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Full Length Research Paper

Application of Taguchi method to analyze the impacts of commonalities in multistage production under bottleneck and uncertainty

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The work wishes to measure the individual and combined impacts of common parts and machines in manufacturing, under bottleneck and uncertain conditions. The system is characterized with multiple products, multi-period and multistage dependent demand. This research uses machine breakdown and quality variation to create uncertainty. The authors examined the delivery performances such as (i) throughput of the finished products, (ii) average production time and (iii) work-in-progress in the system for different experimental scenarios. Taguchi approaches for orthogonal array were employed in designing experiments and these were executed in a WITNESS. Few simulation models are developed based on a live case from a Malaysian company. The models corroborated and confirmed the historical data from the company by face validity. It was viewed that batch size of 12 in bottleneck, 2 common parts and 4 common machines ensure the best outcomes of the system under the storm of uncertainties. The main contribution of this research is to find out the best batch size in bottleneck point under uncertainties, commonalities and capacity constraint.

Key words: Commonality, simulation, uncertainty.

INTRODUCTION

The underlying ideas for commonality are not new. As early as 1914, an automotive engineer demanded the standardization of automobile subassemblies, such as axles, wheels and fuel feeding mechanisms to facilitate a mix-and-matching of components and to reduce costs (Fixson, 2007). The term ‘commonality’, its definition, measurement and models are discussed in Wazed et al. (2010a). Two sources of commonality, namely component/part commonality and process commonality, are identified in the literature. The process commonality index incorporates such concerns as process flexibility, a lot of sizing and scheduling sequencing into one analytical measurement (Jiao and Tseng, 2000). Fewer processes are involved in the production and in the entire plant, thus, making the plant to be more flexible to customer needs. The number and diversity of component parts and the corresponding processes reflect the complexity of design and that of planning and control of products.

Uncertainty refers to the degree of differences between the models and their respective real values or between the estimate and their true values. Errors associated with the model itself and the uncertainties of the model inputs affect uncertainty. The major factors of uncertainty in production are found in the review of Wazed et al. (2009c). Elaborately, the big picture of the field is covered in Wazed et al. (2010c). In this article, component interchangeably uses a part and the entire machine as process, resource and facility.

Modern manufacturing enterprises are facing increasing pressure to respond to production dynamics caused by disruption or uncertainty (Koh and Saad, 2003). Machine breakdown and quality of end items are two leading uncertain factors (Wazed et al., 2009c). Often, these factors act as sources of other unexpected events in the system. Machine breakdown means the failure or stoppage of machine(s) for unknown reason(s) and a representation of interruption in the process (Koh and Saad, 2003). It wields reduction of the capacity level

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Table 1. Earlier studies and issues.

Reference	Issue
Minifie and Davies (1990)	Demand and supply uncertainties.
Brennan and Gupta (1993), Enns (2001), Ho and Carter (1996) and Tito et al. (1999)	Demand and lead time variations.
John and Sridharan (1998)	Late delivery in raw materials, variations in lead times, inter operation (or switching) and waiting times in a manufacturing setting.
Matsuura et al. (1995)	Demand modeling.
Liao and Shyu's (1991)	Probabilistic inventory model, in which lead time is a unique variable.
Ben-Daya and Raouf (1994)	Extended Liao and Shyu (1991) model by considering both lead time and ordering quantity as decision variables neglecting shortages.
Ouyang et al. (1996)	Generalized Ben-Daya and Raouf (1994) model by allowing for shortages with partial backorders.
Moon and Choi (1998) and Hariga and Ben-Daya (1999)	Changed the Ouyang et al. (1996) model by including the reorder point as one of the decision variables.
Ouyang et al. (2007)	Integrated inventory model to decide the best order quantity, reorder point, process quality, lead time and the frequency of deliveries simultaneously.
Porteus (1986) and Rosenblatt and Lee (1986)	Elaborated the relationship between quality defect and lot size.
Keller and Noori (1988)	Extended Porteus (1986) work to probabilistic demand during lead time and allows shortage.
Hwang et al. (1993)	Multiproduct economic lot size models.
Hong and Hayya (1995)	Introduce budget constraint and continuous functions to increase quality and reduce setup cost.
Ouyang and Chang (2000)	Impact of quality under variable lead time and partial backorders.
Ouyang et al. (2002)	Extended Ouyang and Chang (2000) model and explored quality improvement and setup cost simultaneously.
Tripathy et al. (2003)	EOQ model with an imperfect production.
Zhang (1997)	General multi-period, multiproduct, multiple parts model with known lead times.
Benton and Krajewski (1990)	Quality and lead time uncertainty with and without part commonality.
Jiao and Tseng (1999)	Process to establish product families.
Germani and Mandorli (2004)	Procedure to self-configuring components in a product architecture.
Farrell and Simpson (2003)	Steps in model for designing a product family.
Qin et al. (2005)	Commonalize product subsystems.

Table 1. Contd.

Kamrani and Salhieh (2002) and Ulrich and Eppinger (2000)	Procedure in designing modular products and products with common components.
Lin et al. (2006)	Multi-period model of component commonality with lead time.
Nonas (2007)	Optimal inventory level for components in multiple products share the common components in presence of a random demand pattern.
Jans et al. (2008)	Mixed integer nonlinear optimization model to find the optimal commonality decision.
Wazed et al. (2009a)	Impact of common component on performance of multistage production under uncertainty.
Wazed et al. (2010b)	Impact of common process on performance of multistage production under uncertainty.

and delays the release of products or subassemblies (Wazed et al., 2009b). In this study, the authors assumed that no alternative machines are available if the existing machines fail and no alternative routing, except a common process, can be executed if an order needs to be expedited.

Quality is defined as the degree to which a product, part, or workstation meets mentioned needs or customers' expectations (Aas et al., 1992). Also, it is a measure of products' perfection. Quality uncertainty of material not only affects the change of finished products, but also needs an extra time and delays the planned release to the next station. The causes of quality variation were found in Wazed et al. (2009b). This work only performs an inspection at the final stages and simply rejects the defective product. Table 1 summarizes some of the studies and their issues in this regard.

Under the circumstances, although machine uprightness has paramount importance, its maintenance or breakdown and the commonalities (such as, component and process) issues remained unshaded. None of the past studies have pondered on the components and processes commonality in a production system being affected by machine breakdown and quality variations. Impacts of the bottleneck facility have not been considered in any earlier article where the system exploits commonalities (component and/or process) and uncertainties concurrently occured. In this research, the authors have put the real manufacturing facts in analyzing the effects of the bottleneck under uncertain factors (such as, machine breakdown and quality variability) and with/without the inclusion of the commonalities (component and/or process), case-by-case and the combined form in the production system.

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 a bicycle wheel only. There are two different end products, product SL (line 1) and product DL (line 2), of this system. Parts of the products are initially processed in the same sawing machine and then placed in two separate production lines. Each production line contains three different processing (such as assembly, inspection and packing operation) and ended up with a single end product after the assembly operation. Figure 1 is showing the existing production layout of the company. Presently, the company follows the conventional production processes with known lead time and periodic maintenance. They exercise event trigger policy for any unexpected/accidental stoppage/breakdown of the lines. However, the commonality dimensions are not yet introduced.

