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Original article

Application of computer simulation experiment and response surface methodology for productivity improvement in a continuous production line: Case study

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ABSTRACT

This study focused solely on a paint manufacturing industry in Iran that will help managers to effectively manage their enterprise. The goal of this paper is to integrate simulation modeling along with response surface methodology (RSM) and design of experiments (DOE) in order to analyze and improve the productivity in a selected continuous paint manufacturing industry. Computer simulation is developed to propose different scenarios as the inputs of DOE. Based on the final results, the optimum productivity was achieved at the point of 93.5, that is relevant to the number of labor (B) = 26 and failure time of lifter (C) = 56.01 min. Moreover, the other two factors, A (service rate of delpak mixer) and D (number of permil) should be located at a low level. Quality and production managers, engineers as well as academicians can implement the results of the current study in other case studies. This approach can be generalized to other manufacturing systems to improve their productivity in a timely and cost-effective manner.

1. Introduction

In the manufacturing industry, managers and engineers are seeking to find methods in order to eliminate the common problems in production lines such as bottlenecks and waiting times. This is because all these kinds of problems impose an extra cost on companies (Zahraee et al., 2014b). In addition, manufacturing companies are striving to sustain their competitiveness by improving productivity, efficiency, and quality of products. It can be acquired by finding ways to deal with various industrial problems which have affected the productivity of manufacturing systems such as high lead time and Work in Progress (WIP) (Zahraee et al., 2014d). Moreover, some parameters, such as machine capacities and availability of resources have significant effects on aspects such as throughput, cycle time and average delay in a continuous production system. Some of them may have more considerable effects on the system performance compared to the others (Zahraee et al., 2014a). On the other hand, limitations of the use of one or two machines or resources can lead to bottlenecks that cause delays in the whole operation chain. Therefore, it is necessary to handle the bottlenecks in order to enhance the system performance by assessing different parameters that have considerable effects on it. In this regard, it is difficult to find the root of the problem if the production line is plagued with difficulty related to resource availability (Hatami et al., 2014). This can be achieved by finding a suitable and cost-effective way to improve productivity as well as to decrease the occurrences of bottlenecks (Jahangirian et al., 2010). In recent years, big efforts have been done to show the different bottleneck definitions, results and detection approaches. However, there is still no commonly accepted definition or detection method. This is principal because of the diversity of the bottlenecks in different application scenarios. This proves to create challenges and problems in implementing the theoretical results in real life applications. There are some investigations which suggest that approaches, such as DOE help engineers to deal with these problems by recognizing the important factors affecting system productivity (Zahraee et al., 2015a). By conducting experimental designs, engineers are able to predict how changes in input factors affect the responses of an experiment (Barton, 2013). Computer simulation is another suitable and popular approach for estimating the performance of complex systems with complicated processes, especially systems that involve

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random phenomena. Due to these reasons, simulation experiment plays a leading role in projects that are done within time and budget limits. This is because, in these projects, a considerable amount of effort is allocated for developing and validating the model. Hence, within a limited time or budget constraint, simulation will help decision makers to simulate projects in a cost-effective and timely manner (Sargent, 2005). According to a previous study (Hatami et al., 1990), the applications of experimental designs and simulation to improve productivity can lead to significant savings. Additionally, the result will be more credible and reliable as all possible combinations of factors are examined. Furthermore, it is easier to justify the recommendations because the verification runs have validated the result of the model (Hatami et al., 1990).

RSM is another novel statistical method, its combination with computer simulation and DOE can be applied to develop a model that can assess the impact of important factors on manufacturing system. Suggesting a simulation-RSM model for the goal of evaluating production line and productivity rate can be useful and advantageous because; (1) Making key decisions is a significant issue to top management in any manufacturing industries, (2) Productivity of manufacturing industry should be exactly evaluated because of major limitations in labor, time and cost, and (3) Applying different techniques to improve processes deprived of interrupting the operations of the system as well as to assess their effect before implementation (Kouritzin et al., 2014). So in this paper, computer simulation is developed to propose different scenarios as the inputs of DOE. This paper aims at presenting a new idea for using response surface methodology along with the computer simulation experiment to fill the gap in order to improve the productivity of a selected paint production line with a continuous and complex process in Iran's paint industry in a cost-effective and timely manner.

2. Computer simulation and design of experiments applications

Computer simulation is one of the most effective approaches that can be used to deal with the operational difficulties to increase productivity in different fields, such as production line (Zahraee et al., 2014a), port and transportation industry (Shahpanah et al., 2014), supply chain management (Golroudbary and Zahraee, 2015), healthcare system (Zahraee et al., 2015b) as well as construction industry (Zahraee et al., 2014c), all of which are not easy to model. Computer simulation has a significant effect on financial and operational parameters by saving monetary cost of investment, decreasing process cycle time, increasing resource utilization and enhancing throughput (Zahraee et al., 2014a). Moreover, Tsai (2002) claimed that computer simulation plays a vital role in solving the problems related to the integrated manufacturing systems as well as analyzing, designing and scheduling the production systems instead of applying complicated mathematical model equations. Benefits of simulation modeling are (Kikolski, 2017):

- to organize a type of system with experiments implemented on the investigated model.
- to deal with large and complicated decisional issues that cannot be handled with the application of other approaches.
- to prepare decisions quickly as a result of analyzing the impact of experiments carried out for many periods.
- to find an answer to the "what-if…?" questions – simulation experiments help to assess different decisional alternative scenarios.
- to analyze correlations of the effects of factors of a model that can affect the decision selected in different conditions.

There are many companies whose manufacturing systems are subjected to a stochastic behavior (e.g. random arrival of orders) and where frequent changes occur, for example due to fluctuation in the customers' demands. For such types of systems, the starting time and completion times of jobs can be unpredictable (Ferjani et al., 2017).

DOE is a statistical approach that can create a correlation between the significant parameters and the response of a process (Sadeghifam et al., 2015). The adoption of DOE helps to manage the process inputs for optimizing the output of a process (Steibel et al., 2009; Tack and Vandebroek, 2002), hence, several investigations had used DOE and computer simulation to predict a system's behavior. In this light, thanks to a large number of input factors and the high cost of experiments, computer simulation can be a useful and powerful tool for doing experimental tests in cost-effective and reliable conditions (Wang and Halpin, 2004; Ebrahimy et al., 2011; Hassan and Gruber, 2008). Tsai (2002) used DOE, along with computer simulation to assess and optimize the operation of a joined manufacturing system. In another research, Baesler et al. (2004) developed a computer simulation model of sawmill factory in Chile to enhance the productivity of the wood industry by decreasing bottlenecks. Consequently, a DOE experiment was conducted to present the minimum number of physical resources and human that are essential to satisfy the demands. The final results showed that by using this combined approach, productivity was improved by 25%. Furthermore, Nazzal et al. (2006) selected a semiconductor company as a case study to accommodate an easier decision-making process by combining DOE, computer simulation, and economic analysis. Meanwhile, Zahraee et al. (2014d) applied DOE and simulation to find the optimal set of parameters that have a considerable influence on the process productivity in the paint industry. Hatami et al. (2014) assessed the importance of different parameters on a production line using simulation and DOE to improve productivity. Final results showed that the number of workers and failure time of lifter machines have the most considerable impact on performance (Hatami et al., 2014). In another study, the statistical Taguchi method and computer simulation were combined to investigate the impacts of main and uncontrollable parameters on the overall production output in the paint factory. It was cited that the optimum value of productivity will be obtained when the values of main variables, like the service rate of the delpak machine, number of labor, inspection time and number of permil, were equal to UNIF (30, 40), 14, 120 and 5, respectively (Zahraee et al., 2015a). Based on these investigations, the technique has improved the productivity of manufacturing processes and reduced trials and errors to find the best solution (Montevechi et al., 2007). Dengiz et al. (2016) showed how the combination of regression meta-modeling techniques and simulation modeling can be applied to design and improve a real automotive manufacturing system.

