratios - Slope and Linearity. The two problem categories, among others:

1. *Static Problems*:

   Generally, a process to be optimized has several control factors, which directly decide the target or desired value of the output. The optimization then involves determining the best control factor levels so that the output is at the the target value. Such a problem is called as a "STATIC PROBLEM".

   This is best explained using a P-Diagram, which is shown on Figure 5-29 ("P" stands for Process or Product). Noise is shown to be present in the process but should have no effect on the output! This is the primary aim of the Taguchi experiments - to minimize variations in output even though noise is present in the process. The process is then said to have become ROBUST.

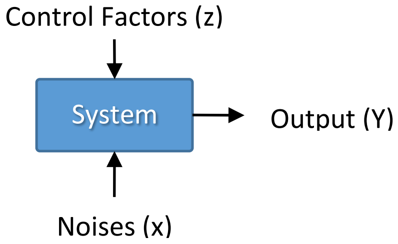


Figure 5-29. P-Diagram for Static Problems

2. *Dynamic Problems*:

   If the product to be optimized has a signal input that directly decides the output, the optimization involves determining the best control factor levels so that the "input signal / output" ratio is closest to the desired relationship. Such a problem is called as a "DYNAMIC PROBLEM". This is best explained by a P-Diagram that is shown on Figure 5-29. Again, the primary aim of the Taguchi experiments to minimize variations in output even though noise is present in the process is achieved by getting improved linearity in the input/output relationship.

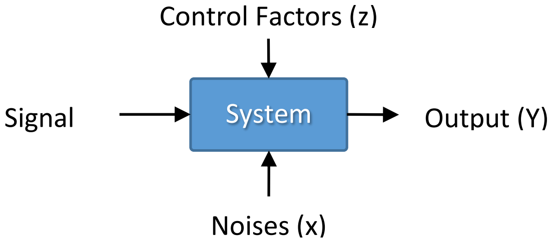


Figure 5-30. P-Diagram for Dynamic Problems

The CHM factory simulation model is include batch process, where each WS in entirely production line model process each product in a batch system. Base on explanation aforementioned, the case of CHM factory is categorized as static problem. The static problem itself is categorized again in to Signal-to-Noise ratios of common interest for optimization of Static Problems among others:

1. *Smaller the better* :

   This is usually the chosen S/N ratio for all undesirable characteristics like "defects", etc., for which the ideal value is zero. Also, when an ideal value is finite and its maximum or minimum value is defined (like maximum purity is 100% or maximum Tc is 92K or minimum time for making a telephone connection is 1 sec) then the difference between measured data and ideal value is expected to be as small as possible. Maximizing this S/N is to minimize the mean and standard deviation. Let the data points be y_1 y_2 … y_n while σ is data deviation and $\bar{y}$ is data mean. The generic form of S/N ratio then becomes,

$$ {}^{S}/_{N} = \eta \text{ dB} = 10 \log \left[\frac{1}{\frac{1}{n} \sum_{i=1}^{n} y_i^2} \right] = 10 \log \left[\frac{1}{\bar{y}^2 + \sigma^2} \right] \qquad (5\text{-}14) $$

2. *Larger the better:*

   Let the data points be y_1 y_2 … y_n

$$S/N = \eta \text{ dB} = 10 \log \left[\frac{1}{\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2}} \right] = 10 \log \left[\frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right] \qquad (5\text{-}15)$$

This case has been converted to smaller the better by taking the reciprocals of measured data and then taking the S/N ratio as in the smaller-the-better case. The example are number of unit production within a day, and from this research is the OEE score (even though the maximum number is 100%), etc.

3. *Nominal the best :*

This case arises when a specified value is MOST desired, meaning that neither a smaller nor a larger value is desirable. The higher the S/N becomes, the smaller the variability is. Maximizing this S/N is equivalent to minimizing standard deviation or variation.

$$S/N = \eta \text{ dB} = 10 \log \left[\frac{\frac{1}{n}(S_m - V_e)}{V_e} \right] \qquad (5\text{-}16)$$

Whereby, V_e is mean square (variance),

$$V_e = \sigma_{n-1}^2 = \sum_{i=1}^{n} \frac{(y_i - \bar{y})^2}{n-1} \qquad (5\text{-}17)$$

In addition, S_m is sum of squares due to mean,

$$S_m = \frac{T^2}{n} \qquad (5\text{-}18)$$

While T is sum of data, with data points be y_1 y_2 … y_n

$$T = \sum_{i=1}^{n} y_i \qquad (5\text{-}19)$$

Examples are; most parts in mechanical fittings have dimensions, which are nominal-the-best type, or ratios of chemicals or mixtures are nominally the best type.

