DESIGN AND SCHEDULING OF GARMENT ASSEMBLY LINE USING SIMULATION-BASED OPTIMIZATION

A Case Study at NYTIL, Jinja, Uganda

BY

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DECLARATION

DECLARATION BY STUDENT

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DEDICATION

I dedicate this thesis to my beloved family, all my relatives and friends. Thank you so much for being close to me and your support towards this fantabulous thesis work.

ABSTRACT

Ready-made garment manufacturing industries are characterized by high variability of the processing times, short product life cycle and huge number of employed resources which contribute to low productivity. Thereby, optimal garment assembly line design is very crucial for achieving high productivity, increasing line efficiency and improving decision making at both levels of production planning. Assembly line design problem has gained attention of many researchers in the past years whereby a number of researches have been done on garment assembly line balancing problem with simulation technique. However, very few have used simulation-based optimization technique to address the design problem. The main objective of study was to design an optimal trouser assembly line with the parameters' settings that maximizes the production throughput. Specifically, the study aimed to analyze current-state of the existing trouser assembly line and develop its simulation model, to generate design alternatives, and to determine the global optimal design alternative. The current-state of existing garment production facility was analyzed using industrial engineering tools which include brainstorming, fishbone diagram, ABC analysis, process mapping, and time study. Then, the discrete event simulation model of the trouser assembly line was developed using Arena simulation software and was validated using one-sample T-test. The trouser assembly line simulation model was accepted at T-value of -0.20 and P-value of 0.842. Sixteen design alternatives were generated by performing experiments on the design points derived from the design of experiment and the metamodel was developed using liner regression method. The metamodel was validated using significant test at alpha value 0.05 and the best setting was adopted as the initial solution for the optimization process. Metaheuristic optimization was performed on the simulation metamodel with the help of OptQuest for Arena to search for the global best design alternative. The effects of bundle size, job release policy, task assignment pattern, number of machines and number of helpers on the production throughput were analyzed. Only two factors; machine numbers and helper numbers and their interaction have significant effect on the throughput. The comparison with the existing trouser assembly line design was made based on the production throughput. The result shows 28.63% increase in the throughput for the trouser assembly line at metamodel design and the overall increase of 53.63% for the optimal design. Consequently, the production efficiency increased to 79.75% and 95.25% at metamodel and optimal design stages, respectively. From the results of the study, it was concluded that simulation-based optimization via design of experiment is suitable for giving an insight of garment assembly line and achieving its optimal design. In the further study, simulation models of garment assembly line can be developed by considering other design parameters which include machines failure and line supervisor functions. In addition, further study can be done with different approaches such as using machine learning and more complex experimental design for developing the metamodels.

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LIST OF ACRONYMS AND ABBREVIATIONS

ANOVA	Analysis of Variance
CAD	Computer-Aided Design
DF	Degree of Freedom
FIFO	First in First Out
GB	Gigabyte
GHz	Gigahertz
IDEF	Integrated Definition
IDEF0	Integrated Definition Zero
LIFO	Last in First Out
MSE	Mean Square Error
PTS	Predetermined Time Standard
RAM	Random Access Memory
RMG	Ready-made Garment
SMV	Standard Minute Value
SPT	Shortest Processing Time
SRNL	Southern Range Nyanza Limited (NYTIL)
UPDF	Uganda People Defense Force
WIP	Work in Progress

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND OF THE STUDY

Globally, textiles represent the fourth largest manufacturing industry, with the apparel sector forming the most valuable component of this industry (Fan & Hunter, 2009). Garment production is the most critical sector in this industry since it is a value addition which is expected to increase revenue and profits for company. In addition, huge number of labour force and resources in the sewing line are the major aspect for complexity of garment assembly line (Fan & Hunter, 2009).

Assembly line system was introduced in 1913 by Henry Ford with the idea of mass production. He designed an assembly line for automobile manufacturing industry which was then adopted in large scale apparel production after the introduction of sewing machines in early age of the second industrial revolution (Aydin, 2013). Since then the apparel production system became more and more sophisticated. Brahim & Alain (2006) coined assembly line as the flowline production whereby a product moves from one workstation to another. In assembly line, tasks are allocated to workstations considering some restrictions including precedence constraints, cycle time, number of workstations, and incompatibility relations between tasks (Alghazi, 2017). Therefore, assembly line design becomes very crucial for the proper functioning of any assembly line production system and more so, the optimal design.

Assembly line design problem often has a complex structure due to multiple components (e.g. tooling, operators, material handling facilities, etc.). For instance, in a single product model assembly line design, a number of design alternatives may exist. The problem can easily become highly complicated if the designer has to consider all the possible combinations of these alternatives. This problem is classified as non-deterministic polynomial (NP) hard problem or complex combinatorial problem (Brahim & Alain, 2006). Therefore, optimal design would provide the best solution for this kind of problem.

In the previous studies, garment assembly lines design have been implemented using different techniques such like manual/practical technique (Karabay, 2014), ranked positional weight techniques, probabilistic line balancing technique (Eryuruk et al., 2008), largest candidate rule techniques, simulation techniques (Guner & Unal, 2008), genetic algorithm (Chen et al., 2014), and combination of simulation and heuristics techniques (Eryuruk, 2012). A number of literature have considered assembly line design as assembly line balancing problem (Dang & Pham, 2016). Kitaw et al (2010) developed an approach for assembly line balancing for garment production using simulation models with Simul8 simulation software. Kursun & Kalaoglu (2009) also conducted simulation study of production line balancing in apparel manufacturing using Enterprise dynamics simulation software. A recent study, comprehensively evaluated the garment assembly line using Anylogic simulation software and has proved that there is need to do optimization (Xu et al., 2017). Simulation technique is only descriptive and does not help in decision making. In order to overcome this limitation in assembly line design, a technique called simulation-based optimization has been proposed.

Simulation-based optimization is the state-of-the-art design technique that combine both simulation and optimization technique. Whereby simulation is majorly used to analyze the behaviour of the system and generate design scenarios while the optimization is used to select the global best design alternative. Simulation-based optimization is not a new approach, it has been applied to solve design problem by a number of researchers in the previous years. For instance, Dang & Pham (2016) designed assembly line for footwear production using simulation-based optimization on Arena software. The authors were able to improve the labour productivity. Juan (2016) conducted study on production planning in manufacturing industry using simulation-based optimization. Another study by Yegul et al (2017) improved the configuration of production line using simulation-based optimization. While Alrabghi & Tiwari (2016) proposed the use of simulation-based optimization for developing industrial maintenance strategies.

In general, simulation-based optimization has not only been in manufacturing sector but also other sectors such as transport and healthcare. For instance, Ibrahim et al. (2017) conducted a study on minimization of patient waiting time in emergency department of public hospital using simulation-based optimization approach. Moreover, Shakibayifar et al. (2018) applied simulation-based optimization technique to rescheduling train traffic in uncertain conditions during disruptions. Based on the previous studies, the combination of discrete event simulation and metaheuristics optimization technique was adopted to solve the garment assembly line design and scheduling problem in the current study.

Assembly line design problem is how to group and assign a given set of tasks to a number of workstations so as to reduce idle time, labor cost and maximize throughput without violating the precedence constraints. While the scheduling problem is how to determine the best sequence of jobs to minimize some performance such as work in progress (Dang & Pham, 2016). In order to tackle the real practical assembly line problem, metaheuristics search algorithm integrated into the simulation environment would provide global optimal solution (Brahim & Alain, 2006). Therefore, the present study focused on assembly line design for garment production using simulation-based optimization via experimental design.

1.2 STATEMENT OF THE PROBLEM

Southern Range Nyanza Limited (Nytil) is a vertically integrated textile industry with garment production as the most critical department because it is the value addition and entails huge number of resources and operations. The garment department receives orders in large quantity from customers such as Healthcare, Uganda police, UPDF, South Sudan Army, etc. Therefore, it is subjected to constant pressure of meeting customer's order due date. However, currently the company is operating at low productivity with production efficiency of 61.25% which is quite hard for the company to achieve its goal even if the operators were to undergo forced overtime.

The manual technique which is currently used in the department is ineffective and inferior for designing this system because manually observing the real garment manufacturing is very difficult, time consuming and inaccurate. These problems result into promising assembly line balancing problems (Chen et al., 2014) such as bottleneck, low utilization, low efficiency and low productivity that hinder the department from achieving its goal/objectives.

A number of researchers have studied assembly line balancing problems in garment production using simulation techniques (Xu et al., 2017). Such approaches have not been used for designing garment assembly line in Uganda and other Sub-Saharan Africa and therefore, the present study is the first of its kind to the best of our knowledge.

This study goes beyond the existing studies on garment assembly line design by using combination of simulation metamodeling technique and the metaheuristics (scatter search, tabu search, and neural network) search algorithms to obtain a global optimal assembly line design.

1.3 JUSTIFICATION OF THE STUDY

Simulation approaches are capable of capturing the uncertainty of the assembly line and accurately reproducing its behaviour. Therefore, various assembly line design problems such as bottleneck, idle time, low resource utilization will easily be identified and eliminated. Hence, the overall productivity improvement of garment production will be achieved. In addition, the assembly line efficiency will be increased by improving the resource utilization. More so, the production capability will be well anticipated and therefore, successfully plan for resources and the need for capacity building or extensions. By combining both simulation and optimization approaches for assembly line design, decision making at both level of production planning i.e. strategic, tactical and operational production planning will be improved. The design of experiment (metamodeling) helps to analyze the behavior of the simulation models so that the effects of varying assembly line design parameters can be explicitly known. Therefore, the conclusion can be drawn that will not only be utilized by case study garment industry but also other garment industries.

1.4 SIGNIFICANCE OF THE STUDY

The study contributes to area of simulation, optimization, design of simulation experiment and metamodeling. The study also contributes to practical application of industrial engineering tools such as ABC analysis, fishbone diagram, process mapping and time study. The study contributes to the digital disruption in apparel manufacturing brought about by the fourth industrial revolution (industry 4.0) which is well known as Apparel 4.0 or Fashion 4.0.

1.5 OBJECTIVES OF THE STUDY

1.5.1 Main objective

The main objective of the study was to design an optimal trouser assembly line with the parameters' setting that maximizes the throughput.

1.5.2 Specific objectives

In order to achieve the main objective of the study, the following specific objectives were accomplished.

i. To analyze the current state of the existing trouser assembly line and develop its simulation model using Arena simulation software
ii. To generate trouser assembly line design scenarios using design of experiment
iii. To determine an optimal trouser assembly line design using OptQuest for Arena.

1.6 SCOPE OF THE STUDY

Garment/apparel production involves pattern design and making, fabric cutting, sewing, finishing, and packaging. However, this study only focused on sewing section since it is the most complex section that uses large number of operations and resources. The study also focused on single product model assembly line. The study considered only single objective optimization problem i.e. the throughput which is the number of finished products delivered per day. The assembly line design problem was focused on the line balancing and resource planning.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

2.1.1 Historical background

The introduction of mass production revolutionized the production system from the traditional craft production system in the early age of the second industrial revolution. The mass production reduced average cycle time for from 8.6 hours to 2.3 minutes. While the introduction of moving assembly line further reduced the average cycle time from 2.3 to 1.9 minutes. However, the complexity of the mass production and assembly line system had introduced bureaucracy on such a vast scale that it brought its own problems, and with no obvious solutions (Degan, 2011).

The mass production paradigm shifts in textile and apparel production took place after the introduction of sewing machines. The technology of sewing underwent tremendous development during the twentieth century as the sewing machines became more affordable to the working class (Rajkishore & Padhye, 2015).

Furthermore, the idea of ready-made garments (RMGs) paved their ways as women (with sewing skill) in large numbers joined the paid workforce. The ready-made garment concept fully utilized mass production system. Although these concepts existed at that time, they were not widely available until the beginning of the twentieth century. Since then, the RMG sector both for men's and women's clothing has seen tremendous growth, and today it has almost replaced the customized production of clothing items (Rajkishore & Padhye, 2015). The result of this tremendous growth has been due to mass production facilitated by assembly line production system. Now days the ready-made garment products are expanding tremendously, the few examples include men's suits, coats, pants, trousers, shirts, dresses, ladies' suits, blouses, blazers, cardigans, pullovers, jeans, shorts, polo shirts, uniforms, jacket, etc.

2.1.2 Definitions and notations

2.1.2.1 Terminology used in assembly system

These are some definitions to describe the assembly system problem and have been used by a number of researchers (Brahim & Alain, 2006; Curry & Feldman, 2011; Ortiz, 2006; Thomopoulos, 2014).

Assembly; an assembly is basically fitting together various parts in order to create a finished product.

Assembly line; Brahim & Alain (2006) defined assembly line as a flow-line production system composed of succession of workstations. The products pass from one workstation to another.

Task; this is a portion of the total work content in an assembly process. Tasks are considered indivisible and they cannot be splitted into smaller work elements without unnecessary additional work.

Precedence constraints; these are the orders in which tasks must be performed (technological restrictions). Precedence indicates the order and priority relationship between operations in the same process (Torenli, 2009).

Processing time; this is the time taken for the task to be completed at workstation or time taken for machine or operator to complete a given job or task.

Cycle time; this is the time between the exits of two consecutive products from the line. It represents the maximal amount of work processed by each station. Cycle time at a workstation is a function of the total operation time and number of operators at that station (Boivie & Hoglund, 2008).

Station time; this is the total process time at the workstation. The work content of a station is referred to as station load.

Throughput; this denotes the average number of products delivered per unit time.

Station idle time; this is the positive difference between the cycle time and the station time. The sum of idle times of all stations is called the delay time.

Line efficiency; this is the measure of capacity utilization of the line. The unused capacity is reflected by the balance delay time (Grzechca, 2016).

Smoothness index; this measures the standard deviation of the distribution of work among the stations (Grzechca, 2016).

Capacity time; the capacity time is defined as the total time available to assemble each product. The capacity time is greater or equal to the sum of process time of all tasks' work content.

Makespan; this is the maximum completion time required to process all operations for a given set of products.

Work in progress/buffer size; this is the number of unfinished products in the assembly line.

Labor productivity; labor productivity is the amount of output that an operator produces in a unit time.

Bottleneck; the bottleneck station is the work center whose capacity is less than the demand placed on it and less than the capacities of all other resources. A bottleneck station determines the capacity of the whole production system. This implies that each operator on the line is a bottleneck for the line and it is of crucial importance to eliminate the balance losses for maximizing line capacity.

2.1.2.2 Important distributions

A number of probability distribution functions are used so frequently and are known by special names (Curry & Feldman, 2011). However, the most important ones have been described as follows (Altiok & Melamed, 2007; Badiru & Omitaomu, 2011; Kelton, Sadowski, & Sturrock, 2007).

Uniform distribution; the uniform distribution is denoted by UNIF (a, b), and is the simplest continuous distribution, where *a* is the minimum value and *b* is the maximum value.

Triangular distribution; the triangular distribution is denoted by TRIA (a, c, b) where *a* is the minimum value, *c* is the most likely value or mode, and *b* is the maximum value.

Exponential distribution; the exponential distribution is denoted by EXPO (ƛ), where ƛ is called the rate parameter.

Normal distribution; the normal distribution is denoted by NORM (μ, σ^2), where μ is the mean (scale parameter) and σ^2 is the variance (shape parameter).

Lognormal distribution; the lognormal distribution is denoted by LOGN (μ, σ), where μ is a scale parameter and σ is a shape parameter.

Gamma distribution; the gamma distribution is denoted by GAMM (α, β), where $\alpha > 0$ is the shape parameter and $\beta > 0$ is the scale parameter.

Erlang distribution; Erlang distribution denoted by ERL (k, ƛ), where, k is the shape parameter and ƛ is the rate parameter.

Beta distribution; the beta distribution is denoted by BETA (α, β), where $\alpha > 0$ and $\beta > 0$ are two shape parameters.

Weibull distribution; the Weibull distribution is denoted by WEIB (α, β), where $\alpha > 0$ is the shape parameter and $\beta > 0$ is the scale parameter.

2.1.3 Garment manufacturing challenges and opportunities

Garment manufacturing also known as apparel manufacturing is labour intensive which has led to the shifting of many apparel manufacturing facilities from developed countries to developing countries because of cheap labor force. Although there is cheap labor in developing countries, garment industries are facing the greatest challenges such as short production life-cycle, high volatility, low predictability, high level of impulse and quick market response (Rajkishore & Padhye, 2015). In order to survive, the garment industries in developing countries are reducing the cost of production by focusing on sourcing cheaper raw materials and minimizing delivery cost rather than labor productivity because of the availability of cheap labor.

Global and local competition is still a major challenge amongst apparel manufactures. Therefore, one can only survive on the market if all unnecessary costs are reduced, the range of production is expanded, and consumers are considered individually. However, the local apparel manufacturers are gradually reducing the production and focusing on performing only the entrepreneurial functions involved in apparel manufacturing such as buying raw materials, designing clothes and accessories, preparing samples and arranging for the production, distribution and marketing of the finished product (Rajkishore & Padhye, 2015).

Rapid technological changes and customer expectations have also imposed a great challenge to apparel manufactures especially in developing countries. Therefore, there is high demand from the manufacturers to improve the quality of fashion products constantly and thus survive in the market (Karthik et al., 2017). In addition, the manufacturers are required to adjust their production system in order to meet market demand in that they have to set a flexible production model that is capable of quick and easy adjustment to modern requirements (Babu, 2012).

Another technological challenge facing apparel manufactures in developing countries is the differences that exist in the process of making clothes of different fashions, which in one way or the other requires a different organization of technological processes (Colovic, 2012). Therefore, this calls for the most economical ways of work and time required to perform work operations, change management, capacity and planning. In addition, it is necessary to implement new solutions in manufacturing, information systems, management techniques, and design, etc. (Colovic, 2011).

The promising challenge facing the apparel industries in developing countries is the indispensability of scientific approach and engineering applications for apparel manufacturing. This implies that the apparel manufactures will find it very difficult to meet the cost of production unless and until manufacturing is done with scientific approach such as implementation of simulation model for line balancing and assembly line design, lean production, etc. (Babu, 2012).

Generally, the apparel industries in the whole world especially in developing countries will not give any pleasing results to the management unless it strives for necessary improvements that will lead to productivity growth, more rational usage of all-natural resources and cost reduction. In most cases these companies do not see the necessity for changes in management, capacity and planning which are negatively impacting many apparel industries today (Karthik et al., 2017).

2.2 Garment manufacturing system

An apparel or garment production system is an integration of materials handling, production processes, personnel, and equipment that direct workflow and generate finished products (Babu, 2012). There are three types of apparel production system that are widely adopted in garment industry, these include; (i) group or modular production system (Sudarshan & Rao, 2014) (ii) progressive bundle production system and (iii) unit production system. In modular production system, operations are done in a contained and manageable work cells that includes a number of specialized resources such as an empowered work team, equipment and work to be executed. This production system has achieved the success of flexibility, however, very high initial capital and investment in training are still the major limitation to its adaptation to most apparel industries (Karthik et al., 2017).

The progressive bundle production system normally referred to as conventional production system is still the most commonly installed production system till to date amongst other garment production system because of its cost effectiveness on high tech-machines. The operation in this system involves moving bundles of cut pieces (5, 10, 20, 30 or 40 pieces) manually to feed the line. Whereby, the operator inside the line drags the bundles by him/herself from the table and transfer the bundle to the next operator after completing his/her task. The major problem with progressive bundle system is the tendency of accumulating very large inventory which impose an extra cost of controlling and handling inventory. In order to overcome the limitation of material handling in progressive bundle system, a new system called unit production system was developed. In this system, the overhead transporter is used to move the garment from one workstation to another workstation for assembly which improves material handling. The success of unit production system is that it improves the production lead times, productivity and space utilization, however, this production system is extremely expensive. In general, the tradeoff of these production system depends on the production volume, product categories, and the cost effectiveness of high-tech machines (Karthik et al., 2017).

2.3 Current state analysis

2.3.1 Time study

The definition of time study was first coined in the early 20th century in industrial engineering, referring to a quantitative data collection method where an external observer captured detailed data on the duration and movements required to accomplish a specific task, coupled with an analysis focused on improving efficiency (Lopetegui et al., 2014). Time study has been considered to be accomplished before any design of assembly line, which involves timing and observing motion of the work associated with building the product. Collecting times data are absolute requirements to improving the assembly operations in the facility (Ortiz, 2006). The advantages of time study method over other work measurement techniques include (Babu, 2012); (i) helps in developing a rational plan; (ii) helps in improving productivity; (iii) helps in balancing assembly lines; (iv) provides the time data for process design; (v) helps in determining operator skill levels. Nevertheless, conducting time study is time consuming and very tiresome especially when the system has many elements to be measured.

However, time study has been the most commonly used amongst studies as it determines accurate time standards, and it is economical for repetitive type of work. Vast number of researches have been done using time study method. For instance, Senthilraja et al. (2018) applied time study technique for improving the operators' productivity in rubber industry. While Khatun (2014) studied the effect of time and motion study on productivity in garment sector. The author postulated that the target productivity can be achieved by time study. The time study technique was adopted in this study because of its industrial applicability, and has fewer limitations than other work measurements methods such as activity sampling, predetermined time standards (PTS), and structured estimating (Babu, 2012).

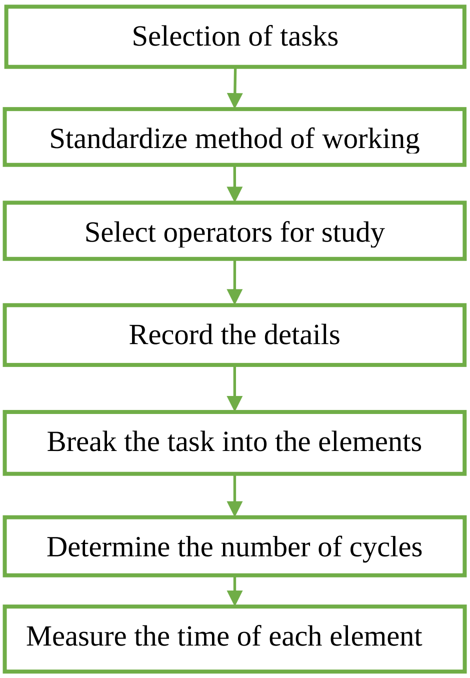


Figure 2.1. Steps used in time study

The basic time study equipment consists of stop watch, study sheet and time study board (Ortiz, 2006). Steps for conducting time study have been presented as shown in Figure 2.1 (Babu, 2012; Russell & Taylor, 2011).

The number of timing cycle for specific activity basically depends on the end use of the time study data. For instance, if the time study data is to be used in probability distribution analysis then a greater number of timing cycle or measurements give better result. For each work element/task, processing time can be recorded 10 times (Kitaw et al., 2010), or 15 times (Sudarshan & Rao, 2014) , 20 times (Kursun & Kalaoglu, 2009) or more, the higher the number of measurement, the better the results. There are two common methods of measuring time with a stopwatch such as fly back and continuous method.

2.3.1.1 Fly back method

Here the stopwatch is started at the beginning of the first element. The readings are then recorded at the end of the element and the stopwatch hand is snapped back to zero. The time of each element is obtained directly. The only advantage of fly back method is that it involves less calculation. However, it has got many limitations such as difficulty in training analyst with this method, requires a lot of skills and difficult to take accounts once the element is missed (Starovoytova, 2017).

2.3.1.2 Continuous method

In this method, the stopwatch is started at the beginning of the first element and then allowed to run continuously throughout the study. The advantages of this method include; missing of any element does not affect the overall time. It is very simple to train the analyst with this method, and it is the most accurate of all other methods. However, this method has got one limitation of taking too much time in making subtraction every time to achieve the individual measurement. The stopwatch readings are recorded on the study sheet at the end of each element. The time for each element is then calculated by successive subtraction. The final reading of the stopwatch gives the total time, known as the observed time (Puvanasvaran et al., 2013; Starovoytova, 2017). Since, this method produces the most accurate result and very simple to apply, it was used in the current study.

When conducting time study in garment sewing line, the component task should be recorded as the smallest measurable task as illustrated in Table 2.1 (Babu, 2012). In addition, all the ethical issues must be observed and considered when conducting time study (Shaw, 2003). For instance, time study engineer should not stand facing the operator being studied. The standing position should be right behind or at the side of the operator being timed.

Table 2.1. Component task classification and when to record

Job	***Component tasks and when to record***		
Sewing machine work	Taking the work piece and placing under	Sewing by machine	Placing on holding table
When to record	Start of needle movement	When needle stops	When hand is taken from the workpiece
Ironing	Taking and placing the workpiece	Ironing/pressing	Placing on holding table
When to record	When iron is picked up	When iron is returned to position	When hand is taken from the workpiece

In most apparel manufacturing, Standard Minute Value (SMV) has been used to estimate the production time for each task. Although the characteristic of SMV is deterministic in nature, some authors have used it to solve the line balancing problem of sewing departments. This implies that the production time has been assumed to be constant for the similar tasks which is not practically realistic (Akter & Hossain, 2017). However, in a real world garment production system, all operations are completed at different times because of their stochastic structure, and the stochasticity of operations makes it almost impossible to follow a fixed time pattern. Therefore, the use of SMV for apparel assembly line design cannot reflect the real production environment because a lot of factors such as performance of machinery (machine failure and set-up), operators variability (fatigue and resting), working environment and quality level (rework) of the product may cause variations on the task time (Kitaw et al., 2010).

