DISCRETE EVENT SIMULATION AS A DECISION-MAKING TOOL FOR IMPROVING OVERALL LINE EFFICIENCY

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Honours) Industrial Engineering

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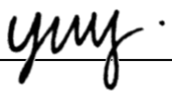
DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

Signature : 

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ABSTRACT

This paper is about formulating a new decision-making framework that integrates discrete event simulation (DES) software to select the best alternative to improve a manufacturing system. Literature pertaining to decision-making tools, performance metrics and frameworks on decision-making as well as process improvement was reviewed. The advantages and limitations of techniques, strategies as well as frameworks adopted by recent researchers were ascertained. The review discovered that there is lack of comprehensive framework on deploying simulation tool as decision-making supporting instrument in process improvement. Vital features of decision-making and process improvement were explored through literature, and a new framework was designated by incorporating the vital features with rectified gaps found in recent works. To validate the feasibility of the proposed framework, it was then applied in a case study conducted at a box manufacturing factory in Sarawak, Malaysia, to improve the factory's overall line efficiency (OLE). The framework provided guidelines in goal, objectives and decision criteria setting, constructing simulation models that was precise in reflecting the real system, identifying root causes, generating relevant solutions, experimenting solutions and selecting the best performing solutions with the aid of WITNESS 20 simulation software, analytic hierarchy process (AHP) as well as analysis of variance (ANOVA). As a result, it was predicted that the OLE will be improved to 89.61 % by enhancing the printer setup efficiency and operators' troubleshooting skill. It was deduced that the new framework is more advantageous in selecting the best alternative in process improvement projects, compared to the conventional framework in various aspects.

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LIST OF SYMBOLS/ABBREVIATIONS

K_{IC}	improvement cost, RM
K_T	total cost, RM
M_G	gluing machine
M_{JDC}	jaw die-cutting machine
M_P	printing machine
M_{RDC}	rotary die-cutting machine
m	number of decision criteria
N_P	number of printing machines
N_{QP}	average setup scrap of printing machine, pieces/setup
n	total number of orders
P_{ij}	performance measure of decision criteria of the solution
$\overline{P}_{ij}$	normalized performance measure of the solution
p	score of significance
Q_A	actual output at bottleneck workstation, pieces
Q_c	corrugator scrap rate, %
Q_d	number of defective goods, pieces
Q_T	theoretical output at bottleneck workstation, pieces
Q_t	total line output, pieces
R	decision criteria
S	consistency relationship
S_I	consistency index
S_A	average value of random consistency index
ST_G	setup time of gluing machine, minutes
ST_{JCD}	setup time of jaw die-cutting machine, minutes
ST_P	setup time of printing machine, minutes
ST_{RDC}	setup time of rotary die-cutting machines, minutes
T_{CT}	cycle time of bottleneck, s

T_i	time taken to complete order i
T_{LT}	loading time, s
ω	criteria weight
$\lambda_{max(i)}$	eigenvector of ω_i
λ_{max}	largest eigenvalue
AFT	average flow time, hours
AHP	analytic hierarchy process
ANOVA	analysis of variance
ANP	analytic network process
CIMS	computer integrated manufacturing system
DCB	die-cut box
DES	discrete event simulation
DOE	design of experiment
ECE	equipment cost efficiency, RM/pieces
EDD	earliest due date
FIFO	first-in-first-out
FMEA	failure mode and effect analysis
FMS	flexible manufacturing system
FSW	friction stir welding
GRA	grey relational analysis
HR	human resource
LIFO	last-in-first-out
LMS	lean manufacturing system
LOD	level of difficulty
MCDM	multi-criteria decision-making
MTBD	mean time between defect, minutes
MTBF	mean time between failure, minutes
MTTR	mean time to repair, minutes
MTTS	mean time to solve, minutes
OEE	overall equipment effectiveness, %
OLE	overall line efficiency, %
PVA	performance value analysis

Q	line scrap rate, %
QC	quality check
QFD	quality function deployment
RSC	regular-slotted container
SMED	single-minute exchange of die
SPT	shortest processing time
TOC	Theory of Constraints
TOPSIS	technique for order preference by similarity to ideal solution
TPM	total productive maintenance
SAFM	simulation application framework for manufacturing
VIS	visual interactive simulation
VSM	value stream mapping
WIP	work-in-process

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CHAPTER 1

INTRODUCTION

1.0 Introduction

This chapter is about the introduction for this project. Section 1.1 discusses the background of essential elements of this project, Section 1.2 discusses the problem statements, Section 1.3 is about the aim and objectives of this project, Section 1.4 describes the scope and Section 1.5 presents the outline of this project report.

1.1 Background

This subsection introduces the background of important elements of this study, which are decision making in Section 1.1.1, discrete event simulation in Section 1.1.2 and overall equipment effectiveness in Section 1.1.3.

1.1.1 Decision Making

The term decision making implies that there are several alternative options to be scrutinized. This is because decision making is the study of determining and selecting alternatives (Mateo, 2012). There are many circumstances that require decision making, such as judgement, problem-solving, planning and many others that can occur in our daily lives. Nevertheless, decision making is not merely about choosing alternative, but also involves integral analysis of the possible solutions. Evaluation of possible solutions results in reducing ambiguity about the alternatives to allow a feasible solution to be chosen (Dureja and Singh, 2011). Subsequently, selection of alternative could be based on the values, experience and preferences of the decision maker or analytical data in a scientific and disciplined way.

In engineering perspective, decision making comprises of a more holistic approach, rather than relying upon intuition or personal experience. For instance, evaluation of alternatives is carried out by using techniques designated for decision making and selection of alternative is supported by data analysis or other tangible information that depicts the superiority of the selected solution. In manufacturing industry, many researchers or engineers have adopted systematic techniques to facilitate decision making such as in process improvement, facility layout design and scheduling. For example, Sudhagar (2017) employed Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a multi-criteria decision-making tool, to identify the best alternative solution to improve one of the processes in aluminium alloy manufacturing. Also, Pankaj and Ajai (2015) used simulation as decision making approach to test run different dispatching rules on the constructed manufacturing system simulation model and chose the dispatching rule that contributes the best performance based on the simulation result.

To ensure efficiency and effectiveness in decision making, few decision-making tools are introduced. With the aid of decision-making tools, decision-making process will be more systematic as well as rational, and critical thinking skills of decision makers can be strengthened. There are two distinct categories of analysis tools that can be adopted to evaluate and select alternative, which are quantitative and qualitative analysis. Quantitative analysis method consists of analytic hierarchy process (AHP), multi-attribute utility theory and decision matrix. This type of analysis encompasses scoring criteria for each alternative, and the alternative which has the highest score is the most favourable solution. Determining weighting of alternatives is necessary and mathematical skill is also vital for intricate decisions that involve multiple criteria and alternatives. On the other hand, some examples of qualitative comparison method are pros and cons analysis, and cost-benefit analysis. The general notion of qualitative comparison method is to select alternative that has significant pros or benefits and less consequential cons. Ultimately, choosing an appropriate tool is also a substantial stage in decision making process because different tools correspond to different needs and complexity of decision making (Baker et al., 2001).

1.1.2 Discrete Event Simulation

Simulation is a renowned tool that implies the development of a set of assumptions to mimic the operation of an actual process or system over time (Banks et al., 2001). Furthermore, discrete event simulation (DES) refers to simulation that is made on a system that varies spontaneously in response to certain discrete event. Simulation has been extensively practiced because in addition to provision of flexibility, it creates vast experiment opportunities as it can be reconfigured easily and allows different scenarios to be tested (Kumar and Sridharan, 2010). Besides, the escalating advancement in simulation technology facilitates translation of real-world operation system to a virtual model where the properties and behaviour of the entire system can be easily inferred. Also, performance measures of existing or proposed system can be obtained through simulation.

Undoubtedly, simulation has been prominent in manufacturing sector. Ingemansson et al. (2002) conducted a survey on deployment of DES in manufacturing industry. The finding advocates that the usefulness of simulation software in manufacturing is versatile and its potential as well as utilization will expand in the future. With the assistance of simulation-generated data, simulation is used to estimate the performance measures of existing manufacturing system and perform analysis to forecast the result of alteration on existing system or to predict the performance of newly designed system over extended period of time (Banks et al., 2001). Performances that can be measured include throughput, flow time, work-in-process (WIP) level and resource utilization. Generally, simulation has prominence in quantifying performance, diminishing possibility of failure, eradicating unforeseen bottleneck, decision-making and optimizing cost as well as performance of a manufacturing system (Ingemansson et al., 2002). Moreover, examples of manufacturing system that can be simulated are facility layout and design, material handling system, operations planning and scheduling as well as inventory control system (Smith, 2003).

Simulation can be performed by using mathematical programming or software. Schruben (2000) introduced that the dynamic of a discrete event system can be expressed by mathematical programming formulation to derive an optimal solution for optimization problem. Matta (2008), who concurred with Schruben (2000), proposed using mathematical programming models, such as mixed integer linear model, linear programming model and stochastic programming model to solve optimization problem for buffer allocation in production line. Furthermore, simulation software is widely used due to its undisputed advantages. Examples of simulation software adopted in manufacturing industry are WITNESS, FlexSim and ProModel. Contrary to mathematical programming formulation, simulation software is more robust and understandable. This is because most complex manufacturing systems can be modelled by using software and the model development time is also shorter. On top of that, models built by software can be flexibly reconfigured, statistical reports are automatically generated and most significantly, dynamic behaviour of the system is animated in a transparent manner (O'Kane et al., 2000). The fascination of graphics and animations in simulation software also smooths communication between specialists and non-specialists.

1.1.3 Overall Equipment Effectiveness

Overall equipment effectiveness (OEE) is an essential metric that is used to quantify and assess performance of a single equipment. It is represented by multiplication of its three mutually exclusive elements, which are availability (A), performance efficiency (P) and quality rate (Q). Therefore, the higher the OEE value, the more effective the equipment is. According to Nakajima (1988), OEE is introduced with the aim of supporting total productive maintenance (TPM) by measuring six big losses that depress the effectiveness of an equipment. The six big losses are equipment failure, setup and adjustment, idling and minor stoppages, reduced speed, defect and rework as well as reduced yield.

In manufacturing industry, OEE is used to measure the performance of a single machine or integrated machine of a manufacturing line (Braglia, 2008; Nakajima, 1988). It is undeniable that OEE is an ultimate performance measuring tool especially in manufacturing sector. By computing the three factors which are A, P and Q, OEE helps in identifying and quantifying the six big losses in manufacturing system. Consequently, improvements can be made to address the losses detected in order to improve system performance. Other than that, OEE can serve as a benchmark that can be used internally to develop improvement objectives, or to strive for world-class standard of OEE level, which is 85 % (Bamber, 2003; Nakajima, 1988). OEE can also be used as a benchmark to assess and monitor the efficacy of improvement made in manufacturing plant. This is because level of improvement can be evaluated by comparing future OEE value with initial OEE value in order to justify the effectiveness of improvement applied (Dal et al., 2000).

There are a few alternative indicators derived from OEE because OEE itself is inadequate to assess the overall performance at factory level. Some examples of alternative metrics of OEE are overall line efficiency (OLE), overall throughput effectiveness, overall labour effectiveness and overall asset effectiveness (Fernandez, 2016). These metrics are similar approaches that compute the ratio between real performance of a system and its ideal circumstance (Braglia, 2008). Furthermore, OLE is an expanded approach of OEE that measures overall performance of a manufacturing line. In a like manner, OLE can also be used as a benchmark to evaluate the effectiveness of improvement made in manufacturing line by comparing the initial and future OLE values.

1.2 Problem Statement

To keep pace with the advancement of technology, intensity of global competition as well as soaring demand, manufacturing systems are becoming more complex as they tend to deploy automation, continuous manufacturing and expand product variants in order to enhance manufacturing productivity and profit. As a consequence, the process of conducting adjustment or initiating new strategies in a manufacturing system such as process improvement and increasing capacity, is relatively complex. Hence, decision problems involve in manufacturing process nowadays are more complex due to broad decision-making areas as well as diverse constraints and attributes (Celen and Djurdjanovic, 2020).

On the other hand, in response to the outbreak of global pandemic COVID-19, remote working is driven to reduce social interaction in workplaces. Certainly, some manufacturing organizations start to transform their working platform to computer-oriented, such as using software to remotely monitor manufacturing operations during the pandemic. In this case, projects such as production planning and decision-making for process improvement have to be conducted remotely. However, the pandemic has stimulated the development of technologies on hardware and software that support manufacturing system and this in turn leads to satisfaction in remote working (Montano Caraballo, 2020). It is believed that implementation of off-site planning, decision-making and system control will be viral in the future even after the pandemic because it can save time and cost, so that more capacities are available for other value-added activities. Hence, adoption of software in decision-making for process improvement in manufacturing system should be promoted.

With regard to this, there is a lack of systematic improvement framework and detailed guiding steps about incorporating simulation software as a remote decision-making approach to improve overall line efficiency of a manufacturing system. Without a coherent structured framework, objective of the improvement project will be obscure and the tools or strategies used may be irrelevant. In addition, the advantages of simulation software in decision making could not be utterly exploited if explicit steps are not demonstrated to practitioners as a guideline. Absence of definite objective and algorithm will also deteriorate the practitioners' motivation because they are unclear about what to strive for and how to do. Thus, lacking of precise framework would eventually cause the improvement project to be sluggish, time-consuming, costly and ineffective.

1.3 Aim and Objectives

The aim of this project is to test the feasibility of a new decision-making framework for system performance improvement. This can be achieved through three objectives:

1) To identify key factors of decision making and using DES software as a decision-making tool for improvement project.
2) To develop a new comprehensive decision-making framework about improving a manufacturing system's performance by employing DES software as a decision support instrument.
3) To validate the framework by conducting a case study at a box manufacturing factory in order to justify the practicality of the framework in real-life situation.

Literature review will be conducted to study the general decision-making framework, contributions of computer simulation software in manufacturing industry, simulation building framework and substantial considerations in enhancing manufacturing system's performance. Besides, the outline and constituents of the framework are intended to be organized, coherent and effective in embodying all considerations from start to end. The validation result will also be analysed to determine the effectiveness and strengths of the framework.

1.4 Scope

The DES software used in this project to model discrete events and dynamic behaviour of a manufacturing system is WITNESS 20 software from Lanner Group. It is one of the simulation software that incorporates virtual interactive modelling and this allows the complex world to be easily visualized. WITNESS 20 is also user-friendly due to its graphical user interface integrated with C++ programming. Other benefits of WITNESS 20 that make it as a preferred tool in this project are the flexibility of model that can be reconfigured, automatic generation of essential statistical data and animation of flow of inventories and resources.

Besides, Minitab software is used to aggregate and analyze statistical data throughout this research. It is an advanced and intelligible data analysis tool as data can be easily input, manipulated and thoroughly interpreted in various forms of statistical analyses, graphs and charts. Therefore, using Minitab to analyze statistical data is fast and in addition, data in Excel sheet can be easily imported into Minitab.

Last but not least, a box manufacturing factory is chosen as the case study's background because its manufacturing system is considered moderately complex due to job shop manufacturing. The nature of job shop manufacturing has arisen many optimization problems in scheduling and material handling as the routes of WIP differ among the product families. There are also many underlying wastes that impede the overall performance of the manufacturing system. Additionally, the complexity of system in the factory enforces the relevancy and strength of DES software as a useful tool to support problematic decision-making process in manufacturing industries.

1.5 Thesis Outline

This thesis is divided into five chapters. In this chapter, the background, problem statement, objectives and scopes of this research are introduced. The remaining chapters of this thesis are organized in such manner: Chapter 2 discusses the review of various literature pertaining to areas of study in this research. Literature about decision making and process improvement is studied and the findings of the reviews are discussed. Chapter 3 provides the flow of this research and development of a new decision-making framework for improving system performance. Chapter 4 discusses the results of this research by applying the proposed framework in a real system to justify its practicability. Lastly, Chapter 5 concludes the finding of this research as well as the feasibility of the new framework.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter discusses literature studies relating to decision making and process improvement in manufacturing system. As mentioned earlier, there are many techniques designated to add value to decision making in respect of making the process more systematic and objective. Additionally, decision analysis for Multi-Criteria Decision Making (MCDM) is relatively complex because it involves multiple objectives to be optimized. To solve decision problems, methods such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), analytic hierarchy process (AHP) and computer-based discrete event simulation (DES) are used.

To thoroughly gain insights on related studies, three circumstances of literature were reviewed, which are decision making, process improvement and decision making for process improvement. Decision making is the process of selecting the best alternative for the particular manufacturing process, for instance, deciding whether or not to implement a new technology in the system or selecting dispatching rule that best suits the system. Process improvement is the generation and implementation of strategy that enhances the performance of manufacturing system. On the other hand, decision making for process improvement differs from the formers in such a way that it implies selection of the best strategy among various alternatives with the aim to enhance the performance of existing system.

This chapter is divided into five subsections as follows: Section 2.1 is about review of decision-making, Section 2.2 discusses review of process improvement, Section 2.3 discusses review of process improvement that involves decision making, Section 2.4 is analysis of literature reviewed and Section 2.5 is an insightful discussion about the literature reviewed.

2.1 Review of Decision Making

In regard to decision making process that takes place in manufacturing industry, Robinson et al. (2001) developed a methodology for decision making with simulation model. Through literature study, it was discovered that visual interactive simulation (VIS) is a good approach as it is user-friendly and the pace of decision making can be accelerated. The methodology constructed comprises of 5 stages. Supplementary tools such as decision matrix, attribute vector and decision tree were used to clarify information. Consequently, it was deduced that VIS is an effective approach for experimentation of alternatives due to its innovative data collection. But, deliberate model building is mandatory to ensure the precision of simulation results.

Moreover, Rao (2006) established steps in assessing alternative types of flexible manufacturing systems (FMS) by adopting digraph and matrix approach. This researcher had studied various mathematical and graphical models proposed by recent literature and found out that there was a lack of simplistic and systematic mathematical approach to enhance quality of decision making. Digraph representation and decision matrix were hence introduced to solve multi-attribute decision problem. Matrix approach was used to quantify the alternative’s impact by evaluating attributes of each alternative. The quantified impact is called selection index. After analysis, alternative ‘A’ which has the highest index among alternatives ‘A’ to ‘X’ is selected to be adopted in the system.

Partovi (2007) proposed an analytical model in determining the best process choice between batch production and continuous production for a new facility of a chemical industry. It was reviewed that production process choice is a strategic decision as a relevant production process must be selected in order to fulfill market demand and save cost. Therefore, an analytical model was formulated and composed of quality function deployment (QFD), analytic hierarchy process (AHP) and analytic network process (ANP) to aid decision making. QFD was firstly used to identify crucial production processes with respect to market requirement and the relative importance was weighed and analysed through AHP as well as ANP. Lastly, continuous production was chosen because of its higher score in weight evaluation and lower cost.

Correspondingly, Bayazit (2005) studied the use of AHP in MCDM whether to implement FMS in a factory or not. It was determined that AHP is suitable to evaluate the applicability of a new system as it is designated to solve multi-criteria decision problems. AHP methodology developed by recent researcher was studied and generalized into three major steps, which are structuring hierarchy, comparing decision alternatives through pairwise comparison and synthesizing results. The steps were followed and as a result, implementing FMS had a higher overall priority score after determining the relative importance of 28 criteria. Subsequently, sensitivity analysis was performed to examine the effect of altering criteria's priority on alternatives' selection. The alternative selection is stable if the importance of main criteria stays within 5 %.

Besides, in order to select the most suitable manufacturing system between two alternatives which are Lean Manufacturing System (LMS) and Computer Integrated Manufacturing System (CIMS), MCDM was carried out by Gurumurthy and Kodali (2008) and the model was known as Performance Value Analysis (PVA). Other than reviewing the background of LMS and CIMS, significant criteria that evaluate the efficacy of manufacturing system were identified and categorized, such as cost, quality and productivity. A step-by-step algorithm of PVA was described. Performance measures that quantify the criteria were also determined and assigned with weight values. Mathematics expressions were used to calculate the partial performance of each category. Then, the partial performance of each category was summed to quantify the overall performance of the manufacturing system. As a result, LMS dominated CIMS due to its higher score for overall performance.

To select the most suitable dispatching rule for job shop scheduling, Sharma and Jain (2015) used simulation software to model a manufacturing system that has sequence-dependent setup times. Based on their literature study, they have pinpointed nine dispatching rules to be incorporated in their simulation model. Each dispatching rule was then experimented by using ProModel software and performance measures such as flow time, makespan and tardiness were collected as well as compared with the aid of bar graphs. The best performing dispatching rule was selected in accordance with the experimental outcomes, which is “job with similar setup and modified earliest due date” due to its low flow time, tardiness and setup time. It was deduced that simulation modelling is the most appropriate approach to study a large and complex manufacturing system.

In addition, Papakostas (2012) had developed an agent-based methodology to address decision-making difficulties in manufacturing system. Agent-based system, a decentralized decision-making method, was proposed to be used because it was found out that centralized solution is deficient to tackle changes in complex system. Hence, an agent decision-making framework was developed. To decentralize decision-making area, correlated manufacturing resources were grouped and assigned to be controlled by an agent. The agent acts as an independent entity where local decision making is involved. Each agent was investigated to identify problems and formulation as well as evaluation of alternatives were performed distinctively. After the best alternative was selected locally for each agent, the best alternative’s performances of all agents were tested on the critical agent for global decision-making. Case study was conducted by applying the framework to determine the best due date of new orders and software was used for data analysis. There were a total of 8 agents and global decision making was performed on the 8^{th} agent. Lastly, due date of 4 days displayed the most satisfactory performances such as tardiness, cost and machine utilization.

A comprehensive framework for decision-making support was also proposed by Göleç (2015) in order to facilitate decision-making in strategic operations plans to expand manufacturing capabilities against competitors. Literature about manufacturing strategy and framework were reviewed and incoherence and inadequacies of recent frameworks were distinguished. A hierarchical framework was developed and can be divided into two parts. The first part is measuring manufacturing performance and determining attributes such as competitive priorities as well as constituents that influence manufacturing strategies. The framework of this part comprises of 9 stages and guiding steps were described for each stage. Extended fuzzy AHP and integral were deployed to determine attributes' weights to compute strategic manufacturing strength. Another part is to decide on strategic operations plans in accordance with the strategic manufacturing strength computed in preceding part.

Apart from that, Sudhagar et al. (2017) had conducted a research about quality improvement in friction stir welding (FSW) of aluminium alloy. They discovered from recent researches that TOPSIS and Grey Relational Analysis (GRA) are simple and effective techniques to solve decision making problems that consist of several attributes with complex relationships between them. This corresponds to FSW because there are many criteria in justifying product quality and product quality is also affected by different attributes in the process. Hence, TOPSIS and GRA were used to determine the optimum values of process parameters to produce high quality products. The results of TOPSIS and GRA are compared and both approaches give the same optimum process parameters for FSW, which are 1000 rpm of rotational speed, 80 mm/min of welding speed and 0 mm of tool offset.

2.2 Review of Process Improvement

On the other hand, literature about process improvement is also examined. Badiger et al. (2008) developed a methodology to improve system performance by using overall equipment effectiveness (OEE) as an indicator. Before proposing the methodology, the team had reviewed the key elements of OEE, advocacies of recent researchers as well as prominent tools or strategies that were adopted for process improvement. A flowchart was used to reveal the improvement steps from beginning to end and strategic techniques incorporated were Kaizen and Poka-yoke. The methodology was also applied on a case study. For the result of the case study, OEE level is successfully improved by 22.42 % and the most significant improvement is availability, which increases from 80.95 % to 93.68 %. It was pointed out that a standardized and systematic methodology can promote an organization's effectiveness in such improvement project.

Besides, Cheah et al. (2020) proposed an integrated improvement framework with explicit steps for OEE. Literature review was performed to study the strengths and shortcomings of frameworks as well as improvement steps of previous research works about OEE. A new improvement methodology was proposed by complementing strengths of steps or frameworks reviewed with the addressed shortcomings. Yet, OEE was deployed as a benchmark. A structured framework was developed by distinguishing the improvement steps into 5 general substantial phases which are initiation, data collection, prioritization, root cause analysis and implementation and lastly, sustainment. Steps under each phase were illustrated distinctively with one flowchart per phase to lead practitioners to accomplish the phase's objective.

Other than OEE, Li et al. (2018) built an improvement framework for enhancing overall line efficiency (OLE) of a production line. This team had reviewed literature about different performance improvement methods and proposed that there is a need of establishing a structured scheme to identify critical parameters to be focused in improvement project. An OLE improvement scheme was formulated and it adopted Fourier amplitude sensitivity test to determine the essential parameters to be aimed on. Stochastic Kriging surrogate model was also deployed to determine the optimal degree of improvement of the parameters. The developed scheme was presented in a flowchart in which the major steps were shown. By applying the scheme on a case study, it is determined that the mean time between stop of 3rd and 4th machine as well as mean time to repair of 4th machine should be 80, 160 and 3.5 hours respectively in order to achieve 85 % in OLE.

2.3 Review of Decision Making for Process Improvement

There are researches that involve decision making in process improvement planning. For instance, a framework for improvement project selection and evaluation was formulated by Aqlan et al. (2017) by using simulation and optimization techniques to solve MCDM problem. Previous frameworks with respect to Lean Six Sigma project selection were reviewed and important considerations in decision making were highlighted. The framework can be generalized into two main parts, which are optimization and simulation. A multi-objective optimization mathematical model was constructed to evaluate projects and filter out those undesirable proposed improvement projects. Subsequently, DES simulation was used to perform scenario experiments for selected project. It is found out that out of 10 projects, 7 of them were tested applicable after considering resource availability, time and cost aspects.

