Using Simulation Modeling To Increase Plant Throughput

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Abstract

Simulation modeling is one of the most important methods used in the manufacturing processes field. The purpose of using the simulation processes is to determine the problems that happen during manufacturing processes and find optimum solutions with better cost and time process. The simulation processes always happen before start applying processes in the plant. This research focuses on finding optimum solutions to the problems in the production lines such as a bottleneck and processing time at each station of the plant. Also, the research will focus on increase productivity of the plant by running simulation models several scenarios in order to reach the optimal case. Arrival time, capacity, expo time are parameters that will study and consider in each station to avoid problems in the plant. In addition, this research will use a design of experiments DOE and response surface methodology RSM to analysis and support the results and find the optimal mathematical model of the production line. Finally, the steepest ascent method will use to determine the optimum region and give a specific point of the optimizing of results.

Keywords
Simulation Modeling, Throughput and Bottleneck, Cycle Time, RSM, Steepest Ascent Method.

1. Introduction

In lean manufacturing environments of advanced manufacturing systems, the flexible production line is designed to manufacture a variety of products in a timely manner with minimal inventories. Such a system is composed of a number of workstations linked together by an automated transfer line, such as robotics or chain or belts or carts, etc.. Furthermore, a computer program carries out the function of production scheduling, operation monitoring and production control. A large number of factors are critical to the effective operations of such flexible production lines including number of product options, manufacturing, operation of each product type, workstation capacity, processing time of the operations at each station, material handling capacity at each workstation, and overall material handling capacity. [4] A Simulation and design of experiments DOE have been used for performance improvement in many applications. [12]

This research will study effects of arrival time, capacity, expo time and affect those variables in the production process and the problems that occur in the production process. Also, simulation processes, modeling, DOE, RSM and Steepest Ascent Method will use to get optimum parameters, optimum scenario that gives better result without problem. The production lines in plants have many stations to treatment or machining the pieces entering to the plants in order to get the desired product such as the plant shown in the Fig.1.

Figure 1. Existing pieces entering, plant and final product

The plant consists of several stations as shown in the Fig. 2, each station used to accomplish a specific process for a billet, also each station contains a number of machines and each machine is responsible to complete a process with specific time for the implementation of the process required. In this project will optimize production processes and study most variables that effect on increases in productivity in the plant with less time. In addition, this research will find out the best solutions of the problems in the production lines.

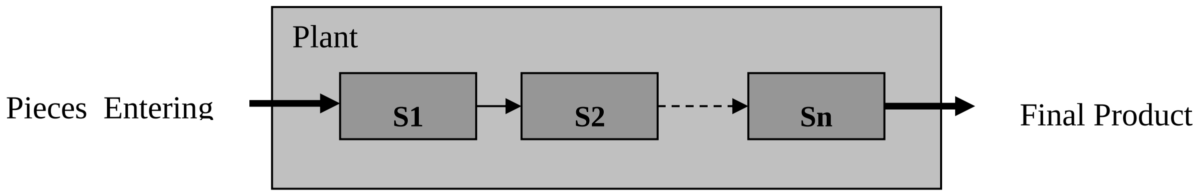

Figure 2. Existing plant with many stations

There are many researchers worked on a production lines problems and find solution of these problems to increase productivity in the plant, such as bottle neck, processing time, etc….. Brown et. al. (1999) focused on cycle time reduction strategies that can be applied to the assembly area of semiconductor manufacturing facilities. [1] Roser (2001) worked on "A Practical Bottleneck Detection Method". The researchers investigated a novel method for detecting the bottleneck in a discrete event system by examining the average duration of a machine being active for all machines. [2]

Faget and Herrmann (2005) studied and described the application of a method for detecting bottlenecks in discrete event models developed by Toyota Motor Company. [3] Ali et. al. (2005) discussed a combination of product mix and production volume is analyzed using a reconfigurable simulation model aiming to improve the performance and optimize designing requirements. The performance under different production scenarios is developed to find the optimal combination of product mix to meet future customer demands. This research provides a re-configurable assembly system modeling by adding flexibility and evaluates alternative designs. The best satisfaction of the production requirements under dynamic production is validated with real application. [4]

ZHOU et al (2006) worked on integrating and analysis methodology composed of four components: visual modeling, simulation, diagnosis and reduction of bottleneck processes of production lines has been presented in this paper. [5] Ali and Seifoddini (2006) studied The realistic used a simulation modeling becomes very essential and effective for designing and managing of manufacturing systems, which needs to be addressed manufacturing dynamics. This research includes manufacturing uncertainties in the form of smart simulation to improve the system's performance in the high-mix low-volume manufacturing systems. It shows how simulation modeling can be used to evaluate alternative designs in a dynamic uncertain manufacturing environment. Fuzzy rule based machine, labor and logistics uncertainties are addressed in this study. A combination of product mix and production volume is analyzed using an intelligent simulation model for an optimal designing of the production system to meet future customer demands. The intelligent knowledge system shows significantly closer to real-life scenario. The proposed intelligent simulation modeling is validated with real life application. [6]

Ali and Souza (2007) worked on presenting a HDD template is designed and developed for modeling and simulation for final assembly of hard disk drive (HDD) manufacturing using Arena. The designed HDD template is a high flexibility and good performance of an internal supply chain level and self-development and improves the system performance significantly. It is developed the intelligent based dynamic machine knowledge, which can capture dynamic based activities with fuzzy system. The study shows how modeling and simulation tools can be used and integrated to implement highly automated systems for industrial processes and deal with flexible products. In such context the researchers designed and developed a prototype for the final assembly of hard disk drive with dynamic and static behavior. [7]

