Assembly Line Balancing and Sensitivity Analysis of a Single-Model Stochastic Sewing Line Using Arena Simulation Modelling

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ARTICLE INFORMATION

ABSTRACT

Assembly line balancing is always a critical responsibility for manufacturers as it controls the efficiency and productivity of the assembly line. There are many techniques to solve line balancing problems, some of which are revealed in the literature review section, but computer-aided simulation modelling is prevalent among them. This study aims to analyze an assembly line balancing problem using a discrete event simulation software (Arena) for the optimal solution and sensitivity analysis of the solution. The empirical study was carried out at Arunima Sportswear Limited garment factory, and a garment style (kid's pants) with 21 operations was taken into account. The computer model was verified by line supervisors and validated by a statistical hypothesis test (t-test). Then, using the Arena OptQuest tool, an optimal solution to the model is achieved. The average throughput of 904 pieces per day was achieved in the proposed model, which was 163 pieces higher than the existing model's output. The line efficiency of the current model (75.76%) was also increased in the proposed model, which was 92.43%. Finally, a sensitivity analysis is performed by varying the values of some key factors (i.e., entities per arrival, process failure time, and operators' absenteeism) to determine the level of uncertainty of the model.

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1. INTRODUCTION

An assembly line refers to the process through which parts are added to a semi-finished product as it moves from one workstation to another in a manufacturing line without violating the precedence relationship (Sime et al., 2019). When an assembly line workload is equally distributed among the workstations, it is called assembly line balancing (ALB). Line balancing is performed to increase efficiency, remove bottleneck activities, enhance productivity and reduce the cycle time of a manufacturing line (Parvez et al., 2017). The primary assembly line balancing problems are the SALB-1 problem and the SALB-2 problem, also referred to as the Type-1 problem and

Type-2 problem, respectively (Scholl & Vob, 1996). However, the assembly line balancing problems can further be categorized into eight types considering the number of models (single-model and multi-model), the nature of task times (deterministic and probabilistic), and the type of assembly line (straight-type and U-type) (Sivasankaran & Shahabudeen, 2014). In this paper, a single-model probabilistic straight-type (SM_P_S) problem of a garment sewing line is discussed. Garments industries are the primary manufacturing industries of Bangladesh; more than 80% of the total export of Bangladesh depends on the garments industries. Low labour wages, abundant workers and duty-free export make Bangladesh the world's second-largest garments manufacturing country. However, the efficiency and productivity of Bangladesh's clothing factories are always low (Islam & Adnan, 2016; Rezaul et al., 2010). As some African countries like Ethiopia, Nigeria, and Ghana are emerging as potential garment manufacturing hubs, Bangladesh has no other option but to increase the efficiency and productivity of its garments factory, for which line balancing is crucial.

In the context of assembly line balancing, the garment industry in Bangladesh heavily relies on production personnel who often lack technological knowledge. At Arunima Sportswear Ltd., where our research was conducted, line balancing is currently carried out using a trial and error method. This approach is not only time-consuming but also inefficient. As a result, when a new style is introduced into the production line, the initial efficiency of that line typically hovers around 30% to 40%. It takes at least two days to increase the line efficiency to 70%. To address this issue, we have introduced simulation modelling to solve line balancing problems. Simulation modelling allows users to predict the efficiency of a production line with a given set of resources before actual production begins, thus saving a significant amount of time.

Assembly line balancing has always been the point of interest of many researchers, and enormous academic research has been conducted regarding assembly line balancing; the number is still going on. Because of higher installation costs and time, balancing an assembly line is critical to manufacturers (Boysen et al., 2007). Garments manufacturers have been using assembly line balancing since its inception. In previous studies, many assembly line balancing techniques of garments sewing lines, such as manual/practical (Tanbin et al., 2018), work sharing method (Parvez et al., 2017), genetic algorithm (Rubinovitz & Levitin, 1995), simulated annealing (Suresh & Sahu, 1994), computer method of sequencing operations for assembly lines (COMSOAL) (Dolgui & Proth, 2013), chance-constrained programming (Ağpak & Gökçen, 2007), simulation (Black & Schroer, 1993), and hybrid (branch and bound optimization algorithm combines with a heuristic technique) (Hoffmann, 1992) have been discussed. However, with the advent of computers and technology, manufacturers prefer simulation modelling for line balancing over other methods. Simulation allows the company to observe a system's behaviour before implementing it; this way, it helps the producer make decisions without being exposed to risk. Besides, simulation modelling lets the producers alter the system's parameters to improve the system performance, which is much more cost-effective than the traditional trial-and-error method (Jamil & Razali, 2016; Kitaw et al., 2010). In this paper, discrete event simulation software Arena professional (Version 14) is used to balance the assembly line of a sewing floor.

Every simulation model requires validation, optimization and risk (or uncertainty) analysis to find a robust solution. Sensitivity analysis may serve all the aforementioned analyses of a simulation model (J. P. C. Kleijnen, 2005). Sensitivity analysis refers to a systematic

investigation of the reaction of the simulation responses to extremely high or extremely low values of the model's input or radical changes in the model's structure (Alexopoulos et al., 1995). Sensitivity analysis addresses the uncertainty within the model. As structural engineers and designers add safety factors to ensure that the structure survives in any inconvenient situation, simulation model designers should also conduct sensitivity analysis to ensure the model's viability during extreme conditions (Chetouane et al., 2012). In this paper, sensitivity analysis is used to observe the change in throughput of the assembly line model upon changing the values of some important factors.