Chan and Spedding (2003) had also composed an integrated multi-dimensional process improvement framework that encompassed productivity, quality and cost dimensions. It was found out that there was absence of systematic methodology that synthesizes productivity optimization, quality control and cost minimization. The framework was graphically outlined and various types of decision support tools such as DES simulation and neural network metamodel were proposed. To demonstrate the adaptivity of the framework, the framework was applied to two case studies with different objectives, which are control chart system design and quality optimization problem. Resultantly, combination of different control charts was determined for precise process control for the former, whereas the best configuration of system was obtained for the latter to achieve optimal quality and productivity at lowest cost.

In addition, AlDurgham et al. (2008) developed a Simulation Application Framework for Manufacturing (SAFM) that aids in decision making and can be adapted to wide range of simulation software. Through literature review, it was discovered that computer simulation is a renowned approach used to design from scratch, test or modify lean system. SAFM and checklists were developed to act as guidelines for simulation-based decision making in decision areas such as material handling system, layout, scheduling and manufacturing strategy. A general framework and major steps for each decision area were explicitly demonstrated in flowchart, and also validated by conducting case study at a real system. In case study, transferring semi-automated bottleneck to full automation contributes the most benefits if compared to current and other proposed models because of its higher throughput and labour productivity based on simulation result.

To enhance quality of decision making, Kibira et al. (2015) had established a scheme that coupled data analytics and simulation methods to support decision making in manufacturing. By reviewing recent works, standards and methods of data mining, simulation and optimization were studied. The procedures for decision analysis that integrated data analytic and simulation method were presented in a flowchart. Data analytic method was performed to determine the attributes that have substantial effect on the system and the attributes were inputs of the simulation model. Simulation modelling was conducted using software to experiment different scenarios by varying the input data to obtain a set of input values that achieves optimization. Other than data and alternative analysis, the steps such as problem formulation, data collection and conceptual model design were described in the proposed decision-making scheme.

Moreover, Sachidananda et al. (2015) used DES modelling as an investment decision support tool in biopharmaceutical manufacturing. Literature about computer-aided modelling methods are reviewed and it was proposed that DES is the most suitable instrument for this research work due to its model's flexibility and capability to visualize dynamic behaviour of the system. A step-by-step DES model construction methodology was developed and illustrated in a simple flowchart. WITNESS 13 was used to model the system and estimate performances of existing and proposed manufacturing processes. The simulation result indicates that the proposed model is worth to be invested as it has better performance than the current model. This is because by implementing the proposed model, the production time is estimated to be reduced by 50 minutes, number of operators required can be reduced by 1 and the operator utilization can be increased from 60 % to 85 %.

A study was also conducted by Subsomboon and Vajasuvimon (2016) to increase utilization and production rate of a job shop manufacturing system with the lowest cost. It was explored that computer simulation features useful statistical analysis that can aid in problem identification and comparison of performance data, especially in optimization problem. Therefore, simulation was used in this research to evaluate the proposed alternative strategies and select the most gainful one. Among the three proposed alternatives, the strategy that comprises adding one worker to operate idle machine was chosen to be implemented in real system. This is due to the strategy's practicability and desirable simulation outcome that shows lower operating cost and higher labour utilization as well as throughput if compared with other alternatives.

Besides, Aqlan and Al-Fandi (2018) proposed a framework to prioritize, evaluate and select process improvement initiatives. Previous frameworks regarding Lean and Six Sigma methodologies were reviewed and it was found out that there was lack of consideration for several important factors during project improvement, such as prioritization of workplace areas and type of problem solving. Therefore, a framework is developed and it consists of three phases. The first phase is identifying workplace areas for improvement prioritization by assigning weights and using mathematical models. The second phase is selecting proper problem-solving methodology according to the type and criteria of problem faced with the guidance of a flowchart. Yet, the last phase is choosing the most preferable improvement projects by using mathematical model as the multi-objective decision analysis approach.

Furthermore, Jurczyk-Bunkowska (2020) had also conducted a case study that employed DES software to plan productivity improvement of a small batch size manufacturing system. By reviewing literature in the context of lean manufacturing, the researcher had highlighted strategies that can be implemented to elevate production's productivity. Computer simulation was used to evaluate the performance of proposed configurations on the virtual system through simulation-generated statistics. Besides, a structured framework regarding process improvement using computer simulation as decision support tool was illustrated in flowchart. Out of 6 proposed model variants, it was found out that 1st and 2nd variants should be quickly implemented, whereas 3rd and 6th variants should be adopted after their implementation enablers are attempted. Ultimately, it is advocated that computer simulation is a time and cost-efficient tool in supporting such decision-making process due to provision of detailed analysis for diverse alternatives.

2.4 Analysis of Literature Reviewed

Table 2.1 shows a summary of the methods employed by the literature reviewed.

Table 2.1: Review of Decision Making and Manufacturing Process Improvement.

Scope	Method		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Decision making	Analytical model	QFD					√															
		Digraph				√																
		AHP			√		√						√									
		ANP					√															
	Mathematical model	TOPSIS																√				
		GRA																√				
		Matrix				√																
		Expressions								√		√	√				√		√			
	Computer-based	DES software	√	√				√				√		√	√	√	√					√
		Other software									√											
	Step		√		√	√	√			√	√	√	√					√				
	Framework		√					√			√	√	√	√			√		√			√
Decision making for process improvement				√				√				√		√		√	√		√			√
Process Improvement	Step								√											√	√	
	Framework			√																	√	√

[1] Robinson et al. (2001) [2] Chan and Spedding (2003) [3] Bayazit (2005) [4] Rao (2006) [5] Partovi (2007) [6] AlDurgham and Barghash (2008) [7] Badiger and Gandhinathan (2008)
[8] Gurumuthy and Kodali (2008) [9] Papakostas et al. (2012) [10] Kibira, Hatim and Kumara (2015) [11] Göleç (2015) [12] Sachidananda et al. (2015) [13] Sharma and Jain (2015)
[14] Supsomboon and Vajasuvimon (2016) [15] Aqlan et al. (2017) [16] Sudhagar et al. (2017) [17] Aqlan and Al-Fandi (2018) [18] Li et al. (2018) [19] Cheah, Prakash and Ong (2020)
[20] Jurczyk-Bunkowska (2020)

2.5 Discussion of Literature Reviewed

This section discusses the outcome of literature review. It is discovered that decision-making approaches reviewed can be classified into three models, which are mathematical model, analytical model and computer-based simulation. All of these approaches are apt to solve intricate decision problems by evaluating numerous criteria of the alternatives. For mathematical and analytical models, the predicted effects of alternatives are expressed numerically so they can be easily compared and the degree of superiority can be observed.

By comparing the approaches, analytical model such as QFD is more understandable than mathematical models because the problems are structured in graphical presentations and procedures are simple as well as organized (John et al., 2014). However, analytical model such as ANP is inadvisable to be used alone. Ho (2008) recommended to integrate ANP with mathematical model, AHP or QFD to enhance the effectiveness of decision-making. In addition, it is discovered that analytical and mathematical models are difficult to represent a real-world system and have limitations to analyze all aspects of decision problems, especially the dynamic impact of alternatives over an extended period of time.

It is important to evaluate alternatives by anticipating their long-term result and this can be achieved by adopting DES computer-based simulation. According to the literature reviewed, DES is extensively used because it features a stochastic real-world system experiment that predicts the outcome of proposed model over time (Caro et al., 2020). Statistical data that depict the dynamic behaviour of the system performance over time can also be easily generated by the software in a short time. Substantially, by taking account of long-term effect, the effectiveness of alternatives in solving root causes and its sustainability can be evaluated. In addition to auto-generation of essential system performances as decision supporting data, flexibility in altering the attribute values for experiments also highlights DES as a vital decision analysis tool (Robinson et al., 2001).

Besides, Abogrean and Latif (2012) claimed that computer simulation is an intelligent tool that can enhance the effectiveness in process improvement. Jurczyk-

Bunkowska (2020) also advocated that DES is time-efficient to solve optimization problem. In addition, Sachidananda et al. (2016) pointed out that DES provides clear visualization of system which facilitates the process of designing improved system and Robinson et al. (2001) revealed that DES can be used to identify problems in the system. Running experiments virtually can help in saving a lot of time and for process improvement, the capability of simulation to visualize real system will allow practitioners to identify undiscovered problems while configuring the existing model and possible solutions. Furthermore, if persistence of problems is observed when experimenting possible solutions, the simulation model can be further investigated to find out the root cause of the problem. This contrasts with inadequacy of analytical and mathematical models as they are limited to just finding solutions to solve known problems. Generally, DES model is more robust than analytical and mathematical models. After scrutinizing the strengths and limitations of different types of decision-making tools, it is deduced that computer-based DES is the most preferred decision-making tool for this study.

Apart from that, as shown in Table 2.1, it is found out that decision making events often take part in process improvement projects to identify the most fruitful alternative to be implemented. However, there is a lack of structured framework that embodies process improvement considerations in strategic decision-making framework. Also, based on some of the literature reviewed, framework is usually absent and steps for decision making or process improvement are illustrated in paragraphs or flowchart. With respect to this, merely revealing steps results in inflexible scheme and vague objectives. Conversely, merely illustrating framework without showing guiding steps will lead to unclear guideline. Table 2.2 shows the elements of frameworks or steps developed in recent researches.

Table 2.2: Components of Decision-Making Frameworks or Steps Reviewed.

	Understand process	Define problem	Define objectives	Design experiment	Determine criteria/ selection attribute	Determine weight value	Identify prioritization	Select proper methodology	Collect data	Analyze data	Build experiment model	Generate alternatives	Evaluate alternatives	Select alternative
1					√				√			√	√	√
2*			√						√	√	√	√	√	
3					√	√	√						√	√
4					√	√							√	√
5					√	√	√						√	√
6*	√		√	√	√						√	√	√	√
7		√	√		√	√						√	√	√
8					√							√	√	√
9*	√		√	√					√	√	√		√	√
10	√				√	√	√		√			√	√	√
11*	√		√	√					√	√	√		√	√
12*									√	√	√		√	√
13					√	√								
14*					√	√	√	√				√	√	√
15*		√										√	√	√

* decision making for process improvement

[1] Robinson et al. (2001) [2] Chan and Spedding (2003) [3] Bayazit (2005) [4] Rao (2006) [5] Partovi (2007) [6] AlDurgham and Barghash (2008) [7] Gurumuthy and Kodali (2008)
[8] Papakostas et al. (2012) [9] Kibira, Hatim and Kumara (2015) [10] Göleç (2015) [11] Sachidananda et al. (2015) [12] Aqlan et al. (2017) [13] Sudhagar et al. (2017) [14] Aqlan and Al-Fandi (2018)
[15] Jurczyk-Bunkowska (2020)

With reference to Table 2.2, most of the decision-making procedures involve three crucial steps in decision making, which are determining decision criteria or selection attributes, evaluating alternatives and selecting the best alternative. Decision criterion is a characteristic or variable in a system that is used to evaluate alternatives in decision making events, so systematically identifying decision criteria is necessary (Rao, 2007). For MCDM, the relative importance of criteria is weighted to seek for alternative that has good performances for the main decision criteria, hence contributing a larger impact in the system. A viable approach that can be used in weighting decision criteria is AHP pairwise comparison method (Bayazit, 2005). To evaluate alternatives, overall performance of an alternative is calculated by computing the performances of criteria with their criteria weights and the score represents the degree of excellence of an alternative in fulfilling decision criteria. The highest score in overall performance implies that the alternative encompasses the most optimized decision variables.

The purpose of reviewing process improvement frameworks is to highlight the important considerations in driving improvement projects. Some instances of important elements in process improvement frameworks are analyzing root causes, prioritizing areas to improve and determining performance indicator as a benchmark (Cheah et al., 2020; Li et al., 2018). However, these factors are predominantly absent in all of the frameworks reviewed regarding decision making for process improvement. Moreover, there is a lack of comprehensive framework that guides practitioners from initiating decision-making event to concluding the selected alternative. Guidelines in most of the frameworks are insufficient as their procedures started from determining decision criteria based on known decision problems. There is a scarcity of guidelines to help in identifying problems from existing manufacturing system, defining objective to commence decision-making event and generating alternatives based on the roots of the problems.

An adaptive framework is substantial to establish sub-objectives that pave the way for achievement of the main objective and on the other hand, guiding steps are perceived as means to support and accomplish each sub-objective. Sharma and Kodali (2008) stated that a proper framework provides directions and guidance for an organization to excel by achieving its objectives. Hence, there is a need to propose a systematic and comprehensive framework with precise steps that serves as a guideline to seek the most expedient alternative in order to effectively improve a manufacturing system. It is discovered that a simple graphical presentation such as flowchart is a suitable tool to illustrate the framework and guiding steps in a clear-cut manner.

CHAPTER 3

METHODOLOGY

3.0 Introduction

This chapter discusses the plan of action for conducting this research as well as the proposed decision-making framework for process improvement. This chapter is organized as follows: Section 3.1 discusses the flow of this research and Section 3.2 reveals the proposed decision-making framework. In regards of the proposed framework, five main stages of proposed framework are explained in Section 3.3, Section 3.4, Section 3.5, Section 3.6 as well as Section 3.7 respectively.

3.1 Flow of Research

In order to achieve aim and objectives, methodology to conduct this research is deliberately planned. The objectives are to identify key factors of decision making for improvement projects, to develop a decision-making framework by employing discrete event simulation (DES) software and to validate the framework by conducting case study at a box manufacturing factory. The aim of this research is to test the feasibility of the decision-making framework for process performance improvement. In regard to these aim and objectives, blueprint of this research is illustrated in flowchart as shown in Figure 3.1.

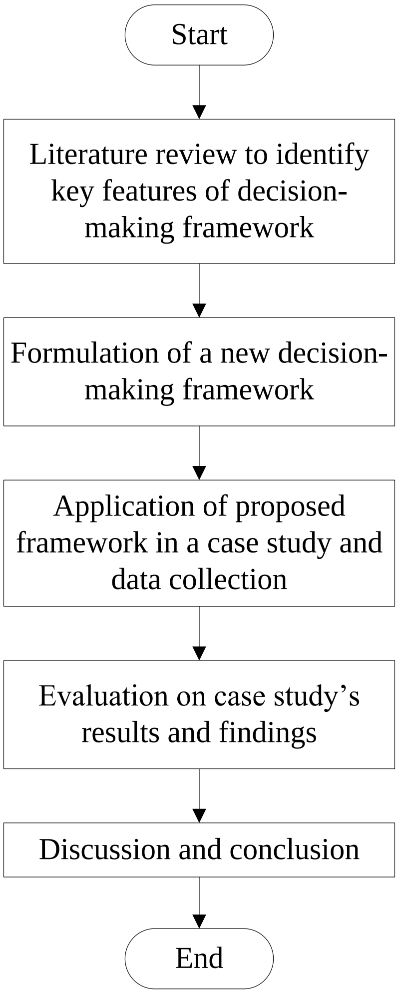

Figure 3.1: Flow of Research.

To gain insights on decision-making events, decision-making tools as well as process improvement projects, literature pertaining to these study areas was reviewed. Key elements and gaps in recent decision-making and improvement frameworks were distinguished to achieve the first objective of this research. In addition, different decision-making techniques were studied to choose the most preferable tool for decision-making in manufacturing system.

As a result, DES software was chosen as a decision-making tool in this research due to its advantageous characteristics such as time-efficient, able to visualize real-world system and etc. Besides, by comparing the components of decision-making procedures reviewed, the fundamentals in a decision-making framework are identifying decision criteria, evaluating alternatives as well as selecting the best alternative. However, key elements in process improvement such as performance benchmark and root cause analysis must also be incorporated in decision-making framework in order to find the best alternative that can effectively improve the performance of a manufacturing system.

Subsequently, with respect to the second objective, a comprehensive decision-making framework for process improvement was formulated by synthesizing the strengths and addressed gaps of the frameworks reviewed. A case study was conducted by applying the proposed framework in real manufacturing system for validation. In order to carry out the case study, data was collected on site and a simulation model of the manufacturing system was constructed by using WITNESS software with reference to the collected data as input values. Proposed framework was abided to seek the best implementation that optimizes the performance measures of the manufacturing system. Then, the results and findings of case study were analytically evaluated to achieve the third objective.

After completing the case study, the capability of the proposed framework was investigated and discussed to determine its advantages in comparison to conventional frameworks. Lastly, a conclusion is made on the feasibility of proposed decision-making tool and framework in enhancing performance of a manufacturing line.

3.2 Development of Framework

A framework plays an integral role in providing directions and guidance for an organization to excel by achieving its objectives (Sharma and Kodali, 2008). In this section, a new decision-making framework that employs DES software as decision-making tool is illustrated in graphical mean as shown in Figure 3.2. The representation of framework comprises of three segments: The upper segment consists of keywords that generally signify the tasks of each main stage. The middle segment states the objective of each stage, whereas the bottom segment is a flowchart of precise steps that elaborates on respective keyword to achieve the objective. The name of the new framework is IMAST, which is the initial of each stage of the framework.

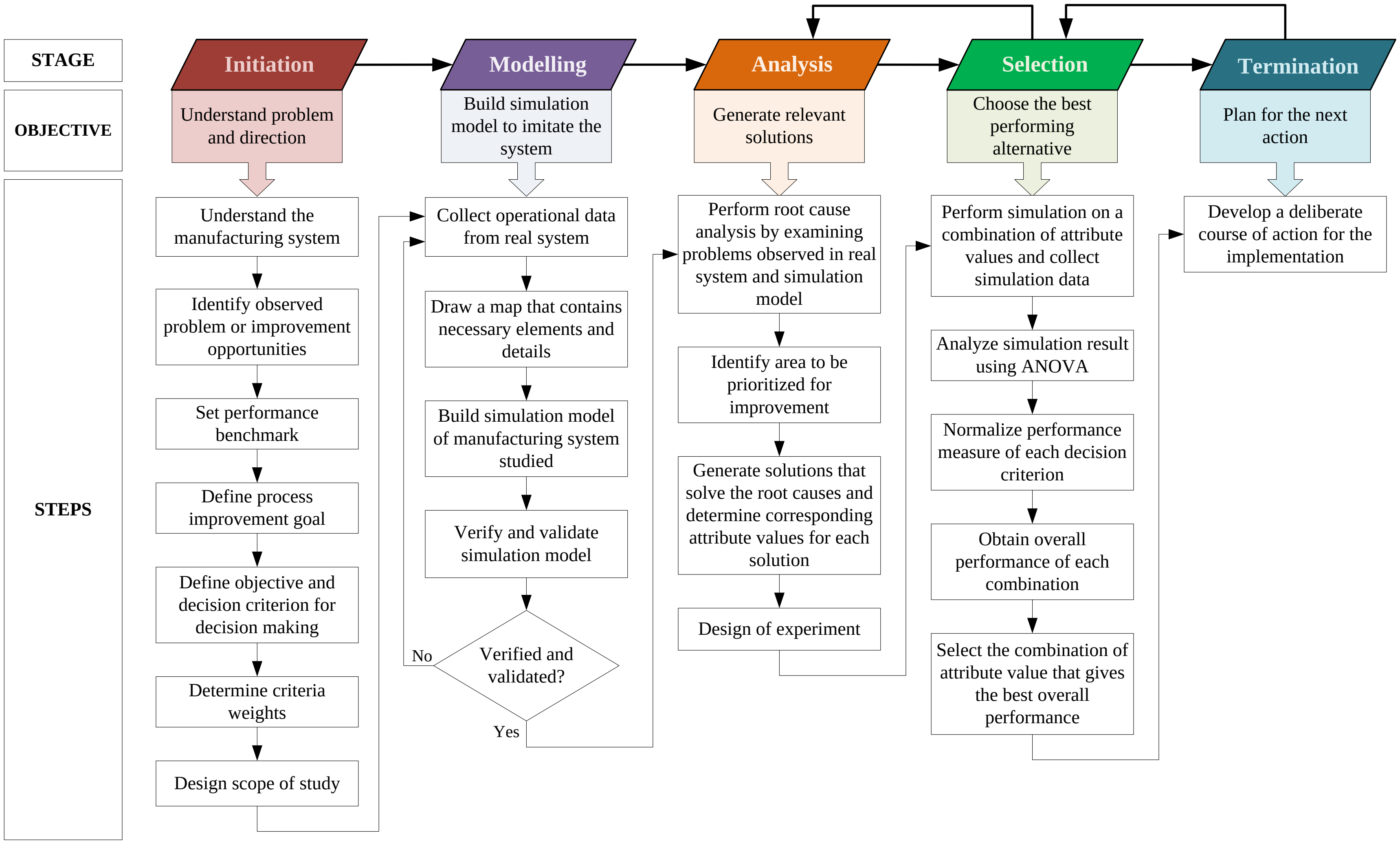

Figure 3.2: Proposed Decision-Making Framework, IMAST.

3.3 Stage 1 - Initiation

The first stage is initiating the decision-making project, which involves planning in advance of project execution. In order to have a definite goal to improve the manufacturing system, practitioners must be conscious about the nature of the manufacturing system to be studied, its existing problems or limitations as well as direction on what to achieve. Steps associated with this stage are illustrated in Figure 3.3.

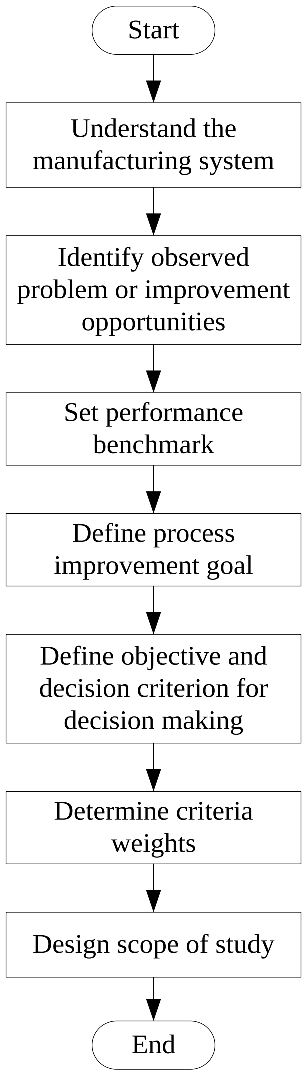

Figure 3.3: Steps for 'Initiation' Stage.

The first step is understanding the manufacturing system. The background of the manufacturing system such as type of production system, manufacturing processes, process flow and existing resources must be distinguished. It is important to ensure that the knowledge possessed about the manufacturing system is sufficient to carry out further investigation. There are many approaches in visualizing the manufacturing systems, such as value stream mapping (VSM) that depicts material as well as information flow and a simple flowchart that illustrates production flow.

The next step is identifying observed problem or improvement opportunities of the manufacturing system. This step is merely a primary investigation on the manufacturing system, which is based on production reports and observation at production floor. There are two aspects that can be looked for, which are adverse problems and improvement opportunities. The former refers to symptoms or facts that reflect the poor performance of the manufacturing system. However, the causes of problems are yet to be discovered but only visible problems are underscored, for example, inability to complete orders on time, high work-in-process (WIP) in production floor and output is lower than planned capacity. Another aspect is improvement opportunities, which is normally for manufacturing system that has addressed performance constraints and looks forward for continuous improvement. With respect to this, spaces that can be improved are discovered to amplify the system performance. Some scopes of improvement opportunities are resource utilization, product quality and waste reduction.

The third step is setting performance benchmark, a proper metric that is capable of quantifying the aspects identified in the previous step. The purpose of identifying performance benchmark is to set a reference point in assessing the effectiveness of the improvement project by comparing initial and future values of the benchmark. Therefore, performance benchmark is used to design the project’s goal in the next step. A team can choose any performance measure as the benchmark in a project, the only criterion is the performance measure selected must be precisely correlated with the aspects to be resolved or improved.

The fourth step is defining process improvement goal according to the problems or improvement opportunities observed in manufacturing system and performance benchmark. A goal provides direction, motivation and focus for an organization, so it is hence important to set a goal that is clear, unambiguous, measurable and practical (Bovend'Eerdt et al., 2009). In the context of process improvement, a goal is the expected outcome of the project in terms of performance benchmark that makes the goal more definitive and motivating. As a simple example, if the problem observed in the manufacturing system is frequent machine breakdown, setting a goal of ‘increase machine availability by at least 15 %’ is more powerful than ‘reduce machine breakdown’. The degree of expected improvement can be set subjectively according to the system’s condition and administration’s expectancy, considering that it is realistic to be achieved.

The step after defining goal is establishing objectives, which are the specific actions to achieve goal. This step is crucial for decision making as the objectives may encompass circumstances that a decision maker needs to consider while generating and assessing alternatives. Then, decision criterion, which is factor that will be used to evaluate alternative, is determined with the aid of objectives. A decision criterion can be classified into measurable and immeasurable. The score of a measurable decision criterion is objectively determined through simulation-generated data. Conversely, scoring of immeasurable decision criterion is fairly subjective by using rating scale. Rating scale is applied to assign a numerical value to evaluate a qualitative statement and the values are subsequently compared in decision making. In order to obtain valid result by using rating scale, each score in the scale must be defined unambiguously, so it is clear that what does the assigned score indicate (Riedl et al., 2010).