Previous investigations in this area indicated that to analyze a system, the simulation outputs can be applied as inputs to the experimental design. Compared to other recent research, this paper presents a novel approach as it implements the response surface methodology to fill the gap, as well as to deal with the bottleneck problems related to the Iran's paint industry which has never been done before.

3. Material and methods

3.1. Case study

For the case study in this research, a paint factory that has a continuous and complex process was selected. This company is one of the primary and most reputable industrial and construction paint manufacturers in Iran. Managers and engineers in this paint industry sector, try to maintain their competitiveness by suggesting high quality, premium products to the customers. This company has a long-term plan to enhance productivity by eradicating the root of bottlenecks. This company fulfills its orders based on customers' demand, and its factory layout was designed according to the job shop system. All of the production units, such as industrial paint, plastic paint, stone putty, and thinner are located separately from the packaging section and laboratory. In order to simulate the production line, the industrial paint production unit was selected as it has the largest number of machines and processes.

3.2. Computer simulation

Data collection is the first step for developing a simulation model. In this paper, data collection was done in the factory by observing the production line. Furthermore, the stop-watch approach was adopted in gathering some of the desired information. It is clear that to construct the simulation model, there is a need to determine the necessary data as the inputs for the developed model. Then, a probability distribution function was fitted for each activity duration. To develop the model, it is necessary to determine different resources in the manufacturing process along with their relationship, duty and activity duration. Table 1

Table 1
Probability distributions fitting of collected data.

Machine	Expression	St. Dev	Min Value	Max Value	Mean	Unit	Number of points	Square error
Permil 1	TRIA(2.18, 3.33, 3.72)	0.475	2.31	3.59	3.08	Minute	5	0.054851
Permil 2	0.65 + 0.11 * BETA(0.983, 0.698)	0.0427	0.66	0.75	0.718	Minute	4	0.106855
Permil 3	0.71 + 0.291 * BETA(0.477, 0.428)	0.123	0.74	1	0.83	Minute	4	0.113645
Permil 4	1.9 + 0.09 * BETA(0.759, 0.804)	0.0495	1.91	1.98	1.94	Minute	2	0.227148
Permil 5	UNIF(1.05, 2.59)	0.202	3.61	4.04	3.08	Minute	4	0.08
Delpak Mixer	0.01 + LOGN(0.0657, 0.0403)	0.0354	0.03	0.13	0.075	Minute	10	0.01142
Big mixer	20 + WEIB(0.408, 0.238)	5.16	20	30	24	Minute	10	0.18136
Preparation	CONT (0.5, 71, 1.0, 74)	2.12	71	74	72.5	Second	2	0.05

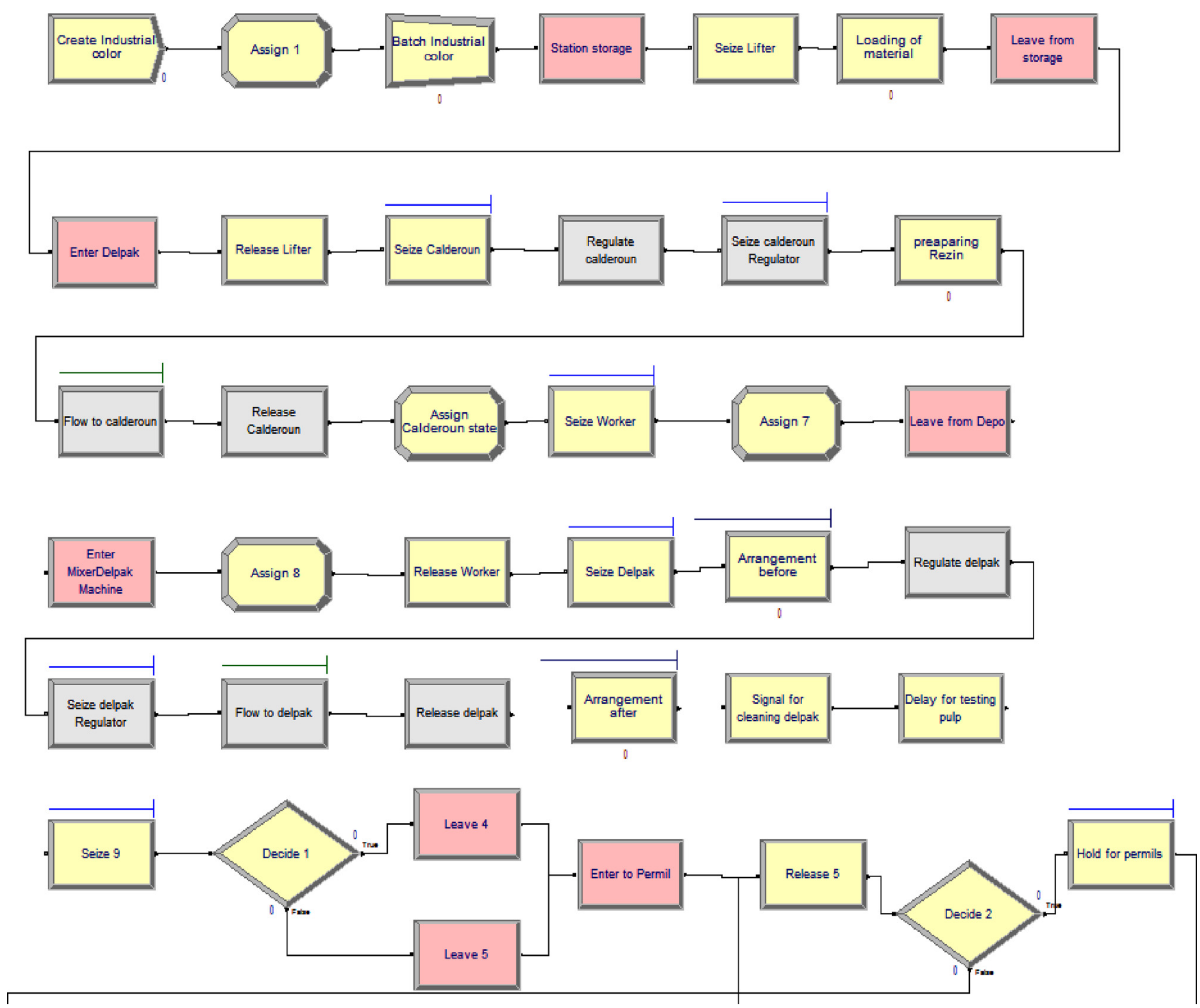

Fig. 1. Logic view of simulation model of production line.