In order to fully represent the apparel production system in the simulation model, the variability of tasks or observed time from time study is very essential. A number of researchers have considered observed times to represent the operation times for tasks in apparel assembly line balancing problem (Bahadır, 2011; Guner & Unal, 2008; Kitaw et al., 2010; Kursun & Kalaoglu, 2009; Wickramasekara & Perera, 2016). However, in the present study, the variability of operation times was considered in developing simulation model. This is because the study aimed to fully represent the real garment assembly line.

Therefore, allowances and operators performance ratings (Yamane et al., 2017) were not considered for this case.

2.3.2 Process mapping

Process mapping is an exercise of identifying all the steps and decisions in a process in a diagrammatic form, with a view to continually improve that process. In literature, two commonly used types of process mapping are; process flowchart (outline process map) and deployment charts. The former is useful for capturing the initial detail of the process. For instance, Kursun & Kalaoglu (2009), Kitaw et al. (2010), Bahadır (2011) and Yamane et al. (2017) used process flowchart as conceptual model in their simulation study with the aim of analyzing and understanding the current state of the studied system. While the latter not only provide a basic overview but also shows who does what along with the interactions between people and departments. This one has been used as a standalone method amongst studies for process improvement. For instance, Uddin (2015) improved production process using value stream mapping as a standalone method. Since, the present study adopted process mapping as tool for conceptual modeling but not as standalone method, the process flowchart method was used.

2.3.3 Observations

Observation is another method that has been used for analyzing the current state of the system amongst studies. However, it has been used alongside interview to capture more data on the current state of the system (Gebrehiwet & Odhuno, 2017). Observation is a very important tool when conducting process mapping and time study. For instance, in garment assembly line, two major areas that can be observed on the sewing machines are; Machine working (positioning, sewing, and dispose) and Machine not working (waiting for repair, waiting for suppliers, personal need for workers and idle (Babu, 2012). The present study combined observation with process mapping for conceptual modeling of the garment assembly line.

2.3.4 Brainstorming

Brainstorming is one of the most common techniques used to generate ideas from the individual or group of people. In most cases, it has been applied in both educational, industrial, commercial, and political field (Al-khatib, 2012). In the previous studies, brainstorming has been combined with other method such as fishbone diagram (cause-and-effect analysis tool) for analyzing the current state of the production system. For instance, Barton (2004) used brainstorming and fishbone diagram to analyze and identify factors that affect the throughput of the production process. Many studies have shown the applicability of brainstorming as the problem solving techniques. Al-khatib (2012) confirmed the effectiveness of using brainstorming as a problem-solving tool. The ability of brainstorming method to generate as many ideas as possible without judgement, has motivated this study to use it for generating ideas on factors that influence the throughput of garment assembly line.

2.3.5 ABC analysis

Traditionally, ABC analysis has been used to classify various inventory items into three categories A, B, and C based on the criterion of dollar volume. In the current globalized hyper-responsive business environment, a single criterion is no longer adequate to guide the management of inventories and therefore, multiple criteria have to be considered (Sibanda & Pretorius, 2011). Other criteria that can be considered for ABC analysis include; lead time, item criticality, durability, scarcity, reparability, stockability, commonality, substitutability, the number of suppliers, mode and cost of transportation, the likelihood of obsolescence or spoilage and batch quantities imposed by suppliers. Consequently, ABC analysis has been adopted amongst researches to make decision on selection of products, machines, production lines, etc. For instance, Pinho & Leal (2007) used ABC analysis to prioritize a production system for their study based on productivity per day criterion. Therefore, in the current situation, ABC analysis tool was also adopted to prioritize the product model and assembly line to be used in this study.

2.3.6 Identification and classification of variables

There are basically four types of variables that exist in any manufacturing systems and are always identified during current state analysis. These are quantities in simulation that need to be identified before conducting a simulation study. The first two classes are the independent variables and dependent variables. Independent variables are known as the decision variables or desired input parameters or factors while dependent variables are knowns as output parameters or responses or performance measures. The second two classes which are considered in simulation experiments are the nuisance variables and intermediate variables. Nuisance variables are known to affect the behavior of the system, but cannot be directly controlled. These are rarely presented in simulation, where all factors are generally under the user’s control. While the fourth variable is intermediate variable that cannot be controlled independently. They are affected by the settings of the independent variables and therefore are not considered dependent variables (Kleijnen, 2008).

It is very important to identify all the four types of variables before conducting a simulation experiment. Dependent variables are always determined by the objective of the study. The examples of dependent variables that were considered by the previous studies includes; cycle time, throughput, operating cost and worker’s utilization. Independent variables are not simple to identify and therefore, they are determined with specified methods (Barton, 2013). The independence variables are further categorized as quantitative and qualitative factors. For instance, in garment production system, the quantitative factors include; number of operators, number of machines, number of workstations, buffer sizes, interarrival time of parts, bundle sizes and many other. While the qualitative factors includes; queue disciples, job release policy, operators skills, task assignment pattern and priority rules (First in First Out (FIFO), Last in First Out (LIFO), and Shortest Processing Time (SPT)) (Kleijnen, 2008; Sanchez et al., 2014). In literature, two methods such as the process diagram (Integrated Definition Zero (IDEF0)), and cause-and-effect diagram (fishbone diagram) have been used for identifying the independent variables.

2.3.6.1 Process diagram (IDEF0)

Process diagram (IDEF0) is the variant of IDEF (integrated definition) diagram which is designed to model the decisions, actions and activities of an organization or other system. It is used for communicating and analyzing the functional perspective of a system (Bosilj-vuksic, 2000). IDEF0 has been applied for identification of independent variable in many manufacturing companies (Presley & Liles, 1998). One of its main strength is simplicity, however, it does not clearly give out the relationship between factors and the effect.

2.3.6.2 Fishbone diagram

Cause-and-effect diagram (fishbone diagram) is another method that has been widely used amongst studies (Barton, 2004). It is an analysis tool that provides a systematic way of looking at effects (performance measures) and the causes (factors or independent variables) that create or contribute to those effects (Hekmatpanah, 2011). One of the underlying benefits of this method is that, it has nearly unlimited application in research, manufacturing, marketing, office operations and so forth. One of its strongest assets is the participation and contribution of everyone involved in the brainstorming process (Hekmatpanah, 2011). The ability of cause-and-effect diagram to clearly identify and categorize factors that affect the performance of the system is one of the major reasons for its adoption in this study.

2.4 Assembly line design techniques

2.4.1 Practical or manual techniques

Practical technique is the conventional assembly line design techniques which is still being used for apparel assembly line balancing in most developing countries. In this design technique, the required amount of workstations shows the percentage workload of the workstation at the same time and also the design can be made according to the expected line efficiency (Karabay, 2014). This design technique is quite simple and cheaper to implement. However, it suffers from inefficiency for complex apparel assembly line design problem. Moreover, it is very risky and difficult to stop the production for reason of altering a design. Nevertheless, the current study deals with complex assembly line design problem, the manual design technique was not adopted.

2.4.2 Heuristics techniques

The second design technique is the heuristics technique which includes the use of one or combination of the following; ranked positional weight technique, probabilistic line balancing technique, Hoffman, and largest candidate rule technique. These heuristic techniques are based on logic and understanding rather than mathematical proofs and formulas (Kayar, 2014). Eryuruk et al. (2008) compared efficiency of using ranked positional weight technique and probabilistic line balancing technique in apparel manufacturing. The authors found that ranked positional weight technique was easier to apply and has higher line efficiencies than the counterpart. However, it assumes deterministic task/operation times which does not apply to real garment production process.

The probabilistic line balancing technique considers the variability in the task times and that means more reliable assembly line balancing results can be obtained. Largest Candidate Rule technique has been applied to redesign the garment assembly line. This technique is the easiest method to understand and can be implemented to mass production industries such as textile, electronics, footwear, automobile and so on. Nevertheless, it often results to bottlenecks due to complexity of assembly system (Ayat et al., 2017). Generally, these heuristic techniques are used to develop solutions which are not optimal but good solutions which approach the true optimum. The main aim of the current study is to achieve an optimal solution. Therefore, heuristic technique is quite ineffective for the design of the garment assembly line under the study.

2.4.3 Analytical techniques

Analytical techniques involve application of collections of mathematical equations whenever solved can be used to predict the expected behavior of the system. For instance, the process models that address the behavior and variability of the process at various steps. Analytical models have been developed using various media; for instance, only paper and pencil are required for a simple system, while more complicated systems require computer program, (e.g. Microsoft Excel, and Macros). Analytical techniques are frequently used to examine queueing systems, inventory control and linear programs (Hewitt, 2002). The examples of analytical techniques used to solve assembly line design problem include; linear programming, constraints programming, etc.

A number of studies have used analytical techniques to solve the assembly line balancing problem in apparel industries (Mcnamara, 2016). Nevertheless, analytical technique is inefficient and ineffective for designing of a complex system since, it is very difficult and tedious to come up with mathematical formulae for such a complex system. Moreover, it cannot explore all the design pattern. Based on those limitations, analytical technique could not be adopted for the present study.

2.4.4 Simulation techniques

A simulation technique uses a simulation program to produce sample histories and therefore a set of statistics computed from these histories are used to form the performance measures of interest. In literature, different simulation models have been used to analyze the problem in the system designs (Altiok & Melamed, 2007). Simulation models are basically classified as continuous simulation, discrete event simulation, combined discrete/continuous (hybrid), and Morte Carlo simulation (Brailsford et al., 2018). The choice of simulation models is based on functional characteristics of the system and the objectives of the study. Discrete event simulation has been used in apparel manufacturing and other manual or semi-automatic production systems such as footwear, electronics and automotive assembly lines.

The basic idea of discrete event simulation paradigm is that the simulation model possesses a state at any point in time. Guner & Unal (2008) investigated and demonstrated the application of computer simulation for the design of a manufacturing process for t-shirt production in a virtual-reality environment. Shumon et al. (2010) also developed a simulation model that represented a real production process of polo-shirt garment products which was aimed to identify bottlenecks and enhance production system. The recent study by Simea et al., (2019) demonstrated the feasibility of using simulation technique for assembly line balancing in Apparel industry.

In order to obtain better results, many studies have combined simulation and heuristic techniques for apparel assembly line design. For instance, Eryuruk (2012) designed apparel assembly line using the combination of simulation and heuristic techniques with the aim to maximize the line efficiency by using optimum machine and worker amount for a constant cycle time. The author considered two heuristics algorithms such as probabilistic line balancing technique and largest candidate rule algorithm.

In the previous studies, the commonly used discrete event simulation software are; Arena, Promodel, Anylogic, Enterprise Dynamics, Simul8 and Quest (Tewoldeberhan et al., 2002). The selection of software to use for simulation study is very important which is majorly based on the criteria such as the ease of use, animation capability, model development and input category (Magno et al., 2018). Arena software has been the most popularly used amongst studies (Prajapat & Tiwari, 2017). Simulation technique is the best for system analysis since it gives a clear insight on the behaviour of the system (Bon & Shahrin, 2016), however, it is only descriptive in nature and does not make decision on the available design alternatives. Therefore, the use of simulation techniques alone is inferior for an optimal assembly line design for which it is the case for the present study.

2.4.5 Metaheuristics technique

Another important design technique is the Metaheuristics technique. This technique involves application of one or a combination of the following algorithms; simulated annealing, genetics algorithm, scatter search, tabu search and artificial neural networks. The commonly applied metaheuristic technique in apparel assembly line design is the genetic algorithm. For instance, Chen et al. (2014) conducted a study on grouping genetic algorithm to solve assembly line balancing problem with different labor skill levels in sewing lines of garment industry. The authors aimed to minimize the number of workstations for a given cycle time. These metaheuristic techniques have been applied for many years in the apparel industries. Nevertheless, for manual or semi-automatic operations oriented system like most apparel industries, it is impossible to gain certain results with these metaheuristics algorithms, and it is quite difficult to predict upcoming events when the production system is modified (Guner & Unal, 2008). Therefore, this technique is not well suited to obtain clear results when used as a standalone for solving optimal design problem. The only solution is to combine it with the simulation technique in order to achieve better results.

2.4.6 Simulation-based optimization technique

Simulation-based optimization which has also been referred to as simulation optimization, black box optimization, parametric optimization, stochastic optimization, and optimization via simulation (Amaran et al., 2016), is a state-of-art design approach that generate a number of scenarios from a probabilistic model and then select the best alternative solution by applying scheduling decisions to these scenarios (Dehghanimohammadabadi et al., 2017). This technique basically combines the simulation technique with optimization/metaheuristic technique.

The complexity of the assembly line and the large number of feasible design alternatives make it extremely difficult for a design engineer to identify a solution that could best satisfy all criteria (Michalos et al., 2015). Thereby, combining the simulation and optimization means that all the advantages of the two design techniques are utilized. Consequently, this technique is well suited for the present design problem and has been adopted for this study. Simulation-based optimization was the best options for the present study because it is not only applied to solve system design problem but also the scheduling problem (Shakibayifar et al., 2018). In general, it has been used to solve a number of industrial engineering problems (Junior et al., 2019). There are three commonly used methods of simulation-based optimization namely; metamodeling, metaheuristic and mixed method (Jeong et al., 2013).

2.4.6.1 Metamodeling method

The metamodeling technique is an approximation of the simulation model, which represents the relationship between design parameters and responses. In a simple term, metamodels approximate the input-output behavior of simulation models. The term indicates a mathematical approximation that models the behavior of another model (Barton, 2015; Ghiasi et al., 2018). The objective of metamodeling is to reduce the computational cost of the simulation model during the optimization process (Antunes et al., 2019; Parnianifard et al., 2019). The most commonly used approaches to metamodel construction are a statistic-based approach and machine-learning approach. The former solely depends on the data received from the simulation experiments. In this approach, the regression models are commonly used in practice because of their manageable characteristics (Jeong et al., 2013).

While the latter is based on neural networking, rule learning, and fuzzy logic (Ghiasi et al., 2018; Østergård, Jensenb, & Maagaard, 2018). This approach uses experimental data from simulations to train the surrogate model. It can provide more comprehensive and accurate solutions than the regression model. On the other hand, insufficient training data sets and inappropriate model validation can yield inaccurate models. That is, building a good learning model often requires a high computational cost. In general, metamodeling method transforms intractable problems into problems that can be solved. It transforms the implicitly stochastic response of the simulation as an explicit deterministic functional form. Nevertheless, in real life design problem, high-dimensional, non-differentiable or discontinuous response surface can exist and metamodeling technique sometimes fails to discover the optimal solution (Jeong et al., 2013).

In general, metamodeling consists of three main steps which include (i) choosing a functional form for the metamodeling function based on the study goal (ii) designing and executing the experiments to fit the metamodel and (iii) model learning/fitting the metamodel and validating the quality of its fit (Batur et al., 2017; Song et al., 2017). Basically, there are two goals/purposes of metamodeling which include; inference and prediction. The former provides an insight of the relationship between different inputs and the response of a system, identifying the most influential inputs, quantifying their impact on the response and detecting important interactions. While the latter requires a metamodel that accurately approximates the system's response, without seeking an explanation for this outcome (Protopapadaki & Saelens, 2019).

2.4.6.2 Metaheuristic method

The metaheuristic method is an iterative process that moves from current solutions to high-quality solutions or global optimal solution by exploring the search space. This method is not problem-specific and make few or no assumptions. Unfortunately, metaheuristics can be ineffective and inefficient if the starting point is at a great distance from the optimal solutions (Jeong et al., 2013). Some researchers have used metaheuristic techniques to design an assembly line as described above and the same techniques are applied in metaheuristic-based optimization such as tabu search, scattered search, neural network, simulated annealing and genetic algorithms.

A number of authors have applied simulation-based optimization for solving different design problems. For instance, Sarhangian et al (2008) applied simulation-based metaheuristic optimization technique to optimize inspection strategies for multi-stage manufacturing processes. In their study, the authors used Arena software for building simulation software and Optquest packages for optimization model development. In addition, Dang & Pham (2016) designed footwear assembly line using simulation based adaptive neighborhood search algorithm heuristics (metaheuristics). Other authors proposed an integrated simulation-optimization framework based on metaheuristic method to overcome an inherited complexity of classical production planning in multi-product/multi-machine production systems and optimizes several production objectives simultaneously (Alvandi et al., 2017).

The primary reasons why metaheuristic algorithms are particularly appropriate for discrete-event simulation optimization are that these methods; (i) can handle both continuous and discrete input parameters in contrast to search methods requiring that input factors be expressed explicitly (ii) deal well with conditions of local optima compared to response surface methods (iii) reduce computational complexity in contrast to other search techniques, thus reducing solution identification speed, and (iv) perform quite well under test conditions comparing a generated optimum with complete enumeration of the solution space (Riley, 2013).

2.4.6.3 Mixed method

Both metamodeling and metaheuristic methods are powerful simulation-based optimization techniques. Nevertheless, they also have weaknesses under certain conditions. However, many researchers have been trying to overcome the drawbacks of each technique by using a combination of the metamodeling and metaheuristic methods. Their common ideas are often very successful, as they achieve combined advantage of metaheuristic methods with the strength of metamodeling methods.

The power of metaheuristic methods is certainly based on the concept of exploring solutions to obtain new trials, while a strength of metamodeling methods is that it reduces the simulation evaluation cost of new trials by filtering the trials (Jeong et al., 2013). A number of previous studies used mixed method to conduct simulation-based optimization. For instance, Ky et al. (2016) reviewed surrogate based method for black box optimization. While, Jeong et al. (2013) integrated both metamodel and metaheuristics method for exploring design parameters in a defense system (hybrid system). In order to reduce the computational burden of the optimization process for the present study, metamodeling method was adopted by going through design of experiment, since the computational cost associated with running a metamodel is negligible in comparison to the cost of simulation runs.

2.5 Simulation- based optimization model

In most previous studies, simulation-based optimization model consisted of two different model which include simulation model and optimization model as illustrated in figure 2.2. However, very few studies have considered design of simulation experiment (metamodel) in simulation-based optimization model. For instance, Barton (2015) demonstrated the importance of using experimental design during simulation experiment. Consequently, the present study adopted it to achieve better results. Both simulation model, metamodel and optimization (metaheuristics) model have been described as shown in Figure 2.2.

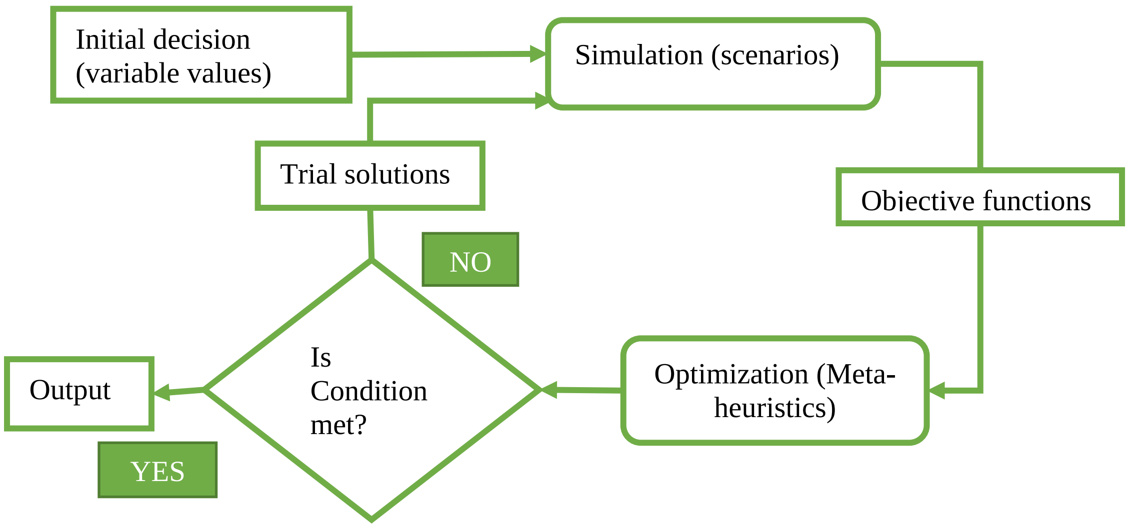


Figure 2.2. Simulation-based optimization framework

2.5.1 Simulation model

Simulation is referred to as an advanced method for analyzing the behavior of the systems. However, the choice of the type of simulation to consider for designing a particular system is very critical. Prajapat and Tiwari (2017) reviewed the application of discrete-event simulation (DES) in the assembly line optimization. Discrete-event simulation has been widely used in the assembly line problem because it captures well the variability and the stochastic behavior of the real complex manufacturing system. Discrete-event simulation represents only the points in time at which the state of the system changes. This means that the system is modelled as a series of events, that is, instants in time when a state change occurs (Anastasia et al., 2018; Silva, 2018).

The discrete-event simulation model consists of three major parts including entities, attributes and variables. Entities are dynamic objects in the simulation that are usually created, move around and then get disposed. Attributes are common characteristics attached to entities to individualize them. Attributes are sometimes confused with variables yet variables are piece of information that reflect some characteristics of the system, regardless of any entities around. Examples of variables include resources, queues, statistical accumulators, events (arrival, departure), simulation clock, starting and stopping (Dehghanimohammadabadi et al., 2017; Kelton et al., 2007). The simulation modeling framework used by previous researches is depicted in Figure 2.3 (Ibrahim et al., 2017; Manuela et al., 2018).

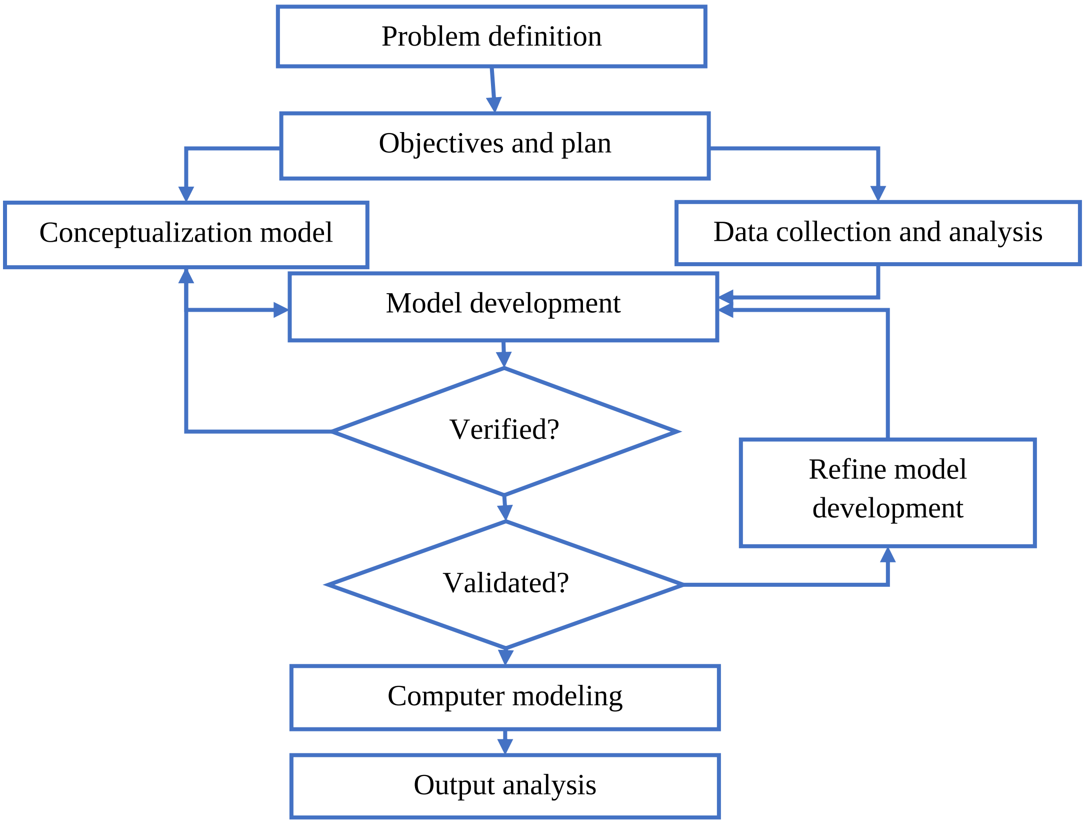


Figure 2.3. Simulation modeling framework

2.5.1.1 Simulation model verification and validation

Verification is actually the process of ensuring the simulation model behaves in the way it was intended according to the modeling assumptions made. There are basically two methods used for verification of simulation model. The first method is to allow only a single entity to enter the system and follow that entity to be sure the model logic and data are correct. Another commonly used method is to replace some or all model data with constants (Kelton et al., 2007). This method is quite simple and it has been the most popularly used amongst studies, and therefore, it was adopted in the current study.

Validation is the process of ensuring that the model behaves as the real system. It is necessary to show that the proposed model has an acceptable level of confidence in performance of all the processes assumed. Several methods have been used to validate the simulation model (Guner & Unal, 2008). The first method involves comparing the results of the model with that of the real system (Kelton et al., 2007). While the second method which has been widely used by researchers is the hypothesis test, whereby model validation is accomplished through hypothesis tests using a throughput with a 95% confidence interval (Guner & Unal, 2008). This method is more accurate than the first method and it is the most commonly used amongst studies. Therefore, it was adopted in this current study.

The hypothesis is;

H_0; $P_F = P_A$, H_0 = Null hypothesis

H_1; $P_F \neq P_A$

Where P_F and P_A are the average production rate for real system and Arena model respectively.