If there are more than one decision criterion, weightage must be assigned to each decision criterion according to their relative importance. The common approach used to assign criteria weights is pairwise comparison in analytic hierarchy process (AHP) (Podvezko, 2009). Steps in determining criteria weight (ω_i) are described as follows. Let R be the decision criteria, i be the ith row, j be the jth column and x be the value of specific row and column. x_{ij} is the score of significance (p_{ij}), that ranges from 1 to 9, by comparing R_i with R_j: if R_i and R_j are equally significant, $p_{ij} = 1$; if R_i is 9 times more significant than R_j, $p_{ij} = 9$; if R_i is 9 times less significant than R_j, $p_{ij} = 1/9$. As the matrix table is symmetrical, thus p_{ji} is the reciprocal of p_{ij}, which is $p_{ji} = 1/p_{ij}$. Then, the criteria weight of R_i (ω_i) is calculated by using the formula shown in Equation 3.1.

Table 3.1: Determination of p_{ij} in AHP pairwise comparison.

		1	2	3
		R1	**R2**	**R3**
1	**R1**	1	p_{12}	p_{13}
2	**R2**	p_{21}	1	p_{23}
3	**R3**	p_{31}	p_{32}	1

$$\omega_i = \frac{\sqrt[m]{\prod_{j=1}^{m} p_{ij}}}{\sum_{i=1}^{m}\sqrt[m]{\prod_{j=1}^{m} p_{ij}}} = \frac{\sqrt[m]{\Pi_i}}{\sum_{i=1}^{m}\sqrt[m]{\Pi_i}} \tag{3.1}$$

where,

m = Number of decision criteria

i = ith row (i = 1, 2, …, m)

j = jth column (j = 1, 2, …, m)

After determining the criteria weights, the consistency of the scores of significance must be calculated to validate the reliability of criteria weights determined. The criteria weights are acceptable if the consistency relationship (S) is lesser or equal to 0.1 or 10 % (Podvezko, 2009). Equation 3.2 shows the formula in obtaining S.

$$S = \frac{S_I}{S_A} \tag{3.2}$$

where,

S_I = Consistency index (see Equation 3.3)

S_A = Average value of random consistency index (see Table 3.2)

$$S_I = \frac{\lambda_{\max} - m}{m-1} \tag{3.3}$$

where,

λ_{max} = Largest eigenvalue (see Equation 3.4)

$$\lambda_{max} = \frac{\sum_{i=1}^{m} \lambda_{max(i)}}{m} \tag{3.4}$$

where,

$\lambda_{max(i)}$ = Eigenvector of ω_i (see Equation 3.5)

$$\lambda_{max(i)} = \frac{\sum_{j=1}^{m} (p_{ij} \times \omega_j)}{\omega_i} \tag{3.5}$$

Table 3.2: Determining S_A (Podvezko, 2009).

m	3	4	5	6	7	8	9	10
S_A	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

The last step of Stage 1 is designing the scope of study, which also implies planning for the subsequent stages. Practitioners have to brainstorm ‘What’ tools to use and ‘How’ to conduct the project. For instance, practitioners have to choose the most suitable DES software and develop the concept of simulation model such as determining elements to be built and variables to be calculated. In addition, formulas that will be used need to be determined.

3.4 Stage 2 - Modelling

The second stage is modelling the manufacturing system by using DES software. The objective of this stage is to ensure that the simulation model constructed is precise in imitating the system’s actual operation so that the experimental outcomes are reliable. Therefore, systematic steps to build a precise simulation model are illustrated in Figure 3.4.

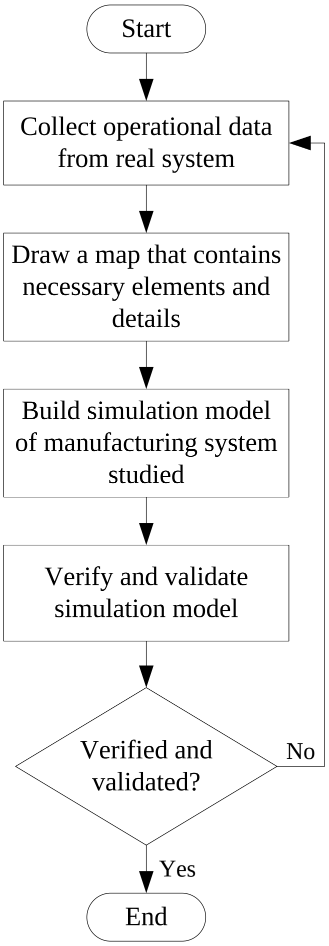

Figure 3.4: Steps for 'Modelling' Stage.

The first step in Stage 2 is collecting operational data from the actual manufacturing system. Followed by knowing what elements to build in the previous step, data collection is carried out on-site to collect input values for the elements to be built in simulation model. In fact, behaviour of operational data in manufacturing system can be categorized into two types, which are deterministic and stochastic. For deterministic behaviour, the value holds a fixed value with no uncertainty. For example, the distance from Machine A to Machine B is always the same. Whereas for stochastic behaviour, the value varies in a certain pattern of randomness that can be depicted by probability distribution. For example, a machine will break down within a time interval, the time between breakdowns is always different but can be depicted by exponential distribution. In this case, statistical analysis is required to compute fluctuating values to identify its probability distribution pattern and the distribution is input into the simulation model.

After essential input values are collected, the next step is drawing a map that illustrates the production flow to be built, by incorporating necessary details of the components. This serves as a draft to aid model construction because all elements and data are visualized easily. VSM can also be constructed to facilitate the investigation on existing manufacturing system.

The third step is building a simulation model of the manufacturing system by using DES software. A simulation model may consist of elements that represent the factory's entities and variables that measure system performance. Then, the simulation model is run and necessary performance data are collected for the following step. It is also required to determine warm-up period for the simulation model to run before starting to collect simulation data. This is to obtain accurate simulation results by performing data collection when the simulation has reached steady-state. A simple technique to determine warm-up period is time-series inspection. By using this technique, time-series of a key output variable, such as flow time, can be constructed to demonstrate its behaviour over time. Thus, warm-up period is the time taken for the time-series to achieve steady line (Robinson and Ioannou, 2007).

The fourth step is verifying and validating the simulation model. The purpose of model verification is to ensure the program of simulation model is correct by checking whether the simulation model corresponds with the intended input and assumptions made. There are many ways in verifying a simulation model and Carson (2002) had suggested a few techniques, such as using manual calculations or timelines to identify theoretical outputs of the simulation model. On the other hand, model validation is to ensure that the simulation model falls within an acceptable range of accuracy with the actual manufacturing system (Sargent, 2013). This can be done by comparing performance measures of the virtual model with the actual manufacturing system's performance, such as flow time and throughput. The accuracy of simulation model is considered satisfactory with a deviation of less than 15 % from the actual one (Zhang et al., 2007).

Furthermore, if either model verification or validation is unsuccessful, it indicates that the simulation model is inaccurate. Practitioners must repeat the first, second and third step in this stage to assure that data collected is ample as well as precise, data is correctly input into the simulation model and there is no flaw in the program of the simulation model.

3.5 Stage 3 - Analysis

The third stage is performing analysis on existing manufacturing system. The objective of this stage is to generate relevant solutions that can effectively solve the problems identified in Stage 1. Figure 3.5 shows steps for this stage.

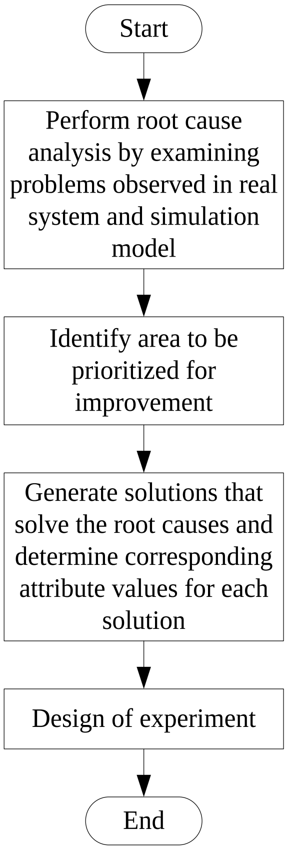

Figure 3.5: Steps for 'Analysis' Stage.

In order to improve the system effectively, the first step in Stage 3 is root cause analysis. In this step, visible problems identified in Stage 1 are investigated to find out first level causes, second level causes and root causes. However, not all problems can be discovered through observation on production floor and reports. As suggested by

Robinson et al. (2001), simulation model can be used to identify problems and causes in a manufacturing system with the assistance of simulation-generated statistical data. For example, overall machine's status such as busy in production, under repair, waiting and etc. is computed automatically in time percentage by simulation software. This helps in identifying the causes of underutilization of machine, which is difficult to observe on-site. Besides, methodologies that can be deployed to analyze root causes are Ishikawa diagram, 5 Whys and 4 Ms principles.

The second step is identifying areas to be prioritized for improvement based on root cause analysis. Although this step is not mandatory, it is important when there are many root causes exist in the manufacturing system but resources are limited. Pareto analysis can be used to identify the most critical root cause that gives the largest impact to the manufacturing system and that root cause will be prioritized for improvement. By focusing on the most significant root cause, the outcome of improvement project can be maximized (Cheah et al., 2020). Supplementary simulation models can also be constructed to visualize the behaviour of the areas to be prioritized for improvement in a detailed manner.

Subsequently, solutions to tackle the root causes are generated. In the meantime, solutions intended for practical implementation are converted to input parameters of simulation model for experimental runs. This is done by designating attribute values of each solution. For example, the solution proposed to reduce machine breakdown is performing time-based preventive maintenance, the input values can be 100, 150 or 200 hours.

The last step in Stage 3 is design of experiment (DOE). This step involves formulating a list of possible combinations of attribute values of different solutions. Thus, one alternative implies one combination of attribute values. There are two types of methods, which are full factorial and fractional factorial experiments. In full factorial experiment, all possible combinations are tested, whereas in fractional factorial, number of combinations is reduced by eliminating statistically insignificant combinations (Antony, 2014).

3.6 Stage 4 - Selection

Stage 4 is a crucial stage in decision making, which is selecting the most expedient alternative among a list of possible combinations. As mentioned earlier, decision making should involve analysis of possible solutions to choose the most superior alternative. Steps to choose the best performing alternative are illustrated in Figure 3.6.

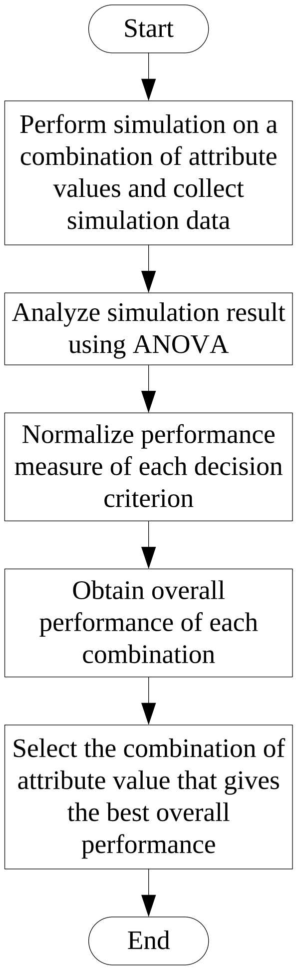

Figure 3.6: Steps of 'Selection' Stage.

After possible combinations of attribute values are listed, each set of attributes is tested in the simulation model as a virtual trial run to estimate its effect on the actual manufacturing system. The input parameters of simulation model are altered according to the attribute values and simulation data for each combination is collected. The performance of decision criteria is also measured or scored for each combination.

The second step is analyzing the experiment result by using analysis of variance (ANOVA) or regression analysis. This is to observe, compare and analyze the major effects of each solution on the performance measures of manufacturing system as well as the interaction between the attribute values of different solutions. Through ANOVA, solutions that do not play impact in improving the manufacturing system are filtered out, and only those impactful solutions will be proceeded for decision-making in the following steps (Hesamian, 2016).

The third step is normalizing the performance measures of respective decision criteria. This step is to establish consistency in values of the performance measures among the decision criteria, so they can be compared with each other. The general notion of normalizing performance measures is to find the relative difference between a value with the best value in that particular category of decision criterion (Gurumurthy and Kodali, 2008). Equation 3.6 shows the method to normalize performance measures in direct category, in which the system performance elevates when the measure increases. Whereas Equation 3.7 shows the method to normalize performance measures in indirect category, in which the system performance declines when the measure increases.

$$\overline{P_{ij}} = \frac{P_{ij}}{\max P_j} \tag{3.6}$$

where,

j = A particular of decision criterion

i = A particular solution

$\overline{P_{ij}}$ = Normalized performance measure of the solution

P_{ij} = Performance measure of decision criteria of the solution

max P_j = Maximum value of performance measure in category j

$$\overline{P_{ij}} = \frac{\min P_j}{P_{ij}} \tag{3.7}$$

where,

min P_j = Minimum value of performance measure in category j

The fourth and last step in this stage is computing the overall performance score for existing system as well as each proposed solution, and selecting the best performing alternative. To compute overall performance score, the performance of each decision criterion is multiplied with respective criteria weight and the scores of individual decision criterion are summed up as shown in Equation 3.8. Then, the alternative with the highest overall performance score will be selected for implementation. However, if the experimental result of all alternatives is unsatisfactory, in which the overall performance scores of all alternatives are lower than the existing system's, Stage 3 must be repeated to analyze the problem again to seek for effective solutions.

$$(\text{Overall performance score})_i = \sum_{j=1}^{m} \left(\omega_j \times \overline{P_{ij}} \right) \tag{3.8}$$

where,

m = Number of decision criteria

3.7 Stage 5 - Termination

In the last stage, findings of decision-making event are concluded. This stage is to develop a strategic blueprint for implementation actions.

According to the attribute values selected in previous stage, deliberate steps of practical implementations are developed and persons-in-charge have to be appointed to apply the solutions in the actual manufacturing system. In real system, it is undeniable that there will be many difficulties and challenges in altering the operation of the system. Therefore, in addition to implementation steps, the course of actions must anticipate challenges of implementation and propose measures to overcome or prevent them. Besides, changes on manufacturing operations might impact other entities, such as personnel and material. Thus, the effects of implementation must be identified and remedies must also be included in the course of action (Cheah et al., 2020). Nevertheless, if the alternative proposed is not approved by the administrators, results in Stage 4 can be used to select the second-best alternative.

CHAPTER 4

RESULTS AND DISCUSSION

4.0 Introduction

This chapter discusses the application of new framework on real case situation to show its practicability and relevance. Section 4.1 introduces the background of the company for the case study. Each of the following sections, from Section 4.2 to Section 4.6 describes the execution of each stage of the framework. Subsequently, Section 4.7 discusses the findings of the case study as well as the new framework.

4.1 Background of the Company for Case Study

The case study was carried out in Company X, a packaging supplier in Sarawak to validate the framework. Company X has customers from different industries such as food and beverages manufacturing, electronics manufacturing, restaurants and etc. As a packaging supplier, the company's customer demand is erratic as it depends on demand forecasted by their customers, who are mostly manufacturers. The company's make-to-order production system leads to frequent urgent orders from customers, which is a ramification of demand volatility in supply chain called bullwhip effect (Chase, 2020).

Company X mainly manufactures customized corrugated box from 2 product families, which are regular-slotted container (RSC) and die-cut box (DCB). In this regard, the factory encompasses 6 product varieties in total, which is two product varieties for RSC and four product varieties for DCB. Moreover, product design is fully customized by their customers. This means that although the product variety is same, the product design can be distinct for different customer orders in terms of size, printing design, paper type and etc. Ultimately, each product variety has unique production route along the factory and each product design requires distinctive material as well as tool during production.

The factory has two 8-hour working shifts and operates every day, excluding public holidays. The morning shift starts from 7 a.m. to 3 p.m., and followed by the evening shift which is from 3 p.m. to 11 p.m. Each shift has 45 minutes of break time.

4.2 Stage 1 - Initiation

There are 6 workstations in the factory that run different processes: corrugating, printing, jaw die-cutting, rotary die-cutting, gluing and packing. A few highlights about the nature of the manufacturing system are described as follows. Firstly, all machines in this factory were shared assets among the product varieties. Secondly, the production route of each product variety was different. Thirdly, the factory produced customized products that have distinctive product designs in batches. Fourthly, work-in-process (WIP) were transported and stored at dedicated area next to the subsequent workstation. All of these imply that this factory practised a push-based job-shop manufacturing system, which means that each lot underwent different processes and required unique setup at a machine during job changeover. The product varieties were denoted as product type A, B, C, D, E and F respectively and their production routes were illustrated in Figure 4.1.

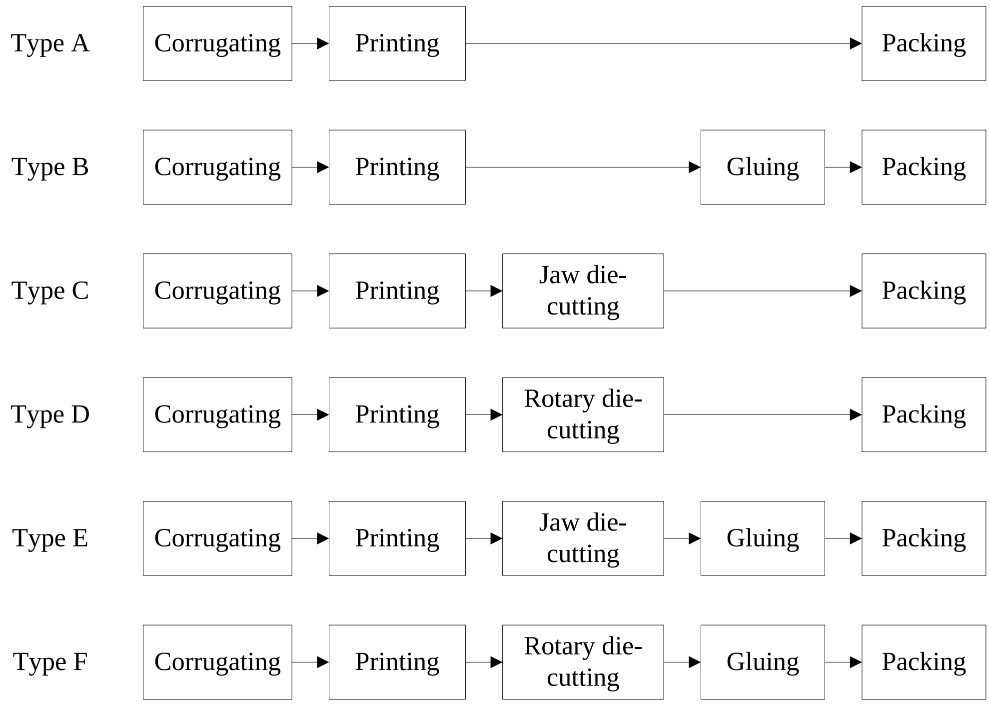

Figure 4.1: Process Route of Product Type A, B, C, D, E and F.

Based on financial and inventory reports, the administration and production personnel had noticed that the gross profit margin did not grow proportionally with the increasing customer order. It was observed that undesired costs, such as overtime allowance and penalty for late delivery as well as poor product quality, were increasing. As performance of a manufacturing system is always closely tied with the financial aspect, this monetary exemplification implied that the manufacturing system had encountered difficulty in coping the surging demand. Also, there was a significant discrepancy between the quantity of raw material issued from store and the actual production output, which meant that large amount of wastes was generated during production. On the other hand, it was observed that the production floor area that was dedicated to store WIP for printers was congested, which in turn occasionally led to process blocking. The upstream machine was forced to stop because of no more space to store WIP.

The performance benchmark determined to measure the manufacturing system's efficiency was overall line efficiency (OLE). OLE was chosen as the benchmark in this project due to its adequacy in quantifying the performance of entire manufacturing line. In other words, only effective solution will affect OLE values because OLE corresponds to the efficiency of system constraint. Hence, if improvements are made on aspects other than the system constraint, OLE will not improve and conversely, the problems in the factory might remain or be exaggerated as improved performance of other aspects would exert more burden on the system constraint. With respect to the administration’s requirement, the goal of the process improvement project was to improve OLE by at least 15 %. It was anticipated that improvement of OLE by 15 % was adequate in propelling the factory’s production rate to be on par with customer demand, which was the ultimate intention of this project. Moreover, the administration pressed for improvement result to show up in near future due to peak customer demand.

The first objective is to find out the root causes of the problems. Secondly, to brainstorm solutions that can resolve or alleviate root causes. Thirdly, to seek for solution(s) that is effective in attaining the goal. Fourthly, to seek for solution(s) that effectively diminishes the company’s cost, by reducing production waste as well as late delivery. Fifthly, to seek for solution(s) that incurs minimal cost and time for implementation.

To ensure that the decision-making outcome meets the goal of the project as well as the company’s requirement, decision criteria were determined with the aid of established objectives, specifically the third to fifth objective. OLE was one of the decision criteria as it was the performance benchmark and enhancing it was the goal of this project. From the fourth objective, line scrap rate (Q) and average flow time per order (AFT) were set as decision criteria because the former reflected amount of production waste generated, whereas the latter is the average time to complete an order, which depicted the capability of the line to meet customer demand. Last but not least, equipment cost efficiency (ECE) was selected to calculate the estimated costs incurred for improvement and the level of difficulty (LOD) accounted the ability of the system and personnel to achieve the expected positive result within specific duration.

As there were more than one decision criteria, criteria weight was assigned to each decision criterion through analytic hierarchy process (AHP) pairwise comparison and the steps are described as follows. Table 4.1 shows the score of significance (*p*) assigned by comparing the relative importance between two decision criteria (*R*).

Referring to the row (*i*) = 1 and 2 ≤ column (*j*) ≤ 5 in Table 4.7(a), the values of p_{1j}, were larger than 1 as this indicates that OLE is more significant than other decision criteria because it is the main goal of this project. The score of significance of OLE was only slightly higher when compared with ECE and Q because these 3 elements were the main focuses of this improvement project. When compared with LOD, the score of significance of OLE was high as the company was willing to allocate many resources to improve OLE. As for AFT, AFT was not very significant when it is compared with OLE because improving OLE will definitely reduce flow time of an order.

For $i = 2$ and $3 \leq j \leq 5$, the values of p_{ij} were also larger than 1 because lower improvement cost was prioritized over all decision criteria, other than the main goal which was OLE. This is because the company was only keen in investing capital to elevate OLE and wants to spend less to improve Q and AFT. In addition, lower improvement cost is also more important than the difficulty level of the implementation. For $i = 3$, LOD is less important than Q because the company was also willing to allocate resources to reduce scrap rate in the manufacturing line. LOD is more significant than AFT because reducing AFT is a minor objective in the project, hence it is not relevant to put many efforts on improving AFT. Lastly, for $i = 5$, Q is more significant than AFT because the company managed to focus more on reducing production waste to save production cost, in comparison to shortening lead time.

Table 4.1: Determination of p_{ij}.

		1	2	3	4	5
		OLE	**ECE**	**LOD**	**Q**	**AFT**
1	**OLE**	1	3	5	2	8
2	**ECE**	0.3333	1	5	3	8
3	**LOD**	0.2	0.2	1	0.5	4
4	**Q**	0.5	0.3333	2	1	5
5	**AFT**	0.125	0.125	0.25	0.2	1

Subsequently, from Table 4.1, criteria weight for decision criterion in i^{th} row (ω_i) was calculated for each decision criterion by using Equation 3.1 and the result is shown in Table 4.2.

Table 4.2: Determination of ω_i.

	OLE	ECE	LOD	Q	AFT	Π_i	$\sqrt[5]{\Pi_i}$	ω_i
OLE	1	3	5	2	8	**240**	**2.9926**	**0.4254**
ECE	0.3333	1	5	3	8	**40**	**2.0913**	**0.2973**
LOD	0.2	0.2	1	0.5	4	**0.08**	**0.6034**	**0.0858**
Q	0.5	0.3333	2	1	5	**1.66667**	**1.1076**	**0.1575**
AFT	0.125	0.125	0.25	0.2	1	**0.00078**	**0.2391**	**0.0340**
						$\sum_{i=1}^{5}\sqrt[5]{\Pi_i}$	**7.0339**	

Then, consistency relationship (S) was calculated to validate the reliability of criteria weights and the steps were described as follows. Table 4.3 shows the calculated values of $\lambda_{max(i)}$ by using Equation 3.5. In the matrix table of Table 4.3, x_{ij} is the product of p_{ij} and ω_j. For instance:

$$x_{12} = p_{12} \times \omega_2$$
$$= 3 \times 0.2973$$
$$= 0.8919$$

Table 4.3: Determination of $\lambda_{max(i)}$.