The procedure that usually implemented in Taguchi method is based on plan-do-check-act or PDCA, (Taguchi et al. 2000), it elaborated to become:

Plan:

Step 1: Define the scope of project

Step 2: Define the boundary of subsystem

Step 3: Define the input signal M and the output response y

Step 4: Develop signal and noise strategies

Step 5: Define control factors and levels

Step 6: Formulate the experiment and prepare for experiment

Do:

Step 7: Conduct the experiment / simulation and collect data

Step 8: Conduct data analysis

Step 8-1: Calculate signal-to-noise ratio and sensitivity for each run

Step 8-2: Generate a response table for S/N, sensitivity, and study and interpret the response tables.

Step 8-3: Conduct two-step optimization

Step 8-4: Make prediction

Check:

Step 9: Conduct confirmation run and evaluate the reproducibility

Act:

Step 10: Document and implement the result

Step 11: Plan the next step

5.4.3 The implementation of Taguchi Method with Simulation

Those PDCA steps is implemented in the company that using Taguchi method as an optimization tools in order to get the best result. However, in this study, the procedure is conducted regarding the research objective.

The first thing, based on the noise factors definition, which aforementioned in this chapter, the noise factors in this research, is not considered. Because the entire CHM model is conducted within the Arena simulation software, in order to mimic the real one.

The second thing is, the Taguchi method procedure (PDCA) is particularly for dynamic problem case. Whereas this research is grouped as a static problem case, consequently there are numerous steps in PDCA is not conducted in this research.

The third thing is, regarding the research objective, is only to measure the control factors responses.

Consequently, the optimization steps in PDCA is not conducted entirely. For the calculation of response tables and determining the orthogonal array, this research employs MiniTab statistical software ver. 16. The detail of the PDCA implementation in this research can be describe as follows:

Plan:

Step 1: Define the scope of project

The scope project is to measure the response of each OEE (overall equipment effectiveness) element through CHM factory model simulation, in order to observe which factors is dominant.

Step 2: Define the boundary of subsystem

The boundary of subsystem is divided in to two focus areas; crimping manufacturing line for "Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation" research and CH4H6 line for "Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line" research as a part of CHM factory model. This research only focus on the availability factor, performance factor, and quality factor in order to measure the OEE elements.

Step 3: Define the input signal M and the output response Y

The system in this research is clustered as static problem model; hence, this step is only determining what kind of the output responses. The output responses for the “Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation” is only the OEE score. In addition, for the “Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line” is the OEE score include with value added cost (VA cost) and non-value added cost (NVA cost).

Step 4: Develop signal and noise strategies

This step is no need to conduct if the problem case is static problem. The noise factors are not considered because of the experiment tool using Arena simulation software, nevertheless the signal to noise (S/N) ratio still can be calculated. Particularly for the research topic “Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation”. Because the weight calculation is using S/N ratio in order to calculate the weight of each WS.

Step 5: Define control factors and levels

To define control factors and its levels is crucial step, because it related to research objective. In this research, the OEE elements is defining as the control factors of the experiments. The availability element, the performance element, and the quality element. All measurement of OEE element is aim to calculating the OEE score in each experiment and each research topic. The levels of each control factor is to measure sensitivity or response of each control factor regarding the variation between level ranges. For research topic, “Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation” is using three levels of variation for each control factor, while for research topic “Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line” is using two levels of variation for each control factor.

Step 6: Formulate the experiment and prepare for experiment

To formulate the experiment is related to define the orthogonal array for the experiment. The orthogonal array is determined by the degree of freedom calculation in each experiments. However this research employing MiniTab statistical software in order to determining the orthogonal which is going to used in the experiment. The orthogonal array for research topic “Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation” is using orthogonal array $L_9(3^4)$, with three levels of variation for each control factor. For research topic “Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line” is using orthogonal array $L_8(2^7)$ with two levels of variation for each control factor. It is necessity to verify and validated the CHM factory simulation model, before running the experiment.