The test is if $t_0 < t_{\frac{\alpha}{2}, n1+n2-2}$, the null hypothesis H_0 was accepted, where;

$$t_0 = \frac{P_F - P_A}{Sp\sqrt{\frac{1}{P_F} + \frac{1}{P_A}}} \quad \text{…… Equation 2.1}$$

$$S_P = \frac{(P_F - 1)S_F^2 + (P_A - 1)S_A^2}{P_F + P_A - 2} \quad \text{…… Equation 2.2}$$

Where S_P^2 is the pooled mean variance, S_F^2 and S_A^2 are the variance for production rate from field system and Arena model respectively.

2.5.1.2 Simulation run setup

The simulation run setup is normally done to specify the appropriate number of replication (sample size, n) for the given run length. There are two methods that have been used for determining the sample size of simulation (Currie & Cheng, 2016; Kelton et al., 2007; Law, 2007).

$$n = t^2_{n-1,1-\alpha/2}\frac{s^2}{h^2} \quad \text{Equation 2.3}$$

Where h is the half width, s is the sample standard deviation and t- distribution. This method has got difficulty because it does not really solve for *n* since the right-hand side of the equation still depends on *n (*i.e. both degree of freedom in the t-distribution, and the standard deviation depend on *n)*. Therefore, this method is not good for approximation of the number of replications. Consequently, a method that does not depends on the sample size *n,* is presented in equation 2.4 (Kelton et al., 2007).

$$n = n_0\frac{h_0^2}{h^2} \quad \text{Equation 2.4}$$

Where, n = sample size, n_0 = initial number of replications, h_0 = half-width of the selected performance measure for that initial number of replications, h = half-width at 95% confidence interval. This method is much more accurate that the first one, hence, it was used in this current study.

2.5.2 Simulation experimental design

Careful planning or designing of simulation experiments is generally of a great help, saving time and effort by providing efficient ways to estimate the effects of changes in the model's inputs (decision variables) on its outputs (performance measures). One of the principal goals of experimental design is to estimate how changes in input factors affect the results, or responses of the experiment i.e. regression metamodel (Kleijnen, 2008).

In literature, two common types of simulation studies that ill-designed experiments have been used were identified. The first type of the study occurs when the analysts perform scenario-oriented experiments, where putting the focus on pre-selected "interesting" combinations of factor settings results in exploring a handful of design points where many factors are changed simultaneously. However, in a real-world, simulation models easily have many or hundreds potential factors. Therefore, a handful of haphazardly chosen scenarios, or a trial-and -error approach, can use up a great deal of time without addressing the fundamental questions (Sanchez et al., 2014). The second type of the study occurs when the researchers or analysts start with a “baseline” scenario and vary one factor at a time, however, in practice, the factors are likely to interact. Therefore, if there are any interactions, one-at-a-time sampling will never uncover them (Sanchez & Wan, 2012).

Design of simulation experiment is the powerful method for simulation studies that overcome all the limitations of the above two common simulation studies. The benefits of experimental design in simulation are tremendous. One of the major benefits is that, the analyst can obtain much insight and information about the simulation model or system in a relatively short amount of time from a well-designed experiment (Sanchez & Wan, 2012). The design of simulation experiment is quite similar to the traditional design of experiment used in physical experiment. Therefore, the different experimental design approaches used in the design of physical experiment can be as well perfectly used in the design of simulation experiment.

Factorial design is one of the simplest designs that is straightforward to construct and readily explainable. Therefore, it is the commonly used design method amongst studies. Factorial design has some nice properties as it can examine more than one factor and can be used to identify important interaction effects. However, when the number of factors becomes moderately large, the number of experiments explodes. In this case, another design approach called fractional factorial design has been used in order to overcome the limitation of the full factorial design by screening some factors and focusing on the main factors (Montevechi et al., 2007).

A fractional factorial design is basically generated from a full factorial experiment by choosing an alias structure. Another interesting property of fractional factorial design is its resolution or the ability to separate main effects and low-order interactions from one another (Sibanda & Pretorius, 2011). This property gave rise to three types of fractional factorial design which includes resolution-III (three), resolution-IV (four) and resolution-V (five) and higher. The resolution-III design allow only main effects to be estimated. While resolution-IV design provide valid estimates of main effects when two-way interactions are present, but preclude estimation of the interaction effects. The more useful fractional factorial design for simulation analysis is the resolution-V design. This design allows all main effects and two-way interactions to be fit (Sanchez et al., 2014). The designs of resolution-V, and higher, are used for focusing on more than just main effects in an experimental situation. In general, these designs enable the estimation of interaction effects and such designs are augmented to a second-order design (Sibanda & Pretorius, 2011). Since, the aim of simulation experimental analysis in the present study concerns both main effects and interaction effects of factors, the resolution-V design was adopted.

2.5.3 Optimization model

Optimization deals basically with the study of those kinds of problems in which one has to minimize or maximize one or more objectives that are functions of some real or integer variables (Bandyopadhyay & Saha, 2013). General simulation optimization problem form has been presented as in table 2.2 (Kandemir & Handley, 2018);

Table 2.2. General simulation optimization formulation

Formulae	***Meaning***
Minimize/ maximize $F(x)$	Objective function
Subject to: Ax< b	Constraints on input variables
$(g_l) < G(x) < (g_u)$	Constraints on the output measures
$l < x < u$	Bounds

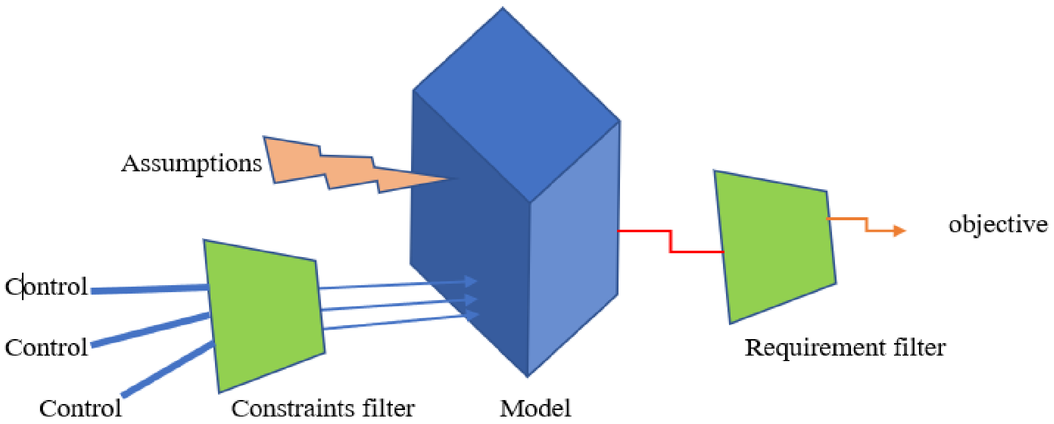


Figure 2.4. Optimization model on OptQuest

Similar to simulation model, the optimization models are also classified as discrete, continuous and combined discrete/continuous. Although the simulation model can provide valuable assistance in analyzing designs and finding good solutions, it cannot obtain an optimum solution.

An optimization model seeks for the optimum solution by maximizing or minimizing some quantity such as profit or cost. It has major element such like control, constraints and objective as illustrated in Figure 2.4 (Rockwell Automation, 2009). Whereby, controls are usually either variables or resources that can be meaningfully manipulated to affect the performance of the simulated system. for example, the number of workers to be assigned to an activity, the amount of product to make and so on. Constraints are the relationships among controls and/ or output (response). For example, constraints might restrict the amount of money allocated among various investment not to exceed a specified amount. Example of constraints used by previous studies include machine availabilities, due date, demands and machines' capacity.

Objective function is basically a mathematical response or an expression used to represent the model objective, such as minimizing queues or maximizing profits in term of statistics collected from the simulation model. Prajapat & Tiwari (2017) reviewed the major sub-categories of objective functions such as time-based, cost-based, bottleneck reduction, throughput, resource management, utilization and other objectives. The authors noticed some overlap between various optimization objectives; for instance, bottleneck reduction will automatically increase the throughput, and the increase in throughput will lead to an increase in sales. Fundamentally many of the objective functions can be interpreted as cost objectives, as they essentially aim to increase the production rate in order to produce more products; this drives sale and increases profit (Prajapat & Tiwari, 2017). Therefore, for the case of the present study, throughput was maximized. It was used as the primary performance metric for garment assembly line design. In most cases, the optimization methods or procedures varies depending on the software package and search strategies used (Rockwell Automation, 2009).

2.6 Effects of factors

In this section, previous studies on the effect of some factors such as resource number, Bundle size, task assignment pattern, job release policy on the manufacturing system was reviewed. In a manufacturing system, resources are substance that can be utilized in the production process. The most common ones are machines, operators, helpers, etc. A number of studies on the effect of varying resource capacity/number have been done. For instance, Anisah et al. (2012) postulated that increasing resource capacity in the bottleneck station also increases the throughput because of the reduction of the cycle time. In their study, an increase of 28% in throughput and decrease of 65% in cycle time of short-sleeve t-shirt production was achieved. While Marsudi & Shafeek (2013) presented the effect of throughput to optimize the resource utilization in manufacturing system using queuing network theory.

In some studies, bundle size has been referred to as lot size depending on the type of the manufacturing system. For instance, Anisah et al.(2012) studied the effect of lot size on performance of manufacturing system. The authors stressed that reducing lot size can reduce cycle time hence increasing the throughput.

Task assignment pattern in any manufacturing is very critical as it affect the workload of the operators. Kandemir (2016) stated that uneven task assignment to the workers can result into uneven workload which increase work in progress hence low throughput.

Job release policy in manufacturing system normally dictate the interval time of the input materials in the production line. Akhavan-tabatabaei & Salazar (2011) studied the effect of varying job release policy at two levels i.e. no policy and policy based on Work in Progress (WIP) threshold. The authors reported that reduction in cycle time and increase in throughput was achieved with the job release policy based on WIP threshold. Moreover, Vinod et al.(2018) demonstrated the positive effect of WIP based job release policy on the performance of manufacturing system.

2.7 Research gaps

2.7.1 Gaps in assembly line design

A number of researches have dealt with assembly line design problem as the line balancing problem, while other have considered the physical layout problem. Consideration of only one aspect of assembly line design problem does not fully capture the real-world system design problem. The other aspect of assembly line design is resource planning which should also be put into consideration.

Another gap that exist is the number and type of design parameters considered in model development. A number of researchers have studied the effect of varying one or two design parameters on the system performance. The most commonly varied design parameters for assembly line balancing are number of workstations and number of operators. However, real-world design problem has a number of parameters to vary in order to obtain realistic results. Lastly, a few numbers of researchers have tried to address garment assembly line design problem using direct simulation-based optimization.

2.7.2 Gaps in experimental design

A number of studies on simulation experiment has been considered as ill-design experiment. The common ill-design experiment includes; scenario-oriented (trial and error) experiment and one-factor at a time experiment. These ill-design experiments consume much time, many important factors can be left out and cannot uncover the interaction effects between factors. Therefore, the present study used design of simulation experiment in order to analyze effects of many factors and also to uncover the interaction effects in case there are interactions between factors.

CHAPTER 3: METHODOLOGY

The present study adopted a multidisciplinary research approach which comprised of both qualitative and quantitative research methods. It was conducted in four phases as illustrated in Figure 3.1.

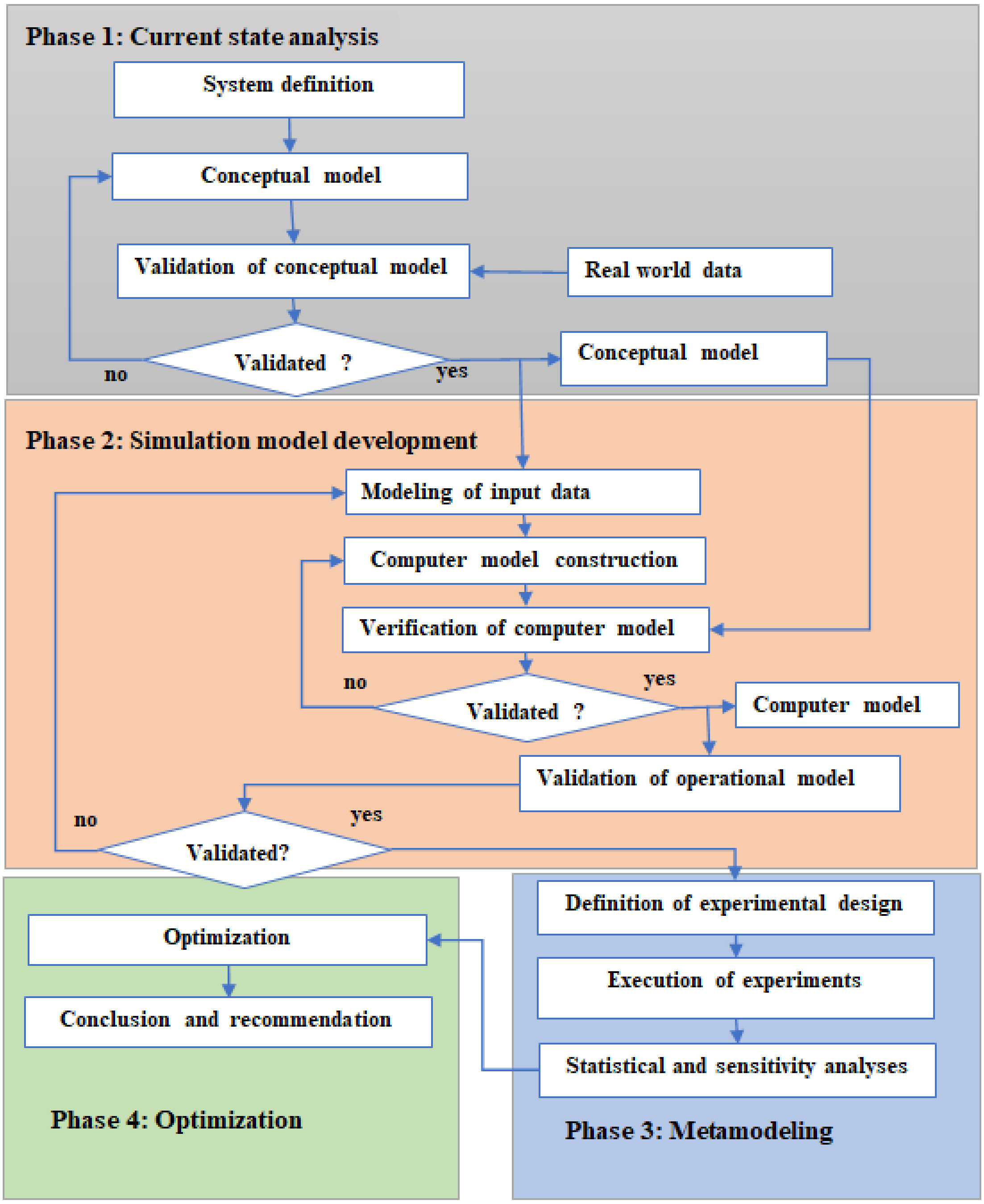


Figure 3.1. Research methodology

3.1 Phase 1: Current state analysis

3.1.1 System definition

NYTIL garment manufacturing facility produces both knit garment wear and woven garment wear. However, other garment manufacturing facilities produce either knit garment or woven garment wear. The present study was focused on the woven garment wear production department. The woven garment manufacturing system consists of nine (9) production sections or stages as shown in Figure 3.2. However, only one section (assembly/ sewing) was selected for this study because it comprises of huge number of resources and high uncertainty in that improving its throughput leads to the overall improvement in productivity of the garment manufacturing facility.

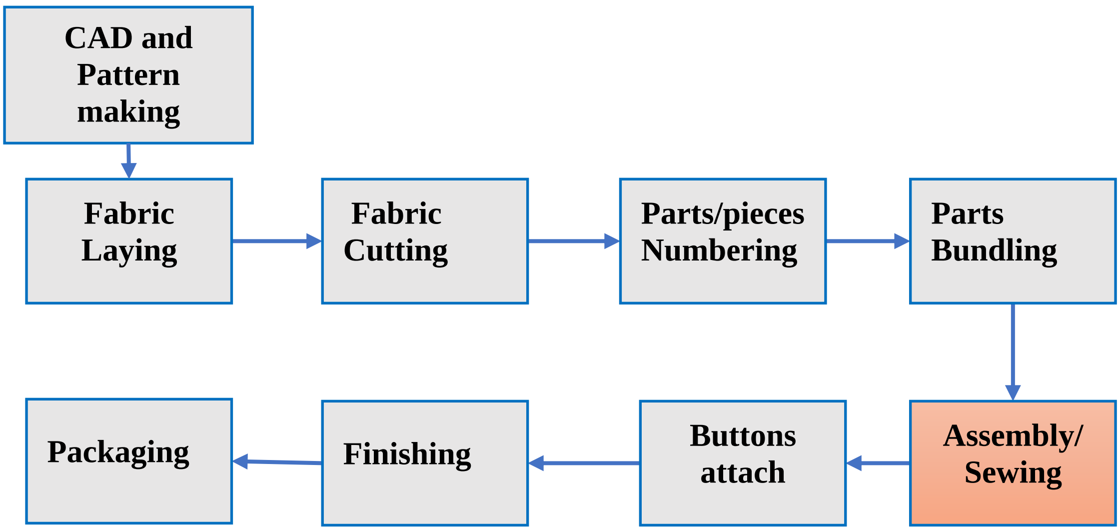


Figure 3.2. Woven garment manufacturing process

The input variables that influence the throughput of the garment sewing line were identified by brainstorming four categories of people in the production department namely; operators, quality personnel, maintenance personnel and line supervisors. The brainstorming was conducted on individual basis at non-working time so that company production is not interrupted. All their ideas were collected and categorized using fishbone diagram (Figure 3.3) based on the big four major category of causes (4M) in a manufacturing system: Manpower, Method, Material and Machine.

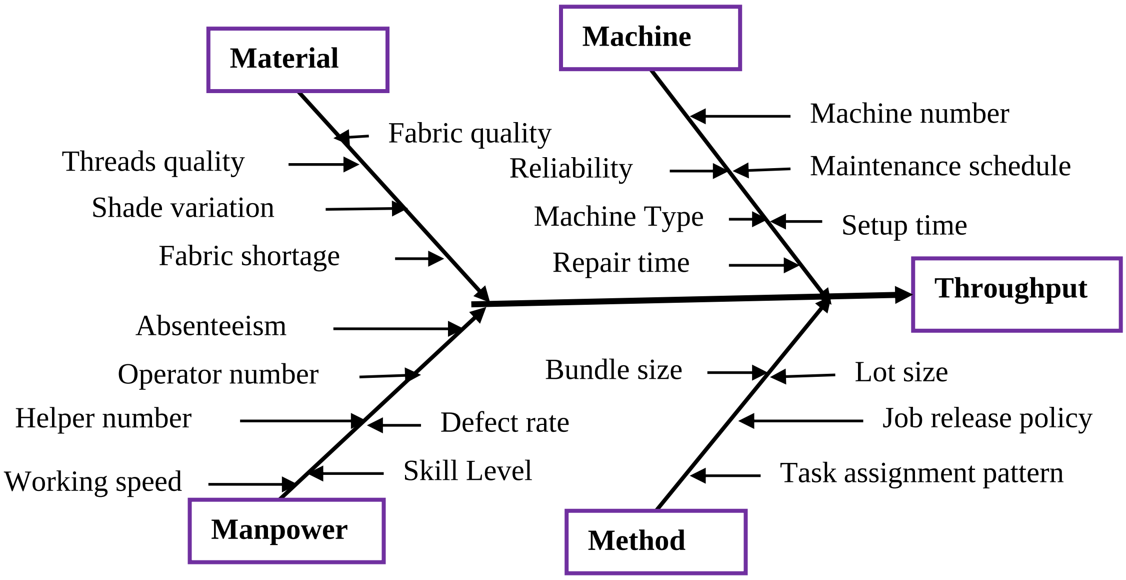


Figure 3.3. Fishbone or cause and effect diagram

From the fishbone diagram, five causes (input variables) such as bundle size, job release policy, task assignment policy, helper number and machine number were identified to be the most critical for the present study. These factors were selected because they have greater influence on the throughput as recommended by team brain stormed. Therefore, their effects on the throughput of the garment assembly line were studied.

The woven garment production system under study consisted of three different sewing line which are involved in producing different product models. However, to narrow the scope of the study, one sewing line and one product model was selected using ABC classification method. The three product models included cap, trouser and jacket. With A-priority given to trouser assembly line, B-priority given to jacket, and C-priority assigned to cap assembly line. Hence, the trouser assembly line was selected for this study. The trouser was selected for the study based on the complexity, time and economical consideration.

The observation of assembly line configurations, process sequence and operators and machines performance were conducted. The observation data was then used for process mapping of the entire trouser assembly line. In addition, the operation lists, machine breakdown and other related information were observed from the history data collected by the company. In sewing section, two major areas that were critically observed on the sewing machines include sewing machine working (positioning, sewing, and dispose) and sewing machine not working (waiting for repair, waiting for suppliers, personal need for workers and idle).

3.1.2 Conceptual model construction

In this step, all the processes involved in trouser assembly line were summarized using the conceptual model, which is simply a series of logical relationships relative to the components and structure of the trouser assembly line. This involved mapping all the processes or tasks associated with making trouser. The precedence diagram to show the relationships between different tasks from all the sub-assembly processes was first sketchily drawn on the paper using the pencil, and then properly drawn using MS. Excel. The different trouser parts to be assembled were identified and illustrated as in Figure 3.4, where a-s are trouser parts as described in Table 3.1.

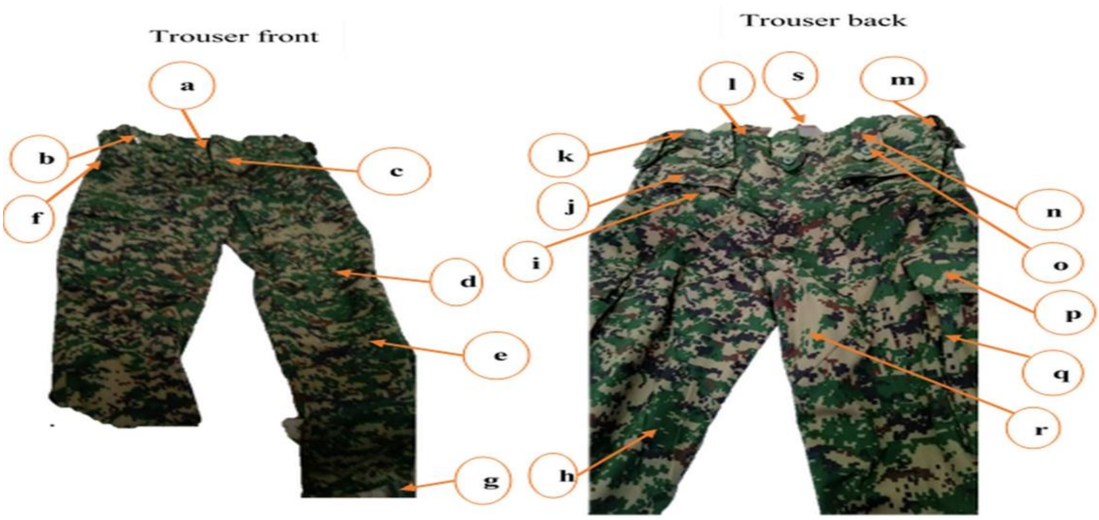


Figure 3.4. Trouser parts

Table 3.1. Trouser parts to be assembled

Trouser part	***Part name***	***Quantity required per trouser***
A	Right flybox	1
B	2nd Adjustable rope	2
C	Left flybox	1
D	Front leg	2 (left and right)
E	Knee patch	2 (left and right)
F	Side pocket	2 (left and right)
G	Bottom rope	2 (left and right)
H	Back leg	2 (left and right)
I	Hip pocket	2 (left and right)
J	Hip flap	2 (left and right)
K	1st adjustable rope	2
L	Waist band	1
M	Small loop	7
N	Big loop	7
O	Button	19
P	Knee flap	2 (left and right)
Q	Knee pocket	2 (left and right)
R	Back patch	2 (left and right)
S	Company tag and size label	2 (tags) and 2 (size label)

3.1.3 Validation of conceptual model

The validation of the conceptual model was done through comparison between the process mapping and the real situation. The precedent diagram of the garment sewing line was presented to be validated by the line supervisors and workers in another department.

3.2 Phase 2: Simulation model development

3.2.1 Modeling of input

3.2.1.1 Time study

The garment assembly line system consists of series of workstations. However, at each workstation, different tasks are completed at different time, therefore, in order to understand the operation of trouser assembly line, time study combined with observation was conducted. In this study, Labour/operators time study was conducted using direct continuous stopwatch method as according to Puvanasvaran et al. (2013).

The observed time in seconds was first converted to standard time units (minutes) and then recorded. In this study, 20 number of measurements for each task element were made at three different period of production seasons so as to capture as much variability in the tasks processing time as possible in the production line. The total of 60 number of time measurements for each task were obtained from the trouser production line.

3.2.1.2 Fitting of processing time probability distributions

Woven garment assembly line presents a unique design problem as some workpieces (parts) move in bundle from operator to another especially in preparation section. While a single workpiece is worked on normally in the main body assembly line. In this study, the processing time measurement for each task was done only on each single part in the bundle. But, since the operators seize and release bundle at a time to the next operator, it is impossible to use a single workpiece processing time in the simulation model. In order to model this situation, the observed time for each task on a single piece was multiplied by the number of bundles (bundle size) to be seized and released by the operators in the production line. This was done based on the assumption that the total time for finishing each task on one bundle correspond to the observed time of single workpiece multiplied by the bundle size (number of the parts in the bundle). In the case study problem, the bundle size was 25, while other bundle sizes such as 10 and 40 were adopted in the simulation model so as to study the effect of varying bundle size on the mean throughput of garment production line.