		1	2	3	4	5			
		OLE	ECE	LOD	Q	AFT	$\sum_{j=1}^{5} x_{ij}$	ω_i	$\lambda_{max(i)}$
1	OLE	0.4254	0.8919	0.4289	0.3149	0.2719	2.3332	0.4254	5.4847
2	ECE	0.1418	0.2973	0.4289	0.4724	0.2719	1.6124	0.2973	5.4235
3	LOD	0.0851	0.0595	0.0858	0.0787	0.1360	0.4450	0.0858	5.1865
4	Q	0.2127	0.0991	0.1716	0.1575	0.1700	0.8108	0.1575	5.1479
5	AFT	0.0532	0.0372	0.0214	0.0315	0.0340	0.1773	0.0340	5.2147
								$\sum \lambda_{max(i)}$	**26.4573**

By using Equation 3.2, 3.3 and 3.4, S was calculated as follows. Based on Table 3.2, S_A is equal to 1.12 because there were 5 decision criteria in this project.

$$\lambda_{max} = \frac{\sum_{i=1}^{m} \lambda_{\max(i)}}{m}$$

$$= \frac{26.4573}{5}$$

$$= 5.2915$$

$$S_I = \frac{\lambda_{\max} - m}{m - 1}$$

$$= \frac{5.2915 - 5}{5 - 1}$$

$$= 0.07288$$

$$S = \frac{S_I}{S_A}$$

$$= \frac{0.07288}{1.12}$$

$= 0.06507$ (< 0.10, criteria weights are acceptable)

As S is smaller than 0.10, the criteria weights were acceptable. Then, the scope of study was determined. Formulas for decision criteria and system performances were obtained from relevant resources. Equation 4.1, 4.2, 4.3 and 4.4 were the key formulas for the decision criteria.

$$\text{OLE} = \frac{Q_A}{Q_T} \times 100\% \tag{4.1}$$

where,

Q_A = Actual output at bottleneck workstation

Q_T = Theoretical output at bottleneck workstation

$$Q = \frac{Q_d}{Q_t} \times 100\% \tag{4.2}$$

where,

Q_d = Number of defective goods

Q_t = Total line output

$$ECE = \frac{K_T \times T_{CT}}{T_{LT}} \left(\frac{OLE - 0.85}{0.85 \times OLE} \right) \tag{4.3}$$

where,

K_T = Total cost, Equipment cost + Maintenance cost + Improvement cost

T_{CT} = Cycle time of bottleneck

T_{LT} = Loading time

OLE = overall line efficiency, in decimal

$$AFT = \frac{\sum_{i=1}^{n} T_i}{n} \tag{4.4}$$

where,

T_i = Time taken to complete order i

n = Total number of orders

Unlike other decision criteria, LOD was evaluated by a 5-point rated scale because it was qualitative. Table 4.4 describes the interpretation of degree of difficulty of each score. The degree of difficulty of a solution was assessed with respect to estimated time needed for implementation, extent of change in work, as well as the likelihood to achieve similar result as per simulation due to uncontrollable aspects such as operators face difficulties in adapting to new work procedure. The extent of change in work procedure was accounted in LOD because this type of changes may require technical skill, professional knowledge or experience of improvement team. In addition, changes in work procedure may lead to skill gap among operators and staffs.

Table 4.4: Description of Rating Scale for Level of Difficulty (LOD).

Score	**Degree**	**Description**
0	No difficulty	Remain unchanged
1	Very easy	Achieve result within 2 weeks
		No or very little change in work procedure
		Result is very likely to be similar as per simulation
2	Easy	Achieve result within 3 weeks
		Acceptable change in work procedure
		Result is likely to be similar as per simulation
3	Moderate	Achieve result within 1 month
		Slightly significant change in work procedure
		Result is slightly likely to deviate from simulated results due to uncontrollable aspects
4	Difficult	Achieve result within 2 months
		Significant change in work procedure
		Result is likely to deviate from simulated results due to uncontrollable aspects
5	Very difficult	Achieve result within 3 months or more
		Very significant change in work procedure
		Result is very likely to deviate from simulated results due to uncontrollable aspects

Additionally, the discrete event simulation software that would be used was WITNESS 20 and the suitable approach to analyze the solutions was analysis of variance (ANOVA) by using Minitab software. Moreover, essential elements to be modelled in the simulation were identified, which were corrugating, printing, jaw die-cutting, rotary die-cutting, gluing and packing machines, buffers and shift pattern. Besides, part attributes must be defined to store information of a part element. Integer and real variables were also needed to calculate and display the fluctuating performance measures during simulation run.

4.3 Stage 2 - Modelling

In this stage, data collection was performed on the elements that were planned to be modelled in Stage 1. The operational data collected included work element time, cycle time of the machine as well as weight of scrap generated. Time study was performed for 1 working day at each workstation to obtain the work element time. From the work element time, setup time and cycle time of machines can be calculated, except for corrugator because production report of corrugating process was generated by computer. All cycle times were converted to unit time per piece. Mean time between failures (MTBF) and mean time to repair (MTTR) data were obtained from the maintenance team and average scrap rate per lot size were computed from collected raw data. Furthermore, distributions that could depict the pattern of number of orders per day and lot size per order were computed.

For corrugating process, non-conforming products would periodically be produced at this machine due to the unstable machine parameters such as temperature and humidity. However, the machine will not be stopped if it was a minor problem because machine stoppage would generate waste and affect productivity. Therefore, causes that induced non-conforming products needed to be solved by performing corrective action while the machine was running. In this case, mean time between defects (MTBD) and mean time to solve (MTTS) were collected through time study and computed into exponential distribution. MTBD depicted the time between consecutive events when non-conforming products were introduced, whereas MTTS was the time to eradicate the production of non-conforming products. MTTS was inclusive of the time to detect sign of defects and perform corrective action. Thus, it was proportional to scrap generated at the machine.

An illustration that embodied the process flow as well as all information collected was drawn as shown in Figure 4.2. As operational data was similar among all product varieties and designs, combination of the two longest process flow (product type E and F) as illustrated in Figure 4.2 was adequate to demonstrate the information of the entire manufacturing line. Figure 4.2 also aided in the construction of simulation model, because the elements as well as production details can be visualized easily.

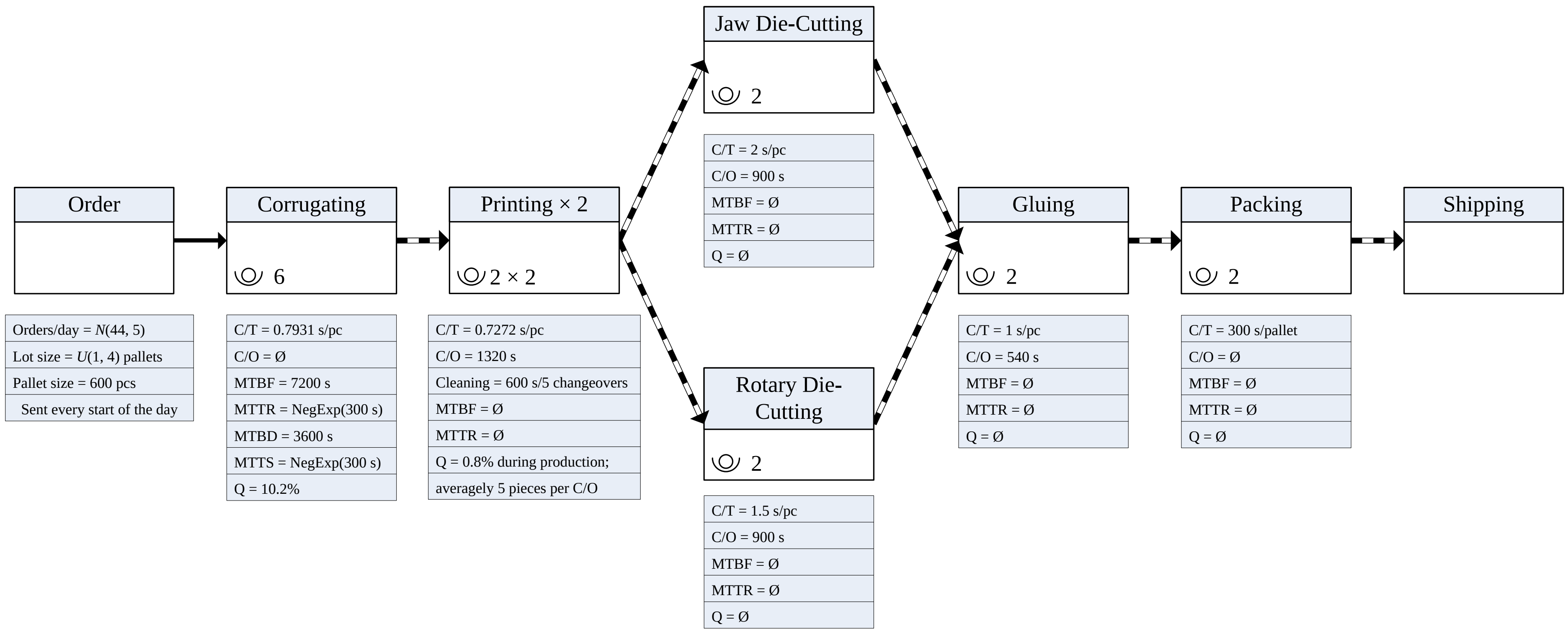

Figure 4.2: Workstations in the Manufacturing Line and Their Respective Information.

Next, a simulation model of the manufacturing line was constructed based on process flow illustrated in Figure 4.1 and information composed in Figure 4.2. Elements used to build the model are shift, machines, buffers, parts, attributes and variables. The shift element was detailed with the two-shift pattern of the factory whereas the machine elements were assigned with process parameters such as cycle time, setup time, breakdown interval and repair time. Cycle time of a machine element was the product of lot size and processing time per piece, except for corrugating and packing. Only for corrugating machine, additional time was needed to replenish the scrapped quantity to avoid underproduction, whereas for packing machine the cycle time was unit time per pallet. Buffers in the model imitated WIP area which stores parts between successive machines that have different production rates. The dispatch rule for all buffers (bOrder, bWIP(1), bWIP(2), bWIP(3), bWIP(4) and bWIP(5)) was first-in-first-out (FIFO). In this model, each part represented one customer order in a lot size of 600, 1200, 1800 or 2400 pieces. Attributes are specific characteristics or values, such as product route, lot size and due date, assigned to a part and the values remain unchanged until they are altered in the machines. Besides, integer and real variables were used to calculate, store and display performance measures such as overall line efficiency, scrap rate, equipment cost efficiency, average flow time, service level, line throughput rate and total line output. Logical operators and built-in commands were incorporated to build a comprehensive virtual manufacturing line.

Figure 4.3 shows the print screen of the simulation model. All processes only comprised of one machine, except for printing process which has 2 printing machines. As there are 6 product routes, logical operators were used to control the flow of the part in simulation model via respective process route attribute. Model description as follows was based on one of the longest product routes, which is product route E. After a part was created with attributes, it arrived at a buffer before corrugator, which is bOrder. Then, the part entered the corrugating machine and was pushed to bWIP(1) after processing. Printing machine would pull part from bWIP(1) to be processed and scrapped quantity will be deducted from the lot size attribute. After printing, the part moved to bWIP(2) and was pulled by jaw die-cutting machine for processing. Subsequently, the part was pushed to bWIP(4) and pulled by gluing machine for processing. After gluing machine, the part was pushed to bWIP(5) and pulled by packing machine for processing. Then, the part was shipped. Additionally, rotary die-cutting machine pulled parts from bWIP(3).

As shown in Figure 4.4, warm-up period of 6000 hours was determined by constructing a timeseries that depicted the behaviour of overall line efficiency and average flow time and the timeseries reached a steady state after 6000 hours in simulation run. To obtain performance data, the duration of simulation run was set to 3 months, which is 2160 hours. Figure 4.5 shows the print screen of simulation model after 2160 hours of simulation run, with the performance measures. Average of the performance measures was recorded as shown in Table 4.5 by running 5 replications of the simulation model.

The last step of this stage is verification and validation of the simulation model to assure its accuracy in reflecting the behaviour of the real manufacturing line. In order to verify the model to ensure no programming flaws, all input values such as lot size, MTBF, MTTR and etc. were set to deterministic values instead of distribution form. A total of 12 parts were tested for model verification, which was 2 parts for each product type. Figure 4.6(a) shows that the deterministic model stopped at 727.545th minute. A time graph was drawn to demonstrate the theoretical time to process 12 parts in the deterministic model. As shown in Figure 4.6(b), the theoretical time for the last part was shipped from the last workstation was equivalent to the ending time of the deterministic model, which was 727.545th minute. Hence, the model was verified.

Subsequently, validation of the simulation model was carried out by comparing the scrap rate of manufacturing line of the simulation model and the monthly waste report evaluated by the administration. The average scrap rates of the line were 13.01 % and 11.328 % respectively for actual report and simulated data. The deviation percentage was 12.93 %, which fell within the acceptable range of 15 % to conclude that the simulation model was viable as a virtual manufacturing line to emulate the behaviour of actual manufacturing line.

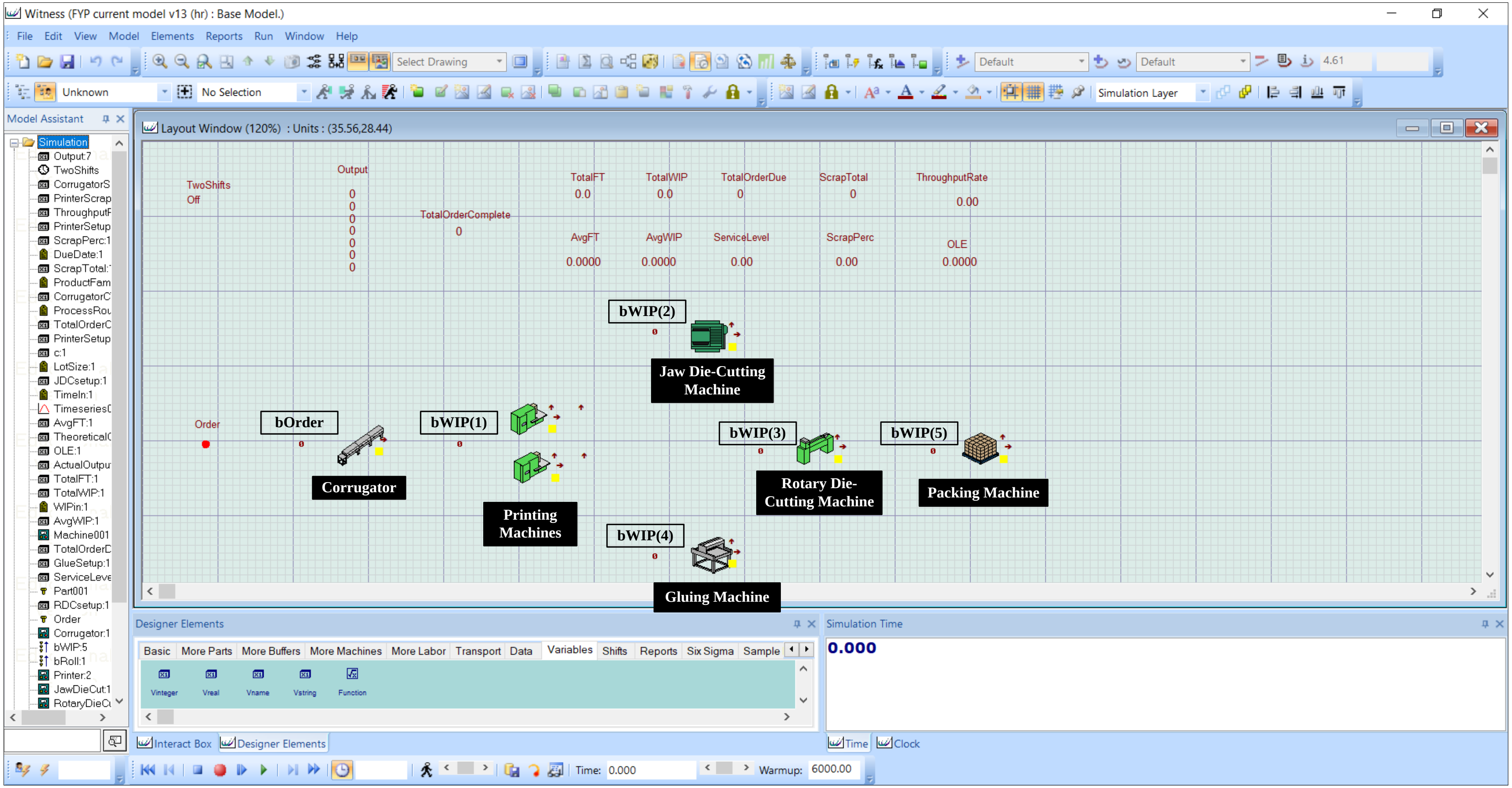

Figure 4.3: Print Screen of Simulation Model of the Manufacturing Line Constructed by Using WITNESS 20.

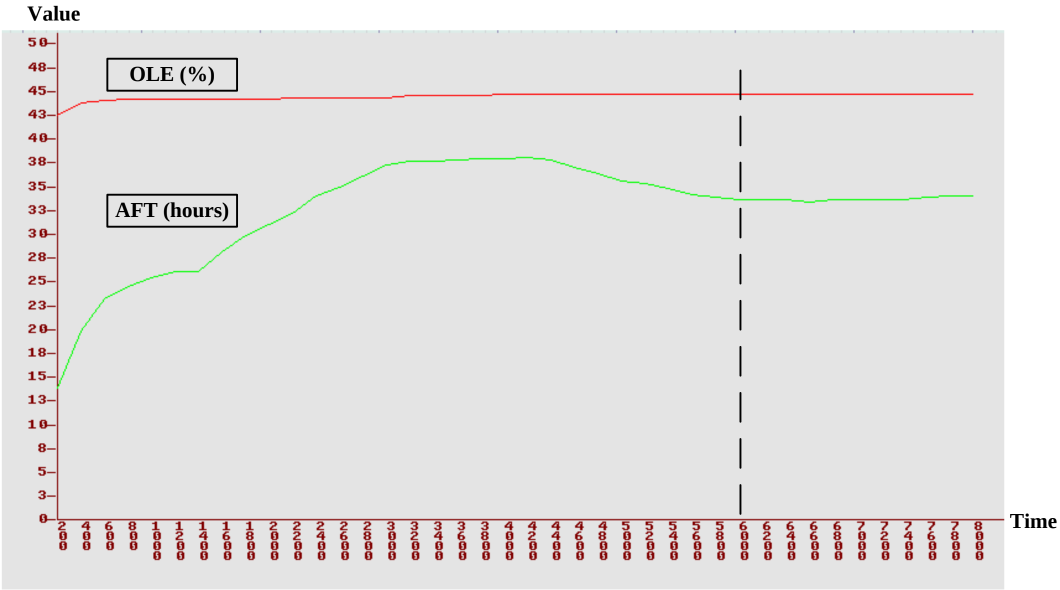

Figure 4.4: Timeseries Graph of OLE and AFT to Determine Warm-Up Period.

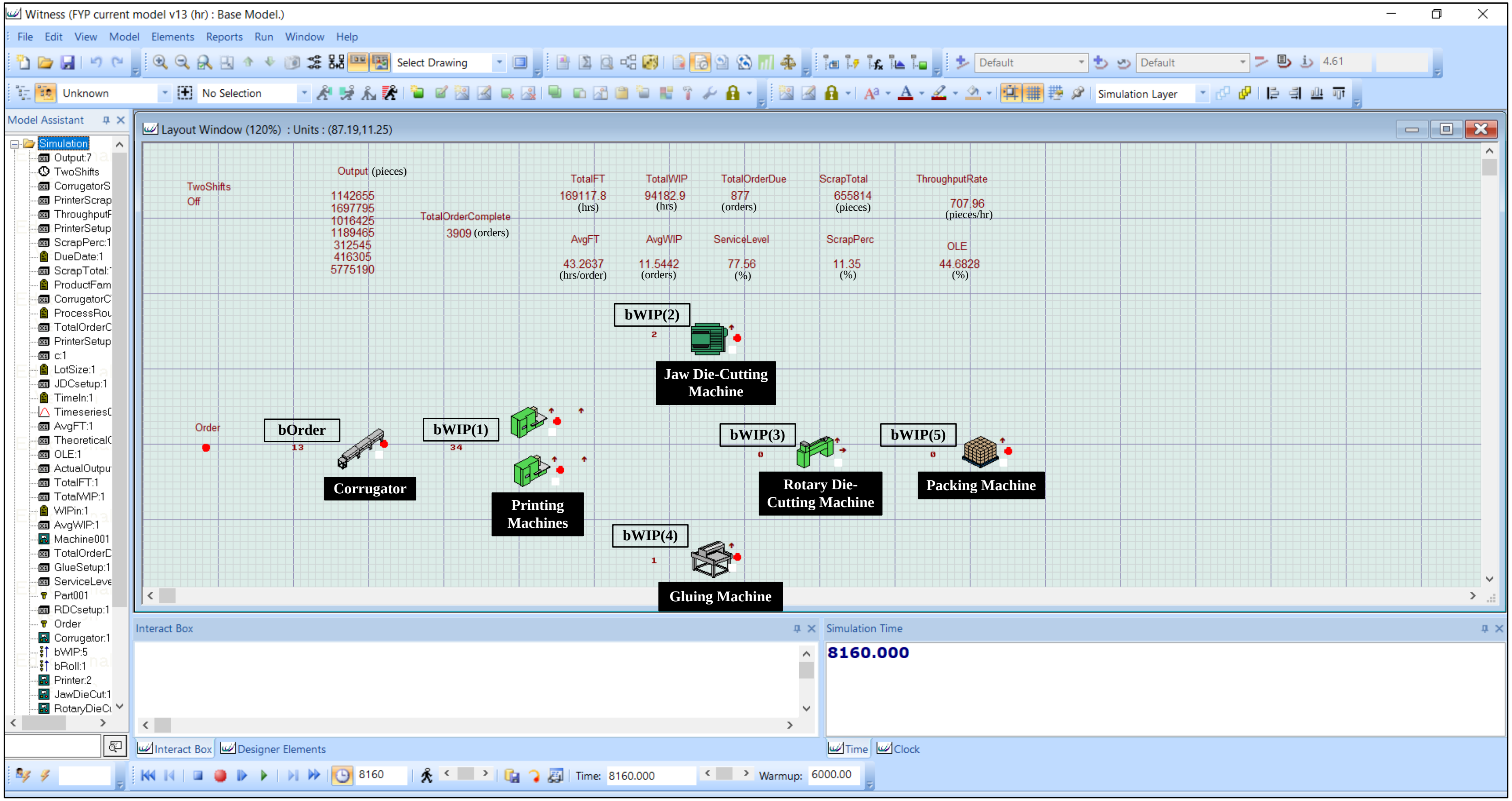

Figure 4.5: Print Screen of Simulation Model with Performance Measures After 6000-Hour Warm-Up and 2160-Hour Simulation Run.

Table 4.5: Average Performance Measures of 2160-Hour Simulation Run.

	Total Order	Average flow time (hrs)	Average WIP	Throughput (pcs/hour)	Line scrap rate (%)	Service level (%)	OLE (%)	ECE (RM/pc)
1st rep	3909	43.2637	11.5442	707.96	11.35	77.56	44.6828	-0.0002978
2nd rep	3893	46.3055	10.5193	711.89	11.24	62.37	44.9091	-0.0002947
3rd rep	3893	48.9506	11.4778	710.89	11.36	67.74	44.8998	-0.0002948
4th rep	3900	40.0268	7.4848	705.99	11.41	73.58	44.572	-0.0002994
5th rep	3871	48.0373	11.1577	716.66	11.28	63.73	45.2369	-0.0002901
Average	**3893.2**	**45.3168**	**10.4368**	**710.678**	**11.328**	**68.996**	**44.8601**	**-0.0002954**

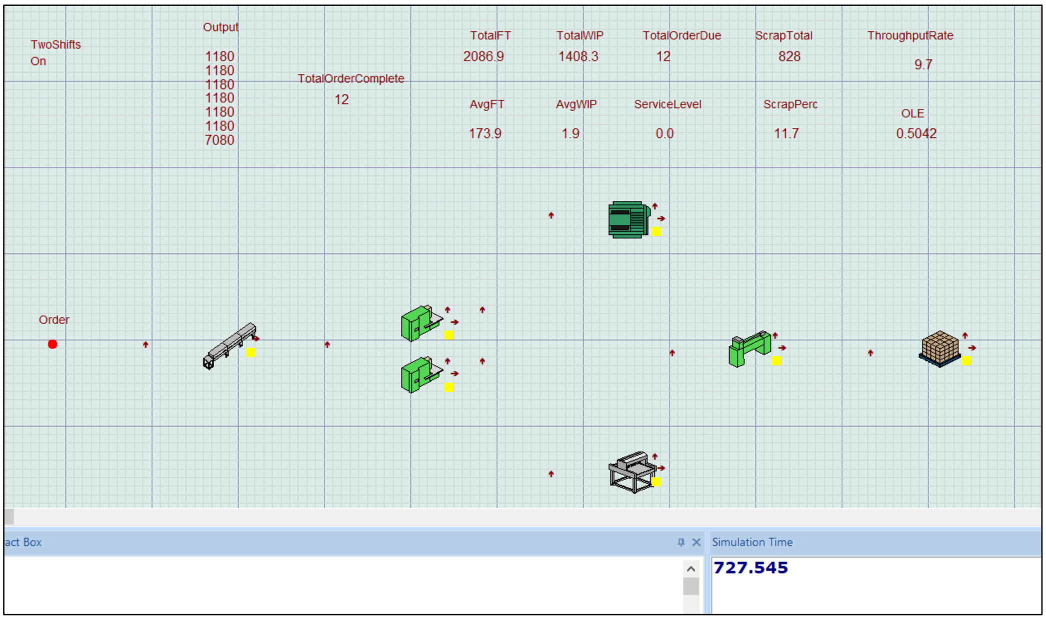

Figure 4.6(a): Print Screen of the Ending Time of Deterministic Model.