Do:

Step 7: Conduct the experiment / simulation and collect data

The simulation is run with ten times replication for each experiment. The control factor for each experiment is related to the OEE elements. The performance element parameter is modified in the process module in each WS in CHM factory simulation model based on matrix experiment and orthogonal array. The availability element parameter is modified on the failure mode and in the resource mode in each WS. While the quality element parameter is modified on the decide module on the testing WS in CH4H6 line (section 3) and CML (section 2). All parameter variation is refer to the matrix experiment and orthogonal array experiment.

Step 8: Conduct data analysis

The data analysis is utilizing the simulation result from Arena simulation software and calculated using Minitab statistical software. The most important results of this experiment are the response tables. Because from this response table, are the baseline for weight calculation for OEE element, as well as the baseline for OEE estimation analysis.

Step 8-1: Calculate signal-to-noise ratio and sensitivity for each run

This step is conducted only for research topic “Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation”, because the weight calculation for OEE is using S/N ratio. For research topic "Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line" is using average data for OEE score, value added cost (VA cost), non-value added cost (NVA).

Step 8-2: Generate a response table for S/N, sensitivity, and study and interpret The response tables for S/N is generated only for research topic "Calculation of Overall Equipment Effectiveness Weight by Taguchi Method with Simulation" based on previous step. For research topic "Overall Equipment Effectiveness Estimation for Priority Improvement in the Production Line" is using average data for response table through OEE score, value added cost (VA cost), non-value added cost (NVA) in order to measure the estimation of OEE score

Step 8-3: Conduct two-step optimization

In this step is not conducted because this research is clustered as static problem.

Step 8-4: Make prediction

This step is to made prediction base on dynamic problem. For the static problem, the prediction is made by utilizing the response tables.

Check:

Step 9: Conduct confirmation run and evaluate the reproducibility

This step is not implemented because this is related to optimization step.

Act:

Step 10: Document and implement the result

To document and implement the result is only for dynamic problem case.

Step 11: Plan the next step

This step is not implemented because this is also related to optimization step.

After all steps is conducted (except all steps related to optimization steps), then analysed it regarding the research objective. Because this study provide two proposal to improve OEE as a KPI. First is “Calculation of OEE Weight by Taguchi Method with simulation” and the second is “OEE Estimation for Improvement in the Production Line”. Those research titles is using the same method, same steps, however different purpose.

Chapter VI

Conclusion

6.1 Conclusion and Future Work

This study pursue to propose two procedures in order to improve the OEE as a key performance indicator (KPI) in the production system, which measure the factory performance through TPM philosophy.

The first research proposal is sought to offer a procedure to cover the drawbacks of weighting OEE elements. From our analysis, it can be concluded that the outcome of this research experiment can be implemented in OEE with a weighted method, among others; for example, in PEE as well as OWEE. A simulation model was chosen because it is able to mimic a real production line and therefore act as a suitable experiment tool. The STP provided characteristic mapping of OEE elements through a response table. The research motivation was initiated by several researches of OEE improvement, which met difficulty when determining the proper weight for each OEE element. The calculation results of OWEE and PEE by STP also showed better results than the original OEE for the CH4H6 line. Naturally, even though STP seems to be difficult to implement, the outcome is worthwhile. Moreover, the company will have obvious data to consider, when making decisions for the improvement of priorities in their production line.

The second research proposal offers OEE enhancement scheme, which provides a company with the appropriate information for decision-making on priority improvement in the production line. By using the Taguchi method and simulation as an experimental tool, this scheme can measure and estimate the contribution for each OEE element to an OEE score. This procedure can be implemented in a specific WS or in a production line if the factory is made up of more than one manufacturing line. There are four types of enhancement information. The first type is the OEE itself, the second is the OEE element contribution measurement, the third is the OEE element measurement by the value added cost (VA cost), and the fourth is the OEE measurement by the non-value added cost (NVA cost). They provide measurements for each OEE element in order to observe the extent of the influence the simulation experiment has on the OEE elements and scores. Other OEE enhancement implementations on another simulation model showed that the procedure could be implemented in other case studies as well. The work plan for the future is to continue with the same procedure and include experiments that are more level in order to observe the characteristic of the OEE elements in relation to the OEE scores.

All of those research proposals are to improve the OEE as a KPI in the factory. In order to meet the objective of the TPM itself, increasing the sustainability of the company by continuous improvements.

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