The processing time for completing the same task on the bundle and a single part was inserted into the Arena input analyzer with the objective of obtaining the candidate probability distributions and fitted probability distribution. Arena input Analyzer was used to fit the distribution of the processing time for each operation or task involved in trouser production. All the fitted processing time probability distribution have been summarized and presented in a table based on the bundle sizes (See Appendix A, B, and C). Some examples of the fitted processing time probability distribution for some tasks performed on 25 bundle size such as button hole on left flybox, left front rise, and knee patch attach are illustrated by the histogram as shown in Figure 3.5, 3.6 and 3.7.

a) Button hole on Left flybox bundle

Distribution: Erlang Expression: 6.05 + ERLA (0.39, 6); Square Error: 0.015878

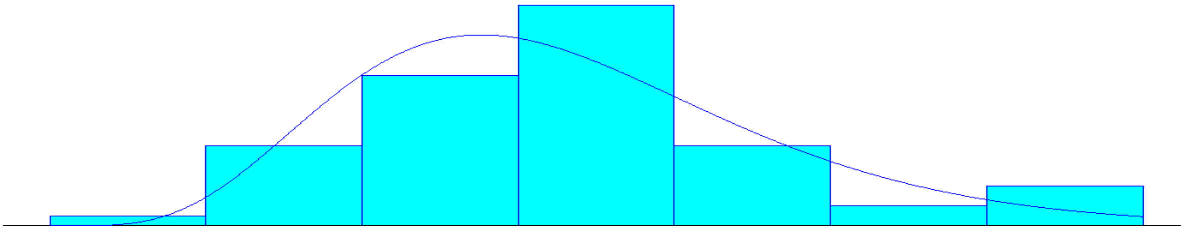


Figure 3.5. Button hole on Left flybox operation time probability distribution

b) Left front rise operation

Distribution: Beta Expression: 4 + 6.88 * BETA (1.95, 3.37) Square Error: 0.004843

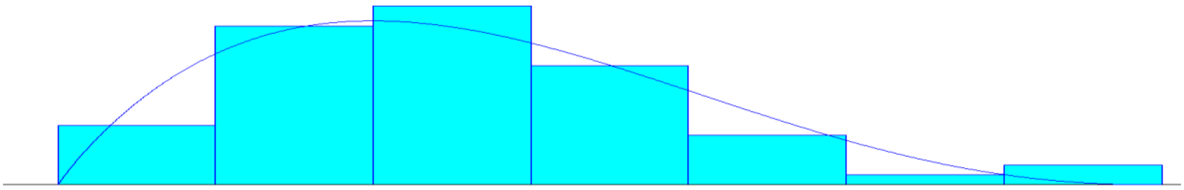


Figure 3.6. Front rise operation time fitted probability distribution

c) Knee patch attach bundle processing time

Distribution: Beta Expression: 20 + 21 * BETA (1.95, 3.37) Square Error: 0.004843

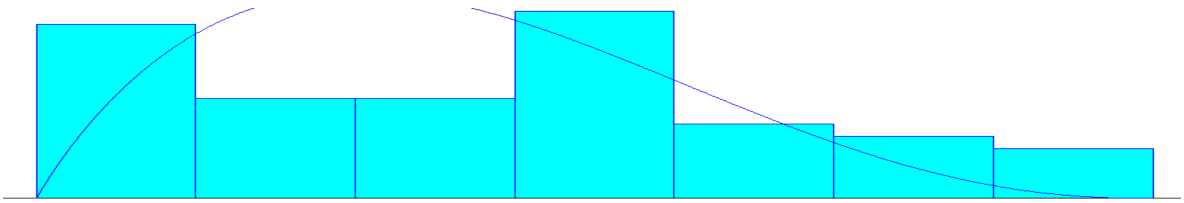


Figure 3.7. Knee patch attach operation time fitted probability distribution

3.2.2 Construction of computer model

The computer model of the trouser assembly line was constructed based on discrete event simulation using Arena software (Academic license version 16). The trouser assembly line simulation model was built on a 64 bits notebook computer with a 2.00 GHz Intel core i3 CPU and 4.00 GB RAM. Due to the low processing speed of the notebook computer, 32 bits Arena software category was well-suited to be installed instead of the 64 bits. Therefore, the simulation model was well-developed and run smoothly without freezing the computer.

Apart from processing times, the following input variables were essential in developing the computer model; number of machines, number of operators, number of tasks, number of helpers, quantity of input material per day, interarrival time of parts, productivity per day, working hours, task precedence relations, bundle sizes, job release policy, machine type and production target.

In the construction of computer model (see Appendix D), the following Arena elements were used; entity, variables, resources, process, attribute and many other transfer and control logic elements. The following model assumptions were used for simulation model development in this present study.

i. The input materials arrive in production line at constant time i.e. every day and there was no shortage of material from the cutting section.
ii. There was no breakdown of the machines in the production line

iii. There are no absenteeism of the operators and so machines are never stopped due absent of the operators.

iv. Each operator and helper were assigned to perform a single task in the production line and only operators were assigned to sewing machines. Therefore, the number of operators were equal to the number of machine and increasing machine number also increases operator number and vice versa.

v. Production only runs for 8 hours in a day and there was no overtime.

vi. All defected trousers at 8% defect rate per day were reworked by only one workstation with a single needle lockstitch machine.

3.2.3 Verification of computer model

In this step, simulation runs were conducted to verify if the model follows the logic pointed out in the conceptual model. Verification is basically the process of ensuring that the model behaves as intended. More specifically, it is known as debugging the model. Therefore, Trace and animation techniques (Figure 3.8) were used to verify that each program path is correct (see Appendix D). Several programming errors were identified and corrected. Moreover, the model verification was also done through testing and observing the simulation model at varying situation such as changing the interarrival time, process time, run length and replication time. After confirming that model is running well, the last task on verification process was to reconvene the company's managers and other expert of garment manufacturing (Figure 3.9).

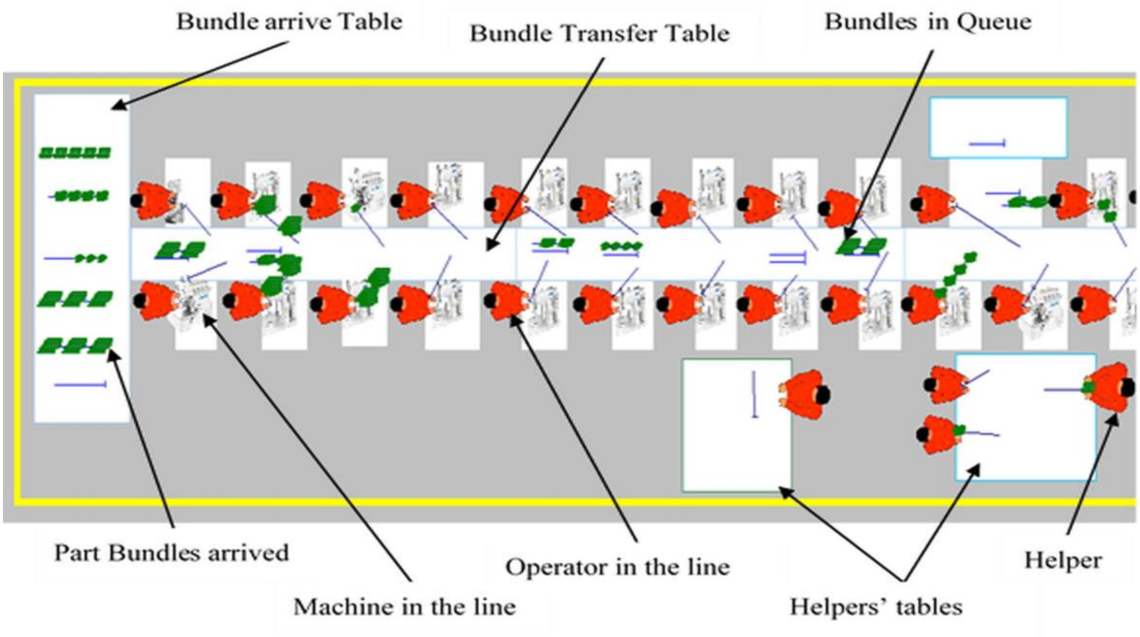


Figure 3.8. Animation of a section of trouser assembly line simulation

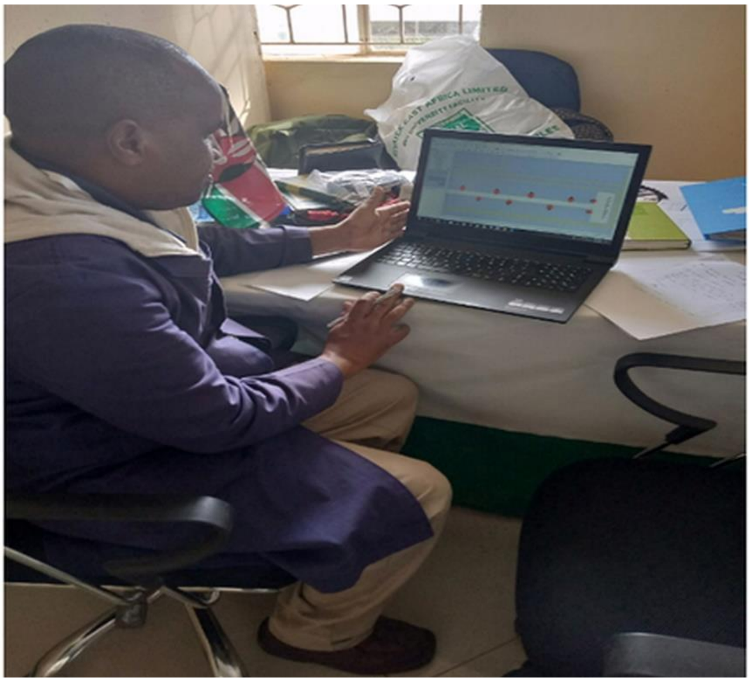


Figure 3.9. Verification by a garment production expert

3.2.4 Validation of operational model

After verification was successfully completed, the simulation replication length (n) was determined with the run length of one month. By using the Equation 2.4 adopted from Kelton et al. (2007) , the simulation replication number was approximated.

After the approximation of the simulation replication number for the intended half width of the throughput, the simulation model was then validated. The simulation model was validated to ensure that its performance and behavior is closed to the real production system under the study.

Since, Arena simulation model only generates output with calculated mean values for the number of replications; the mean of throughput from Arena simulation model was used for validation as the hypothesized mean (μ_A). In order to obtain the same production period (run length) for one month, the production throughput data was collected for a period of one month. In this case, one-sample-T hypothesis test with confidence interval of 95% was used to compare the mean throughput from the Arena simulation model and the throughput sample from the real production system with the mean throughput (μ_R). The hypothesis test was successfully accomplished with the help of Minitab statistical software (version 18) and the null hypothesis was accepted.

3.3 Phase 3: Metamodeling

3.3.1 Definition of experimental design

In the design of simulation experiment, factors and their levels were defined. The factors for this study were selected from the fishbone diagram in the phase 1 above. These factors correspond to those that were defined by the team brainstormed. From the views the team, these factors are most probable of having contribution in throughput of the assembly line. The number of levels of factors considered for this study were two (i.e. low and high).

Hypothetically, there exist main factors and their interactions that might influence the throughput of the assembly line. Therefore, resolution-V fractional factorial design was used for case of this present study to test this hypothesis. This is because of resolution-V design has greater ability to allow all main effects and two-way interactions to be fitted. Minitab statistical software (version 18) was used for generation and analysis of model design. The factors and their levels used in this study were described as follows:

Factor A (Bundle size). It is the number of cut pieces of each part of the trouser (or any other woven garment product) which are moved from one operator to another. Different bundle sizes are being used in garment manufacturing. Therefore, two levels such as 10 and 40 were used in this study to determine their effect on the overall throughput of the production line.

Factor B (Job release policy). This is the method of availing input materials into the production line. In this study, the effect of two levels on the throughput were studied. The levels include; no policy and policy, in ‘no policy’ means the input materials are made available to the production line at constant rate i.e. every day. While for ‘Policy level’ the input materials are made available depending on the WIP threshold of the bottleneck station.

Factor C (Task assignment pattern). This is the method of distributing work to the operators performing the same task in the production line. Two levels such as random and equal task assignment pattern were studied. In random task assignment, the work load of operators performing similar task are randomly distributed. While, Equal task assignment pattern, the work load of operators performing similar tasks are equally distributed.

Factor D (Machine number). This is the input variable that was also studied in two level such as increase and decrease. For case of increase level, three single needle lockstitch and one iron press were added in the production line. While, in the decrease level, three single needle lockstitch and one button hole machines were removed from the production line.

Factor E (Helper number). Helpers are the workers in the production line who are not attached to any machine, they don’t operate any machine but perform tasks such as bundle handling, trimming, separating bundles, transporting bundles, matching part, and manual attaching of rope to the trouser. The effect of increasing and decreasing their number in the production line were also studied. Where, three helpers were added and three were removed from the production line. The two levels include; reduce and increase.

3.3.2 Execution of simulation experiments

After designing simulation experiment using Minitab software, 16 runs or design points were the outcomes from the design of experiment. The number of runs represented different design scenarios for the simulation model of the garment assembly line. This implies that 16 different design scenarios were generated. The simulation experiment was performed on each design scenario with the same replication length of 1 month of 8 hours working days and the warm up period of 2 days. The replication number of 10 was considered for each design scenario. The warm up period and replication number for the steady-state simulation were specified in accordance to Law (2007).

3.3.3 Statistical and sensitivity analyses

Statistical analysis was performed to develop regression metamodel for obtaining the local best solution for optimization process, and for analyzing effects of factors on throughput of the garment production line in order to answer the following questions; which factors are important? How do the factors influence the simulation response (throughput)? What are the possible interaction effects between factors? The basis of this effect analysis is based on the design matrix as defined by the design of experiment (resolution-V design). This is also known as sensitivity analysis (Montevechi, Miranda, & Friend, 2012). The statistical and sensitivity analyses were performed with the help of Minitab statistical software (version 18). The fitted metamodel was checked to see if the fidelity is adequate for the intended use. For this study, a simple significance checks (Barton, 2015) was used to validate the regression metamodel.

The design point or experiment number (design scenario) which produces the greatest effect on the response was selected to be the local optimal best solution of garment assembly line design. Therefore, the factor setting responsible for the highest throughput was retained for optimization process in order to determine the global optimal best solution.

3.4 Phase 4: Optimization Model development

In this phase, the objective function for the optimization was determined from the regression metamodel. While the constraints, and upper and lower bounds were determined based on the discussion with the management of NYTIL garment facility. The optimization was performed on the factor setting of the metamodel or design scenario that produced the best throughput. This was used as the initial best solution in the optimization problem.

A black box optimization on the trouser assembly line simulation model was performed using OptQuest for Arena. OptQuest treats the simulation model as a black box because it observes only the input/output of the simulation model. OptQuest combines the metaheuristics of tabu search, neural networks, and scatter search into a single search heuristic. The fundamental principal behind OptQuest optimization process is that if a candidate solution does not fit the constraints, then that solution is eliminated and

OptQuest explores candidates that are more likely to be better. OptQuest accord the simulation analysts to explicitly determine integer and linear constraints on the deterministic simulation inputs (Kleijnen & Wan, 2007).

The implicit mathematical formulation of the optimization problem is defined as shown in Equation 3.1;

$Max(Throughput)$ = $f_i(A_C, A_S, A_L)$ at constant (A_S, A_L)

Subjected to: $h_i\ (A_C, A_S, A_L)\} \leq A_I$ ……………………. Equation (3.1)

Where; $f_i(A_C, A_S, A_L)$ = model input function, $h_i(A_C, A_S, A_L)$ = function of constraints on the model control, model stochastic factors and model logic and A_I= set of constraints.

- Model control factors (A_C) are known as decision variables such as machine number and helper number. The important model control factors were determined by regression analysis.
- Model stochastic factors (A_S) are fixed variables that were used for building the computer model (e.g. processing time, availability of resources, defect rate, rework, machine reliability, interarrival and inter-departure time).
- Model logic control (A_L) are fixed qualitative variables that are more logical or structural in nature coded in the Arena simulation software (e.g. process routing, queue discipline, dispatching rule).
- Model constraints (A_i) (e.g. precedence constraints, limits on the production resources, constraints on model control factors such as maximum number of machines and helpers to be increased). These were identified from the real system.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Current state analysis and simulation model

4.1.1 Validated conceptual model

The whole production line was divided into three main sections and subsections, the main section includes front preparation, back preparation, and trouser body assembling. While the subsections include side pocket preparation, hip pocket preparation, back patch preparation, hip flap preparation, knee pocket preparation, knee flap preparation, big loop preparation, small loop preparation, adjustable loop preparation as shown in Figure 4.1. The major reason for breaking down the production line into small sections was to make it easy to capture all the activities involved in the production. The tasks' precedence can be altered and thus it has effect on the overall performance of the production line. The Figure 4.1 shows the conceptual model, whereby 1-72 represent the operations as described in Table 4.1, and a-q are input trouser parts to assembled.

Table 4.1. Trouser assembly tasks description

OPS	***Tasks***	***OPS***	***Tasks***	***OPS***	***Tasks***
1.	Left flybox pressing	25.	Hip flap attach	49.	Big loop turning
2.	Buttonhole on Left flybox	26.	Hip pocket finish	50.	Big loop runstitch
3.	Left front rise overlock	27.	Back prep bundling	51.	Big loop button hole
4.	Right front rise overlocks	28.	Front and back bundling	52.	Small loop runstitch
5.	Knee patch attach	29.	Side seam overlock	53.	Small loop, big loop and waistband attach
6.	Side pocket flatlock	30.	Side seam topstitch	54.	Waistband topstitch
7.	Side pocket overlocks	31.	Knee pocket point marking	55.	Waist band closing with size and label tags
8.	Right flybox overlock	32.	Knee pocket topstitch	56.	Inseam Overlock
9.	Side pocket attach	33.	Knee pocket tacking	57.	Trouser turning
10.	Side pocket topstitch	34.	Knee pocket Overlock	58.	Inseam topstitch
11.	Right flybox attach	35.	Knee pocket hemming	59.	Button hole on Hip band
12.	Left fly box tacking	36.	Knee pocket ironing	60.	Button hole on the bottom leg
13.	Fly attach	37.	Knee pocket attach	61.	Bottom rope attach
14.	Front prep bundling	38.	Knee flap folding	62.	Bottom hemming
15.	Back marking	39.	Button hole on knee flap	63.	Small loop tacking
16.	Back patch pressing	40.	Knee flap runstitch	64.	Final Bar tacking
17.	Back patch attach	41.	Knee flap turning	65.	Adjustable rope cutting
18.	Hip pocket cutting	42.	Knee flap topstitch	66.	Adjustable hemming
19.	Hip pocket overlocks	43.	Knee flap attach	67.	1st adjustable rope attach
20.	Hip flap folding	44.	Bar tacking	68.	2nd adjustable rope attach
21.	Button Hole on hip flap	45.	Back rise overlocks	69.	Button point marking
22.	Hip flap runstitch	46.	Back rise Topstitch	70.	Trimming
23.	Hip flap turning	47.	Big loop matching	71.	Quality checking
24.	Hip flap topstitches	48.	Big loop runstitch	72.	Rework

OPS= operation sequence

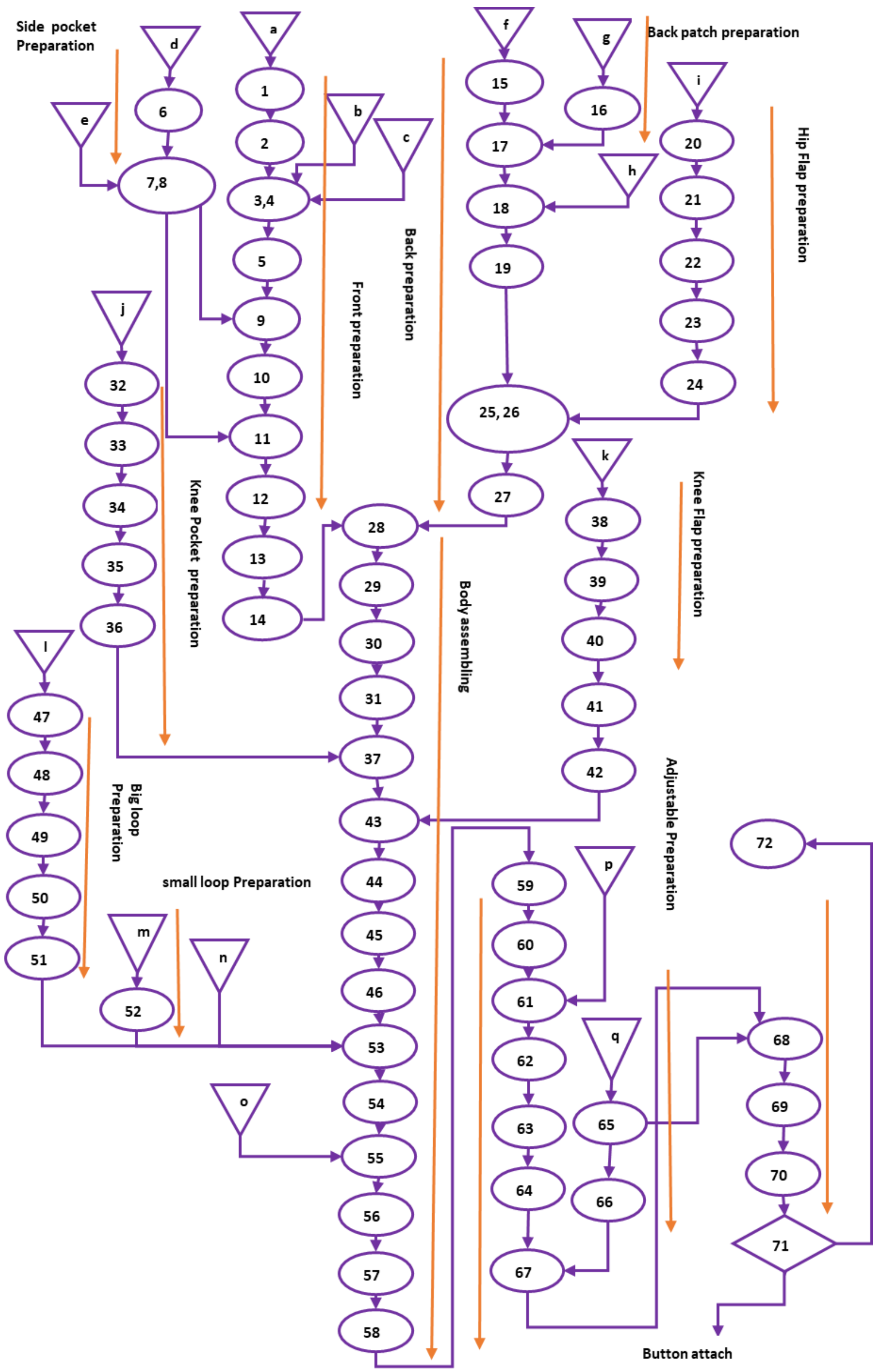


Figure 4.1. Conceptual model of trouser assembly line

a - left flybox , b - leg front, c - knee patch, d - side pocket, e - right flybox, f - leg back, g - back patch, h - hip pocket, i - hip flap, j - knee pocket, k - knee flap, l - big loop, m - small loop, n - waistband, o - company tags, p - leg bottom rope, q - adjustable rope

4.1.2 Validated Simulation model

4.1.2.1 Simulation run length and replication numbers

In the present study, a steady-state simulation was performed with a warm-up period of 2 days, the total run length of 28 days (one month's) of 8 production hours and the replication number of 10. Simulation run was executed with no animation/batch mode and it took 2 mins 39 seconds to complete the simulation run on a 2.0 GHz notebook computer. The results show the mean throughput of 496 pieces per day with the minimum and maximum average of 470 and 501, respectively with the confidence interval half width of 6.62 as shown in the Arena crystal report (Figure 4.2).

Values Across All Replications

TROUSER ASSEMBLY LINE DESIGN

Replications: 10   Time Units: Hours

User Specified

Output

Output	Average	Half Width	Minimum Average	Maximum Average
defect stat	43.9000	1.09	42.0000	47.0000
throughput per day stat	496.10	6.62	470.00	501.00

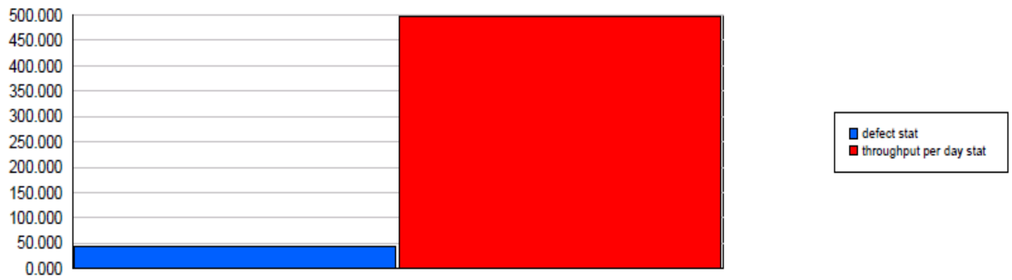


Figure 4.2. Average throughput of the simulation model

4.1.2.2 Validation using One-sample-T test

The sample production throughput data from the real trouser assembly line are shown in Appendix E. When the mean throughput of the trouser production line from Arena model was compared with the sample data of throughput from the real-world trouser production line, the result was observed using the boxplot as depicted in the Figure 4.3. The results of the descriptive statistics for the sample throughput of the real garment production line is presented in the Table 4.2; where, N is the sample number, μ is the mean of the real system throughput (pieces per day).