Experimental design

The authors have constructed few simulation models based on the existing production layout (Figure 1) of the company. The layout is modified to introduce the common component(s) and/or process(es) in the system. Figure 2 shows the abstracted layout that incorporates commonality dimensions. Only four, among the models developed in simulation, namely the base model (Figure 3a), the model with a common process (Figure 3b) and component (Figure 3c) and the model with both a common component and process (Figure 3d) are shown. However, the models are developed in WITNESS simulation package. The models in Figure 3 are only some candidates of all layouts and are designed to investigate the scenarios. The prominent uncertainty factors (machine breakdown and quality variability) are applied separately and in combination in the simulation exercises with and without inclusion of commonalities.

In this study, three factors (batch size, common part and common process) are considered and the effects of these factors on the system performance are tested. The levels of commonalities (process and component) and production batch size at blockage station are considered as a control factor or decision variable. The

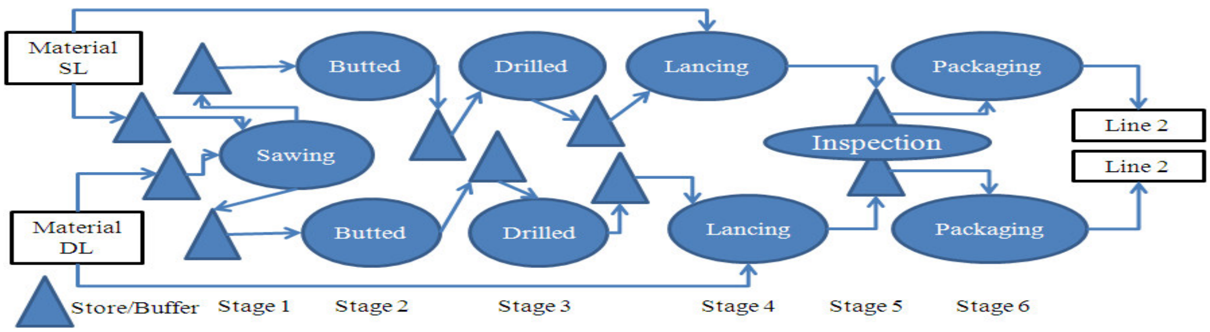


Figure 1. Existing production layout of XDE.

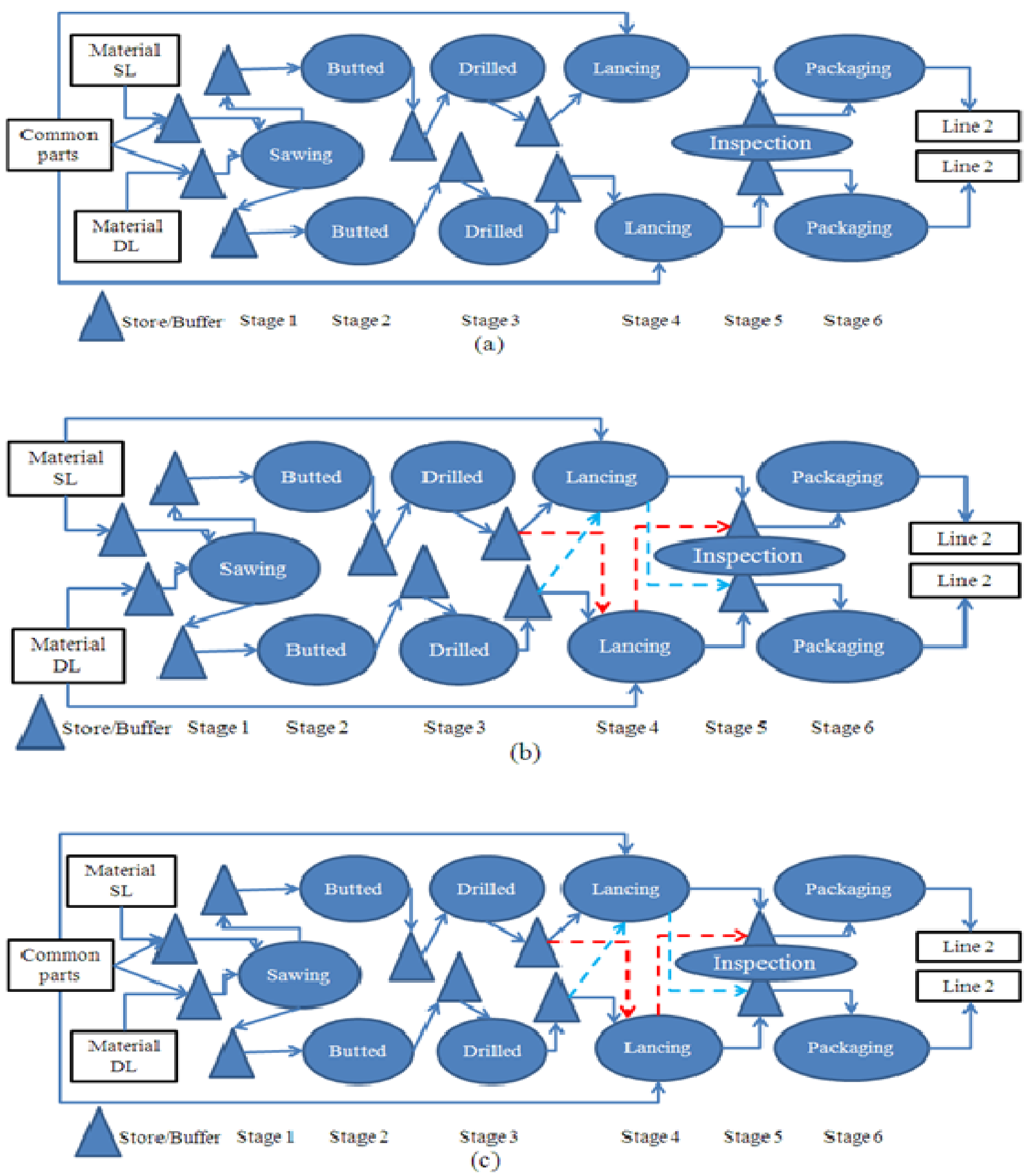


Figure 2. Sample modified production layouts of XDE [(a) Component, (b) Process and (c) both component and process commonality].