Khadem and Ali studied modeling and simulation for an assembly line of a car battery manufacturing for cost effectiveness. The proposed approach improves cycle time, productivity and rework. Validation is performed for different periods and compared to actual production applications. The study proposes changing the manual operation to automation. [8] Sihombing et.al. (2011) worked on discussing this study performed the line balancing method through a simulation model in order to reduce the line unbalancing causes and relocate the workforce associated with idle time, eliminating the bottleneck, and at the same time maintaining improving the productivity. [9]

The following remarks could be summarized from the previous literature survey, the research used simulation the modeling based on the parameters of each report that will be given to the program, Most of the researchers focused on solving the problems cycle time, bottleneck and cost, data collection and input distribution. Analysis of the results generated from each simulation modeling in order to get optimal result.

2. Proposed System

This research studies the production line of the Liquids Bottling plant and diagnoses the problems during a production process. Before that, should identify in the plant on stations, machines and the time that takes each process to complete the required process, this because to get an idea of the plants before start simulating the production lines in the plants. The most of fluids plants (water, juice, oil, etc….) consist of a number of stations, each station is performance a process to complete the final product, so that the last station, the product must be ready for marketing to the consumer. Therefore, in this part of the research will identify on each station in the proposed system, such as shown in the Fig.3:

- **Injection Machine** is the first station will enter the small piece (pit) that will be injected into a bottle.
- **Machine of Wash and Inject Liquid** in this station will wash and the inject liquid in the bottle.
- **Covering** in this station will close the bottles.
- **Label Machine** in this station will be stick a product label.
- **Inspection** in this station will be checked and test each bottle before collection process**.**
- **Shrink Machine** in this station will collect the product in a package, each package contains a number of the bottles.
- **Storage Area** is the last station in the plant, in this station will collect the product before shipping.

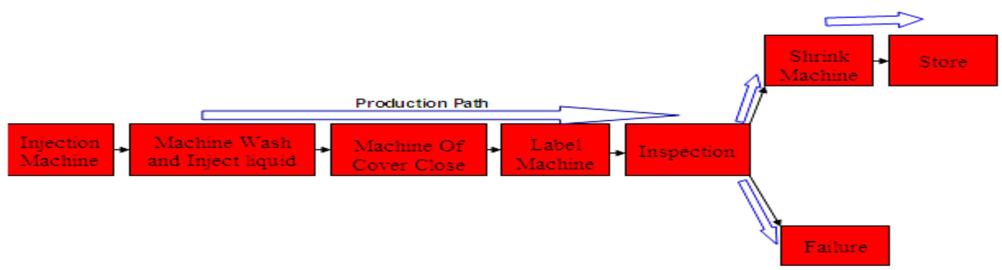

Figure 3. Existing planning of the liquids bottling plant

3. Data Collection

A processing data are a core of this research, and the data are normally collected, and save on the hard drive of each machine. Connected through a network, one could have used a USB drive to collect months' worth of data from the master computer. Unfortunately, access is not available to the people with the right skills, and the researchers feared if others were to attempt to access these data they could cause an alteration of a key component of the operating software thus shutting down the plant and invoking massive losses, it has happened more than once before. For that matter, the researcher used data that were highly reliable, however, needed some work to rearrange and sort. [12]

So in this paper we suggested all data for each station and machine arrival time, capacity and expo time, So from the analysis such as shown tin the Fig. 4, the data represent the best distribution for the data reading by using an input analyzer program.

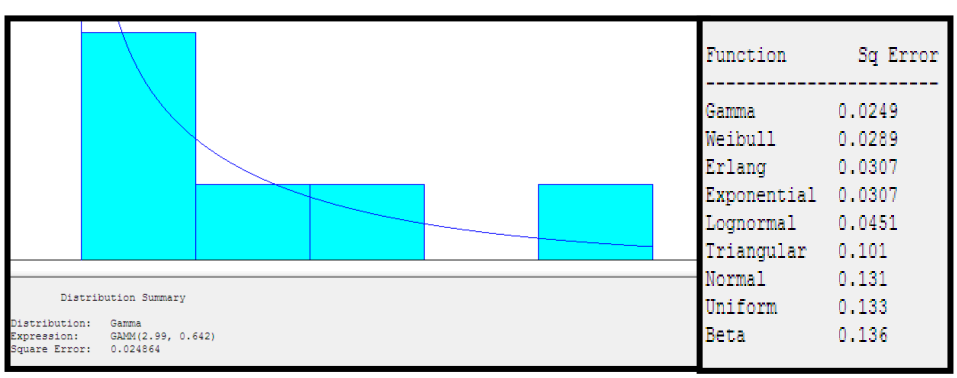

Figure 4. Existing Data distribution

4. Simulation Modeling for Existing and Proposed System

In this section will explain how to build steps to get on the optimization of the proposed system by using the methods that will help to get on an optimum path, such as DOE, RSM and steepest ascent method in order to identify the steps that will follow in this research to reach the desired goal for the proposed system, and determine the problems and find the solutions for these problems. Also will work on the study to increase production and efficiency by changing the variables that were fed to the simulation model, and work to install the variables that give the best result and the desired goal (to increase production, reduce bottlenecks and cycle time). Fig. 5 illustrates steps followed for this search to get optimization model.