Table 4.2. Descriptive statistic for the real system throughput sample

N	**Mean**	**StDev**	**SE Mean**	**95% CI for μ**
23	490.8	124.2	25.9	(437.1, 544.5)

From the test result, the null hypothesis (H_0) was accepted because the hypothesized mean or the mean throughput of Arena model falls within the 95% confidence interval for the mean throughput of the real production system. Moreover, the T- Value of -0.20 and P-Value of 0.842 was estimated.

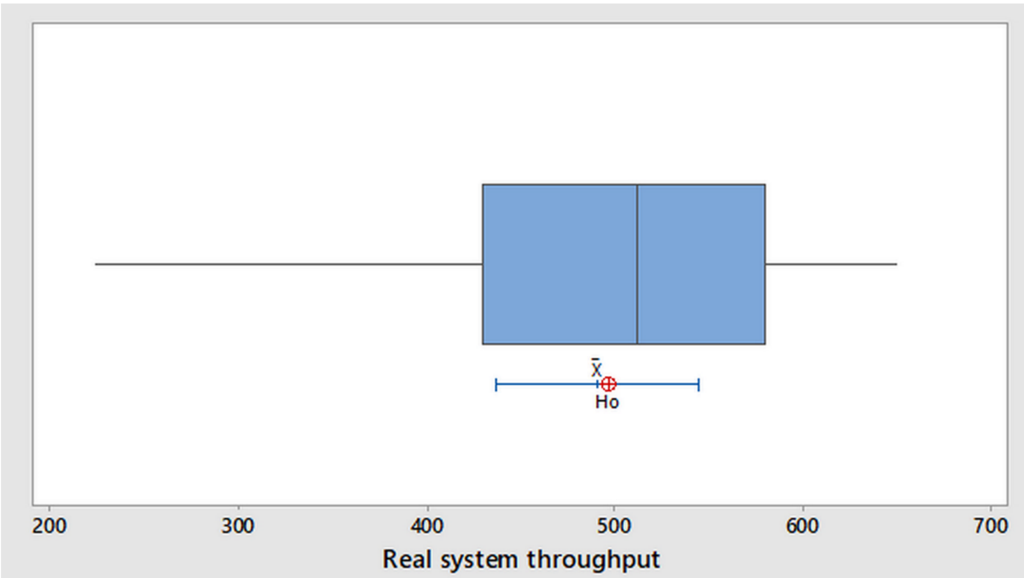


Figure 4.3. One-sample T-test Boxplot

The simulation model was an acceptable approximate of the existing trouser assembly line at T-value (-0.20). This is because the P-value (0.842) is greater than the alpha value

(0.05). Therefore, it failed to reject the null hypothesis. This indicates that the effect size (the difference between real-world throughput sample data and the hypothesized Arena simulation throughput mean) is not statistically significance at p-value 0.842. The little difference could be due to the high variation in the throughput sample data obtained from the real system. Nevertheless, there is no significant difference between the mean throughput from Arena model and that of the real system, hence, all the assumptions used in the simulation model development were validated.

4.2 Metamodel of trouser assembly line simulation model

4.2.1 Resolution-V design

Fractional factorial design (resolution-V design) was used to study the effect of the selected factors on the response (throughput). The selection of this design method was based on the hypothesis that three factors and higher order interactions are insignificant. The resolution-V design was developed using Minitab software, the result of design specifications is as shown in the Table 4.3.

Table 4.3. Experimental design specification

Factors	Level	Base design	Resolution	Run	Replicates	Fraction	Blocks	Center point
5	(- /+)	5,16	V	16	1	1/2	1	1

Design generator: E= ABCD, Defining relation; I= ABCDE, Alias structure for the design is presented as; I+ABCDE, A+BCDE, B+ACDE, C+ABDE, D+ABCE, E+ABCD, AB+CDE, AC+BDE, AD+BCE, AE+BCD, BC+ADE, BD+ACE, BE+ACD, CD+ABE, CE+ABD, DE+ABC.

The resolution-V design confounds main effects with four-factors interactions and two-factors interactions with three-factors interactions as represented above as the alias structure. This implies that the model for resolution-V design can contain all of the main effects and two-factor interactions. The three-factors and higher order interaction are rare so it is generally safe to ignore them. The experimental design result from the Minitab software in coded values with 16 design points (runs) and single block for each run as presented in Table 4.4.

Table 4.4. Experimental design table

Run	***Blk***	***A***	***B***	***C***	***D***	***E***
1	1	+	-	-	+	+
2	1	-	-	+	+	+
3	1	-	+	-	+	+
4	1	+	-	+	+	-
5	1	+	-	-	-	-
6	1	+	+	+	+	+
7	1	-	-	+	-	-
8	1	-	+	+	-	+
9	1	+	-	+	-	+
10	1	+	+	+	-	-
11	1	+	+	-	-	+
12	1	-	-	-	-	+
13	1	-	+	+	+	-
14	1	-	+	-	-	-
15	1	-	-	-	+	-
16	1	+	+	-	+	-

Blk= Blocks, (A, B, C, D, E) = Factors, - and + = Levels (low and high)

4.2.2 Design scenarios

The validated simulation model of the garment assembly line was used to perform the different experimental runs. The simulation model was altered depending on the different design points generated from the design of experiment. This resulted into development of 16 different simulation models which are also known as design scenarios or design alternatives. The experiment was performed for each design alternative while their mean throughput was observed. The experimental result for each design alternative (runs number) is presented as shown in Table 4.5.

Table 4.5. The mean throughput for each design scenario

Design scenario	***Factors***					***Throughput Mean (pieces per day)***
	A	B	C	D	E	
1	40	no policy	random	increase	increase	609
2	10	no policy	equal	increase	increase	638
3	10	Policy	random	increase	increase	583
4	40	no policy	equal	increase	reduce	496
5	40	no policy	random	reduce	reduce	465
6	40	Policy	equal	increase	increase	607
7	10	no policy	equal	reduce	reduce	467
8	10	Policy	equal	reduce	increase	467
9	40	no policy	equal	reduce	increase	467
10	40	Policy	equal	reduce	reduce	467
11	40	Policy	random	reduce	increase	429
12	10	no policy	random	reduce	increase	467
13	10	Policy	equal	increase	reduce	496
14	10	Policy	random	reduce	reduce	439
15	10	no policy	random	increase	reduce	496
16	40	Policy	random	increase	reduce	496

A= Bundle size, B= Job release policy, C= Task assignment pattern, D= Machine number, E= Helper number.

4.2.3 Analysis and validation of regression metamodel

The regression metamodel was analyzed using regression analysis with the help of Minitab software. The factorial regression analysis of the response (throughput) versus factors (bundle size, job release policy, task assignment pattern, machine number, and helper number) for different design scenarios was performed using analysis of variance (ANOVA). The results are summarized as shown in Table 4.6.

Table 4.6. Analysis of Variance

Source	***DF***	***Contribution***	***Adj SS***	***Adj MS***
Model	15	100.00%	64529.8	4302.0
Linear	5	77.24%	49845.3	9969.1
Bundle size	1	0.03%	20.2	20.2
Job release policy	1	1.44%	930.3	930.3
Task assignment pattern	1	1.44%	930.2	930.2
Machine number	1	55.06%	35532.2	35532.2
Helper number	1	19.27%	12432.3	12432.3
2-Way Interactions	10	22.76%	14684.5	1468.4
Bundle size*Job release policy	1	0.20%	132.2	132.2
Bundle size*Task assignment pattern	1	0.20%	132.2	132.2
Bundle size*Machine number	1	0.00%	2.3	2.3
Bundle size*Helper number	1	0.47%	306.2	306.2
Job release policy*Task assignment pattern	1	0.33%	210.2	210.2
Job release policy*Machine number	1	0.00%	2.2	2.2
Job release policy*Helper number	1	0.47%	306.2	306.2
Task assignment pattern*Machine number	1	0.02%	12.2	12.2
Task assignment pattern*Helper number	1	0.37%	240.2	240.2
Machine number*Helper number	1	20.67%	13340.3	13340.3
Error	0	*	*	*
Total	15	100.00%		

The result shows the model's total degree of freedom (DF) of 15, whereby, 5 DF for Linear model and 10 DF for two-way interaction model. The degree of freedom for error was zero for the designed model. This means that the observed mean response (throughput) value is equal to the model predicted mean throughput. This is because the mean throughput from the simulation model has already been fitted for the different runs and replications. Unlike the physical experiment, computer experiment is deterministic hence there is no random errors for each replication (Barton, 2015). In addition, the regression analysis of resolution-V design is incomplete because the experiment is saturated, and all of the available degrees of freedom are consumed by the metamodel. This result into zero degree of freedom for residual error(s), and the adjusted mean square (Adj MS) of the error is not defined for the metamodel giving the R^2 =1. In addition, the adjusted sums of squares (Adj SS) is also not defined for the error, hence, there is no residual plots for this metamodel design. This result shows a biased approximation of simulation model. Nevertheless, it shows that the metamodel is a good approximation of the simulation model since mean square error (MSE) equal to zero. In order to distinguish significant regression coefficient from insignificant one, the normal effect plot (Figure 4.4) was used.

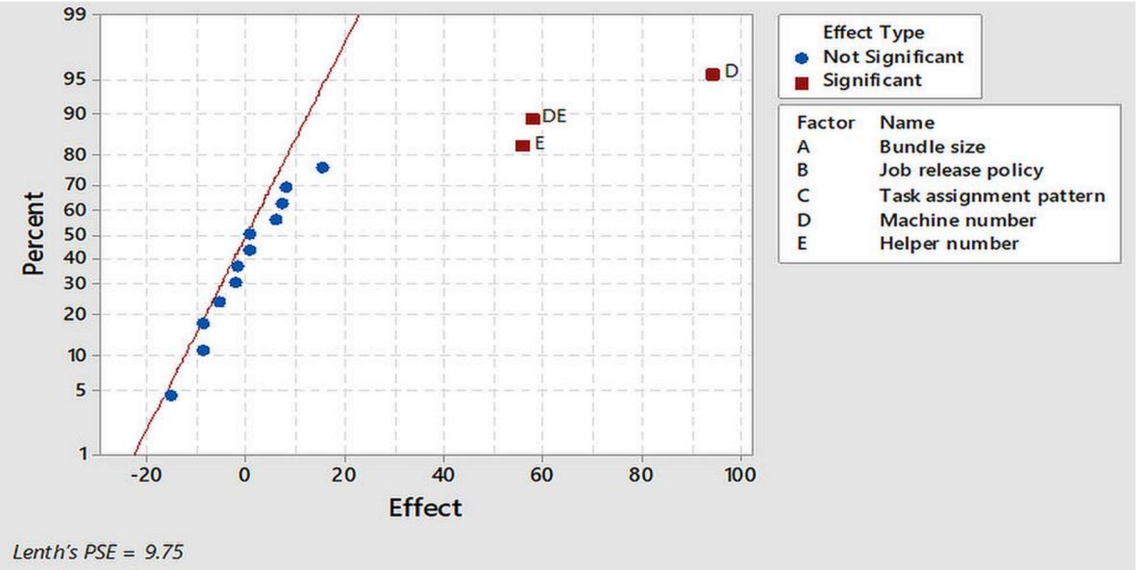


Figure 4.4. Normal plot of the effects

The plot indicates that there are many terms (factors and their interactions) of near zero effect which are considered insignificant but that the outliers (E, DE and D) are considered significant. Since then, some terms (two factors and one interaction) are statistically significant, the regression metamodel is validated but all the insignificant terms were removed and only the significant terms are retained in the metamodel. The regression equation for the metamodel is presented as shown Equation 4.1;

$Throughput = 507.5 - 0.075A - 12.42B + 12.42C + 46.5D + 35.17E + 0.1917AB - 0.1917AC + 0.025AD - 0.2917AE + 3.625BC + 0.375BD - 4.375BE - 0.875CD + 3.875CE + 28.88DE$ ………………………… (Equation 4.1)

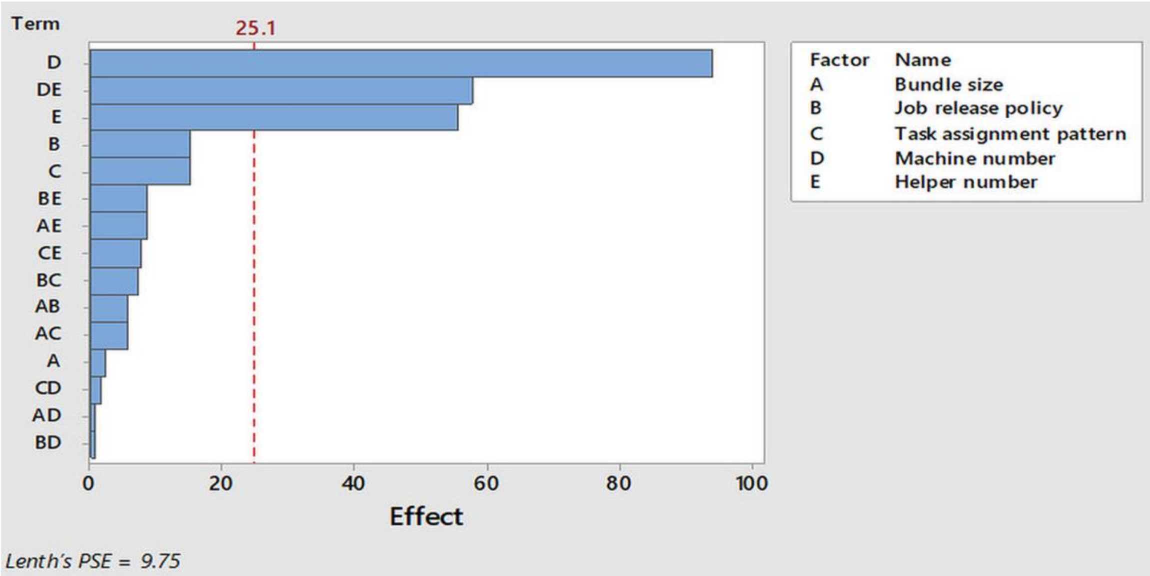


Figure 4.5. Pareto chart of the effects

By analyzing Pareto Chart of the effects, insignificant terms were removed from the metamodel. The Figure 4.5 illustrates that only the effect of the terms: two main factors (D and E) and one interaction (DE) exceeded the margin of error line at effect level (25.1) with Lenth's Pseudo Standard Error (PSE) = 9.75. These were retained in the regression metamodel while the terms having effects below the reference line were safely removed. In this respect, a new linear regression metamodel including two inputs (D and E) with two-way interaction (DE) was obtained (Equation 4.2).

The new regression equation for the metamodel is;

$Throughput = 507.5 + 46.5D + 35.17E + 28.88DE$ ………………… (Equation 4.2)

Where, 507.5 is the estimated value for the intercept term. The *P*-vector of parameters or parametric coefficient for D, E and DE terms are 46.5, 35.17 and 28.88, respectively.

The best factor setting (Table 4.7) for the metamodel was selected from the dataset in the experimental results was adopted as the initial solution for the Optquest optimization process.

Table 4.7. Best parameter setting for the metamodel

S/N	***Decision variables***	***Settings***
1	Bundle size	25
2	Job release policy	No policy
3	Task assignment pattern	Equal
4	Machine number	Increase (1 iron and 3 single needle lockstitch)
5	Helper number	Increase (3 helpers)

4.2.4 Sensitivity Analysis for main factors and interaction effects

4.2.4.1 Main factors effects

The main factors effect of the five factors (Bundle size, job release policy, task assignment pattern, machine number and helper numbers) on the production throughput are shown in Figure 4.6 and interpreted as follows.

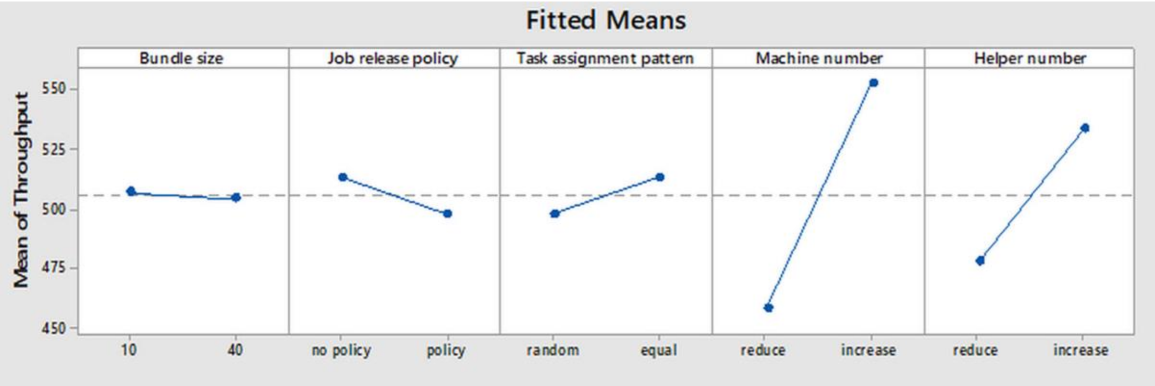


Figure 4.6. Main effects plot for throughput

Bundle size effect plot. With all factors kept constant, the mean throughput decreased by a very small value when the bundle size was changed from 10 to 40. Thus, if the same quantity of input materials were kept constant for all levels of bundle sizes, a very small decrease would be observed in the mean throughput when the bundle size of 40 is used. This is explained by the longer time it takes for each preparation section to complete tasks on bundles while keeping the main body assembly idle. This implies a longer warm up time for the production line resulting into low throughput.

Job release policy effect plot. The plot connotes that if all other factors were kept constant, changes in the level of job release policy would have a greater change in the mean throughput when compared to that of the bundle size. A decrease in the mean throughput was observed when the job release policy was changed from no policy to policy level. This is because at no policy level, the quantity of input materials is kept constant in the production line and every preparation section is capable of preparing enough parts for the main body assembly section. As for the case of policy system which was based on the WIP threshold of the bottleneck workstation, there is a lot variability in the throughput of the different sections as they have to wait for the input materials and thus, affecting the productivity of the main body assembly. This therefore reduces the overall throughput of the production line. For instance, big loop preparation has to be done at a faster rate than other sub-assembly processes because seven loops are required to be assembled on one trouser. For this reason, any delays in the preparation process could cause starvation of the main body assembly as well as the extreme workstations resulting into low throughput. In previous studies, job release policy based on WIP threshold of the bottleneck workstation was observed to increase throughput (Akhavan-tabatabaei & Salazar, 2011; Vinod et al., 2018). In contrast, the present study achieved lower throughput. A plausible explanation is that previous studies considered the assembly line problem which does involve parts preparation processes. Consequently, keeping WIP of one workstation does not starve the extreme workstations, thus increasing the throughput. It should be emphasized that job release policy based on WIP threshold of the bottleneck workstation does not work well on the assembly line problem that requires part preparation process as it leads to starvation of the main body assembly resulting into low throughput.

Task assignment pattern effect plot. There was a small increment in the average throughput when random task assignment pattern was changed to equal task assignment. With the random task assignment, there is unequal workload for operators performing similar tasks in the workstation. Thus, the workstation cycle and idle times are increased, resulting into low throughput. On the other hand, equal task assignment maintains the same workload among operators, reducing the cycle and idle times which ultimately increases the overall throughput. The present study is in complete agreement with the report of Kandemir & Handley (2018) who reiterated that equal task assignment had higher production throughput and efficiency due to equal workload of the operators and minimization of workstation idle time.

Machine number effect plot. The effect of machine numbers on the throughput was found to be statistically significant at $\alpha = 0.05$. This means that, the throughput increases when machine number is increased in the workstation and vice versa. This is because increasing machine number in the bottleneck workstation reduces cycle and parts waiting times as well as the WIP.

Helper number effect plot. Similarly, helper number had a significant effect on the mean throughput though its effect was smaller when compared to machine number. The work of helpers in the production line normally influences the feeding of parts to the extreme workstations. When the number of helpers is increased, the extreme workstation is never starved of materials due to reduction of helper's workstation cycle time and WIP. Subsequently, a higher throughput is realized. Contrastingly, decreasing the number of helper results in an increase in their workstation cycle time, leading to starvation of the extreme workstations thus a lower throughput.

4.2.4.2 Interaction effect of factors

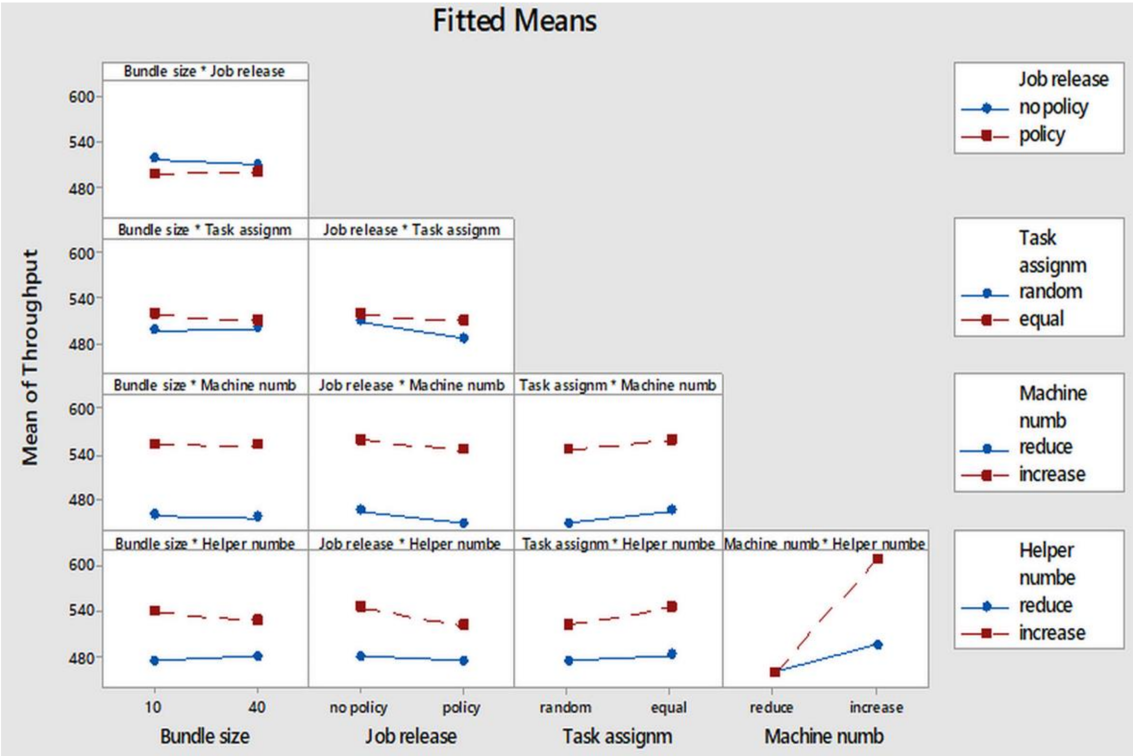


Figure 4.7. Interaction plot for throughput

The interaction effect of the factors on the production throughput is illustrated in **Figure 4.7**. Each plot represents the interaction between two factors. When the red and blue lines of the factor levels are with considerably different slopes, it indicates that there is an interaction between the two factors. In this respect, the interaction effects of the factors were interpreted as follows.

Bundle size and job release policy effect plot. This interaction plot indicated that there is very little interaction between bundle size and job release policy as the no policy and policy lines took slightly different slopes. With the bundle size of 10, the average throughput decreased by a large value when the job release policy was changed from no policy to policy level. While with the bundle size of 40, the throughput decreased by a very small value and almost did not change at all when the job release policy was changed from no policy to policy level.

Bundle size and task assignment pattern effect plot. There was also an insignificant effect of the interaction between bundle size and task assignment. Nonetheless, there was little interaction effect as the slopes of random and equal lines are not parallel. This implies that with the bundle size of 10, the mean throughput increased by a large value when task assignment pattern changed from random to equal level. With the bundle size at 40, the mean throughput increased by a very small value when the task assignment pattern changed from random to equal level.

Bundle size and machine number effect plot. There was actually no interaction between bundle size and the number of machines since there was no significant difference in the slopes of the reduce and increase levels considered. This points out that there could not be any differences even if the alpha value were increased.

Bundle size and helper number effect plot. The slope of the reduce and increase lines of the two levels of the helper numbers differed slightly. The plot indicates that if the bundle size is at 10, the mean throughput increases by a larger value when the helper number is changed from reduce to increase level (helper number is increased). The reverse would be true if the bundle size is at 40.

Job release policy and task assignment pattern effect plot. The slope of random and equal lines of the two levels of task assignment pattern took slightly different directions. Consequently, significant interactions can exist when the alpha value is increased. The plot connotes that, if the job release policy is at no policy, there is almost no change or a very small increase in the throughput when the task assignment pattern changes from random to equal level. But if the job release policy is set at policy level, the throughput increases by a bigger value when the task assignment pattern changes from random to equal level.

Job release policy and machine number effect plot. There is likely to be no interaction between job release policy and machine number at all even if the alpha value is further increased because the slope of the reduce and increase levels of machine number are parallel.

Job release policy and helper number effect plot. There is an insignificant interaction between job release policy and helper number at $\alpha = 0.05$. Notwithstanding, the reduce and increase levels of helper number took slightly different slopes. Thus, their interaction could be significant when the alpha value is further increased at some point.