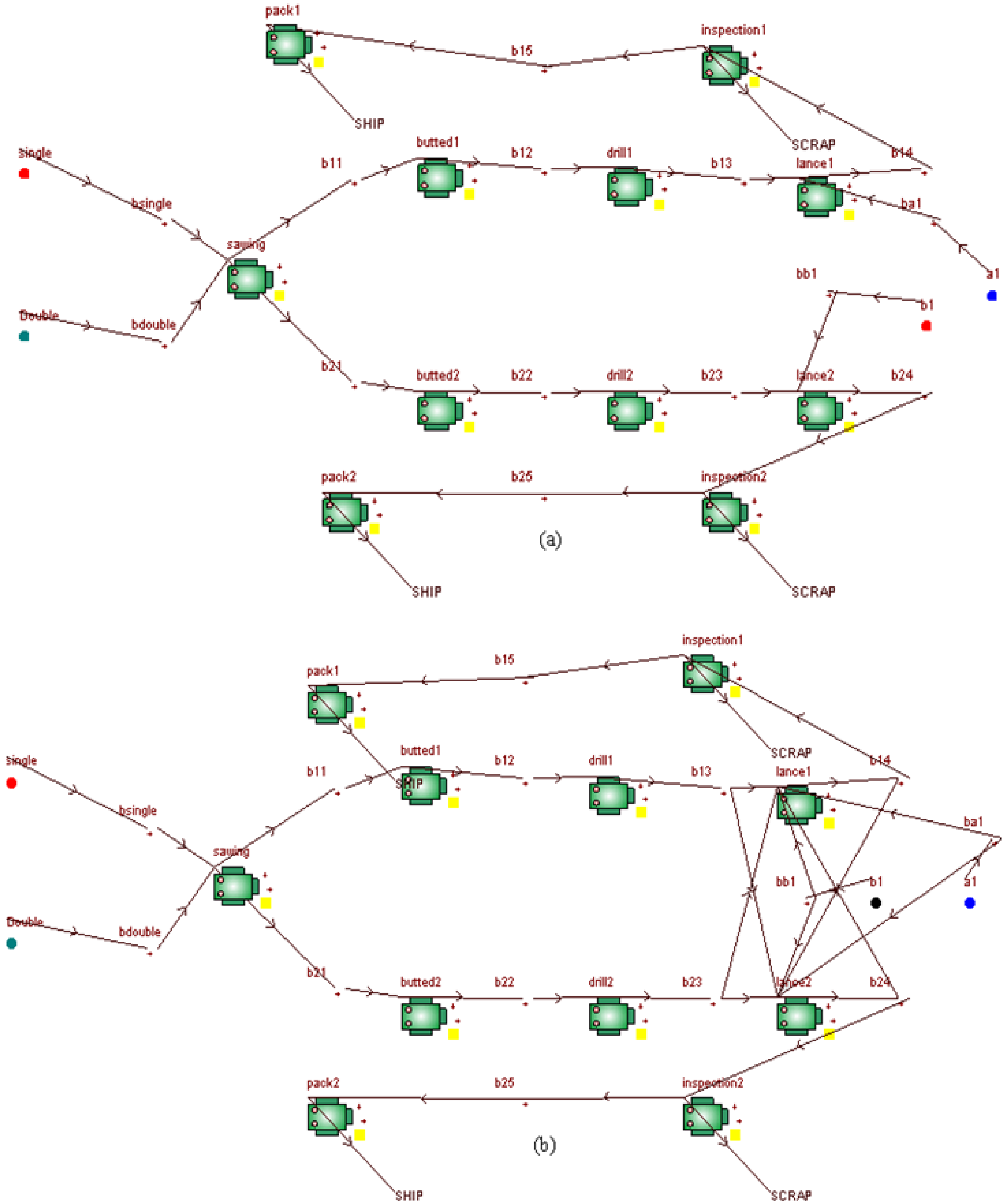


Figure 3. (a) Base, (b) Common process.

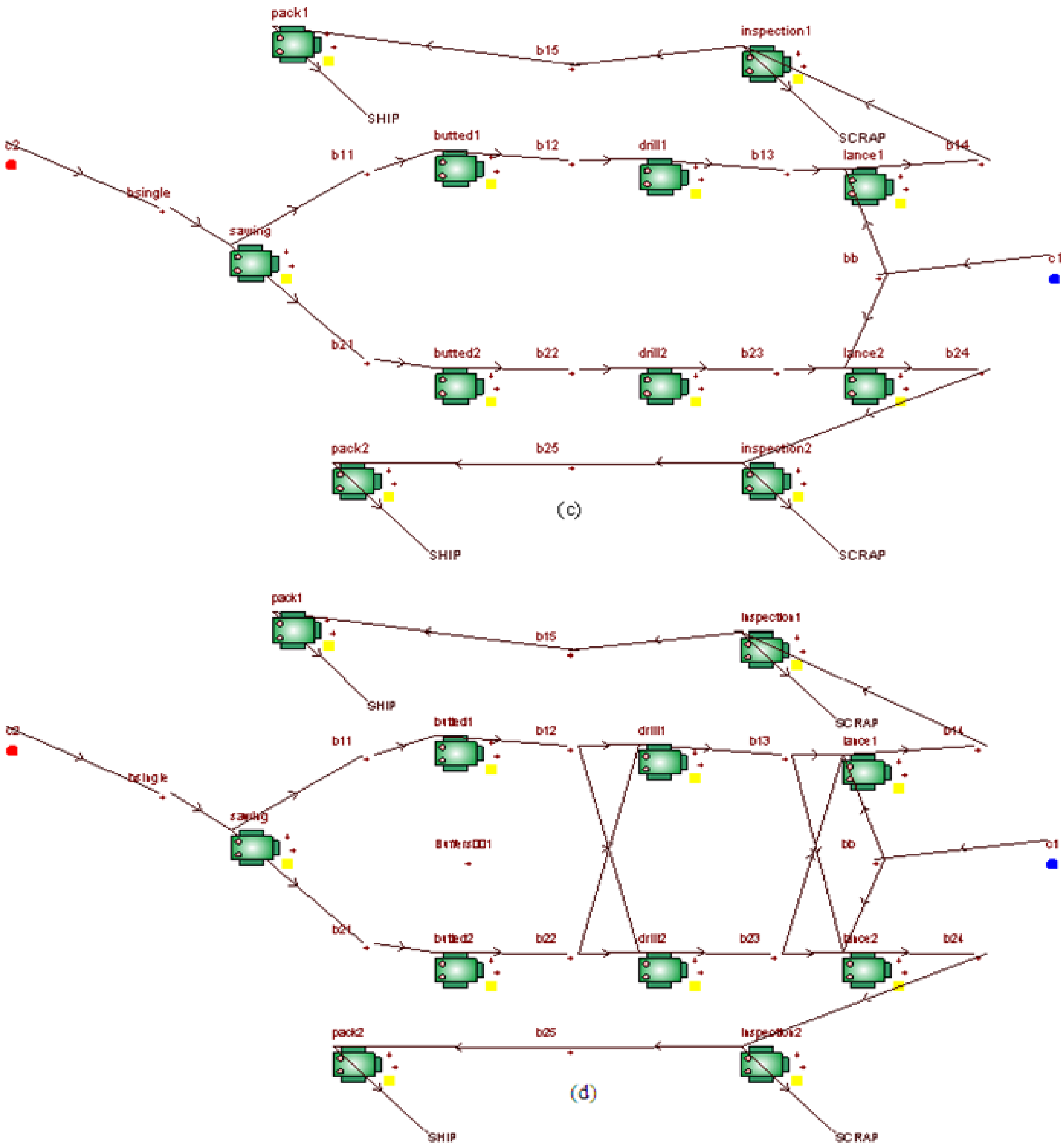


Figure 3 contd. (c) Common component and (d) Both common process and component models in WITNESS.