2. LITERATURE REVIEW

Many researchers have worked with simulation modelling to design a new system, improve the existing system, and analyze the system performance by changing system parameters. Although simulation modelling has some drawbacks, such as failure to imitate the actual production line fully and failure to incorporate human error or skills in the model, it is prevalent among researchers and manufacturers because of its flexibility. For example, Jamil and Razali (Jamil & Razali, 2016) balanced a mixed-model assembly line of charcoal canister products (fuel's vapour filter) using ProModel simulation software. The model helped them to identify the blockage and idle time within the assembly line. By conducting some what-if analysis, they were able to eradicate the reasons causing the blockage and get an optimal solution. Buyuksaatci et al. (Büyüksaatçi et al., 2015) used Arena simulation software to balance an assembly line of LCD TV. They used two approaches to balance the assembly line: the 'Worker constant' approach and the 'Ranked positional weight' approach. They then compare the result of a simulation model of these two approaches to find the best one. Greasly (Greasley, 2008) developed a discrete event simulation model for a storage facility. He found that simulation allows users to see the queuing level at every product level and allows decision-makers to debate over different system assumptions. Shakibayifar et al. (Shakibayifar

et al., 2018) showed in their paper that a simulation-based optimization model to reschedule railway traffic is more efficient than any other commercial model. They considered a wide array of disruptions that cause blockage in the railway and the time to recover it as input parameters. The model's output was a set of new departure times, dwell times and train running times which significantly reduced train arrival delays. Simulation-based optimization has also been used in different industries to solve several industrial engineering problems (Trigueiro de Sousa Junior et al., 2019).

Simulation modelling is also used in garment manufacturing companies for assembly line balancing. Various research work has been done in this regard. As the complexities of garments manufacturing are growing day by day, simulation modelling is becoming popular among researchers to solve complex problems. Bongomin et al. (Bongomin et al., 2020) presented a simulation-based optimization model for a complex sewing line of 72 operations. They balanced the assembly line using Arena software which enabled them to increase the line efficiency and throughput from 61.2% and 490 pcs to 79.7% and 762 pcs, respectively. Yemane et al. (Yemane et al., 2020) balanced an assembly line of a sewing floor using a combination of manual line balancing techniques with computer-aided simulation modelling. The combined line-balancing approach helped them increase system utilization and efficiency. Kursun and Kalaoglu (Kursun Bahadir & Kalaoglu, 2009) showed in their paper that simulation modelling could be used to balance an assembly line of sweatshirt production. They minimized the labour intensity and removed the bottlenecks of the production line using their designed simulation model. Yemane and Santelices Malfanti (Yemane & Santelices Malfanti, 2017) used Arena software, AutoCAD, and POM software to design a model and measure the performance of an existing sewing line. With simulation modelling, they were able to balance the sewing line and design an optimal layout for the line.

The typical presumption of the 'line balancing problem' is that task times are deterministic.

But those tasks that require human skills show a noticeable difference in task times. Many researchers consider stochastic task time instead of deterministic so that they can find a realistic solution to assembly line balancing problems. For instance, Kottas and Lau (Kottas & Lau, 1981) developed heuristic procedures to design paced production lines with stochastic task time in an attempt to balance the incompletion and labor costs. Sarin et al. (Sarin et al., 1999), used a branch-and-bound procedure to balance a stochastic assembly line. It provided a better solution than Kottas and Lau's to minimize the incompletion and labor costs. Zheng et al. (Zheng et al., 2018) proposed a distribution-free model for disassembly line balancing problems with stochastic task processing time. This model aims to reduce workstation operational costs and hazardous component processing costs. Sensitivity analysis is part and parcel of any simulation modelling. Sensitivity analysis of a simulation model is performed to see how the model responds upon changing one or two input parameters. Wang and Zhu (Wang & Zhu, 2017) developed an Arena simulation model of a call centre to study the influence of customers' impatience behaviours on the system performance. They conducted a sensitivity analysis of the simulation model by varying different model parameters like baulking probability and reneging probability to see the changes in the call centre's performance. Nikakhtar et al. (Nikakhtar et al., 2012) developed a simulation model for a construction process and performed a sensitivity analysis to find the best combination of resources. Kleijnen & Rubinstein (Kleijnen & Rubinstein, 1996) showed in their paper how to perform sensitivity analysis of computer-aided discrete-event static systems and discrete-event dynamic systems using the score function method.

3. METHODOLOGY

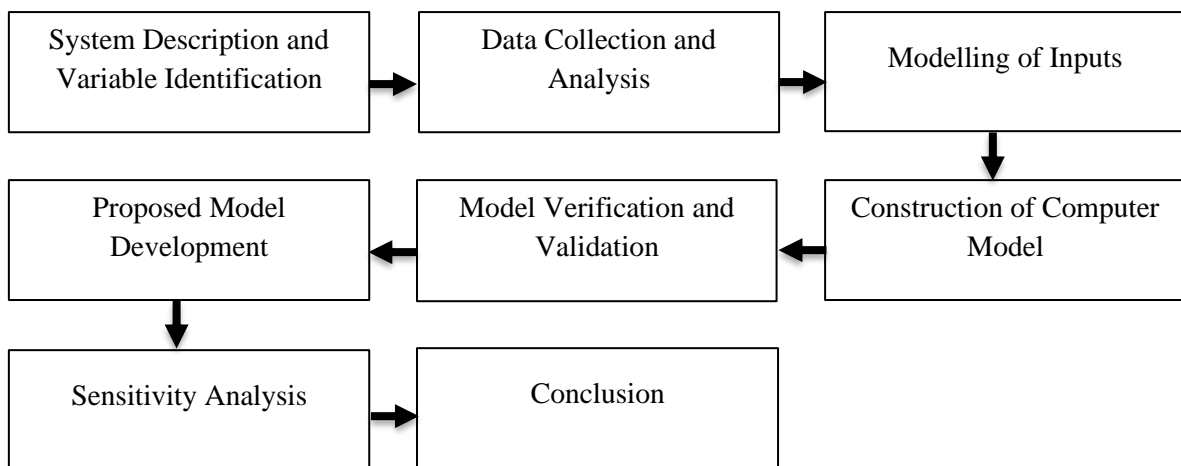The methodology adopted for this research work is depicted in Fig. 1.