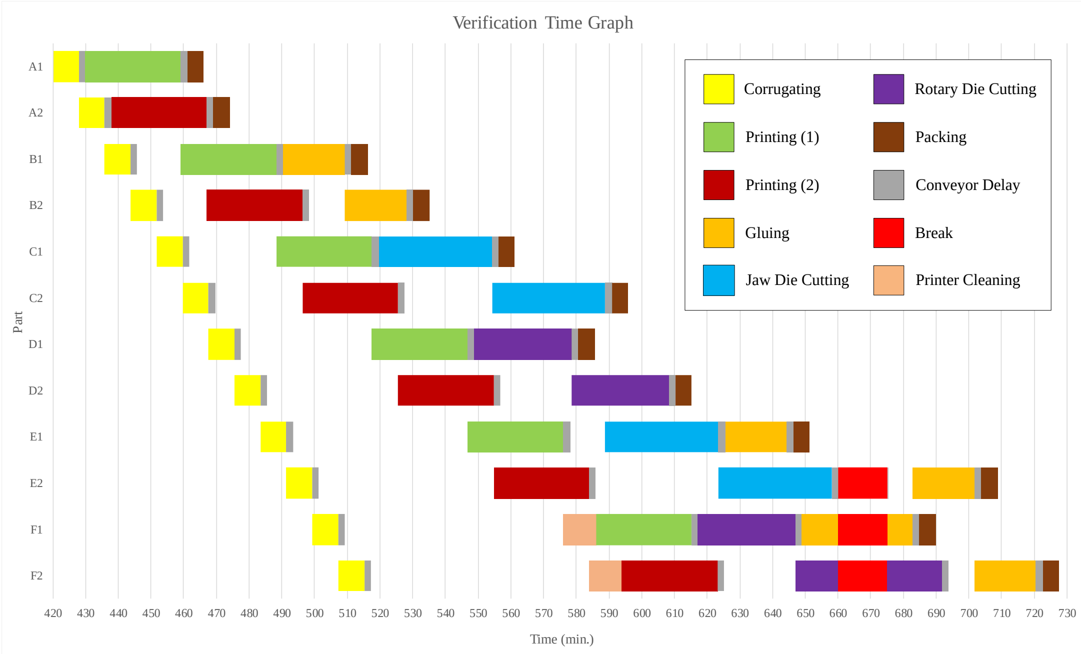

Figure 4.6(b): Time Graph Showing the Theoretical Ending Time of Deterministic Model.

4.4 Stage 3 - Analysis

After running the simulation model, production reports and simulation results were scrutinized together in order to thoroughly ascertain the problems in the factory as well as their root causes. Based on observation, problems that emerged in the factory were large amount of waste, congested WIP area and unable to meet customer demand. As for simulation model, the statistical data generated by the software had tangibly supported the problems observed at the factory through the values of performance measures. Production waste, WIP intensity and fulfilment of customer demand were depicted respectively by scrap rate, buffer report and service level.

In addition, it can be identified from the statistical report of simulation model that printing workstation was the bottleneck of the manufacturing line. This is because three abnormal aspects were observed from the simulation model as shown in Figure 4.7. Firstly, the buffer report showed that the maximum number of parts presented in the buffer before the printers, bWIP(1), was equivalent to the maximum limit that the buffer can store. Secondly, the corrugating machine report showed that blockage occurred, in which corrugating machine cannot push its finished parts to the printers' buffer. Thirdly, the printers were the only workstation that had zero idle time. Blockage occurred at the workstation's upstream process and starvation occurred at its downstream processes despite it was fully utilized for production. On the other hand, it was revealed from production reports that the scrap rate of the manufacturing line was very high and based on the simulation model, most of the waste was introduced by the corrugating process.

A fishbone diagram was drawn to find out the root causes of observed problem. As illustrated in Figure 4.8, the fishbone diagram comprised of 4 categories, which were man, machine, method and inventory. The comments in brackets are statistical data computed in simulation that reflects the problem.

WITNESS

Buffer Statistics Report by On Shift Time

Name	bWIP(1)	bWIP(2)	bWIP(3)	bWIP(4)	bWIP(5)	bRoll
Max	45	6	6	6	4	86
Min	16	0	0	0	0	0
Avg Size	37.33	0.73	0.65	0.61	0.19	33.29
Avg Time	20.44	1.76	1.28	0.81	0.11	18.28
Avg Delay Time	20.41	1.73	1.24	0.78	0.07	
Min Time	6.69	0.03	0.03	0.03	0.03	0.00
Max Time	32.69	13.96	13.20	11.64	8.87	38.85

Figure 4.7(a): Buffer Statistical Report.

WITNESS

Machine Statistics Report by On Shift Time

Name	Corrugator	Printer	JawDieCut	RotaryDieCut	Gluing	Packing
% Idle	0.36	0.00	26.42	27.64	29.62	62.77
% Busy	98.89	45.05	56.55	51.31	51.74	37.23
% Filling	0.00	0.00	0.00	0.00	0.00	0.00
% Emptying	0.00	0.00	0.00	0.00	0.00	0.00
% Blocked	0.75	0.00	0.00	0.00	0.00	0.00
% Cycle Wait Labor	0.00	0.00	0.00	0.00	0.00	0.00
% Setup	0.00	54.95	17.03	21.05	18.64	0.00
% Setup Wait Labor	0.00	0.00	0.00	0.00	0.00	0.00
% Broken Down	0.00	0.00	0.00	0.00	0.00	0.00
% Repair Wait Labor	0.00	0.00	0.00	0.00	0.00	0.00
No. Of Operations	3922	3910	890	1099	1622	3909

Figure 4.7(b): Machine Statistical Report.

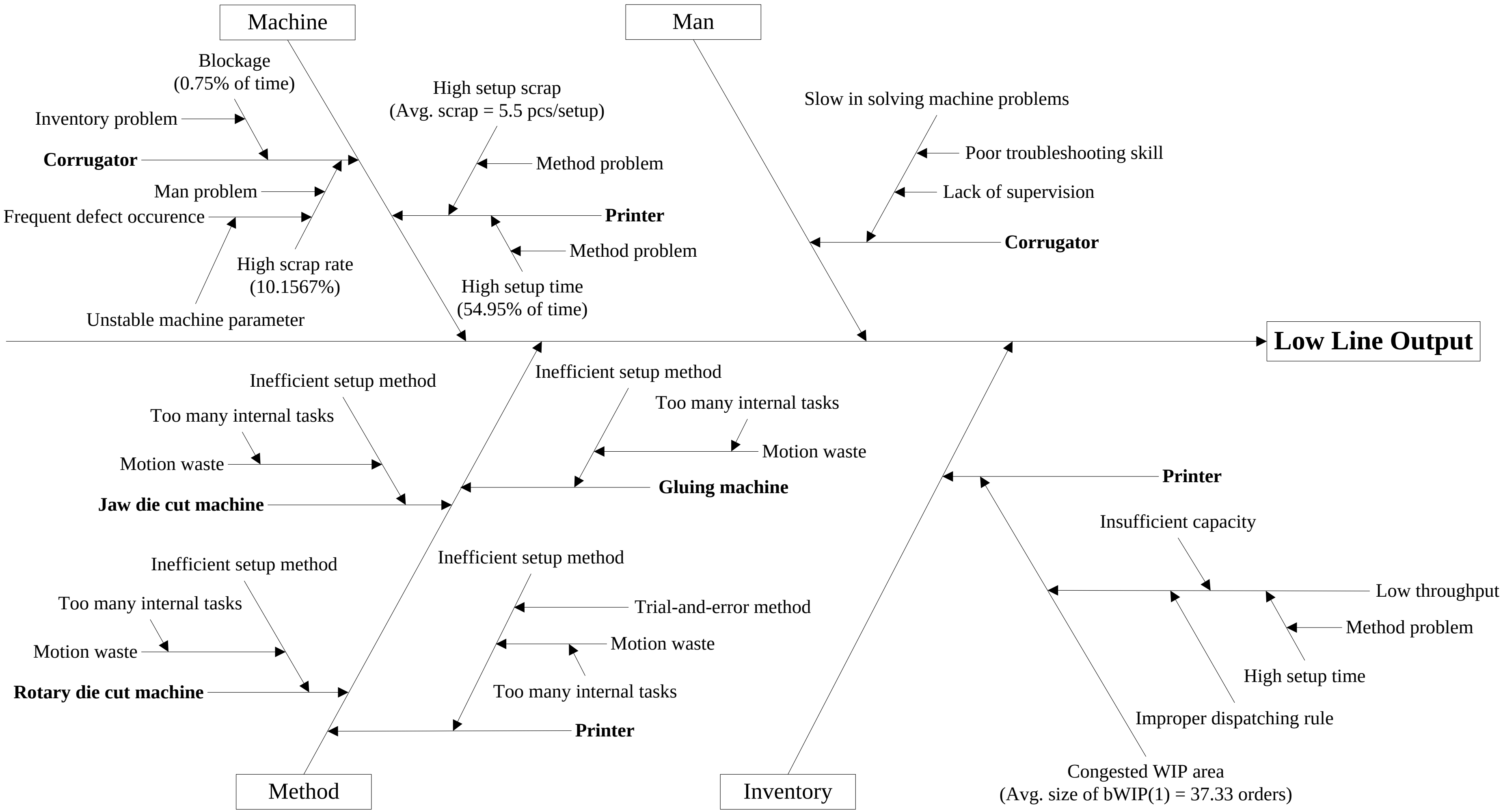

Figure 4.8: Fishbone Diagram.

Under the machine category, there are problems observed from corrugator and printing machine. At corrugator, blockage occurred for 0.75 % of the simulation time, which was 16.2 hours in 3 months, due to inventory issue. The high scrap rate of 10.1567 % was resulted from frequent occurrence of defective or non-conforming product because of the unstable machine parameters, but man problem had caused significant ramification on the scrap rate too. Whereas for printer, the setup time and setup scrap were high. The printer setup time had occupied 54.95 % of simulation time and there was an average of 5.5 pieces of scraps being generated from each setup. Both of these were due to improper setup method.

For the man category, the high scrap rate at corrugator was caused by slow response of operators. This is because operators played important role in detecting early signs of defect and executing corrective actions effectively. It was determined that the operators were lacking of competent troubleshooting skills and the delay in corrective actions had led to abundant production scrap. Lacking of supervision had also kindled the negligent attitude among operators during work.

On the other hand, the method category described the causes of high setup time of jaw die-cutting, rotary die-cutting, gluing and printing machines. Particularly for printing machines, trial-and-error approach which mainly depended on operator’s intuition was used while tuning the machines for the upcoming job, despite that there were many aspects of specifications involved in printing process. In this case, a unit of WIP was used to test if the machine parameters were correctly tuned according to the product specifications. If not, the operator would adjust the machine parameter and use another unit of WIP to test again. This cycle was repeated until the printed product met the specifications, hence it was time-consuming and generating undesirable amount of setup scrap. Besides, there were too much motion wastes during setups as the operators had to leave their workstation to get the WIP, equipment as well as material of the next job.

Lastly, the inventory category consisted of WIP congestion issue in front of the printing workstation. The capacity limit of bWIP(1) was reached at some point in time which caused blockage at corrugator machine and there was an average of 37.33 orders in the buffer. The printing workstation, as a bottleneck, had created huge amount of inventory at the buffer because it had the lowest throughput rate in the manufacturing line. There were few factors that might lead to low throughput, which were insufficient capacity to meet customer demand, improper job scheduling or dispatching rule as well as high setup time.

By summarizing the fishbone diagram, the root causes of problems that needed to be tackled were inefficient printer setup method, low throughput at printing workstation, as well as poor troubleshooting skills among operators. Subsequently, it was determined that areas where improvement should be prioritized in this case study were printing and corrugating workstations. This is because according to the Theory of Constraints (TOC), improving the performance of bottleneck, which is the system constraint, corresponds to heightening the overall performance of the entire system (Şimşit et al., 2014). Therefore, it would be effective by focusing on improvement at the bottleneck (printers) and its upstream process (corrugator). Potential solutions to solve or mitigate corresponding root causes are described in Table 4.6.

Table 4.6: Description of Possible Solutions to Solve Corresponding Root Causes.

No.	Root Cause	Solution	Description
1	Inefficient printer setup method	Enhance printer's setup efficiency	Quality check (QC) form: Used to record the discrepancies occurred at the first setup trial run. Then, the operator can tune the machine according to the form and all deviated machine parameters can be fixed in one shot.
			Single-minute exchange of die (SMED): To shorten changeover time in printers. For example, machine parameters such as position of printing moulds and cutting blades, as well as their rotating speeds, are calculated and printed on the particular job sheet. Therefore, the operator could just tune the machine according to the job sheet.
2		Increase worker for external setup	This solution can eliminate motion waste as the operators do not have to leave their workstation during setup as the required job changeover equipment, material and WIP will be sent in advance by the setup workers.
3	Low throughput rate at printing workstation	Increase number of printers	There were two unutilized printers in the factory but to save labour cost, the management was reluctant to hire more workers to run more printing machines. Hence in this solution, additional workers are hired to run the printers to elevate workstation's throughput.
4		Revise existing job scheduling or dispatching rules	Instead of FIFO, other dispatching rules will be tested to improve workstation's throughput.
5	Poor troubleshooting skills among operators at corrugator	Improve troubleshooting skill	Troubleshooting skill of the operators should be enhanced through measures such as training and supervision. This is to improve the operators’ agility and resourcefulness in handling machinery issues as well as assuring good product quality.

After determining the potential solutions, attribute values were designated for different alternatives of each solution so that each solution was converted into measurable input parameters in order to test its impact on the manufacturing line's model. In addition, difficulty score was assigned for each alternative. In order to obtain the measurable attribute values of the first and last solution, two supplementary simulation models were built for printer setup process as well as corrugating process.

Supplementary Model 1 - Printer Setup Process:

A simulation model was constructed to imitate the changeover steps for printing machines (M_P). The model consisted of two operators and they performed their tasks separately. As illustrated in Figure 4.9, operator A would search for the required WIP for the next job in the WIP area and transport the pallet to the machine through roller conveyor. Then, the operator would load the WIP onto the machine's feeding section. Whereas operator B prepared the job sheet, equipment and material that were required for the next job and installed the printing mould on the machine. Once the printing mould were installed and the parts were loaded, setup trial runs were conducted to tune the machine. Figure 4.10 shows the elements that were constructed to model printer setup. The input parameters of the existing simulation model were revised to the expected or estimated result of the implementation of new method as shown in Table 4.7. For instance, implementation of a quality check form was estimated to reduce the setup trial runs from 4 to 7 times to 2 or 3 times. Therefore, this parameter was changed and total setup time (ST_P) as well as average setup scraps (N_{QP}) were affected. New values of total setup time and average setup scraps will be input into the line's simulation model to obtain the overall performance of the virtual manufacturing line.

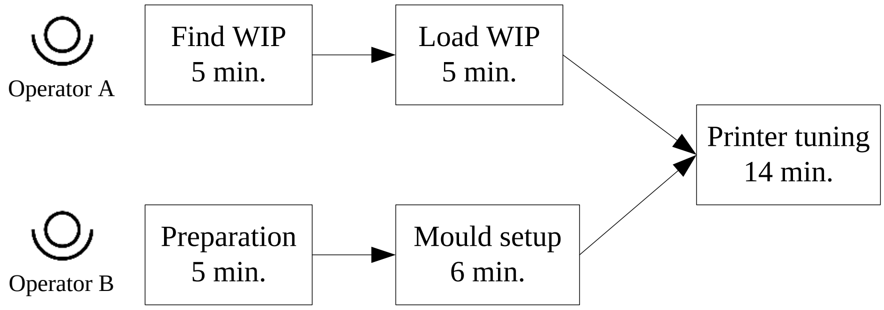

Figure 4.9: Printer Setup Steps.

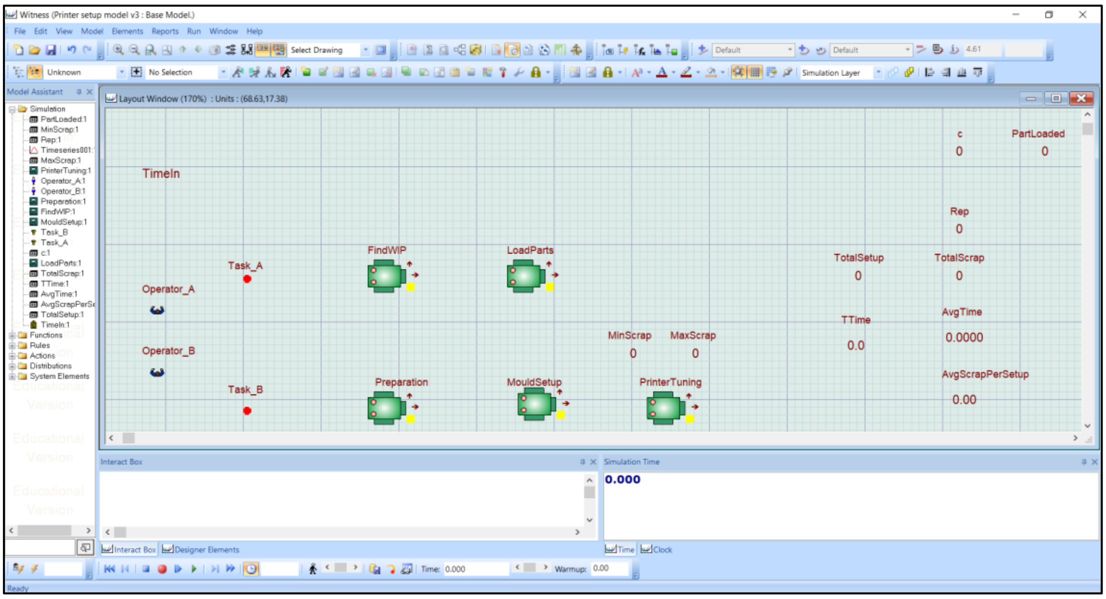

Figure 4.10: Print Screen of Simulation Model of Printer Setup Steps.

Table 4.7: Simulation Results for Printer Setup Steps.

	Number of Trial Runs	ST_p (min.)	N_{QP} (pcs)
Current method	4 - 7 times	22.006	5.502
SMED	1 - 3 times	15	2.002
QC form	2 - 3 times	16.002	2.5
SMED + QC form	1 - 2 times	14.002	1.502

Supplementary Model 2 - Corrugating Process:

Another simulation model was built for the corrugating workstation to obtain the corrugator's scrap rate (Q_c) when the operators' troubleshooting skills were enhanced. The workstation consisted of two processes, which were machining and stacking as demonstrated in Figure 4.11 and Figure 4.12. There are a lot of ways to improve operator's troubleshooting skills such as periodic training, toolbox meeting and other troubleshooting techniques. Table 4.8 shows the simulation result of the corrugator model for current and improved troubleshooting skill. If operators possess good troubleshooting skill, the mean time to solve (MTTS) technical issues of the machine will reduce. The simulated corrugator scrap rate will be input into the line’s simulation model for experimentation.

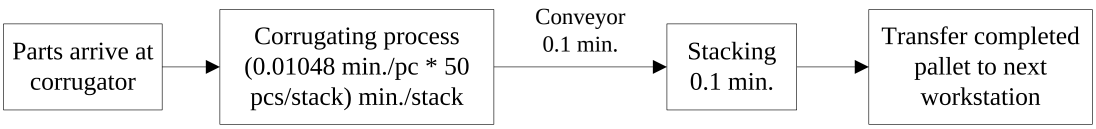

Figure 4.11: Flow in Corrugating Workstation.

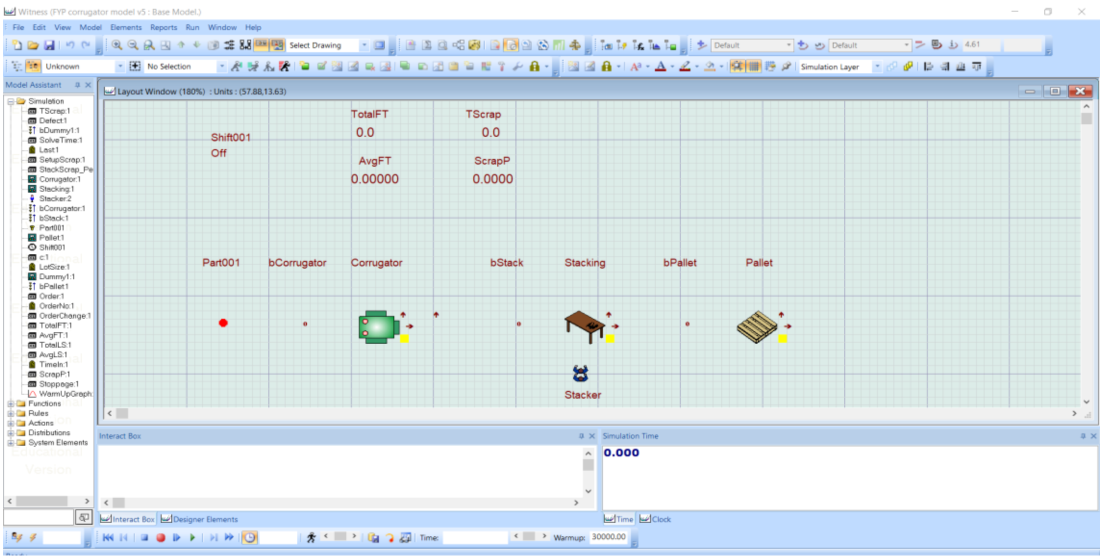

Figure 4.12: Print Screen of Simulation Model of Corrugating Workstation.

Table 4.8: Simulation Result of Corrugator Model.

	MTTS (min.)	Q_C (%)
Current	NegExp(5)	10.1567
Improved	NegExp(2)	5.1183

For the second, third and fourth solution, parameters can be amended in the line’s simulation model. To enhance setup efficiency, additional workers were hired to perform external setup tasks and this can reduce the setup time of printing machine as ‘Find WIP’ and ‘Preparation’ steps as shown in Figure 4.9 were eliminated. Although this case study focused on the improvement of corrugating and printing workstations, it was not realistic to hire extra workers to perform setup tasks of printing machines only because the labor's utilization will be low. Therefore, in this case, 1 or 2 workers will be hired to perform setup tasks for other machines too according to the factory layout. One worker will be in-charged of setup tasks of printing and jaw die-cutting (M_{JDC}) machines whereas another worker is in-charged of setup tasks of rotary die-cutting (M_{RDC}) and gluing (M_G) machines. The setup times of printing (ST_P), jaw die-cutting (ST_{JCD}) and rotary die-cutting (ST_{RDC}) machines will be reduced by 5 minutes whereas setup time of gluing machine (ST_G) will be reduced by 4 minutes. Besides, to increase printing workstation's capacity, elements that needed to be changed was the number of printing machines (N_P) in the workstation. However, there was a trade-off to increase the workstation's capacity, which were additional labor and maintenance costs. The additional cost was represented by improvement cost (K_{IC}), a parameter of ECE as shown in Equation 4.3. The two alternatives of this solution were utilizing 3 or 4 machines. Whereas for the fourth solution, job scheduling rules such as shortest processing time (SPT), last-in-first-out (LIFO) and earliest due date (EDD) can be tested in the simulation model.

Table 4.9 summarizes the attribute values as well as difficulty score of each alternative. Design of experiment (DOE), particularly full factorial experiment, was performed by formulating the possible combinations of attribute values of different solutions and each combination will be experimented on the line's simulation model. The original attribute values were retained while formulating the combination because it was not necessary to implement all improvement solutions due to limited resources and there was no guarantee that the solutions brainstormed will definitely improve the system performance. The total number of combinations is the product of number of sets of attribute values for each solution. Hence, the total number of experiments to run in this case study is 4×3×4×3×2 = 288 experiment runs.

Table 4.9: Attribute Values and Level of Difficulty of Each Alternative.

No.	Solution	Alternatives		Input Values	LOD
A	Enhance printer's setup efficiency	1	Current	ST_P = 22.006 min. N_{QP} = 5.502 pcs	0
		2	SMED	ST_P = 16.002 min. N_{QP} = 2.5 pcs	2
		3	QC form	ST_P = 15 min. N_{QP} = 2.002 pcs	4
		4	QC form + SMED	ST_P = 14.002 min. N_{QP} = 1.502 pcs	5
B	Increase worker for external setup	1	Current (No setup worker)	ST_P = ST_P from Solution 1 ST_{JCD} = 15 min. ST_{RCD} = 15 min. ST_G = 9 min.	0
		2	1 setup worker	ST_P = ST_P from Solution 1 – 5 min. ST_{JCD} = 10 min. ST_{RCD} = 15 min. ST_G = 9 min. K_{IC} = RM1800/month	1
		3	2 setup workers	ST_P = ST_P from Solution 1 – 5 min. ST_{JCD} = 10 min. ST_{RCD} = 10 min. ST_G = 5 min. K_{IC} = RM3600/month	1
C	Increase number of printers	1	Current (2 printers)	N_P = 2	0
		2	3 printers	N_P = 3 K_{IC} = RM 6600/month	1
		3	4 printers	N_P = 4 K_{IC} = RM 13200/month	1
D	Revise job scheduling rule	1	Current (FIFO)	-	0
		2	SPT	-	3
		3	LIFO	-	3
		4	EDD	-	2
E	Improve troubleshooting skill	1	Current	Q_C = 10.1567 %	0
		2	Improved	Q_C = 5.1183 %	5

4.5 Stage 4 - Selection

WITNESS 20 is featured with experimenter function that allows user to run simulation repetitively with different set of variables for each run. Variables to change for each run (as shown in Table 4.9) were added in the simulation model because they were input parameters of the experimenter function.

