Original Article

Simulation Metamodeling Approach to Complex Design of Garment Assembly Lines

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Abstract: The today competitive advantage of Ready-made garment industries depends on the ability to improve the efficiency and effectiveness of resource utilization. Ready-made garment industries have long historically adopted fewer technological and process advancement as compared to automotive, electronics and semiconductor industries. Simulation modeling of garment assembly line system has attracted a number of researchers as one way for insightful analysis of system behaviour and improving its performance. However, most of simulation studies have considered ill-defined experimental design which cannot fully explore the assembly line design alternatives and does not uncover the interaction effects of the input variables. Simulation metamodeling is an approach to assembly line design which has recently been of interest to so many researchers. However, its application in garment assembly line design has never been well explored. In this paper, simulation metamodeling of trouser assembly line with 72 operations has been demonstrated. The linear regression metamodel technique with resolution-V design was used. The effects of five factors: bundle size, job release policy, task assignment pattern, machine number and helper number on the production throughput of the trouser assembly line were studied. The increase of 28.63% of the production throughput was achieved for the best factors' setting of the metamodel.

Keywords: Arena software, Discrete event simulation, Design of simulation experiment, Metamodeling, Regression metamodel, Simulation modeling, NYTIL, Resolution V design, Experimental design, Throughput

1. Introduction

The disruptive transformations in industries are being experienced in Garment manufacturing more rapidly than most of the industries. This is because garment and textile industries are among the oldest industrial sectors that has received very low technological advancement. For this reason they are experiencing disruptive technological leapfrogging and enormous competitions in the business environment in this era of industry 4.0 [1, 2]. Therefore, for the garment industries to remain competitive [3], they must be able to satisfy their customers' demand by improving garment assembly line efficiency and productivity through proper adaptation of advanced assembly line techniques such as simulation and metamodeling.

Simulation is one of the key disruptive technologies that has remained emblematic of industry 4.0 although it is an old technology [2, 4]. Simulation has been majorly applied for analysis of complex systems to give extensive insightful of systems' behaviour. In assembly line design, simulation modeling has been used to generate design alternatives and it enables tactical and strategic management of the stochastic nature of assembly or production systems for many years in manufacturing industries [5]. Unfortunately, simulation modeling of a garment assembly line is a very complex task because it comprises of many hard-to-predict variables which need to be considered during the process. In addition, software for complex assembly line design is computationally intensive, and most scenarios-based simulations are typically performed with complex "black box" models with many variable design parameters in which the users normally have no clear understanding of the underlying equations and how the inputs interact with each other [6, 7]. This makes computer simulation very tedious and impractical to run thousands of simulations for thorough design space exploration, sensitivity analysis and optimization. Therefore, This computational limitation of simulation modeling can be overcome by incorporating metamodels [6, 8, 9].

Metamodels, also well-known as meta-models, surrogate models, or emulators are used in several fields of research to contravene runtime issues with analyzing and experimentation of computational demanding simulation models [10]. For instance, regression techniques of metamodeling have been used to estimate relations between model inputs and outputs based on results of a probabilistic sensitivity analysis [10–12]. More specifically, metamodels build a closed-form mathematical expression to approximate the input and output relationship implied by the simulation model based on simulation experiments runs at selected design points in advance [13, 14]. This can be easily evaluated in a spreadsheet environment "on demand" to answer what-if questions without needing to run lengthy simulations [15].

Metamodels have got many real-world application areas. For example, metamodeling has already been applied in health economics [10]. It has also found a potential application in agriculture such as statistical modeling of maize crop [16]. The metamodeling has also been extensively used in analysis of building structures [17]. While the other application areas of metamodeling include cyber-physical systems [18] and grid system low carbon energy technology [19].

In this paper, simulation metamodeling was proposed as a technique to obtain inexpensive evaluation of garment assembly line design and determine the relationship between input variables and the response. Although metamodeling is extensively used in various engineering domains, no application for the design of complex garment assembly line system is available [19]. Consequently, the present paper demonstrates the applicability and suitability of designing a complex garment assembly line using simulation metamodeling. The paper is organized as follows; Section 2 briefly provide the relevant literature on the study, while section 3 describes the methodology of the study. Finally, section 4 presents the results and discussions of the study.

2. Literature Review

Metamodeling technique is an approximation of simulation model, which represents the relationship between design parameters and responses. Simply put, metamodels approximate the input-output behavior of simulation models. The term indicates a mathematical approximation that models the behavior of another model [8, 12]. The objective of metamodeling is to reduce the computational cost of the simulation model during the optimization process [9, 14].

The most commonly used approaches to metamodel construction are statistic-based and machine-learning approaches. 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 [20]. While the latter is based on neural networking, rule learning and fuzzy logic [6, 8, 21]. On one hand, this approach uses experimental data from simulations to train the surrogate model, and can provide more comprehensive and accurate solutions than regression models. 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. All in all, 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 [13, 20].

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 [15, 22]. Basically, there are two goals/purposes of metamodeling: 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 the outcome [19].

Designing and execution of simulation experiment is one of the fundamental steps in regression metamodeling [23]. In most previous simulation studies, two types of ill-designed experiments have been used. The first type occurs when the analysts perform scenario-oriented experiments, where putting the focus on pre-selected interesting combinations or a trial-and -error approach which can use up a great deal of time without addressing the fundamental questions [24]. The second one 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 factors interactions, one-at-a-time sampling will never uncover them [25]. Tout assemble, the evidences for the previous studies indicate that most simulation experiments have been ill-defined for garment assembly line balancing [26–29].

Design of simulation experiment is quite similar to the traditional design of experiment used in physical experiment. Several 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 most commonly used experimental 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 [30]. In this case, another design approach called fractional factorial design has been adopted to overcome the limitation of the full factorial design by screening some factors and focusing on the main factors [31].

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 [32]. This property gave rise to three types of fractional factorial design which includes resolution-III (three), resolution-IV (four), resolution-V (five), and resolution-VI and higher. The resolution-III design allows only main effects to be estimated. While resolution-IV design provides valid estimates of main effects when two-way interactions are present, but preclude estimation of the interaction effects. The most 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 [24]. The designs of resolution-V and higher order, are used for focusing on more than just main effects in an experimental situation. On the whole, these designs enable the estimation of interaction effects and such designs are augmented to a second-order design [32]. Since then, the aim of simulation experimental analysis in the present study concerns both main effects and interaction effects of factors, the resolution-V design is well-suited.

3. Methodology

3.1. Data Colloection

The empirical data to support the simulation modeling was obtained from Southern Range Nyanza Limited (NYTIL) garment manufacturing facility with the objective of improving the throughput of trouser assembly line. Industrial engineering tools: time study, process mapping, fishbone diagram, brainstorming and observations were used to obtain the empirical data.

3.2. Identification of Input Variables

The input variables that influence the throughput of the garment sewing line were identified by brainstorming four categories of people in garment production department namely; operators, quality personnel, maintenance personnel and line supervisors. The brainstorming was conducted on an individual basis at non-working time so that company production is not interrupted. All their ideas were collected and categorized using fishbone diagram based on the Big four major category of causes (4M) in a manufacturing system: Manpower, Method, Material and Machine as illustrated in Figure 1.