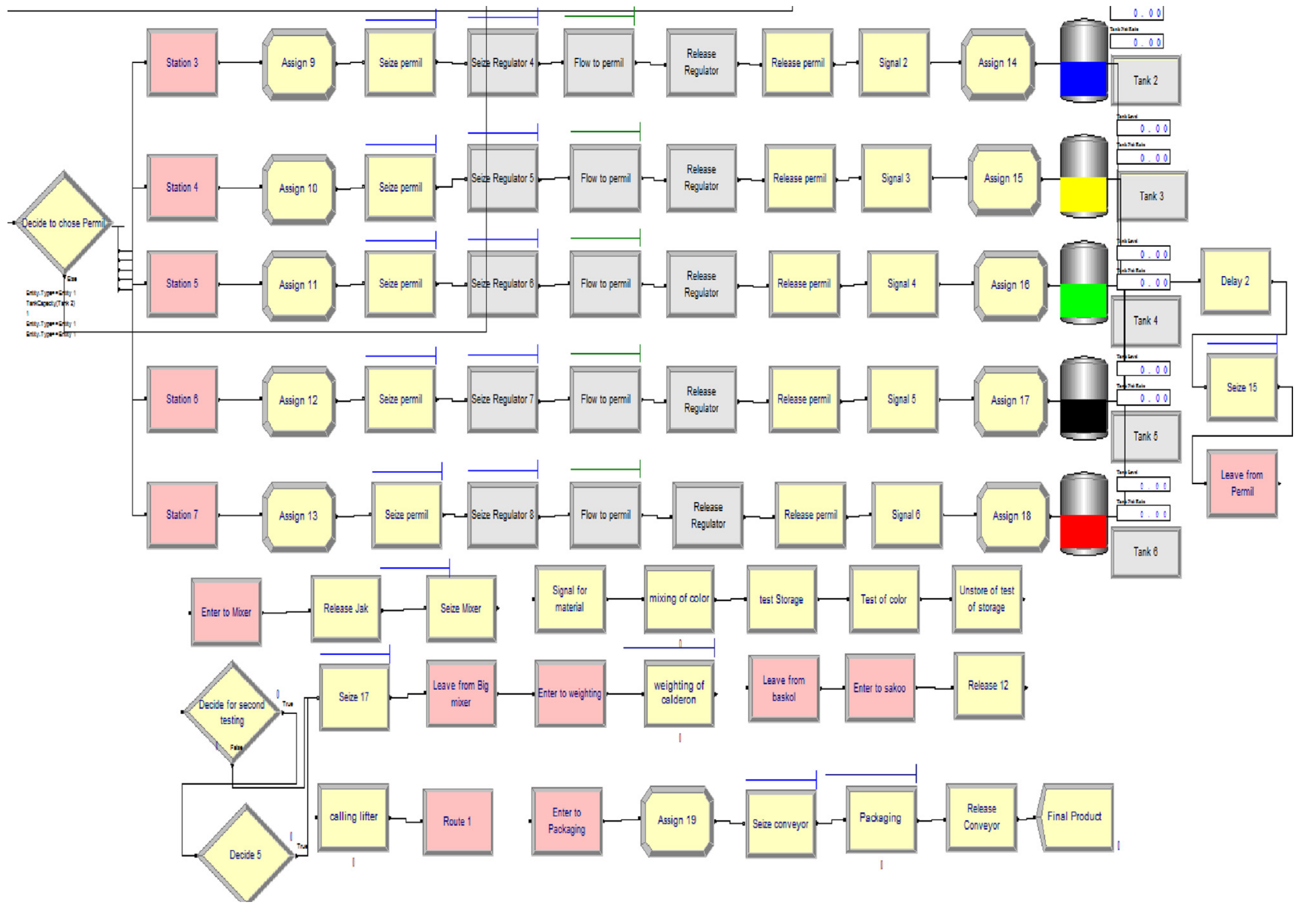

Fig. 1 (*continued*)

shows some samples for probability distributions fitting of the collected data. In this paper, the Arena 13.9 simulation software was used to construct the simulation model. Fig. 1 indicates the logic view of the simulation model.

3.3. Experiment design

The experimentation is focused on identifying any parameters that have a considerable effect on the process productivity, hence, there is a need for a systematic approach for analyzing and answering the above question. DOE is a statistical technique for analyzing and organizing the experiments. Consequently, in DOE, the factors comprise different parameters which are controlled by the researcher, meanwhile the response represents the dependent variable, which in this case, refers to productivity. The 2^k factorial design is one of the very useful type of DOE approaches, and, each of the factors is allowed to take on two values or levels, High and Low. It has been investigated to be economical and effective in indicating interaction effects (Montgomery, 2009). Therefore, this paper used the 2^k factorial design to assess the effects of several parameters on productivity.

3.3.1. Choosing the factors, levels and response variable

In order to select the factors, at first, the company's managers and executives discussed to evaluate and analyze different parameters that could potentially help to improve the productivity of production line. The influential factors were selected from previous investigations and production engineer's feedbacks. Then, all selected factors were assessed and reviewed to be finalized. Lastly, the managers agreed to choose four most potential factors which were service rate of delpak mixer (A), number of labor (B), failure time of lifter (C) and number of permil (D). Table 2 shows the factors and their levels.

Consequently, the response variable investigated was process productivity that can be determined as follow:

$$\text{Process Productivity } (\%) = (\text{Total unit out}/\text{Total unit in}) * (100)$$

3.4. Response surface methodology

The response surface approach uses the designs and models to assess continuous treatments to determine the optimum solution or to describe the response (Owolabi et al., 2016; Farouk et al., 2017). Therefore, the main goal of response surface approach is to determine the optimal response. If there are more than one response, it is essential to identify the compromised optimum that does not optimize one result (Krishnaiah et al., 2015). In addition,

Table 2
Factors and Levels.

FACTOR	LEVEL		
	Low (−1)	Center (0)	High (1)
Service rate of DELPAK Mixer[1] (A)	UNIF(20, 40)	UNIF(25, 40)	UNIF (30, 40)
Number of Labor (B)	14	17	20
Failure time of lifter[2]	30 min	45 min	60 min
Number of Permil	3	4	5

[1] Service Rate: The rate of doing a process.
[2] Failure time of lifter: the time is spent to repair the lifter.

RSM, as an important issue in DOE, comprises mathematical and statistical approaches which are useful to model and analyze a system to determine whether a response is affected by a variety of factors. In this light, its main goal is to optimize this response by finding the best setting for the controllable factors (Kleijnen, 2008). In the meantime, sequential experimentation can be done by starting a full factorial design to find the significant factors. As a result, a regression model was developed for the response and the path of steepest ascent was followed to maximize the response (Montgomery, 2008).

