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Impacts of Common Components in Multistage Production System under Uncertain Conditions

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Abstract

The work desires: i) to determine the optimum level of batch size in bottleneck facility and ii) to analyze the effect of common components on work-in-process (WIP) level and cycle time in a multistage production system under uncertainties. The uncertainty is created by machine breakdown and quality variation. Few simulation models are developed based on a live case from a company. The models are verified and validated with the historical data from the company and by face validity. Taguchi approach for orthogonal array is used in designing experiments and these are executed in WITNESS. It is observed that the variation in level of common component in the system has significant impact on the production WIP level and cycle time. The main contribution of this research is determination of the optimal level of batch size in a bottleneck resource under the uncertainties. This approach can be generalized to any multistage production system, regardless of the precedence relationships among the various production stages in the system.

Keywords
Simulation, Quality, Machine breakdown, Work-in-process, Cycle time

1. Introduction

The classical lot sizing model assumes the output of the production process is of perfect quality. However, in real manufacturing system, nonconforming items may produce as time goes. These nonconforming items need to be screened out. The presence of defective product motivate in a smaller lot size. Optimum lot size for each stages even more complicated in multistage production system when cycle time for each stage is different. The number of defectives may vary in multistage production system where the products move from one stage to another. Depending on proportion of defective items, the optimal batch sizes in the stages also varies. However, small batch size may reduce the productivity and stock out and this increase the total expected cost. Thus, an optimum lot size must be obtained when quality is stochastic.

Multi-stage production planning is a system which transforms or transfer inventories through a set of connected stages to produce the finished goods. The stages represent the delivery or transformation of raw materials, transfer of work-in-process between production facilities, assembly of component parts, or the distribution of finished goods. The fundamental challenge of multi-stage production is the propagation and accumulation of uncertainties that influences the conformity of the outputs [1]. The present study is concern with such a multistage system and simulation is chosen to analysis the objectives.

A simulation model is a surrogate for experimenting with a real manufacturing system. It is often infeasible or not cost-effective to do an experiment in a real process. Thus, it is important for an analyst to determine whether the simulation model is an accurate representation of the system being studied. Further the model has to be credible; otherwise, the results may never be used in the decision-making process, even if the model is “valid” [2]. Few simulation models are used to analyze various effects of uncertain factors namely machine breakdown and quality variability.

Machine breakdown means the failure or stoppage of machine(s) for unknown reason(s) and a representation of interruption in the process [3]. It wields a reduction of capacity level and delay the release of products or subassemblies [4]. In this study, the authors assumed that no alternative machines are available if the existing machines fail and no alternative routing can be executed if an order needs to be expedited. Short manufacturing cycle time is accepted as the central underlying factor for successfully accomplishing the world-class manufacturing goals such as on-time delivery [5], quality [6, 7], flexibility [8] and productivity [9]. Manufacturing cycle time is now often used as a measure of a firm's competitiveness.

Quality defines as the degree to which a system, component, or process meets specified requirements or meets customers' expectations [10]. Quality of a product is a measure of perfection. A quality uncertainty of the unacceptable material condition not only affects the change of finished products, but also creates an additional time required at a resource to rework the parts. Such additional time spent at a resource, delays the planned work to be released to the resource. The factors of quality variation are found at Wazed et al. [4]. In this article, the inspection is performed at the final stages only and the defective product(s) is simply rejected.

The effects of the reworking of defective items on the economic production quantity (EPQ) model with backlogging has studied by Peter Chiu [12]. In his study, a random defective rate is considered, and when regular production ends, the reworking of defective items starts immediately. Ouyang et al. [13] have investigated the integrated vendor-buyer inventory problem. In their model, it is assumed that an arrival order lot may contain some defective items, and the defective rate is a random variable. Also, shortage is allowed and the production cycle time is controllable and reducible by adding extra crashing cost. Yang and Pan [14] have developed an integrated inventory model that minimizes the sum of the ordering/ setup cost, holding cost, quality improvement investment and crashing cost. They simultaneously optimize the order quantity, lead time, process quality and number of deliveries while the probability distribution of the lead time demand is normal. But they did not think of common component.