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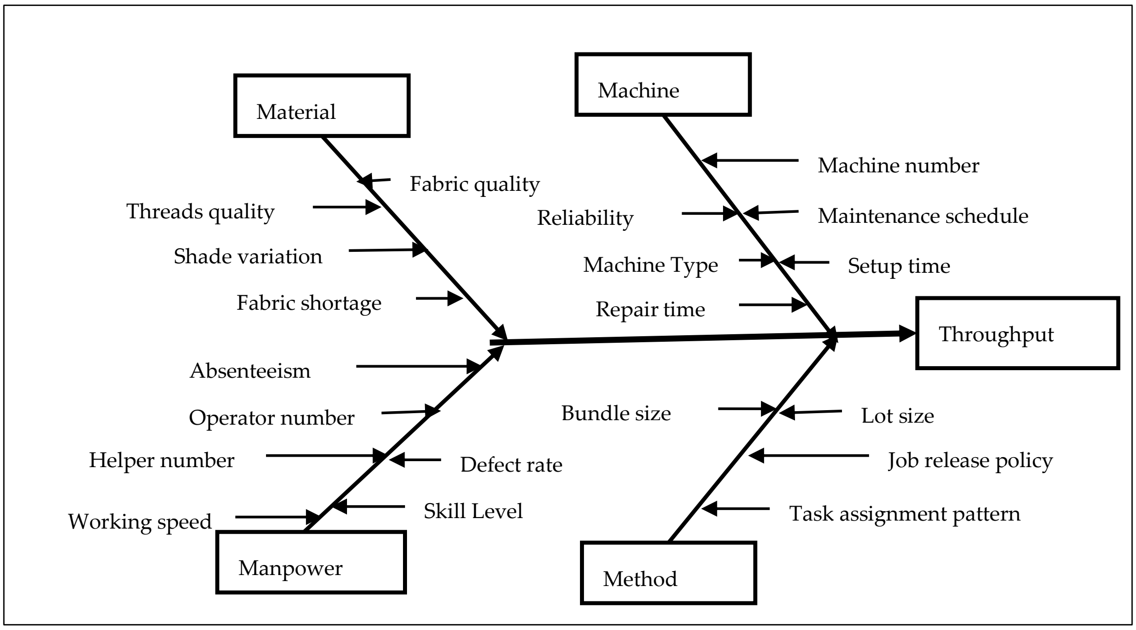

Figure 1. The fishbone (cause-and-effect) diagram

3.3. Conceptual Modeling

To this end, all processes involved in trouser assembly line were summarized using the conceptual model. It is simply a series of logical relationships relative to the components and structure of trouser assembly line. The conceptual modeling involved mapping all the processes or tasks associated with making the trouser. In order to capture all trouser assembly line processes, the assembly line was broken down into 10 preparatory sections: Adjustable preparation, knee flap preparation, knee pocket preparation, hip flap preparation, back preparation, front preparation, big loop preparation, small loop preparation, back patch preparation, and side pocket and flybox preparation as illustrated in Figure 2. Where, (1-72) represents the trouser assembly line tasks perform by the machine operators or helpers and (a-q) are the trouser parts to be assembled. The validation of the conceptual model was done through comparison between the process mapping and the real trouser assembly line. The precedence diagram of the garment sewing line was presented to be validated by the line supervisors and workers in another department.

3.4. Simulation Model Development

3.4.1. Modeling of Processing Times

The processing times data is the heart of Arena simulation modeling and was obtained using continuous stopwatch time study combined with observation [33]. The observed task time for a part in a bundle was multiplied by the total number of parts in the bundle to estimate the total processing times for one bundle, for example, the processing time for bundle size 25 (25 parts in a bundle). The time study was conducted at three interval of different production seasons each with 20 measurements per task, a total of 60 measurements per task were obtained for analysis so as to capture most of the processing times variabilities. Arena input analyzer was used to analyze these processing times in order to obtain the candidate probability distributions and fitted probability distribution. The examples of the fitted processing time probability distribution for some of the tasks: knee patch attach and button hole on left flybox are shown in Figure 3. The fitting of the processing times was done for all tasks involve in trouser assembly line. The fitted processing time probability distribution for each task was then used in building discrete event simulation model. The processing time distribution of different garment bundle sizes 10, 25 and 40 are presented in Appendix A.

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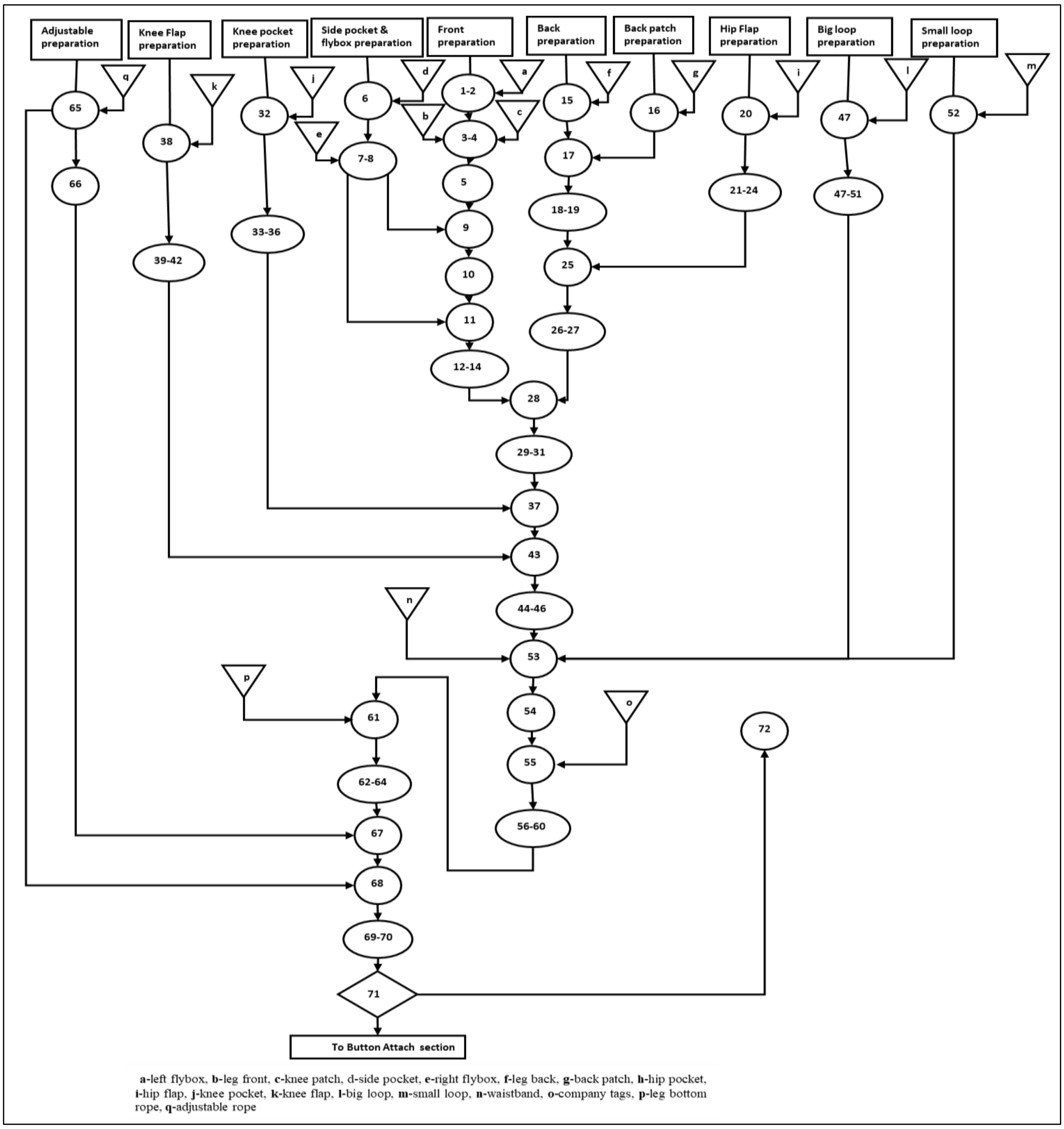