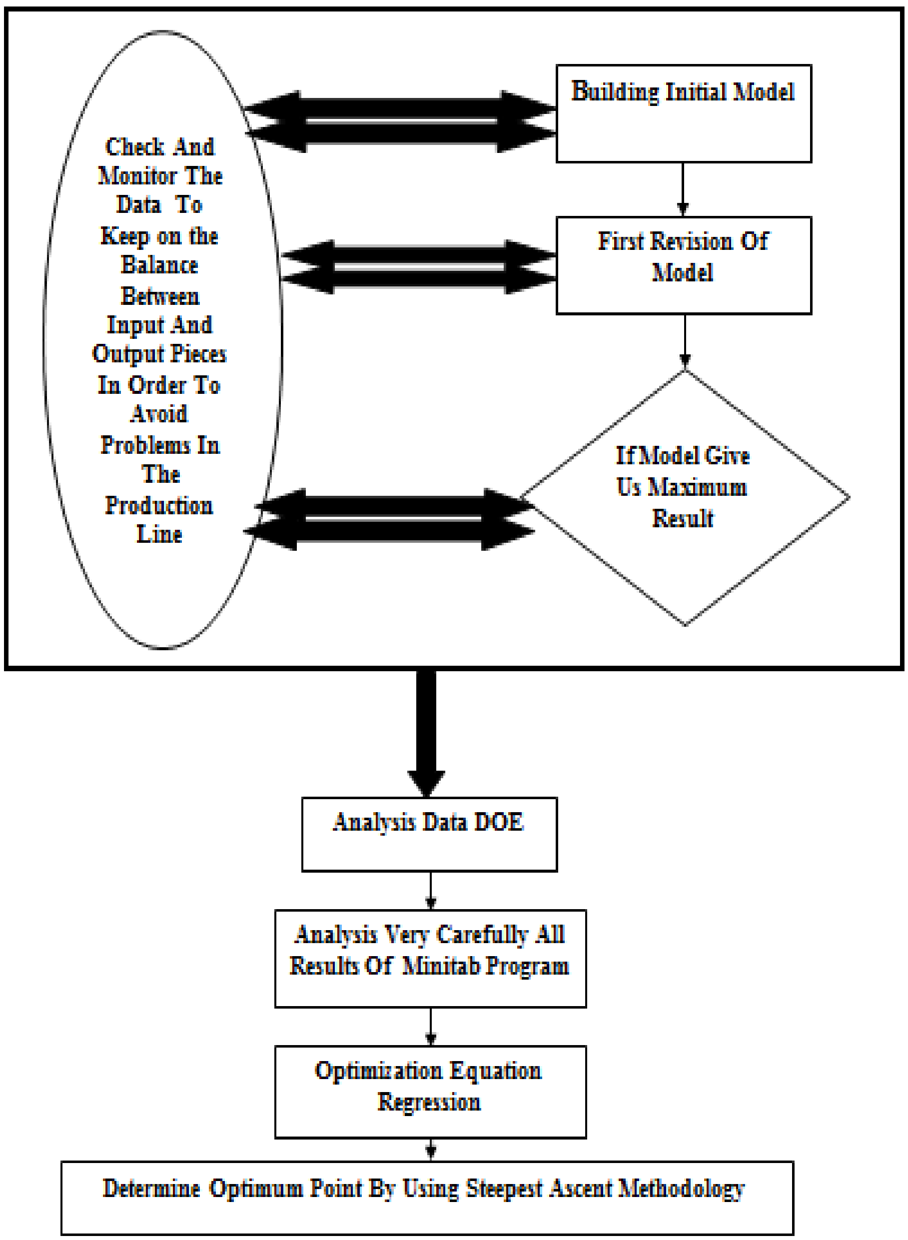

Figure 5. Existing flowchart shows represent simulation modeling for the plant

Figs. 6 and 7 show the normal and the improved simulation model, the target is to get model has short time, increase production, treated bottleneck problems and balance between input and output pieces when the run of the program for 24 hours. Re-change the variables that have been fed to the model simulations more than once in order to get the best of the situation and get the balance between production and the problems that occur in each station. Fig. 7 shows the optimal model to obtain a higher output with minimizing the problems that occur in production line, also in this research made 32 tests to get the improved model in the Fig. 7.