Porteus [15] has developed, the earliest EOQ model. It has shown a relationship between lot size and quality. Porteus research has encouraged many researchers to deal with modelling the quality improvement problems. Zhang and Gerchak [16] have considered a joint lot sizing and inspection policy studied under an EOQ model where a random proportion of units are defective. Makis and Fung [17] have studied the effect of machine failures on the optimal lot size and on the optimal number of inspections in a production cycle. Ouyang et al. [18] have investigated the lot size, reorder point inventory model involving variable lead time with partial backorders, where the production process is imperfect. Chan et al. [19] provide a framework to integrate lower pricing, rework and reject situations into a single EPQ model. To identify the amount of good quality items, imperfect quality items and defective items in each lot, a 100% inspection is performed. Ben-Daya and Rahim [20] developed a multistage lot-sizing model for imperfect production processes. The effect of inspection errors in screening non-conforming items at each stage has been incorporated. These writings unfortunately neglect the event of resource breakdown and component commonality.

There are few batch sizing models those explicitly take production cycle time into account in a stochastic manufacturing system. In these researches, the manufacturing facility is usually modelled by a queuing system. Karmarkar [21] has examined the relationships between manufacturing cycle times, WIP inventories and batch size. Karmarker et al. [22] have presented a multi-item batching heuristic with the objective of minimizing the queuing delays. They developed upper and lower bounds on the optimal batch size. Based on the bounds, three batch sizing heuristics are presented and tested. These studies have ignored the uncertainties and commonality.

Hong [23] has developed a mathematical model to study the effect of reduction in manufacturing cycle time and increase in process quality on lot size computation and total relevant cost. Kuik and Tielemans [24] have present a batch sizing model that minimizes the average queuing delay for a multi-item, single-machine work-centre. Later, they investigate the relationship between batch size and lead time variability. Machine breakdown and common components are not considered for conclusions.

The major limitations of the earlier studies are: i) the combined effects of quality and machine breakdown in a multistage production system are ignored; ii) None of the studies have considered a multistage production problem in determining the optimal lot size in a bottleneck facility; iii) None of the models/studies have included common component and brought out live case. Under such circumstances, the authors studied the effects of component commonalities and two uncertain factors, namely machine breakdown and quality variation in a multistage production system. The main objective of this study is to analyze the throughput and average production cycle time of the assembly lines in a company, consisting of two products under component commonality in a disturbed environment.

2. The Production System

The company namely XDE (a given name) located in Malaysia produces bicycle wheels. This research deals with the production and assembly line of bicycle wheel only. There are two different end products, product SL (line 1) and product DL (line 2) of this system. The products details are in Table 1. Parts are initially process in same sawing machine then placed in two separate production lines. Each production line contains 3 (three) different processing (viz. assembly, inspection and packing operation) and ended up with single end products after the assembly operation. Figure 1 is showing the existing production layout of the company. Presently the company use the conventional production processes with known lead time. They exercise event trigger policy for any stoppage/break down of the lines.

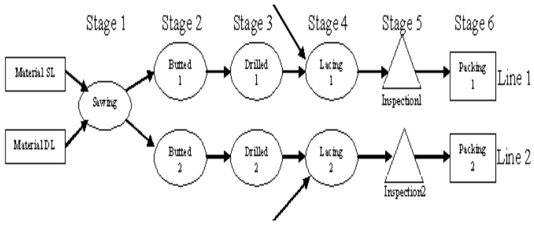
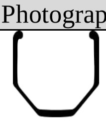
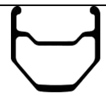


Figure 1: Existing production layout of XDE

Table 1: The products details for XDF

Photograph	Details
	Single layer rim (SL), 26 inch diameter, 32 holes, Triple butted spokes (2.3/1.8/2.0mm)
	Double layer rim (DL), 26 inch diameter, 28 holes, Double butted spokes (2.0/1.8/2.0mm)

3. Experimental Design

This study developed few simulation models based on the existing production layout (Figure 1) of the company. The existing layout is modified to introduce common component(s) in the system. Figure 2 shows the proposed layout that incorporates commonality dimension. Two models, namely the base model (Figure 3a) and the commonality model (Figure 3b and Figure 3c) are developed in WITNESS simulation package. The prominent uncertainty factors - machine breakdown and quality variability are applied separately and in combined form in simulation exercises with/without the inclusion of common components for analysis.

In this study, two factors are considered and the effects of these factors on the system performance are tested. The levels of commonality and production batch size at blockage station are considered as control factor or decision variable. The machine breakdown and fraction of non-conforming items are considered as noise factor. Analysis of mean value, signal to noise ratio and ANOVA are used to analyze the effect of batch size and common component on production cycle time and throughput quantity. Interaction effects are observed to make sure that the characteristic of the control factors is additive.