Table 3
Result of simulation experiment.

Run order	Service rate of Delpak mixer (A)	Number of labor (B)	Failure time of Lifter (C)	Number of permil (D)	Response (Productivity * 100)		
					Replicate 1	Replicate 2	
1	1	14	30	5	43.51	50.10	
2	1	20	30	3	49.24	62.45	
3	−1	14	30	5	57.50	54.20	
4	−1	20	60	3	73.30	75.26	
5	1	14	30	3	50.20	58.30	
6	1	20	60	3	71.08	60.08	
7	−1	14	60	5	60.31	53.22	
8	1	20	30	5	63.22	61.20	
9	−1	14	30	3	48.12	55.00	
10	1	20	60	5	57.20	72.34	
11	−1	20	30	5	74.10	57.32	
12	−1	20	60	5	73.08	55.10	
13	−1	14	60	3	73.10	60.90	
14	1	14	60	3	62.00	52.36	
15	−1	20	30	3	72.12	62.50	
16	1	14	60	5	61.50	60.30	
17	0	17	45	4	83.28	84.01	86.54

Table 4
Analysis of variance (ANOVA) for productivity.

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	4	1113.93	1113.93	278.48	5.89	0.003
2-Way Interactions	6	148.22	148.22	24.70	0.52	0.784
3-Way Interactions	4	144.59	144.59	36.15	0.76	0.562
4-way Interaction	1	73.66	73.66	73.66	1.56	0.228
Curvature	1	1577.05	1577.05	1577.05	33.35	0.000
Residual Error	18	851.24	851.24	47.29		
Pure Error	18	851.24	851.24	47.29		
Total	34	3908.68				

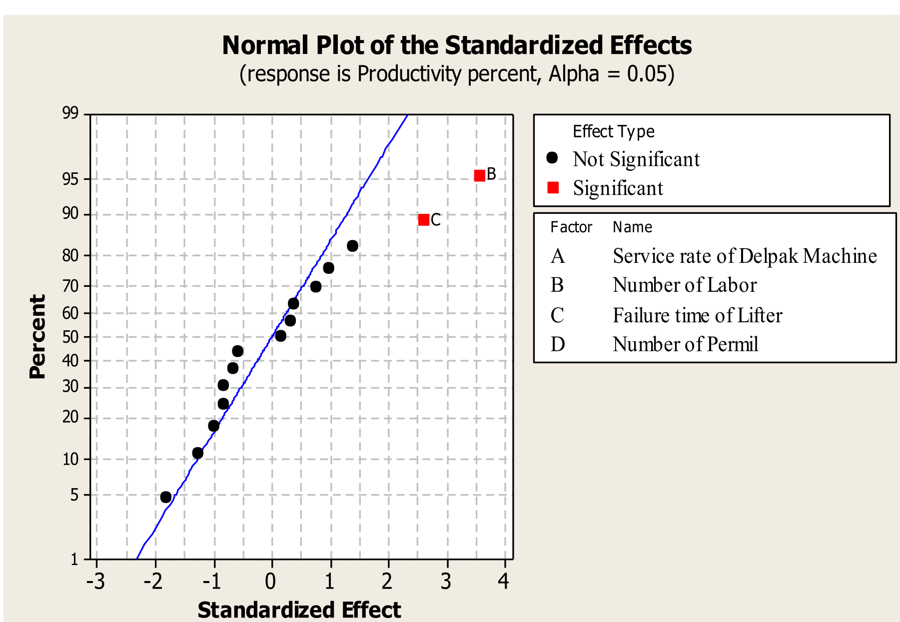

Fig. 2. Normal Plot of the Standardized Effects.

3.4.1. Steps of conducting RSM

These following steps can be taken to implement RSM (Farouk et al., 2017):

1. Brainstorming and screening experiments.
2. Improving the process by using the Path of Steepest Ascent (POSA).
3. Finding the optimum result (Center Composite Design (CCD)).

Inherently, the execution of these three steps has helped to identify the optimum combination and value for the significant factors.

4. Results and discussion

4.1. Simulation experiment results

After determining the factor settings and experimental conditions, data collection was conducted by running the simulation experiment. As mentioned earlier, a full factorial design was chosen. This design included 16 experiments with two replicates, which were done to decrease potential errors. Additionally, three center points were considered to analyze the curvature of the suggested model. In all, 35 experiments were conducted by running the simulation model.

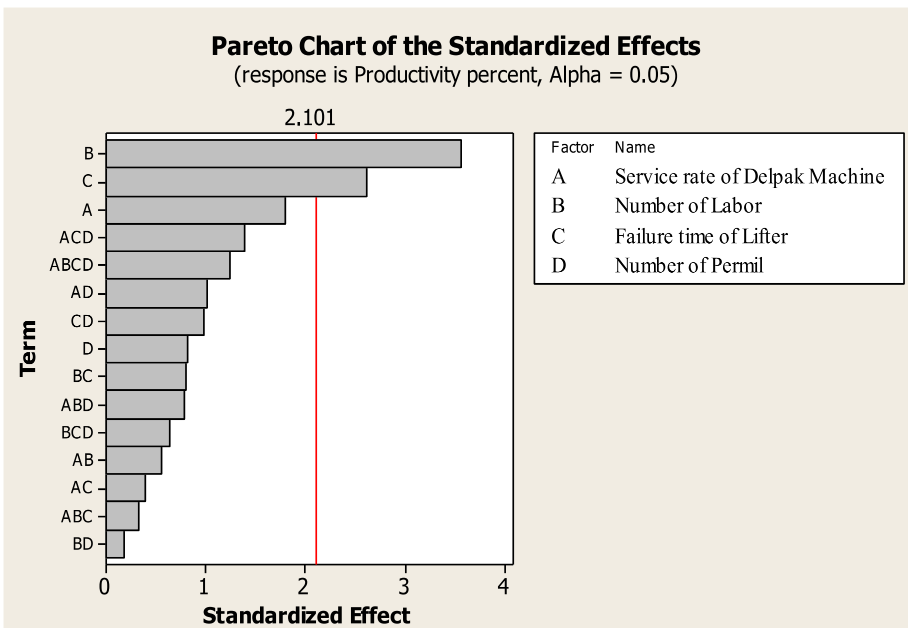

Fig. 3. Pareto Chart.