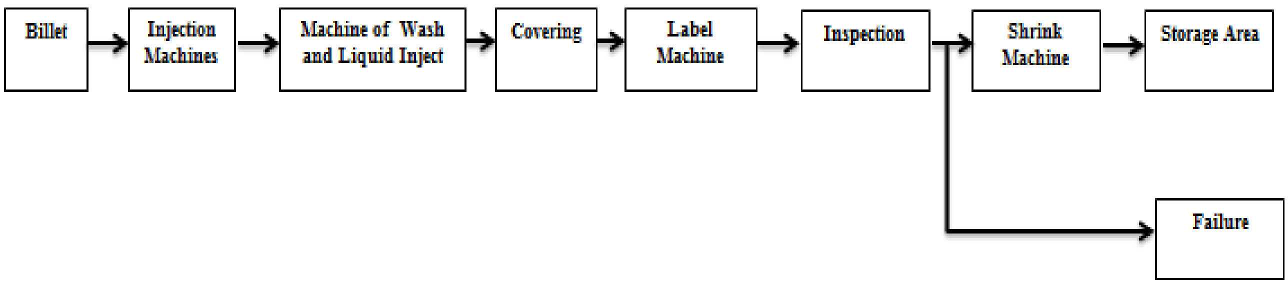

Figure 6. Existing Simulation model for the plant of liquid bottling

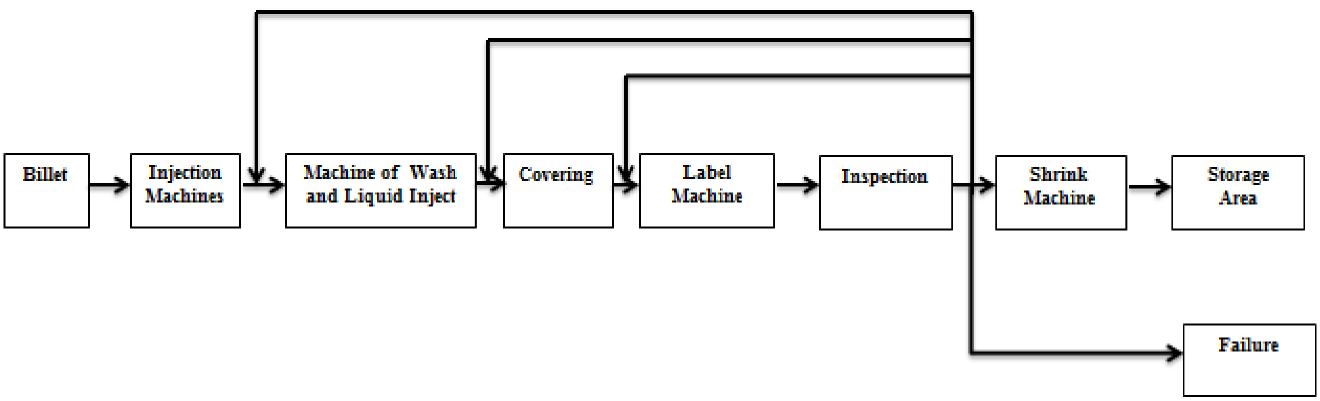

Figure 7. Existing Simulation model for the plant of liquids bottling

5. Results and Discuss

In order to get accurate results and full knowledge of the plant in this research must be run, modify and improve the simulation model in order to get a balanced result between the best time with productivity and reduce the problems that occur in the stations during running the production line. Table (1) shown the results that obtained from the improved simulation model compared with the normal simulation model during 24 hours as shown in the Fig. 7**.** Fig.8 shows the waiting time for each station and notice that the Improved Model has waiting time regular if has been compared to the normal model was irregular and very long**.** Figs. 9 and 10 shows the total time per entity and the number waiting (queue) for each station and notice that the Improved Model has a regular result, convergent and very little disparity if has been compared to the Normal Model be irregular and very long**.** Fig. 11 shows the instantaneous utilization for each station and we notice that the Improved Model has instantaneous utilization a regular, convergent and very little disparity if has been compared to the Normal Model be irregular**.**

Table 1. Compared Improved model results with Normal model results model

Station No.	Waiting Time Per Entity		Total Time Per Entity		Number Waiting (Queue)		Instantaneous Utilization	
	Improved model	Normal Model	Improved model	Normal Model	Improved model	Normal Model	Improved model	Normal Model
1	0.1917	0.012134	0.3909	0.2135	1.3564	0.00388	0.7045	0.06442
2	0.139	5.1228	0.3371	7.1495	0.9258	1.7484	0.6598	0.6911
3	0.2067	2.9408	0.4059	4.8272	1.51	1.0196	0.7281	0.5911
4	0.2437	0.008217	0.4454	0.1527	1.7822	0.00262	0.7371	0.04624
5	0.1775	67.885	0.3783	70.92	1.2196	22.3972	0.6656	0.5541
6	0.1632	3.2835	0.3664	5.2863	1.0687	0.9084	0.6727	0.507
7	0.1792	2.0019	0.3847	3.8398	1.1736	0.5522	0.6886	0.9725
Productivity by using normal model					331 piece			
Productivity failed by using normal model					43 piece			
Productivity by using improved model					7854 piece			
Productivity failed by using improved model					118 piece			

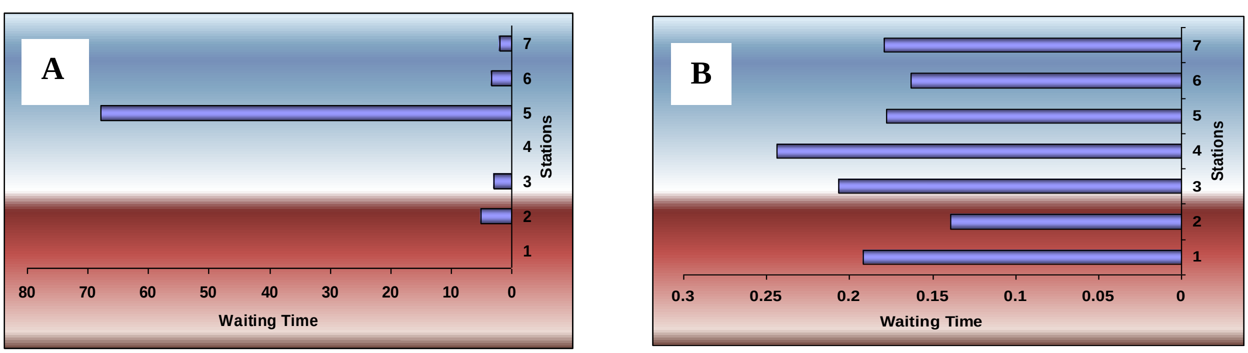

Figure 8. Existing Waiting Time Per Entity for each station
(A) Normal Model (B) Improved Model