Since this study contains two control factors of three levels and two noise factors of three levels for each, thus $\left(3^2 \times 3^2\right) = 81$ design points are required in case of full (or complete) factorial design. Each experiment is simulated with nine replications (two noise factors of three levels each) and the average value and its signal to noise ratio are obtained and analyzed. In order to evaluate the experimental results statistically, analysis of variance (ANOVA) is applied. The same are used to see the effect of the interaction. Statistical significance tests of effects are made at 5% significance level. The ranges of factor levels are selected based on capacity limitation and in consultation with the engineers in the company (Table 2).

Table 2: Control factors and their levels for Taguchi method

Control Factors	Level 1	Level 2	Level 3
Batch size at the bottleneck station (i.e. Lancing), A	2	6	12
Common component, B	0	1	2

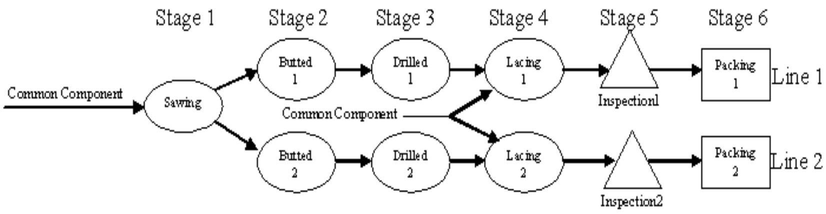


Figure 2: Proposed/modified production layout of XDE

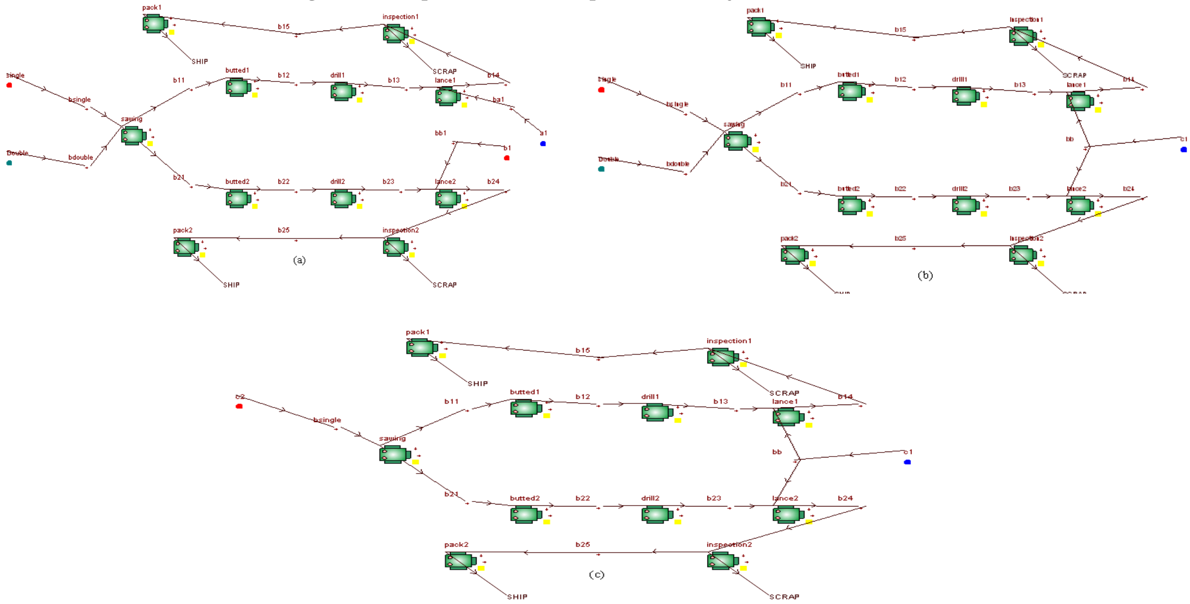


Figure 3: Base (a) and Commonality (b & c) Models in WITNESS

4. Data Collection and Validation

In order to build the simulation models, and to set the initial level of various factors in the model, data were collected. The data includes processing time at each stages, setup time, average defective proportion, machine breakdown etc. The time required to position each part into fixed place before operation is carried out is setup time per piece. Setup time per batch is the time to load the batch material and prepare the machine. Processing time is the period during which a part is actually works on. The historical data under deterministic condition are collected from the company. The cycle time and setup time for lancing station are much higher than the others. It is the bottleneck of the system. Therefore, in this article different levels of batch size are considered to analyze the effects of production quantity and cycle time. Data are needed for building the simulation model, validating the model and to serve as guideline in determining the level of the noise factor. Validation of data are performed to ensure that these are for the right issue and useful. The recorded data were scrutinized by the production engineers who are familiar with the specific processes.