Figure 2. Conceptual model of trouser assembly line

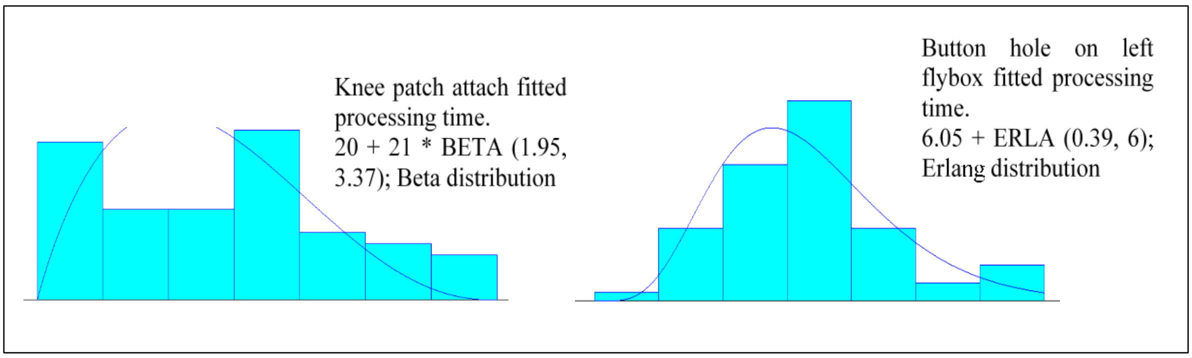

Figure 3. Fitted processing time probability distributions from Arena input analyzer

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3.4.2. Computer Model Construction

The computer model of the trouser assembly line was constructed using Arena simulation environment. Two categories (32 and 64 bits) of the Arena simulation software (academic license version 16) were obtained from Rockwell Automation. Due to the low processing speed of this 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 64 bits notebook computer with a 2.00 GHz Intel core i3 CPU and 4.00 GB RAM. In this respect, the computer modeling of preparatory sections of trouser assembly line including front and back were done separately and then combined using Arena Match modules to form one complex trouser assembly line [34]. The main trouser assembly line sections include main body assembly (MBA), front (FP), back (BP), big loop preparation (BLP) as well-illustrated in Figure 4. The important user interface of Arena simulation environment is the three elements in the project bar: basic process, advanced process and transfer which were used for building the simulation model.