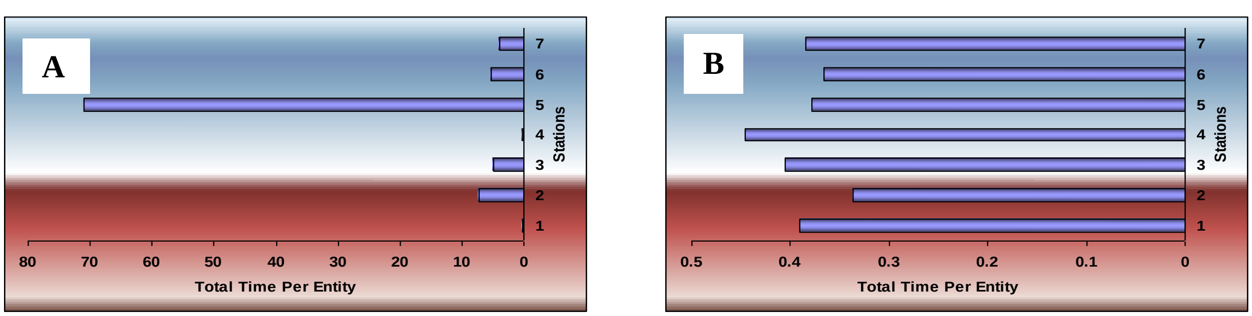

Figure 9. Existing Total Time Per Entity for each station
(A) Normal Model (B) Improved Model

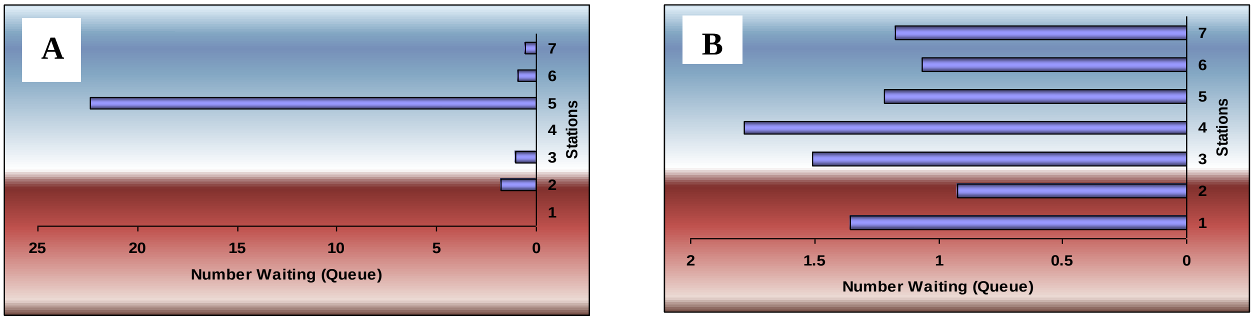

Figure 10. Existing Number Waiting (Queue) for each station
(A) Normal Model (B) Improved Model

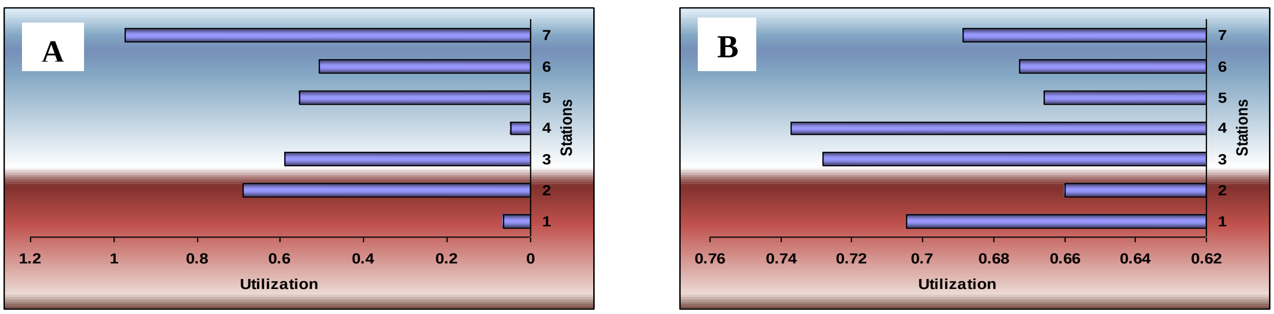

Figure 11. Existing Instantaneous Utilization for each station
(A) Normal Model (B) Improved Model

6. Design of Experiments (DOE)

DOE originated in the 1920's by a British scientist, Sir R. A. Fisher, as a method to maximize the knowledge gained from experimental data and it has evolved over the last 70 years. Most experimentation involves several factors and are conducted in order to optimize processes and or investigate and understand the relationships between the factors and the characteristics of the process of interest. [11]

In this research used the variables (arrival time, expo time and capacity) as variables that will study their effects on the productivity of the plant. In addition, many of experiments applied several to build a mathematical model by using DOE. The number of experiments depends on the number of variables of the DOE, the Fig. 12 shows the results after had been fed the variables in the simulation program. Furthermore, the number of experiments can calculate from 2^m (m is the number of variables). The prediction equation is shown below:

$$Y = B0 + B1\,X1 + B2\,X2 + B3\,X3 + B12\,X1\,X2 + B23\,X2\,X3 + B13\,X1\,X3 + B123\,X1\,X2\,X3 \tag{1}$$

Where:
Bo, Bi, m, n: coefficients of recorded model
Xn: natural variable
The prediction equation :
Y=4097-3713 Arrival Time-15 Capacity+7 Expo

Table 2. Variable levels and their values

Factor	-1	+1
A: Arrival time	0.15	3
B: Capacity	2	6
C: Expo	0.15	0.20

Factorial Fit: Results versus A; B; C

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Estimated Effects and Coefficients for Results (coded units)

Term        Effect   Coef  SE Coef        T      P
Constant             4097    9.205   445.12  0.000
A            -7427  -3713    9.205  -403.43  0.000
B              -31    -15    9.205    -1.67  0.193
C               14      7    9.205     0.75  0.509
A*B*C           11      5    9.205     0.58  0.600


S = 26.0344      PRESS = 14459.6
R-Sq = 100.00%   R-Sq(pred) = 99.99%   R-Sq(adj) = 100.00%
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Figure 12. Existing analysis data by Using Minitab Program.