Task assignment pattern and machine number effect plot. There is no interaction between task assignment and machine number as the slope of the reduce and increase levels of machine number took the same direction.

Task assignment pattern and helper number effect plot. It can be observed from the plot that the slope of the reduce and increase lines of helper number are parallel. The plot therefore means that, if the task assignment pattern is at random level, the average throughput insignificantly increases when the helper number is increased. However, if the task assignment pattern is at equal level, the average throughput increases by a larger value when the helper number is increased.

Machine number and helper number effect plot. There was a statistically significant interaction between machine number and helper number at $\alpha = 0.05$. It is observed that the slope of the reduce and increase lines of helper number differed significantly. The plot means that if the machine number is at reduce level, there is no change in the mean throughput when the helper number is increased. The reverse is true when the machine number is at increase level. It can be noted that increasing helper number when the machine number is at reduce level does not change the average throughput because helpers perform simple tasks in the production line and their tasks depends on the workstations with machines. Reducing helper number contributes to high WIP and idle time in the workstations for the helpers but the throughput remains constant because only the cycle time of the helpers is changed. However, increasing the helper number when the machine number is at increase level increases throughput because the cycle and idle times as well as the WIP of both the machine and the helper workstations are reduced.

4.3 Optimal assembly line design

4.3.1 Objective function, Controls and constraints

The objective function for the optimization model was derived from the metamodel regression equation and presented as in Equation 4.3;

$$Max\{Throughput\} = Max\{507.5 + 46.5D + 35.17E + 28.88DE\} < Constraints$$

……………………………………………………………………… (Equation 4.3)

Where D, (machine number) and E (helper number) are the model control factors, DE is factors interaction. The set of constraint for this optimization problem consisted of the constraint on the machine number, constraint on the helper number and constraint on the throughput are presented as follows;

Machine number ≤ 10, Helper number ≤ 5, and lower and upper bound was set to be 1and 3, respectively (i.e. $1 \leq x \leq 3$).

The optimization problem considered in this study is stochastic in nature because the simulation model has some input data that are probabilistic such as the processing time, etc. It is a nonlinear optimization problem because the objective function has some factors interaction (DE). It is a discrete optimization problem because the model control factors have discrete values. Moreover, it is a single objective optimization problem because only one response (Throughput) is maximized.

All the optimization model elements such as objective function, controls, constraints, lower and upper bounds were entered into the OptQuest. The OptQuest automated the Arena simulation model and it generated many design alternatives (number of simulation). It was allowed to search for the best solution through 100 simulations (design alternatives) as shown the Figure 4.8.

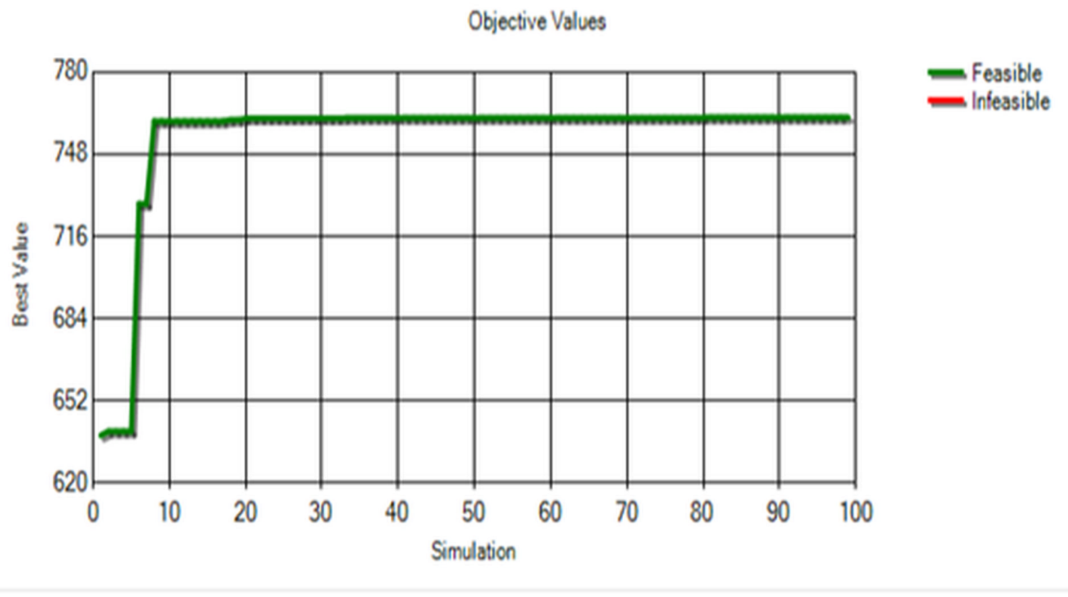


Figure 4.8. OptQuest optimization process

At the end of the Optimization process, Optquest presented 20 best solutions for each simulation out of 100 total simulations performed as presented in the Table 4.8.

Therefore, simulation 80 was determined to be the global optimal solution since it has the highest objective value.

Table 4.8. Best solutions from OptQuest optimization process

Simulation	***Objective value***	***Number of resources (machine and helper) added***			
		5threads overlock	***Bartack machine***	***Helper***	***Single needle lockstitch***
80	762.3	1	2	2	4
40	762.2	1	1	2	5
43	762.2	1	1	2	5
33	762.1	1	1	2	4
81	762.1	2	2	2	3
45	762.0	1	1	2	4
20	761.9	1	0	2	5
32	761.8	1	1	2	3
74	761.6	1	2	2	4
77	761.6	1	2	2	3
18	761.4	2	1	2	4
29	761.3	1	1	2	5
79	761.3	1	0	2	6
28	761.2	2	0	2	4
42	761.1	2	0	2	5
34	761.0	1	0	2	5
41	761.0	0	1	2	6
8	760.9	1	0	2	3
30	760.9	1	0	2	5
71	760.7	1	2	2	5

4.3.2 Comparison of the three model designs

The comparison of the three models such as base model (existing design), metamodel and optimal design (best solution from OptQuest) was made based on the resource number and the mean throughput (Table 4.9 and Table 4.10). Furthermore, the comparison was also made on three designed models based on the resource number assigned to the respective workstation of the production line as presented in Appendix F. The surface plot (Figure 4.9) shows the comparison of the total resource number and the throughput for the three model designs. The plot illustrates that maximizing the production throughput is centred around increasing the resource number.

Table 4.9. Comparison of different model designs based on the resource number

s/n	***Resource type***	***Resource number***		
		Existing/ Base model design	***Metamodel design***	***Optimal design***
1.	Single needle lockstitch machine	47	50	54
2.	Double needle lockstitch machine	3	3	3
3.	Flatlock machine	1	1	1
4.	Overlock machine (3 and 5threads)	9	9	10
5.	Feed of arm	4	4	4
6.	Automatic wallet machine	1	1	1
7.	Iron press machine	3	4	4
8.	Bartack machine	4	4	6
9.	Button hole sewing machine	6	6	6
10.	Small loop sewing machine	1	1	1
11.	Turning machine	4	4	4
12.	Operator	83	87	94
13.	Helper	19	22	24
14.	Quality personnel	2	2	2
	Total	**187**	**198**	**214**

Table 4.10. Comparison based on the total resource number and the throughput

Design	***Total resource number***	***Throughput (pieces per day)***	***Percentage Throughput increase (%)***	***Efficiency (%)***
Existing (Based model)	187	496	0	61.25
Metamodel	198	638	28.63	79.75
Optimal	210	762	53.63	95.25

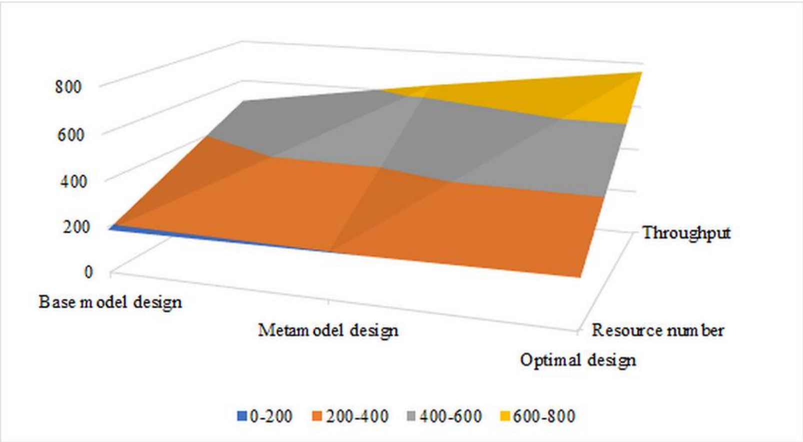


Figure 4.9. Surface plot of the three designed models

Table 4.11. Comparison of the designs based on the design variables

S/N	***Design variables***	***Existing design***	***Optimal design***
1.	Total machine number	83	94
2.	Total operator number	83	94
3.	Total helper number	19	24
4.	Bundle size	25	25
5.	Job release policy	No policy	No policy
6.	Task assignment pattern	Equal	Equal

The operator number is equal to the machine number because one operator is allowed to operate only one machine in the production line. Since the assumption made was that increasing or decreasing machine number automatically changes the operator number with equivalent value. In the optimization process, the constant bundle size of 25 was used because the effect of varying its level (10 to 40 bundle sizes) was insignificant.

The result shows that an increase of 53.63% on the throughput was achieved with the trouser assembly line optimal design. While an increase of 28.63% on the throughput was achieved at the metamodel design stage. Consequently, the production efficiency increased to 79.75% and 95.25% for metamodel and optimal design stages, respectively. This result is very much closed the study reported by Anisah et al. (2012). In order for the company under case study to achieve that an increase in the production throughput, an optimal design is required to be implemented by making possible changes (Table 4.11) in their trouser assembly line. It was also noted that increasing resource number has direct effect on the throughput. However, it is only true if the resources are added in the bottleneck workstations otherwise the effect cannot be realized. There were total of 15 bottleneck workstations identified and eliminated in the trouser assembly line as highlighted in Appendix F. With seven (7) bottleneck workstations identified at metamodel design stage, and eight (8) were identified at optimal design stage. The bottleneck workstation is the one whose capacity is less than the demand placed on it and less than the capacities of all other resources. It was effectively determined through extensive simulation of the assembly line while observing the WIP at each workstation. Therefore, NYTIL garment facility is recommended to implement the global optimal line balancing solution in order to achieve an increase in the throughput, and attain the sustainability of their assembly systems.

CHAPTER 5: CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The present study has demonstrated garment assembly line design using simulation-based optimization via design of experiment. The aim of study was to design an optimal trouser assembly line with the parameters' setting that maximizes the throughput. Several conclusions were drawn from the present study.

The conceptual model was constructed based on the current practice in trouser assembly line which was validated by line supervisors. Most details on trouser production process was captured during conceptual model construction which simplified the development of the simulation model. The study showed that simulation model is an acceptable approximate of real-world trouser assembly line at 95% confidence interval. This was validated using one-sample T-test with the t-value of as low as -0.20 at p-value (0.842). The steady-state discrete event simulation on Arena is well suited for capturing the behavior of the complex garment assembly line with the consideration of stochastic task times and bundle processing.

The result showed that the developed metamodel is a biased approximation of trouser simulation model with the $R^2 = 1$ and MSE = 0. Therefore, this metamodel is not suitable for prediction. But, based on the purpose of metamodeling in this study, the metamodel was used to give an insight of the relationship between factors and the throughput, identifying the most influential factors, quantifying their impact on the throughput and detecting important interactions.

The effect of five factors such as bundle size, job release policy, task assignment pattern, machine number and helper number were analyzed. The study showed that increasing resource (machine and helper) number has great effect on the production throughput of garment assembly line. In the regression analysis, only two factors (machine number and helper number) were significant and retained in the metamodel because the other factors have very minimal effect on the workstation cycle time as well as the work in progress. Hence, the overall throughput is slightly changed when these factors are varied in their levels. The increase of 28.63% in the production throughput with the efficiency of 79.75% was achieved for the best setting of the metamodel. The machine number showed no interaction with other factors except with helper number. Although, insignificant interaction effect was observed for other factors, the interaction effect of machine number and helper number was significant at alpha value 0.05.

The study also showed that 53.63% increase in production throughput and efficiency of 95.25% can be achieved with the optimal design. This confirmed the suitability of designing an assembly line using simulation-based optimization via design of experiment. The initial design solution obtained from the metamodel narrowed down the search space of the Optquest optimization process. The nonlinear single objective optimization with discrete control values was considered in the present study.

5.2 Recommendation

The garment industries should implement the optimal design solution from this study so as to evaluate the practical implication of the optimal design model. Further study can be done to improve the present simulation model by considering other design parameters which include machine failure and line supervisor functions.

Further study should adopt machine learning approach in developing the metamodel. In addition, more factors can be studied using resolution-VI and higher order experimental design. In order to overcome the biasness of the metamodel, the future study can use a space-filling experimental design such as Latin hypercube design and orthogonal array.

In the present study, single objective optimization was considered, therefore, further study can develop a profound optimization model with at least two objective functions which include production cost, cycle time and resource utilization. Further study can be performed to compare the results of this study with the direct simulation-based optimization method in terms of the optimal throughput values and the computation cost.

The garment assembly line configuration/layout optimization was beyond the scope of the present study. Therefore, further study can be directed toward optimization of the garment assembly line layout or physical design.

REFFERENCES

Akhavan-tabatabaei, R., & Salazar, C. F. R. (2011). Effective WIP dependent lot release policies: A discrete event simulation approach. In *Proceedings of the 2011 Winter Simulation Conference* (pp. 1976–1985). Bogotá, Colombia: IEEE.

Akter, S., & Hossain, K. R. (2017). Analysis on the proper utilization of man and machine to improve the efficiency and a proper line balancing of a sewing line: A case study. *International Journal of Scientific & Engineering Research*, *8*(12), 778–784.

Al-khatib, B. A. (2012). The Effect of Using Brainstorming Strategy in Developing Creative Problem Solving Skills among Female Students in Princess Alia University College Department of Psychology and Special Education. *American International Journal of Contemporary Research*, *2*(10), 29–38.

Alghazi, A. A. (2017). *Balancing and Sequencing of Assembly Lines*. Heidelberg: Physica-Verlag HD.

Alrabghi, A., & Tiwari, A. (2016). A novel approach for modelling complex maintenance systems using discrete event simulation. *Reliability Engineering and System Safety*, *154*, 160–170.

Altiok, T., & Melamed, B. (2007). *Simulation modeling and analysis with Arena*. Burlington, USA: Elsevier Inc.

Alvandi, S., Li, W., & Kara, S. (2017). An Integrated Simulation Optimisation Decision Support Tool for Multi-Product Production Systems. *Modern Applied Science*, *11*(6), 56–71.

Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization : A review of algorithms and applications. *Annals of Operations Research*, *240*, 351–380.

Antunes, F., Amorim, M., Pereira, F. C., & Ribeiro, B. (2019). Active learning metamodeling for policy analysis: Application to an emergency medical service simulator. *Simulation Modelling Practice and Theory*, *97*, 1–11.

Atan, S. anisah, Ramlan, R., & Foong, T. G. (2012). Cycle Time Reduction of a Garment Manufacturing Company Using Simulation Technique. In *Proceedings International Conference of Technology Management, Business and Entrepreneurship* (pp. 124–131). Melaka, Malaysia.

Ayat, M., Sarfraz, T., & Karachi, T. (2017). Assembly line Balancing in a Manufacturing Industry Uisng Largest Candidate Rule Algorithm. In *Proceeding of the 8th International Conference on Management Research ICMR 2017 (pp. 14-28).* Superior University Lahore.

Aydin, D. (2013). *Two-Sided Assembly Line Balancing Using Teaching-Learning Based Optimization Algorithm and Group Assignment Procedure*. Master Thesis; Dokuzeylul University, Graduate School of Natural and Applied Sciences.

Babu, V. R. (2012). *Industrial engineering in apparel production*. New Delhi, India: Woodhead Publishing India Pvt. Ltd.

Badiru, A. B., & Omitaomu, O. A. (2011). *Handbook of Industrial Engineering*

Equations, Formulas, and Calculations. Boca Raton: Taylor and Francis Group, LLC.

Bahadır, S. K. (2011). Assembly Line Balancing in Garment Production by Simulation. In W. Grzechca (Ed.), *Assembly Line - Theory and Practice* (pp. 67–82). Rijeka, Croatia: InTech.

Bandyopadhyay, S., & Saha, S. (2013). Some Single-and Multiobjective Optimization Techniques. In *Unsupervised Classification: Similarity Measures, Classical and Metaheuristic Approaches, and Applications* (pp. 17–58). Springer-Verlag Berlin Heidelberg.

Barton, R. R. (2004). Designing Simulation Experiments . In R. G. Ingalls, M. D. Rossetti, J. S. Smith, & B. A. Peters (Eds.), *Proceedings of the 2004 Winter Simulation Conference* (pp. 73–79). University Park, USA.

Barton, R. R. (2013). Designing Simulation Experiment. In R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, & M. E. Kuhl (Eds.), *Proceedings of the 2013 Winter Simulation Conference* (pp. 342–353). University Park, USA: IEEE.

Barton, R. R. (2015). Tutorial: Simulation metamodeling. In L. Yilmaz, W. K. V. Chan, I. Moon, T. M. K. Roeder, C. Macal, & M. D. Rossetti (Eds.), *Proceedings of the 2015 Winter Simulation Conference* (pp. 1765–1779). University Park, USA: IEEE.

Batur, D., Bekki, J. M., & Chen, X. (2017). Quantile regression metamodeling: Toward improved responsiveness in the high-tech electronics manufacturing industry. *European Journal of Operational Research*, 1–13.

Boivie, F., & Hoglund, M. (2008). *Production system design and optimization*. Master's Thesis. Goteborg, Sweden: Chalmers University of Technolog, Division of Production System.

Bon, A. T., & Shahrin, N. N. (2016). Assembly Line Optimization using Arena Simulation. In *Proceedings of the 2016 International Conference on Industrial Engineering and Operations Management* (pp. 2225–2232). Kuala Lumpur, Malaysia: IEOM society international.

Bosilj-vuksic, V., Giaglis, G. M., & Hlupic, V. (2000). IDEF Diagrams and Petri Nets for Business Process Modeling : Suitability , Efficacy , and Complementary Use. Zagreb, Croatia.

Brahim, R., & Alain, D. (2006). *Assembly Line Design; The Balancing of Mixed-Model Hybrid Assembly lines with Genetic Algorithms*. (P. Prof. D.T, Ed.). London: Springer-Verlag London Limited.

Brailsford, S. C., Eldabi, T., Kunc, M., Mustafee, N., & Osorio, A. F. (2018). Hybrid simulation modelling in operational research : A state-of-the-art review. *European Journal of Operational Research*, *278*(3), 721–737.

Chen, J. C., Chen, C., Yuan, C., Li, C., Lin, Y., Lin, C., & Chen, T. Y. (2014). Assembly Line Balancing Problem of Sewing Lines in Garment Industry. In *International Conference on Industrial Engineering and Operations Management* (pp. 1215–1225). Bali, Indonesia.

Colovic, G. (2011). *Management of Technology Systems in Garment Industry*. New Delhi, India: Woodhead Publishing India Pvt. Ltd.

Colovic, G. (2012). *Strategic Management in the Garment Industry*. *Woodhead Publishing India Pvt Ltd*.

Currie, C. S. M., & Cheng, R. C. H. (2016). A Practical Introduction to Analysis of Simulation Output Data. In T. M. K. Roeder, P. I. Frazier, R. Szechtman, E. Zhou, T. Huschka, & S. E. Chick (Eds.), *Proceedings of the 2016 Winter Simulation Conference* (pp. 118–132). Southampton, UK: IEEE.

Curry, G. L., & Feldman, R. M. (2011). *Manufacturing Systems Modeling and Analysis* (2nd ed.). London/New York: Springer-Verlag Berlin Heidelberg.

Dang, Q. V., & Pham, K. (2016). Design of a Footwear Assembly Line Using Simulation-based ALNS. *Procedia CIRP*, *40*, 596–601.

Degan, R. J. (2011). *Fordism and Taylorism are responsible for the early success and recent decline of the U.S. motor vehicle industry* (Working paper No. 81/2011). *Glob Advantage: Center of research in international business & strategy*. Leiria, Portugal.

Dehghanimohammadabadi, M., Keyser, T. K., & Cheraghi, S. H. (2017). A novel Iterative Optimization-based Simulation (IOS) framework: An effective tool to optimize system's performance. *Computers & Industrial Engineering*, *111*, 1–17.

Eryuruk, S. H., Kalaoglu, F., & Baskak, M. (2008). Assembly line balancing in a clothing company. *Fibres and Textiles in Eastern Europe*, *16*(1), 93–98.

Eryuruk, Selin Hanife. (2012). Clothign Assembly line Design Using Simulation and Heuristic line Balancing Techniques. *Tekstil Ve Konfeksiyon*, *4*, 360–368.

Fan, J., & Hunter, L. (2009). *Engineering Apparel Fabrics and Garments*. Boca Raton, USA: Woodhead Publishing Limited and CRC Press LLC.

Gebrehiwet, T. B., & Odhuno, A. M. (2017). Improving the Productivity of the Sewing Section through Line Balancing Techniques: A Case Study of Almeda Garment Factory. *International Journal of Sciences: Basic and Applied Research (IJSBAR)*, *36*(1), 318–328.

Ghiasi, R., Ghasemi, M. R., & Noori, M. (2018). Comparative studies of metamodeling and AI-Based techniques in damage detection of structures. *Advances in Engineering Software*, 1–12.

Grzechca, W. (2016). Manufacturing in Flow Shop and Assembly Line Structure. *International Journal of Materials, Mechanics and Manufacturing*, *4*(1), 25–30.

Guimarães, A. M. C., Leal, J. E., & Mendes, P. (2018). Discrete-event simulation software selection for manufacturing based on the maturity model. *Computers in Industry*, *103*, 14–27.

Guner, M. G., & Unal, C. (2008). Line balancing in the apparel industry using simulation techniques. *Fibres and Textiles in Eastern Europe*, *16*(2), 75–78.

Hekmatpanah, M. (2011). The application of cause and effect diagram in the oil industry in Iran : The case of four liter oil canning process of Sepahan Oil Company. *African Journal of Business Management*, *5*(26), 10900–10907.

Hewitt, S. (2002). *Comparing Analytical and Discrete-Event Simulation Models of Manufacturing Systems*. Master's Thesis, University of Maryland.

Ibrahim, I. M., Liong, C.-Y., Bakar, S. A., Ahmad, N., & Najmuddin, A. F. (2017). Minimizing patient waiting time in emergency department of public hospital using simulation optimization approach. *AIP Conference Proceedings*, *1830*(060005), 1–8.

Jeong, H. H., Kyung-Min, S., & Kim, T. G. (2013). Simulation-based optimization for design parameter exploration in hybrid system: a defense system example. *Simulation: Transactions of the Society for Modeling and Simulation International*, 1–19.

Juan, E. L. D. (2016). *Simulation-Based Optimization for Production Planning: Integrating Meta-Heuristics, Simulation and Exact Techniques to Address the Uncertainty and Complexity of Manufacturing Systems*. D.Phil. Thesis: Alliance Manchester Business School.

Junior, W. T. D. S., Montevechia, J. A. B., Miranda, R. de C., & Campos, A. T. (2019). Discrete simulation-based optimization methods for industrial engineering problems: A systematic literature review. *Computers & Industrial Engineering*, *128*, 526–540.

Kandemir, C. (2016). *Improvement of Work Process Performance with Task Assignments and Mental Workload Balancing*. Old Dominion.

Kandemir, C., & Handley, H. A. H. (2018). Work process improvement through simulation optimization of task assignment and mental workload. *Computational and Mathematical Organization Theory*.

Karabay, G. (2014). A Comparative Study on Designing of a Clothing Assembly Line. *Tekstil Ve Konfeksiyon*, *24*(1), 124–133.

Karthik, T., Ganesan, P., & Gopalakrishnan, D. (2017). *Apparel Manufacturing Technology*. Boca Raton, USA: Taylor & Francis.

Kayar, M. (2014). Applying Different Heuristic Assembly Line Balancing Methods in the Apparel Industry and their Comparison. *Fibres and Textiles in Eastern Europe*, *22*(6(108)), 8–19.

Kelton, W. D., Sadowski, R. P., & Sturrock, D. T. (2007). *Simulation with Arena* (4th ed.). New York: McGraw-Hill.

Khatun, M. M. (2014). Effect of Time and Motion Study on Productivity in Garment Sector. *International Journal of Scientific & Engineering Research*, *5*(5), 825–833.

Kitaw, D., Matebu, A., & Tadesse, S. (2010). Assembly Line Balancing Using Simulation Technique in a Garment Manufacturing Firm. *Journal of EEA*, *27*, 69–80.

Kleijnen, J. P. C. (2008). *Design and Analysis of Simulation Experiments*. (H. Fred, Ed.). Tilburg, Netherlands: Springer Science+Business Media, LLC.

Kleijnen, J. P. C., & Wan, J. (2007). Optimization of simulated systems: OptQuest and alternatives. *Simulation Modelling Practice and Theory*, *15*(3), 354–362.

Kursun, S., & Kalaoglu, F. (2009). Simulation of production line balancing in apparel manufacturing. *Fibres and Textiles in Eastern Europe*, *17*(4(75)), 68–71.

Ky, V. K., Ambrosio, C. D., Hamadi, Y., & Liberti, L. (2016). Surrogate-based methods for black-box optimization. *International Transactions in Operational Research*, 1–

26.