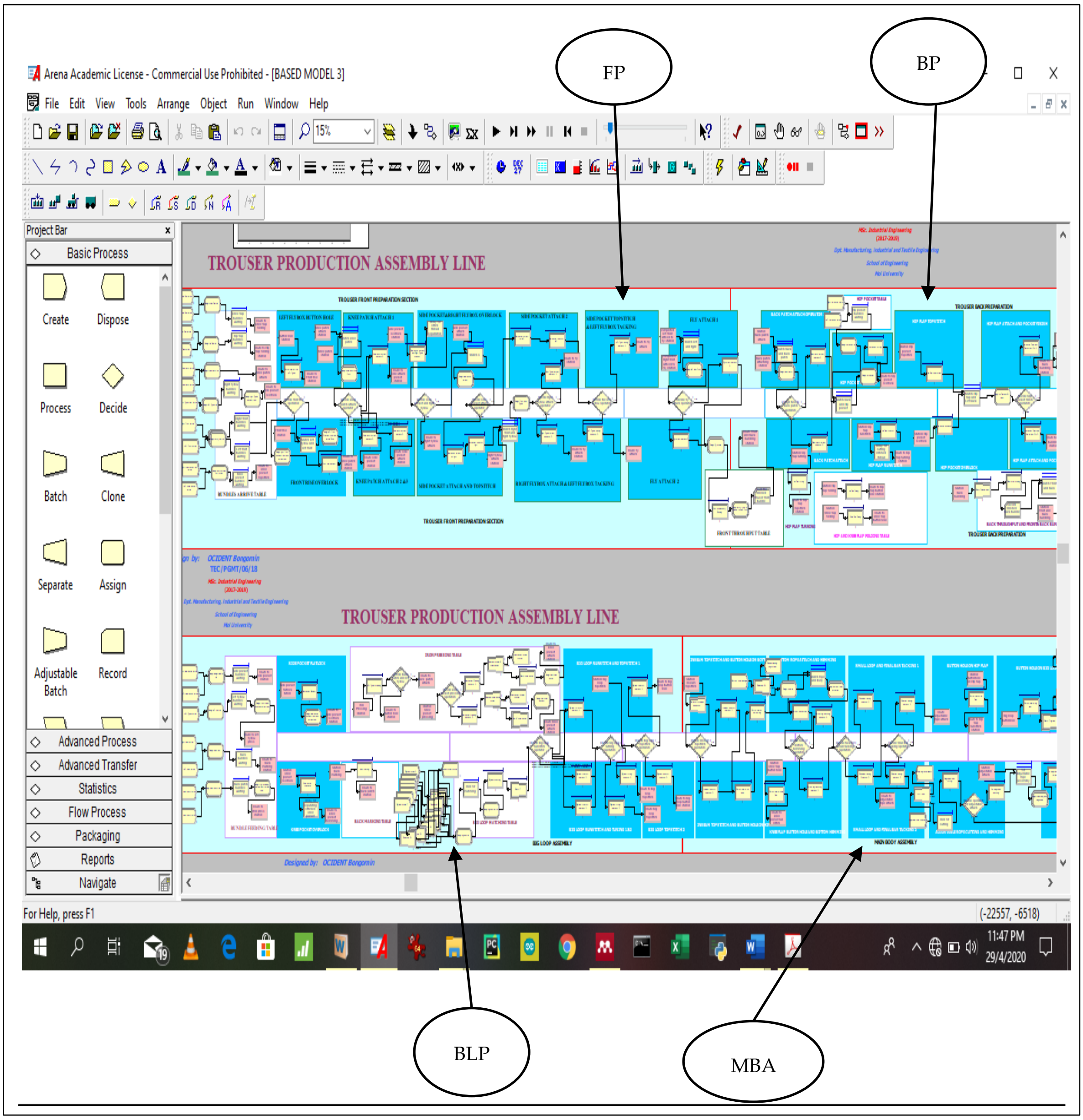

Figure 4. Arena simulation model of trouser assembly line

3.4.3. Model Verification and Validation

The simulation model was verified using traces and animation technique (Appendix B). Then, one-sample-T-test with confidence interval of 95% was used to compare the mean throughput (496 pieces per day) from the Arena simulation model and the throughput sample from the real trouser production line system. The hypothesis test was successfully accomplished with the help of Minitab statistical software (version 18) and the null hypothesis (H_0) was accepted to validate the simulation model with a t-value (-0.20) and p-value (0.842) as shown in Figure 6.

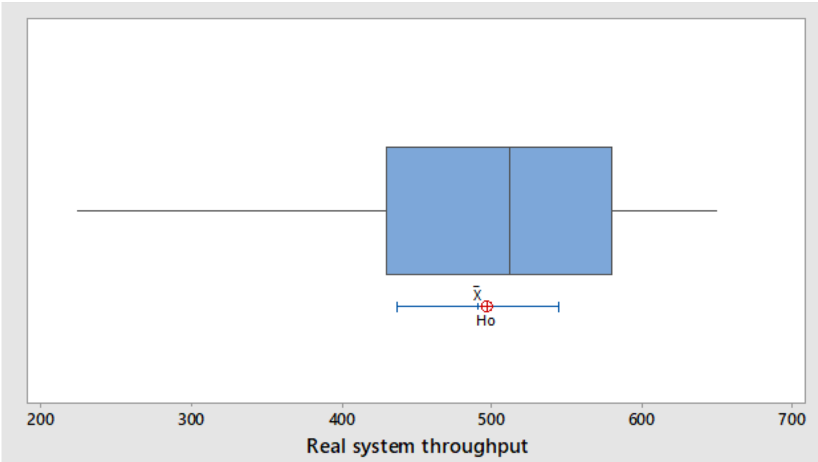

Figure 5. Boxplot of real system throughput with H_0 and 95%t-CI

3.5. Metamodeling

3.5.1. Definition of Experimental Design

The metamodeling process was conducted in accordance to Wallach [16] as shown in Figure 6. The definition of simulation experimental design is the first stage of metamodeling. The dependent variable (throughput) is determined so that it meet the objective of this study. While the independent variables (input factors) are very critical, therefore, they were selected from the fishbone diagram. These factors correspond to those that were defined by the team brainstormed in the garment manufacturing company. As agreed by the team that these factors are most probable of having contribution in throughput of the garment 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 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.

Fractional factorial design (resolution-V design) was used to study the effect of the selected input factors on the response (throughput). The selection of the 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 (version 18) with the design specifications as shown in Table 1.

Table 1. Experimental design specification

Factors	Level	Base design	Resolution	Run	Replicates	Fraction	Blocks	Center point
5	(- /+)	5,16	V	16	1	½	1	1

Design generator: E= ABCD, Defining relation; I= ABCDE, Alias structure; 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.

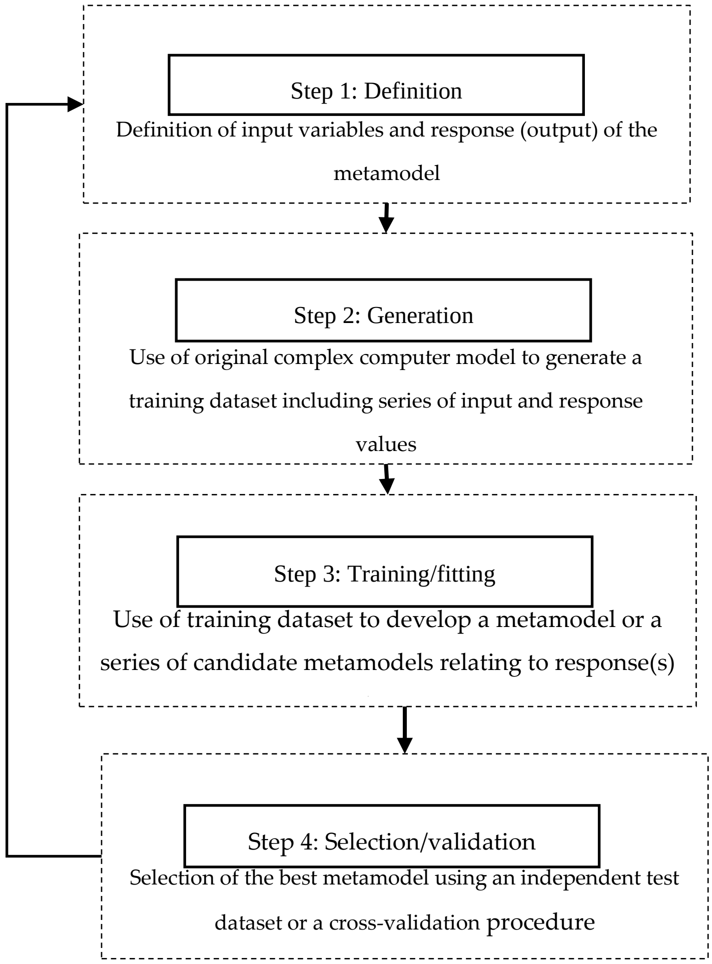

Figure 6. Metamodeling approach

The resolution-V design confounds main factors effects with four-factors interactions and two-factors interactions with three-factors interactions as represented in 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 they was ignored [23]. The experimental design in coded values is presented in Table 2. The input factors and their levels used in this study are described;

Table 2. Experimental design table

Run	Block	A	B	C	D	E
1	1	+	-	-	+	+
2	1	-	-	+	+	+
3	1	-	+	-	+	+
4	1	+	-	+	+	-
5	1	+	-	-	-	-
6	1	+	+	+	+	+
7	1	-	-	+	-	-
8	1	-	+	+	-	+

Run	Block	A	B	C	D	E
9	1	+	-	+	-	+
10	1	+	+	+	-	-
11	1	+	+	-	-	+
12	1	-	-	-	-	+
13	1	-	+	+	+	-
14	1	-	+	-	-	-
15	1	-	-	-	+	-
16	1	+	+	-	+	-

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

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: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. The effect of two levels on the throughput were studied including no-policy and policy. No policy level 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 (work in progress) WIP threshold of the bottleneck station.

Factor C (Task assignment pattern); this is the method of distributing workload to the operators performing the same task in the production line. Two levels studied are random and equal task assignment pattern. With the random task assignment, the workload of operators performing similar task are randomly distributed. While, equal task assignment pattern, the workload of operators performing similar tasks are equally distributed.