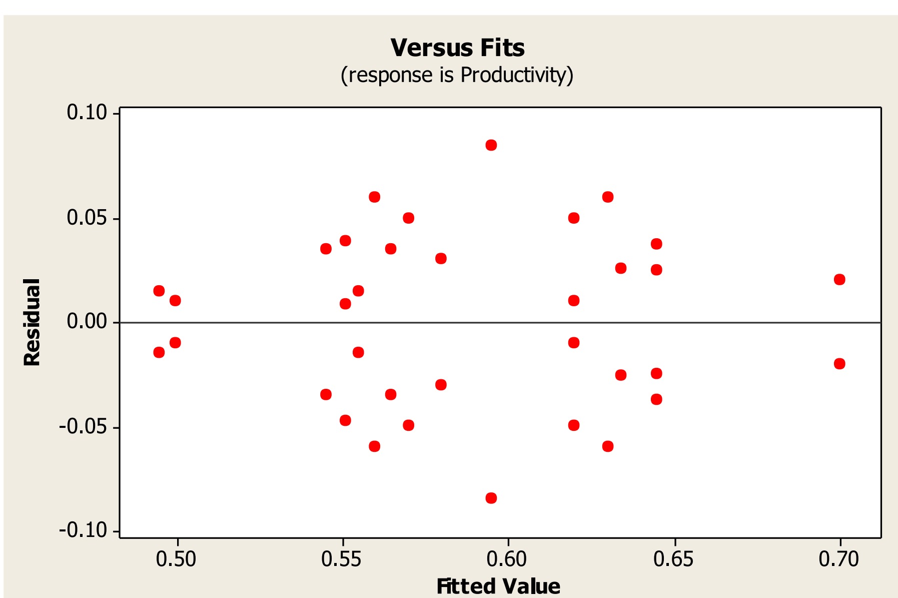

Fig. 4. Residual versus fitted value.

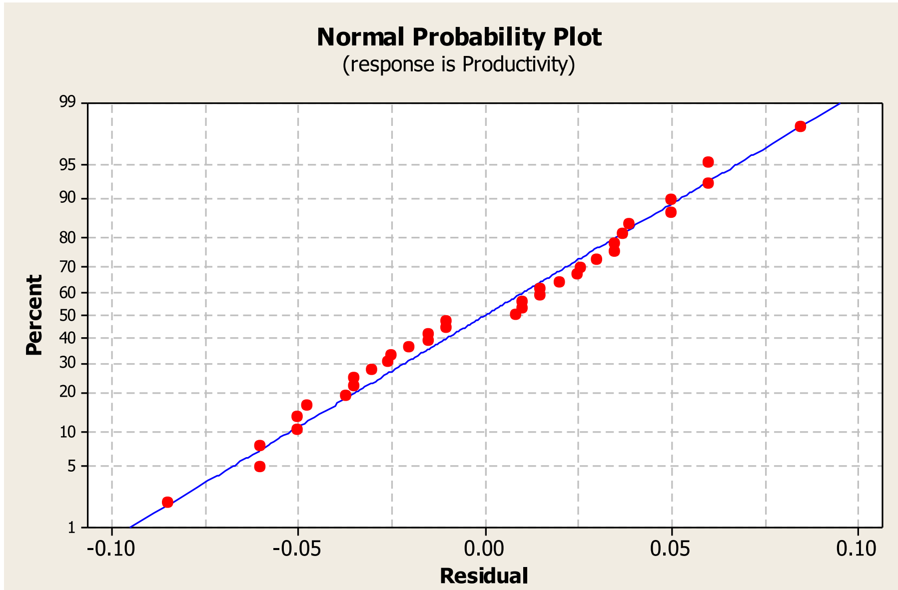

Fig. 5. Normal Plot of the Standardized Effects.

Table 5
Responses at new design points.

Steps	x_b	x_c	E_1	E_2	Response
Origin	0	0	17	45	82.2
Δ = Step Size	1	0.734			
Origin + 1 Δ	1	0.734	20	56.01	83.5
Origin + 2 Δ	2	1.468	23	67.03	86.1
Origin + 3 Δ	3	2.202	26	78.04	84.5
Origin + 4 Δ	4	2.936	29	89.06	78.1
Origin + 5 Δ	5	3.67	32	100.07	69.2

In summary, the experimental conditions are explained as follows: Number of Factors: 4; Number of Levels: 2; Number of Replicates: 2; Number of Center points: 3; Number of experiments = 2^4 * 2 (replicates) + 3 (Center Points) = 35. Table 3 shows the results of the simulation experiment.

Table 6
New levels and center point.

Factor	Symbol	Levels		
		−1	(0)	+1
Number of labor	B	20	23	26
Failure time of lifter	C	56.01	67.03	78.04

4.2. Statistical analysis

Minitab is one of the software used for conducting statistical analyses, and the results of ANOVA for productivity are presented in Table 4. As observed, P-value is an important parameter that was used to identify statistically significant factors which indicate that they have a significant influence on productivity. As a result, all factors with P-values that are less than 0.05, are considered as significant. In contrast, factors with P-values that are greater than

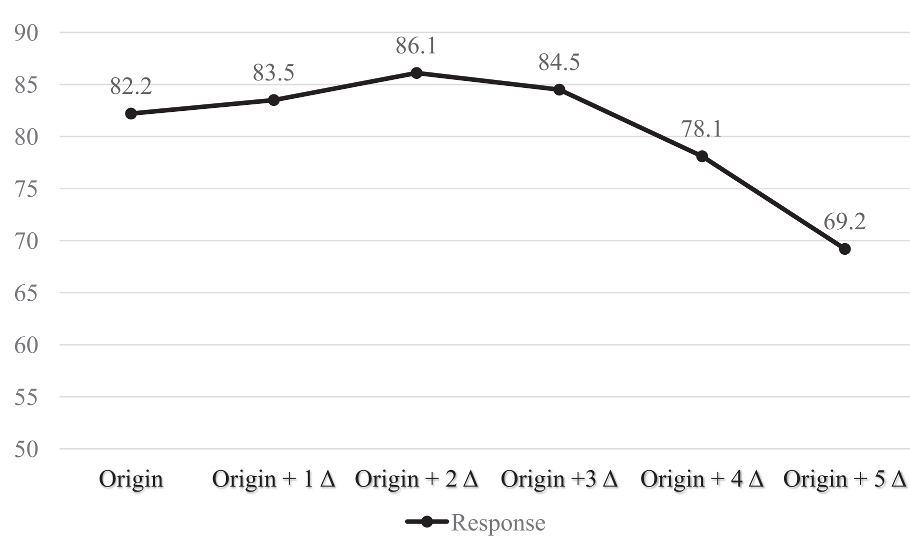

Fig. 6. Result of (POSA) approach.

Table 7
Responses based on the new center point.

Run order	Coded Variables		Natural Variables		Responses (Productivity * 100)
	X_B	X_C	E_B	E_C	
	Number of labor	Failure time of lifter	Number of labor	Failure time of lifter	
1	0	−1.4142	23	51.45	88.1
2	0	0	23	67.03	86.2
3	0	0	23	67.03	85.82
4	0	0	23	67.03	86.93
5	0	0	23	67.03	87
6	−1	1	20	78.04	79.45
7	−1.4142	0	18.76	67.03	75.28
8	0	1.4142	23	82.60	80.5
9	1	−1	26	56.01	93.5
10	1	1	26	78.04	84.67
11	1.4142	0	27.24	67.03	89.35
12	0	0	23	67.03	84.25
13	−1	−1	20	56.01	80.1

Table 8
ANOVA for response surface quadratic model.