machine breakdown and fraction of non-conforming items are considered as a noise factor. The effects of these factors will be more realistic and mimic to the real system because the system is normally subjected to these uncertainties. By a variation in the level of the factors, the work-in-progress (WIP), that is, throughputs and cycle time, is adjusted for an optimized total cost and reasonable machine productivity. Three levels of the factors are expected to have better chance of identifying the influence of both linear and nonlinear behaviors. The ranges of these factors levels are selected based on capacity limitation and in consultation with the engineers in the company (Table 2). Batch size bears its usual meaning and its different levels are imposed only on the bottleneck facilities. The second factor, that is, component commonality is estimated to have only three levels (0, 1 and 2 for no, one and two common

Table 2. Control factors and their levels for Taguchi method.

Control factors	Level 1	Level 2	Level 3
Batch size at the bottleneck station (that is, lancing), A	2	6	12
Common component, B	0	1	2
Common process, C	0	2	4

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	140.22
Mean cycle time for DL (min)	137.56	133.68

components in the system, respectively). The third factor, that is, process commonality is estimated to have also three levels (0, 2 and 4 for no, two and four common processes in the system, respectively). As a result, the factors and their levels are used in setting experiments.

The noise factors (quality and machine breakdown) are projected to have three levels for each and the levels are selected based on the historical data. The three levels of quality (that is, defective rates) are considered as 3, 5 and 7% and the machine breakdowns are taken as 40, 20 and 10 operations. It is worthy to mention that the inspection on the products is conducted at the inspection stations only and the defective products are simply rejected. The interval of machine breakdown is measured in a number of operations. For example, the number 40 means that after 40 operations, the resource will break down. The breakdown levels are used in all machines and the quality dimensions are applied in the inspection stage.

Since this study contains three control factors of three levels and two noise factors of three levels for each, $\left(3^3 \times 3^2\right) = 243$ design points are thus required in the case of a full (or complete) factorial design. However, each experiment is simulated with nine replications (two noise factors of three levels each). The average value and its signal to noise ratio based on the settings are obtained and analyzed. Analysis of mean value, signal to noise ratio and ANOVA are used to analyze the effect of batch size and commonalities (component and process) on production throughput, cycle time and WIP quantity. Interaction effect is observed before the results are confirmed, to make sure that the characteristic of the control factors is additive. In order to evaluate the experimental results statistically, analysis of variance (ANOVA) is applied. Also, the same procedure is used to check the effect of the interaction. Statistical significance tests of effects are made at 5% significance level.

Data collection and validation

In order to build and validate the simulation models and serve as a guideline to set the initial level of various factors in the model, data were collected. The data include processing time at each stage, setup time, average defective proportion, machine breakdown, etc. Validation of data is performed to ensure that these data are for the right issue and are useful. The recorded data were scrutinized by the production engineers who were familiar with the specific processes.

The time required to position each part into a fixed place before operation is set up 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 worked on. The historical data under a deterministic condition were collected and fitted to a known distribution. The cycle time for all processes, except for inspection and packaging, is well fitted to a triangular distribution and the others are to a normal distribution. The cycle and setup time for lancing station is much higher than the others and it is the bottleneck of the system. Therefore, in this article, different levels of batch size at lancing stations (that is, bottleneck facilities) are considered to analyze the effects on production quantity and cycle time.

Model validation

The simulation models are validated by comparing its output with historical data collected from the floor and also by face validity. The models have been run for 5 days after a warm-up period of 2×5 days. In other words, the simulated results are collected after two test runs of the models for each experimental setting. The running time of a 9 h shift for 5 days is 9×60×5 min, which is same with the weekly operation schedule of the lines; however, the warm-up period is used to assure the accurate result. Throughputs for the real system and simulation models are shown in Table 3. The authors have authenticated the models by an expert and authorized a WITNESS trainer for face validity. The base models were tested in front of him with master data and his recommendations were adjusted before experiments. As the variation in the throughputs between the real system and simulation model is not large and also, as the face validation is permitted with good recommendations, the simulation models are therefore acceptable in analyzing the system. After validating the base model, various uncertainties are imposed to the models to investigate the case wise impacts.

DATA ANALYSIS AND DISCUSSION

The authors have conducted a total of 243 experiments. The outcomes of WIP level, production cycle times and production quantity for both lines with corresponding S/N ratio for each exercise are observed. The smaller the

Table 4(a). Response table for the production system of WIP (the smaller the better).

Level	Mean			S/N ratio		
	Batch size	Common		Batch size	Common	
		Component	Process		Component	Process
Level 1	546.8	517.4	517.7	-54.76	-54.26	-54.26
Level 2	491.9	505.1	503.9	-53.83	-54.06	-54.04
Level 3	485.4	501.6	502.4	-53.72	-54.00	-54.01
Diff	61.4	15.8	15.3	1.03	0.26	0.25
Rank	1	2	3	1	2	3
Opt	12	2	4	12	2	4

Table 4(b). Response table for lines 1 and 2 cycle time (the smaller the better).

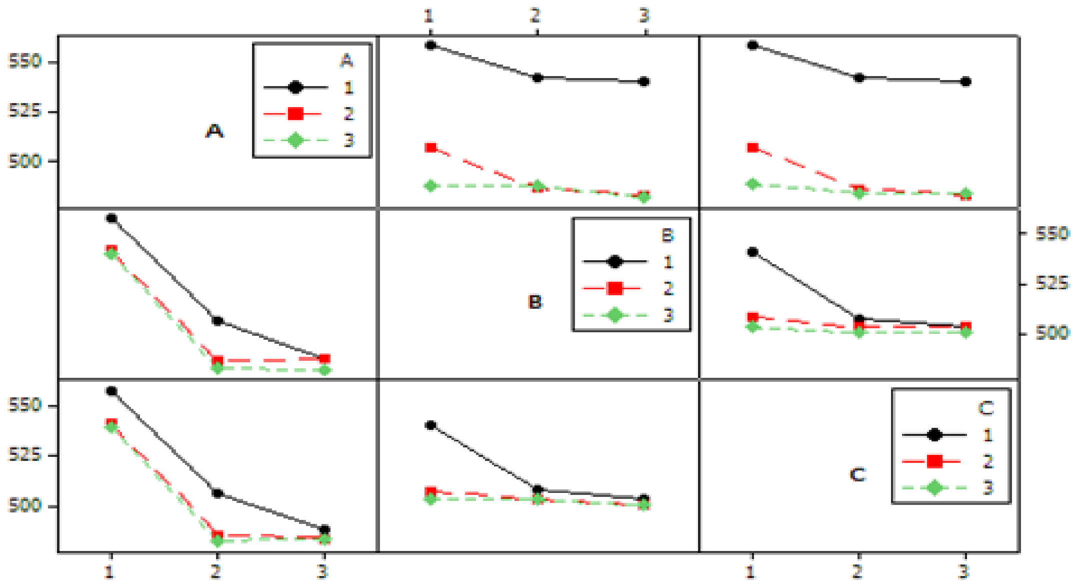
Level	Line 1						Line 2					
	Mean			S/N ratio			Mean			S/N ratio		
	Batch size	Common component	Common process	Batch size	Common component	Common process	Batch size	Common component	Common process	Batch size	Common component	Common process
Level 1	26.30	25.96	25.95	-28.40	-28.28	-28.28	26.31	25.97	25.96	-28.40	-28.29	-28.28
Level 2	26.29	25.73	25.70	-28.40	-28.20	-28.19	26.30	25.74	25.71	-28.40	-28.21	-28.20
Level 3	24.70	25.60	25.64	-27.85	-28.16	-28.17	24.71	25.61	25.65	-27.86	-28.16	-28.18
Diff	1.60	0.36	0.31	0.55	0.12	0.11	1.61	0.37	0.32	0.55	0.12	0.11
Rank	1	2	3	1	2	3	1	2	3	1	2	3
Opt	12	2	4	12	2	4	12	2	4	12	2	4