Factor D (Machine number); here, the machine number was considered as categorial factor because of different machine type and several workstations involved in trouser assembly line. Therefore, the machine number to be varied was determined for the bottleneck and idle workstations. Also, it was studied at two levels: increase and decrease. For case of increase level, three single needle lockstitch and one iron press machines 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 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. Just like the machine number, the effect of increasing and decreasing helper number in the production line was also studied. Where, three helpers were added and three were removed from the production line.

3.5.2. Generation of training dataset or design scenarios

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 (training datasets) were generated. The simulation experiments were 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. Replication number of 10 was considered for each design scenario. The replication run length, warm up period and replication number for the steady-state simulation were specified according to Law [35].

To this end, the complex simulation model of the garment assembly line was used to perform 16 experimental runs. The simulation model was altered depending on 16 design points generated from the design of experiment. This results into development of different simulation models as known as design scenarios or design alternatives. Therefore, 16 design alternatives were created from the simulation experiments [34]. Experiments run were performed for each design alternative while observing their mean throughput as shown in the Table 3.

Table 3 The design scenarios (training dataset)

Design scenario	**Factors**					**Average throughput (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.

3.5.3. Training/fitting of the model and Validation

Statistical-based approach was used to develop regression metamodel 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 on the design matrix as defined by the design of experiment (resolution-V design). This was accomplished by statistical analysis of the sixteen (16) training datasets or design scenarios. The analysis variance (ANOVA) was 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 [12] was used to validate the regression metamodel.

4. Results and Discussion

4.1. Regression Metamodel

The regression metamodel was analyzed using regression analysis with the help of Minitab software. Table 4 shows the factorial regression analysis of the response (throughput) versus factors: bundle size, job release policy, task assignment pattern, machine number and helper number for the 16 design scenarios (training dataset).

Table 4. Analysis of Variance of the design scenarios

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%		

DF- Degree of Freedom, AdjSS- Adjusted sums of squares, AdjMS- Adjusted mean square

The result shows the model's total DF of 15, whereby, 5 DF for Linear model and 10 DF for two-way interaction model. The DF for error was zero for the designed model. This means that the observed mean response (throughput) value is equal the model predicted mean throughput. This is because the throughput mean from the simulation model has already been automatically fitted for the different runs and replications. Unlike the physical experiment, computer experiment is deterministic hence there is no random errors for each replication [12]. 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 [23]. 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. Further, 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. The regression metamodel is presented as shown the Eqn. 1.

$$Throughput = 507.5 - 0.075A - 12.42B + 12.42C + 46.5D + 35.17E + 0.1917AB - 0.1917AC + 0.025AD - 0.2917AE + 3.625BC + 0.375BD - 4.375BE - 0.875CD + 3.875CE + 28.88DE \quad (1)$$

Simple significance check was used to validate the regression metamodel. The present of significance factors in the metamodel validate the metamodel. The plots in Figure 7 indicate that there are many terms (factors and their interactions) of near zero effect which are considered insignificant. This is because at 95% confidence interval (α=0.05) and Lenth's pseudo square error (Lenth's PSE =9.75), it is assumed that variation in the smallest effects are due to random errors. However, the outliers (E, DE and D) are considered significant because they have large effect on the response. By applying the pareto analysis, insignificant terms were removed from the metamodel. Figure 8 illustrates that only the terms (two factors and one interaction) with their effect exceeding the reference line at effect level (25.1) with the Lenth's PSE (9.75) can be retained in the regression metamodel. While the terms having effects below the reference line can be safely removed from the metamodel. In this respect, the new regression metamodel is given in Eqn. 2.

$$Throughput = 507.5 + 46.5D + 35.17E + 28.88DE \quad (2)$$

The new regression metamodel presented can be adopted for predictions without going through complex simulation modeling for experiments. However, it could not work for the case of this study. This is because of the different resource type and large number of workstations involved in this trouser assembly line system. It could be impractical by mere feeding the machine numbers or helper numbers in the Eqn. 2 to determine the average throughput without undergoing through simulation. Using metamodel for prediction is suitable for single machine shop but becomes impractical for application in assembly line system (series of different and identical machines) [30]. For this reason, the best parameters' setting was selection from the training dataset with the highest throughput (Table 5). The bundle size of 25 was adopted instead of 10, because varying bundle sizes has insignificant effect on the mean throughput. Moreover, using bundle size of 10 produces high idle times for the preparatory sections, hence, the normal bundle size 25 was suitable. The best parameter's setting achieved an average throughput of 638 pieces per day, resulting into 28.63% increase of production throughput from the existing design (with the average of throughput = 490). Similarly, Anisah *et al.*[36] showed that increasing resource in the bottleneck workstation increases average throughput. This is because adding the resource in the bottleneck workstation reduces both cycle time and work in progress (WIP). In spite of the fact that the metamodel was not used for further model prediction, the present study found it most suitable for inference [19] and initial solution (local optimal) for optimization process [37]. The inference was drawn from the regression metamodel to analyze the factors' effects on the production throughput. This is very useful for garment assembly line production planning because being insightful on the effect of factors can ease the decision making on which factors to play-with for improving the production throughput and efficiency.

Table 5. The best parameter setting of 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)