Source	Sum of Squares	DF	Mean Square	F Value	Prob > F	Remarks
Model	271.77	5	54.35	48.06	<0.0001	significant
B	185.45	1	185.45	163.97	<0.0001	significant
C	51.15	1	51.15	45.22	0.0003	un significant
B^2	17.41	1	17.41	15.39	0.0057	significant
C^2	2.42	1	2.42	2.14	0.1872	unsignificant
BC	16.73	1	16.73	14.79	0.0063	significant
Residual Error	7.92	7	1.13			
Lack-of-Fit	2.93	3	0.98	0.78	0.5630	unsignificant
Pure Error	4.99	4				
Cor Total	279.69	12				

Table 9
Model accuracy.

Std. Dev.	1.06	R-Squared	0.9717
Mean	84.70	Adj R-Squared	0.9515
C.V.	1.26	Pred R-Squared	0.8977
PRESS	28.60	Adeq Precision	23.792

0.05, are deemed as not significant (Montgomery, 2009). Based on Fig. 2, the main factors B (number of labor) and C (failure time of lifter) are considered as significant which show that they have considerable effects on productivity. Furthermore, Table 4 presents that the curvature is significant, which shows that there is a non-linear correlation between the factors and productivity. The sequencing of statistical significance of both the main and interaction effects is also shown in the Pareto chart as depicted in Fig. 3.

Residual versus predicted value plot and normal probability plot of residuals are two graphical approaches that are used to check the validity of a regression model (Montgomery, 2009). Residual versus predicted value plot shows the difference between the predicted values and the observed values. If the residuals have an obvious pattern, it will infer that the suggested model is not adequate (Montgomery, 2009). As can be seen in Fig. 4, the residuals have a constant pattern. So it indicates that the suggested model is not adequate and it creates a need to obtain the second order regression model. Moreover, residuals in the normal probability plot should be laid in a straight line (Montgomery, 2009). As can be seen in Fig. 5, it can be claimed that the model is not adequate.

4.3. Productivity optimization

4.3.1. RSM implementation

The path of steepest ascent (POSA) approach was implemented to improve the process, and in return, enable the execution of RSM. First, the step size for doing the experiments should be defined by using macro programming in Minitab software. The result of macro programming showed that the step sizes are equal to 1 and 0.734, respectively. Then, the values were calculated by using Eqs. (1) and (2). Consequently, the new series of simulation experiments were conducted to achieve the maximum response. Table 5 shows the result of experiments which indicates that the optimum point lies between the highlighted areas. Meanwhile, Fig. 6 illustrates the schematic view of the POSA result. The optimum point was calculated using the second order model which refers to the second order response surface in the next step.

Table 10
Estimated regression coefficients for productivity.

Factor	Coefficient	DF	Standard Error	95% CI Low	95% CI High
Intercept	86.04	1	0.48	84.92	87.16
B-Number of labor	4.81	1	0.38	3.93	5.70
C-Failure time of lifter	−2.53	1	0.38	−3.42	−1.64
B^2	−1.58	1	0.40	−2.54	−0.63
C^2	−0.59	1	0.40	−1.54	0.36
BC	−2.04	1	0.53	−3.30	−0.79

$$X_b = \frac{E_1 - 17}{3}, \quad B(14,\ 20) \tag{1}$$

$$X_c = \frac{E_2 - 45}{15}, \quad C(30,\ 60) \tag{2}$$

In order to conduct new experiments by adding the new center points (Table 6), the augmentation approach was used for fitting the second order model. To do this, Central Composite Design (CCD) was implemented by adding four points ($x_1 = 0$, $x_2 = \pm 1.414$) and ($x_1 = \pm 1.414$, $x_2 = 0$) to the experiment. Table 7 shows the result of the new experimental design.

As observed in Table 8, the result of ANOVA for the second order model showed that there are three significant factors B, B^2 and BC. The Model F-value of 48.06 indicates that the model is significant. Additionally, there is only a 0.01% chance that a "Model F-Value" this large could happen because of noise, while the "Lack of Fit F-value" of 0.78 shows that it is not significant relative to the pure error. Moreover, there is a 56.30% chance that a "Lack of Fit F-value" this large could happen due to noise. Finally, non-significant lack of fit indicates that the model is fit (Montgomery, 2009).

Additionally, Table 9 verifies the model's accuracy. A high determination coefficient (R-Squared = 0.9717) implies that the model explains all of the variability of the response data around its mean. In addition, Pred R-Squared of 0.8977 is in good agreement with the Adj R-Squared of 0.89779 and the "Adeq Precision" measures the signal to noise ratio, where a ratio greater than 4 is desirable. Hence, the obtained ratio of 23.792 indicates an adequate signal and this model can be used to navigate the design space. Moreover, a very small value of Coefficient of Variation (C.V.) = 1.26, clearly shows a very high degree of precision and a good reliability of the experimental values (Montgomery, 2008).

4.3.2. Second order regression model

As the relationship between the independent factors and response is generally unknown, a low order polynomial model is suggested to explain the response surface. This model is a commonly reasonable approximation in a specific region of the response surface. In this regard, both the first-order and second-order models were used based on the approximation of the unknown function. It should be noted that when the curvature is significant, it can be concluded that the first-order model is not sufficient. Therefore, a second-order model is effective and flexible in approximating a part of the correct response surface with parabolic curvature (Montgomery, 2009). In this light, Design-Expert software was used to calculate the coefficients of the regression equation. Table 10 shows the regression coefficient of each factor and Eqs. (3) and (4) were obtained:

$$\hat{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + \beta_{11} X_{11}^2 + \beta_{22} X_{22}^2 \tag{3}$$

$$\hat{Y} = 86.04 + 4.81B - 2.04BC - 1.58B^2 \tag{4}$$

4.3.3. Residual analysis

In order to evaluate the model validity, the residuals from the least squares play an important role. As can be seen in Fig. 7, the straight line confirms that the model is adequate and correct. Moreover, the structure-less pattern of the residual versus predicted value confirms that the developed model is adequate and has a constant error (Fig. 8).

4.3.4. Confirmation test

In this Section, 3 more verification runs were designed and implemented for confirming the adequacy of the developed model (Table 11). Moreover, the predicted values (obtained from Eq. (4)) and the actual values (obtained from the simulation model) were compared and the percentage of error was calculated. Table 11 shows that the percentage of error for all three experiments was less than 10%. Therefore, the result shows the accuracy of the acquired quadratic model (Montgomery, 2008).

4.4. Discussion, 3D response surface, and contour plot

The analysis of optimum setting is essential after the development of a second-order regression model. In this light, graphical visualization plays a leading role in explaining the second-order response surface, and as observed in Figs. 9 and 10, the 2D contour and 3D response surface plots are the main graphical representation of the regression equation. The main role of these plots is to show the optimal values of the factors so that the response can

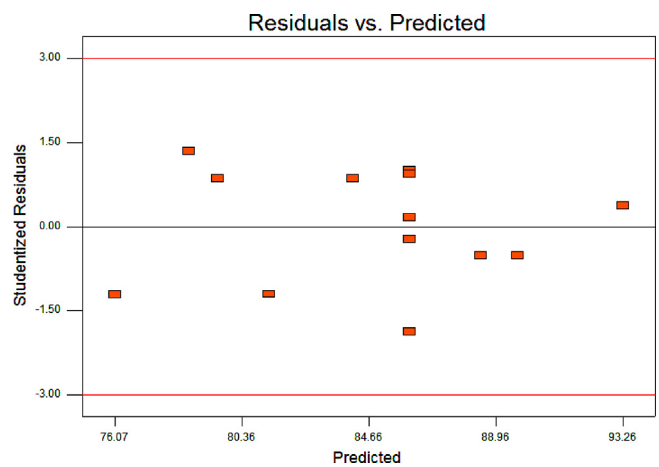

Fig. 7. Residual versus Predicted Value for productivity.