Table 4(c). Response table for lines 1 and 2 production quantity (the larger the better).

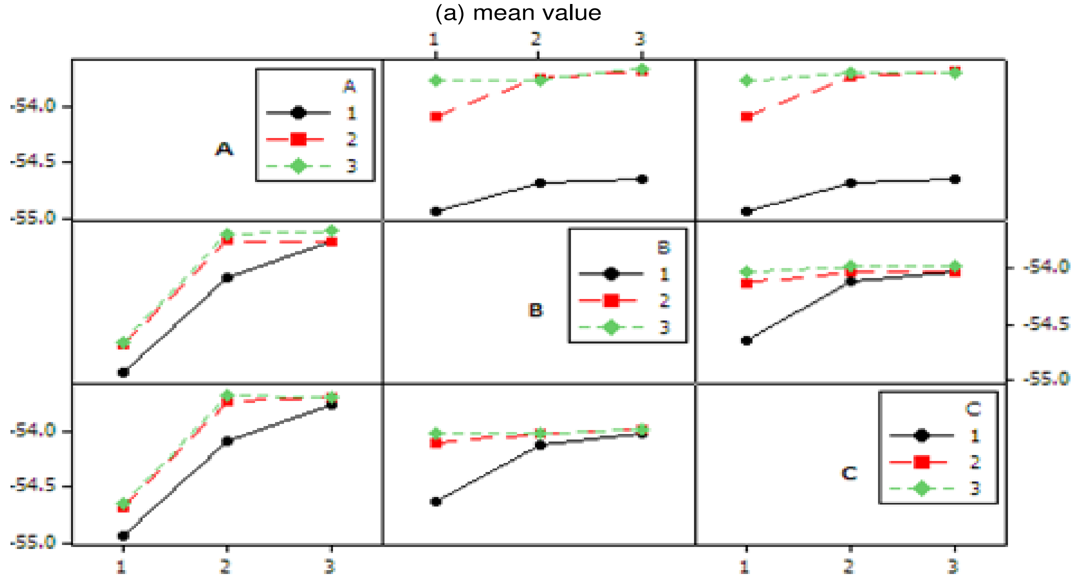
Level	Line 1						Line 2					
	Mean			S/N ratio			Mean			S/N ratio		
	Batch size	Common component	Common process	Batch size	Common component	Common process	Batch size	Common component	Common process	Batch size	Common component	Common process
Level 1	51.58	78.84	79.54	34.07	37.19	37.36	51.80	79.06	79.65	34.10	37.21	37.37
Level 2	95.60	92.70	92.06	39.52	38.76	38.69	95.72	92.81	92.28	39.53	38.77	38.71
Level 3	122.4	98.05	97.99	41.64	39.29	39.19	122.63	98.27	98.21	41.66	39.30	39.20
Diff	70.83	19.21	18.44	7.57	2.10	1.82	70.83	19.21	18.56	7.56	2.09	1.83
Rank	1	2	3	1	2	3	1	2	3	1	2	3
Opt	12	2	4	12	2	4	12	2	4	12	2	4

better characteristic is used for WIP and cycle times, while in contrast, the larger the better policy is applied for production quantity. Since the experiment design is orthogonal, the effects of batch size and common component and/or process for different levels is separated outrightly.

Table 4 shows the response for mean and S/N ratio (a) for WIP level, (b) production cycle times and (c) throughput of the lines. As a result, the smaller the better policy is adopted for evaluation of the performance based on WIP and cycle time. Consequently, they are chosen based on smaller mean and larger S/N ratio. However, the throughput is chosen based on larger mean and larger S/N ratio. All the selections use larger S/N ratio,



(a) mean value



(b) S/N ratio of WIP level.

Figure 4. Full interaction plot matrix for (a) mean value and (b) S/N ratio of WIP level.

because the larger the S/N ratio the smaller the variance is around the desired value. Thus, based on response tables (Table 4a to c), the batch size, common components and processes are chosen as 12, 2 and 4 respectively. The same tables show that the influences of the factors, A, B and C, are ranked respectively as 1, 2 and 3. It means that proper management of a bottleneck resource must improve the performances. Hence, the impacts of factors B (that is, common component) and C (that is, common process) are almost the same. However, factor B is ranked over factor C and this is because the common components provide more flexibility in design, scheduling and control.

It is pellucid that an increase in the batch size and commonalities yield a decrease in WIP level in the system. The production cycle time also decreases with the increase in batch size, common components and processes. These are supported by the corresponding S/N ratio. The WIP and production cycle times are found at the least level and the production quantities are at the peak when the batch size, common components and processes are set respectively at 12, 2 and 4. It is observed that under the combined effects of commonalities (component and process), the WIP and cycle time reduced by 11 and 6%, respectively and throughputs increased by 137%.