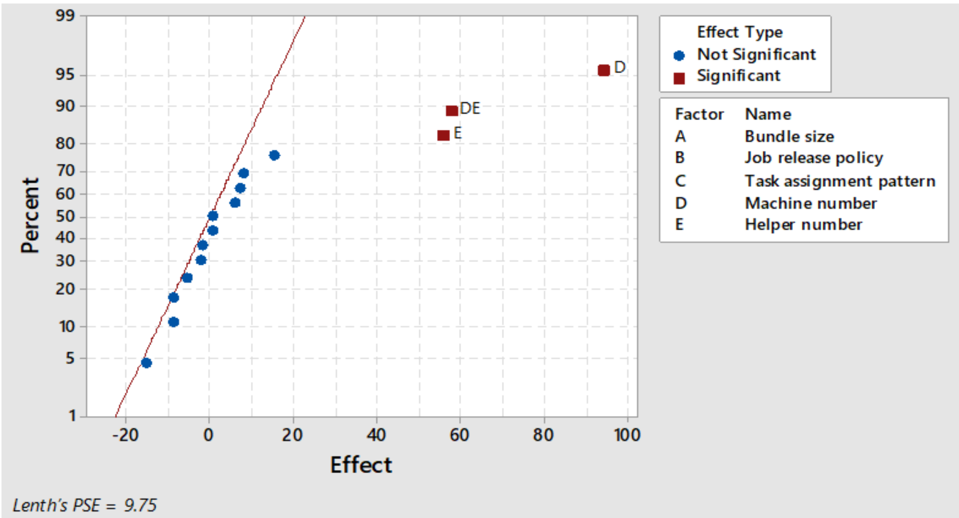

Figure 7. Normal plot of the effects

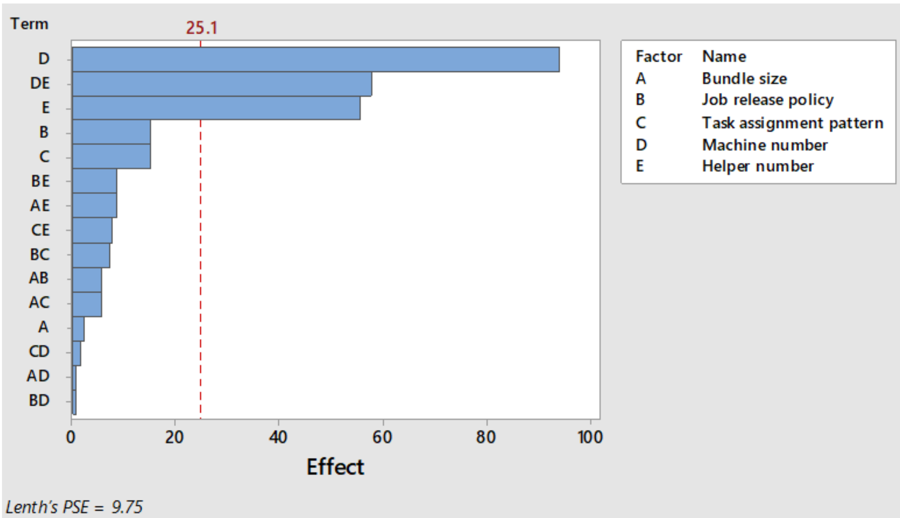

Figure 8. Pareto chart of the effects

4.2. The Main Factors Effect

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 9. The main factors effect on the throughput has been interpreted.

Bundle size effect plot; if all factors are kept constant, the mean of throughput decreases with very small value when 10 bundle size changes to 40. Thus if the same quantity of input materials is kept constant for all level of bundle size, very small decrease observed in the mean of throughput when 40 bundle size is used could be because of the longer time it takes for trouser preparation sections to complete one bundle of the garment while keeping the trouser main body assembly section idle. So, longer warm up time for the overall production line resulting into low throughput.

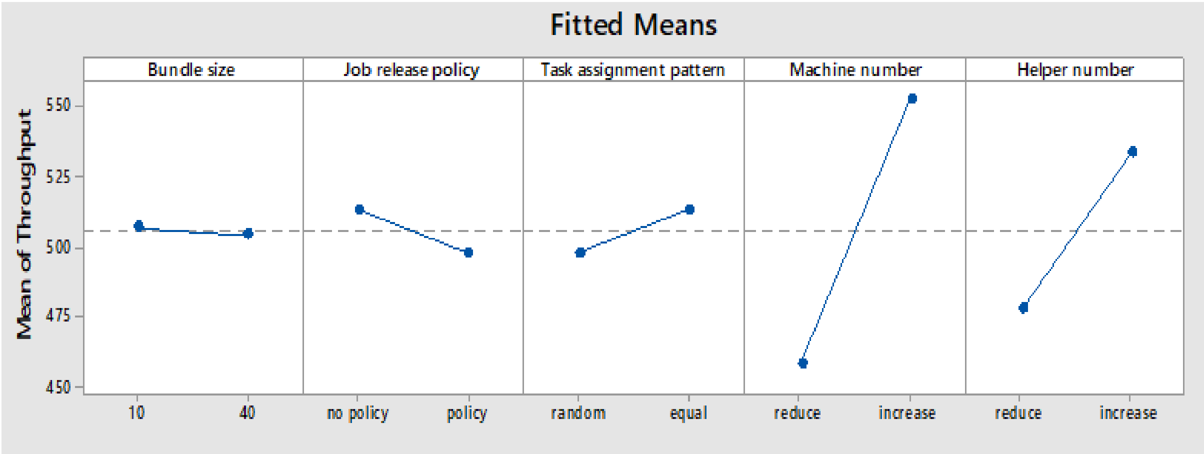

Figure 9. Main effects plot for throughput

Job release policy effect plot; the plot connotes that if all other factors are kept constant, changes in the level of job release policy shows a greater change in the mean of throughput when compared to that of the bundle size. The decrease in the mean of throughput was observed when the no policy changes to policy level. This is because at no policy level, the quantity of input materials is kept constant in the production line, every preparation section is capable of preparing enough part for the main body assembly. As for the case of policy system which was based on the WIP threshold of the bottleneck station, 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 section. Thence, reduction of the overall throughput of the production line. For instance, big loop preparation has to be done at a faster rate than other sections because seven loops are required to be assembled on one trouser. For this reason, any delay in the preparation process could cause starvation of the main body assembly as well as the extreme workstations resulting into low throughput. In the previous studies, job release policy based on WIP threshold of the bottleneck station was observed to increase throughput [38, 39]. Yet, the present study achieved low throughput. The point is that the previous studies considered the assembly line problem which does involve parts preparation process. Consequently, keeping WIP of one workstation does not starve the extreme workstations in that the throughput can be increased. This can be concluded that job release policy based on WIP threshold of the bottleneck does not work well on the assembly line problem that requires part preparation process as it leads to starvation of the main body assembly section resulting into low throughput.

Task assignment pattern effect plot; small changes in the mean of throughput was observed when the level of task assignment pattern is changed. There was small increase in the mean of throughput when random task assignment pattern changes to equal task assignment pattern. With the random task assignment, there is unequal work load for each operator in the workstation (performing similar task). Thus, the workstation cycle time and idle time could be increased which resulted into low throughput of the production line. While equal task assignment maintains the same work load among operators in the workstation. Hence, reduces the cycle time and idle time of the workstation, and thus increases the overall throughput of the production line. The present study agreed with the study done by Kandemir & Handley [40] which reiterated that equal task assignment produces high production throughput and efficiency due to equal workload of the operators and minimization of workstation idle time.

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Machine number effect plot; the effect of machine number on the throughput was considered to be statistically significant at α= 0.05. This means that, the throughput increases when machine number is increased in the workstation while it decreases when the machine number is reduced. This is because increasing machine number in the bottleneck workstation reduces the cycle time of the workstation as well as the WIP and parts waiting time. Whilst reducing machine number in the workstation increases cycle time, WIP and parts waiting time, therefore, low throughput of the production line.

Helper number effect plot; similarly, helper number has significant effect on the mean throughput though its effect is smaller when compared to machine number. The work of helpers on the production line normally influence the feeding of parts to the upstream workstations. When number of helpers is increased, it means that the extreme workstation is never starved with materials due to reduction of helper's workstation cycle time and WIP. So, high throughput of the production line could be realized. While decreasing their number could result into increase in the helper workstation cycle time leading to starvation of the extreme workstations leading to low throughput of production line.

4.3. The Interaction Effect

The interaction effect of factors on the production throughput is illustrated in Figure 10. As shown, each plot represents the interaction between two factors. The example is the bundle size and job release policy effect plot. Therefore, each interaction effect plot has been interpreted. In the main, it is interpreted that when the red and blue lines of the factor levels are with considerably different slope, it indicates that there is interaction between two factors. In this respect, the interaction effect of factors was interpreted as follows.