5. Model Validation

The simulation models are validated by comparing the simulated output with historical data collected from the floor and also by face validity. The models run for 5 days after a warm-up period of 2×5 days and then the simulated results are generated. The run time for a 9 hour shift for 5 days is 9×60×5 minutes, which is same with the operation schedule of the lines. The warm-up period is used to assure the accurate result. Throughput quantity for the real system and simulation model are shown in Table 3. The authors have authenticated the models by an expert and authorized WITNESS trainer for face validity. As the variation in the throughputs between the real system and simulation model is not large and also the face validation permitted with good recommendations, hence the simulation models are acceptable for analyzing the system. After validating the base model, various uncertainties are imposed to the models to investigate the case wise impacts.

Table 3: Comparison between the existing system and simulation model

Response	Existing System	Simulation Model
Mean yearly throughput for SL	114	116
Mean yearly throughput for DL	133	135
Mean cycle time for SL (min)	143.28	146.22
Mean cycle time for DL (min)	137.56	139.68

6. Data Analysis and Discussions

The authors have conducted a total of 81 experiments. Table 4 is showing the summary of experimental results for the WIP level and production cycle times for both of the lines with corresponding S/N ratio for each exercise. The smaller the better characteristic is used for WIP and cycle times and in calculating the corresponding S/N ratios.

Table 4: Experimental result for each experiment

Experiment No.	Batch size	Common component	WIP level		Cycle time			
					Line 1		Line 2	
			S/N ratio Smaller	Mean	S/N ratio Smaller	Mean	S/N ratio Smaller	Mean
1	1	1	-49.6194	302.6667	-27.0731	22.5756	-27.0849	22.6056
2	1	2	-46.1358	202.6667	-22.9643	14.0656	-23.0822	14.2567
3	1	3	-46.3895	208.6667	-22.9753	14.0833	-23.0517	14.2067
4	2	1	-46.2211	204.6667	-20.8778	11.0622	-20.9726	11.1833
5	2	2	-40.3968	104.6667	-14.8383	5.5189	-14.8832	5.5467
6	2	3	-46.3895	208.6667	-14.7910	5.4889	-14.7412	5.4567
7	3	1	-46.2211	204.6667	-18.1118	8.0456	-18.1538	8.0844
8	3	2	-40.3968	104.6667	-13.0514	4.4933	-13.1102	4.5233
9	3	3	-49.6194	302.6667	-12.4857	4.2100	-12.8106	4.3700

Since the experiment design is orthogonal, the effect of batch size and common component for different levels are separated out. Table 5 shows the response for mean and S/N ratio for WIP level and for production cycle times of production lines. Since the characteristic of these factors are the smaller the better, they are chosen based on smaller mean and larger S/N ratio. Because the larger the S/N ratio the smaller the variance are around the desired value. It is pellucid that an increase in the batch size and common commonality yield a decrease in WIP level in the system. The production cycle time also decreases with the batch size and common component(s). But they are restrained by the capacity limitation of the lancing stations. The WIP level is least when the batch size is 6 or 12 and the system uses 2 common components. The minimum cycle times for each of production lines are achieved when the batch size is 12 and 2 common components are introduced. Thus, based on response table (Table 5), the batch size and commonality are chosen as 12 and 2 respectively.