Figures 4 to 8 show the interaction effects of variation in levels of control factors for (a) mean value and (b) S/N

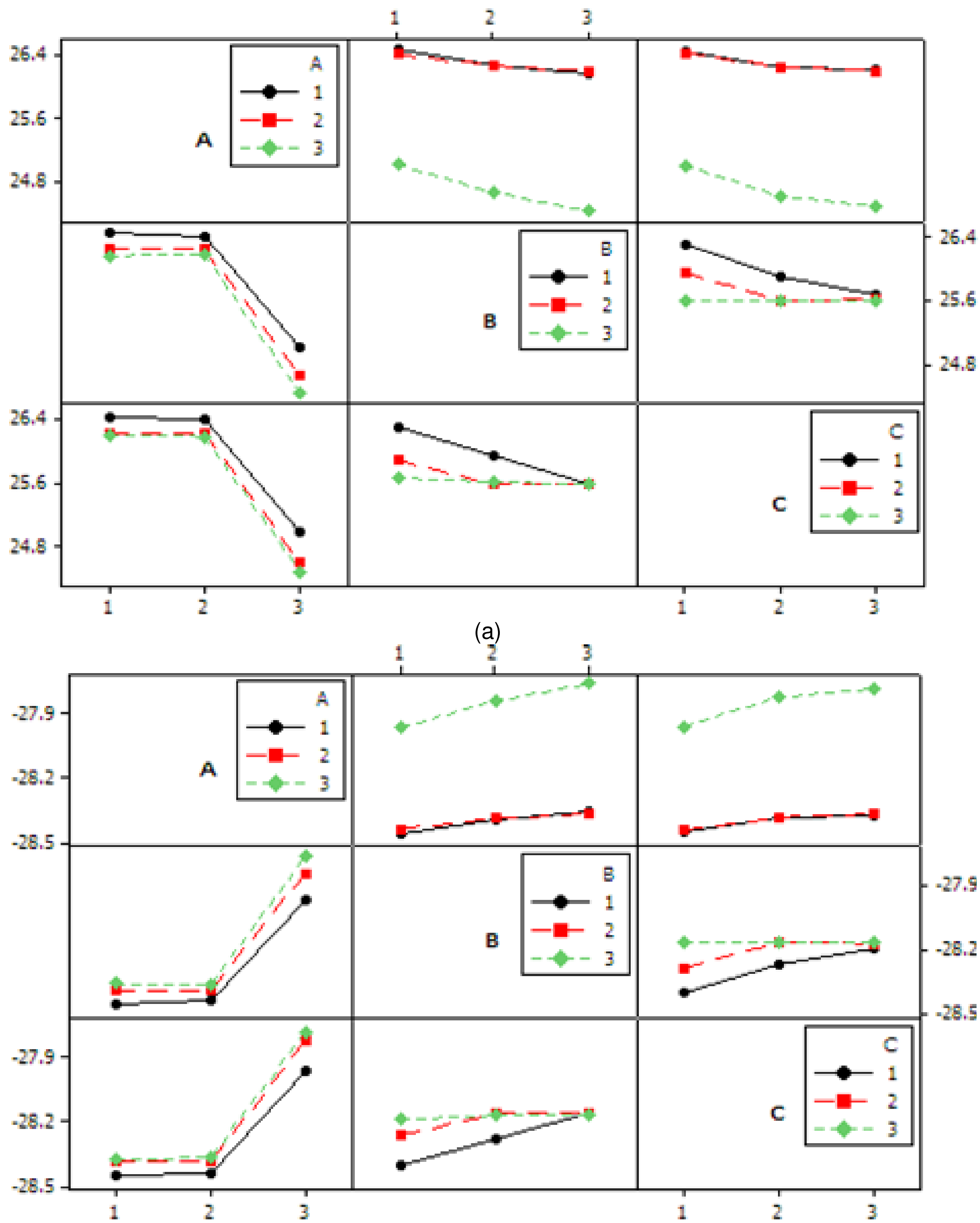


Figure 5. Full interaction plot matrix for (a) mean value and (b) S/N ratio of cycle time for line 1.

ratio of WIP, cycle times and throughput for lines 1 and 2, respectively. The interaction graphs between the commonalities (factors B and C) and batch size (factor A) show that the effect of batch size on WIP, throughputs and cycle times at various levels of commonalities is different. This implies an interaction between these factors. From the figures, when factor A (batch size at lancing station) is at level 1, there is no interaction among the factors. This is because the bottleneck center restrains the system performances. However, at the highest level of all factors, they are very interactive. The WIP and cycle times are at the least level and the throughputs are at the peak when the batch size (factor A), common component (factor B) and process (factor C) are at the top level. This is very obvious, because the commonalities (component and process) increase the

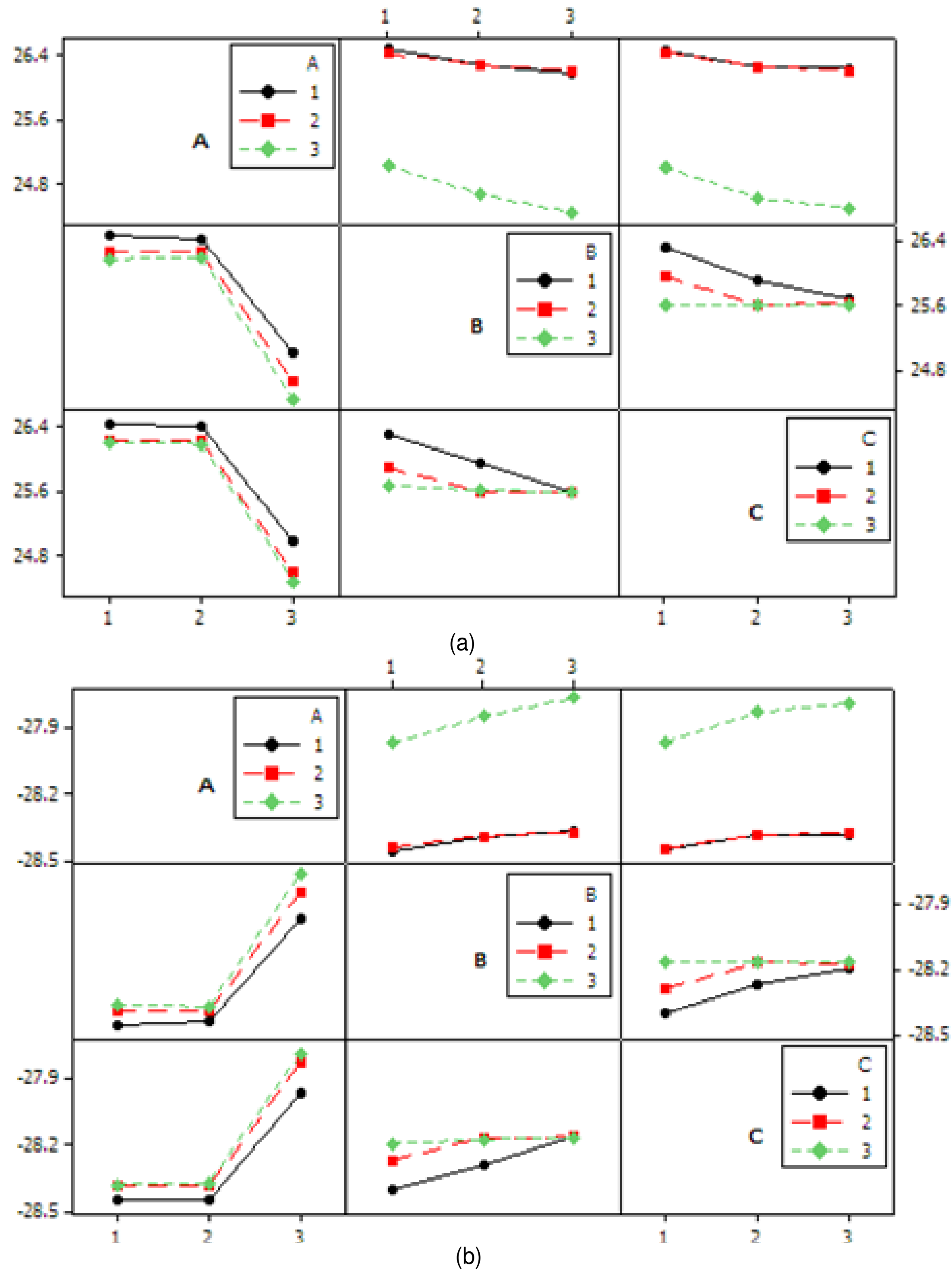


Figure 6. Full interaction plot matrix for (a) mean value and (b) S/N ratio of cycle time for line 2.

flexibility and dampen the uncertainty of the system.