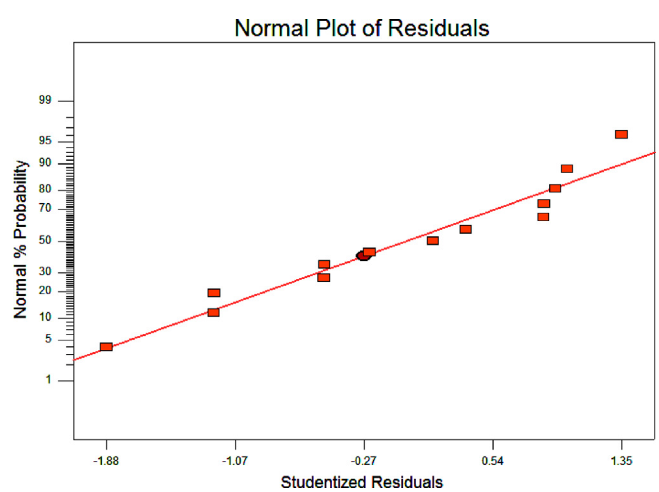

Fig. 8. Normal Plot of Residuals.

Table 11
Result of confirmation test.

Factor (Coded)		Predicted Value	Actual Value	Error%
Number of labor (B)	Failure time of lifter (C)	Base on Model	Real test	Percent
0	0	86.04	86.2	0.18%
1	1	87.23	84.67	2.93%
0	1.412	86.04	80.5	6.4%

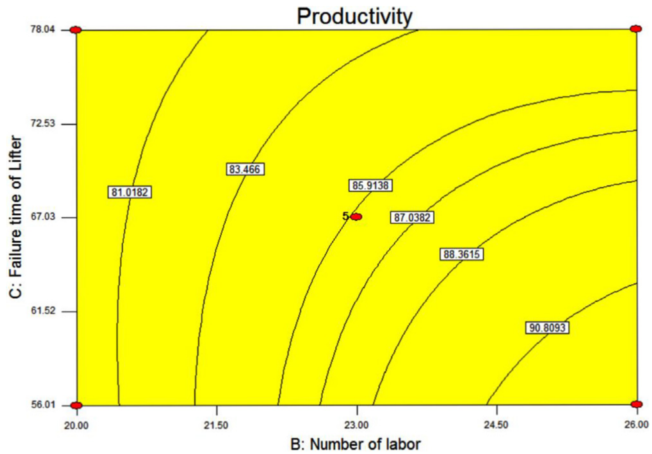

Fig. 9. Contour Plot.

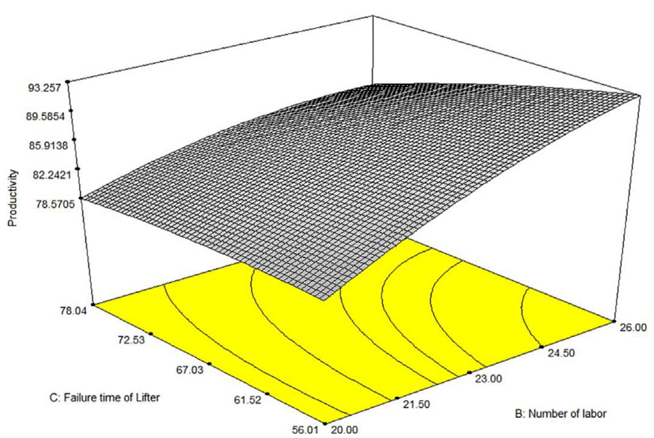

Fig. 10. 3D Surface Plot.

Table 12
Optimum setting of factors for maximum productivity.

Factor	Result of RSM	Current state of factory
Service rate of Delpak machine (A)	UNIF (20, 40)	UNIF (20, 40)
Number of labor (B)	26	20
Failure time of lifter (C)	56.01 (min)	60
Number of permil (D)	3	5
Productivity (%)	93.5%	73.08%

Productivity Improvement = $\frac{93.5-73.08}{93.5}$ = 21.84%.
Implemented results = 16.5%.

be maximized. At the highest level of the surface inclination in Fig. 9, the maximum productivity was achieved at the highest level of the number of labor (B) = 26 and failure time of lifter (C) = 56.01 min, based on the contour trend. As shown in Fig. 10, the maximum response occurred at the point of 93.5 that is relevant to the number of labor (B) = 26 and failure time of lifter (C) = 56.01 min.

Finally, Table 12 shows the optimum value of each factor to achieve the maximum productivity. The obtained results from this research would improve productivity by approximately 21.84% in comparison to the current state in the factory.

4.5. Implications

This paper contributes to show some implications and propose that response surface methodology can be combined with simulation modeling and DOE to improve the productivity of the manufacturing industry. The suggested approach helps the quality managers, production managers and engineers to improve their productivity in a timely and cost-effective manner without stopping or changing the layout of production line or resources, because it is not possible to end or delay the operating system or replace the layout due to limitations of labor, time, cost and many other parameters. It should be noted that the obtained optimal values have been applied in reality at the production line that cause a 16% increase in productivity of the factory. Hence, practitioners and engineers working in the manufacturing industries can do easily similar simulation-RSM approach for their companies.

5. Conclusion

Industrial problems, such as waiting times and bottlenecks in manufacturing companies that have continuous and complex processes, have a significant effect on productivity. In response, engineers continuously try to solve them, as these kinds of problems can increase production costs. This research chose a paint factory with a continuous and complex process as the case study, and based on the discussion with managers and engineers working in the company, the research team believed that increasing productivity is an important research issue. So, in order to gain a high level of profit, there is a need to implement a new approach by considering time and cost factors. This present research is the first research that implements the novel response surface methodology to improve productivity. The main goal of this paper is to identify how a new technique, specifically, the response surface methodology can be combined with simulation modeling and experimental design to improve the productivity in the paint industry in a cost-effective and timely manner. After conducting the simulation experiment, two factors, B (number of labor) and C (failure time of lifter) were identified as significant factors. Next, the steepest ascent method and response surface methodology were implemented to determine the optimum setting of the significant factors. Based on the final results and the regression model, the optimum productivity was achieved at the point of 93.5, that is relevant to the number of labor (B) = 26 and failure time of lifter (C) = 56.01 min. Moreover, the other two factors, A (Service rate of delpak mixer) and D (number of permil) should be located at a low level. This means that they are equal to UNIF (20, 40) and 3, respectively. As this paper is focused on finding the local optimum, other approaches like meta-heuristic algorithms can be used to find the global optimum. Further studies can also be done by selecting other response variables such as resource utilization, cycle time and cost.