Fig. 1 Methodology used for present research work

4. EXPERIMENTAL SETUP

4.1 SYSTEM DESCRIPTION AND VARIABLE IDENTIFICATION

Arunima Sportswear Ltd. (Ashulia, Dhaka, Bangladesh), a renowned garment factory in Bangladesh, has been chosen for this study. A garment style, i.e. Kid's Pant, having twenty-one operations, was selected for this research work. Twenty-eight operators were involved in the assembly line. The conceptual model of the assembly line was developed through observation and consulting with production personnel. The conceptual model, as depicted in Fig. 2, is simply the sequence of operations of the garment. The number in the circle refers to

the operations according to their position in the list (Table 1).

There are a number of system variables, such as processing time (the time required to complete each task in the assembly line), entities per arrival (number of cutting parts arriving in the line at a time), machine breakdown (machine failure time), rework, operator's absenteeism, operators fatigue, machine delay, etcetera. Some of these factors have been considered in this study.
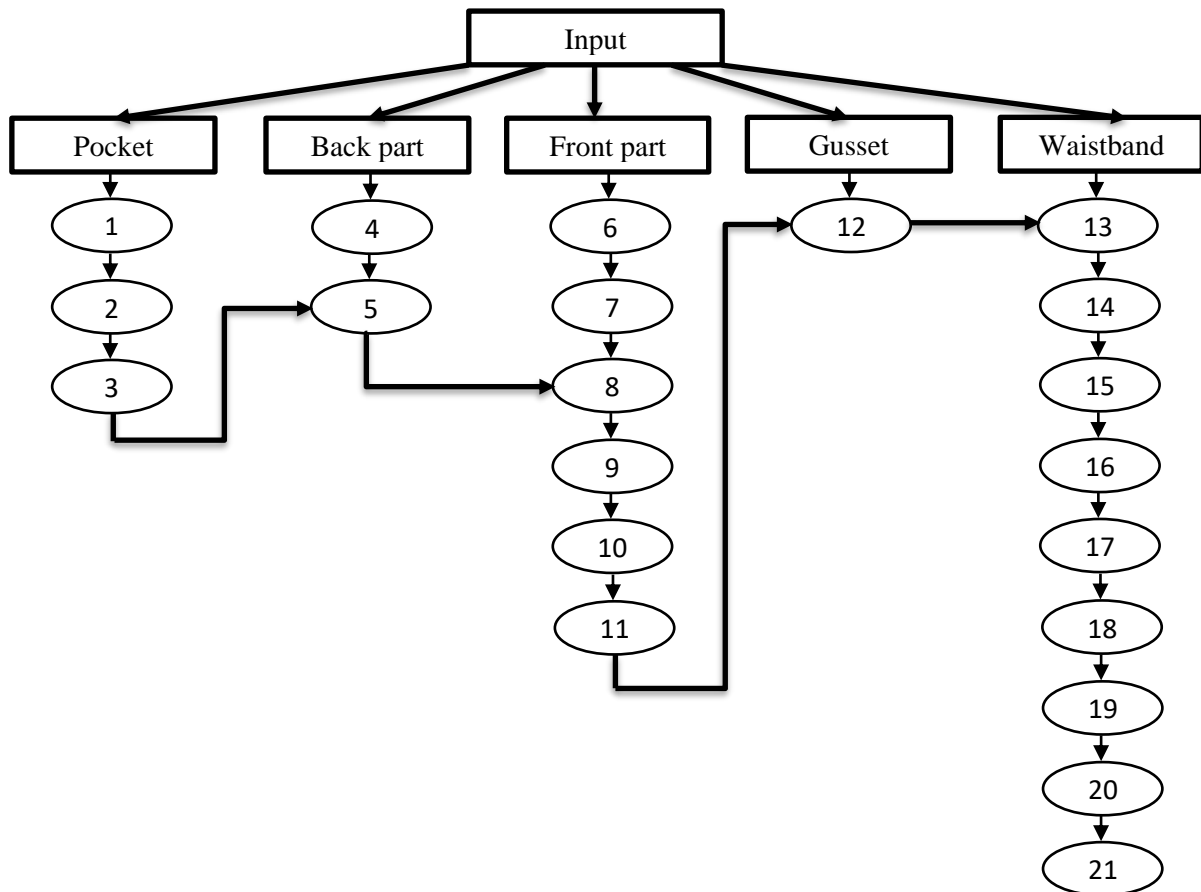

Fig. 2 Production process flowchart of selected garment style

4.2 DATA COLLECTION AND ANALYSIS
In this experiment, data were collected on task processing time, interval time between entities, machine breakdown time, operator absenteeism, and rework time. The interval time of entities arrival and the number of entities per arrival were collected from the floor. A bundle of 36 pieces of garments part were fed into the line every 10 minutes. Task processing time was collected through work-study; twenty processing times were taken for each task. The apparatus used in collecting time were a stopwatch, clipboard, pen, and paper. Rework time was also determined similarly, and the number of defective parts was collected from quality-checking documents. For machine breakdown time, we took the help of 'Data entry Personnel', who keeps records of the machine failure time of every operator on a daily basis. Finally, operators' absenteeism information was taken from the human resource department.