ANOVA is conducted to see whether the factors are statistically significant. Table 5 shows ANOVA in mean and S/N ratio for the WIP level of the study. The same for

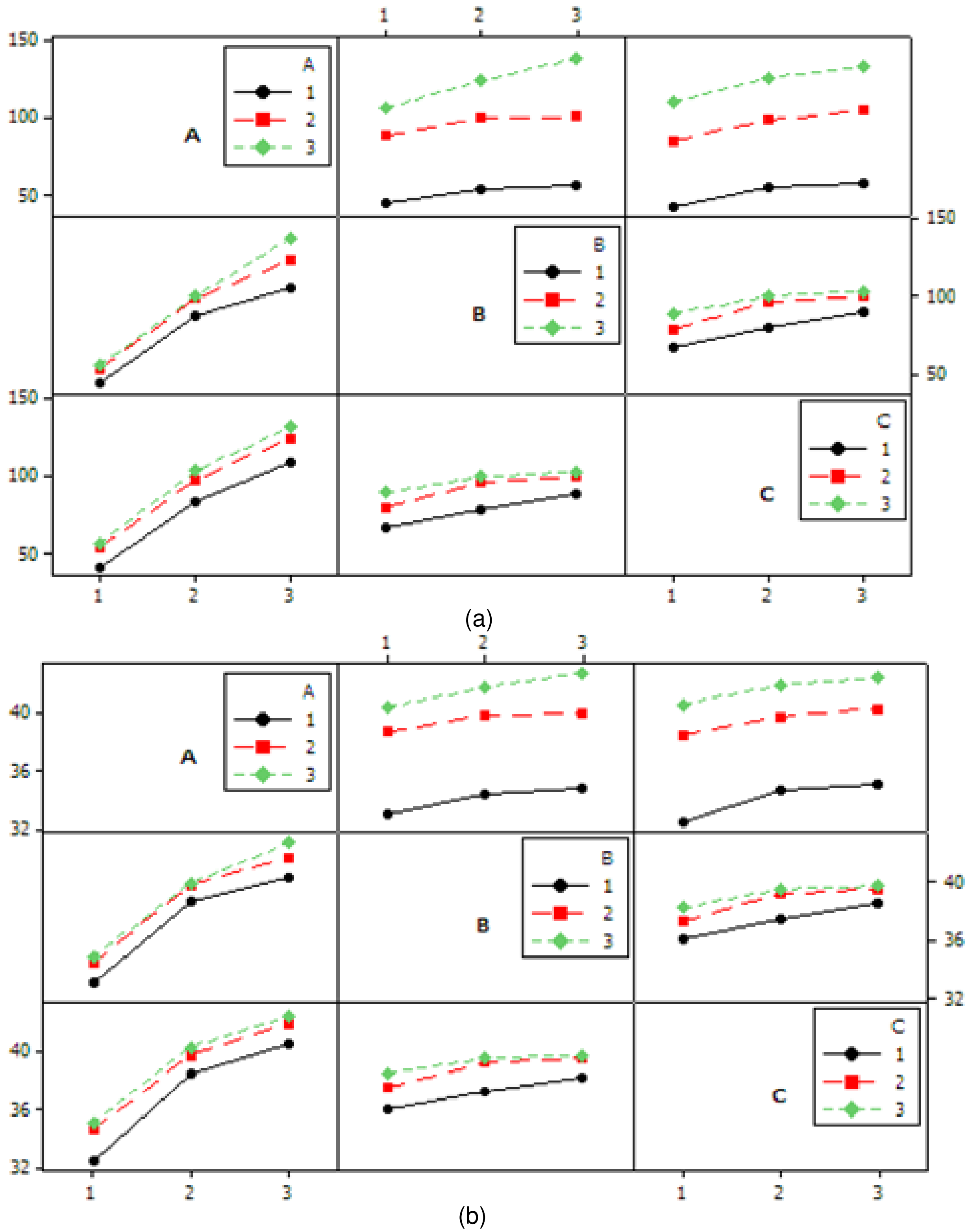


Figure 7. Full interaction plot for (a) mean value and (b) S/N ratio of production quantity for line 1.

the production cycle times and production quantity of lines 1 and 2 are displayed in Tables 6, 7, 8 and 9, respectively These tables show the relative importance of the control factors affecting WIP, cycle times and