Fig. 13 shows that the arrival time (A) has an effect on the productivity while the capacity (B) and expo time (C) do not have any significant effect**.**

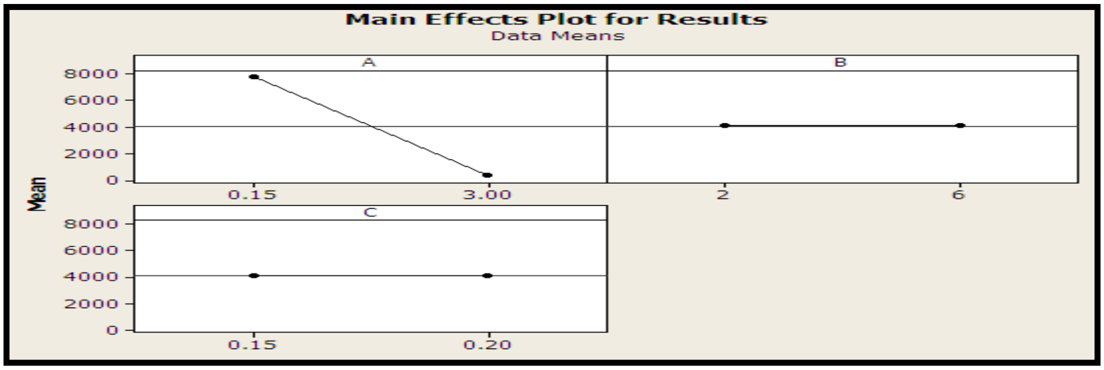


Figure 13. Shows main effects for variables on the production

Fig. 14 shows interaction plot and effect arrival time (A), capacity (B) and expo time (C) on the result, all lines are parallel and there is no interaction between the lines, that mean variables are independent**.**

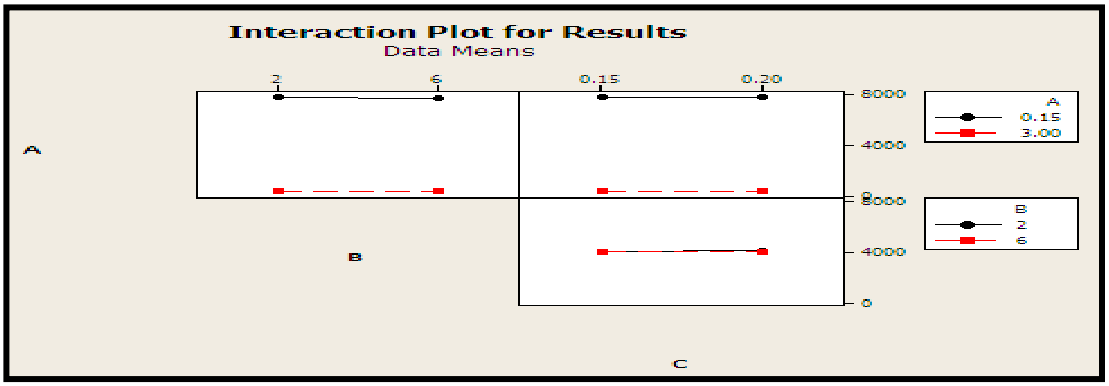


Figure 14. Existing interaction plot

Fig. 15 shows surface plot, contour plot and effect arrival time and capacity on the results**,** notice from the figure below to increase the productivity will happen by decreasing arrival time, capacity and the expo time and there is not significant effect between capacity and expo time**.**

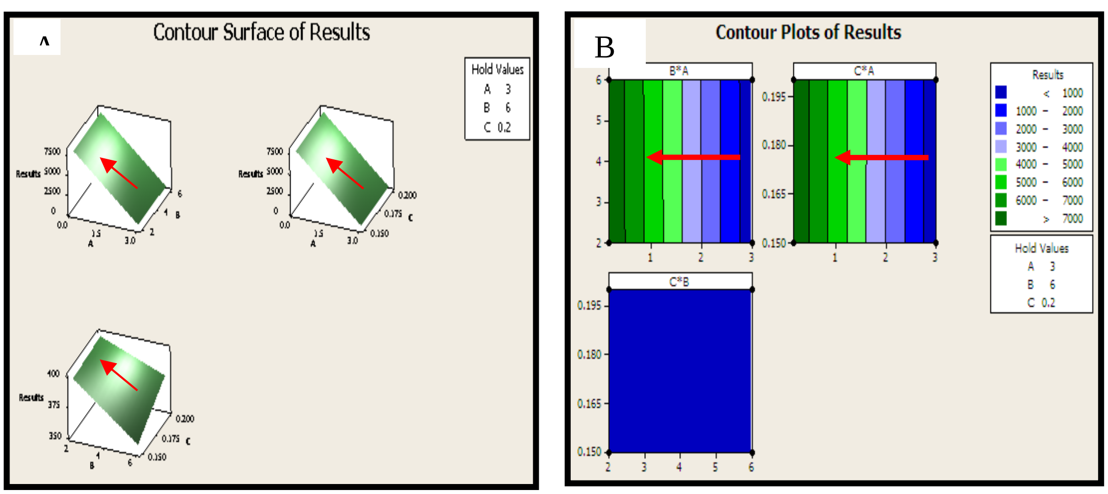


Figure 15. Shows plots of (A) Surface plot. (B) Contour plot

From Fig. 16 all points of probability plot are along the line, that means the desired purpose, also from the Fig. 16B that the variable (A) is very effective on the productivity.