References

Baesler, F.F., Araya, E., Ramis, F.J., Sepúlveda, J.A., 2004. The use of simulation and design of experiments for productivity improvement in the sawmill industry. In: Simulation Conference, Ieee. pp. 1218–1221.
Barton, R.R., 2013. Designing simulation experiments. In: Simulation Conference, Ieee. pp. 342–353.
Dengiz, B., İc, Y.T., Belgin, O., 2016. A meta-model based simulation optimization using hybrid simulation-analytical modeling to increase the productivity in automotive industry. Math. Comput. Simul 120, 120–128.
Ebrahimy, Y., Abourizk, S.M., Fernando, S., Mohamed, Y., 2011. Simulation modeling and sensitivity analysis of a tunneling construction project's supply chain. Eng. Constr. Archit. Manage. 18, 462–480.
Farouk, H., Zahraee, S.M., Atabani, A., Mohd Jaafar, M.N., Alhassan, F.H., 2017. Optimization of the esterification process of crude jatropha oil (CJO) containing high levels of free fatty acids: a malaysian case study. Biofuels, 1–8.
Ferjani, A., Ammar, A., Pierreval, H., Elkosantini, S., 2017. A simulation-optimization based heuristic for the online assignment of multi-skilled workers subjected to fatigue in manufacturing systems. Comput. Ind. Eng. 112, 663–674.
Golroudbary, S.R., Zahraee, S.M., 2015. System dynamics model for optimizing the recycling and collection of waste material in a closed-loop supply chain. Simul. Model. Pract. Theory 53, 88–102.

Hassan, M.M., Gruber, S., 2008. Simulation of concrete paving operations on interstate-74. J. Constr. Eng. Manage. 134, 2–9.
Hatami, M., Zahraee, S.M., Khademi, A., Shahpanah, A., Rohani, J.M., 2014. Evaluating The effect of main factors in manufacturing production line based on simulation experiment. Appl. Mech. Mater. 606, 199–203.
Hatami, S., Cowley, E., Morey, C., 1990. Using experimental design to improve the efficiency of simulation modeling-a manufacturing perspective. In: Simulation Conference. Ieee. pp. 310–313.
Jahangirian, M., Eldabi, T., Naseer, A., Stergioulas, L.K., Young, T., 2010. Simulation in manufacturing and business: a review. Eur. J. Oper. Res. 203, 1–13.
Kikolski, M., 2017. Study of production scenarios with the use of simulation models. Procedia Eng. 182, 321–328.
Kleijnen, J.P., 2008. Response surface methodology for constrained simulation optimization: an overview. Simul. Model. Pract. Theory 16, 50–64.
Kouritzin, M.A., Newton, F., Wu, B., 2014. A graph theoretic approach to simulation and classification. Comput. Stat. Data Anal. 70, 281–294.
Krishnaiah, D., Bono, A., Sarbatly, R., Nithyanandam, R., Anisuzzaman, S., 2015. Optimisation of spray drying operating conditions of morinda citrifolia l. fruit extract using response surface methodology. J. King Saud Univ. Eng. Sci. 27, 26–36.
Montevechi, J.A.B., De Pinho, A.F., Leal, F., Marins, F.A.S., 2007. Application of design of experiments on the simulation of a process in an automotive industry. In: Proceedings of the 39th Conference on Winter Simulation: 40 Years! The Best Is Yet To Come. Ieee Press. pp. 1601–1609.
Montgomery, D., 2009. Basic Experiment Design for Process Improvement Statistical Quality Control. John Wiley and Sons Inc, USA.
Montgomery, D.C., 2008. Design and Analysis of Experiments. John Wiley & Sons.
Nazzal, D., Mollaghasemi, M., Anderson, D., 2006. A simulation-based evaluation of the cost of cycle time reduction in agere systems wafer fabrication facility—a case study. Int. J. Prod. Econ. 100, 300–313.
Owolabi, R.U., Usman, M.A., Kehinde, A.J., 2016. Modelling and optimization of process variables for the solution polymerization of styrene using response surface methodology. J. King Saud Univ. Eng. Sci. 30, 22–30.
Sadeghifam, A.N., Zahraee, S.M., Meynagh, M.M., Kiani, I., 2015. Combined use of design of experiment and dynamic building simulation in assessment of energy efficiency in tropical residential buildings. Energy Build. 86, 525–533.
Sargent, R.G., 2005. Verification and validation of simulation models. In: Proceedings of The 37th Conference on Winter Simulation. pp. 130–143.
Shahpanah, A., Poursafary, S., Shariatmadari, S., Gholamkhasi, A., Zahraee, S.M., 2014. Optimization waiting time at berthing area of port container terminal with hybrid genetic algorithm (GA) and artificial neural network (ANN). Adv. Mater. Res. 902, 431–436.
Steibel, J.P., Rosa, G.J., Tempelman, R.J., 2009. Optimizing design of two-stage experiments for transcriptional profiling. Comput. Stat. Data Anal. 53, 1639–1649.
Tack, L., Vandebroek, M., 2002. An adjustment algorithm for optimal run orders in design of experiments. Comput. Stat. Data Anal. 40, 559–577.
Tsai, C.-S., 2002. Evaluation and optimisation of integrated manufacturing system operations using taguch's experiment design in computer simulation. Comput. Ind. Eng. 43, 591–604.
Wang, S., Halpin, D.W., 2004. Simulation experiment for improving construction processes. In: Simulation Conference, Ieee. pp. 1252–1259.
Zahraee, S.M., Chegeni, A., Rohani, J.M., 2015a. Characterization of manufacturing system computer simulation using taguchi method. Jurnal Teknologi 72, 77–82.
Zahraee, S.M., Golroudbary, S.R., Hashemi, A., Afshar, J., Haghighi, M., 2014a. Simulation of manufacturing production line based on arena. Adv. Mater. Res. 933, 744–748.
Zahraee, S.M., Hatami, M., Rohani, J., Mihanzadeh, H., Haghighi, M., 2014b. Comparison of different scenarios using computer simulation to improve the manufacturing system productivity: case study. Adv. Mater. Res. 845, 770–774.
Zahraee, S.M., Rezaei, G., Shahpanah, A., Chegeni, A., Rohani, J.M., 2014c. Performance improvement of concrete pouring process based resource utilization using taguchi method and computer simulation. Jurnal Teknologi 69, 17–24.
Zahraee, S.M., Rohani, J.M., Firouzi, A., Shahpanah, A., 2015b. Efficiency improvement of blood supply chain system using taguchi method and dynamic simulation. Procedia Manuf. 2, 1–5.
Zahraee, S.M., Shariatmadari, S., Ahmadi, H.B., Hakimi, S., Shahpanah, A., 2014d. Application of design of experiment and computer simulation to improve the color industry productivity: case study. Jurnal Teknologi 68, 7–11.