After conducting the experimental runs, a report that consists of performance measures of each combination of attribute values was generated and exported to Minitab software and Microsoft Excel. For each experiment, 5 replications were run and the performance measures recorded as shown in Appendix A were the average performance measures of those 5 replications. For the variable names of Table A.1 in Appendix A, alphabet denotes the solution and number denotes the alternative based on Table 4.9. For example, variable 'A2' represents the input values of SMED method in printer setup. Besides, LOD in Table A.1 represents the summation of individual LOD of each alternative.

One-way ANOVA was performed to justify the effectiveness of each solution on each performance measure. Table 4.10 summarizes the impact of solutions on the manufacturing line's performance. A '√' indicated that the solution had a significant impact on the particular performance measure. From the table, it was deduced that changing the job scheduling rule had no impact on the line performance. Therefore, the combinations of alternatives that involved changing job scheduling rule were eradicated, preserving the impactful solutions for decision-making.

Table 4.10: Impact of Each Solution on Particular Performance Measure.

Performance measures / Solutions	Average flow time	Average work-in-process	Throughput Rate	Scrap rate	Service level	Overall line efficiency	Equipment cost efficiency
Enhance printer's setup efficiency	√	√	√		√	√	√
Increase worker for external setup	√	√			√		
Increase number of printers	√	√			√	√	√
Revise job scheduling rule							
Improve troubleshooting skills	√		√	√	√		

Subsequently, the performance measures recorded was normalized. Table 4.11 shows a set of performance measures of one of the combinations of alternatives that is extracted from Appendix B to demonstrate calculation steps. With respect to the decision criteria, OLE fell under direct category, which means that larger values of performance measures are desirable. Whereas AFT, Q and LOD belonged to indirect category, in which larger values of performance measure are unfavourable. For ECE, it comprised of positive and negative values, and the value of this performance measure is favourable when it is near to zero because zero ECE indicates that there is no wasted cost in performance loss and no excess cost in achieving performance excellence (Liew, Prakash and Ong, 2021). To simplify this, its absolute value was computed and it was considered indirect category. Performance measures under direct and indirect categories were normalized by using Equation 3.6 and 3.7 respectively. The steps of normalizing performance measures of respective decision criteria are illustrated below.

$$\overline{OLE_1} = \frac{OLE_1}{\max OLE}$$

$$= \frac{44.6782}{89.7563}$$

$$= 0.4978$$

$$\overline{AFT_1} = \frac{\min AFT}{AFT_1}$$

$$= \frac{12.4372}{42.3905}$$

$$= 0.2934$$

$$\overline{Q_1} = \frac{\min Q}{Q_1}$$

$$= \frac{5.96}{6.25}$$

$$= 0.9536$$

$$\overline{LOD_1} = \frac{\min LOD}{LOD_1}$$

$$= \frac{1}{5}$$

$$= 0.2$$

$$\overline{ECE_1} = \frac{\min|ECE|}{|ECE_1|}$$

$$= \frac{5.6031\times10^{-7}}{|-2.9791\times10^{-4}|}$$

$$= 0.0019$$

The overall performance score of each combination of alternatives was computed, which as multiplying the normalized performance value ($\overline{P_{ij}}$) of the decision criterion with its corresponding criteria weight (ω_j) as shown in Equation 3.8.

(Overall performance score)$_1$

$$= \sum_{j=1}^{m}\left(\omega_j \times \overline{P_{ij}}\right)$$

= (0.034 × 0.2934) + (0.1575 × 0.9536) + (0.4254 × 0.4978) + (0.2973 × 0.0019) + (0.0858 × 0.2)

= 0.3896

Based on the overall performance scores calculated for all combinations of alternatives, it was concluded that enhancing the printers' setup efficiency and improving operators troubleshooting skill were the most desirable implementations because it had the highest overall performance score, which was 0.9219 as shown in Table 4.12.

Table 4.11: Calculation of Overall Performance Score for a Combination of Alternatives.

No.	Variables					AFT (hrs)	Q (%)	OLE (%)	ECE (RM/pc)	LOD	Normalized Performance Measure					Criteria Weight					**Overall Score**
											AFT	Q	OLE	ECE	LOD	AFT	Q	OLE	ECE	LOD	
1	A1	B1	C1	D1	E2	42.3905	6.25	44.6782	-2.9791×10^{-4}	5	0.2934	0.9536	0.4978	0.0019	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.3896**

Table 4.12: Combination with the Highest Overall Performance Score as Selected Alternative.

No.	Variables					AFT (hrs)	Q (%)	OLE (%)	ECE (RM/pc)	LOD	Normalized Performance Measure					Criteria Weight					**Overall Score**
											AFT	Q	OLE	ECE	LOD	AFT	Q	OLE	ECE	LOD	
37	A3	B1	C1	D1	E2	13.2263	6.03	89.6092	5.60312E-07	7	0.9403	0.9884	0.9984	1.0000	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.9219**

In other words, among five possible solutions that could be implemented on respective aspects, the result had suggested that only two of the aspects required improvement whereas others can retain their current method. The chosen combination of solutions was an optimized implementation that improved OLE and reduced scrap rate in a significant extent, in addition to low improvement cost. The experimented OLE was 89.61 %, which was 100.05 % higher than the existing OLE value. The drastic improvement of OLE was due to the resolved bottleneck (printing workstation) by enhancing the printers' setup efficiency. As OLE was improved by more than 15 %, the goal of this project was achieved.

4.6 Stage 5 - Termination

There are two elements to be improved in the manufacturing line, which involved corrugating and printing workstation. The first solution was enhancing printer's setup efficiency by deploying QC form. The LOD score rated for this alternative was 2, which was an easy implementation because it involved change in working procedure that do not require new technical skill. Therefore, operators can adapt quickly with the changes made in their work elements during setup.

Based on the attribute values, it was targeted to only run at most 3 setup trials if QC form is deployed. This is to reduce the printer setup time from 22 minutes to 16 minutes as well as reduce setup scrap from 5.5 pieces to 2.5 pieces per setup in average. The potential person-in-charge of this implementation was Quality Department, as they have to design a comprehensive QC form that is helpful in facilitating the setup process to achieve the target. Moreover, it was presumed that filling QC form might incur some time losses during setup. To mitigate this issue, it was suggested that both operators must involve in the machine tuning process, instead of one. One of the operators will be responsible in assessing the conformity of the trial product while another help to record the discrepancies that needed to be corrected in machine tuning.

On the other hand, the second solution was reducing production scrap by improving troubleshooting skills among corrugating operators. The LOD score of this alternative was 5, which indicated that there will be difficulties to overcome in achieving desirable results. The main concern was human factor, in which operators might be unable to meet expectation due to their limitation in regards of their skill, knowledge and personality.

The targeted MTTS value for improved troubleshooting skill was equal or less than 2 minutes, in order to achieve outcome that is similar to the simulation result. To improve troubleshooting skills, training sessions must be conducted for the operators to cultivate their skills, knowledge and resourcefulness in solving machine problems that affect product quality. Techniques that aid in quick troubleshooting can be adopted, such as failure modes and effects analysis (FMEA) for engineers to establish precautions and immediate corrective actions when machine abnormality arises as well as a clear-cut illustration of troubleshooting guide for operators.

Additionally, the persons-in-charge of this implementation were Human Resource (HR) and Production Department. HR department must arrange training sessions for the operators periodically and production personnel who are experienced in handling machinery issues must devise strategies that can improve the operators' troubleshooting skill. To achieve targeted MTTS value and overcome difficulties implied in LOD, production supervisors should constantly keep track of the operators' performance and behaviour to ensure the effectiveness of training sessions as well as the operator's ability to perform their work well. Also, strict supervision is important to prevent backslides of the operators' performance after training.

4.7 Findings and Discussion

The conventional framework that has been used in improving manufacturing system is defining goal, collecting data, analysing data, implementing solutions and sustaining them. Identifying problems, performing RCA and deriving solutions are still the major elements that are similar to this new framework. However, the selection of best solution to implement tends to be subjective in the conventional way of factory improvement as it is mostly based on experience. The solution's outcome is also predicted in a qualitative manner, without a concrete supporting data that proves the confidence of the solution in improving the manufacturing system to a certain degree. This in turn leads to a time-consuming, uneconomical and risky improvement project.

For example, trial-and-error of potential solutions is the most common traditional way in decision-making for process improvement project. This method is normally carried out at a process that is intended to be improved, during off-shift time or on a selected batch of product type during production time. Nevertheless, solution trials during production time is considered non-value-added because it may affect the process's productivity and manpower is needed to instruct and monitor the operators to temporarily implement the new work pattern. In addition, experimenting possible solutions during off-shift time incurs overtime cost. Not to mention that the solution might fail, time and resources are wasted in conducting multiple attempts to obtain the best parameter for the solution.

The new framework couples contemporary approaches with the major steps of factory improvement comprised in the conventional framework. In the 'Initiation' stage, this framework provides guidelines in setting performance benchmark, goal and objectives, which are present in conventional framework. Additionally, decision criteria and criteria weights were determined through AHP pairwise comparison based on the goals and objectives of the improvement project to ensure that all alternatives were assessed with reference to the objectives.

In 'Modelling' stage, data collection is involved in conventional framework, but this framework guides practitioners to utilize the collected data to build a comprehensive simulation model by using discrete event simulation (DES) software. Next, in 'Analysis' stage, root cause analysis and solution brainstorming that exist in conventional framework were adapted into the new framework, in which simulation model is used to facilitate root cause analysis.

Nevertheless, the fourth stage is the phase that is absent in conventional framework. In 'Selection' stage, the simulation model was used to predict the system performance of new implementation. Then, ANOVA was used to filter out solutions that do not play impact on the system performance and the performance measures of respective decision criteria are computed into an overall performance score that reflects the effectiveness of the solution in attaining project goal and objectives. As a result, the superiority of the solutions is tangible and decision-making is carried out based on the overall performance score of the alternatives.

In ‘Termination’ stage, both frameworks consist of formulating blueprint for the new implementation. However, the targeted values or performance to acquire in the actual implementation are distinguished in the proposed framework, in order to achieve outcome that is comparable to the performance estimated in the simulation model. Therefore, course of actions to achieve the targeted values are also incorporated in the implementation blueprint. Ultimately, the purpose of deploying simulation model in the new framework is to visualize system’s dynamic behaviour, investigate problems and root cause, predict the long-term effects of the possible solution(s) on the system performance, as well as obtaining targeted values or parameters for actual implementation.

Another main contribution of the new framework is remote decision-making. This is an adaption to the evolving work nature as the global pandemic has stimulated computer-based work environment and many organizations tend to continually deploy this work nature even though the movement restriction has relieved. With the proposed framework, the efficiency in process improvement can be highly enhanced because decision-making can be conducted regardless of location and time. This contrasts with the conventional way that encounters resource availability constraints as it requires practitioners to schedule a specific time to attend the particular machine for trials. In certain circumstances, the entire proposed decision-making framework can be accomplished remotely when the operational data for model construction can be accessed from the production documentations, so on-site data collection is not necessary. Hence, provided that practitioners have the knowledge of using simulation software and AHP, this framework is more relevant than the conventional one because it supports remote decision-making that is presently prevailing, brings convenient due to lesser constraints, and amplifies improvement efficiency as it helps in avoiding non-value-added activities that had incurred in conventional factory improvement.

Apart from that, comparing the conventional way with the new framework, the new framework emphasizes on the quality of the solution selected for implementation. The conventional framework is lack of clear guidelines in evaluating alternatives, such as assessment of the objectives' priorities and followed by quantification of solution's effectiveness with reference to the objectives. Therefore, the ability of the solution to achieve objectives is vague until it is actually implemented, because it is difficult to instinctively foresee the efficacy of the solution when multiple objectives involves. On the other hand, the proposed framework assures the successfulness of the implementations by evaluating alternatives in a measurable way based on the project's goal and objectives. The computed performance score explicitly expresses the extent of the successfulness of a particular alternative in attaining goals and objectives, so that it can be compared with others. This assures the quality of selected solutions by obtaining solutions that fulfil multiple objectives. In other words, conventional method aims in seeking for a suitable solution, and the proposed framework strives for optimization.

Moreover, the new framework differs that it facilitates improvement project involving different aspects or workstations and predicts the long-term effects of the solutions on the manufacturing line. Commonly, improvement in the factory mainly focuses on a specific workstation or machine and the effectiveness of the solutions can only be justified based on performance of the particular machine during trials, in which the effectiveness of the solutions in improving entire line's efficiency is uncertain. The proposed framework has conquered these restrictions by improving the manufacturing line as a whole. Several exceptional factors that can be assessed through the new framework are the impacts and relationships of a solution for a process, a combination of solutions for a process and a combination of solutions for different processes towards the whole manufacturing system in a long run. Thus, it is a beneficial approach in manufacturing line improvement because improvement of different processes in the factory can be conducted concurrently and long-term effects can be predicted.

In fact, the new framework is versatile and can be applied extensively. It can be applied on wide range of manufacturing systems. Furthermore, the evaluation of alternatives is not restricted to quantitative performance measures, but also converting subjective opinions to a numerical value. Taking the case study as an example, evaluating LOD of a solution is important because it assimilates the practitioners' judgement on the solution's practicability into decision-making and counterbalances unforeseeable events that could not be integrated in simulation model. By deploying a systematic framework, ambiguity of proposed solutions can be mitigated, thus reducing the risk of project failure.

There are many other advantages of adopting simulation in process improvement. The statistical report generated by the simulation is helpful in spotting problems in the factory as well as determining the root causes of the problem. This is because the reports clearly depict the status of every element in the simulation model over an extended period of time, and this information is difficult to be obtained through observation and data collection. Lastly, in conventional improvement method, minimal amount of possible solutions can only be suggested because the solutions are speculated through intuitive approach and there is limited resource to conduct physical trials. But, a great number of solutions can be evaluated through simulation and the most effective combination of solutions can be identified, as per scenario described in the case study. This encourages creativity in brainstorming possible solutions because the team members are not confined to the risky way in evaluating ideas, as the effectiveness of their proposals will be tested and proven through simulation run.

CHAPTER 5

CONCLUSION

5.0 Introduction

This chapter discusses the summary of this research as well as the future research that can be conducted. Section 5.1 summarizes the findings of this research by highlighting the essence of previous chapters. Section 5.2 lists out the potential research opportunities that can be carried out in the future.

5.1 Summary of Research

Decision-making tools and performance metrics are vital elements in manufacturing process improvement. Due to the growing complexity of manufacturing systems as well as stimulation of computer-based technologies by the global pandemic, software and remote working are extensively adopted in most of the organizations to enhance work efficiency. In manufacturing aspect, recent researches had conducted study pertaining to process improvement and decision-making, but there is lack of comprehensive framework on integrating simulation software with decision-making in process improvement, particularly for remote working. Thus, a new decision-making framework is necessary in order to serve as a guideline for deploying a contemporary decision-making tool to establish remote and effective decision-making process in process improvement.

Literature review was carried out to gain insights on previous research work. Decision-making tools and techniques, performance metrics in manufacturing system as well as frameworks of decision-making and process improvement that were adopted or formulated by previous researchers were analysed. As a result, important elements of decision-making as well as process improvement frameworks were identified. Besides, discrete event simulation (DES) software was selected as the decision-making supporting tool in this research as it can visualize the dynamic behaviour of manufacturing system as well as investigate problem and predict effectiveness of an implementation. If multi-criteria decision-making (MCDM) is involved, analytic hierarchy process (AHP) pairwise comparison method will be used to assign criteria weights for decision criteria.

In this research, a new decision-making framework was formulated after identifying the key features of decision-making framework in literature review. The proposed framework was then applied in a case study and its practicability was discussed. The proposed framework consists of five major stages, which are initiation, modelling, analysis, selection and termination. ‘Initiation’ stage provides guidelines in understanding existing problems and setting direction for the project. ‘Modelling’ stage is about building a precise simulation model that can imitate the manufacturing system. ‘Analysis’ stage provides guidelines to generate possible solutions that are relevant in solving root causes. ‘Selection’ stage provides steps in selecting the best performing solution among various alternatives. Lastly, ‘Termination’ stage is about planning and recommendation for future implementation.

A case study was carried out at a box factory by applying the new framework to improve its overall line efficiency (OLE). MCDM was involved so AHP pairwise comparison was used to assign criteria weights to each decision criterion. The descending order of the significance of decision criteria was OLE, equipment cost efficiency (ECE), line scrap rate (Q), level of difficulty (LOD) and average flow time (AFT). A simulation model of the manufacturing line and two supplementary models each for corrugating and printer setup processes were constructed. After root cause analysis and solution brainstorming, a total of 288 experiment runs were carried out, and the performance of each trial was computed into overall performance score for decision-making.

Based on overall performance scores of the alternatives, the best combination of solutions was enhancing printer setup process by deploying quality check (QC) form and improving the troubleshooting skill among corrugator operators. Among five solutions that were proposed in 'Analysis' stage, implementing two of them was sufficient to attain project goal. In addition, the best attribute values for each solution were obtained to act as targets in future implementation. As such, OLE of the factory was expected to be improved from 44.68 % to 89.61 %. All of these had proven the feasibility of simulation software in decision-making because an optimized solution can be sought, in which goals are achieved with minimal resources. Besides, it is deduced that this new framework is more beneficial than the conventional one as it contributes in remote decision-making, exploiting the usefulness of simulation software as well as systematic evaluation of alternatives to assure the success of process improvement projects.

5.2 Recommendations for Future Research

Several recommendations for future research regarding this framework are listed as follows:

- Rectify the gaps of the proposed framework after implementation was done in the factory. The case study conducted was decision-making and justification on the framework's validation was merely based on the decision-making process. After implementation, relevancy of the selected solutions through the framework can be evaluated, and subsequently, gaps, insufficiencies or improvement opportunities of the framework can be identified as well as resolved.
- Apply the proposed framework on different types of product variety in the same factory. Other than boxes, the company also manufactures packing materials such as air bubble wraps and polyethylene foams. The manufacturing lines are distinct for different product varieties. Hence, the proposed framework can be applied to improve the efficiencies of different lines.

- Apply the proposed framework on different types of manufacturing system such as flow production process, cellular manufacturing and pull system. The proposed framework was applied on a job shop and make-to-order production process. It can be applied on other types of manufacturing system to validate its versatility as an adaptable framework that can be used extensively in the field of manufacturing.
- Employ different types of DES software, such as ProModel and FlexSim. In the case study, WITNESS 20 was used due to its integration of C++ programming language and graphical user interface. Practitioners who are competent in using manufacturing simulation software can employ more intricate simulation software to add value to the simulation models in terms of visualization and extended features.

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APPENDICES

Appendix A: Simulation Results.

Table A.1 shows the simulated performances measures recorded for each combination of alternatives. The value recorded is the average value of five replications of simulation run. For the variable names, alphabet denotes the solution and number denotes the alternative based on Table 4.9. ‘No. 0’ represents the methods that were used in existing system. The abbreviations used in the title of Table A.1 are explained as follows.

WIP = Work-in-process
OLE = Overall line efficiency
ECE = Equipment cost efficiency
K_{IC} = Improvement cost
T_{CT} = Cycle time of bottleneck
LOD = Level of difficulty of implementation (summation of individual LOD of each alternative)

Table A.1: Performance Measures of Simulation Runs.

No.	Variable					Total Order	Average flow time (hrs)	Average WIP	Throughput (pcs/hour)	Scrap rate (%)	Service level (%)	OLE (%)	ECE (RM/pc)			LOD
													K_{IC}	T_{CT} (s)	ECE	
0	A1	B1	C1	D1	E1	3909	43.2637	11.5442	707.96	11.35	77.56	44.6828	0	0.3636	-0.0002978	0
1	A1	B1	C1	D1	E2	3910	42.3905	12.9672	708.05	6.25	78.03	44.6782	0	0.3636	-0.0002979	5
2	A1	B1	C1	D2	E1	3901	57.3835	12.7672	707.11	11.66	60.22	44.6462	0	0.3636	-0.0002984	3
3	A1	B1	C1	D2	E2	3901	57.7295	13.4889	706.21	6.26	60.42	44.6369	0	0.3636	-0.0002985	8
4	A1	B1	C1	D3	E1	3904	38.3718	3.0836	706.02	11.34	78.82	44.5864	0	0.3636	-0.0002992	3
5	A1	B1	C1	D3	E2	3907	36.6084	2.3643	706.94	6.25	79.58	44.6094	0	0.3636	-0.0002989	8
6	A1	B1	C1	D4	E1	3907	29.2392	2.855	707.62	11.34	83.34	44.66	0	0.3636	-0.0002982	2
7	A1	B1	C1	D4	E2	3907	26.3032	2.9367	706.94	6.26	85.44	44.6369	0	0.3636	-0.0002985	7
8	A1	B1	C2	D1	E1	3924	21.1066	1.7543	709.99	11.33	89.35	89.7563	6600	0.0120	0.0000012	1
9	A1	B1	C2	D1	E2	3918	13.2683	1.6972	709.26	6.25	95.71	89.6092	6600	0.0120	0.0000012	6
10	A1	B1	C2	D2	E1	3924	21.3787	1.8817	709.77	11.33	89.17	89.7563	6600	0.0120	0.0000012	4
11	A1	B1	C2	D2	E2	3917	13.6289	1.869	709.05	6.25	95.3	89.6092	6600	0.0120	0.0000012	9
12	A1	B1	C2	D3	E1	3923	21.0881	1.7426	709.92	11.33	89.47	89.7563	6600	0.0120	0.0000012	4
13	A1	B1	C2	D3	E2	3918	13.3735	1.7463	709.07	6.25	95.51	89.6092	6600	0.0120	0.0000012	9
14	A1	B1	C2	D4	E1	3924	21.1398	1.7654	709.84	11.33	88.58	89.7563	6600	0.0120	0.0000012	3
15	A1	B1	C2	D4	E2	3917	13.2857	1.7059	709	6.25	94.72	89.6092	6600	0.0120	0.0000012	8
16	A1	B1	C3	D1	E1	3924	21.1155	1.7546	709.99	11.33	89.3	89.7563	13200	0.0120	0.0000018	1
17	A1	B1	C3	D1	E2	3918	13.2607	1.6935	709.26	6.25	95.69	89.6092	13200	0.0120	0.0000018	6
18	A1	B1	C3	D2	E1	3924	21.3895	1.8847	709.77	11.33	89.12	89.7563	13200	0.0120	0.0000018	4
19	A1	B1	C3	D2	E2	3917	13.6306	1.8676	709.05	6.25	95.3	89.6092	13200	0.0120	0.0000018	9
20	A1	B1	C3	D3	E1	3923	21.0081	1.7397	709.92	11.33	89.32	89.7563	13200	0.0120	0.0000018	4
21	A1	B1	C3	D3	E2	3918	13.3571	1.7385	709.07	6.25	95.48	89.6092	13200	0.0120	0.0000018	9
22	A1	B1	C3	D4	E1	3924	21.1463	1.7646	709.84	11.33	88.56	89.7563	13200	0.0120	0.0000018	3
23	A1	B1	C3	D4	E2	3917	13.2756	1.7009	709	6.25	94.74	89.6092	13200	0.0120	0.0000018	8

24	A1	B2	C1	D1	E1	3923	20.9407	1.6645	709.71	11.33	89.34	44.8067	1800	0.3636	-0.0003849	1
25	A1	B2	C1	D1	E2	3917	13.1519	1.629	708.98	6.25	95.66	44.7517	1800	0.3636	-0.0003859	6
26	A1	B2	C1	D2	E1	3922	21.1554	1.7799	709.51	11.33	89.39	44.8067	1800	0.3636	-0.0003849	4
27	A1	B2	C1	D2	E2	3915	13.4572	1.778	708.79	6.25	95.4	44.7517	1800	0.3636	-0.0003859	9
28	A1	B2	C1	D3	E1	3921	20.9216	1.6664	709.44	11.33	89.44	44.8067	1800	0.3636	-0.0003849	4
29	A1	B2	C1	D3	E2	3916	13.2053	1.6589	708.75	6.25	95.71	44.7517	1800	0.3636	-0.0003859	9
30	A1	B2	C1	D4	E1	3923	20.9418	1.6732	709.78	11.33	88.73	44.8067	1800	0.3636	-0.0003849	3
31	A1	B2	C1	D4	E2	3918	13.1767	1.6421	709.04	6.25	94.61	44.7517	1800	0.3636	-0.0003859	8
32	A1	B2	C2	D1	E1	3923	20.8543	1.6242	709.71	11.33	89.52	89.7563	8400	0.0120	0.0000014	2
33	A1	B2	C2	D1	E2	3917	12.9969	1.5618	708.97	6.25	95.76	89.6092	8400	0.0120	0.0000013	7
34	A1	B2	C2	D2	E1	3923	21.0902	1.7371	709.71	11.33	89.37	89.7563	8400	0.0120	0.0000014	5
35	A1	B2	C2	D2	E2	3916	13.3312	1.7174	708.99	6.25	95.43	89.6092	8400	0.0120	0.0000013	10
36	A1	B2	C2	D3	E1	3922	20.8022	1.6015	709.63	11.33	89.5	89.7563	8400	0.0120	0.0000014	5
37	A1	B2	C2	D3	E2	3917	13.081	1.6024	708.93	6.25	95.61	89.6092	8400	0.0120	0.0000013	10
38	A1	B2	C2	D4	E1	3923	20.8523	1.6249	709.78	11.33	88.86	89.7563	8400	0.0120	0.0000014	4
39	A1	B2	C2	D4	E2	3917	13.0197	1.5693	708.97	6.25	94.89	89.6092	8400	0.0120	0.0000013	9
40	A1	B2	C3	D1	E1	3923	20.8639	1.6309	709.7	11.33	89.5	89.7563	15000	0.0120	0.0000020	2
41	A1	B2	C3	D1	E2	3917	13.0058	1.5649	708.97	6.25	95.74	89.6092	15000	0.0120	0.0000020	7
42	A1	B2	C3	D2	E1	3923	21.1054	1.7444	709.7	11.33	89.37	89.7563	15000	0.0120	0.0000020	5
43	A1	B2	C3	D2	E2	3916	13.3482	1.7277	708.99	6.25	95.43	89.6092	15000	0.0120	0.0000020	10
44	A1	B2	C3	D3	E1	3922	20.8224	1.6111	709.63	11.33	89.42	89.7563	15000	0.0120	0.0000020	5
45	A1	B2	C3	D3	E2	3917	13.1127	1.6153	708.93	6.25	95.56	89.6092	15000	0.0120	0.0000020	10
46	A1	B2	C3	D4	E1	3923	20.8621	1.6307	709.78	11.33	88.71	89.7563	15000	0.0120	0.0000020	4
47	A1	B2	C3	D4	E2	3917	13.0271	1.5748	708.97	6.25	94.92	89.6092	15000	0.0120	0.0000020	9
48	A1	B3	C1	D1	E1	3923	20.5786	1.4969	709.72	11.33	89.78	44.8067	3600	0.3636	-0.0004738	1
49	A1	B3	C1	D1	E2	3916	12.763	1.4434	708.77	6.25	95.97	44.7517	3600	0.3636	-0.0004750	6
50	A1	B3	C1	D2	E1	3924	20.7737	1.5948	709.77	11.33	89.65	44.8067	3600	0.3636	-0.0004738	4
51	A1	B3	C1	D2	E2	3916	13.0255	1.5691	708.76	6.25	95.76	44.7517	3600	0.3636	-0.0004750	9