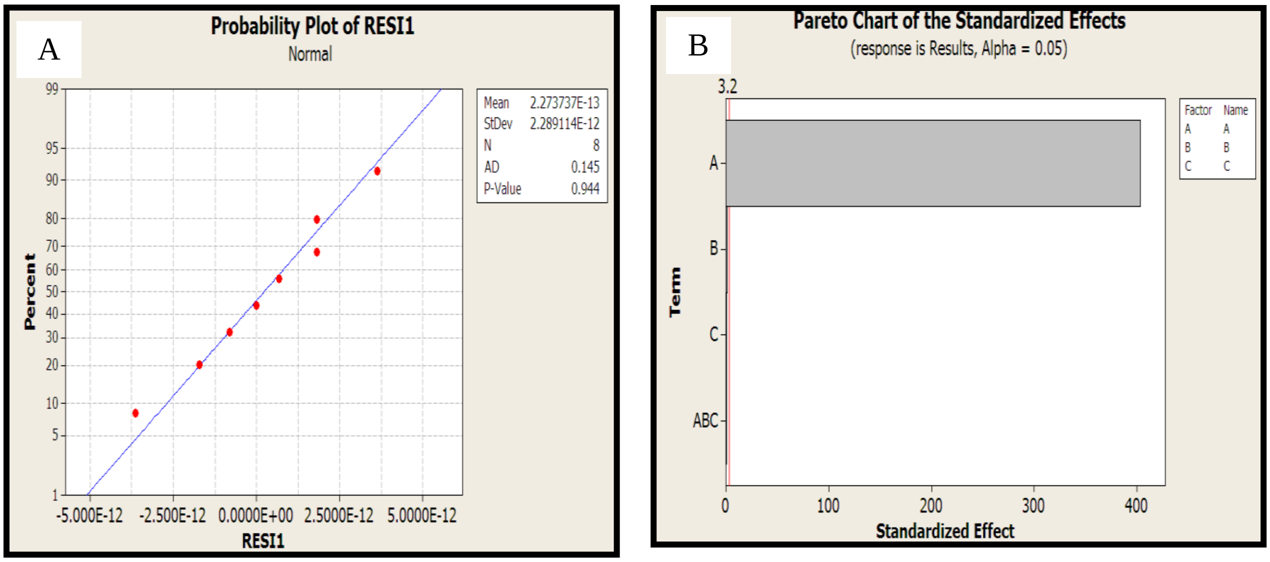
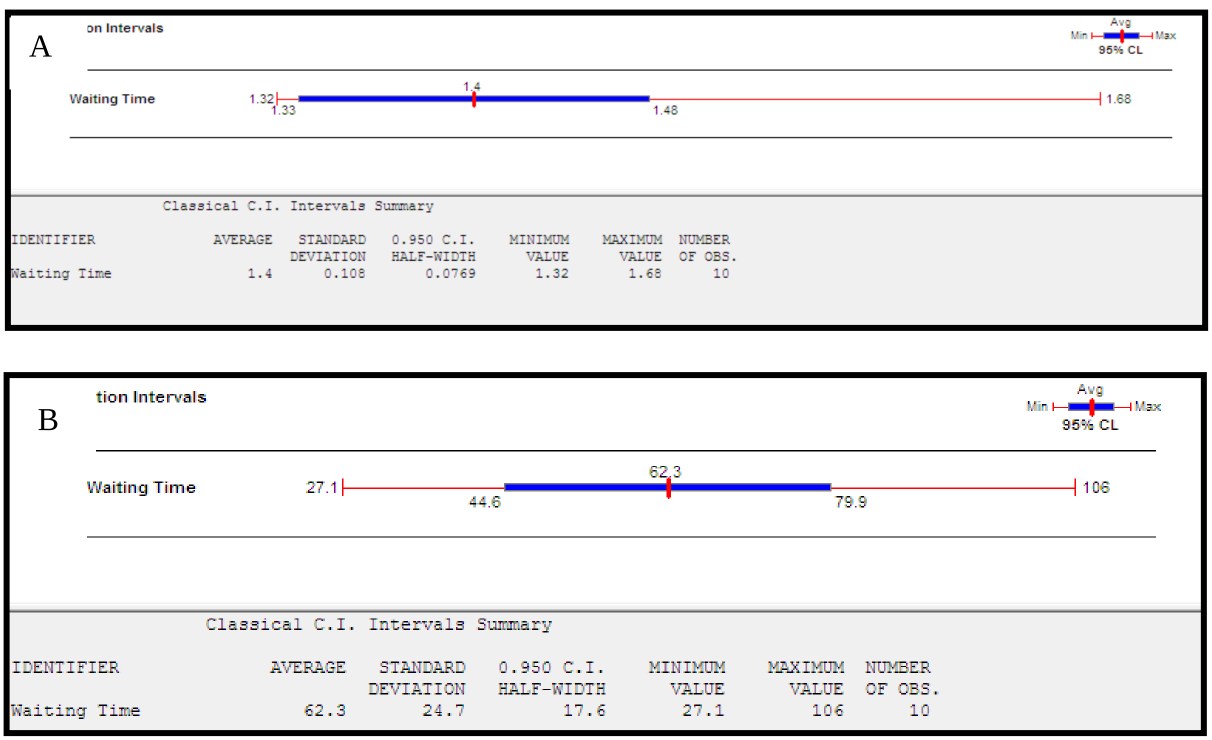