4.3 MODELLING OF INPUTS
Prior to being used in the following stage, the raw data of processing time were analyzed using Arena Input Analyzer software and stored in Table 1. The program offers a variety of integrated distribution functions that

automatically fit the histogram of the actual data. For instance, the processing time analysis result for the '2 N set hip pocket' operation, as in Fig. 3 shows that the distribution function for this particular task is expressed as 0.45 + 0.22 * BETA (1.72, 2.04) with a minimum square error of 0.001504.

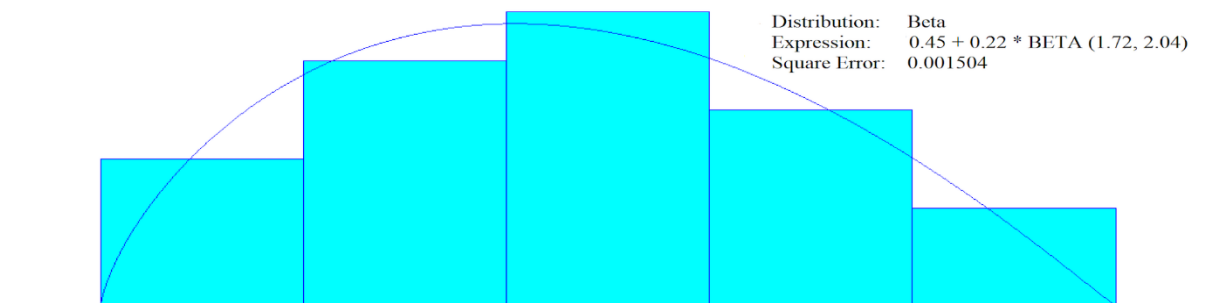| Distribution: | Beta |
| Expression: | 0.45 + 0.22 * BETA (1.72, 2.04) |
| Square Error: | 0.001504 |

Fig. 3. 2 N set hip pocket fitted processing time distribution

Table 1. Fitted processing time distribution

OPN	Operations Description	Resource	Qty	Processing Time Distribution
1	2N Hem Hip Pocket	2 N Fixed Bar	1	TRIA(0.28, 0.313, 0.46)
2	Hip pkt Deco & Attach Lather Join	Cycle Sewing M/C	2	NORM(0.545, 0.0527)
3	Crease Hip Pocket	Iron	2	0.5 + WEIB(0.158, 2.75)
4	Mark Hip Pocket Position	Helper	1	NORM(0.345, 0.0302)
5	2N Set Hip Pocket	2N Lock Stitch	2	0.45 + 0.22 * BETA(1.72, 2.04)
6	Mark Front pocket & J Stitch	Helper	2	TRIA(0.51, 0.6, 0.81)
7	2N Front pocket & J Stitch Deco	2 N Fixed Bar	2	NORM(0.845, 0.103)
8	Assembly Part Match Body	Helper	1	0.27 + 0.19 * BETA(1.99, 3.2)
9	Safety Stitch Outseam	5 Thread O/L	1	TRIA(0.4, 0.514, 0.6)
10	2N Top Stitch Outseam	Feed of the Arm	1	0.43 + 0.22 * BETA(1.66, 1.47)
11	Gusset Mark	Helper	1	NORM(0.294, 0.0222)
12	Gusset join	5 Thread O/L	2	0.53 + LOGN(0.115, 0.0675)
13	Waistband Elastic Tack	1N Lock Stitch	1	0.31 + WEIB(0.105, 2.15)
14	Serge Hem	3 Thread O/L	1	0.29 + ERLA(0.0128, 4)
15	Hem Elastic Tack	1N Lock Stitch	1	0.32 + 0.24 * BETA(2.02, 3.57)
16	Hem Elastic Join	1N Lock Stitch	1	0.42 + LOGN(0.134, 0.0775)
17	Waistband Elastic Join	1N Lock Stitch	1	0.49 + LOGN(0.102, 0.0624)
18	Attach Care Label	1N Lock Stitch	1	0.18 + 0.13 * BETA(2.1, 3.22)
19	Top Stich Waistband	Waistband M/C	1	0.33 + WEIB(0.0968, 1.94)

| 20 | Hem Bottom | 1N Lock Stitch | 2 | TRIA(0.68, 0.689, 1.2) |
| 21 | Tack Front Pocket, Fly & Crotch | Bar Tack | 1 | TRIA(0.31, 0.361, 0.45) |

*OPN – Operation No., M/C – Machine, O/L – Overlock, Qty - Quantity

4.4 CONSTRUCTION OF COMPUTER MODEL

A model of the assembly line for the selected garment (Kid's Pant) was developed using a discrete event simulation software (Arena). The model, as illustrated in Fig. 4, was constructed based on the production process flow of the sewing line. Several Arena simulation modules, such as create, process, batch, record, assign, decide, dispose, etcetera, were used to make the model. The following assumptions were considered while developing the simulation model.

    I.   Setup times of the machine were not taken into consideration because the setup processes were usually accomplished either at the beginning or at the end of the working time.

    II.   Material transportation was not performed by assembly line operators.

    III.   Each operator and helper were assigned to perform a single task on the assembly line.

    IV.   The production floor operated for 8 hours (480 minutes) daily, and there was no overtime.

    V.   Reworks were done by the operators who made mistakes, and reworking time was considered operation failure time.

To determine the optimal replication number, we ran the model for n = 10 replications and found a sample mean μ_A = 739, a sample standard deviation s = 18.371, and the half-width of the 95% confidence interval turned out to be

$$t_{n-1,1-\alpha/2}\frac{S}{\sqrt{n}} = 2.262\frac{18.371}{\sqrt{10}} = 2.262*5.809 = 13.14$$

It is probably obvious that the way to reduce the half-width of the confidence interval on the expected output is to increase the replication number (Kelton et al., 2014). To find the approximate required replication number, we need to set a specific half-width h and solve for n:

$$n = t_{n-1,1-\alpha/2}^2 \frac{S^2}{n^2}$$

$n = z_{1-\alpha/2}^2 \frac{S^2}{n^2}$, replaced t distribution critical value by z, corresponding normal critical value.