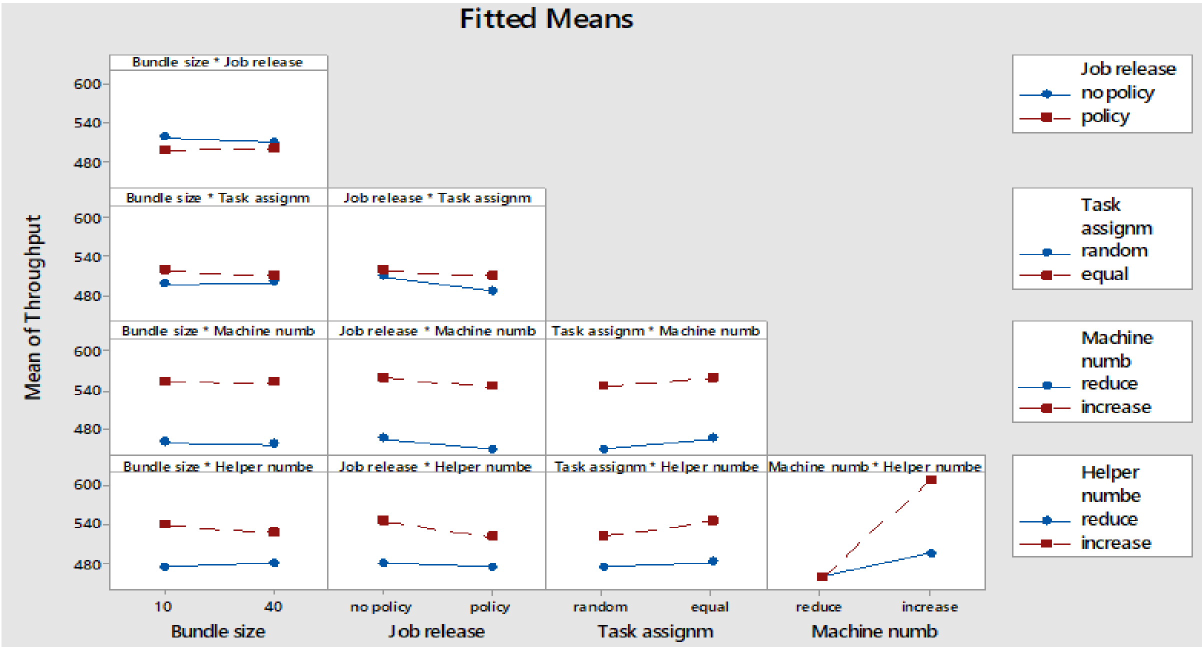

Figure 10. Interaction plot for throughput

Bundle size and job release policy effect plot; this interaction plot indicates that there is very little interaction between bundle size and job release policy as the no policy and policy lines of job release policy take a slightly different slope. If the bundle size is 10, the mean of throughput decreases with large value when the job release policy is changed from no policy to policy level. While if the bundle size is 40, the mean of throughput decreases with a very small value almost no change at all when the job release policy is changed from no policy to policy level.

Bundle size and task assignment pattern effect plot; there is also insignificant effect of the interaction between bundle size and task assignment pattern. Nonetheless, there is little interaction effect as it can be observed that the slopes of random and equal lines are not parallel. This implies that if the bundle size is 10, the mean throughput increases with large value when task assignment pattern changes from random to equal level. Whilst if the bundle size is 40, the mean throughput increases with very small value almost no increase at all when the task assignment pattern changes from random to equal level.

Bundle size and machine effect plot; there is actually no interaction between bundle size and machine since there is no significant different in the slope of reduce and increase lines of the two levels of the machine number. This point out that there could not be any different even if the alpha value is increased.

Bundle size and helper number effect plot; the slope of reduce and increase lines of the two levels of the helper number differ slightly. The plot signals that if the bundle size is at 10, the mean of throughput increases with larger value when the helper number changes from reduce to increase level (helper number is increased). While if the bundle size is at 40, the mean of throughput increases with smaller value when the helper number is increased.

Job release policy and task assignment pattern effect plot; as observed from the plot, the slope of random and equal lines of the two levels of task assignment pattern take slightly different direction. Consequently, significant interaction 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 very small increase in the throughput when the task assignment pattern changes from random to equal level. But if the job release policy is at policy level, the throughput increases with larger 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 increase because the slope of the reduce and increase lines of the two levels of machine number are parallel (take the same direction).

Job release policy and helper number effect plot; there is also insignificant interaction between job release policy and helper number at $\alpha = 0.05$. Notwithstanding, as observed from the plot, the reduce and increase lines of the two levels of helper number take a slightly different slope. Thus, their interaction can be significant when the alpha value is further increased at some point.

Task assignment and machine number effect plot; there is no interaction between task assignment pattern and machine number as the slope of reduce and increase lines of the two level of machine number are parallel or take the same direction.

Task assignment and helper number effect plot; it can be observed from the plot that the slope of the reduce and increase lines of the two level of the helper number are parallel. The plot therefore means that, if the task assignment pattern is at random level, the mean of throughput increases with smaller value when the helper number is increased. Whilst if the task assignment pattern is at equal level, the mean of throughput increases with larger value when the helper number is increased.

Machine number and helper number plot; there is 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 the two levels of helper number differ significantly. The plot means that if the machine number is at reduce level, there is no change in the mean of throughput when the helper number is increased. While if the machine number is at increase level, there is great increase in the mean of throughput when the helper number is increased (changes from reduce to increase level). It can be concluded that increasing helper number when the machine number is at reduce level does not change the mean of throughput. This is because helpers perform simple tasks in production line and their task depend on the extreme workstations with machines. Notably, reducing helper number contributes to high WIP and idle time for the helpers in the extreme workstation but the throughput remains constant because the cycle time of the workstations (with machines) is not changed, rather only the cycle time of the workstations (with helpers) could be changed. Whilst, increasing helper number when the machine number is at increase level result into increase of the production throughput because the cycle time of both the machine and helper workstations are reduced.

Conclusion

The present study has successfully demonstrated garment assembly line design using simulation metamodeling with 28.63% increase of the production throughput achieved for the best setting of the metamodel. However, the developed metamodel was a biased approximation of trouser simulation model with the $R^2 = 1$ and means square error (MSE) = 0. Therefore, this metamodel is not suitable for prediction but it can be used for inference. Hence, 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. In order to overcome the biasness of the metamodel, the further study can use a space-filling experimental design such as Latin hypercube design and orthogonal array. Further, profound metamodeling technique involving machine learning approach should be investigated.

Funding: This research received funding from Africa Center of Excellence II in Phytochemicals, Textiles and Renewable Energy (ACE II-PTRE) at Moi University (Credit No. 5798-KE)

Acknowledgments: The authors acknowledge the Rockwell Automation for providing Arena software academic research license (version 16). The authors are also grateful to the management of Southern range nyanza limited (NYTIL) for acceptance of the research to be conducted in their company.