Fig. 16. Shows (A) Probability plot (B) Pareto chart

the average of the waiting time to improved model is 1.4 and 62.3 for normal model with simulation models 95% CI such as shown in Fig. 17.



Classical C.I. Intervals Summary

IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
Waiting Time	1.4	0.108	0.0769	1.32	1.68	10

Classical C.I. Intervals Summary

IDENTIFIER	AVERAGE	STANDARD DEVIATION	0.950 C.I. HALF-WIDTH	MINIMUM VALUE	MAXIMUM VALUE	NUMBER OF OBS.
Waiting Time	62.3	24.7	17.6	27.1	106	10

Fig. 17. Existing average waiting time (A) Improved model (B) Normal time

The average of the total time per entity to improved model is 2.88 and 73.2 for normal model with simulation model 95% CI. The queue average waiting time to Improved Model is 0.202 and 0.0128 for Normal Model with simulation models 95% CI. The scheduled utilization to Improved Model is 0.707 and 0.0648 for Normal Model with simulation model 95% CI.

This research has tested the results by some techniques like t-test to support and prove the validity of the results.

- $$R^2 = 1 - \frac{SS_R}{SS_T} \qquad (2)$$

$$R^2 = 1 - \frac{231}{231} = \%\,100$$

The above value is the percentage of the variation of the response.

- $$t = \frac{\beta}{\sqrt{\sigma^2 w_d}} \qquad (3)$$

$$|t_A| = 20.6630 \succ t_{0.025,4} = 2.776$$

$$|t_B| = 0.0834 \prec t_{0.025,4} = 2.776$$

$$|t_C| = 0.0389 \prec t_{0.025,4} = 2.776$$

From t-test results, the arrival time (A) has an effect on the model because it has a larger value than t-test value, but the capacity (B) and the expo time (C) don't have any effect on the model because their values less than the values of t-test.

7. Steepest Ascent Method

There are many other methods used to build a mathematical model for optimization. The purpose of building second model determines a specific point of the optimization, the model is called Meta-Model. A statistical analyst is armed with mathematical and analytical techniques, the purpose is to optimize the process. [13] In this section will optimize variables by using the steepest ascent method, this method depends on the mathematical model that has been calculated from DOE, and the procedures explain how the Meta-Model will build.

Y=4097-3713 A- 15 B+ 7 C (4)

The table 3 below shows the minimum and maximum level for each variable

Table 3. Variable levels and their values

Factor	Design Units	
	-1	+1
A: Arrival Time	0.15	3
B: Capacity	2	6
C: Expo	0.15	0.2

Then select Δ A=1 because it has largest coefficient in equation (4) to calculate increment value for coding parameter. Δ A=-1, Δ B= (-15/-3713) =0. 004 and Δ C= ((7/-3713) = -0.00188. After that, calculate increment value for normal or natural variables

Δ Arrival Time = -1
Δ Capacity = (0.004) * (6-2/2) =0. 008
Δ Expo = (0.001) * (0.2-0.15/2) = -0.000025

The table below represents the path of steepest ascent method for the coded variables and natural variables, should experiment all the variables that calculated to reach the ideal situation. Also in this step used only until (Base +3 Δ) because in this research assumed all variables without limit, but some paper they took (Base +9 Δ) or more than that, this because some researchers wanted to access to the specific results, so maybe they will take more (Base +n Δ) because the results will obtain from (Base +1…9Δ) are not the desired result.

Table 4. Coded and natural variables of steepest ascent method

Factor	Coded Variables			Natural Variables		
	A	B	C	Arrival Time	Capacity	Expo
Base	0	0	0	1.575	4	0.175
Incremental Δ	-1	0.004	-0.001	1	0.008	-0.000025
Base + Δ	-1	0.004	-0.001	2.575	4.008	0.174975
Base +2 Δ	-2	0.008	-0.002	3.575	4.016	0.17495
Base +3 Δ	-3	0.012	-0.003	4.575	4.024	0.174925

8. Conclusions

All the tables and charts the previous shown the results of the proposed simulation model, the results have compared between two assumed models. This research did a balance between the variables to reduce a disparity between the stations in the production line, the purpose of this step is to reduce the bottleneck during the production process. On the production line should do a control between the number of billet that will enter each station, processing time of each billet and the billet number that will complete. Therefore, the productivity of the proposed simulation model is 23 times than the natural simulation model. The DOE method used to analyze the results that produced from the proposed simulation model to get optimum analysis and to determine the more variables effect on the productivity, form probability plot we note that all the points around the diagonal line that is indicating the desired purpose. In addition, The charts, results and t-test proved the arrival time has effect on the productivity, the interaction plot does not have interaction lines all the lines are parallel that prove the production process is stable. The productivity increase with increase arrival time relative to the capacity and expo time that has proved from the contour surface. Finally, we determined better region to give the best results by using the steepest ascent method.

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