52	A1	B3	C1	D3	E1	3923	20.5784	1.4993	709.76	11.33	89.8	44.8067	3600	0.3636	-0.0004738	4
53	A1	B3	C1	D3	E2	3917	12.8293	1.4752	708.84	6.25	95.97	44.7517	3600	0.3636	-0.0004750	9
54	A1	B3	C1	D4	E1	3923	20.6185	1.513	709.79	11.33	89.22	44.8067	3600	0.3636	-0.0004738	3
55	A1	B3	C1	D4	E2	3917	12.7987	1.4583	708.87	6.25	95.23	44.7517	3600	0.3636	-0.0004750	8
56	A1	B3	C2	D1	E1	3923	20.5041	1.4549	709.72	11.33	89.73	89.7563	10200	0.0120	0.0000016	2
57	A1	B3	C2	D1	E2	3915	12.6185	1.3769	708.7	6.25	96.07	89.6092	10200	0.0120	0.0000015	7
58	A1	B3	C2	D2	E1	3924	20.6892	1.548	709.79	11.32	89.6	89.7563	10200	0.0120	0.0000016	5
59	A1	B3	C2	D2	E2	3916	12.8854	1.5071	708.91	6.25	95.84	89.6092	10200	0.0120	0.0000015	10
60	A1	B3	C2	D3	E1	3923	20.4849	1.4469	709.79	11.32	89.75	89.7563	10200	0.0120	0.0000016	5
61	A1	B3	C2	D3	E2	3916	12.6888	1.4107	708.84	6.25	95.86	89.6092	10200	0.0120	0.0000015	10
62	A1	B3	C2	D4	E1	3923	20.5321	1.4694	709.79	11.32	89.4	89.7563	10200	0.0120	0.0000016	4
63	A1	B3	C2	D4	E2	3916	12.6368	1.3843	708.8	6.25	95.53	89.6092	10200	0.0120	0.0000015	9
64	A1	B3	C3	D1	E1	3923	20.5205	1.464	709.72	11.33	89.73	89.7563	16800	0.0120	0.0000022	2
65	A1	B3	C3	D1	E2	3915	12.6261	1.3824	708.7	6.25	96.09	89.6092	16800	0.0120	0.0000021	7
66	A1	B3	C3	D2	E1	3923	20.6945	1.5533	709.72	11.33	89.6	89.7563	16800	0.0120	0.0000022	5
67	A1	B3	C3	D2	E2	3916	12.8894	1.5113	708.91	6.25	95.86	89.6092	16800	0.0120	0.0000021	10
68	A1	B3	C3	D3	E1	3923	20.4843	1.4488	709.79	11.32	89.73	89.7563	16800	0.0120	0.0000022	5
69	A1	B3	C3	D3	E2	3916	12.6985	1.4186	708.84	6.25	95.84	89.6092	16800	0.0120	0.0000021	10
70	A1	B3	C3	D4	E1	3923	20.5422	1.4753	709.79	11.32	89.37	89.7563	16800	0.0120	0.0000022	4
71	A1	B3	C3	D4	E2	3916	12.6464	1.391	708.8	6.25	95.51	89.6092	16800	0.0120	0.0000021	9
72	A2	B1	C1	D1	E1	3924	20.9745	1.6846	711.44	11.1	89.4	89.7563	0	0.0120	0.0000006	4
73	A2	B1	C1	D1	E2	3918	13.1803	1.6443	710.71	6.03	95.64	89.6092	0	0.0120	0.0000006	9
74	A2	B1	C1	D2	E1	3924	21.2268	1.8159	711.22	11.1	89.3	89.7563	0	0.0120	0.0000006	7
75	A2	B1	C1	D2	E2	3917	13.5184	1.8008	710.5	6.04	95.38	89.6092	0	0.0120	0.0000006	12
76	A2	B1	C1	D3	E1	3924	20.9627	1.683	711.52	11.1	89.5	89.7563	0	0.0120	0.0000006	7
77	A2	B1	C1	D3	E2	3917	13.2101	1.6554	710.26	6.04	95.74	89.6092	0	0.0120	0.0000006	12
78	A2	B1	C1	D4	E1	3924	21.0037	1.7012	711.3	11.1	88.51	89.7563	0	0.0120	0.0000006	6
79	A2	B1	C1	D4	E2	3919	13.1921	1.6535	710.77	6.04	94.59	89.6092	0	0.0120	0.0000006	11

80	A2	B1	C2	D1	E1	3924	20.9432	1.6661	711.44	11.1	89.42	89.7563	6600	0.0120	0.0000012	5
81	A2	B1	C2	D1	E2	3918	13.0844	1.6008	710.71	6.03	95.76	89.6092	6600	0.0120	0.0000012	10
82	A2	B1	C2	D2	E1	3924	21.2049	1.7936	711.22	11.1	89.3	89.7563	6600	0.0120	0.0000012	8
83	A2	B1	C2	D2	E2	3917	13.4573	1.775	710.5	6.04	95.35	89.6092	6600	0.0120	0.0000012	13
84	A2	B1	C2	D3	E1	3923	20.9057	1.6512	711.37	11.1	89.45	89.7563	6600	0.0120	0.0000012	8
85	A2	B1	C2	D3	E2	3918	13.1845	1.6482	710.52	6.04	95.48	89.6092	6600	0.0120	0.0000012	13
86	A2	B1	C2	D4	E1	3924	20.9678	1.6782	711.29	11.1	88.66	89.7563	6600	0.0120	0.0000012	7
87	A2	B1	C2	D4	E2	3919	13.1184	1.6122	710.77	6.03	94.77	89.6092	6600	0.0120	0.0000012	12
88	A2	B1	C3	D1	E1	3924	20.9514	1.672	711.44	11.1	89.42	89.7563	13200	0.0120	0.0000018	5
89	A2	B1	C3	D1	E2	3918	13.0884	1.6041	710.71	6.03	95.76	89.6092	13200	0.0120	0.0000018	10
90	A2	B1	C3	D2	E1	3924	21.2204	1.8012	711.22	11.1	89.27	89.7563	13200	0.0120	0.0000018	8
91	A2	B1	C3	D2	E2	3917	13.4651	1.7816	710.5	6.04	95.35	89.6092	13200	0.0120	0.0000018	13
92	A2	B1	C3	D3	E1	3923	20.9096	1.6583	711.37	11.1	89.45	89.7563	13200	0.0120	0.0000018	8
93	A2	B1	C3	D3	E2	3918	13.199	1.6572	710.52	6.04	95.46	89.6092	13200	0.0120	0.0000018	13
94	A2	B1	C3	D4	E1	3924	20.9778	1.6829	711.29	11.1	88.63	89.7563	13200	0.0120	0.0000018	7
95	A2	B1	C3	D4	E2	3919	13.1246	1.6175	710.77	6.03	94.77	89.6092	13200	0.0120	0.0000018	12
96	A2	B2	C1	D1	E1	3923	20.6408	1.5252	711.16	11.1	89.75	89.7563	1800	0.0120	0.0000008	5
97	A2	B2	C1	D1	E2	3916	12.832	1.4742	710.21	6.04	95.84	89.6092	1800	0.0120	0.0000007	10
98	A2	B2	C1	D2	E1	3923	20.8907	1.6463	711.16	11.1	89.5	89.7563	1800	0.0120	0.0000008	8
99	A2	B2	C1	D2	E2	3916	13.151	1.6202	710.33	6.04	95.61	89.6092	1800	0.0120	0.0000007	13
100	A2	B2	C1	D3	E1	3922	20.6347	1.5188	711.09	11.11	89.65	89.7563	1800	0.0120	0.0000008	8
101	A2	B2	C1	D3	E2	3916	12.8743	1.4911	710.09	6.04	95.94	89.6092	1800	0.0120	0.0000007	13
102	A2	B2	C1	D4	E1	3923	20.6556	1.5332	711.23	11.1	89.04	89.7563	1800	0.0120	0.0000008	7
103	A2	B2	C1	D4	E2	3917	12.8456	1.4782	710.26	6.04	95	89.6092	1800	0.0120	0.0000007	12
104	A2	B2	C2	D1	E1	3923	20.6578	1.5343	711.16	11.1	89.75	89.7563	8400	0.0120	0.0000014	6
105	A2	B2	C2	D1	E2	3917	12.8292	1.4718	710.42	6.04	95.89	89.6092	8400	0.0120	0.0000013	11
106	A2	B2	C2	D2	E1	3923	20.8844	1.6495	711.16	11.1	89.57	89.7563	8400	0.0120	0.0000014	9
107	A2	B2	C2	D2	E2	3916	13.1594	1.6284	710.44	6.04	95.58	89.6092	8400	0.0120	0.0000013	14

108	A2	B2	C2	D3	E1	3922	20.6128	1.5131	711.08	11.11	89.7	89.7563	8400	0.0120	0.0000014	9
109	A2	B2	C2	D3	E2	3917	12.9163	1.5133	710.31	6.04	95.74	89.6092	8400	0.0120	0.0000013	14
110	A2	B2	C2	D4	E1	3923	20.6684	1.5422	711.23	11.1	89.06	89.7563	8400	0.0120	0.0000014	8
111	A2	B2	C2	D4	E2	3918	12.8569	1.4835	710.48	6.04	95	89.6092	8400	0.0120	0.0000013	13
112	A2	B2	C3	D1	E1	3923	20.6653	1.5377	711.16	11.1	89.75	89.7563	15000	0.0120	0.0000020	6
113	A2	B2	C3	D1	E2	3917	12.839	1.4774	710.42	6.04	95.89	89.6092	15000	0.0120	0.0000020	11
114	A2	B2	C3	D2	E1	3923	20.9011	1.6563	711.16	11.1	89.55	89.7563	15000	0.0120	0.0000020	9
115	A2	B2	C3	D2	E2	3916	13.1734	1.6382	710.43	6.04	95.56	89.6092	15000	0.0120	0.0000020	14
116	A2	B2	C3	D3	E1	3922	20.6274	1.5178	711.08	11.11	89.67	89.7563	15000	0.0120	0.0000020	9
117	A2	B2	C3	D3	E2	3917	12.9182	1.5172	710.31	6.04	95.66	89.6092	15000	0.0120	0.0000020	14
118	A2	B2	C3	D4	E1	3923	20.6789	1.5475	711.23	11.1	89.01	89.7563	15000	0.0120	0.0000020	8
119	A2	B2	C3	D4	E2	3918	12.8672	1.4893	710.48	6.04	95	89.6092	15000	0.0120	0.0000020	13
120	A2	B3	C1	D1	E1	3923	20.304	1.3628	711.17	11.1	89.98	89.7563	3600	0.0120	0.0000009	5
121	A2	B3	C1	D1	E2	3915	12.4593	1.2925	710.15	6.04	96.27	89.6092	3600	0.0120	0.0000009	10
122	A2	B3	C1	D2	E1	3924	20.5179	1.4582	711.25	11.1	89.78	89.7563	3600	0.0120	0.0000009	8
123	A2	B3	C1	D2	E2	3916	12.7234	1.4135	710.36	6.04	96.04	89.6092	3600	0.0120	0.0000009	13
124	A2	B3	C1	D3	E1	3923	20.324	1.3656	711.25	11.1	89.83	89.7563	3600	0.0120	0.0000009	8
125	A2	B3	C1	D3	E2	3916	12.4835	1.3013	710.29	6.04	96.22	89.6092	3600	0.0120	0.0000009	13
126	A2	B3	C1	D4	E1	3923	20.3419	1.3787	711.25	11.1	89.5	89.7563	3600	0.0120	0.0000009	7
127	A2	B3	C1	D4	E2	3917	12.488	1.3013	710.4	6.04	95.58	89.6092	3600	0.0120	0.0000009	12
128	A2	B3	C2	D1	E1	3923	20.2983	1.3661	711.17	11.1	90.01	89.7563	10200	0.0120	0.0000016	6
129	A2	B3	C2	D1	E2	3915	12.4488	1.2867	710.15	6.04	96.27	89.6092	10200	0.0120	0.0000015	11
130	A2	B3	C2	D2	E1	3924	20.5018	1.4565	711.24	11.1	89.86	89.7563	10200	0.0120	0.0000016	9
131	A2	B3	C2	D2	E2	3916	12.7207	1.4154	710.36	6.04	96.04	89.6092	10200	0.0120	0.0000015	14
132	A2	B3	C2	D3	E1	3923	20.295	1.3562	711.24	11.1	89.96	89.7563	10200	0.0120	0.0000016	9
133	A2	B3	C2	D3	E2	3916	12.5167	1.3212	710.29	6.04	96.04	89.6092	10200	0.0120	0.0000015	14
134	A2	B3	C2	D4	E1	3923	20.3295	1.3788	711.24	11.1	89.55	89.7563	10200	0.0120	0.0000016	8
135	A2	B3	C2	D4	E2	3916	12.4721	1.2984	710.25	6.04	95.63	89.6092	10200	0.0120	0.0000015	13

136	A2	B3	C3	D1	E1	3923	20.3112	1.3733	711.17	11.1	90.01	89.7563	16800	0.0120	0.0000022	6
137	A2	B3	C3	D1	E2	3915	12.4648	1.2954	710.15	6.04	96.22	89.6092	16800	0.0120	0.0000021	11
138	A2	B3	C3	D2	E1	3923	20.5099	1.4639	711.17	11.1	89.83	89.7563	16800	0.0120	0.0000022	9
139	A2	B3	C3	D2	E2	3916	12.7344	1.4229	710.36	6.04	96.02	89.6092	16800	0.0120	0.0000021	14
140	A2	B3	C3	D3	E1	3923	20.3085	1.3659	711.24	11.1	89.96	89.7563	16800	0.0120	0.0000022	9
141	A2	B3	C3	D3	E2	3916	12.5217	1.3288	710.29	6.04	96.07	89.6092	16800	0.0120	0.0000021	14
142	A2	B3	C3	D4	E1	3923	20.3439	1.3858	711.24	11.1	89.55	89.7563	16800	0.0120	0.0000022	8
143	A2	B3	C3	D4	E2	3916	12.4843	1.3053	710.25	6.04	95.61	89.6092	16800	0.0120	0.0000021	13
144	A3	B1	C1	D1	E1	3924	21.0217	1.7082	711.44	11.1	89.3	89.7563	0	0.0120	0.0000006	2
145	A3	B1	C1	D1	E2	3918	13.2263	1.6662	710.71	6.03	95.61	89.6092	0	0.0120	0.0000006	7
146	A3	B1	C1	D2	E1	3924	21.2755	1.8362	711.22	11.1	89.22	89.7563	0	0.0120	0.0000006	5
147	A3	B1	C1	D2	E2	3917	13.5623	1.825	710.48	6.04	98.33	89.6092	0	0.0120	0.0000006	10
148	A3	B1	C1	D3	E1	3924	21.0216	1.7102	711.51	11.1	89.37	89.7563	0	0.0120	0.0000006	5
149	A3	B1	C1	D3	E2	3917	13.2492	1.6801	710.25	6.04	95.71	89.6092	0	0.0120	0.0000006	10
150	A3	B1	C1	D4	E1	3924	21.0394	1.7172	711.3	11.1	88.48	89.7563	0	0.0120	0.0000006	4
151	A3	B1	C1	D4	E2	3919	13.2315	1.6713	710.77	6.03	94.64	89.6092	0	0.0120	0.0000006	9
152	A3	B1	C2	D1	E1	3924	20.9678	1.681	711.44	11.1	89.42	89.7563	6600	0.0120	0.0000012	3
153	A3	B1	C2	D1	E2	3918	13.1064	1.6148	710.71	6.03	95.76	89.6092	6600	0.0120	0.0000012	8
154	A3	B1	C2	D2	E1	3924	21.2341	1.8057	711.22	11.1	89.25	89.7563	6600	0.0120	0.0000012	6
155	A3	B1	C2	D2	E2	3917	13.4765	1.7881	710.5	6.04	95.35	89.6092	6600	0.0120	0.0000012	11
156	A3	B1	C2	D3	E1	3923	20.9306	1.6655	711.37	11.1	89.45	89.7563	6600	0.0120	0.0000012	6
157	A3	B1	C2	D3	E2	3918	13.2008	1.6581	710.52	6.04	95.48	89.6092	6600	0.0120	0.0000012	11
158	A3	B1	C2	D4	E1	3924	20.9923	1.6889	711.29	11.1	88.63	89.7563	6600	0.0120	0.0000012	5
159	A3	B1	C2	D4	E2	3919	13.1383	1.6249	710.77	6.03	94.77	89.6092	6600	0.0120	0.0000012	10
160	A3	B1	C3	D1	E1	3924	20.9716	1.6859	711.44	11.1	89.42	89.7563	13200	0.0120	0.0000018	3
161	A3	B1	C3	D1	E2	3918	13.1112	1.6161	710.71	6.03	95.76	89.6092	13200	0.0120	0.0000018	8
162	A3	B1	C3	D2	E1	3924	21.2521	1.8154	711.22	11.1	89.22	89.7563	13200	0.0120	0.0000018	6
163	A3	B1	C3	D2	E2	3917	13.4897	1.7945	710.5	6.04	95.35	89.6092	13200	0.0120	0.0000018	11

164	A3	B1	C3	D3	E1	3923	20.9384	1.6733	711.37	11.1	89.42	89.7563	13200	0.0120	0.0000018	6
165	A3	B1	C3	D3	E2	3918	13.2255	1.6688	710.59	6.04	95.46	89.6092	13200	0.0120	0.0000018	11
166	A3	B1	C3	D4	E1	3924	20.9978	1.6936	711.29	11.1	88.61	89.7563	13200	0.0120	0.0000018	5
167	A3	B1	C3	D4	E2	3918	13.1443	1.629	710.7	6.03	94.77	89.6092	13200	0.0120	0.0000018	10
168	A3	B2	C1	D1	E1	3923	20.6843	1.5452	711.16	11.1	89.73	89.7563	1800	0.0120	0.0000008	3
169	A3	B2	C1	D1	E2	3917	12.8623	1.4877	710.42	6.04	95.84	89.6092	1800	0.0120	0.0000007	8
170	A3	B2	C1	D2	E1	3923	20.9282	1.6695	711.16	11.1	89.5	89.7563	1800	0.0120	0.0000008	6
171	A3	B2	C1	D2	E2	3916	13.1826	1.6387	710.44	6.04	95.61	89.6092	1800	0.0120	0.0000007	11
172	A3	B2	C1	D3	E1	3922	20.6666	1.5361	711.08	11.11	89.65	89.7563	1800	0.0120	0.0000008	6
173	A3	B2	C1	D3	E2	3917	12.8982	1.5047	710.31	6.04	95.89	89.6092	1800	0.0120	0.0000007	11
174	A3	B2	C1	D4	E1	3923	20.6949	1.5533	711.23	11.1	89.04	89.7563	1800	0.0120	0.0000008	5
175	A3	B2	C1	D4	E2	3918	12.8872	1.4982	710.48	6.04	94.97	89.6092	1800	0.0120	0.0000007	10
176	A3	B2	C2	D1	E1	3923	20.6868	1.547	711.15	11.1	89.73	89.7563	8400	0.0120	0.0000014	4
177	A3	B2	C2	D1	E2	3917	12.8516	1.4846	710.42	6.04	95.89	89.6092	8400	0.0120	0.0000013	9
178	A3	B2	C2	D2	E1	3923	20.9089	1.6613	711.15	11.1	89.57	89.7563	8400	0.0120	0.0000014	7
179	A3	B2	C2	D2	E2	3916	13.1796	1.6421	710.43	6.04	95.56	89.6092	8400	0.0120	0.0000013	12
180	A3	B2	C2	D3	E1	3922	20.6368	1.5255	711.08	11.1	89.67	89.7563	8400	0.0120	0.0000014	7
181	A3	B2	C2	D3	E2	3917	12.9429	1.528	710.31	6.04	95.69	89.6092	8400	0.0120	0.0000013	12
182	A3	B2	C2	D4	E1	3923	20.6906	1.555	711.23	11.1	89.04	89.7563	8400	0.0120	0.0000014	6
183	A3	B2	C2	D4	E2	3918	12.8812	1.4972	710.48	6.04	95	89.6092	8400	0.0120	0.0000013	11
184	A3	B2	C3	D1	E1	3923	20.6978	1.5535	711.15	11.1	89.65	89.7563	15000	0.0120	0.0000020	4
185	A3	B2	C3	D1	E2	3917	12.8627	1.4899	710.42	6.04	95.89	89.6092	15000	0.0120	0.0000020	9
186	A3	B2	C3	D2	E1	3923	20.9315	1.6713	711.15	11.1	89.47	89.7563	15000	0.0120	0.0000020	7
187	A3	B2	C3	D2	E2	3916	13.2002	1.6521	710.43	6.04	95.53	89.6092	15000	0.0120	0.0000020	12
188	A3	B2	C3	D3	E1	3922	20.6577	1.5317	711.08	11.11	89.6	89.7563	15000	0.0120	0.0000020	7
189	A3	B2	C3	D3	E2	3917	12.9401	1.532	710.31	6.04	95.63	89.6092	15000	0.0120	0.0000020	12
190	A3	B2	C3	D4	E1	3923	20.7035	1.5602	711.23	11.1	88.96	89.7563	15000	0.0120	0.0000020	6
191	A3	B2	C3	D4	E2	3918	12.8934	1.5041	710.48	6.04	95	89.6092	15000	0.0120	0.0000020	11

192	A3	B3	C1	D1	E1	3923	20.3354	1.3831	711.17	11.1	89.93	89.7563	3600	0.0120	0.0000009	3
193	A3	B3	C1	D1	E2	3915	12.4915	1.3059	710.15	6.04	96.25	89.6092	3600	0.0120	0.0000009	8
194	A3	B3	C1	D2	E1	3924	20.5464	1.4793	711.24	11.1	89.76	89.7563	3600	0.0120	0.0000009	6
195	A3	B3	C1	D2	E2	3916	12.7536	1.429	710.36	6.04	96.02	89.6092	3600	0.0120	0.0000009	11
196	A3	B3	C1	D3	E1	3923	20.3601	1.3868	711.24	11.1	89.88	89.7563	3600	0.0120	0.0000009	6
197	A3	B3	C1	D3	E2	3916	12.5221	1.319	710.29	6.04	96.2	89.6092	3600	0.0120	0.0000009	11
198	A3	B3	C1	D4	E1	3923	20.3709	1.4	711.24	11.1	89.5	89.7563	3600	0.0120	0.0000009	5
199	A3	B3	C1	D4	E2	3916	12.5196	1.3179	710.25	6.04	95.56	89.6092	3600	0.0120	0.0000009	10
200	A3	B3	C2	D1	E1	3923	20.3294	1.379	711.17	11.1	89.98	89.7563	10200	0.0120	0.0000016	4
201	A3	B3	C2	D1	E2	3915	12.4749	1.3015	710.15	6.04	96.22	89.6092	10200	0.0120	0.0000015	9
202	A3	B3	C2	D2	E1	3924	20.5283	1.4702	711.24	11.1	89.83	89.7563	10200	0.0120	0.0000016	7
203	A3	B3	C2	D2	E2	3916	12.7475	1.4293	710.35	6.04	96.02	89.6092	10200	0.0120	0.0000015	12
204	A3	B3	C2	D3	E1	3923	20.3255	1.374	711.24	11.1	89.91	89.7563	10200	0.0120	0.0000016	7
205	A3	B3	C2	D3	E2	3916	12.5412	1.3362	710.29	6.04	96.04	89.6092	10200	0.0120	0.0000015	12
206	A3	B3	C2	D4	E1	3923	20.3581	1.3917	711.24	11.1	89.57	89.7563	10200	0.0120	0.0000016	6
207	A3	B3	C2	D4	E2	3916	12.496	1.3122	710.24	6.04	95.63	89.6092	10200	0.0120	0.0000015	11
208	A3	B3	C3	D1	E1	3923	20.3416	1.3871	711.17	11.1	89.98	89.7563	16800	0.0120	0.0000022	4
209	A3	B3	C3	D1	E2	3915	12.4889	1.3051	710.15	6.04	96.22	89.6092	16800	0.0120	0.0000021	9
210	A3	B3	C3	D2	E1	3923	20.5341	1.4788	711.17	11.1	89.8	89.7563	16800	0.0120	0.0000022	7
211	A3	B3	C3	D2	E2	3916	12.752	1.4336	710.35	6.04	96.02	89.6092	16800	0.0120	0.0000021	12
212	A3	B3	C3	D3	E1	3923	20.3363	1.3804	711.24	11.1	89.88	89.7563	16800	0.0120	0.0000022	7
213	A3	B3	C3	D3	E2	3916	12.5438	1.3388	710.29	6.04	96.04	89.6092	16800	0.0120	0.0000021	12
214	A3	B3	C3	D4	E1	3923	20.3767	1.4017	711.24	11.1	89.55	89.7563	16800	0.0120	0.0000022	6
215	A3	B3	C3	D4	E2	3916	12.508	1.3168	710.24	6.04	95.61	89.6092	16800	0.0120	0.0000021	11
216	A4	B1	C1	D1	E1	3924	20.9336	1.666	711.92	11.02	89.42	89.7563	0	0.0120	0.0000006	5
217	A4	B1	C1	D1	E2	3918	13.1361	1.6241	711.19	5.96	95.71	89.6092	0	0.0120	0.0000006	10
218	A4	B1	C1	D2	E1	3924	21.1947	1.7976	711.71	11.03	89.3	89.7563	0	0.0120	0.0000006	8
219	A4	B1	C1	D2	E2	3917	13.4771	1.7822	710.98	5.96	95.36	89.6092	0	0.0120	0.0000006	13