Table 5: Response table for WIP and cycle time (the smaller the better)

Level	WIP				Cycle time							
					Line 1				Line 2			
	Mean		S/N ratio		Mean		S/N ratio		Mean		S/N ratio	
	Batch size	Common component	Batch size	Common component	Batch size	Common component	Batch size	Common component	Batch size	Common component	Batch size	Common component
Level 1	276.6	247.2	-48.66	-47.67	17.023	13.958	-24.41	-22.07	16.908	13.894	-24.34	-22.02
Level 2	172.7	237.3	-44.34	-47.35	7.396	8.109	-16.87	-17.03	7.357	8.026	-16.84	-16.95
Level 3	172.7	137.3	-44.34	-42.31	5.659	8.011	-14.69	-6.87	5.583	7.927	-14.55	-16.75
Diff	103.9	109.9	4.32	5.36	11.364	5.947	9.71	5.20	11.325	5.967	9.79	5.27
Rank	2	1	2	1	1	2	1	2	1	2	1	2

Opt	3	3	2 or 3	3	3	3	3	3	3	3	2 or 3	3

Figures 4-6 show the interaction effects of variation in levels of control factors for (a) mean value and (b) S/N ratio of WIP and cycle times for the lines (1 & 2) respectively. The figures show that there is an interaction between the batch size and number of common component used in the system. The interaction graphs between commonality (factor B) and batch size (factor A) show that the effect of batch size on production level and cycle time at different levels of common component is not the same. This implies that there is an interaction between these two factors. The WIP is least when the batch size (factor A) is at level 2 and common component (factor B) is at the highest level. However, the cycle times for both of the lines (1 and 2) are least when both of the factors (A and B) are at high levels It implies that inclusion of common components accelerate to achieve WIP target earlier than the cycle time.

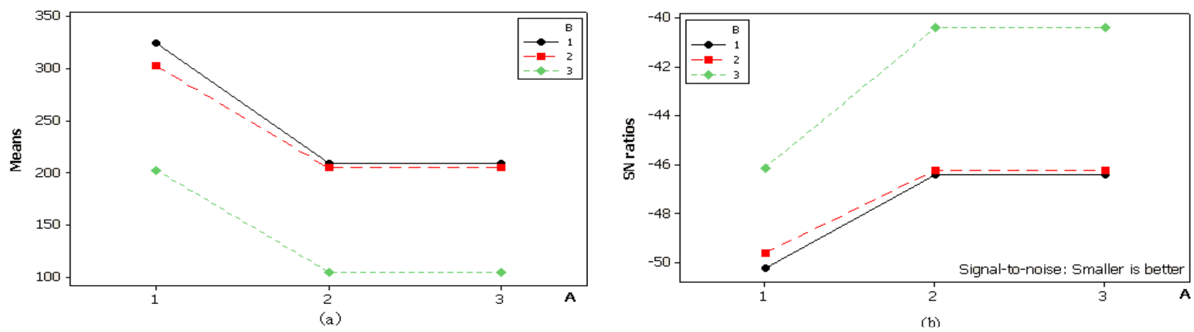


Figure 4: Interaction plot for (a) mean value and (b) S/N ratio of WIP level

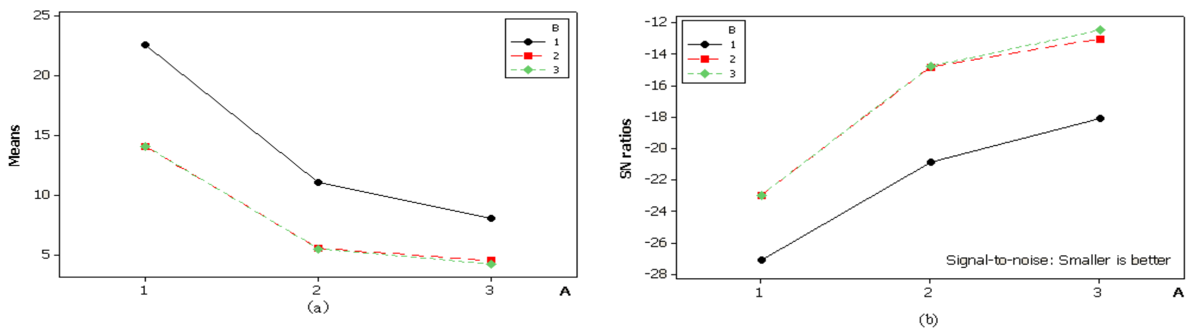


Figure 5: Interaction plot for (a) mean value and (b) S/N ratio of cycle time for Line 1