An easier but slightly different approximation is

$$n \cong n_o \frac{h_o^2}{h^2}$$

Where n_0 is the initial number of replications and h_0 is the half-width we got from initial replications.

We set our desired half-width h = 3

$$n \cong 10 \ \frac{13.14^2}{3^2} \cong 192$$

Therefore, we considered 200 replications for the model.

The run length of the steady-state simulation model was determined to be 12 hours (8 hours daily production with a 4 hours warm-up period) (Kelton et al., 2014).
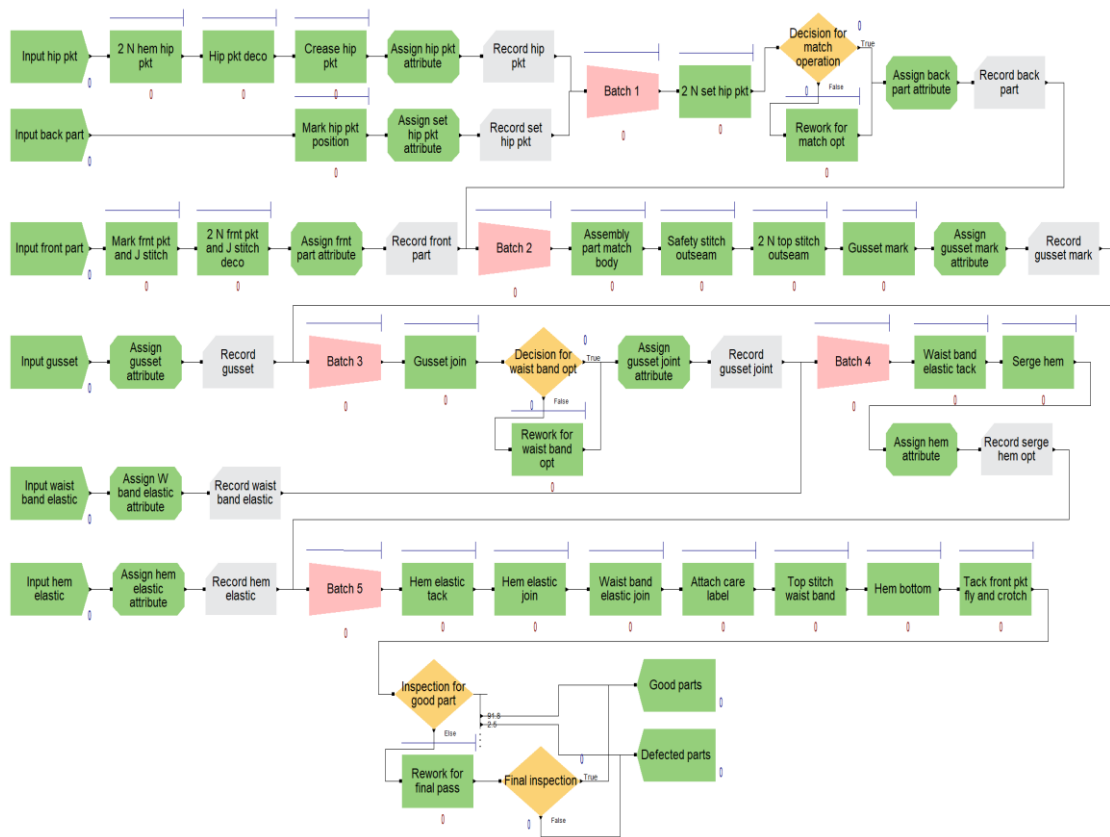
Fig. 4. Arena simulation model of 'kids pant' assembly line

4.5 MODEL VERIFICATION AND VALIDATION

Identifying whether a simulation model is a valid model or whether it accurately represents the actual system being examined is one of the most challenging tasks facing a simulation analyst. There are some techniques to verify and validate a simulation model (Law & Kelton, 2015).

The model was verified by running the simulation with different input parameters and checking whether the output was reasonable or not. We also traced and debugged the simulation model step by step.

A 95% confidence level hypothesis test is used to validate the model (Güner & Ünal, 2008). Here, the t-test hypothesis is used since it is often recommended for comparing data from small samples, typically fewer than 30.

The hypotheses are:

H_0: $\mu_{Field} = \mu_{Arena}$

H_1: $\mu_{Field} \neq \mu_{Arena}$

The test is if $t_0 < t_{\alpha/2, nF + nA - 2}$, we would accept the null hypothesis H_0, where,

$$t_0 = \frac{\mu_F - \mu_A}{S_p \sqrt{\frac{1}{n_F} + \frac{1}{n_A}}}$$

$$S_P^2 = \frac{(n_F - 1)S_F^2 + (n_A - 1)S_A^2}{n_F + n_A - 2}$$

Where,

α - 'significance level'- is the probability of rejecting the null hypothesis when the null hypothesis is true.

μ_F is the mean throughput from the field

μ_A is the mean production rate from the ARENA model

n_F is the number of field samples

n_A is the number of replications or runs of the model

S_F^2 is the variance of throughput from the field

S_A^2 is the variance of production rate from the ARENA model

$S_P^2 =$ is the pooled mean-variance

In order to perform the hypothesis test, twenty days of data on the actual throughput of the assembly line was collected. The gathered data are summarized, and the results of the statistical parameter calculations are shown in Table 2.