Law, A. M. (2007). Statistical Analysis of simulation output data: The practical state of the Art. In S. G. Henderson, B. Biller, M.-H. Hsieh, J. Shortle, J. D. Tew, & R. R. Barton (Eds.), *Proceedings of the 2007 Winter Simulation Conference S.* (pp. 77–83). Tucson, USA: IEEE.

Lopetegui, M., Yen, P. Y., Lai, A., Jeffries, J., Embi, P., & Payne, P. (2014). Time motion studies in healthcare: What are we talking about? *Journal of Biomedical Informatics*, *49*, 292–299.

Manuela, Q., Laurindo, G., Peixoto, T. A., José, J., & Rangel, D. A. (2018). Communication mechanism of the discrete event simulation and the mechanical project softwares for manufacturing systems. *Journal of Computational Design and Engineering*, *6*, 70–80.

Marsudi, M., & Shafeek, H. (2013). Production Line Performance by Using Queuing Model. In *7th IFAC Conference on Manufacturing Modelling, Management, and Control* (Vol. 46, pp. 1152–1157). Saint Petersburg, Russia: IFAC.

Mcnamara, T. (2016). *A Brief Review of the Literature on Assembly Line Balancing as it Relates to the Apparel Industry*.

Michalos, G., Fysikopoulos, A., Makris, S., Mourtzis, D., & Chryssolouris, G. (2015). Multi criteria assembly line design and configuration – An automotive case study. *CIRP Journal of Manufacturing Science and Technology*, *9*, 69–87.

Montevechi, J. A. B., Miranda, R. de C., & Friend, J. D. (2012). Sensitivity Analysis in Discrete-Event Simulation Using Design of Experiments. In *Discrete Event Simulations – Development and Applications* (pp. 63–101). IntechOpen.

Montevechi, J. A. B., Pinho, A. F. de, Leal, F., & Marins, F. A. S. (2007). Application of Design of Experiments on the Simulation of a process in an Automotive Industry. In *Proceedings of the 2007 Winter Simulation Conference* (pp. 1601–1609). IEEE.

Ortiz, C. A. (2006). *Kaizen Assembly: Designing, Constructing, and Managing a Lean Assembly Line*. *Assembly Automation* (Vol. 27). Boca Raton: Taylor & Francis.

Østergård, T., Jensenb, R. L., & Maagaard, S. E. (2018). A comparison of six metamodeling techniques applied to building performance simulations. *Applied Energy*, *211*, 89–103.

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2019). Comparative study of metamodeling and sampling design for expensive and semi-expensive simulation models under uncertainty. *Simulation: Transactions of the Society for Modeling and Simulation International*, 1–22.

Prajapat, N., & Tiwari, A. (2017). A review of assembly optimisation applications using discrete event simulation. *International Journal of Computer Integrated Manufacturing*, *30*(2–3), 215–228.

Presley, A., & Liles, D. H. (1998). The Use of IDEF0 for the Design and Specification of Methodologies. University of Texas at Arlington.

Protopapadaki, C., & Saelens, D. (2019). Towards metamodeling the neighborhood-level grid impact of low-carbon technologies. *Energy & Buildings*, *194*, 273–288.

Puvanasvaran, A. P., Mei, C. Z., & Alagendran, V. A. (2013). Overall Equipment Efficiency Improvement Using Time Study in an Aerospace Industry. *Procedia Engineering*, *68*, 271–277.

Rajkishore, N., & Padhye, R. (2015). *Garment Manufacturing Technology*. Cambridge,UK: Elsevier Ltd.

Riley, L. A. (2013). Discrete-Event Simulation Optimization : A Review of Past Approaches and Propositions for Future Direction. In *Proceeding of 2013 Summer Computer Simulation Conference (Article No. 4, pp. 1-8)*. Toronto Ontario Canada: Society for Modeling & Simulation International.

Robinson, S. (2018). Introduction to Discrete-event Simulation: How it Works. In A. Anastasia, M. Rudabeh, F. Masoud, & R. Duncan (Eds.), *proceeding of 2018 the operation Research Society simulation workshop 2018 (SW18)* (pp. 13–28). Warwickshire: The Operational Research Society.

Rockwell Automation. (2009). *OptQuest for Arena User's Guide*. *ARENAO-UM001E-EN-P*. Rockwell Automation Technologies.

Russell, R. S., & Taylor, B. W. (2011). *Operations Management: Creating Value Along the Supply Chain* (7th ed.). US: John Wiley and Sons, Inc.

Sanchez, S. M., Sanchez, P. J., & Wan, H. (2014). Simulation Experiments : Better Insights by Design. In *Proceedings of the 2014 Winter Simulation Conference* (pp. 1–9). Monterey, USA: Calhoun.

Sanchez, S. M., & Wan, H. (2012). Work Smarter, Not Harder: A Tutorial on Designing and Conducting of Simulation Experiments. In C. Laroque, J. Himmelspach, R. Pasupathy, O. Rose, & A. M. Uhrmacher (Eds.), *Proceedings of the 2012 Winter Simulation Conference* (pp. 1929–1943). Monterey, USA: IEEE.

Sarhangian, V., Vaghefi, A., Eskandari, H., & Ardakani, M. K. (2008). Optimizing inspection strategies for multi-stage manufacturing processes using simulation optimization. In S. J. Mason, R. R. Hill, L. Monch, O. Rose, T. Jefferson, & J. W. Fowler (Eds.), *Proceedings of the 2008 Winter Simulation Conference* (pp. 1974–1980). Tehran, IRAN: IEEE.

Senthilraja, V., Aravindan, P., & Sathesh, kumar A. (2018). Man Power Productivity Improvement through Operator Engagement Time Study. In *1st International Conference on Recent Research in Engineering and Technology 2018* (Vol. 4, pp. 1052–1065). Tamil Nadu, India: Exporations on Engineering Letters.

Shakibayifar, M., Sheikholeslami, A., & Corman, F. (2018). A simulation-based optimization approach to rescheduling train traffic in uncertain conditions during disruptions. *Scientia Iranica*, *25*(2), 646–662.

Shaw, I. F. (2003). Ethics in Qualitative Research and Evaluation. *Journal of Social Work*, *3*(1), 9–29.

Shumon, R. H., Arif-uz-zaman, K., & Rahman, A. (2010). Productivity Improvement through Line Balancing in Apparel Industries. In *Proceedings of the 2010 International Conference on Industrial Engineering and Operations Management* (pp. 100–110). Dhaka, Bangladesh.

Sibanda, W., & Pretorius, P. (2011). Application of Two-level Fractional Factorial Design to Determine and Optimize the Effect of Demographic Characteristics on HIV Prevalence using the 2006 South African Annual Antenatal HIV and Syphilis Seroprevalence data. *International Journal of Computer Applications*, *35*(12), 15–20.

Silva, M. (2018). On the history of Discrete Event Systems. *Annual Reviews in Control*, 1–10.

Sime, H., Jana, P., & Panghal, D. (2019). Feasibility of Using Simulation Technique for Line Balancing In Apparel Industry. *Procedia Manufacturing*, *30*, 300–307.

Song, W., Han, K., Wang, Y., Friesz, T. L., & Castillo, E. del. (2017). Statistical metamodeling of dynamic network loading. *Transportation Research Part B*, 1–17.

Starovoytova, D. (2017). Time study of Rotary Screen Printing Operation. *Industrial Engineering Letters*, *07*(04), 24–35.

Sudarshan, B., & Rao, D. N. (2014). Productivity improvement through modular line in Garment industries. In *5th International & 26th All India Manufacturing Technology, Design and Research Conference (AIMTDR)* (pp. 1–6). Assam, India.

Tewoldeberhan, T. W., Alexander, V., Valentin, E., & Gilles, B. (2002). An Evaluation and Selection Methodology for Discrete-event Simulation Software. In E. Yücesan, C.-H. Chen, J. L. Snowdon, & J. M. Charnes (Eds.), *Proceeding of the 2002 Winter simulation conference* (pp. 67–75). Delft, Netherlands.

Thomopoulos, N. T. (2014). *Assembly Line Planning and Control*. Springer Cham Heidelberg New York Dordrecht London: Springer International Publishing Switzerland.

Torenli, A. (2009). *Assembly line design and optimization*. Master thesis. Goteborg, Sweden: Chalmers University of technology, Division of Production Systems.

Uddin, M. M. (2015). *Productivity Improvement of Cutting, Sewing and Finishing Sections of a Garment Factory Through Value Stream Mapping – a Case Study*. Master Thesis, Dhaka: Bangladesh University of Engineering and Technology, Department of industrial and production engineering.

Vinod, K. T., Prabagaran, S., & Joseph, O. A. (2018). Simulation modeling and analysis of job release policies in scheduling an agile job shop with process sequence dependent setting time. *International Journal of Engineering & Technology*, *7*(1.1), 177–183.

Wickramasekara, A. N., & Perera, H. S. C. (2016). An Improved Approach to Line Balancing for Garment Manufacturing. *Vjm*, *02*(1), 23–40.

Xu, Y., Thomassey, S., & Zeng, X. (2017). Comprehensive evaluation of garment assembly line with simulation. *IOP Conference Series: Materials Science and Engineering*, *254*(162013), 1–6.

Yegul, M. F., Erenay, F. S., Striepe, S., & Yavuz, M. (2017). Improving configuration of complex production lines via simulation-based optimization. *Computers and Industrial Engineering*, *109*, 295–312.

Yemane, A., Haque, S., & Malfanti, I. (2017). Optimal Layout Design by Line Balancing Using Simulation Modeling. In *Proceedings of the International Conference on*

Industrial Engineering and Operations Management (pp. 228–245). Bogotá, Colombia: IEOM society international.

APPENDICES

Appendix A. Fitted processing time probability distribution for 25 bundle size

Sequence	Operations description	Resource type	Resource number	Processing time distribution (for a one resource)	Bundle size
1	Left flybox pressing	Iron press	1shared	TRIA (3, 5.12, 5.9)	25
2	Buttonhole on Left flybox	BH	1	6.05 + ERLA (0.39, 6)	25
3	Left front rise overlock	3thread O/L	1	4 + 6.88 * BETA (1.95, 3.37)	25
4	Right front rise overlocks			2.29 + ERLA (0.239, 5)	25
5	Knee patch attach	S/NL	3	20 + 21 * BETA (0.856, 1.33)	25
6	Side pocket flatlock	F/L	2	4 + 4 * BETA (1.94, 2.74)	25
7	Side pocket overlocks	5thread O/L	1	2 + ERLA (0.555, 2)	25
8	Right flybox overlock			1.6 + LOGN (0.719, 0.418)	
9	Side pocket attach	S/NL	2	7 + 11 * BETA (1.67, 1.67)	25
10	Side pocket topstitch	S/NL	2	10 + GAMM (1.44, 2.7)	25
11	Right flybox attach	S/NL	2	TRIA (13, 20.7, 25)	25
12	Left fly box tacking	S/NL	2	9 + WEIB (3.39, 2.09)	25
13	Fly attach	S/NL	2	12.1 + GAMM (0.955, 3.94)	25
14	Front prep bundling	Helper	1	5 + 10 * BETA (1.27, 2.07)	25
15	Back marking	Helper	1	3 + 4.65 * BETA (1.55, 2.76)	25
16	Back patch pressing	Iron press	1shared	TRIA (3, 8.29, 9.73)	25
17	Back patch attach	S/NL	2	10 + 11 * BETA (0.737, 0.96)	25
18	Hip pocket cutting	AWM	1	TRIA (3.17, 3.99, 7)	25
19	Hip pocket overlocks	5t O/L	1	5 + 3.83 * BETA (2.14, 3.14)	25
20	Hip flap folding	Helper	1	NORM (4.77, 0.65)	
21	Button Hole on hip flap	BH	1	3.55 + GAMM (0.194, 5.47)	25
22	Hip flap runstitch	S/NL	1	3 + LOGN (2.72, 1.83)	25
23	Hip flap turning	TM	1	NORM (3.25, 0.551)	25
24	Hip flap topstitches	S/NL	1	3 + 5 * BETA (1.7, 1.88)	25
25	Hip flap attach	S/NL	2	5.45 + LOGN (1.44, 0.936)	25
26	Hip pocket finish			19 + 10 * BETA (1.46, 1.46)	
27	Back prep bundling	Helper	1	3 + 2 * BETA (0.889, 0.968)	25
28	Front and back bundling	Helper	1	2 + 6.86 * BETA (1.18, 2.11)	25
29	Side seam overlock	5thread O/L	2	NORM (1.21, 0.115)	Not bundled
30	Side seam topstitch	F/A	2	TRIA (0.52, 0.747, 0.94)	Not bundled
31	Knee pocket point marking	Helper	1	0.32 + 0.57 * BETA (0.889, 1.18)	Not bundled
32	Knee pocket topstitch	S/NL	2	11 + ERLA (1.89, 2)	25
33	Knee pocket tacking	S/NL	1	4 + 3 * BETA (1.33, 1.75)	25
34	Knee pocket Overlock	5thread O/L	1	2 + 4 * BETA (0.831, 2.05)	25
35	Knee pocket hemming	S/NL	1	2 + 4 * BETA (1.41, 1.13)	25

36	Knee pocket ironing	Iron press	2	8 + 5.78 * BETA (0.957, 1.06)	25
37	Knee pocket attach	S/NL	2	0.88 + 0.92 * BETA (1.77, 1.96)	25
38	Knee flap folding	Helper	1	3.63 + 3.13 * BETA (3.89, 2.38)	25
39	Button hole on knee flap	BH	1	4.27 + WEIB (1.21, 1.99)	25
40	Knee flap runstitch	S/NL	1	TRIA (2.37, 3.81, 6.88)	25
41	Knee flap turning	TM	1	NORM (4.02, 1.01)	25
42	Knee flap topstitch	S/NL	1	4 + 5.78 * BETA (0.903, 2.11)	25
43	Knee flap attach	D/NL	2	TRIA (0.67, 1.04, 1.7)	25
44	Bar tacking	BT	2	NORM (1.25, 0.266)	25
45	Back rise overlocks	5thread O/L	1	0.26 + LOGN (0.185, 0.0881)	25
46	Back rise Topstitch	D/NL	1	NORM (0.439, 0.0494)	25
47	Big loop matching	Helper	1	NORM (0.0663, 0.018)	25
48	Big loop runstitch	S/NL	3	0.12 + 0.3 * BETA (2.89, 5.28)	25
49	Big loop turning	Helper	2	0.07 + GAMM (0.0143, 7.47)	25
50	Big loop runstitch	S/NL	2	0.09 + 0.19 * BETA (1.78, 2)	25
51	Big loop button hole	BH	1	TRIA (0.04, 0.055, 0.11)	25
52	Small loop runstitch	LM	1	TRIA (0.11, 0.134, 0.18)	Not bundled
53	Small loop, big loop and waistband attach	S/NL	3	1.58 + ERLA (0.068, 7)	Not bundled
54	Waistband topstitch	S/NL	2	TRIA (0.73, 1.34, 1.5)	Not bundled
55	Waist band closing with size and label tags	S/NL	2	0.77 + GAMM (0.0607, 3.58)	Not bundled
56	Inseam Overlock	5thread O/L	2	0.49 + WEIB (0.483, 6.16)	Not bundled
57	Trouser turning	Helper	1	0.2 + LOGN (0.218, 0.112)	Not bundled
58	Inseam topstitch	F/A	2	0.32 + 0.56 * BETA (1.98, 1.61)	Not Bundled
59	Button hole on Hip band	BH	1	TRIA (0.31, 0.344, 0.47)	Not bundled
60	Button hole on the bottom leg	BH	1	0.32 + 0.2 * BETA (2.7, 3.33)	Not bundled
61	Bottom rope attach	Helper	1	0.5 + LOGN (0.251, 0.168)	Not bundled
62	Bottom hemming	S/NL	2	0.71 + 0.73 * BETA (2.04, 2.6)	Not bundled
63	Small loop tacking	S/NL	2	TRIA (0.82, 1.17, 1.37)	Not bundled
64	Final Bar tacking	BT	2	TRIA (0.74, 0.851, 1.05)	Not bundled
65	Adjustable rope cutting	Helper	1	TRIA (0.1, 0.145, 0.19)	Not bundled
66	Adjustable hemming	S/NL	1	TRIA (0.1, 0.136, 0.2)	Not bundled
67	1st adjustable rope attach	S/NL	1	NORM (0.75, 0.0479)	Not bundled
68	2nd adjustable rope attach	S/NL	1	0.53 + 0.32 * BETA (3.19, 2.1)	Not bundled
69	Button point marking	Helper	1	0.55 + GAMM (0.0328, 6.16)	Not bundled
70	Trimming	Helper	7	NORM (4.84, 0.345)	Not bundled
71	Quality checking	Quality personnel	2	0.82 + LOGN (0.332, 0.154)	Not bundled
72	Rework	S/NL	1	TRIA (2, 3.5, 4.7)	Not bundled

BH=button hole machine, SN/L=single needle lockstitch machine, DN/L=double needle lockstitch machine, BT= Bartack machine, O/L= overlock machine, TM= Turning machine, LM= loop stitching machine, F/A= Feed of arm machine, F/L=Flatlock machine, AWM= automatic wallet machine

Appendix B. Fitted Processing time probability distribution for 10 bundle size

Sequence	Operations description	Resource type	Resource number	Processing time distribution (for one resource)	Bundle size
1	Left flybox pressing	Iron press	1shared	1.18 + 1.18 * BETA (3.53, 2.6)	10
2	Buttonhole on Left flybox	BH	1	2.42 + WEIB (1.06, 2.57)	10
3	Left front rise overlock	3thread O/L	1	1.35 + GAMM (0.229, 5.48)	10
4	Right front rise overlocks			NORM (1.39, 0.201)	10
5	Knee patch attach	S/NL	3	8 + 9 * BETA (1.07, 1.82) TRIA (8, 8.19, 10)	10
6	Side pocket flatlock	F/L	2	1.56 + 1.68 * BETA (2.09, 2.94)	
7	Side pocket overlocks	5thread O/L	1	0.68 + LOGN (0.567, 0.307)	10
8	Right flybox overlock			0.63 + LOGN (0.296, 0.163)	10
9	Side pocket attach	S/NL	2	3 + 4.61 * BETA (1.6, 2.09)	10
10	Side pocket topstitch	S/NL	2	4 + GAMM (0.576, 2.7) NORM (5.31, 0.593)	10
11	Right flybox attach	S/NL	2	TRIA (5, 8.21, 10)	10
12	Left fly box tacking	S/NL	2	3.41 + ERLA (0.279, 5)	10
13	Fly attach	S/NL	2	5 + WEIB (1.49, 1.9)	10
14	Front prep bundling	Helper	1	2 + 4 * BETA (1.27, 2.07)	10
15	Back marking	Helper	1	1.14 + 1.86 * BETA (1.64, 2.63)	10
16	Back patch pressing	Iron press	1shared	TRIA (1.15, 3.3, 3.89)	10
17	Back patch attach	S/NL	2	4 + 4.73 * BETA (0.829, 1.22)	10
18	Hip pocket cutting	AWM	1	TRIA (1.26, 1.6, 2.83)	10
19	Hip pocket overlocks	5thread O/L	1	2 + 1.53 * BETA (2.01, 2.98)	10
20	Hip flap folding	Helper	1	NORM (1.91, 0.26)	10
21	Button Hole on hip flap	BH	1	1.42 + GAMM (0.0777, 5.47)	10
22	Hip flap runstitch	S/NL	1	1.14 + LOGN (1.14, 0.698)	10
23	Hip flap turning	TM	1	NORM (1.3, 0.22)	10
24	Hip flap topstitches	S/NL	1	TRIA (1.01, 2.15, 3.29)	10
25	Hip flap attaches &	S/NL	2	2.17 + LOGN (0.584, 0.37)	10
26	Hip pocket finish			TRIA (7.7, 8.82, 10)	10
27	Back prep bundling	Helper	1	TRIA (1.11, 1.56, 2)	10
28	Front and back bundling	Helper	1	0.64 + 2.91 * BETA (1.57, 2.43)	10
29	Side seam overlock	5thread O/L	2	NORM (1.21, 0.115)	Not bundled
30	Side seam topstitch	F/A	2	TRIA (0.52, 0.747, 0.94)	Not bundled
31	Knee pocket point marking	Helper	1	0.32 + 0.57 * BETA (0.889, 1.18)	Not bundled
32	Knee pocket topstitch	S/NL	2	4.16 + ERLA (0.584, 3) 4.29 + 1.32 * BETA (1.31, 1.59)	10
33	Knee pocket tacking	S/NL	1	1.48 + 1.44 * BETA (2.45, 3.05)	10
34	Knee pocket Overlock	5t O/L	1	0.65 + 1.8 * BETA (1.48, 2.88)	10
35	Knee pocket hemming	S/NL	1	TRIA (0.75, 1.91, 2.55)	10
36	Knee pocket ironing	Iron	2	TRIA (3, 4.97, 5.51)	10
37	Knee pocket attach	S/NL	2	0.88 + 0.92 * BETA (1.77, 1.96)	Not bundled
38	Knee flap folding	Helper	1	1.45 + 1.26 * BETA (3.95, 2.44)	10

39	Button hole on knee flap	BH	1	1.71 + WEIB (0.482, 1.98)	10
40	Knee flap runstitch	S/N	1	TRIA (1, 1.38, 2.75)	10
41	Knee flap turning	TM	1	NORM (1.61, 0.406)	10
42	Knee flap topstitch	S/NL	1	1.39 + LOGN (0.915, 0.627)	10
43	Knee flap attach	D/NL	2	TRIA (0.67, 1.04, 1.7)	Not bundled
44	Bar tacking	BT	2	NORM (1.25, 0.266)	Not bundled
45	Back rise overlocks	5t O/L	1	0.26 + LOGN (0.185, 0.0881)	Not bundled
46	Back rise Topstitch	D/NL	1	NORM (0.439, 0.0494)	Not bundled
47	Big loop matching	Helper	1	NORM (0.0663, 0.018)	Not bundled
48	Big loop runstitch	S/NL	3	0.12 + 0.3 * BETA (2.89, 5.28)	Not bundled
49	Big loop turning	Helper	2	0.07 + GAMM (0.0143, 7.47)	Not bundled
50	Big loop runstitch	S/NL	2	0.09 + 0.19 * BETA (1.78, 2)	Not bundled
51	Big loop button hole	BH	1	TRIA (0.04, 0.055, 0.11)	Not bundled
52	Small loop runstitch	LM	1	TRIA (0.11, 0.134, 0.18)	Not bundled
53	Small loop, big loop and waistband attach	S/NL	3	1.58 + ERLA (0.068, 7)	Not bundled
54	Waistband topstitch	S/NL	2	TRIA (0.73, 1.34, 1.5)	Not bundled
55	Waist band closing with size and label tags	S/NL	2	0.77 + GAMM (0.0607, 3.58)	Not bundled
56	Inseam Overlock	5thread O/L	2	0.49 + WEIB (0.483, 6.16)	Not bundled
57	Trouser turning	Helper	1	0.2 + LOGN (0.218, 0.112)	Not bundled
58	Inseam topstitch	F/A	2	0.32 + 0.56 * BETA (1.98, 1.61)	Not Bundled
59	Button hole on Hip band	BH	1	TRIA (0.31, 0.344, 0.47)	Not bundled
60	Button hole on the bottom leg	BH	1	0.32 + 0.2 * BETA (2.7, 3.33)	Not bundled
61	Bottom rope attach	Helper	1	0.5 + LOGN (0.251, 0.168)	Not bundled
62	Bottom hemming	S/NL	2	0.71 + 0.73 * BETA (2.04, 2.6)	Not bundled
63	Small loop tacking	S/NL	2	TRIA (0.82, 1.17, 1.37)	Not bundled
64	Final Bar tacking	BT	2	TRIA (0.74, 0.851, 1.05)	Not bundled
65	Adjustable rope cutting	Helper	1	TRIA (0.1, 0.145, 0.19)	Not bundled
66	Adjustable hemming	S/NL	1	TRIA (0.1, 0.136, 0.2)	Not bundled
67	1st adjustable rope attach	S/NL	1	NORM (0.75, 0.0479)	Not bundled
68	2nd adjustable rope attach	S/NL	1	0.53 + 0.32 * BETA (3.19, 2.1)	Not bundled
69	Button point marking	Helper	1	0.55 + GAMM (0.0328, 6.16)	Not bundled
70	Trimming	Helper	7	NORM (4.84, 0.345)	Not bundled
71	Quality checking	Quality personnel	2	0.82 + LOGN (0.332, 0.154)	Not bundled
72	Rework	S/NL	1	TRIA (2, 3.5, 4.7)	Not bundled