Conflicts of Interest: The authors declare no conflict of interest

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 doi:10.20944/preprints202005.0048.v1

Appendices

Appendix A

Fitted Processing time probability distribution for bundle size-10

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
1	Left flybox pressing	Iron press	1	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	1	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

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
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 press	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

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
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

OPN- Operation Number, S/NL- Single needle lockstitch, BH- Button hole machine, F/A- Feed of arm, 5t O/L- 5 threads overlock machine, LM- loop stitching machine, D/NL- Double needle lockstitch, BT- Bartack machine, QP- quality personnel, TM- turning machine, AWM- automatic wallet machine, 3t O/L- 3 thread overlock machine, F/L- Flatlock machine, Qty- Quantity

Fitted processing time distribution for Bundle size-25

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
1	Left flybox pressing	Iron press	1	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	3t 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	5t 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	1	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)	25
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

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
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	5t 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	5t 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)	Not bundled
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/N	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)	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	5t 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

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
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	QP	2	0.82 + LOGN (0.332, 0.154)	Not bundled
72	Rework	S/NL	1	TRIA (2, 3.5, 4.7)	Not bundled

OPN- Operation Number, S/NL- Single needle lockstitch, BH- Button hole machine, F/A- Feed of arm, 5t O/L- 5 threads overlock machine, LM- loop stitching machine, D/NL- Double needle lockstitch, BT- Bartack machine, QP- quality personnel, TM- turning machine, AWM- automatic wallet machine, 3t O/L- 3 thread overlock machine, F/L- Flatlock machine, Qty- Quantity.

Fitted processing time probability distribution for bundle size-40

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
1	Left flybox pressing	Iron press	1	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	1	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

OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
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

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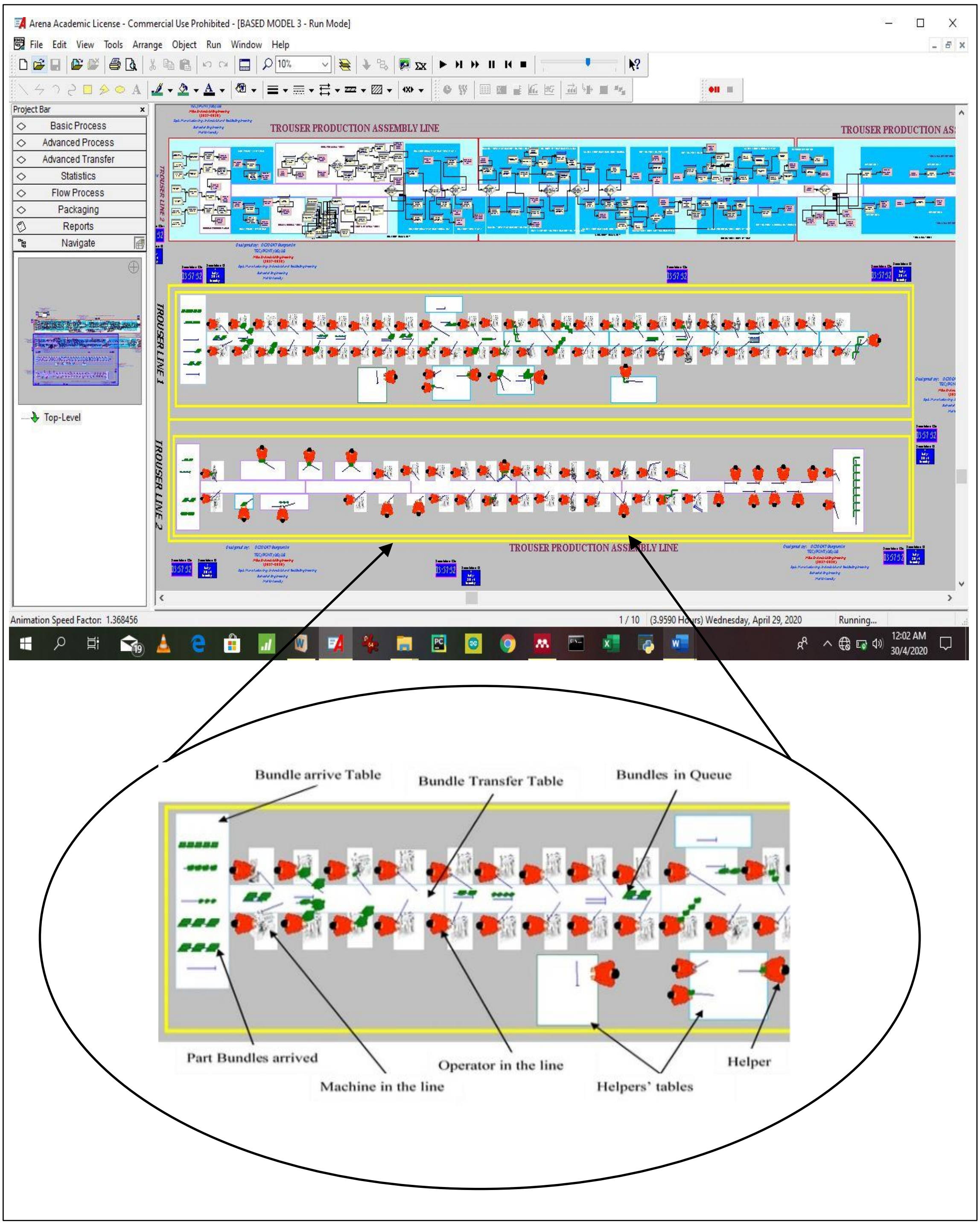
OPN	Operations description	Resource	Qty	Processing time distribution per resource	Bundle size
59	Button hole on Hip band	BH	1	TRIA (0.31, 0.344, 0.47)	Not bundled
60	Button hole on the bottom leg	BH	1	0.32 + 0.2 * BETA (2.7, 3.33)	Not bundled
61	Bottom rope attach	Helper	1	0.5 + LOGN (0.251, 0.168)	Not 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	1^{st} adjustable rope attach	S/NL	1	NORM (0.75, 0.0479)	Not bundled
68	2^{nd} 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

OPN- Operation Number, S/NL- Single needle lockstitch, BH- Button hole machine, F/A- Feed of arm, 5t O/L- 5 threads overlock machine, LM- loop stitching machine, D/NL- Double needle lockstitch, BT- Bartack machine, QP- quality personnel, TM- turning machine, AWM- automatic wallet machine, 3t O/L- 3 thread overlock machine, F/L- Flatlock machine, Qty- Quantity.

doi:10.20944/preprints202005.0048.v1

Appendix B



This Arena discrete event simulation of trouser assembly line is complex in such way that finished trouser can only be achieved when all parts are processed from their respective preparatory section. Otherwise, no trouser throughput can be obtained. The entities (trouser parts) generation has been limited by the Arena model sizes license restriction thus reduced the run length. For this reason, the run length of one months (28 days) with daily 8hours production shift was used.