Table 2. Actual system throughput and simulation output data

Actual Throughput per 8 hours shift		Output Rate from Simulation	
Sample data:	730, 750, 770, 745, 690, 780, 720, 775, 790, 695, 765, 770, 750, 790, 785, 780, 720, 820, 775, 715	Simulation output:	720, 784, 681, 708, 737, 741, 765, 754, 747, 731, 702, 764, 718, 754, 703, 707, 786, 760, 765, 779
Sample size (n_F)	20	No. of rep. (n_A)	20
Mean value (μ_F)	755.75	Mean value (μ_A)	740.3
Variance (S_F^2)	1140.69	Variance (S_A^2)	881.1
Std. deviation (S_F)	33.77	Std. deviation (S_A)	29.68

From the abovementioned formulas, S_P is calculated to be 31.79, which in turn, generates the t_0 value of 1.54. From the t-table at a 95% confidence interval,

$$t_{\alpha/2, nF + nA - 2} = t_{0.025, 38} = 2.024$$

Since $t_0 < t_{\alpha/2, nF + nA - 2}$, this suggests that the means are not significantly different from one another. As a result, the simulation model is reliable and accurately depicts the real system.

5. PROPOSED MODEL DEVELOPMENT

In this paper, the assembly line of a selected garment has been studied using Arena simulation software. After creating the existing model in Arena using actual data, we determined the optimal replication number (200) and a warm-up period (4 hours) for the model then we ran the model for 8 hours of daily production. The result showed that the model has an average throughput of 741 pieces per day and a half width less than 5.79 at a 95%

confidence interval. Furthermore, the efficiency of the assembly line (75.76%), the number of bottlenecks in the line, resource utilization, and the number of parts waiting in the queue were also obtained from the simulation result.

There are hundreds of different combinations of scenarios which can improve the model output, but checking each of them individually is both arduous and inefficient. We used OptQuest, an optimization tool of Arena, to find the best combination of resources for the model. The optimization constraints included added machine number ≤ 6 and throughput ≤ 950. The upper and lower bounds of each machine in the control list were set to be 1 and 3, respectively. Finally, the objective was set to maximize the output. After providing all the information about controls, constraints and objectives into the OptQuest, an optimization process was executed for 100 simulations with

varying replications from 10 to 200. Each simulation presented different throughput for a

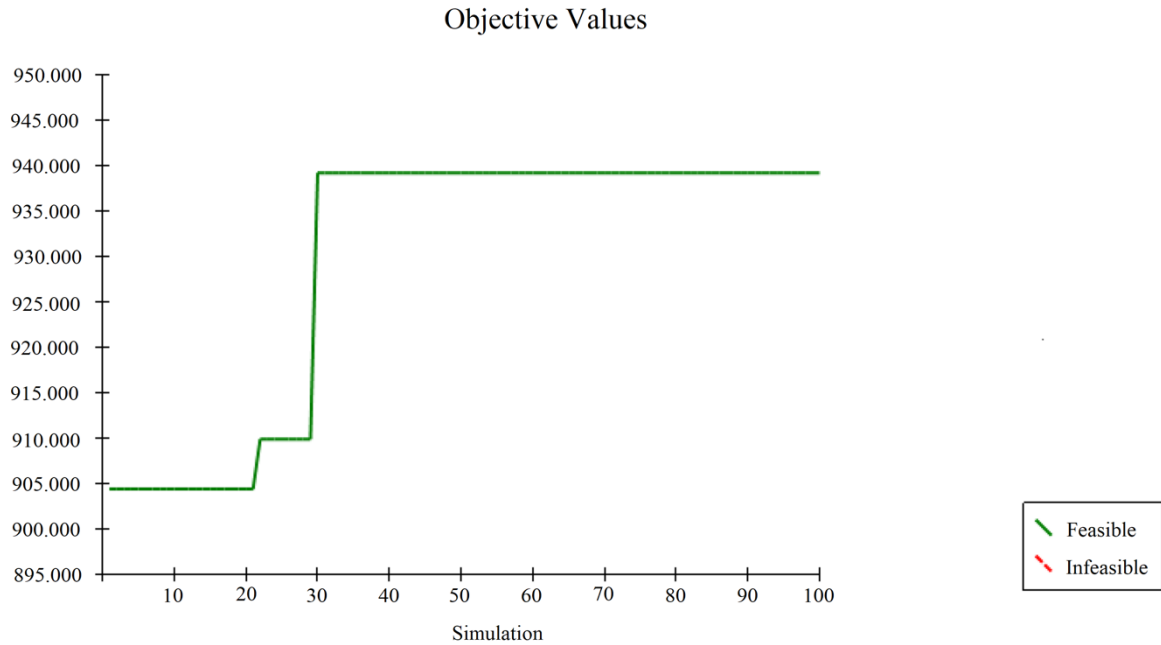different combination of resources, as depicted in Fig. 5.

Fig. 5. OptQuest optimization result

At the end of the optimization process, OptQuest offered the top 25 solutions for each simulation out of 100, as shown in Table 3. It was challenging to choose one of the 25 best solutions. Still, considering the number of resources and space constraints in the assembly line, we selected simulation number 1 as our proposed model because it only added four

resources to the existing model. The average throughput of 904 pieces per day was achieved in the proposed model, which was 163 pieces higher than the existing model's output. The line efficiency of the current model (75.76%) was also increased in the proposed model, which was 92.43%.