220	A4	B1	C1	D3	E1	3923	20.9268	1.6665	711.85	11.03	89.52	89.7563	0	0.0120	0.0000006	8
221	A4	B1	C1	D3	E2	3917	13.1618	1.6335	710.95	5.97	95.57	89.6092	0	0.0120	0.0000006	13
222	A4	B1	C1	D4	E1	3924	20.9648	1.6827	711.78	11.03	88.63	89.7563	0	0.0120	0.0000006	7
223	A4	B1	C1	D4	E2	3919	13.1479	1.6347	711.25	5.96	94.64	89.6092	0	0.0120	0.0000006	12
224	A4	B1	C2	D1	E1	3924	20.9118	1.6534	711.92	11.02	89.45	89.7563	6600	0.0120	0.0000012	6
225	A4	B1	C2	D1	E2	3918	13.0609	1.5863	711.19	5.96	95.76	89.6092	6600	0.0120	0.0000012	11
226	A4	B1	C2	D2	E1	3924	21.1787	1.7823	711.7	11.03	89.35	89.7563	6600	0.0120	0.0000012	9
227	A4	B1	C2	D2	E2	3917	13.4398	1.762	710.98	5.96	95.33	89.6092	6600	0.0120	0.0000012	14
228	A4	B1	C2	D3	E1	3923	20.8854	1.6427	711.85	11.03	89.47	89.7563	6600	0.0120	0.0000012	9
229	A4	B1	C2	D3	E2	3918	13.1627	1.6354	711	5.96	95.53	89.6092	6600	0.0120	0.0000012	14
230	A4	B1	C2	D4	E1	3924	20.9406	1.6675	711.78	11.03	88.69	89.7563	6600	0.0120	0.0000012	8
231	A4	B1	C2	D4	E2	3919	13.093	1.5998	711.25	5.96	94.77	89.6092	6600	0.0120	0.0000012	13
232	A4	B1	C3	D1	E1	3924	20.9269	1.6594	711.92	11.02	89.42	89.7563	13200	0.0120	0.0000018	6
233	A4	B1	C3	D1	E2	3918	13.0735	1.5936	711.19	5.96	95.76	89.6092	13200	0.0120	0.0000018	11
234	A4	B1	C3	D2	E1	3924	21.1949	1.7891	711.7	11.03	89.3	89.7563	13200	0.0120	0.0000018	9
235	A4	B1	C3	D2	E2	3917	13.4514	1.7715	710.98	5.96	95.33	89.6092	13200	0.0120	0.0000018	14
236	A4	B1	C3	D3	E1	3923	20.8909	1.6462	711.85	11.03	89.47	89.7563	13200	0.0120	0.0000018	9
237	A4	B1	C3	D3	E2	3918	13.1834	1.6446	711	5.96	95.48	89.6092	13200	0.0120	0.0000018	14
238	A4	B1	C3	D4	E1	3924	20.9552	1.6723	711.78	11.03	88.66	89.7563	13200	0.0120	0.0000018	8
239	A4	B1	C3	D4	E2	3919	13.1074	1.6069	711.25	5.96	94.77	89.6092	13200	0.0120	0.0000018	13
240	A4	B2	C1	D1	E1	3923	20.6208	1.5166	711.64	11.02	89.78	89.7563	1800	0.0120	0.0000008	6
241	A4	B2	C1	D1	E2	3916	12.8068	1.4634	710.69	5.97	95.81	89.6092	1800	0.0120	0.0000007	11
242	A4	B2	C1	D2	E1	3923	20.8784	1.6412	711.96	11.02	89.5	89.7563	1800	0.0120	0.0000008	9
243	A4	B2	C1	D2	E2	3916	13.1283	1.6118	710.81	5.97	95.58	89.6092	1800	0.0120	0.0000007	14
244	A4	B2	C1	D3	E1	3923	20.6129	1.507	711.61	11.03	89.63	89.7563	1800	0.0120	0.0000008	9
245	A4	B2	C1	D3	E2	3916	12.8474	1.4836	710.57	5.97	95.91	89.6092	1800	0.0120	0.0000007	14
246	A4	B2	C1	D4	E1	3923	20.6365	1.5269	711.71	11.02	89.04	89.7563	1800	0.0120	0.0000008	8
247	A4	B2	C1	D4	E2	3917	12.8203	1.4675	710.75	5.97	95	89.6092	1800	0.0120	0.0000007	13

248	A4	B2	C2	D1	E1	3923	20.6327	1.5221	711.64	11.03	89.78	89.7563	8400	0.0120	0.0000014	7
249	A4	B2	C2	D1	E2	3917	12.8154	1.4662	710.9	5.97	95.86	89.6092	8400	0.0120	0.0000013	12
250	A4	B2	C2	D2	E1	3923	20.8476	1.6365	711.64	11.03	89.6	89.7563	8400	0.0120	0.0000014	10
251	A4	B2	C2	D2	E2	3917	13.1401	1.6179	711.03	5.96	95.56	89.6092	8400	0.0120	0.0000013	15
252	A4	B2	C2	D3	E1	3922	20.5948	1.5018	711.57	11.03	89.7	89.7563	8400	0.0120	0.0000014	10
253	A4	B2	C2	D3	E2	3917	12.8806	1.4973	710.79	5.97	95.74	89.6092	8400	0.0120	0.0000013	15
254	A4	B2	C2	D4	E1	3923	20.6458	1.5294	711.71	11.03	89.09	89.7563	8400	0.0120	0.0000014	9
255	A4	B2	C2	D4	E2	3918	12.8372	1.4729	710.96	5.96	95.02	89.6092	8400	0.0120	0.0000013	14
256	A4	B2	C3	D1	E1	3923	20.6494	1.528	711.64	11.03	89.8	89.7563	15000	0.0120	0.0000020	7
257	A4	B2	C3	D1	E2	3917	12.8222	1.4675	710.9	5.97	95.89	89.6092	15000	0.0120	0.0000020	12
258	A4	B2	C3	D2	E1	3923	20.8806	1.6444	711.64	11.03	89.57	89.7563	15000	0.0120	0.0000020	10
259	A4	B2	C3	D2	E2	3916	13.1553	1.625	710.91	5.97	95.53	89.6092	15000	0.0120	0.0000020	15
260	A4	B2	C3	D3	E1	3922	20.6084	1.509	711.56	11.03	89.62	89.7563	15000	0.0120	0.0000020	10
261	A4	B2	C3	D3	E2	3917	12.9017	1.5103	710.79	5.97	95.76	89.6092	15000	0.0120	0.0000020	15
262	A4	B2	C3	D4	E1	3923	20.6536	1.5339	711.71	11.0.	89.09	89.7563	15000	0.0120	0.0000020	9
263	A4	B2	C3	D4	E2	3918	12.8477	1.479	710.96	5.96	95.02	89.6092	15000	0.0120	0.0000020	14
264	A4	B3	C1	D1	E1	3924	20.2807	1.349	711.75	11.03	90.01	89.7563	3600	0.0120	0.0000009	6
265	A4	B3	C1	D1	E2	3915	12.4372	1.282	710.63	5.97	96.25	89.6092	3600	0.0120	0.0000009	11
266	A4	B3	C1	D2	E1	3922	20.4851	1.4409	711.39	11.03	89.93	89.7563	3600	0.0120	0.0000009	9
267	A4	B3	C1	D2	E2	3916	12.6866	1.4001	710.84	5.97	96.09	89.6092	3600	0.0120	0.0000009	14
268	A4	B3	C1	D3	E1	3923	20.2997	1.3492	711.54	11.03	89.91	89.7563	3600	0.0120	0.0000009	9
269	A4	B3	C1	D3	E2	3916	12.4683	1.2956	710.68	5.97	96.17	89.6092	3600	0.0120	0.0000009	14
270	A4	B3	C1	D4	E1	3923	20.3205	1.3653	711.54	11.03	89.55	89.7563	3600	0.0120	0.0000009	8
271	A4	B3	C1	D4	E2	3917	12.4564	1.2885	710.88	5.97	95.61	89.6092	3600	0.0120	0.0000009	13
272	A4	B3	C2	D1	E1	3924	20.2812	1.3564	711.75	11.03	90.04	89.7563	10200	0.0120	0.0000016	7
273	A4	B3	C2	D1	E2	3915	12.4451	1.2821	710.63	5.97	96.22	89.6092	10200	0.0120	0.0000015	12
274	A4	B3	C2	D2	E1	3925	20.485	1.4461	711.83	11.03	89.86	89.7563	10200	0.0120	0.0000016	10
275	A4	B3	C2	D2	E2	3916	12.7022	1.4025	710.84	5.97	96.02	89.6092	10200	0.0120	0.0000015	15

276	A4	B3	C2	D3	E1	3924	20.2862	1.3508	711.83	11.03	89.93	89.7563	10200	0.0120	0.0000016	10
277	A4	B3	C2	D3	E2	3916	12.4879	1.3047	710.77	5.97	96.04	89.6092	10200	0.0120	0.0000015	15
278	A4	B3	C2	D4	E1	3924	20.3106	1.3672	711.83	11.03	89.55	89.7563	10200	0.0120	0.0000016	9
279	A4	B3	C2	D4	E2	3917	12.4532	1.2882	710.88	5.97	95.66	89.6092	10200	0.0120	0.0000015	14
280	A4	B3	C3	D1	E1	3923	20.2956	1.3627	711.65	11.02	90.03	89.7563	16800	0.0120	0.0000022	7
281	A4	B3	C3	D1	E2	3915	12.4538	1.2862	710.63	5.97	96.25	89.6092	16800	0.0120	0.0000021	12
282	A4	B3	C3	D2	E1	3923	20.4985	1.4544	711.65	11.02	89.83	89.7563	16800	0.0120	0.0000022	10
283	A4	B3	C3	D2	E2	3916	12.7173	1.4139	710.83	5.97	96.02	89.6092	16800	0.0120	0.0000021	15
284	A4	B3	C3	D3	E1	3923	20.3083	1.3619	711.72	11.02	89.88	89.7563	16800	0.0120	0.0000022	10
285	A4	B3	C3	D3	E2	3916	12.5005	1.3167	710.77	5.97	96.07	89.6092	16800	0.0120	0.0000021	15
286	A4	B3	C3	D4	E1	3923	20.3192	1.3717	711.72	11.02	89.57	89.7563	16800	0.0120	0.0000022	9
287	A4	B3	C3	D4	E2	3916	12.4704	1.2979	710.72	5.97	95.66	89.6092	16800	0.0120	0.0000021	14

Appendix B: Computing Overall Performance Score.

Table B.1 shows the overall performance score obtained for each combination of alternatives. The row that is highlighted in green (No. 37) is the selected alternatives to be implemented in the manufacturing system due to its highest overall performance score. The abbreviations used in the title of Table B.1 are explained as follows.

AFT = Average flow time
Q = Line scrap rate
OLE = Overall line efficiency
ECE = Equipment cost efficiency
LOD = Level of difficulty of implementation

Table B.1: Calculation of Overall Performance Score.

No.	Variables					AFT (hrs)	Q (%)	OLE (%)	ECE (RM/pc)	LOD	Normalized performance score					Criteria weight					**Overall score**
											AFT	Q	OLE	ECE	LOD	AFT	Q	OLE	ECE	LOD	
0	A1	B1	C1	D1	E1	43.2637	11.35	44.6828	-0.00029782	1	0.2875	0.5251	0.4978	0.0019	1.0000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.3906**
1	A1	B1	C1	D1	E2	42.3905	6.25	44.6782	-0.00029791	5	0.2934	0.9536	0.4978	0.0019	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.3896**
2	A1	B1	C2	D1	E1	21.1066	11.33	89.7563	1.21222E-06	1	0.5893	0.5260	1.0000	0.4622	1.0000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7515**
3	A1	B1	C2	D1	E2	13.2683	6.25	89.6092	1.17666E-06	6	0.9374	0.9536	0.9984	0.4762	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7626**
4	A1	B1	C3	D1	E1	21.1155	11.33	89.7563	1.84719E-06	1	0.5890	0.5260	1.0000	0.3033	1.0000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7043**
5	A1	B1	C3	D1	E2	13.2607	6.25	89.6092	1.793E-06	6	0.9379	0.9536	0.9984	0.3125	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7140**
6	A1	B2	C1	D1	E1	20.9407	11.33	44.8067	-0.00038494	1	0.5939	0.5260	0.4992	0.0015	1.0000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.4016**
7	A1	B2	C1	D1	E2	13.1519	6.25	44.7517	-0.00038594	6	0.9457	0.9536	0.4986	0.0015	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.4092**
8	A1	B2	C2	D1	E1	20.8543	11.33	89.7563	1.38539E-06	2	0.5964	0.5260	1.0000	0.4044	0.5000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6917**
9	A1	B2	C2	D1	E2	12.9969	6.25	89.6092	1.34475E-06	7	0.9569	0.9536	0.9984	0.4167	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7436**
10	A1	B2	C3	D1	E1	20.8639	11.33	89.7563	2.02036E-06	2	0.5961	0.5260	1.0000	0.2773	0.5000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6539**
11	A1	B2	C3	D1	E2	13.0058	6.25	89.6092	1.96109E-06	7	0.9563	0.9536	0.9984	0.2857	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7046**
12	A1	B3	C1	D1	E1	20.5786	11.33	44.8067	-0.00047378	1	0.6044	0.5260	0.4992	0.0012	1.0000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.4019**
13	A1	B3	C1	D1	E2	12.763	6.25	44.7517	-0.00047501	6	0.9745	0.9536	0.4986	0.0012	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.4101**
14	A1	B3	C2	D1	E1	20.5041	11.33	89.7563	1.55857E-06	2	0.6066	0.5260	1.0000	0.3595	0.5000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6787**
15	A1	B3	C2	D1	E2	12.6185	6.25	89.6092	1.51284E-06	7	0.9856	0.9536	0.9984	0.3704	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7308**
16	A1	B3	C3	D1	E1	20.5205	11.33	89.7563	2.19354E-06	2	0.6061	0.5260	1.0000	0.2554	0.5000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6477**
17	A1	B3	C3	D1	E2	12.6261	6.25	89.6092	2.12919E-06	7	0.9850	0.9536	0.9984	0.2632	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6989**
18	A2	B1	C1	D1	E1	20.9745	11.1	89.7563	5.77247E-07	4	0.5930	0.5369	1.0000	0.9707	0.2500	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8402**
19	A2	B1	C1	D1	E2	13.1803	6.03	89.6092	5.60312E-07	9	0.9436	0.9884	0.9984	1.0000	0.1111	0.0340	0.1575	0.4254	0.2973	0.0858	**0.9193**
20	A2	B1	C2	D1	E1	20.9432	11.1	89.7563	1.21222E-06	5	0.5939	0.5369	1.0000	0.4622	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6847**
21	A2	B1	C2	D1	E2	13.0844	6.03	89.6092	1.17666E-06	10	0.9505	0.9884	0.9984	0.4762	0.1000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7628**
22	A2	B1	C3	D1	E1	20.9514	11.1	89.7563	1.84719E-06	5	0.5936	0.5369	1.0000	0.3033	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6375**

23	A2	B1	C3	D1	E2	13.0884	6.03	89.6092	1.793E-06	10	0.9502	0.9884	0.9984	0.3125	0.1000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7142**
24	A2	B2	C1	D1	E1	20.6408	11.1	89.7563	7.50421E-07	5	0.6026	0.5369	1.0000	0.7467	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7696**
25	A2	B2	C1	D1	E2	12.832	6.04	89.6092	7.28406E-07	10	0.9692	0.9868	0.9984	0.7692	0.1000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8503**
26	A2	B2	C2	D1	E1	20.6578	11.1	89.7563	1.38539E-06	6	0.6021	0.5369	1.0000	0.4044	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6650**
27	A2	B2	C2	D1	E2	12.8292	6.04	89.6092	1.34475E-06	11	0.9694	0.9868	0.9984	0.4167	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7448**
28	A2	B2	C3	D1	E1	20.6653	11.1	89.7563	2.02036E-06	6	0.6018	0.5369	1.0000	0.2773	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6272**
29	A2	B2	C3	D1	E2	12.839	6.04	89.6092	1.96109E-06	11	0.9687	0.9868	0.9984	0.2857	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7058**
30	A2	B3	C1	D1	E1	20.304	11.1	89.7563	9.23595E-07	5	0.6125	0.5369	1.0000	0.6067	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7283**
31	A2	B3	C1	D1	E2	12.4593	6.04	89.6092	8.965E-07	10	0.9982	0.9868	0.9984	0.6250	0.1000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8084**
32	A2	B3	C2	D1	E1	20.2983	11.1	89.7563	1.55857E-06	6	0.6127	0.5369	1.0000	0.3595	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6520**
33	A2	B3	C2	D1	E2	12.4488	6.04	89.6092	1.51284E-06	11	0.9991	0.9868	0.9984	0.3704	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7320**
34	A2	B3	C3	D1	E1	20.3112	11.1	89.7563	2.19354E-06	6	0.6123	0.5369	1.0000	0.2554	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6210**
35	A2	B3	C3	D1	E2	12.4648	6.04	89.6092	2.12919E-06	11	0.9978	0.9868	0.9984	0.2632	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7001**
36	A3	B1	C1	D1	E1	21.0217	11.1	89.7563	5.77247E-07	2	0.5916	0.5369	1.0000	0.9707	0.5000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8616**
37	A3	B1	C1	D1	E2	13.2263	6.03	89.6092	5.60312E-07	7	0.9403	0.9884	0.9984	1.0000	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.9219**
38	A3	B1	C2	D1	E1	20.9678	11.1	89.7563	1.21222E-06	3	0.5932	0.5369	1.0000	0.4622	0.3333	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6962**
39	A3	B1	C2	D1	E2	13.1064	6.03	89.6092	1.17666E-06	8	0.9489	0.9884	0.9984	0.4762	0.1250	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7649**
40	A3	B1	C3	D1	E1	20.9716	11.1	89.7563	1.84719E-06	3	0.5930	0.5369	1.0000	0.3033	0.3333	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6489**
41	A3	B1	C3	D1	E2	13.1112	6.03	89.6092	1.793E-06	8	0.9486	0.9884	0.9984	0.3125	0.1250	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7163**
42	A3	B2	C1	D1	E1	20.6843	11.1	89.7563	7.50421E-07	3	0.6013	0.5369	1.0000	0.7467	0.3333	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7810**
43	A3	B2	C1	D1	E2	12.8623	6.04	89.6092	7.28406E-07	8	0.9669	0.9868	0.9984	0.7692	0.1250	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8524**
44	A3	B2	C2	D1	E1	20.6868	11.1	89.7563	1.38539E-06	4	0.6012	0.5369	1.0000	0.4044	0.2500	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6721**
45	A3	B2	C2	D1	E2	12.8516	6.04	89.6092	1.34475E-06	9	0.9678	0.9868	0.9984	0.4167	0.1111	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7464**
46	A3	B2	C3	D1	E1	20.6978	11.1	89.7563	2.02036E-06	4	0.6009	0.5369	1.0000	0.2773	0.2500	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6343**
47	A3	B2	C3	D1	E2	12.8627	6.04	89.6092	1.96109E-06	9	0.9669	0.9868	0.9984	0.2857	0.1111	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7075**
48	A3	B3	C1	D1	E1	20.3354	11.1	89.7563	9.23595E-07	3	0.6116	0.5369	1.0000	0.6067	0.3333	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7397**
49	A3	B3	C1	D1	E2	12.4915	6.04	89.6092	8.965E-07	8	0.9957	0.9868	0.9984	0.6250	0.1250	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8105**

50	A3	B3	C2	D1	E1	20.3294	11.1	89.7563	1.55857E-06	4	0.6118	0.5369	1.0000	0.3595	0.2500	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6591**
51	A3	B3	C2	D1	E2	12.4749	6.04	89.6092	1.51284E-06	9	0.9970	0.9868	0.9984	0.3704	0.1111	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7337**
52	A3	B3	C3	D1	E1	20.3416	11.1	89.7563	2.19354E-06	4	0.6114	0.5369	1.0000	0.2554	0.2500	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6281**
53	A3	B3	C3	D1	E2	12.4889	6.04	89.6092	2.12919E-06	9	0.9959	0.9868	0.9984	0.2632	0.1111	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7017**
54	A4	B1	C1	D1	E1	20.9336	11.02	89.7563	5.77247E-07	5	0.5941	0.5408	1.0000	0.9707	0.2000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8365**
55	A4	B1	C1	D1	E2	13.1361	5.96	89.6092	5.60312E-07	10	0.9468	1.0000	0.9984	1.0000	0.1000	0.0340	0.1575	0.4254	0.2973	0.0858	**0.9203**
56	A4	B1	C2	D1	E1	20.9118	11.02	89.7563	1.21222E-06	6	0.5947	0.5408	1.0000	0.4622	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6825**
57	A4	B1	C2	D1	E2	13.0609	5.96	89.6092	1.17666E-06	11	0.9522	1.0000	0.9984	0.4762	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7640**
58	A4	B1	C3	D1	E1	20.9269	11.02	89.7563	1.84719E-06	6	0.5943	0.5408	1.0000	0.3033	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6353**
59	A4	B1	C3	D1	E2	13.0735	5.96	89.6092	1.793E-06	11	0.9513	1.0000	0.9984	0.3125	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7153**
60	A4	B2	C1	D1	E1	20.6208	11.02	89.7563	7.50421E-07	6	0.6031	0.5408	1.0000	0.7467	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7674**
61	A4	B2	C1	D1	E2	12.8068	5.97	89.6092	7.28406E-07	11	0.9711	0.9983	0.9984	0.7692	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8515**
62	A4	B2	C2	D1	E1	20.6327	11.03	89.7563	1.38539E-06	7	0.6028	0.5403	1.0000	0.4044	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6635**
63	A4	B2	C2	D1	E2	12.8154	5.97	89.6092	1.34475E-06	12	0.9705	0.9983	0.9984	0.4167	0.0833	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7460**
64	A4	B2	C3	D1	E1	20.6494	11.03	89.7563	2.02036E-06	7	0.6023	0.5403	1.0000	0.2773	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6257**
65	A4	B2	C3	D1	E2	12.8222	5.97	89.6092	1.96109E-06	12	0.9700	0.9983	0.9984	0.2857	0.0833	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7070**
66	A4	B3	C1	D1	E1	20.2807	11.03	89.7563	9.23595E-07	6	0.6133	0.5403	1.0000	0.6067	0.1667	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7260**
67	A4	B3	C1	D1	E2	12.4372	5.97	89.6092	8.965E-07	11	1.0000	0.9983	0.9984	0.6250	0.0909	0.0340	0.1575	0.4254	0.2973	0.0858	**0.8096**
68	A4	B3	C2	D1	E1	20.2812	11.03	89.7563	1.55857E-06	7	0.6132	0.5403	1.0000	0.3595	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6505**
69	A4	B3	C2	D1	E2	12.4451	5.97	89.6092	1.51284E-06	12	0.9994	0.9983	0.9984	0.3704	0.0833	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7332**
70	A4	B3	C3	D1	E1	20.2956	11.02	89.7563	2.19354E-06	7	0.6128	0.5408	1.0000	0.2554	0.1429	0.0340	0.1575	0.4254	0.2973	0.0858	**0.6196**
71	A4	B3	C3	D1	E2	12.4538	5.97	89.6092	2.12919E-06	12	0.9987	0.9983	0.9984	0.2632	0.0833	0.0340	0.1575	0.4254	0.2973	0.0858	**0.7013**