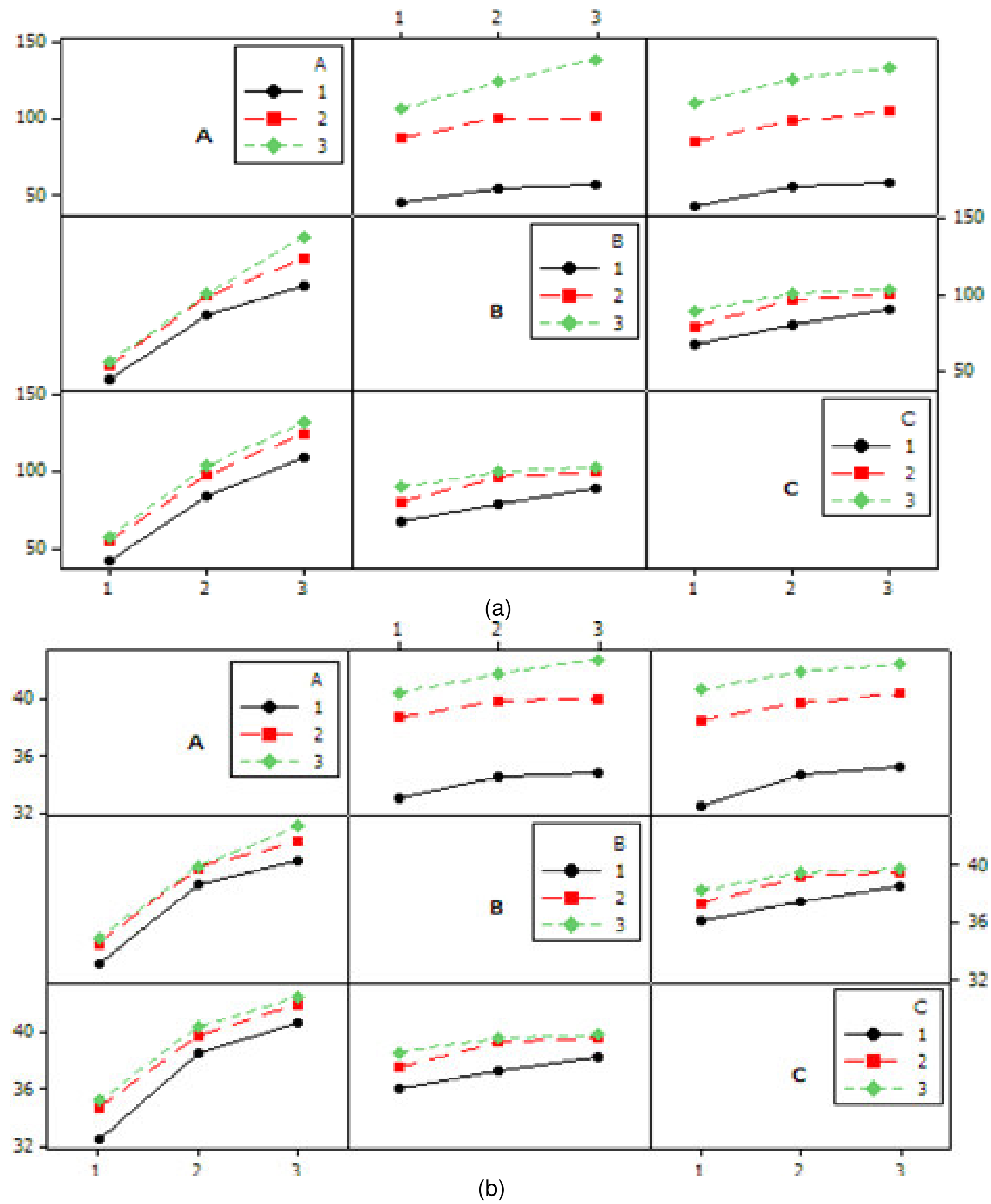


Figure 8. Full interaction plot for (a) mean value and (b) S/N ratio of production quantity for line 2.

Table 5. 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	20474.1	10237.1	68.38	0.000	5.7985	2.8993	73.16	0.000
B	2	1244.6	622.3	4.16	0.031	0.3358	0.1679	4.24	0.029
C	2	1284.8	642.4	4.29	0.028	0.3464	0.1732	4.37	0.027
Error	20	2994.2	149.7			0.7926	0.0396		
Total	26	25997.7				7.2732			
S = 12.2356; R-Sq = 88.48%; R-Sq(adj) = 85.03%						S = 0.199072; R-Sq = 89.10%; R-Sq(adj) = 85.83%			

Table 6. 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	15.3063	7.6531	244.05	0.000	1.78313	0.89157	232.69	0.000
B	2	0.6155	0.3077	9.81	0.001	0.07070	0.03535	9.23	0.001
C	2	0.4983	0.2491	7.94	0.003	0.05712	0.02856	7.45	0.004
Error	20	0.6272	0.0314			0.07663	0.00383		
Total	26	17.0472				1.98759			
S = 0.177086; R-Sq = 96.32%; R-Sq(adj) = 95.22%						S = 0.0619001; R-Sq = 96.14%; R-Sq(adj) = 94.99%			

Table 7. 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	15.3465	7.6732	244.86	0.000	1.78661	0.89330	233.34	0.000
B	2	0.6212	0.3106	9.91	0.001	0.07136	0.03568	9.32	0.001
C	2	0.5017	0.2509	8.01	0.003	0.05748	0.02874	7.51	0.004
Error	20	0.6267	0.0313			0.07657	0.00383		
Total	26	17.0962				1.99201			
S = 0.177022; R-Sq = 96.33%; R-Sq(adj) = 95.23%						S = 0.0618738; R-Sq = 96.16%; R-Sq(adj) = 95.00%			

Table 8. ANOVA for mean value and S/N ratio of production quantity of line 1.

Source	Mean value					S/N ratio			
	DF	SS	MS	F	P	SS	MS	F	P
A	2	23019.1	11509.5	301.44	0.000	274.383	137.192	527.47	0.000
B	2	1596.1	798.0	20.90	0.000	15.997	7.998	30.75	0.000
C	2	1769.4	884.7	23.17	0.000	21.417	10.708	41.17	0.000
Error	20	763.6	38.2			5.202	0.260		
Total	26	27148.3				316.999			
S = 6.17916; R-Sq = 97.19%; R-Sq(adj) = 96.34%						S = 0.509994; R-Sq = 98.36%; R-Sq(adj) = 97.87%			

Table 9. ANOVA for mean value and S/N ratio of production quantity of line 2.

Source	Mean value					S/N ratio			
	DF	SS	MS	F	P	SS	MS	F	P
A	2	23007.7	11503.8	298.99	0.000	273.251	136.626	522.05	0.000
B	2	1616.8	808.4	21.01	0.000	16.090	8.045	30.74	0.000
C	2	1763.8	881.9	22.92	0.000	21.284	10.642	40.66	0.000
Error	20	769.5	38.5			5.234	0.262		
Total	26	27157.8				315.859			
S = 6.20289; R-Sq = 97.17%; R-Sq(adj) = 96.32%						S = 0.511577; R-Sq = 98.34%; R-Sq(adj) = 97.85%			

throughputs. Both mean and signal to noise ANOVA indicates that batch sizes in lancing station (factor A), use of common component (factor B) and process (factor C) are statistically significant. The factors have very strong impacts on the measured performances of the system.

However, F-values for factors A, B and C exceeded the critical limits for mean and S/N ratio, respectively. This confirms that the variance effect of these factors is significantly different from the error effect. Hence, the variation in production quantity, cycle time and WIP level is truly accounted for by the change in the value of the factors (A, B and C) and the deviation due to the fact that the experimental errors are small. Consequently, these indicate that no important factor is omitted from the experiments.

Based on response tables (Table 4) and ANOVA (Tables 5 to 9), it is obvious that batch size of 12 in the lancing station (factor A in level 3), 2 common components (factor B in level 3) and 4 common processes (factor C in level 3) yield the lowest cycle time and WIP level and the maximum throughputs in the system.

Conclusions

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

(i) Batch size in the bottleneck (that is, lancing station) in combination of commonalities (parts and process) drastically improve the measured system deliveries. ANOVA for mean and S/N ratio for cycle time, WIP and throughput indicate that no important factor is omitted from the experiments.
(ii) There is a significant interaction among the commonalities (component and process) and the batch sizes in the bottleneck facility (that is, lancing station). Component and process commonality shows momentous dealings among them as well. It is observed that under the combined effects of commonalities (component and process), the WIP and cycle time reduced by 11 and 6%, respectively and throughputs increased by 137%.
(iii) Based on the manufacturing cycle time, WIP and system throughput, the batch size of 12 in the bottleneck (that is, lancing stations), 2 common components and 4 common processes ensure the best outcomes of the system under the storm of uncertainties.

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