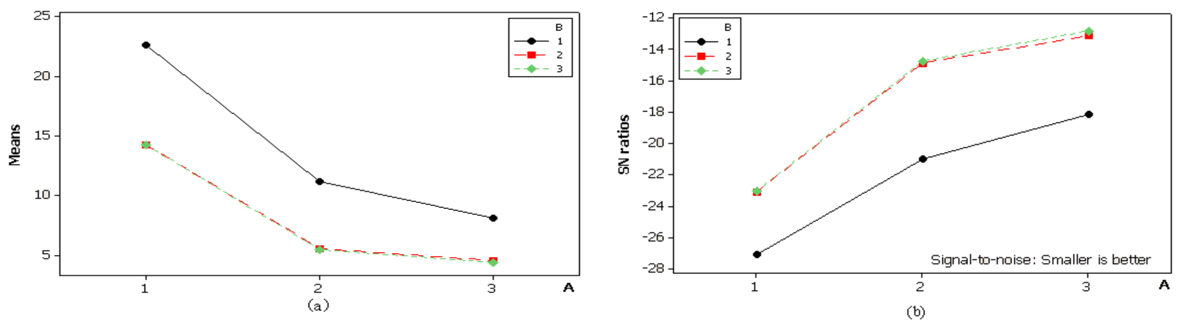


Figure 6: Interaction plot for (a) mean value and (b) S/N ratio of cycle time for Line 2

Tables 6-8 show the ANOVA for WIP level and cycle times of both of the lines (1 and 2) in mean and S/N ratio respectively. These tables show the relative importance of the control factors affecting the WIP and cycle time. Both mean and signal to noise ANOVA indicates that batch sizes in lancing station (factor A) and use of common component (factor B) is statistically significant. The factors have very strong impacts on WIP and cycle times.

Table 6: ANOVA for Mean value and S/N ratio of WIP

Source	Mean value					S/N ratio			
	DF	SS	MS	F	P	SS	MS	F	P
A	2	21585.8	10792.9	311.22	0.000	37.3694	18.6847	36.13	0.003
B	2	22173.4	11086.7	319.69	0.000	54.2324	27.1162	52.43	0.001
Error	4	138.7	34.7			2.0686	0.5171		
Total	8	43897.9				93.6703			
S = 5.889; R-Sq = 99.68%; R-Sq(adj) = 99.37%						S = 0.7191; R-Sq = 97.79%; R-Sq(adj) = 95.58%			

Table 7: ANOVA for Mean value and S/N ratio of cycle time of Line 1

Source	Mean value					S/N ratio			
	DF	SS	MS	F	P	SS	MS	F	P
A	2	222.637	111.318	56.66	0.001	157.308	78.6541	222.95	0.000
B	2	70.055	35.027	17.83	0.010	53.517	26.7583	75.85	0.001
Error	4	7.859	1.965			1.411	0.3528		
Total	8	300.550				212.236			
S = 1.402; R-Sq = 97.39%; R-Sq(adj) = 94.77%						S = 0.5940; R-Sq = 99.34%; R-Sq(adj) = 98.67%			

Table 8: ANOVA for Mean value and S/N ratio of cycle time of Line 2

Source	Mean value					S/N ratio			
	DF	SS	MS	F	P	SS	MS	F	P
A	2	224.835	112.418	59.75	0.001	155.964	77.9822	200.84	0.000
B	2	69.582	34.791	18.49	0.010	52.547	26.2733	67.66	0.001
Error	4	7.526	1.882			1.553	0.3883		
Total	8	301.944				210.064			
S = 1.372; R-Sq = 97.51%; R-Sq(adj) = 95.01%						S = 0.6231; R-Sq = 99.26%; R-Sq(adj) = 98.52%			

Based on ANOVA (Tables 7-9) and response table (Table 6), it is obvious that batch size of 12 in the lancing station and 2 common components yield the lowest cycle time and WIP level in the system.

7. Conclusions

From the experiences of the analysis and from the outcomes of the models, the authors would like to conclude that –

i. The developed simulation models for the production system of the company under consideration are verified and validated with the historical data and by face validity. The comparison shows that simulated deliveries are acceptable for further investigations.

ii. The lancing stations process a batch of parts at a time and they are bottleneck of the system. Based on the least manufacturing cycle time and WIP level, the optimum batch size of 12 in lancing stations and two common components could ensure the best outcomes of the system.

iii. Batch sizes in lancing stations and using two common components, the system outcomes improve significantly. ANOVA for mean and S/N ratio for cycle time and WIP indicate that no important factor is omitted from experiments.

iv. There is an interaction among the common component and the batch sizes in lancing stations. The WIP and cycle time is least when the batch size and common component are at high levels.

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