Table 3. Best solutions from OptQuest

Simulation	Objective value	Added Number of Resources				
		1 N lock stitch	2 N fixed bar	5 thread overlock	Feed of the arm	Helper
30	939.2	3	0	1	2	0
22	909.9	3	0	1	1	1
1	904.4	2	0	1	1	0
52	900.3	3	0	1	1	0
47	896.5	2	1	1	1	0
36	894	2	0	1	2	0

Simulation	Objective value	Added Number of Resources				
		1 N lock stitch	2 N fixed bar	5 thread overlock	Feed of the arm	Helper
41	875.7	2	0	2	2	0
27	873.4	3	0	1	2	0
43	858.7	3	1	0	1	1
15	855.2	3	1	0	1	0
7	835.8	4	0	1	2	-1
19	835.4	2	0	0	2	-1
25	835.3	3	0	2	2	-1
28	833.7	4	-1	0	1	0
18	832	4	1	1	1	-1
24	805.6	2	0	3	1	0
16	804	2	1	1	1	0
45	798.1	2	0	1	2	1
12	796.9	4	-1	-1	0	0
33	792.6	1	1	3	1	0
49	791.7	1	0	3	2	0
4	787	1	1	1	2	1
17	784	2	1	2	0	0
11	782.3	3	1	3	0	-1
31	772.8	5	-1	-1	2	-1

The comparison of resource utilization of existing and proposed lines is given in Fig. 6. It is seen from the figure that because of line balancing, the resources of the proposed line are better utilized than the resources of the existing line.
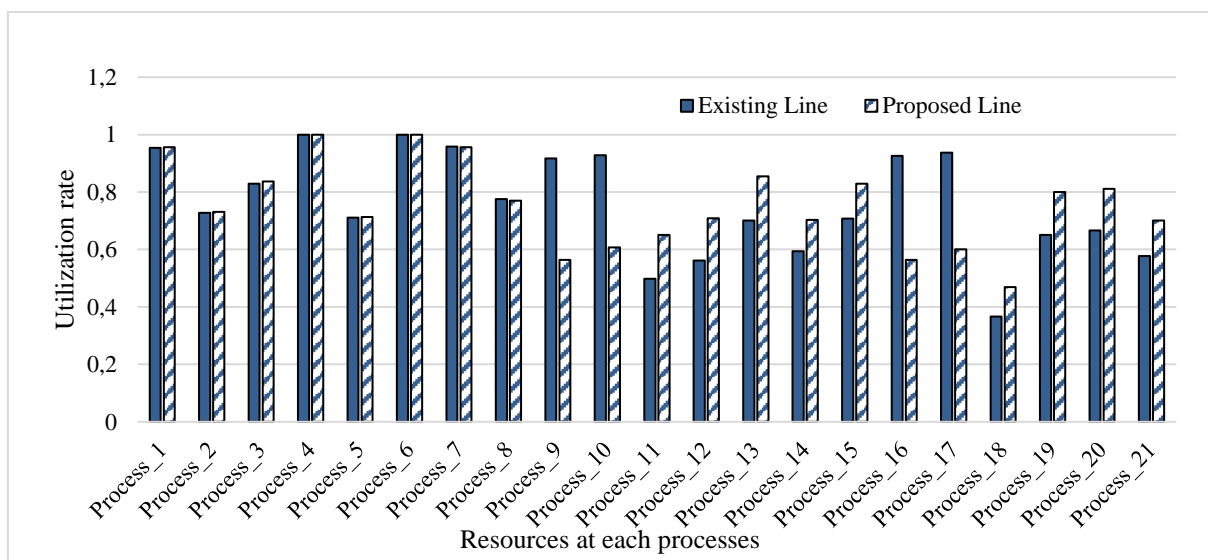

Fig. 6. Resource utilization of the existing line and the proposed line

6. SENSITIVITY ANALYSIS

Simulation analysts use quantitative techniques to evaluate the accuracy of different components of the overall model. Sensitivity analysis is an important technique to identify which model factors significantly affect the intended performance metric. In this study, we considered three factors (i.e. entities per arrival, process failure time, and operators' absenteeism) for sensitivity analysis. Entities per arrival (bundle size) are insensitive to the model output; we run the simulation model with different bundle sizes and found no significant changes in daily throughput. On the other hand, process failure time and operators' absenteeism greatly impacted the model output.

Machine breakdown time, thread breakage, quality issue, and preventive maintenance constitute process failure time. The failure time was collected from machine maintenance documents and 'data entry personnel who keep records of the machine failure time of every operator. We collected twenty days' data on machine failure. The time was then analyzed with the help of the Arena input analyzer to find out the fitted distribution of each data with less square error. Table 4 shows the approximate time between two successive machine breakdowns and the repair time of the corresponding machine of the current model.

Table 4. Fitted process failure time distribution

Serial No.	Machine name	Interval Distribution	Downtime Distribution
1	2 N fixed bar	360 + EXPO(92.4)	7.5 + GAMM(11.9, 1.22)
2	Cycle sewing machine	NORM(463, 61.7)	9.5 + 91 * BETA(0.638, 1.33)
3	2 N lock stitch angular	375 + EXPO(74.2)	9.5 + 76 * BETA(0.51, 1.74)
4	5 thread overlock	315 + EXPO(96.3)	14 + EXPO(23.5)
5	3 thread overlock	NORM(456, 96.2)	NORM(35.8, 24)
6	Feed of the arm	TRIA(240, 360, 615)	9.5 + GAMM(11.3, 1.43)
7	1 N lock stitch	NORM(444, 92.8)	9.5 + 41 * BETA(0.628, 1.4)
8	Waistband	NORM(429, 98.3)	9 + LOGN(18.5, 30.5)
9	Bar tack	TRIA(270, 420, 570)	NORM(23.4, 8.67)