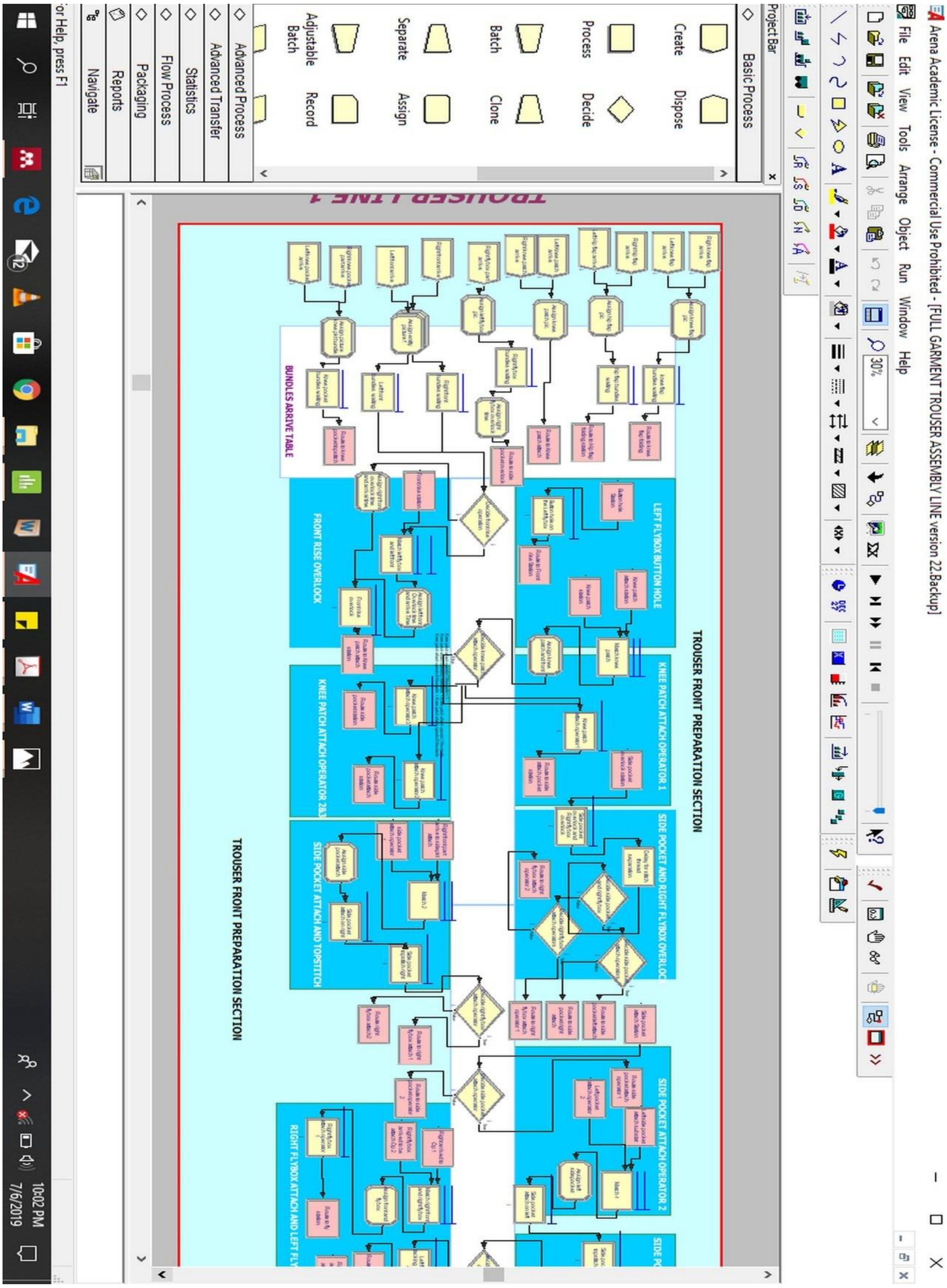
Appendix C. Fitted processing time probability distribution for 40 bundle size

Sequence	Operations description	Resource type	Resource number	Processing time distribution (for one resource)	Bundle size
1	Left flybox pressing	Iron press	1shared	TRIA (5, 8, 9.44)	40
2	Buttonhole on Left flybox	BH	1	10 + WEIB (3.87, 2.34)	40
3	Left front rise overlock	3 thread O/L	1	NORM (10.4, 2.09)	40
4	Right front rise overlocks			NORM (5.58, 0.805)	40
5	Knee patch attach	S/NL	3	32 + 34 * BETA (0.868, 1.4)	40
6	Side pocket flatlock	S/NL	2	6.24 + 6.72 * BETA (2.09, 2.94)	40
7	Side pocket overlocks	5thread O/L	1	3 + LOGN (2.03, 1.45)	40
8	Right flybox overlock			2.55 + LOGN (1.16, 0.664)	40
9	Side pocket attach	S/NL	2	12 + 17 * BETA (1.43, 1.61)	40
10	Side pocket topstitch	S/NL	2	17 + ERLA (2.61, 2)	40
11	Right flybox attach	S/NL	2	TRIA (20, 32.9, 40)	40
12	Left fly box tacking	S/NL	2	NORM (19.2, 2.39)	40
13	Fly attach	S/NL	2	20 + WEIB (5.97, 1.9)	40
14	Front prep bundling	Helper	1	8 + 15 * BETA (1.11, 1.67)	40
15	Back marking	Helper	1	5 + 7 * BETA (1.2, 2.26)	40
16	Back patch pressing	Iron press	1shared	5 + 10 * BETA (1.31, 1.07)	40
17	Back patch attach	S/NL	2	16 + 18 * BETA (0.766, 1.04)	40
18	Hip pocket cutting	AWM	1	5.07 + ERLA (0.937, 3)	40
19	Hip pocket overlocks	5t O/L	1	8 + 6 * BETA (1.97, 2.83)	40
20	Hip flap folding	Helper	1	NORM (7.63, 1.04)	40
21	Button Hole on hip flap	BH	1	NORM (7.38, 0.687)	40
22	Hip flap runstitch	S/NL	1	5 + LOGN (4.18, 3.1)	40
23	Hip flap turning	TM	1	NORM (5.19, 0.881)	40
24	Hip flap topstitches	S/NL	1	4.04 + 8.96 * BETA (2.41, 2.34)	40
25	Hip flap attach	S/NL	2	9 + LOGN (2.07, 1.77)	40
26	Hip pocket finish			NORM (41.9, 5.51)	40
27	Back prep bundling	Helper	1	TRIA (4.47, 6.24, 8)	40
28	Front and back bundling	Helper	1	3 + 11 * BETA (1.28, 2.11)	40
29	Side seam overlock	5thread O/L	2	NORM (1.21, 0.115)	Not bundled
30	Side seam topstitch	F/A	2	TRIA (0.52, 0.747, 0.94)	Not bundled
31	Knee pocket point marking	Helper	1	0.32 + 0.57 * BETA (0.889, 1.18)	Not bundled
32	Knee pocket topstitch	S/NL	2	18 + 16 * BETA (1.07, 1.96)	40
33	Knee pocket tacking	S/NL	1	TRIA (6, 7.22, 11.7)	40
34	Knee pocket Overlock	5thread O/L	1	3 + ERLA (1.02, 2)	40
35	Knee pocket hemming	S/NL	1	TRIA (3, 7.5, 10)	40
36	Knee pocket ironing	Iron press	2	12 + 10 * BETA (1.31, 1.22)	40
37	Knee pocket attach	S/NL	2	0.88 + 0.92 * BETA (1.77, 1.96)	Not bundled
38	Knee flap folding	Helper	1	6 + 4.82 * BETA (3.53, 2.31)	40
39	Button hole on knee flap	BH	1	7 + WEIB (1.73, 1.74)	40

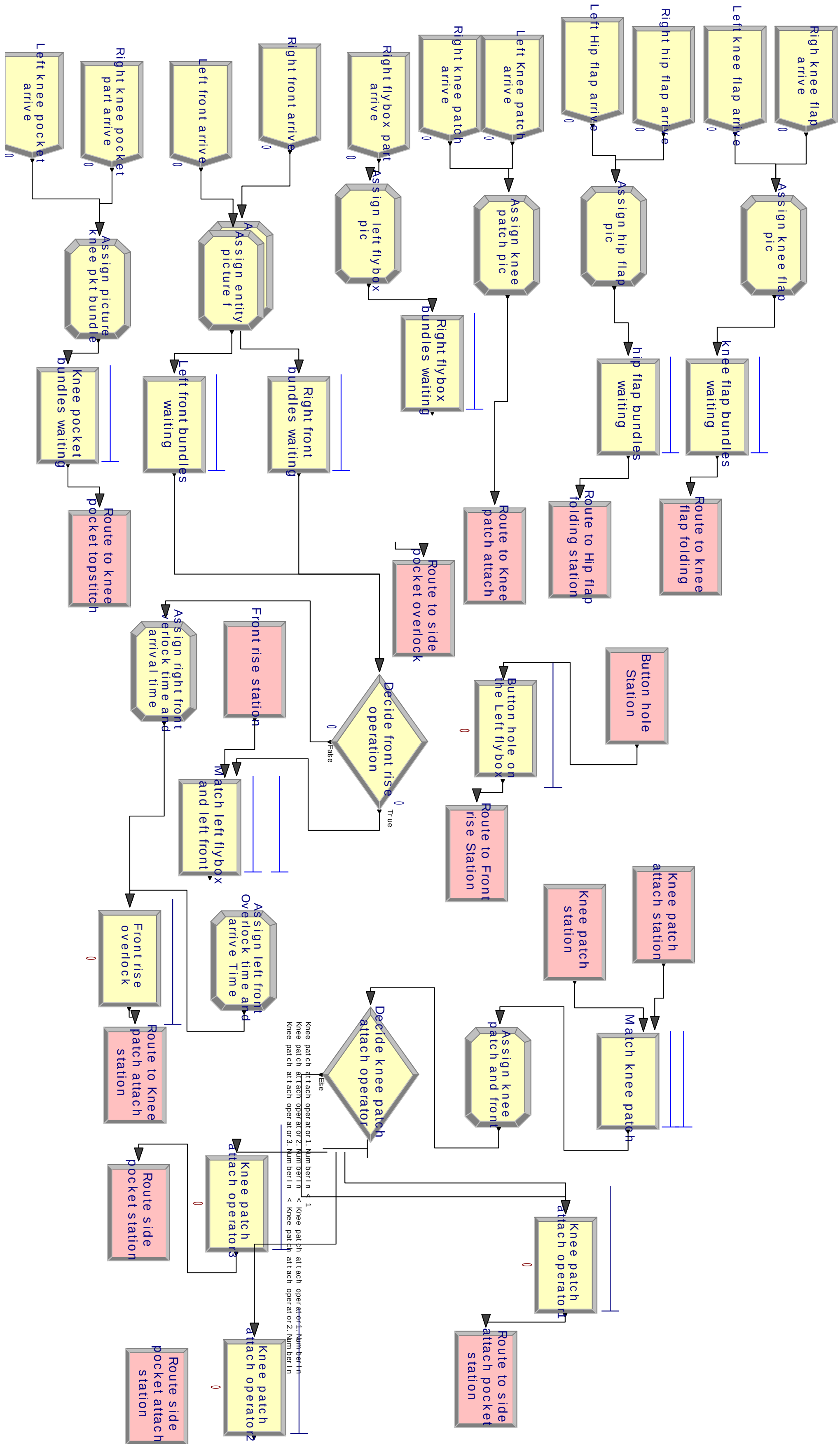
40	Knee flap runstitch	S/NL	1	TRIA (4, 5.5, 11)	40
41	Knee flap turning	TM	1	3 + WEIB (3.87, 2.24)	40
42	Knee flap topstitch	S/NL	1	6 + ERLA (1.58, 2)	40
43	Knee flap attach	D/NL	2	TRIA (0.67, 1.04, 1.7)	Not bundled
44	Bar tacking	BT	2	NORM (1.25, 0.266)	Not bundled
45	Back rise overlocks	5thread O/L	1	0.26 + LOGN (0.185, 0.0881)	Not bundled
46	Back rise Topstitch	D/NL	1	NORM (0.439, 0.0494)	Not bundled
47	Big loop matching	Helper	1	NORM (0.0663, 0.018)	Not bundled
48	Big loop runstitch	S/NL	3	0.12 + 0.3 * BETA (2.89, 5.28)	Not bundled
49	Big loop turning	Helper	2	0.07 + GAMM (0.0143, 7.47)	Not bundled
50	Big loop runstitch	S/NL	2	0.09 + 0.19 * BETA (1.78, 2)	Not bundled
51	Big loop button hole	BH	1	TRIA (0.04, 0.055, 0.11)	Not bundled
52	Small loop runstitch	LM	1	TRIA (0.11, 0.134, 0.18)	Not bundled
53	Small loop, big loop and waistband attach	S/NL	3	1.58 + ERLA (0.068, 7)	Not bundled
54	Waistband topstitch	S/NL	2	TRIA (0.73, 1.34, 1.5)	Not bundled
55	Waist band closing with size and label tags	S/NL	2	0.77 + GAMM (0.0607, 3.58)	Not bundled
56	Inseam Overlock	5thread O/L	2	0.49 + WEIB (0.483, 6.16)	Not bundled
57	Trouser turning	Helper	1	0.2 + LOGN (0.218, 0.112)	Not bundled
58	Inseam topstitch	F/A	2	0.32 + 0.56 * BETA (1.98, 1.61)	Not Bundled
59	Button hole on Hip band	BH	1	TRIA (0.31, 0.344, 0.47)	Not bundled
60	Button hole on the bottom leg	BH	1	0.32 + 0.2 * BETA (2.7, 3.33)	Not bundled
61	Bottom rope attach	Helper	1	0.5 + LOGN (0.251, 0.168)	Not bundled
62	Bottom hemming	S/NL	2	0.71 + 0.73 * BETA (2.04, 2.6)	Not bundled
63	Small loop tacking	S/NL	2	TRIA (0.82, 1.17, 1.37)	Not bundled
64	Final Bar tacking	BT	2	TRIA (0.74, 0.851, 1.05)	Not bundled
65	Adjustable rope cutting	Helper	1	TRIA (0.1, 0.145, 0.19)	Not bundled
66	Adjustable hemming	S/NL	1	TRIA (0.1, 0.136, 0.2)	Not bundled
67	1st adjustable rope attach	S/NL	1	NORM (0.75, 0.0479)	Not bundled
68	2nd adjustable rope attach	S/NL	1	0.53 + 0.32 * BETA (3.19, 2.1)	Not bundled
69	Button point marking	Helper	1	0.55 + GAMM (0.0328, 6.16)	Not bundled
70	Trimming	Helper	7	NORM (4.84, 0.345)	Not bundled
71	Quality checking	Quality personnel	2	0.82 + LOGN (0.332, 0.154)	Not bundled
72	Rework	S/NL	1	TRIA (2, 3.5, 4.7)	Not bundled

Appendix D. Trouser assembly line model development using Arena

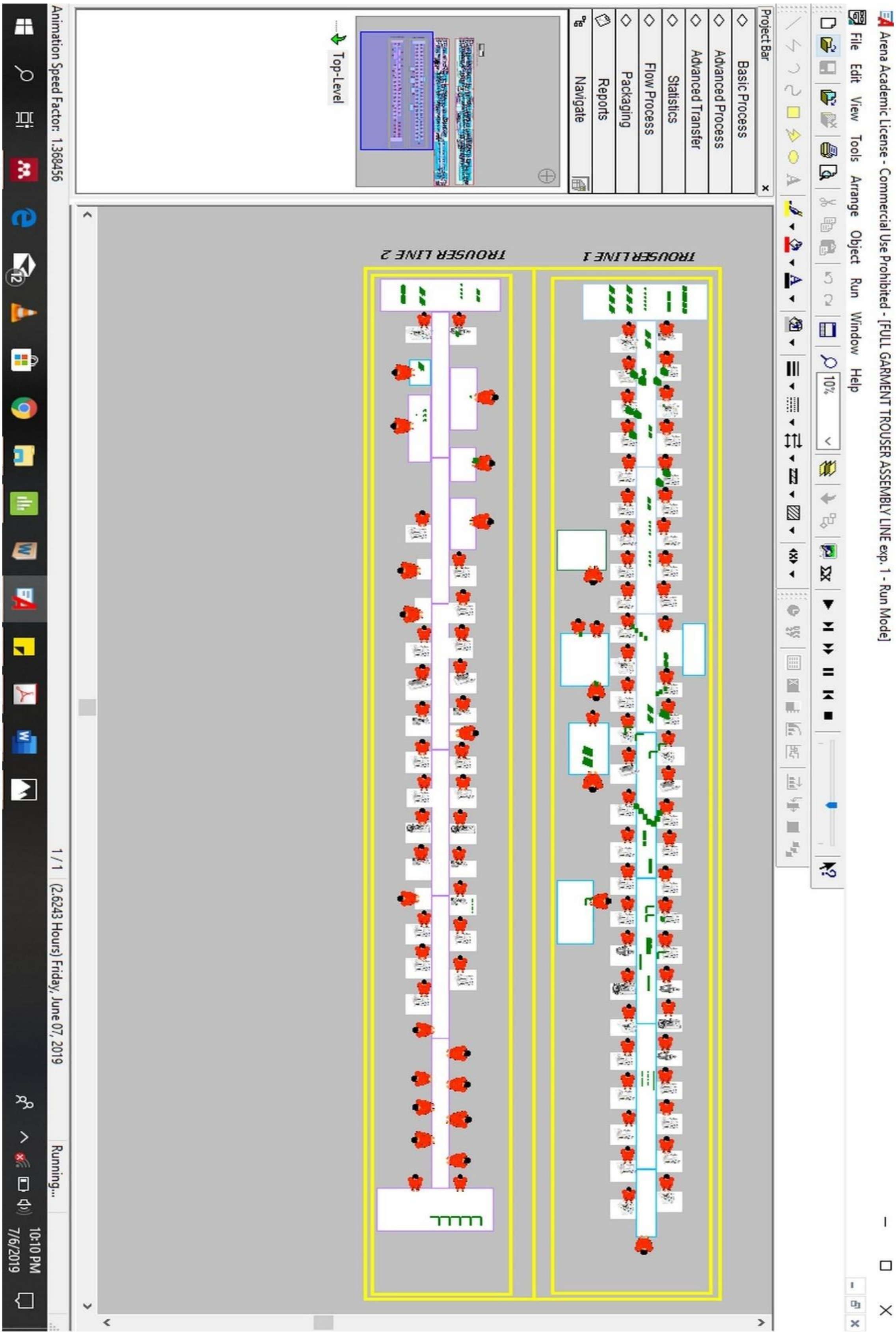
Arena software user interface showing the different modules used for building the trouser assembly line simulation model



A section of arena simulation model of trouser assembly line



Animation of trouser assembly line simulation model



Appendix E. Trouser Assembly line production data

Throughput data set 1		
s/n	**Date**	Throughput (pieces per day)
1	9/10/2018	301
2	10/10/2018	390
3	11/10/2018	395
4	12/10/2018	605
5	13/10/2018	603
6	16/10/2018	130
7	17/10/2018	601
8	19/10/2018	515
9	20/10/2018	495
10	22/10/2018	315
11	25/10/2018	525
12	26/10/2018	531
13	27/10/2018	485
14	29/10/2018	447
15	30/10/2018	276

Throughput data set 2		
s/n	Date	Throughput (pieces per day)
1	26/03/2019	239
2	27/03/2019	570
3	28/03/2019	430
4	29/03/2019	580
5	30/03/2019	600
6	01/04/2019	570
7	02/04/2019	464
8	03/04/2019	440
9	04/04/2019	306
10	05/04/2019	544
11	06/04/2019	347
12	09/04/2019	350
13	10/04/2019	600
14	11/04/2019	650
15	12/04/2019	580
16	13/04/2019	600
17	14/04/2019	224
18	15/04/2019	468
19	17/04/2019	145
20	18/04/2019	512
21	19/04/2019	500
22	20/04/2019	512
23	23/04/2019	552
24	24/04/2019	650

Cutting section trouser parts feeding sheet….					
Date	S/N	Bundle number	Trouser size	Quantity	Total
29/03/2019	1	233		25	
		234		25	
		235		25	
		236		25	
		237	L1	25	
		238		25	
		239		25	

		240		25	
					200
	2	241		25	
		242		25	
		243		25	
		244	L2	25	
		245		25	
		246		25	
		247		25	
		248		25	
					200
	3	249		25	
		250		25	
		251		25	
		252		25	
		253	XL1	25	
		254		25	
		255		25	
		256		25	
					200
	4	257		25	
		258		25	
		259		25	
		260	XL2	25	
		261		25	
		262		25	
		263		25	
		264		25	
					200 = **800**

Cutting section trouser parts feeding sheet					
Date	S/N	Bundle size	Trouser size	Quantity	Total
10.04.2019	16	281		25	
		282		25	
		283		25	
		284	S1	25	
		285		25	
		286		25	
		287		27	
		288		28	
					205
	17.	289		25	
		290		25	
		291	S2	25	
		292		25	
		293		25	
		294		25	
		295		27	
		296		28	
					205
	18.	297		25	
		298		25	
		299		25	
		300	S	25	
		301		25	
		302		25	
		303		27	
		304		28	
					205

	19.	305		25	
		306		25	
		307		25	
		308	2XL	25	
		309		25	
		310		25	
		311		27	
		312		28	
					205 = **820**

Appendix F. Detail comparison of the three designs based on resource number

WSN	OPS	Operations description	Resource			
			Type	Number		
				Base model design	***Metamodel design***	***Optimal design***
1-**B**	1	Left flybox pressing	Iron press	1shared	1	1
2	2	Buttonhole on Left flybox	Buttonhole machine	1	1	1
3	3	Left front rise overlock	3 threads overlock	1	1	1
	4	Right front rise overlocks				
4-**B**	5	Knee patch attach	Single needle lockstitch	3	4	4
5	6	Side pocket flatlock	Flatlock machine	1	1	1
6	7	Side pocket overlocks	5 threads overlock	1	1	1
	8	Right flybox overlock				
7-**B**	9	Side pocket attach	Single needle lockstitch	2	2	3
8	10	Side pocket topstitch	Single needle lockstitch	2	2	2
9	11	Right flybox attach	Single needle lockstitch	2	2	2
10	12	Left fly box tacking	Single needle lockstitch	2	2	2
11	13	Fly attach	Single needle lockstitch	2	2	2
12	14	Front prep bundling	Helper	1	1	1
13	15	Back marking	Helper	1	1	1
14-**B**	16	Back patch pressing	Iron press	1shared	1	1
15	17	Back patch attach	Single needle lockstitch	2	2	2
16	18	Hip pocket cutting	Automatic wallet machine	1	1	1
17	19	Hip pocket overlocks	5 threads overlock	1	1	1
18	20	Hip flap folding	Helper	1	1	1
19	21	Button Hole on hip flap	Button hole machine	1	1	1
20	22	Hip flap runstitch	Single needle lockstitch	1	1	1
21	23	Hip flap turning	Turning machine	1	1	1
22	24	Hip flap topstitches	Single needle lockstitch	1	1	1
23-**B**	25	Hip flap attaches &	Single needle lockstitch	2	3	3
	26	Hip pocket finish				
25	27	Back prep bundling	Helper	1	1	1
26	28	Front and back bundling	Helper	1	1	1
27-**B**	29	Side seam overlock	5 threads overlock	2	2	3
28	30	Side seam topstitch	Feed of Arm	2	2	2
29-**B**	31	Knee pocket point marking	Helper	1	1	2
30	32	Knee pocket topstitch	Single needle lockstitch	2	2	2
31	33	Knee pocket tacking	Single needle lockstitch	1	1	1
32	34	Knee pocket Overlock	5 threads overlock	1	1	1
33	35	Knee pocket hemming	Single needle lockstitch	1	1	1
34	36	Knee pocket ironing	Iron press	2	2	2
35-**B**	37	Knee pocket attach	Single needle lockstitch	2	2	3
36	38	Knee flap folding	Helper	1	1	1
37	39	Button hole on knee flap	Button hole machine	1	1	1
38	40	Knee flap runstitch	Single needle lockstitch	1	1	1
39	41	Knee flap turning	Turning machine	1	1	1
40	42	Knee flap topstitch	Single needle lockstitch	1	1	1
41	43	Knee flap attach	Double needle lockstitch	2	2	2
42-**B**	44	Bar tacking	Bartack machine	2	2	4
43	45	Back rise overlocks	5 threads overlock	1	1	1
44	46	Back rise topstitches	Double needle lockstitch	1	1	1
45-**B**	47	Big loop matching	Helper	1	2	2
46	48	Big loop runstitch	Single needle lockstitch	3	3	3
47	49	Big loop turning	Turning machine	2	2	2
48	50	Big loop runstitch	Single needle lockstitch	2	2	2
49	51	Big loop button hole	Button hole machine	1	1	1
50	52	Small loop runstitch	Loop stitch machine	1	1	1
51-**B**	53	Small loop, big loop and waistband attach	Single needle lockstitch	3	4	4
52	54	Waistband topstitch	Single needle lockstitch	2	2	2

53	55	Waist band closing with size and label tags	Single needle lockstitch	2	2	2
54	56	Inseam Overlock	5 threads overlock	2	2	2
55	57	Trouser turning	Helper	1	1	1
56	58	Inseam topstitch	Feed of arm	2	2	2
57	59	Button hole on Hip band	Button hole machine	1	1	1
58	60	Button hole on the bottom leg	Button hole machine	1	1	1
59	61	Bottom rope attach	Helper	1	2	2
60	62	Bottom hemming	Single needle lockstitch	2	2	2
61	63	Small loop tacking	Single needle lockstitch	2	2	2
62	64	Final Bar tacking	Bartack machine	2	2	2
63	65	Adjustable rope cutting	Helper	1	1	1
64	66	Adjustable hemming	Single needle lockstitch	1	1	1
65-**B**	67	1st adjustable rope attach	Single needle lockstitch	1	1	2
66-**B**	68	2nd adjustable rope attach	Single needle lockstitch	1	1	2
67-**B**	69	Button point marking	Helper	1	1	2
68-**B**	70	Trimming	Helper	7	8	8
69	71	Quality checking	Quality personnel	2	2	2
70	72	Rework	Single needle lockstitch	1	1	1

WSN= workstation number, OPS= operation sequence