The throughput of the proposed model decreases if the failure time increases, and when the failure time decreases, the daily output of the model increases. The phenomena are depicted in Fig. 7 and Fig. 8, respectively. Fig. 7 shows a negative correlation between the daily throughput and the failure time; if the failure time is increased by 10% to 50%, the model output will go down from 893 pieces to 820 pieces per day. Fig. 8, on the other hand, shows a positive correlation between the model output and machine breakdown time, and if the machine breakdown time is decreased by 10% to 50%, the daily throughput will increase from 931 pieces to 1025 pieces per day.
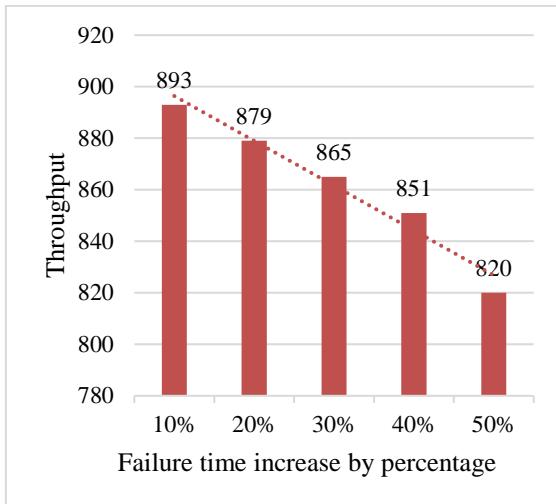
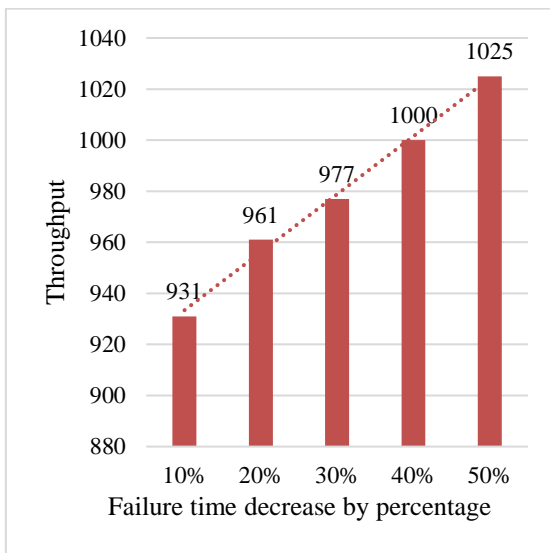**Fig. 7.** Relationship between throughput and increased failure time

Fig. 8. Relationship between throughput and decreased failure time.

Operators' absenteeism also plays a vital role in the daily production output; even a single operator's absence can cause a vast production drop in the assembly line. In our model, 6% of total operators' absenteeism is acceptable as there are ready replacements for 6% absenteeism. However, if absenteeism occurs more than 6% (2 people), it will hamper the total production of the line. In this study, we assume that all the assembly line operators are equally skilled in running any machine. So, if any absenteeism occurs, the line could still be arranged in the best possible way to maximize

production and reduce the bottlenecks. Our proposed model has 32 operators; we reduce the number of operators or machines one by one and conduct an optimization test using OptQuest to find out the best arrangement of resources for a specific machine number. The relationship between resource number and daily throughput is delineated in Fig. 9. The figure shows that the first removal of a resource from the assembly line causes a huge production drop, but the second, third, and fourth removal of resources does not change the output of the assembly line that much. It is because, after the first removal of a resource, some other resources become underutilized, and when second, third and fourth removal occurs, those resources become utilized, which causes no change in the output. The fifth and sixth removal of machines again causes the production to drop.
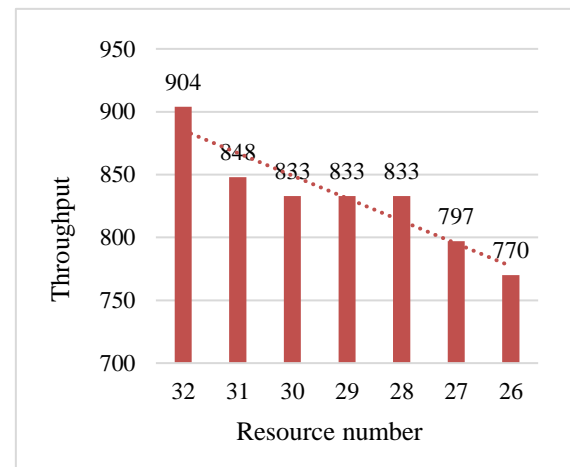

Fig. 9. Changes in production output with the changes in resources

Sensitivity analysis allows the simulation analyst to determine the uncertainty associated with a simulation model. Failure time and operators' absenteeism have a crucial effect on the simulation model of an assembly line. Changes at any degree of these two factors can significantly change the model output.

7. CONCLUSION
Simulation is one of the most popular methods in operations-research and management-science. Many assembly line balancing

problems, scheduling problems, and other industrial engineering problems can be solved by simulation modelling. This study analyses an assembly line balancing problem using discrete event simulation modelling software (Arena). The conceptual model successfully depicts the sequence of operations of the assembly line. Multiple times of each process were collected through the time-study method and then analyzed using the Arena input analyzer. The computer model of the assembly line was verified by production personnel and validated by a 95% confidence level hypothesis test. The run length and warm-up period were also determined by statistical tools. The current throughput of the existing model was 741 pieces per day with a line efficiency of 75.76%, but after an optimization using OptQuest, the throughput became 904 pieces per day with a line efficiency of 92.43%. At last, a sensitivity analysis was conducted to determine the level of uncertainty of the proposed model, and two factors (failure time and operators' absenteeism) were found to be very sensitive to the model output.

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